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JEL Classification: F21, Q56

Keywords: FDI, Foreign acquisition, foreign divestment, energy intensity, Indonesia

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Good for the Environment, Good for Business: Foreign Acquisitions and Energy Intensity

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This version: June 2019

Abstract

The link between foreign ownership and environmental performance remains a controversial issue. This paper contributes to our understanding of this subject by analyzing the impact of foreign acquisitions on plant-level energy intensity. The analysis applies a difference-in-differences approach combined with propensity score matching to the data from the Indonesian Manufacturing Census for the period 1983-2001 (or 1983-2008 in robustness checks). It covers 210 acquisition cases where an acquired plant is observed two years before and at least three years after an ownership change and for which a carefully selected control plant exists. The results suggest that while foreign ownership increases the overall energy usage due to expansion of output, it decreases the plant's energy intensity. Specifically, acquired plants reduce energy intensity by about 30% two years after acquisition, relative to the control plants. In contrast, foreign divestments tend to increase energy intensity. At the aggregate level, entry of foreign-owned plants is associated with industry-wide reduction in energy intensity.

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1 Introduction

Foreign direct investment (FDI) has been a powerful force of convergence across countries. In addition to bringing capital and creating jobs, FDI stimulates economic growth by enhancing firm-level efficiency. It does so directly by transferring cutting-edge technologies and management practices to its affiliates (Arnold and Javorcik, 2009; Chen, 2011; Javorcik and Poelhekke, 2017) and encouraging product and process innovation (Guadalupe et al., 2012) as well as indirectly through knowledge spillovers (Javorcik, 2004; Havranek and Irsova, 2011).

The spectacular growth in FDI flows, along with the increasing importance of developing economies as host countries, has raised concerns about the potential effect of FDI on the natural environment (Zarsky, 1999). On the one hand, environmentalists argue that highly polluting multinationals relocate to countries with weaker environmental standards in order to circumvent costly regulations in their home country (Hanna, 2010; Millimet and Roy, 2015; Cai et al., 2016). In this way, they increase pollution levels not only in host countries but also globally.[1] On the other hand, supporters of globalization point to studies that fail to find evidence of multinationals in polluting industries being attracted to locations with weak regulations (Dean et al., 2009; Javorcik and Wei, 2004) and point out that FDI may have a positive effect on natural environment because multinationals tend to use more advanced technologies and production methods than their domestic counterparts.[2] Since the existing literature (reviewed below) has produced mixed results, the issue remains controversial (Kellenberg, 2009; Cole et al., 2017).

This study contributes to our understanding of the link between FDI and environmental protection by taking a novel approach. Rather than examining whether FDI flows are influenced by environmental standards in the destination countries or whether polluting industries are more likely to engage in FDI, we examine the impact of foreign acquisitions on energy consumption and carbon dioxide (CO_2) emissions of acquired plants.[3] We use plant-level panel data from the Indonesian Manufacturing Census covering the period 1983-2001 (or 1983-2008 in a robustness check). To investigate the impact of foreign acquisitions on plant performance, we combine a difference-in-differences approach with propensity score matching, where matching is done within industry-year cells. This allows us to account for selection on observables and unobservable time-invariant plant heterogeneity and for confounding factors that affect both domestic and foreign-owned establish-

[1] Anecdotal evidence abound. For instance, in 2013, the smoke haze from Indonesia's palm oil production, which was dominated by foreign investors, elevated to dangerous levels and caused significant health hazards not only in Indonesia, but also in Malaysia and Singapore (Chachavalpongpun, 2013).

[2] Rondinelli and Berry (2000) list a number of examples showcasing how multinationals and their affiliates help improve the environmental condition of their host country. Blackman and Wu (1999) use survey results to demonstrate that FDI plants outperform their Chinese counterparts in terms of energy efficiency, largely due the use of advanced efficiency-enhancing generation technologies.

[3] A foreign acquisition takes place when a firm headquartered abroad buys a significant stake (of at least 10%) in a domestic firm in order to assume partial or full control over it. This case is distinct from 'greenfield investment'– a foreign direct investment where a parent company establishes an entirely new facility.

ments within the same industry in the same year. To the best of our knowledge, this study is the first to employ such an approach in determining the effect of foreign ownership on plant-level environmental performance.

The ideal measure of a plant's environmental performance is the total amount of pollution the plant emits at a particular time period, principally because it accounts for (potentially) different pollution abatement technologies applied by different firms. However, getting data on plant-level emissions across periods remains extremely difficult, particularly in developing countries. This is the reason why a number of studies resort to approximations of environmental performance using plant-level expenditures on pollution-emitting inputs such as energy (see, for example, Eskeland and Harrison, 2003; Cole et al., 2008a; Barrows and Ollivier, 2014, 2018). Building upon this literature, we approximate plant-level environmental performance by considering energy usage in physical units and converting it into CO_2 emissions using standard conversion factors specific to each type of energy input.

We can observe fuel switching because the dataset includes plant-level expenditures (in Rps) and physical usage (e.g., in metric tons or liters) of each energy input. The energy inputs consist of fuels and lubricants and electricity. Fuels and lubricants are divided into more detailed inputs, which include gasoline, diesel, diesel oil, kerosene, lubricant, bunker oil, coal, coke, public gas, liquefied petroleum gas (LPG), firewood, and charcoal. We have information on the amount of fuels and lubricants that are used for electricity generation, as some of the plants produce electricity for their own consumption and for sale to other end users. With this information, any reallocation to lower-carbon inputs is captured in our emission measure.[4]

Our analysis is based on 210 foreign acquisition cases where an acquired plant is observed two years before and at least three years after an ownership change and for which a carefully selected control plant exists. The results suggest that, while foreign ownership increases total energy use and carbon dioxide (CO_2) emissions in acquired plants due to expansion of the production scale, it lowers the energy and emission intensity of output. The reduction in energy use relative to output is nontrivial, ranging from 26% in the acquisition year to 30% two years later. These results are robust to different matching and estimation procedures, a longer time horizon, accounting for the potential effect of markups, and taking into account competitive pressures from foreign affiliates within the same local market. They are also robust to extending the sample time period to 1983-

[4] A global pollutant, such as CO_2, may be of lesser interest compared to local pollutants (e.g., particulate matter and sulfur dioxide). Nonetheless, CO_2 is extremely difficult to abate. This was particularly true in Indonesia during our sample period, which would make our energy and emissions measures a close approximation of total CO_2 emissions. To date, there are three kinds of fossil-fuel-based carbon abatement technologies: (1) higher efficiency conversion processes; (2) fuel switching to lower carbon alternatives; and (3) carbon capture and storage (CCS). Differences in combustion efficiency are already captured by differences in plant-level total energy usage, on which we have information. It is also unlikely that the CCS technology was available in Indonesia during our sample period, as the first wave of feasibility studies for CCS in the country were conducted in early 2003 to 2005 (Best et al., 2011).

2008. While this extension allows us to consider more acquisition cases, it comes at the price of less disaggregated data on fuel usage, which is why we focus on the shorter time period in the main analysis.

We also find that the reduction in fuel intensity takes place immediately after the ownership change, while the reduction in electricity intensity happens more slowly and is somewhat less pronounced. Our results also indicate that plants with different initial energy intensity benefit from acquisition differently. In particular, plants with higher energy intensity (possibly smaller and less efficient plants) tend to reduce their energy and emission intensities more than those that are already less energy intensive. This finding might explain why previous literature on the relationship between foreign ownership and plant-level energy intensity produced mixed results (see, for example, Eskeland and Harrison, 2003; Cole et al., 2008a).

To shed light on the channels through which foreign ownership leads to improvements in energy efficiency we bring in an additional dataset and demonstrate that our conclusions hold even if we restrict attention to plants with next to no changes in the output mix and when we control for contemporaneous changes in output. In other words, we eliminate the possibility that foreign ownership works solely through changes to the production structure or the scale channel. Our findings are thus very suggestive of foreign acquisitions being associated with improvements to the production process taking place through introduction of better technologies and better management.

In an additional exercise, which is quite novel relative to the existing literature, we consider foreign divestments, i.e., sales of foreign affiliates to domestic owners. We find that such divestments are accompanied by an increase in energy and emission intensities as well as a decline in output. The increase in energy use relative to output is quite substantial, reaching 29% two years after the ownership change. This finding is consistent with the conclusions of Javorcik and Poelhekke (2017) who show deterioration in performance after foreign divestments and conclude that the productivity advantage associated with foreign ownership result from continuous injections of knowledge and management practices from the parent company.

In a motivating exercise conducted at the aggregate level, we find that energy and emission intensities in Indonesian manufacturing as a whole improved by 31% from 1983 to 2001. We show that at the industry level the decline in the aggregate weighted energy intensity is positively associated with the increased presence of foreign affiliates. The improvement seems to be driven by both within-plant reduction in energy intensity as well as reallocation of market shares towards more energy-efficient producers.[5]

[5]As we employ data on FDI inflows to Indonesia, our results capture the impact of FDI flows from (mostly) developed countries to a developing economy. While there is no reason to believe that FDI from developing regions to developed regions would reduce energy intensity, it would be interesting to know if energy intensity would also decline when FDI come from developing countries with about the same level of environmental stringency. Our dataset, unfortunately, does not provide information on source countries to shed light on this issue.

Our paper contributes to the literature examining how foreign ownership influences plant-level environmental performance. Within this broad literature, there are very few papers that study firm's actual energy use or pollution emissions, and the evidence is still mixed. Pargal and Wheeler (1996) use information on plant-level emissions of water pollution, measured in terms of biological oxygen demand (i.e., kilograms of oxygen needed over 5 days to completely oxidize the organic pollutants emitted), which was collected by the Indonesian Environment Ministry's PROKASIH (Clean Rivers) program for 1989-90. After controlling for plant scale, age and efficiency, they find that foreign ownership does not have a significant effect on water pollution emissions. Their results rely on cross-sectional data and thus capture correlations rather than a causal effect. Eskeland and Harrison (2003) examine plant-level data from Cote d'Ivoire, Mexico and Venezuela and find that the energy share, i.e., the cost of energy use divided by the total value of the plant's output, is negatively related to foreign ownership. Although the authors control for plant demand for other inputs and some plant characteristics, data limitations prevent them from controlling for plant fixed effects. Their results should be interpreted as correlations. Cole et al. (2008a) use plant-level data from Ghana and find no strong evidence of foreign ownership influencing total energy use. Instead, and perhaps correlated with foreign ownership, plants with foreign-trained managers are found to have lower energy intensity. Again, the study is unable to take into account unobservable plant heterogeneity and captures correlations. Albornoz et al. (2009) employ a cross-section of approximately 1,200 firms in Argentina and find a positive correlation between foreign ownership and implementation of environmental management systems.[6]

Our paper extends this literature in several ways. First, we take into account selection into foreign ownership, i.e., the possibility that foreign investors choose to acquire local plants with better environmental performance, and thus our results come much closer to capturing a causal effect of foreign ownership. Second, we work with panel data and hence we are able to take into account unobservable plant heterogeneity and examine the stability of the estimated effects over time. Third, we are also able to measure energy use in physical units and provide a more detailed analysis on the types of fuel used.

Our work also makes a contribution to the relatively new literature examining the effects of foreign acquisitions on the acquired plants. This literature relies on propensity score matching combined with a difference-in-differences approach (Arnold and Javorcik, 2009; Chen, 2011; Wang and Wang, 2015; Bircan, 2019) or uses inverse probability of treatment weighting (Guadalupe et al., 2012) to address selection into foreign ownership. We use the former methodology, which is well established in this literature, but focus on a completely different outcome. While the existing studies focus

[6] In a related study, Cole et al. (2011) consider per-capita emissions of pollutants in 112 major Chinese cities during the 2001-4 period. They find that the share of output of foreign-owned firms increases emissions while output of firms from Hong Kong, Macao, and Taiwan either reduces pollution or has no effect. The aggregated nature of the data (city level) makes it difficult to draw conclusions about the effect of foreign ownership on firm-level environmental performance.

on plant-level total factor productivity, export and import intensity, profitability and innovation, we aim to capture plant-level environmental performance by examining plant-level energy intensity and CO_2 emission intensity. These outcomes have not been considered by the existing studies.

The rest of the paper is organized as follows. Section 2 provides background information on Indonesia and on why multinational owners are more likely to invest in energy efficiency. It also describes how we measure energy usage and emissions. Section 3 presents motivation for our analysis: an industry-level exercise demonstrating correlations between energy efficiency and the presence of foreign owned plants. Section 4 discusses our empirical approach to understanding the link between FDI and plant-level energy intensity. In section 5, we present the main results from our analysis. Section 6 deepens the analysis by looking at changes in use of individual energy inputs, channels through which foreign ownership may affect energy efficiency and nonlinear effect arising from different pre-acquisition energy intensity. Section 7 examines the effects of foreign divestments. Section 8 concludes by considering potential policy implications of our findings.

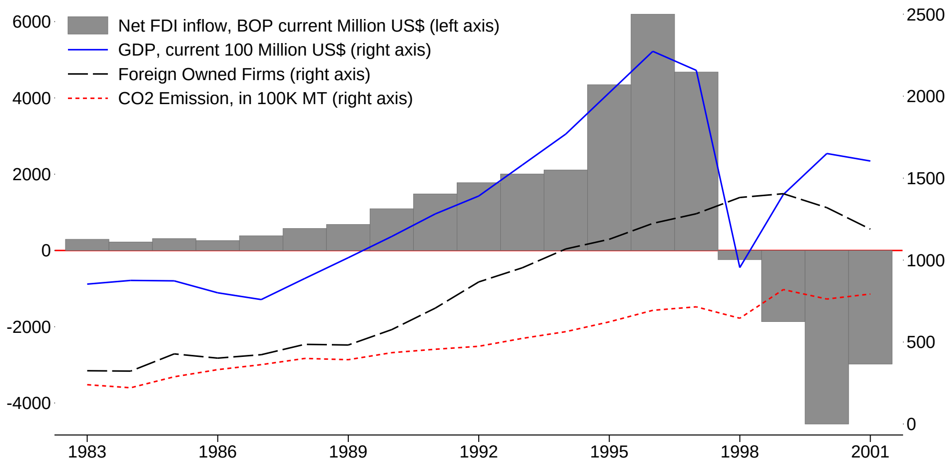
2 Background Information

2.1 Overview of Indonesia

Indonesia is a suitable setting for studying the effects of foreign acquisitions on plant-level energy efficiency. This is for two reasons. First, the country received significant inflows of FDI, ranking as the 5^{th} largest recipient of FDI among developing countries in the mid 1990s (see Arnold and Javorcik, 2009). The influx of FDI was in part driven by significant reductions in trade barriers and industrial deregulation in the early 1980s and 1990-1996. The period of high capital inflows also coincided with economic recessions in the United States, Japan and some European countries. During this period, competing FDI destinations, such as Thailand, experienced a rise in labor cost and had limited infrastructure, which may have prompted investors to reallocate their portfolios to other emerging economies, including Indonesia. Second, as pointed out by Garcia et al. (2007), environmental protection in Indonesia was generally weak and ineffective during the country's impressive industrial growth in the 1980s and 1990s. Thus, the results of our analysis will not be influenced by pollution-related policies in the host country and will give us a cleaner picture of the impact of FDI on plant performance in terms of energy efficiency.

Figure 1 illustrates Indonesia's net FDI inflows, Gross Domestic Product (GDP), CO_2 emissions and the number of foreign-owned plants from 1983 to 2001. The vertical bars represent the net FDI inflows from balance-of-payment statistics measured in million US$, the solid line indicates the country's GDP in 100 million US$, the dashed line is the number of foreign-owned plants (calculated based on the Census of Manufacturing) and the dotted line is the CO_2 emissions in 100,000 metric tons (based on Oak Ridge National Laboratory data). The graph shows an upward trend in all the variables, with the number of foreign plants picking up in 1984, followed by the GDP and net FDI flows increasing around 1987. Interestingly, the GDP increased at a much faster pace than did emissions, suggesting that emissions per dollar unit of output may have declined during the period. Both the GDP and FDI inflows experienced a significant decline following the 1997-1998 Asian financial crisis.

Figure 1: Indonesia's Net FDI inflows, Gross Domestic Product, CO_2 Emissions and Foreign-Owned Firms, 1983-2001.



Sources of Data: The World Bank, Oak Ridge National Laboratory, Indonesian Census of Manufacturing

2.2 Why would we expect foreign acquisitions to improve energy efficiency?

Improvements in energy use amongst plants can be achieved through different methods, ranging from those that call for little or no investment to obtain immediate paybacks to those that would require a sizable commitment of capital funds. The low- or no-cost opportunities include installing energy-saving lighting options, influencing employee behavior by keeping employees informed about the plants' energy-efficiency goals and progress and recognizing them for their role in supporting these initiatives, and partnering with utility providers to identify appropriate procurement or demand-side management plans. Other channels that might entail some capital costs include introducing new technology (e.g., reducing process-heating costs by introducing waste-heat recovery technology) and improving mechanical performance by altering operation procedures of machinery or replacing old machinery with more energy efficient one. Plants may also implement environmental/energy management standards (e.g., ISO 14001). Other channels, which may require significant capital costs, include improving facility design, continuous research and development or hiring energy managers.

There are several reasons why foreign acquisitions may improve energy efficiency. First, foreign acquisitions tend to increase production volume by boosting productivity and facilitating access to foreign markets through the distribution network of the foreign parent (Arnold and Javorcik (2009)). This makes investments in improving energy efficiency more worthwhile as the sales base becomes large enough to cover the fixed cost of investment.[7]

Second, investments in energy efficiency amongst multinationals may be driven by factors inherent to companies involved in a global supply chain. For example, multinationals based in OECD countries may employ more energy-efficient and cleaner technologies in compliance with more stringent regulations or standards implemented in the region, compared with other companies in developing countries (Cole et al., 2008b). The use of these energy-efficient technologies and management practices may be passed on to their affiliates in developing countries to maintain their production standards and meet the requirements of their environmentally conscious export markets. These technologies and management systems can be also indirectly passed on to the affiliates' suppliers to maintain their global standards and reputation.

Third, investment in energy efficiency fundamentally involves decisions on higher initial capital costs and uncertain lower future energy costs at present values (Gillingham et al., 2009). Consequently, firm-level characteristics can be crucial in determining a firm's propensity to invest in improving energy efficiency (DeCanio and Watkins, 1998). Some domestic firms may under-invest in energy efficient technologies due to capital constraints or financial issues (Anderson and Newell, 2004). Information problems, such as shortsightedness and bounded rationality of management, may also force locally owned firms to resort to sub-optimal alternatives (DeCanio, 1993, 1998). In contrast, these issues are less serious for foreign affiliates as they generally dominate locally-owned firms in terms of investment (Arnold and Javorcik, 2009) and in international training and experience of decision makers within the firm (Cole et al., 2008a).

Fourth, superior management practices are widely believed to be a characteristic of multinational companies. And better management practices make it easier to introduce low-cost efficiency improvements described at the beginning of this subsection.

Anecdotal evidence supports the view that foreign affiliates tend to be more energy efficient than local plants. For instance, Byrne et al. (2014) report that multinational cement companies in Sub-Saharan Africa are more energy efficient than locally owned companies producing mainly for their local markets. The authors also find that locally owned firms have poorer access to knowledge on low-carbon technologies and have weaker incentives to innovate.

[7] This type of argument has been made by (Guadalupe et al., 2012) in the context of foreign ownership encouraging product and process innovation, and by (Barrows and Ollivier, 2014; Forslid et al., 2018) in the context of exporting encouraging better environmental performance.

2.3 Measuring energy usage and emissions

We use data from *Survei Manufaktur*, the Indonesian Census of Manufacturing conducted by the National Statistical Office (BPS). The data encompass all manufacturing plants with 20 or more employees on an annual basis since 1975. The census has detailed information on fuel and electricity use, both in terms of values and physical quantities.[8] The sample available to us spans the period from 1983 to 2001 covering about 40,000 plants with 300,400 plant-year observations.

The main advantage of our data is the availability of detailed information on plant-level expenditures and physical usage (e.g., in metric tons, kWh or liters) of each energy input. The energy inputs consist of fuels and lubricants and electricity. Fuels and lubricants are divided into more detailed inputs, which include: gasoline, diesel, diesel oil, kerosene, lubricant, bunker oil, coal, coke, public gas, liquefied petroleum gas (LPG), firewood, and charcoal. We also have information on the amount of fuel and lubricants used for electricity generation, as some of the plants produce electricity for their own consumption and for sale to other end users. The detailed information on the kind of energy inputs used will allow us to capture any reallocation to lower-carbon inputs that may be associated with ownership changes.

Our data set also includes information on the amount of electricity sold and the amount bought from the state-owned power company *Perusahaan Listrik Negara* (PLN) and from other independent power producers (non-PLN). When calculating the total energy usage, we use total electricity purchased less electricity sold. Recognizing that some of the plants were generating their own electricity, we also account for the total amount of fuel used to generate their own electricity.

The original data set includes 300,400 plant-year observations. 61,561 of these contain positive energy expenditure on a particular energy input but do not include the information on energy use in physical units. We impute the plant-level physical energy consumption using the following equation:

$$lny_{it} = \beta lnCost_{it} + ISIC_k + PROV_l + YEAR_m + u_{it} \tag{1}$$

where y_{it} is the physical measure of energy inputs (e.g., gasoline in liters) and $Cost_{it}$ is total cost of energy inputs (e.g., gasoline in '000 Rps). $ISIC$, $PROV$ and $YEAR$ are industry (ISIC 4-digit level), province and year fixed effects, respectively. We estimate this specification separately for each energy input.[9] In this way, we impute the usage of each energy input in physical units. Except for kerosene, the model explains more than 90% of the variation of energy use in physical units.[10]

The energy and emission content of each energy input (in British Thermal Units or BTUs) is

[8] The survey questionnaires and other relevant information about the dataset can be accessed online at `http://www.rand.org/labor/bps/statistik_industri.html`.

[9] Table B.1 reports the list of energy inputs as well as the goodness-of-fit from estimating equation 1.

[10] There are also observations where there are physical units but total cost is missing. We regard these observations as missing in the data.

calculated using conversion factors from reliable US agencies and institutions found in Table B.2.[11][12] When calculating CO_2 emissions, we take into account the mix of source fuels used to generate electricity in Indonesia. Namely, we used the conversion factors for electricity generated from bituminous and sub-bituminous coal – the primary source of electricity in the country.

The key variables of interest are energy intensity (defined in two ways) and emission intensity. Following Eskeland and Harrison (2003), we first define energy intensity as total expenditure on energy per 1000 Rps of real output. It is plausible that acquired firms, possibly due to greater reliance on international markets, use technologies that utilize more expensive but cleaner energy inputs. Thus, energy expenditure per unit of output may remain constant (or even increase) but actual energy use (in BTUs) per unit of output may decline. In order to address this issue, we also express energy intensity as the total physical energy use (in MBTUs) per currency unit of output. We repeat the same process to calculate a plant's emission intensity, which is defined as total carbon dioxide emissions (in kg CO_2) per currency unit of output.

3 Motivating Exercise at the Industry Level

To motivate our plant-level analysis we first describe the developments in the aggregate energy intensity for the entire Indonesian manufacturing sector during our sample period. We decompose these developments into changes in the unweighted average energy intensity and reallocation effects. Then we examine how aggregate energy and the two components are affected by the number of foreign affiliates participating in the local industry.

Following Olley and Pakes (1996) and Pavcnik (2002), we compile the aggregate energy intensity measure W_t, which is the average of the plants' individual energy intensities (i.e., energy expenditure/output) weighted by the plant's share in total manufacturing output s_{it}. We calculate W_t for the entire Indonesian manufacturing sector for each year t. Then we decompose the aggregate energy intensity into the unweighted aggregate energy intensity (i.e., the average energy intensity taken over all plants) and the covariance between plant's share of the entire sector's output and its

[11] British Thermal Unit (BTU) is a traditional unit of energy. The US Energy Information Administration interprets BTU as the amount of energy needed to heat one pound of water from 39 to 40 degrees Fahrenheit (EIA, 2011).

[12] A sample calculation of the energy usage of a plant using 100 barrels of diesel fuel at a certain time period is illustrated below:

$$\text{100 barrels diesel x } \frac{\text{5.825 million BTUs (MBTUs)}}{\text{1 barrel}} = \text{582.50 MBTUs}$$

We follow the same procedure for calculating CO_2 emissions (in kg CO_2). Using the same example above, we calculate the CO_2 emissions as below:

$$\text{582.50 MBTUs x } \frac{\text{71.80 kg CO}_2}{\text{1 MBTU}} = 41,845.04 \text{ kg CO}_2$$

Note that the conversion factors are time-invariant, which implicitly assumes that abatement cost is constant over time. Foreign firms may have resorted to more efficient conversion processes over time, which is not observed in the data.

energy intensity:

$$\underbrace{W_t = \sum_i s_{it}\, lnEIP_{it}}_{\substack{\text{Aggregate weighted}\\\text{energy intensity}}} = \underbrace{\overline{lnEIP}_t}_{\substack{\text{Unweighted average}\\\text{energy intensity}}} + \underbrace{\sum_i (s_{it} - \overline{s}_t)(lnEIP_{it} - \overline{lnEIP}_t)}_{Covariance} \tag{2}$$

where s_{it} is the share of plant i's output in the total manufacturing output at time t, $\overline{s}_t$ is the average output share, $lnEIP_{it}$ is firm i's log(energy expenditure/output), $\overline{lnEIP}_t$ is the average log(energy expenditure/output) over all plants in the sector.

A change in the first term (unweighted average energy intensity) captures within-plant improvements in energy intensity. The second term (covariance), if positive, indicates that more output is produced by more energy intensive producers. A change in the covariance captures the effects of reallocation of market shares and resources across firms with different energy intensity levels.

Our calculations show that aggregate energy intensity for the entire Indonesian manufacturing sector has declined by 31% in 2001 relative to the 1983 levels. We also find that the aggregate energy intensity is negatively associated with increases in foreign affiliates, particularly before the 1997 financial crisis, and net FDI inflows (see Figure 2).

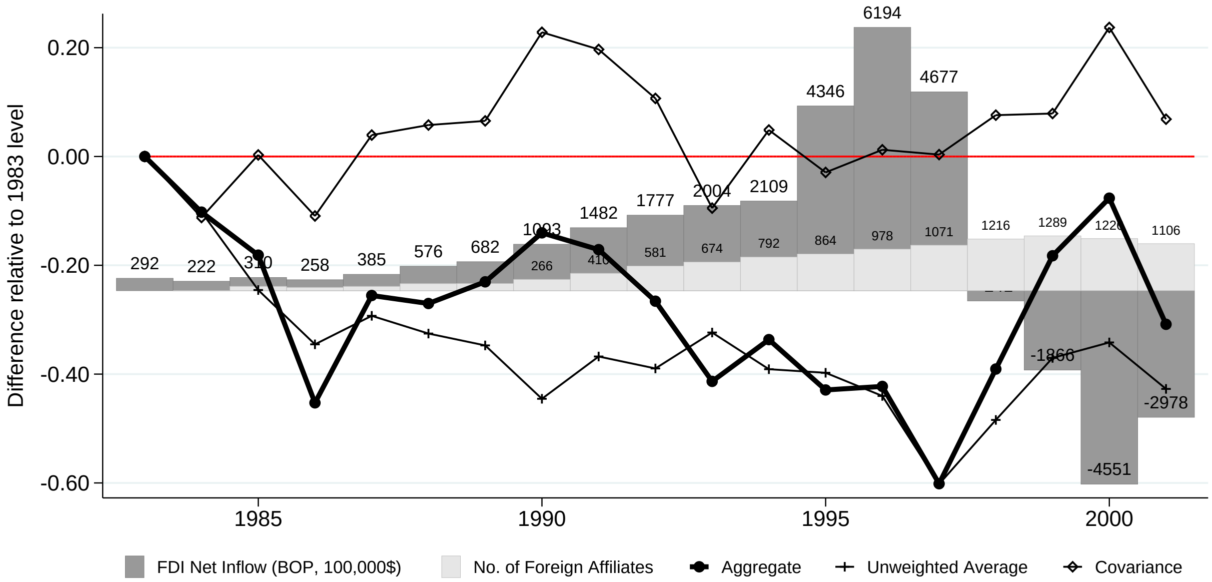
Given the strong downward trend of aggregate energy intensity as more foreign affiliates enter the market, it is natural to ask how changes in the number of participating foreign affiliates are associated with industry-wide aggregate energy intensity. To answer this question, we regress aggregate energy intensity and each of its components on the number of foreign affiliates in a particular industry. More specifically, we calculate the aggregate weighted energy intensity, unweighted average energy intensity and covariance at the 4-digit ISIC level. Then following Harrison et al. (2012) and Javorcik and Li (2013), we estimate the following equation:

$$Y_{jst} = \beta ForeignAffiliates_{jt} + \gamma_j + \lambda_{st} + \varepsilon_{jst} \tag{3}$$

where Y_{jst} is the aggregate energy intensity and its components relevant to 4-digit ISIC industry j operating in 2-digit ISIC sector s in year t and $ForeignAffiliates$ is the log-transformed number of foreign affiliates in the industry.[13] γ_j and λ_{st} are industry and sector-year fixed effects, respectively. We weight all observations using the maximum number of plants observed in each industry during the entire sample period to ensure that industries with large plant populations receive higher weight, which makes our result representative of the national level. We cluster standard errors at

[13] A foreign affiliate is defined as a plant with at least 20% of foreign equity. As some industry-year cells have no foreign affiliates, we add 1 to the number of foreign affiliates before transforming it into logarithm.

Figure 2: Aggregate energy intensity, its components and the number of foreign affiliates in the Indonesian manufacturing industry, 1983-2001.



Note: Aggregate energy intensity figures are relative to 1983 levels.
Source: No. of Foreign Affiliates (Indonesian Census of Manufacturing); Aggregate energy intensity measures (Authors' calculation); Net FDI Inflows (The World Bank).

the industry level.

To test the robustness of our result, we repeat the above regression using the share of foreign affiliates in the industry output as our indicator of foreign affiliates' participation in the market. We also look at the different aggregate measures of environmental performance, including energy and CO_2 emission intensities normalized either by output or by expenditure on materials (the latter to check for potential markup effects). Table 1 presents our results.

Our estimation results imply that participation of foreign affiliates is negatively associated with industry-level aggregate energy and emission intensities. This suggests that foreign affiliates' participation may be facilitating improvements in aggregate measures of environmental performance. We find that both within-plant improvement and reallocation towards bigger and less energy-intensive plants drive the improvement in aggregate energy intensities, though the impact on reallocation is not robust to measuring foreign affiliate presence in terms of output shares.

Table 1: Regression results: Decomposition of weighted aggregate energy intensity

	Measure based on number of FAs			Measure based on output share of FAs		
	W_t	$\overline{lnEIP}$	Covariance	W_t	$\overline{lnEIP}$	Covariance
Log (Energy Expenditure/Output)						
Foreign Affiliates	**-0.226*** **	**-0.086** **	**-0.140*** **	**-0.772* **	**-0.552** **	-0.219
	(0.041)	**(0.034)**	**(0.044)**	**(0.410)**	**(0.276)**	(0.318)
Adj. R-sq.	0.853	0.829	0.774	0.842	0.827	0.764
Observations	1408	1408	1408	1408	1408	1408
Log (Energy Use/Output)						
Foreign Affiliates	**-0.215*** **	**-0.070** **	**-0.146*** **	**-0.740* **	**-0.490* **	-0.250
	(0.039)	**(0.034)**	**(0.040)**	**(0.401)**	**(0.271)**	(0.336)
Adj. R-sq.	0.859	0.852	0.784	0.850	0.851	0.775
Observations	1408	1408	1408	1408	1408	1408
Log (CO2 Emissions/Output)						
Foreign Affiliates	**-0.217*** **	**-0.077** **	**-0.140*** **	**-0.761* **	**-0.521* **	-0.239
	(0.039)	**(0.035)**	**(0.040)**	**(0.405)**	**(0.277)**	(0.328)
Adj. R-sq.	0.853	0.834	0.783	0.844	0.833	0.775
Observations	1408	1408	1408	1408	1408	1408
Log (Energy Expenditure/Materials)						
Foreign Affiliates	**-0.254*** **	**-0.093** **	**-0.161** **	**-0.822* **	**-0.698** **	-0.125
	(0.061)	**(0.043)**	**(0.065)**	**(0.454)**	**(0.307)**	(0.381)
Adj. R-sq.	0.873	0.874	0.789	0.863	0.874	0.779
Observations	1407	1407	1407	1407	1407	1407
Log (Energy Use/Materials)						
Foreign Affiliates	**-0.243*** **	**-0.076* **	**-0.167*** **	**-0.788* **	**-0.628** **	-0.160
	(0.058)	**(0.041)**	**(0.060)**	**(0.444)**	**(0.299)**	(0.392)
Adj. R-sq.	0.881	0.882	0.804	0.872	0.883	0.794
Observations	1407	1407	1407	1407	1407	1407
Log (CO2 Emissions/Materials)						
Foreign Affiliates	**-0.244*** **	**-0.082** **	**-0.162*** **	**-0.804* **	**-0.657** **	-0.147
	(0.057)	**(0.041)**	**(0.060)**	**(0.450)**	**(0.301)**	(0.386)
Adj. R-sq.	0.877	0.872	0.805	0.868	0.873	0.796
Observations	1407	1407	1407	1407	1407	1407
No. of industries (4-digit ISIC)	79	79	79	79	79	79
No. of sectors (2-digit ISIC)	9	9	9	9	9	9
No. of years	19	19	19	19	19	19

Note: Period coverage is 1983-2001. Each regression includes 4-digit ISIC industry and 2-digit ISIC-year fixed effects. FA stands for foreign affiliates. Robust standard errors clustered at the 4-digit ISIC industry level are in parentheses. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

4 Main Analysis: Empirical Strategy

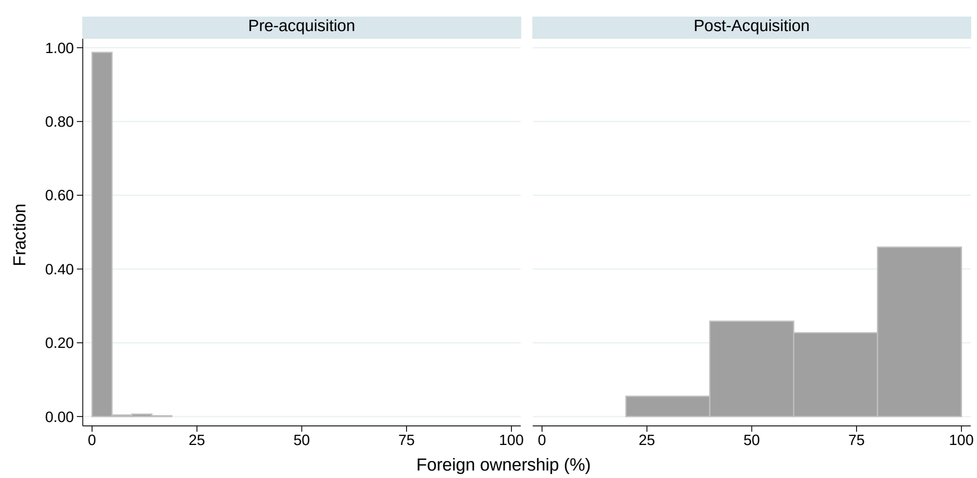
4.1 Identifying foreign acquisitions

Following Arnold and Javorcik (2009), we define a foreign acquisition as a change in the foreign ownership share from less than 20% to at least 20%. The exact value of the threshold does not affect our results because more than 99% of future acquisition targets have a foreign capital share equal to zero in the pre-acquisition period. And in 95% of the cases, the post-acquisition foreign ownership shares is at least 25%. In more than 75% of cases, it is at least 50% (Figure 3).

Acquired plants are distributed across a wide range of industries, but mostly concentrated in energy-intensive sectors. The main one is manufacturing of fabricated metal products, machinery and equipment which comprises 25.6% of the acquired plants in the sample data. 21.8% are involved in textile and wearing apparel industries, and 19.1% are in manufacture of chemicals and chemical, petroleum, coal, rubber and plastic products.[14]

The first three columns of Table 2 provides summary statistics for plants that have gone through a foreign acquisition and for plants that have always remained domestic. Acquired plants outperform domestic plants in terms of almost all the economic variables. For example, they are on average much bigger, employ a higher share of skilled labor, rely more on international markets and invest more in machinery. In terms of environmental attributes, they spend more on energy in absolute terms and emit more CO_2. Their production process is, however, less energy intensive and produces lower CO_2 emissions per unit of output.

Figure 3: Distribution of foreign ownership in acquired firms, 1983-2001.



Source: Indonesian Census of Manufacturing

[14]For more description on the distribution of acquired plants by industry and acquisition cases by year, see Figures A.1 and A.2 in the Appendix, respectively.

The empirical strategy used to identify the effect of foreign ownership on plant-level energy efficiency is anchored on three foundations. First, the study focuses on the changes from domestic to foreign ownership taking place within the same plant. In particular, we consider plants that are observed for at least five consecutive years and which have initially less than 20% foreign equity and at least 20% of equity belonging to foreign owners thereafter.[15] By focusing on ownership change we are able to take into account the selection bias that would plague a comparison of domestic plants to all foreign plants, due to the possibility that foreign affiliates may choose the most energy-efficient domestic plants. This approach, however, dramatically reduces the number of observations that can be considered. Fortunately, thanks to large FDI inflows into Indonesia during the sample period, we are able to observe enough acquisition cases to allow us to generalize the results with confidence.

Second, we use a difference-in-differences approach to compare the performance of foreign-acquired plants with the performance of plants remaining in domestic hands. This approach eliminates the influence of all unobservable elements of the acquisition decision that are constant or strongly persistent over time.

The main challenge is how to develop a reasonable estimate of the counterfactual, that is, the change in the variables of interest that would have been observed had the acquisition not occurred. It is well recognized that the estimates obtained by comparing a treatment group with the remainder of the population could be biased if the two groups have significant differences in pre-treatment observable characteristics (Dehejia and Wahba, 2002). As shown in the left panel of Table 2, the domestic plants are different from acquired plants even before they were acquired in almost all the aspects, including their output and energy consumption, suggesting that running a simple difference-in-differences may not yield an unbiased estimate of the impact of foreign acquisition on plant-level environmental performance.

Thus, third, in order to develop a reasonable counterfactual, we employ a one-to-one propensity score matching (PSM) (Rosenbaum and Rubin, 1983, 1985). That is, for each treated plant that will be acquired by foreign investors next period we identify a control plant with similar characteristics using the procedure developed by Leuven and Sianesi (2012). We ensure that each acquired plant is paired with a domestic plant that is operating in the same sector and year and has very similar output and energy intensity in each of the two years preceding the ownership change.[16]

[15] We focus only on the first ownership change within plant that meets these criteria. We are unable to observe whether the same foreign firm acquired multiple domestic plants.

[16] See Table 2 for a list of variables used in matching. Austin (2011) argues that there is a lack of consensus in the applied literature as to which variables should be included in the propensity score. There is merit in including only those that affect the outcome, and there is merit in including those that affect both the outcome and the treatment (Austin et al., 2007). However, a larger number of included variables, while deemed safe, tends to result in fewer matched pairs. This will be particularly true in our case, as there are many missing observations in certain baseline covariates. Therefore, we chose the variables that are strongly correlated with the outcome variables and which could bring the highest number of matched pairs while ensuring balance.

Matching within the industry-year cell ensures that we control for sector- and time-specific confounding factors that affect both domestic and acquired firms. We use a matching procedure with replacement. In robustness checks, we will also employ other methods, such as, coarsened exact matching (Iacus et al., 2011) and inverse propensity to treatment weighting (Hirano and Imbens, 2001).

The underlying assumption for the validity of the procedure is that conditional on the observable characteristics that are relevant for the acquisition decision, potential outcomes for the treated and control plants are orthogonal to treatment status. Thus, we need to argue that both the treated and the control plants most likely faced the same business and regulatory environments, energy prices, sector-specific and macroeconomic shocks, and trends before the acquisition taking place. This is partly established by matching within the same industry-year cell. When we compare the sample means of the variables used in matching procedure between the treatment group (210 acquired plants) and the control group (210 domestic plants), we find that there is no statistically significant difference in the pre-acquisition period (see columns labeled "Matched sample" in the top panel of Table 2). It is even more comforting that, except for the share of imported materials, there is no significant difference between the means of variables not used in matching (presented in the bottom panel of the table). These observations suggest that our matching procedure has performed quite well in obtaining control units that are comparable to acquired plants on nearly all observed covariates.

We also assess whether our matched acquired plants are representative of all foreign acquisitions found in the data that fulfill the minimum criteria for data completeness. First, 210 matched plants comprise about 40% of 555 acquired plants in the sample. Second, the distribution of the 210 acquired plants across industries is roughly the same as that of the all acquired plants, except for the textile industry (see Figure A.3). This is because the textile industry is dominated by foreign-owned plants which makes it difficult to find a suitable domestic control plant for all acquisition cases within the same industry-year cell and within our specified caliper. Third, we find no statistically significant difference between the matched acquired plants and all acquisition cases in terms of the key variables used in matching, such as, energy expenditure/output at $t-1$ and $t-2$ and output at t-2 (see the right hand side panel in Table 2). There is also no statistically significant difference in terms of pre-acquisition employment, exporter status, share of imported inputs,CO_2 emission intensity as well as all the pre-acquisition trends considered. However, the matched acquisitions seem to operate at a somewhat larger scale in terms of output and hence total energy use and emissions in the pre-acquisition period.

Table 2: Balancing test for matched domestic and acquired plants.

Variables	Unmatched data (555 acquired vs 39,652 domestic)			Matched sample (210 treated vs 210 controls)			Matched vs unmatched Acquisitions (210 matched vs 555 all acquisitions)		
	Acquired	**Domestic**	**p-value**	**Treated**	**Controls**	**p-value**	**Matched**	**All Acquisitions**	**p-value**
Used in matching									
Log (Output)t-1	9.55	7.74	0.000	9.89	9.88	0.951	9.89	9.55	0.024
Log (Energy expenditure/output)t-1	-3.98	-3.82	0.005	-3.87	-3.83	0.752	-3.87	-3.98	0.302
Log (Output)t-2	9.82	7.79	0.000	9.74	9.74	0.997	9.74	9.82	0.602
Log (Energy expenditure/output)t-2	-3.93	-3.81	0.132	-3.93	-3.86	0.574	-3.93	-3.93	0.973
Unused in matching									
Log (Energy expenditure)t-1	5.59	4.00	0.000	6.02	6.04	0.868	6.02	5.59	0.005
Log(Energy use)t-1	8.51	6.96	0.000	8.95	9.00	0.779	8.95	8.51	0.005
Log (CO2 emissions)t-1	12.90	11.35	0.000	13.33	13.38	0.760	13.33	12.90	0.007
Log (Employment)t-1	5.04	4.12	0.000	5.18	5.29	0.338	5.18	5.04	0.143
Exporter dummy t-1	0.21	0.08	0.000	0.19	0.18	0.706	0.19	0.21	0.646
Share of imported materials t-1	0.27	0.08	0.000	0.26	0.19	0.050	0.26	0.27	0.641
Share of skilled workers t-1	0.21	0.14	0.000	0.24	0.22	0.291	0.24	0.21	0.034
Log(Investment in machinery)t-1	7.65	5.46	0.000	8.19	7.80	0.105	8.19	7.65	0.015
Log(Energy use/output)t-1	-1.06	-0.86	0.001	-0.94	-0.87	0.645	-0.94	-1.06	0.252
Log(CO2 emissions/output)t-1	3.33	3.53	0.001	3.44	3.50	0.612	3.44	3.33	0.332
Log(Energy exp./materials exp.)t-1	-3.08	-2.98	0.188	-2.87	-3.07	0.201	-2.87	-3.08	0.111
Δ Log (Output)t-1	0.19	0.05	0.000	0.15	0.14	0.893	0.15	0.19	0.578
Δ Log (Energy expenditure)t-1	0.17	0.06	0.032	0.21	0.17	0.644	0.21	0.17	0.619
Δ Log (Energy use)t-1	0.17	0.07	0.080	0.22	0.20	0.887	0.22	0.17	0.587
Δ Log (CO2 emissions)t-1	0.17	0.08	0.102	0.21	0.20	0.857	0.21	0.17	0.591
Δ Log (Energy expenditure/output)t-1	-0.02	0.01	0.593	0.06	0.03	0.684	0.06	-0.02	0.307
Δ Log(Energy use/output)t-1	-0.02	0.03	0.465	0.06	0.06	0.975	0.06	-0.02	0.296
Δ Log(CO2 emissions/output)t-1	-0.02	0.03	0.408	0.06	0.05	0.938	0.06	-0.02	0.299
Δ Log(Energy exp./materials exp.)t-1	-0.03	0.01	0.550	0.02	0.04	0.842	0.02	-0.03	0.549

Source: Indonesian Census of Manufacturing

After obtaining the matched pairs, we examine the effect of foreign acquisitions on outcomes of interest using a difference-in-differences approach. More specifically, we estimate the following equation on the matched sample which is observed in the pre-acquisition period and in one of the post-acquisition periods:

$$y_{it} = \alpha_i + \gamma Post_t + \beta(Post_t * Acquired_i) + \varepsilon_{it} \tag{4}$$

where i denotes plant and t is the year. We compare two periods, i.e., $t = T - 1$, $T + s$ where T is the acquisition year and s =0,1,2. A separate model is estimated for each s.

5 Results

This section presents the main results of the paper. We start by analyzing the influence of foreign acquisition on selected outcome variables in a simple OLS framework, ignoring the potential selection bias. Next, we present the results from estimating equation 4 using our matched sample. We then address a number of potential other concerns and perform a series of robustness checks to test the stability of our estimates.

5.1 OLS results

Before we go into the matching results, we perform a difference-in-differences estimation on the unmatched sample ignoring the selection bias and controlling only for 4-digit ISIC-industry-year fixed effects. The results, presented in Panel A of Table 3, show that acquired plants experience a large, persistent and statistically significant increase in output, accompanied by an increase in energy use (both in terms of expenditure and physical units) and CO_2 emissions. Meanwhile, there is also a substantial, persistent and statistically significant decline in energy cost of output and in CO_2 emissions per unit of output.[17]

In Panel B, we additionally control for unobserved time-invariant plant-level heterogeneity. Doing so effectively controls for pre-acquisition characteristics of acquired affiliates. The effect on the variables of interests remains the same, except that the magnitude of effect becomes smaller. This pattern suggests that there may be some unobserved non-random plant-level characteristics associated with acquisition decisions that are influencing the outcome variables. The results indicate that it is important to address selection bias in the analysis.

[17]The energy and emission content of each energy input (in British Thermal Units or BTUs) is calculated using conversion factors from reliable US agencies and institutions found in Table B.2. A sample calculation is found in footnote 12.

Table 3: Difference-in-differences on the unmatched sample.

	Panel (A)			Panel (B)			Panel (C)		
	Always domestic + acquired plants			Always domestic + acquired plants			Always domestic + matched acquired plants		
	t	t+1	t+2	t	t+1	t+2	t	t+1	t+2
Log(Output)	2.156***	2.339***	2.423***	1.034***	1.197***	1.245***	0.839***	0.974***	0.949***
Log(Energy Expenditure)	1.770***	1.938***	1.985***	0.766***	0.906***	0.916***	0.647***	0.763***	0.703***
Log(Energy Use, in MBTUs)	1.724***	1.913***	1.967***	0.712***	0.868***	0.891***	0.584***	0.721***	0.703***
Log (CO_2 Emissions)	1.743***	1.927***	1.971***	0.727***	0.878***	0.890***	0.621***	0.746***	0.721***
Log(Energy Expenditure/Output)	-0.347***	-0.373***	-0.414***	-0.249***	-0.269***	-0.323***	-0.194**	-0.214**	-0.266***
Log(Energy Use/Output)	-0.393***	-0.398***	-0.431***	-0.302***	-0.307***	-0.348***	-0.257***	-0.256***	-0.267**
Log (CO_2 Emissions/Output)	-0.374***	-0.384***	-0.428***	-0.287***	-0.297***	-0.349***	-0.220**	-0.230***	-0.248**
Log(Energy Expenditure/Materials)	-0.331***	-0.333***	-0.412***	-0.295***	-0.288***	-0.395***	-0.252**	-0.217**	-0.384***
Log(Energy Use/Materials)	-0.369***	-0.357***	-0.433***	-0.342***	-0.327***	-0.418***	-0.308***	-0.264***	-0.378***
Log (CO_2 Emissions/Materials)	-0.350***	-0.342***	-0.427***	-0.330***	-0.321***	-0.423***	-0.280***	-0.245**	-0.370***
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Sample Size	169,141 - 180,901			165,905 - 177,840			165,307 - 177,155		

Note: The table shows the results of a difference-in-differences analysis on the unmatched sample. The dependent variables are as listed in each panel. Each entry corresponds to a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. All panels include plants that have always been domestic. Panels A and B also include all domestic plants that have undergone foreign acquisitions. In Panel C only those acquired plants that are used in matching regressions are included. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

In Panel (C), we repeat the exercise from Panel (B) dropping the acquisition cases that are not included in our matched sample as described in Section 4. Doing so makes the estimated effects slightly smaller and somewhat less significant. This improves our confidence in the estimates because it indicates that there is little evidence of sample selection when it comes to which acquisition cases are included in the final matching exercise. If anything, focusing on the smaller sample will lead us to underestimate the effects of foreign acquisition on the variables of interest.

5.2 Results from the Difference-in-Differences on the Matched Sample

Perhaps the most transparent and intuitive way of presenting the impact of acquisition on plant-level environmental performance is through a graph where the outcomes for the matched domestic and acquired plants are placed side-by-side before and after the acquisition (see Figure 4). There is a number of features of the graph that are worth discussing. First, it appears that the matching procedure created a set of domestic and acquired plants that are very comparable to each other prior to the time of acquisition. Both groups display very similar paths two years prior to the ownership change. This comparability holds true across all variables of interest. Second, the paths start to diverge already in the acquisition year and the gap between the groups increases over the two subsequent years. Third, the figure suggests an increase in the use of energy, both in terms of value and physical units, and in CO_2 emission levels of the acquired plants. The increase in energy use and emissions is intuitive because these variables are positively associated with the expansion of output. However, acquired plants experience a substantial decrease in their energy consumption and emissions per unit of output relative to the plants that remain in domestic hands. The difference between energy and emission intensities of acquired plants and those of the control group gets larger over time.

The effect of foreign acquisitions is formally tested by estimating equation 4, and the results are presented in Table 4. The results suggest that the acquired plants experience a statistically significant increase in output relative to the control group already during the acquisition period.[18] The effect is sizeable as the acquired plants outperform the controls by 83.8 log points or about 131%.[19] The difference between the two groups increases to 101.3 log points or about 175% in the subsequent two years. This pattern is consistent with the findings of Arnold and Javorcik (2009) who looked at the effect on foreign acquisitions on the scale of production.

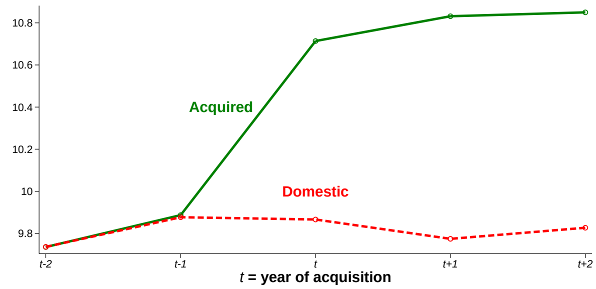
The expansion in output coincides with significant increases in energy consumption, both in terms of expenditure and physical units (measured in monetary terms or in MBTUs, respectively), although

[18] One of the reasons for this immediate effect is that foreign firms transplant their management practices to host countries (Bloom et al., 2012), and that just within months improvements in management practices translate into better performance (Bloom et al., 2013).

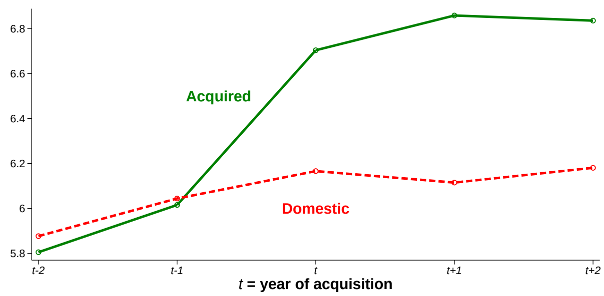
[19] The change in the variable of interest associated with the foreign acquisition dummy is calculated as $e^{(\beta)} - 1$. In this case, the change is $e^{(0.838)} - 1 = 1.311$.

Figure 4: Trajectories of output, energy expenditure and energy intensities: Matched acquired vs. domestic plants

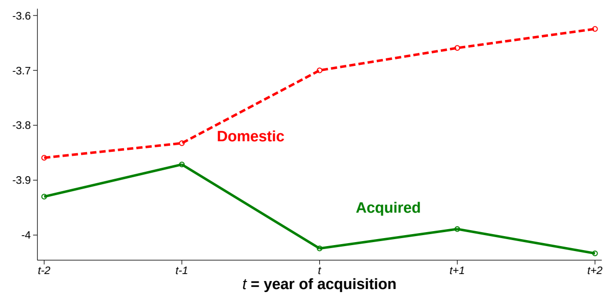
(a) Log(output)



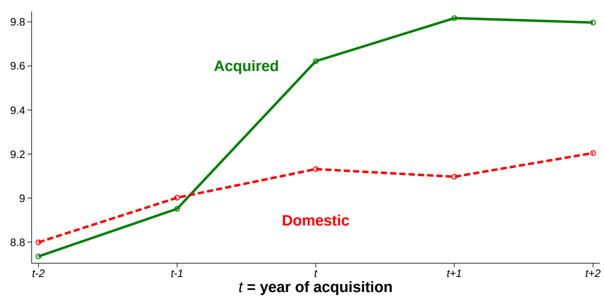
(b) Log(energy expenditure in Rps)



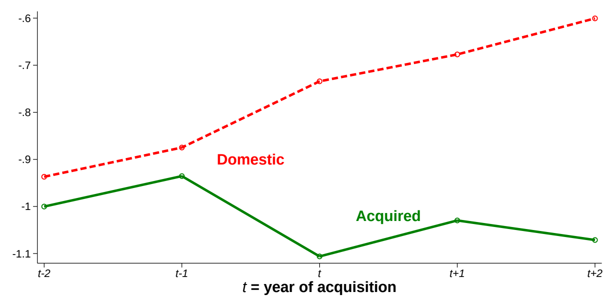
(c) Log(energy expenditure/output)



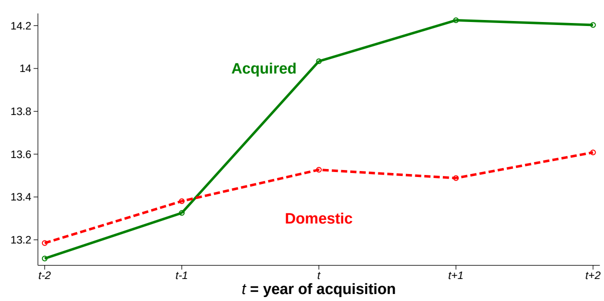
(d) Log(energy use in MBTUs)



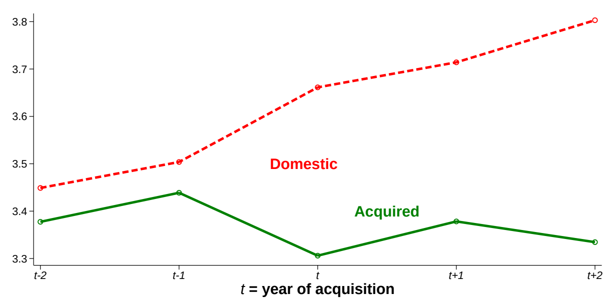
(e) Log(energy use/output)



(f) Log(CO_2 emissions in kg CO_2)



(g) Log(CO_2 emissions/output)



The figure illustrates the average value of each variable of interest in a given time period for the treated (acquired) and control (domestic) group. The horizontal axes indicate the year relative to the period t where treated plants are acquired.

Table 4: Difference-in-differences analysis on the matched sample.

	Acquisition Year	1 Year Later	2 Years Later
	Log(Output)		
Post*Acquired	**0.838*** **	**1.047*** **	**1.013*** **
	(0.113)	**(0.117)**	**(0.122)**
R-sq. (within)	0.203	0.240	0.229
No. of Obs.	840	840	840
	Log (Energy Expenditure in Rps)		
Post*Acquired	**0.567*** **	**0.773*** **	**0.705*** **
	(0.118)	**(0.126)**	**(0.132)**
R-sq. (within)	0.145	0.178	0.163
No. of Obs.	838	838	835
	Log(Energy Use in MBTUs)		
Post*Acquired	**0.539*** **	**0.770*** **	**0.664*** **
	(0.118)	**(0.130)**	**(0.136)**
R-sq. (within)	0.138	0.178	0.168
No. of Obs.	838	838	835
	Log (CO_2 Emissions)		
Post*Acquired	**0.562*** **	**0.792*** **	**0.673*** **
	(0.120)	**(0.130)**	**(0.137)**
R-sq. (within)	0.150	0.188	0.176
No. of Obs.	838	838	835
	Log (Energy Expenditure/Output)		
Post*Acquired	**-0.276** **	**-0.282** **	**-0.326** **
	(0.119)	**(0.118)**	**(0.127)**
R-sq. (within)	0.013	0.014	0.016
No. of Obs.	838	838	835
	Log (Energy Use/Output)		
Post*Acquired	**-0.304** **	**-0.285** **	**-0.367*** **
	(0.120)	**(0.125)**	**(0.137)**
R-sq. (within)	0.015	0.014	0.019
No. of Obs.	838	838	835
	Log (CO_2 Emissions/Output)		
Post*Acquired	**-0.282** **	**-0.262** **	**-0.357*** **
	(0.119)	**(0.124)**	**(0.136)**
R-sq. (within)	0.014	0.015	0.021
No. of Obs.	838	838	835

Note: The table shows the result of estimating equation 4 on the matched sample described in Section 4. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign affiliates were acquired. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. *Post* dummy and plant fixed effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

the latter effect is of a lesser magnitude. For example, energy expenditure increases by about 76% during the year of acquisition while the physical energy use goes up by 71%. CO_2 emissions follow the same trend although the estimated magnitude are smaller. It should also be noted that the increases in energy and emission levels are substantially smaller when compared to increases in output.

Next we focus on energy and emission intensities, which are obtained by dividing energy consumption (measured in monetary terms and in MTBUs) and CO_2 emissions by the total value of output. The estimated magnitudes are economically meaningful. They suggest that the share of energy cost in the total value of output falls in the acquired plants (relative to the control group) by 24% in the year after the acquisition with a further decline to 28% after two years. In terms of physical energy use, the acquired plants reduce their energy intensity by 26% during the acquisition year and by about 30% two years after. We find a similar pattern for CO_2 emission intensity. Overall, the results suggest that acquired plants tend to use less energy intensive and perhaps cleaner production techniques. The finding that CO_2 emission intensity and energy intensity decline at about the same rate suggests that the observed reductions in CO_2 emission intensity are merely a by-product of the acquired firms' effort to reduce overall energy use for privately appropriable reasons.

Below we subject our findings to a series of robustness checks.

5.3 Are our findings a result of increased local competition from foreign affiliates?

One may be concerned that increased competition resulting from entry of foreign affiliates may be influencing our results. For instance, acquired plants may increase competitive pressures on the control group by seizing some of their market share. This can lead to less energy efficient production processes in the control plants due to a smaller scale. Failure to account for this effect might lead us to overestimate the effects of foreign acquisitions on energy and CO_2 intensity.

To address this concern, we follow Javorcik and Poelhekke (2017) and adjust the matching procedure so that the matched acquired and domestic plants are located in different counties ("*kabupaten*"). In this way, we avoid the potential effects of competition in the local market which may confound our results. The estimates are presented in Table 5. They are very similar to our baseline findings. The reduction in energy and emission intensities remain negative and statistically significant.

Table 5: Difference-in-differences analysis on the matched sample: Accounting for potential spillovers of foreign affiliates to local competitors.

	Acquisition Year	1 Year Later	2 Years Later
	Log(Output)		
Post*Acquired	**0.829*** **	**1.037*** **	**1.008*** **
	(0.114)	**(0.116)**	**(0.123)**
R-sq. (within)	0.199	0.238	0.225
No. of Obs.	836	836	836
	Log (Energy Expenditure in Rps)		
Post*Acquired	**0.573*** **	**0.758*** **	**0.701*** **
	(0.118)	**(0.126)**	**(0.134)**
R-sq. (within)	0.145	0.173	0.161
No. of Obs.	834	834	831
	Log (Energy Use in MBTUs)		
Post*Acquired	**0.546*** **	**0.769*** **	**0.651*** **
	(0.119)	**(0.131)**	**(0.138)**
R-sq. (within)	0.137	0.176	0.165
No. of Obs.	834	834	831
	Log (CO_2 Emissions in kg CO_2)		
Post*Acquired	**0.560*** **	**0.785*** **	**0.653*** **
	(0.120)	**(0.132)**	**(0.140)**
R-sq. (within)	0.150	0.186	0.174
No. of Obs.	834	834	831
	Log (Energy Expenditure/Output)		
Post*Acquired	**-0.262** **	**-0.286** **	**-0.324** **
	(0.119)	**(0.119)**	**(0.128)**
R-sq. (within)	0.012	0.015	0.016
No. of Obs.	834	834	831
	Log (Energy Use/Output)		
Post*Acquired	**-0.288** **	**-0.276** **	**-0.374*** **
	(0.120)	**(0.126)**	**(0.139)**
R-sq. (within)	0.014	0.014	0.021
No. of Obs.	834	834	831
	Log (CO_2 Emissions/Output)		
Post*Acquired	**-0.275** **	**-0.259** **	**-0.372*** **
	(0.119)	**(0.124)**	**(0.138)**
R-sq. (within)	0.013	0.016	0.024
No. of Obs.	834	834	831

Note: The table shows the result of estimating equation 4 on the matched sample described in Section 4. Matched plants do not come from the same county or *kabupaten*. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign affiliates were acquired. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. *Post* dummy and plant fixed effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

5.4 Are our findings driven by increases in markups and pre-existing global value chain relationship?

It is possible that Indonesian producers acquired by foreign investors increase their markups and that higher markups are responsible for our finding of a lower energy intensity.[20] Although it would not invalidate our results, as after all energy usage per unit value of output is a meaningful outcome, it is still interesting to shed some light on this issue. Therefore, we normalize energy expenditure, physical energy use and emission level by the value of expenditures on material inputs. If our result is an artifact of changes in markups, then we would not expect to see foreign acquisitions affecting these redefined energy-intensity measures.

The results, presented in the top three panels of Table 6, show that our initial findings are robust to the alternative definition of energy and emission intensities. They show that acquired plants experience a reduction in energy costs per unit cost of materials relative to domestic plants. We also see similar declines in physical energy use and CO_2 emissions per unit cost of materials. The estimated decline is actually slightly larger than when output normalization was used.

Next we check whether pre-acquisition participation in global value chains influences the extent to which foreign acquisitions lead to increased energy efficiency. To do so, we interact $Post * Acquired$ with the pre-acquisition export share. Doing so has no impact on the acquisition effect, and the additional term is not statistically significant. Similarly, we interact $Post * Acquired$ with pre-acquisition share of imported inputs. The additional interaction terms is not statistically significant, while the overall effect of acquisitions increases in magnitude.

5.5 Robustness Checks

In this section, we subject our results to other sensitivity and robustness checks. In particular, we test whether our results hold if we exclude the period of the Asian financial crisis, include a longer time horizon, or employ a different matching procedures.

5.5.1 Excluding the Asian financial crisis

Another possible concern is that the effect of the 1997-1998 Asian financial crisis may be influencing our results. Some studies find that, thanks to access to financing from parent companies, foreign affiliates performed significantly better than domestic firms during the crisis (see, among others, Blalock et al., 2008; Alfaro and Chen, 2012). If that's the case, then the smaller scale of production in domestic establishments resulting in lower energy efficiency could be driving our findings. Failure to account for this effect might lead to biased estimates of the effect of foreign acquisition on output and consequently on energy consumption and CO_2 emissions.

[20] Javorcik and Poelhekke (2017) show that changes in ownership are associated with changes in markups.

Table 6: Difference-in-differences analysis on the matched sample: Accounting for potential markup and GVC effects.

	Acquisition Year	1 Year Later	2 Years Later
	Log(Energy Expenditure/Materials Expenditure)		
Post*Acquired	**-0.310****	**-0.266****	**-0.382****
	(0.123)	**(0.128)**	**(0.147)**
R-sq. (within)	0.021	0.011	0.018
No. of Obs.	808	810	807
	Log(Energy Use/Materials Expenditure)		
Post*Acquired	**-0.339*****	**-0.279****	**-0.426*****
	(0.124)	**(0.134)**	**(0.153)**
R-sq. (within)	0.024	0.011	0.019
No. of Obs.	808	810	807
	Log(CO_2 Emissions/Materials Expenditure)		
Post*Acquired	**-0.328*****	**-0.266****	**-0.428*****
	(0.124)	**(0.134)**	**(0.153)**
R-sq. (within)	0.020	0.010	0.020
No. of Obs.	808	810	807
	Log(Energy Expenditure/Output)		
Post*Acquired	**-0.275****	**-0.250***	**-0.358****
	(0.130)	**(0.128)**	**(0.140)**
Post*Acquired*Pre-acquisition export share	-0.000	-0.003	0.002
	(0.004)	(0.004)	(0.004)
R-sq. (within)	0.014	0.016	0.018
No. of Obs.	838	838	835
	Log(Energy Expenditure/Output)		
Post*Acquired	**-0.331****	**-0.309****	**-0.433*****
	(0.152)	**(0.152)**	**(0.154)**
Post*Acquired*Pre-acquisition share of Imported materials	0.154	0.053	0.363
	(0.330)	(0.316)	(0.366)
R-sq. (within)	0.019	0.018	0.024
No. of Obs.	838	838	835

Note: The table reflects the result of estimating equation 4 on the matched sample described in Section 4. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Heteroskedasticity-robust standard errors are in parentheses. *Post* dummy and plant fixed effects are included in all specifications. Panels 4 and 5 also include *Post*Pre-acquisition export share* and *Post*Pre-acquisition share of imported materials*, respectively. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

To address this concern, we dropped years beyond 1997 to avoid the effects of the Asian financial crisis which may confound our results. A graph showing the unconditional mean of the variables of interest after dropping the Asian crisis period and beyond for the matched treated and control plants are presented in Figure C.1. Pre-acquisition parallel trends in all outcome variables are still observed, as well as the divergence in the acquisition year and two subsequent years. Meanwhile, the estimates are presented in Table C.1. We still observe significant reduction in energy intensity during the acquisition year and two years after. The effects for the year following the acquisition, though still negative, are not statistically significant.

5.5.2 Longer time horizon

Our analysis so far has focused on a relatively short period and, due to missing values, the number of observations fluctuated between time periods. To further check the robustness of our findings, we extend the time horizon to six years under foreign ownership. This exacerbates the problem of missing values to a large extent because we now have fewer post-treatment observations for acquisitions taking place towards the end of the sample period. To maintain comparability across periods, we keep the sample constant; that is, we focus only on plants that have non-missing observations in all periods considered for all the outcome variables.

Table C.2 present the summary of the results. While the number of observations inevitably decreases, our result remain robust and consistent with our baseline estimation. Even if we control for the potential effect of increased local competition from foreign affiliates; that is, we restrict the control group to those plants that are situated in different countries or *kabupatens*, our results remain consistent with our baseline findings (see Table C.3).

5.5.3 Are our results dependent on a particular matching procedure?

We also test the robustness of our results to different matching procedures. In order to show this, we employ a one-to-one coarsened exact matching (CEM) procedure following Iacus et al. (2009) and Iacus et al. (2011).[21] A detailed procedure is presented in Appendix Appendix D and the results summarized in Table D.2. The results are qualitatively the same, with output, energy use and emissions increasing up to two years after the acquisition, while energy and emission intensities being significantly reduced. The treatment effects are notably larger in magnitude and more precisely estimated.

Another potential concern is that a one-to-one matching procedure requires us to drop many ob-

[21]The application of CEM is not without precedence. For example, Wang et al. (2010) use CEM to estimate the magnitude of spillovers generated by academic "superstars" to their collaborators' publication rates. Singh and Agrawal (2011) use the same matching technique to determine how firms are making use of their recruits' prior stock of ideas. Beatty and Tuttle (2015) employ CEM in studying the effect of the unprecedented increase in Supplemental Nutrition Assistance Program on participants' expenditure on food.

servations. To address this concern, we use the propensity score from the previous matching procedures to reweight observations in our difference-in-differences estimation (as, for instance, done by Guadalupe et al. (2012)). A detailed procedure is presented in Appendix E and the results summarized in Table E.1. Our results remain consistent with baseline estimates, suggesting that are findings are robust to changing the empirical approach.

5.5.4 Do our results hold in more recent data?

Another potential concern is the absence of more recent plant-level information, which may cast doubt on the applicability of our findings to a more recent time period. To address this concern, we extended our dataset up to 2008. Although this results in a larger number of acquisition cases considered, it comes at the price of much less disaggregated information on energy inputs. This is due to the fact that the post-2001 surveys aggregate some important energy inputs (such as, natural gas) into the ”other” category. This makes it impossible to estimate the total energy use in physical units and to convert it into CO_2 emissions. Although one could potentially ignore the natural gas usage, doing so would bias the estimates because the average share of natural gas in total energy use had been increasing since 1983. Moreover, other factors, such as, the 2008 global financial crisis, might confound our estimates for the more recent years.

Nevertheless, with these limitations in mind, we conduct several robustness checks using the extended dataset. The results confirm that foreign acquisition increase output much more than they increase energy expenditure, resulting in a decline in energy intensity. This effect is already visible in the acquisition year and remains statistically significant in the following five years (see Table E.2). Normalizing energy expenditure by cost of materials, thus controlling for potential changes in markups, does not affect these conclusions.[22]

In sum, we conclude that our findings can be generalized to a more recent time period.

6 Structural Change and Heterogeneous Effects

In this section, we deepen our analysis by looking at whether acquired plants undergo structural changes in their production processes, considering channels through which foreign ownership may affect energy efficiency and testing whether there exist heterogeneous effects among target plants with different pre-acquisition energy intensities.

[22]The balancing test for the extended data can be found in Table F.1. We fail to reject the null hypothesis that the mean difference between the domestic and acquired plants is zero for the variables we used in matching as well for the variables related to energy intensity (i.e., lagged energy intensity levels and trends).

6.1 Do acquired plants reallocate across energy inputs?

Do acquired plants change their mix of energy inputs? We investigate this question in Table F.3 which considers as outcome variables the plants' expenditures on major energy sources: fuel and lubricants, electricity (net of own generation), and their respective intensities. The left panel corresponds to results using expenditure-based measures, while in the right panel we consider energy consumption measured in physical units.

The results indicate that foreign ownership affects the plant's mix of energy sources. During the acquisition year, expenditures on fuel and lubricants in acquired plants increase by 39% relative to the control group with the gap increasing to almost 72% two years after. Meanwhile, consumption of electricity in acquired plants increases at a much higher rate, beginning at 114% during the acquisition period, then increases to 117% a year later before declining at 100% in the subsequent year. All of these changes are statistically significant. The results using energy use in physical units are almost identical and consistently significant.

As for energy intensity, we observe a significant reduction in the cost of fuel and lubricants per unit of output during the acquisition period. The acquired plants' fuel intensity declines by 34% during the acquisition period and by about 35% two years after. We also observe evidence suggesting a reduction in the electricity cost per unit of output due to foreign acquisition, although the estimates are less precise. The magnitude of reduction is also consistently lower than that of fuel and lubricants, which might suggest that the expansion in production associated with foreign acquisition is largely driven by increased consumption of electricity.

We conjecture that expansion of acquired firms is fueled mostly by electricity because of the relatively lower electricity rates prevailing in Indonesia compared to its neighboring countries. This conjecture is consistent with the findings of other studies suggesting that the kind of technology a firm will use to reduce emissions (either through pollution abatement or increasing energy efficiency) may be effectively influenced by policies that directly affect factor prices (see, for example, Khanna and Zilberman, 2001; Harrison et al., 2015). Indonesia's lower industrial electricity tariffs might also explain why a lot of FDI inflows into the country during the sample period were directed to electricity-intensive industries (e.g., manufacture of machinery). The low electricity tariffs are due to the country's generous subsidies (Mourougane, 2010).

We also test whether the acquired plants' reallocation are due to possible energy subsidies provided by the government to foreign investors or multinationals. In other words, we check if acquired plants faced lower fuel and electricity prices after the acquisition and in subsequent years. We find no evidence in favor of this view (see Table G.1).

6.2 Are our findings driven purely by economies of scale?

As we have shown, acquired plants tend to expand their production significantly after the acquisition. However, larger output can be associated with less energy per unit of output if there are economies of scale in energy use. Therefore, it is possible that the improvement in energy efficiency in the acquired plants stems purely from expansion of output, and thus are not necessarily specific to foreign acquisition.[23]

In order to address this concern, we examine the relationship between energy expenditure and output allowing for a different intercept and a different slope for the acquired plants.[24] More specifically, we estimate the following equation:

$$exp_{it} = \alpha + \beta_1(Post_t * Acquired_i) + \beta_2 y_{i,t-1} + \beta_3(Post_t * Acquired_i) * y_{i,t-1} + \gamma_i + \delta_t + \varepsilon_{it} \quad (5)$$

where exp_{it} is firm i's energy expenditure (in logarithm) at year t, $Acquired$ is foreign acquisition dummy as previously defined, $Post$ is the post-acquisition period, y is real output (in logarithm) and γ_i and δ_t are plant and year fixed effects, respectively. We cluster standard error at the plant level.

We estimate equation 5 using the full as well as the matched sample. We then plot the estimated relationship for varying lagged output levels to get the combined marginal effect of the regressors at different lagged output levels, while eliminating common-to-firms and year-specific factors that may confound the results. We do so separately for acquired plants and for plants that remained in domestic hands. The idea is that if energy intensity is all attributed to the scale effect, then we can expect the trajectory of energy use as output grows to be parallel between the two groups. In other words, we want to test whether foreign acquisition affects energy use, controlling for the effect of economies of scale.

Panels (a) and (b) of Figure G.1 illustrate the results from estimating equation 5 on the unmatched and the matched sample, respectively.[25] In both panels, the lines are clearly not parallel between the two groups. In particular, the acquired plants have flatter relationship compared to that of domestic plants suggesting a smaller increase in energy use as the output expands. Even if we choose comparatively similar domestic plants, energy expenditure for acquired plants rises at a significantly slower rate (see Panel b).

We also find evidence to support the view that domestic plants undergo structural changes once they

[23] Note, however, that even if the improvement in energy intensity were due to expansion of output, these economies-of-scale effect of foreign acquisitions would still lead to higher energy efficiency at the aggregate level. We will come back to this issue later in the paper.

[24] We also estimate a regression using contemporaneous output a regressor, taking note that this regression is subject to serious reverse causality issues. Notwithstanding, our results remain consistent with the baseline regression.

[25] For the detailed regression result, see Table G.2.

are acquired by foreign firms. In particular, we find that while acquired plants tend to increase both their capital stock and employment, they also tend to become more capital-intensive (see Table G.3). We do not observe strong evidence suggesting that acquired plants tend to invest more, although we see very strong and economically significant increase in purchases of machinery. The above observations, coupled with the fact that we see an indication of relatively higher reliance on electricity, suggests that our results cannot be just driven completely by the scale effect.

6.3 Are our findings driven purely by changes in the product mix?

It is possible that the improvement in energy efficiency observed in the aftermath of a foreign acquisition is due to changes in the mix of products produced by acquired plants. In other words, foreign owners could be increasing energy efficiency solely by shifting the output profile of the acquired plant towards less energy-intensive goods.

To shed light on this issue, we bring in new data that allow us to observe the value of production at the level of 5-digit ISIC products for each plant during the 1998-2008 period.[26] We use the new data to calculate the Hirschman-Herfindahl Index (HHI) of production concentration for each plant.[27] We then focus on plants with next to no change in the output mix (i.e., less than a 5% change in their HHI throughout the period considered) in the belief that such plants were unlikely to shift their production structure to cleaner products and examine whether we can still observe improvements in energy efficiency in these plants.

The new data also allow us to calculate the average energy intensity of each 5-digit ISIC product produced by Indonesian plants in years 2000-2008. We focus only on domestic plants, as we are interested in capturing energy intensity of the domestic production process. We choose not to use the years 1998 and 1999 because they were affected by the Asian crisis. In cases where no domestic plant produced a given product, we assign the average value for the 4-digit industry to the product.

We follow the same one-to-one propensity score matching as in our baseline analysis. However, our matching exercise is based just on plants with little change in the production structure (as defined above). We still match treated plants with control plants from the same industry-year cell. As shown in Table H.1, this process ensures that the treated and the control group are balanced in terms of output and energy efficiency in each of the two years prior to the ownership change. They are also balanced in terms of many characteristics not used in matching. In terms of energy intensity

[26] The time period covered by the new data is different from the period covered by our baseline estimation (1983-2001) because we were unable to get access to product-level information in earlier years. Moreover, our baseline analysis finishes in 2001 because the post-2001 surveys no longer report me important energy inputs (such as, for instance, natural gas) as a separate category. This makes it impossible to estimate the total energy use in physical units and to convert it into CO_2 emissions.

[27] The HHI is defined as the sum of squared product shares within each plant: $HHI_{it} = \sum_{k \in Kit} s_{kit}^2$, where s_k is the output share of product k produced by plant i in year t.

Table 7: Robustness check on additional data: Plants with little change in product mix.

	Log (Energy Expenditure/Output)		
	Acquisition Year	1 Year Later	2 Years Later
Post*Acquired	**-0.548****	**-0.528***	**-0.442***
	(0.276)	(0.285)	(0.254)
R-sq. (within)	0.036	0.033	0.035
Obs	222	222	222
	Acquisition Year	1 Year Later	2 Years Later
Post*Acquired	**-1.854*****	**-1.727****	**-1.503****
	(0.676)	(0.718)	(0.680)
Post*Acquired*log(Pre-acquisition predicted energy intensity)	0.023*	0.021	0.019
	(0.013)	(0.013)	(0.012)
R-sq. (within)	0.072	0.061	0.062
Obs	222	222	222
	Acquisition Year	1 Year Later	2 Years Later
Post*Acquired	**-1.590****	**-1.465****	-1.116
	(0.705)	(0.729)	(0.699)
Post*Acquired*log(Pre-acquisition predicted energy intensity)	0.019	0.018	0.014
	(0.013)	(0.013)	(0.012)
Log (Output)	-0.205	-0.179	-0.221
	(0.163)	(0.153)	(0.148)
R-sq. (within)	0.103	0.084	0.105
Obs	222	222	222
	All years	All years	ll years
Post*Acquired	-0.078	**-1.694****	**-1.516****
	(0.258)	(0.670)	(0.665)
Post*Acquired*log(Pre-acquisition predicted energy intensity)		0.021*	0.018
		(0.012)	(0.012)
Log (Output)			-0.119
			(0.087)
R-sq. (within)	0.025	0.048	0.062
Obs	444	444	444

Note: The table reflects the result of estimating equation 4 on the matched sample utilizing new data. Estimates are relative to pre-acquisition period. Each column in each panel is a separate regression for a particular outcome variable covering the two time periods. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. *Post* dummy, its interaction with pre-acquisition energy intensity and plant fixed effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

predicted by their output structure (defined as the product-specific energy intensity weighted by output shares), they appear to be slightly less energy efficient (with test p-values of 0.042 and 0.089 when the predicted energy efficiency is based on a continuous measure of product energy intensity and percentile of product energy intensity in the distribution for all products, respectively).

The results, presented in the top panel of Table 7, show a significant decline in energy intensity taking place after a foreign acquisition. The magnitudes are somewhat larger than those found in the baseline analysis. In the next panel of the same table, we allow for the impact of a foreign acquisition to differ based on the pre-acquisition energy intensity predicted from the plant production structure. This augmented model confirms the link between foreign acquisitions and improvements in energy efficiency. The pre-acquisition production structure does not appear to matter. In the third panel, we additionally control for contemporaneous changes in output aiming in this way to eliminate the possibility that scale effects are responsible for our findings. The results for the first two periods are robust but they cease to be statistically significant in the last period. As our sample in this exercise is based on a relatively small number of observations, in the lowest panel of the table we repeat all three specifications but pool together observations for all years.[28] The pooled regressions confirm our previous findings that foreign acquisitions are associated with a decline in energy intensity.

To summarize, the aim of this subsection was to shed light on the channels through which foreign ownership may lead better to energy performance. By focusing on plants with next to no changes to the output mix, we first eliminated the possibility that foreign ownership works solely through changes in the production structure. Then by controlling for the contemporaneous output we shut down the scale channel. The fact that we still found a positive impact of foreign acquisitions on energy efficiency is very suggestive of foreign acquisitions being associated with improvements to the production process taking place through the introduction of better technologies or better management.

In an unreported additional exercise, we checked whether foreign acquisitions in general resulted in shifting the output mix of acquired plants towards less energy-intensive products. We did not uncover any statistically significant patterns.

6.4 Pre-acquisition energy intensity

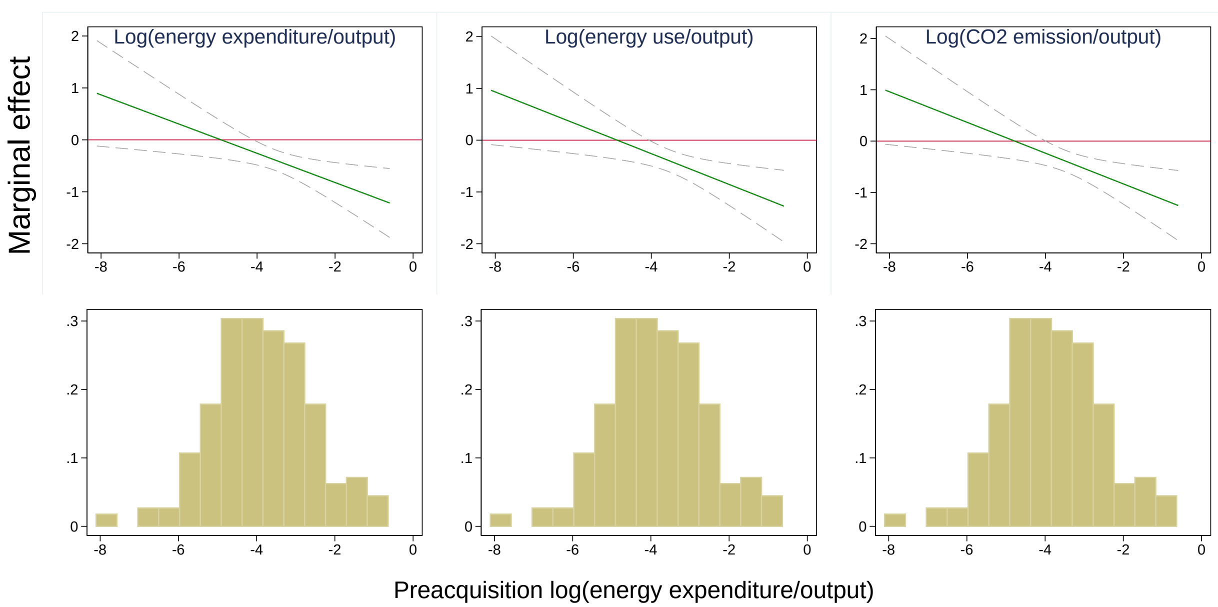
The evidence presented thus far suggests that foreign acquisitions lower energy consumption and emission levels per unit of output. Nonetheless, it is not obvious whether these effects are similar across all plants. It could be that the effect of a change in ownership on plant-level environmental performance is stronger for plants that were initially smaller and less energy efficient. In other words, the improvement in the production technique may be larger for plants that were initially

[28] Note that in each exercise in the previous panels, half of all the observations (N) pertain to the pre-acquisition period. Thus in the pooled exercise the total number of observations is not 3N but rather (3N+N)/2 = 2N.

further from the technological frontier.

To test this hypothesis, we estimate equation 4 augmented with an interaction term between the foreign acquisition dummy and the plant's actual energy intensity level in the pre-acquisition year. We focus on the period one year after the acquisition where we expect the treatment to have the most significant effect. The results are presented in Table 8 and are also plotted in Figure 5. In the figure, the solid line corresponds to point estimates, while dashed lines denote 95% confidence intervals. We observe that the magnitude of the decline in the cost of energy per unit of output is larger at higher levels of pre-acquisition energy intensity. This is also true of energy use and emissions per unit of output. These results indicate that relatively more energy intensive (and perhaps less efficient and smaller) plants tend to benefit more in terms of reducing energy use and emission intensities from foreign acquisitions. This finding might explain why previous literature had mixed results on the effect of foreign acquisitions on plant-level environmental performance (see, for example, Eskeland and Harrison, 2003; Cole et al., 2008a).

Figure 5: Effect of acquisition on energy and emission intensities at varying pre-acquisition energy intensities.



The figure illustrates estimated combined coefficients of foreign acquisition dummy and its interaction with pre-acquisition energy intensity in equation 4 using the matched sample. The dashed lines correspond to the 95-percent confidence interval. The period focuses at one year after the acquisition (i.e., $t + 1$) and estimates are relative to the pre-acquisition period.

Table 8: Matched difference-in-differences estimates: Testing for non-linear effect of acquisition at varying pre-acquisition energy intensity.

	Log(Energy Expenditure/Output)	Log(Energy Use/Output)	Log(CO_2 Emissions/Output)
Post*Acquired	**-1.759*** **	**-1.738*** **	**-1.643*** **
	(0.359)	**(0.382)**	**(0.358)**
Post*Acquired*Pre-acq. Energy Intensity	**-0.409*** **	**-0.392*** **	**-0.378*** **
	(0.092)	**(0.097)**	**(0.093)**
R-sq. (within)	0.213	0.191	0.185
No. of Obs.	814	814	814
Threshold	-4.30	4.43	-4.35
Pre-acq. Energy Intensity¿threshold			
(% share of treated plants)	60.48	68.57	64.29

Note: The table reflects the result of estimating equation 4 on the matched sample described in Section 4. The period is one year after the acquisition (i.e., $t+1$) and estimates are relative to pre-acquisition period. The dependent variables are as listed in each panel and expressed in logarithms. Each column in each panel is a separate regression for a particular outcome variable covering the two time periods Except for the dummy variables, all variables are in logarithm. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. *Post* dummy, its interaction with pre-acquisition energy intensity and plant fixed effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

7 Do Foreign Divestments Lead to Lower Energy Efficiency?

If foreign acquisitions lead to improvements in energy efficiency, it is not unreasonable to expect that foreign divestments (i.e., foreign affiliates being sold by their parents to local owners) would have the opposite effect. This would be consistent with the existing literature that finds that foreign divestments wipe out some of the benefits brought by foreign ownership. For instance, Javorcik and Poelhekke (2017) find that foreign divestments in Indonesia are associated with a drop in the total factor productivity and a decline in output, markups, as well as export and import intensities.

Javorcik and Poelhekke (2017) discuss the factors that can explain why divestments might take place. The first set of factors may results from shocks experienced by the parent company and its home country. The second set of factors relate to the whole network of subsidiaries belonging to the parent company and divestments may result from relative changes in growth rates, production costs, regulation and others in all countries where these subsidiaries operate. The third set of factors relate to the affiliate's characteristics and performance, which may be significant in terms of the level of uncertainties during the acquisition period or when coupled with certain events that influences the affiliate's profitability. Finally, divestments may occur as a result of shocks associated with buyer's purchasing behavior.

We consider the impact of losing a foreign parent on energy-related performance. We follow the same approach as before (see Section 4), but rather than focusing on foreign acquisitions we consider the cases of divestment. More specifically, we consider plants that had at least 20% of foreign equity and where foreign ownership dropped to less than 20% and remained below this threshold for at least three years. We compare the performance of these divested plants to the performance of the plants that remained in foreign hands. This is different from the previous analysis where our control plants are those that remain domestic. We perform this exercise first using the OLS and then focusing on the matched sample.

7.1 OLS results

The results of our difference-in-differences estimation on the unmatched sample, which ignores the selection bias and controls only for 4-digit-ISIC-industry-year fixed effects, are presented in Panel (A) of Table 9. The sample includes all divested foreign affiliates and all affiliates remaining under foreign ownership throughout. We find that divested affiliates experience a large, persistent, and statistically significant drop in output. The output shrinkage is accompanied by a decline in energy consumption and CO_2 emissions. More importantly from the perspective of our study, we observe a persistent and statistically significant increase in energy cost per output and emission intensity.

In Panel (B), we additionally control for unobserved firm heterogeneity to take into account pre-divestment characteristics of divested affiliates. The effects of divestment on output, energy and emission levels and intensities are all consistent with the previous estimation procedure. However, the magnitude of effect are uniformly smaller in magnitude, which indicates that it is important to address selection bias in the analysis.

in Panel (C), we repeat the exercise in Panel (B) but drop cases that are not included in our matched sample. Doing so makes the estimates slightly larger than in Panel (B), while maintaining the statistical significance. Nonetheless, these estimates are much smaller than those from Panel (A) where unobserved firm heterogeneity is not taken into account.

Table 9: Difference-in-differences on the unmatched sample: Divestments.

	Panel (A)			Panel (B)			Panel (C)		
	Always foreign and divested plants			Always foreign and divested plants			Always foreign and matched divested plants		
	t	t+1	t+2	t	t+1	t+2	t	t+1	t+2
Log(Output)	-1.248***	-1.254***	-1.248***	-0.490***	-0.501***	-0.497***	-0.540***	-0.544***	-0.536***
Log(Energy Expenditure in Rps)	-1.001***	-0.999***	-0.995***	-0.392***	-0.385***	-0.388***	-0.427***	-0.421***	-0.426***
Log(Energy Use in MBTUs)	-0.990***	-0.989***	-0.984***	-0.367***	-0.362***	-0.365***	-0.402***	-0.396***	-0.403***
Log (CO_2 Emissions)	-0.990***	-0.989***	-0.984***	-0.370***	-0.366***	-0.369***	-0.405***	-0.399***	-0.407***
Log(Energy Expenditure/Output)	0.227***	0.234***	0.234***	0.093***	0.108***	0.105***	0.104***	0.114***	0.104***
Log(Energy Use/Output)	0.238***	0.244***	0.245***	0.118***	0.131***	0.127***	0.130***	0.139***	0.127***
Log (CO_2 Emissions/Output)	0.238***	0.244***	0.244***	0.115***	0.127***	0.123***	0.127***	0.136***	0.123***
Log(Energy Expenditure/Materials)	0.243***	0.251***	0.254***	0.098***	0.113***	0.117***	0.119***	0.131***	0.126***
Log(Energy Use/Materials)	0.253***	0.260***	0.264***	0.124***	0.137***	0.141***	0.146***	0.157***	0.150***
Log (CO_2 Emissions/Materials)	0.253***	0.260***	0.264***	0.123***	0.135***	0.139***	0.145***	0.156***	0.149***
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Sample Size		22566-23926			22400 - 23807			21722-23039	

Note: The table shows the results of difference-in-differences analysis on the unmatched sample. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

7.2 Results from Difference-in-Differences on matched sample

We now turn to our difference-in-differences analysis on the matched sample. Here, we are able to analyze 256 divested plants (out of 597 divestment cases) for the period 1983-2001 that had carefully selected control plants within the 4-digit-ISIC-industry-year cell.[29] We follow the matching procedure in Section 4, resulting in a well-balanced matched sample even in variables that were not used in the matching (see the last panel of Table I.1).

The results are summarized in Table 10. We find that divested plants experience a drop in output relative to the control group. Output declines by 27% in the year of ownership change and the decline persists in the two subsequent years. In other words, divested affiliates would have seen a much faster increase in output had they remained foreign owned.

The decline in output is accompanied by an increase in energy cost per unit of output, starting with a 34% rise in the year of divestment and persisting in the two subsequent years. We observe the same pattern for physical energy use (in MBTUs) and CO_2 emissions per unit of output. We also note that the effect of divestment, while pointing in the opposite direction, is quite similar in magnitude to the effect of acquisition on energy and emission intensities.

We also normalize the energy use and emission levels using material expenditure to test for the possible effect of reduced markups. The idea is that divested plants may rely less on exports, which consequently would reduce their markups (Javorcik and Poelhekke, 2017). If this is the case, then we should expect to see a larger effect when we normalize energy and emission levels with a variable that is less likely to be influenced by markups. This conjecture finds some support in the data. We find that divestment causes a plant's energy expenditure (and use in MBTUs) per unit of material expenditure to increase by 46%. This effect persists in two years after the year of divestment. The pattern also holds for CO_2 emission levels when normalized by expenditures on materials.

Overall, these findings are suggestive of the deterioration in energy efficiency that may be due to the loss of headquarter services and foreign managers after the ownership change. It is also possible that after foreign divestment the plant is unable to use the same production process, perhaps due to licensing requirements or other restrictions related to protection of intellectual property rights.

[29] During our sample period, there were 1,174 plants that remained on foreign hands throughout.

Table 10: Difference-in-differences analysis on the matched sample: Divestments

	Divestment Year	1 Year Later	2 Years Later
		Log(Output)	
Post*Divested	**-0.318*****	**-0.397*****	**-0.313*****
	(0.081)	**(0.092)**	**(0.091)**
R-sq. (within)	0.030	0.038	0.035
No. of Obs.	1024	1024	1024
		Log (Energy Expenditure/Output)	
Post*Divested	**0.296*****	**0.406*****	**0.290****
	(0.099)	**(0.108)**	**(0.121)**
R-sq. (within)	0.021	0.035	0.016
No. of Obs.	1022	1022	1022
		Log (Energy Use/Output)	
Post*Divested	**0.296*****	**0.454*****	**0.258****
	(0.106)	**(0.119)**	**(0.126)**
R-sq. (within)	0.019	0.036	0.017
No. of Obs.	1022	1022	1022
		Log (CO_2 Emissions/Output)	
Post*Divested	**0.289*****	**0.453*****	**0.249****
	(0.106)	**(0.120)**	**(0.126)**
R-sq. (within)	0.019	0.036	0.018
No. of Obs.	1022	1022	1022
		Log(Energy Expenditure/Materials)	
Post*Divested	**0.382*****	**0.429*****	**0.369*****
	(0.111)	**(0.122)**	**(0.136)**
R-sq. (within)	0.030	0.040	0.029
No. of Obs.	1007	1003	1002
		Log (Energy Use/Materials)	
Post*Divested	**0.381*****	**0.478*****	**0.338****
	(0.118)	**(0.133)**	**(0.143)**
R-sq. (within)	0.027	0.040	0.030
No. of Obs.	1007	1003	1002
		Log (CO_2 Emissions/Materials)	
Post*Divested	**0.375*****	**0.476*****	**0.327****
	(0.118)	**(0.133)**	**(0.143)**
R-sq. (within)	0.027	0.041	0.033
No. of Obs.	1007	1003	1002

Note: The table reflects the result of estimating equation 4 on the matched sample described in Section 4, but focusing on divestments. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to divestment (as listed in each column) and a year before initially foreign-owned plants become domestic. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. *Post* dummy and plant fixed effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

8 Conclusions

This study contributes to literature by examining the effect of FDI on plant-level environmental performance. More specifically, it asks how foreign acquisitions influence plant-level energy and CO_2 emission intensities using data from the Census of Indonesian Manufacturing covering the period 1983-2001. Our analysis improves on the previous literature in three important respects. First, we focus on physical consumption of energy and carbon dioxide emissions, instead of relying on energy expenditure which is a less suitable proxy. Second, we examine the changes in ownership taking place within the same plant. This allows us to focus on changes in plant-level energy efficiency introduced by foreign ownership. Third, we also consider foreign divestments and demonstrates that they undo the positive effects of foreign acquisitions.

Our measure of pollution impact is far from perfect. The analysis is limited to global pollution (i.e., CO_2 emissions) and ignores the impact of FDI on local pollutants, which may be of greater interest when analyzing the impact of cross-country differences in local environmental regulations. Devising a close approximation of plant-level emissions of local pollutants is extremely challenging as it requires information on plant-level pollution abatement which is not available in our data set. Moreover, our analysis does not address the potential technological and management spillover effects of FDI on domestic plants or the possible outsourcing of the "dirty" part of the multinational to other sectors or other countries.

Despite these methodological imperfections, the data show remarkable plant-level operational changes associated with ownership changes. First, we see a positive and significant effect of a foreign acquisition on plant output, and consequently, its levels of energy use and CO_2 emissions. More interestingly from the perspective of the study is the second effect, namely, the improvement in the efficiency of using energy inputs due to FDI-induced innovations and investments. We see indications of falling energy use and emission intensities, which implies that each additional unit of output is produced with lower energy and CO_2 content. There is also an indication that foreign acquisitions are actually facilitating structural changes in production processes relating to energy use and emissions, suggesting that the improvement in energy use is not solely due to economies of scale or changes in the product mix. The opposite effects are observed when we analyze the effect of divestments on plant-level energy and CO_2 emission intensities.

At the aggregate level, we find that the entry of foreign affiliates is negatively related to industry-wide average energy intensity. It is possible that, besides the direct effects, increased foreign participation in the domestic market may also have an indirect effect on other plants' energy consumption and emission patterns. More future research is, however, needed to examine the developments in energy and emission efficiency spillovers in the aftermath of foreign acquisitions and divestments.

Our findings also provide a way to reconcile the conflicting results within the broad literature of foreign ownership and plant-level environmental performance. Our results indicate that the discrepancy between the findings of previous studies may be a consequence of failing to account for the initial energy intensity (or efficiency) levels of acquired plants. The impact of acquisition on more energy intensive domestic plants is found to be more significant and larger than on those that are already less energy intensive (and presumably more efficient) domestic plants. Moving forward, it would interesting to empirically investigate other dimensions influencing the heterogeneity of acquisition-induced effects on plant-level emissions.

The results of our study have broader implications, particularly in terms of promoting "green growth" in response to the threats of climate change and environmental degradation. More specifically, they suggest that FDI may serve as a channel for international transfer of environmentally-friendly technologies and practices, thus directly contributing to environmental progress.

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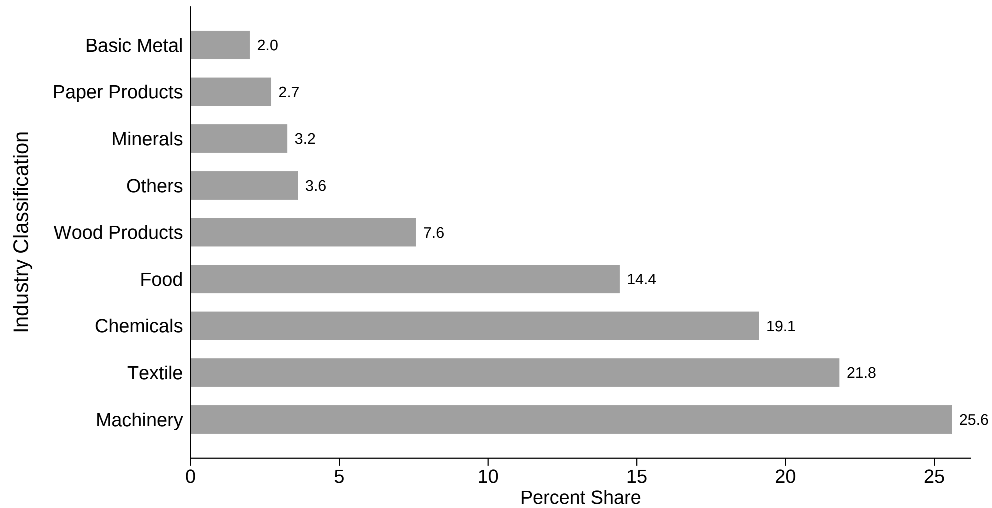
List of Appendices
(for Online Publication)

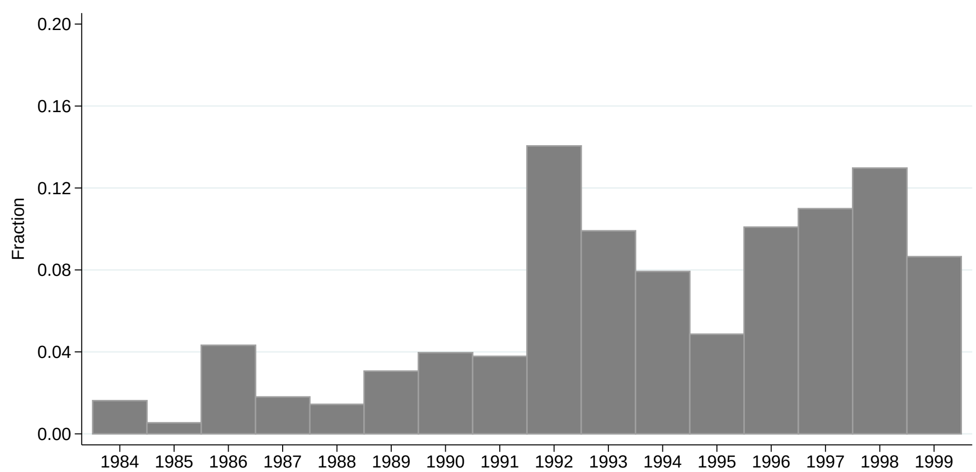
Appendix A Distribution of acquisition cases, matched and unmatched

Figure A.1: Distribution of acquired plants, by sector.



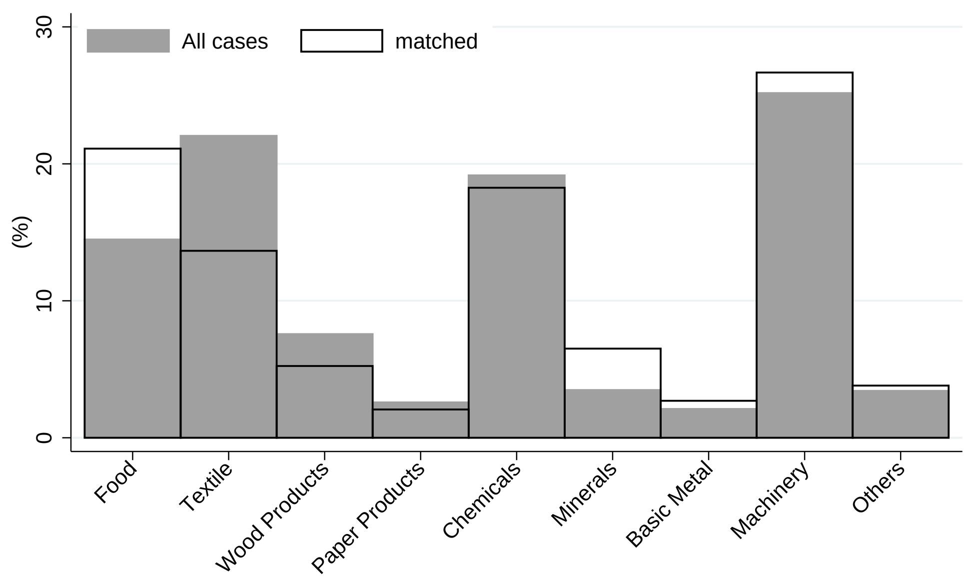
Note: Industry classification is based on International Standard Industry Classification (ISIC) Rev2 2-digit level.
Source: Indonesian Census of Manufacturing

Figure A.2: Distribution of acquisition cases, by year.



Source: Indonesian Census of Manufacturing

Figure A.3: Distribution of acquisition cases, matched vs. unmatched, by industry.



Source: Indonesian Census of Manufacturing

Appendix B Measuring Energy Use and Emissions, Conversion Factors

Table B.1: Goodness-of-Fit in estimating plant-level energy use (in physical units).

	Obs.	R.sq.	Adj. R-sq.	RMSE
Fuel and Lubricant (Total)				
Gasoline	140,744	0.993	0.993	0.144
Diesel	198,309	0.992	0.992	0.208
Diesel Oil	30,279	0.966	0.966	0.564
Kerosene	104,509	0.696	0.695	1.164
Lubricant	213,705	0.944	0.944	0.520
Bunker Oil	2,049	0.999	0.999	0.102
Coal	1,370	0.975	0.973	0.640
Coke	2,912	0.942	0.940	0.633
Public Gas	9,598	0.931	0.930	0.812
LPG	11,906	0.993	0.993	0.175
Firewood	9,089	0.990	0.990	0.218
Charcoal	1,460	0.988	0.987	0.236
Fuel and Lubricant (Elec. Generation)				
Gasoline	1,435	0.983	0.982	0.303
Diesel	37,683	0.987	0.987	0.285
Diesel Oil	2,538	0.966	0.965	0.580
Kerosene	317	0.981	0.974	0.449
Lubricant	22,606	0.972	0.972	0.357
Bunker Oil	179	0.996	0.995	0.258
Coal	29	0.997	0.988	0.401
Coke	6	1.000	.	-
Public Gas	93	0.991	0.983	0.402
LPG	110	0.985	0.969	0.488
Firewood	44	0.983	0.945	0.760
Charcoal	16	1.000	.	-
Electricity Use				
Sold	702	0.978	0.974	0.489
PLN	216,193	0.979	0.979	0.349
Non-PLN	5,022	0.974	0.974	0.465

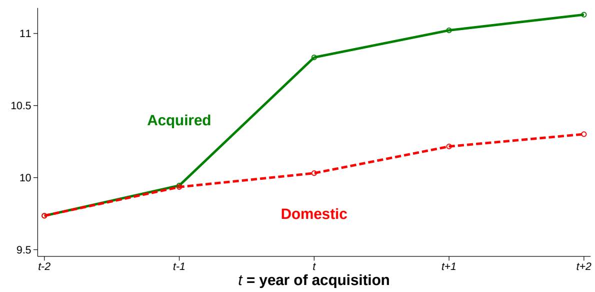
Note: The table reports the goodness-of-fit in estimating equation 1. Each variable is expressed in log. LPG denotes liquefied petroleum gas. PLN refers to amount of electricity bought from Indonesia's state-owned power company *Perusahaan Listrik Negar*, while non-PLN refers to those that are bought from independent power producers.
Source: Indonesian Census of Manufacturing

Table B.2: Sources of Conversion Factors

Conversion to Energy (in MBTUs)	
Gasoline	Silverman, D. (Univ. of California, Irvine)
Diesel	US Energy Information Administration
Fuel Oil/Bunker Oil	US Energy Information Administration
Kerosene	US Energy Information Administration
Lubricants	US Energy Information Administration
Coal	US Environmental Protection Agency
Coke	US Energy Information Administration
Public Gas	US Bureau of Mines
Liquefied Petroleum Gas	US Environmental Protection Agency
Firewood	Silverman, D. (Univ. of California, Irvine)
Charcoal	Oak Ridge National Laboratory
Electricity	US Energy Information Administration
Conversion to Carbon Dioxide (in Kg/C)	
Gasoline	US Energy Information Administration
Diesel	US Environmental Protection Agency
Fuel Oil/Bunker Oil	US Environmental Protection Agency
Kerosene	US Environmental Protection Agency
Lubricants	US Energy Information Administration
Coal	US Energy Information Administration
Coke	US Energy Information Administration
Public Gas	US Energy Information Administration
Liquefied Petroleum Gas	US Energy Information Administration
Firewood	Partnership for Policy Integrity
Charcoal	Akagi et al. (2011)
Electricity	US Environmental Protection Agency

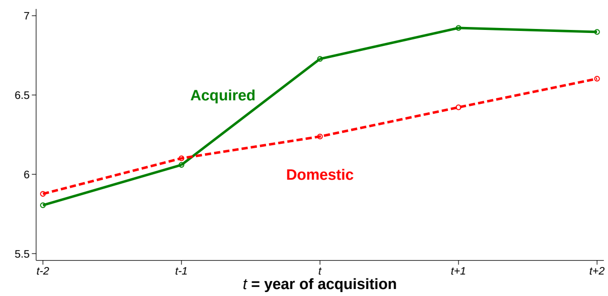
Appendix C Tables and Figures for Robustness Checks

Figure C.1: Trajectories of output, energy expenditure and energy intensity: Acquired vs. domestic plants, excluding post-1997 crisis.

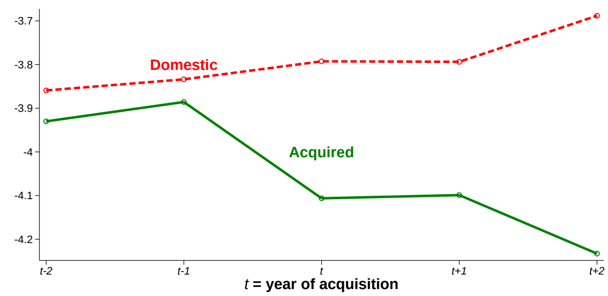


(a) Log(output)

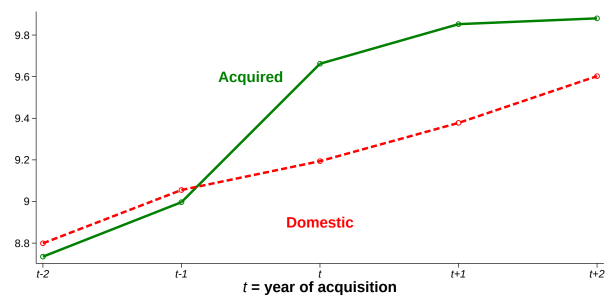
(b) Log(energy expenditure in Rps)



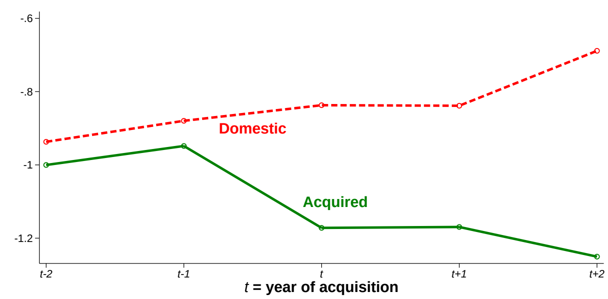
(c) Log(energy expenditure/output)



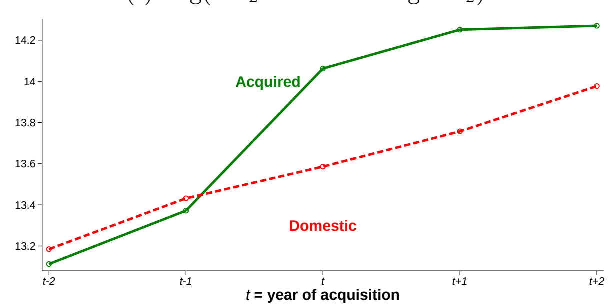
(d) Log(energy use in MBTUs)



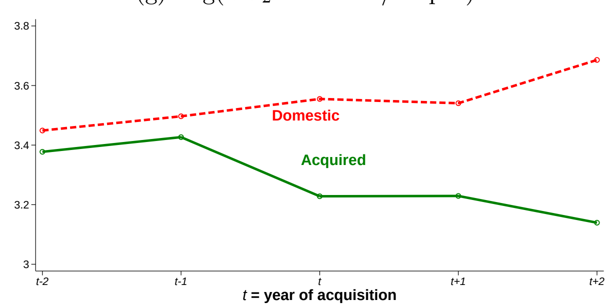
(e) Log(energy use/output)



(f) Log(CO_2 emission in kg CO_2)



(g) Log(CO_2 emissions/output)



The figure illustrates the average value of each variable of interest in a given time period for the treated (acquired) and control (domestic) group. The horizontal axes indicate the year relative to the period t where treated plants are acquired.

Table C.1: Matched difference-in-differences estimates: Excluding post-1997 financial crisis period.

	Acquisition Year	1 Year Later	2 Years Later
		Log(Output)	
Post*Acquired	**0.793*** **	**0.777*** **	**0.798*** **
	(0.125)	**(0.134)**	**(0.156)**
R-sq. (within)	0.236	0.281	0.291
No. of Obs.	714	654	614
		Log (Energy expenditure in Rps)	
Post*Acquired	**0.519*** **	**0.647*** **	**0.492*** **
	(0.133)	**(0.152)**	**(0.184)**
R-sq. (within)	0.134	0.174	0.136
No. of Obs.	714	654	613
		Log (Energy use in MBTUs)	
Post*Acquired	**0.486*** **	**0.597*** **	**0.474*** **
	(0.135)	**(0.156)**	**(0.182)**
R-sq. (within)	0.130	0.155	0.147
No. of Obs.	714	654	613
		Log (CO_2 emissions in kg CO_2)	
Post*Acquired	**0.494*** **	**0.601*** **	**0.473** **
	(0.136)	**(0.157)**	**(0.184)**
R-sq. (within)	0.142	0.167	0.158
No. of Obs.	714	654	613
		Log (Energy expenditure/Output)	
Post*Acquired	**-0.273** **	-0.130	**-0.310* **
	(0.131)	(0.130)	**(0.160)**
R-sq. (within)	0.019	0.012	0.031
No. of Obs.	714	654	613
		Log (Energy use/Output)	
Post*Acquired	**-0.307** **	-0.180	**-0.328** **
	(0.135)	(0.138)	**(0.166)**
R-sq. (within)	0.020	0.015	0.026
No. of Obs.	714	654	613
		Log (CO_2 emissions/Output)	
Post*Acquired	**-0.299** **	-0.176	**-0.329** **
	(0.133)	(0.137)	**(0.164)**
R-sq. (within)	0.017	0.011	0.022
No. of Obs.	714	654	613

Note: The table reflects the result of estimating equation 4 on the matched sample described in Section 4 but drops years after 1997. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. *Post* dummy and plant fixed effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Table C.2: **Constant sample over a longer time horizon.**

	Acquisition Year	1 Year Later	2 Years Later	3 Years Later	4 Years Later	5 Years Later
			Log(Output)			
Post*Acquired	**0.728*** **	**0.839*** **	**0.813*** **	**1.033*** **	**1.104*** **	**1.118*** **
	(0.135)	**(0.139)**	**(0.150)**	**(0.170)**	**(0.180)**	**(0.192)**
R-sq. (within)	0.247	0.316	0.281	0.299	0.292	0.278
No. of Obs.	462	462	462	462	462	462
			Log (Energy Expenditure in Rps)			
Post*Acquired	**0.430*** **	**0.593*** **	**0.500*** **	0.306	**0.420** **	**0.647*** **
	(0.152)	**(0.159)**	**(0.183)**	(0.198)	**(0.186)**	**(0.185)**
R-sq. (within)	0.124	0.184	0.141	0.138	0.206	0.221
No. of Obs.	454	454	454	454	454	454
			Log (Energy Use in MBTUs)			
Post*Acquired	**0.337** **	**0.542*** **	**0.429** **	0.227	**0.318***	**0.598*** **
	(0.151)	**(0.162)**	**(0.182)**	(0.200)	**(0.187)**	**(0.193)**
R-sq. (within)	0.112	0.166	0.149	0.153	0.208	0.200
No. of Obs.	454	454	454	454	454	454
			Log (CO_2 Emissions in kg CO_2)			
Post*Acquired	**0.314** **	**0.524*** **	**0.406** **	0.192	0.311	**0.589*** **
	(0.154)	**(0.164)**	**(0.184)**	(0.203)	(0.191)	**(0.194)**
R-sq. (within)	0.118	0.171	0.154	0.161	0.219	0.212
No. of Obs.	454	454	454	454	454	454
			Log (Energy Expenditure/Output)			
Post*Acquired	**-0.308** **	**-0.272** **	**-0.345** **	**-0.718*** **	**-0.675*** **	**-0.489*** **
	(0.134)	**(0.126)**	**(0.161)**	**(0.157)**	**(0.155)**	**(0.155)**
R-sq. (within)	0.025	0.024	0.019	0.087	0.084	0.037
No. of Obs.	454	454	454	454	454	454
			Log (Energy Use/Output)			
Post*Acquired	**-0.401*** **	**-0.323** **	**-0.416** **	**-0.797*** **	**-0.777*** **	**-0.537*** **
	(0.136)	**(0.135)**	**(0.164)**	**(0.168)**	**(0.164)**	**(0.164)**
R-sq. (within)	0.041	0.030	0.025	0.091	0.099	0.040
No. of Obs.	454	454	454	454	454	454
			Log (CO_2 Emissions/Output)			
Post*Acquired	**-0.424*** **	**-0.341** **	**-0.439*** **	**-0.832*** **	**-0.784*** **	**-0.547*** **
	(0.139)	**(0.136)**	**(0.166)**	**(0.172)**	**(0.168)**	**(0.165)**
R-sq. (within)	0.039	0.028	0.026	0.095	0.101	0.042
No. of Obs.	454	454	454	454	454	454

Note: The table reflects the result of estimating equation 4 on the matched sample described in Section 4 but ensures that the included plants have non-missing observations in each time period. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. *Post* dummy and plant fixed effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Table C.3: Constant sample over a longer time horizon (matching outside the same county).

	Acquisition Year	1 Year Later	2 Years Later	3 Years Later	4 Years Later	5 Years Later
			Log(Output)			
Post*Acquired	**0.707*** **	**0.827*** **	**0.803*** **	**1.039*** **	**1.126*** **	**1.090*** **
	(0.134)	**(0.136)**	**(0.149)**	**(0.170)**	**(0.179)**	**(0.192)**
R-sq. (within)	0.242	0.315	0.276	0.302	0.295	0.267
No. of Obs.	454	454	454	454	454	454
			Log (Energy Expenditure in Rps)			
Post*Acquired	**0.442*** **	**0.589*** **	**0.547*** **	**0.363* **	**0.495*** **	**0.714*** **
	(0.154)	**(0.159)**	**(0.186)**	**(0.201)**	**(0.188)**	**(0.189)**
R-sq. (within)	0.122	0.175	0.134	0.122	0.193	0.203
No. of Obs.	446	446	446	446	446	446
			Log (Energy Use in MBTUs)			
Post*Acquired	**0.354** **	**0.569*** **	**0.467** **	**0.268**	**0.392** **	**0.663*** **
	(0.153)	**(0.163)**	**(0.184)**	**(0.202)**	**(0.189)**	**(0.198)**
R-sq. (within)	0.109	0.163	0.141	0.136	0.195	0.183
No. of Obs.	446	446	446	446	446	446
			Log (CO2 Emissions in kg CO2)			
Post*Acquired	**0.328** **	**0.551*** **	**0.443** **	**0.232**	**0.381** **	**0.654*** **
	(0.156)	**(0.166)**	**(0.187)**	**(0.206)**	**(0.193)**	**(0.198)**
R-sq. (within)	0.115	0.167	0.146	0.144	0.206	0.195
No. of Obs.	446	446	446	446	446	446
			Log (Energy Expenditure/Output)			
Post*Acquired	**-0.275** **	**-0.263** **	**-0.287* **	**-0.667*** **	**-0.624*** **	**-0.394** **
	(0.134)	**(0.126)**	**(0.162)**	**(0.159)**	**(0.154)**	**(0.155)**
R-sq. (within)	0.020	0.024	0.014	0.077	0.072	0.023
No. of Obs.	446	446	446	446	446	446
			Log (Energy Use/Output)			
Post*Acquired	**-0.363*** **	**-0.284** **	**-0.368** **	**-0.763*** **	**-0.727*** **	**-0.444*** **
	(0.136)	**(0.133)**	**(0.165)**	**(0.169)**	**(0.163)**	**(0.165)**
R-sq. (within)	0.034	0.025	0.019	0.085	0.088	0.026
No. of Obs.	446	446	446	446	446	446
			Log (CO2 Emissions/Output)			
Post*Acquired	**-0.389*** **	**-0.302** **	**-0.392** **	**-0.798*** **	**-0.738*** **	**-0.454*** **
	(0.139)	**(0.134)**	**(0.167)**	**(0.173)**	**(0.167)**	**(0.166)**
R-sq. (within)	0.033	0.023	0.020	0.087	0.091	0.027
No. of Obs.	446	446	446	446	446	446

Note: The table reflects the result of estimating equation 4 on the matched sample (not belonging to the same province or *kabupaten*) described in Section 4 but ensures that the included plants have non-missing observations in each time period. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. *Post* dummy and plant fixed effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Appendix D Coarsened exact matching

Coarsened exact matching (CEM) procedure (Iacus et al., 2009, 2011), unlike propensity score matching that relies on estimating a scalar (i.e., the propensity score), is a nonparametric method used to identify a control group for the treated observations. In our context, this is helpful because we do not observe the pollution abatement technology each plant has, which we think could be a factor that can help predict the probability of a plant being acquired. While it has some advantages over propensity score matching (e.g. balance on selected covariates *ex ante*), it suffers from the "curse of dimensionality" where the proportion of matched observations decreases rapidly with the number of strata (Azoulay et al., 2010).

The first step in implementing CEM is to identify a set of covariates on which we can balance the treated (i.e. acquired plants) and the control (i.e. domestic plants) observations. In our context, we used the same set of covariates that we used in the propensity score matching in order to maintain comparability. Similar to our baseline matching procedure, we implement CEM in each year-industry cell, thus creating 1,415 bins. In each bin, we coarsen the joint distribution of the selected covariates, resulting in about 200 strata in each bin on the average (ranging from 3 to 604 strata). Within each stratum, we identify a control plant for each of the treated plants. If there are multiple choices, ties are broken randomly. In this procedure, we are to identify a control plant for 264 acquired plants.

The first 4 columns of Table D.1 show that our matched treated and control plants are well balanced in the set of covariates that we used in the matching procedure. Similar to our baseline matching procedure, we also evaluate CEM on potential "selection on observables" bias by looking at mean differences between treated and control plants on a covariates that were not used in matching. In all of these covariates, we find no statistically significant mean differences. Meanwhile, Table D.2 shows that our baseline estimate is consistent even if we use a different matching procedure.

Table D.1: Balancing hypothesis under various matching procedures.

Variables	CEM (N=418)			PSM (no same county) (N=440)			IPTW (N=143,216)	
	Treated	Control	p-value	Treated	Control	p-value	F-Stat	p-value
Used in matching								
Log $(\text{Output})_{t-1}$	9.03	9.03	0.99	9.86	9.86	0.90	4.43	0.04
Log $(\text{Energy Expenditure/Output})_{t-1}$	-3.71	-3.71	0.99	-3.82	-3.82	0.65	0.80	0.37
Log $(\text{Output})_{t-2}$	9.59	9.62	0.90	9.86	9.86	0.90	5.91	0.02
Log $(\text{Energy Expenditure/Output})_{t-2}$	-3.77	-3.79	0.92	-3.82	-3.82	0.65	0.02	0.89
Not used in matching								
Log $(\text{Energy Expenditure})_{t-1}$	5.33	5.33	0.99	6.03	6.03	0.84	6.23	0.01 9
Log $(\text{Energy Use})_{t-1}$	8.25	8.26	0.95	8.99	8.99	0.77	5.42	0.01
Log $(\text{CO2 Emission})_{t-1}$	12.65	12.66	0.94	13.36	13.36	0.78	0.02	0.02
Log $(\text{Employment})_{t-1}$	4.85	4.72	0.26	5.26	5.26	0.40	4.59	0.00
Exporter Dummy_{t-1}	0.15	0.18	0.30	0.18	0.18	0.80	14.42	0.03
Share of Imported Materials_{t-1}	0.20	0.18	0.56	0.19	0.19	0.05	12.14	0.00
Share of Skilled Workers_{t-1}	0.19	0.20	0.63	0.21	0.21	0.25	17.91	0.00
Log$(\text{Investment in Machinery})_{t-1}$	7.15	6.93	0.43	7.86	7.86	0.20	0.61	0.00
Log$(\text{Energy Use/Output})_{t-1}$	-0.80	-0.79	0.93	-0.87	-0.87	0.56	0.22	0.43
Δ Log $(\text{Energy Expenditure})_{t-1}$	0.14	0.08	0.19	0.15	0.15	0.55	0.03	0.90
Δ Log $(\text{Energy Use})_{t-1}$	0.17	0.09	0.19	0.18	0.18	0.72	0.00	0.87
Δ Log $(\text{CO2 Emissions})_{t-1}$	0.17	0.09	0.22	0.18	0.18	0.70	10.36	0.97
Log$(\text{CO2 Emissions/Output})_{t-1}$	3.61	3.62	0.92	3.51	3.51	0.57	7.45	0.64
Log$(\text{Energy Exp./Materials})_{t-1}$	-2.80	-2.81	0.93	-3.03	-3.03	0.32	0.39	0.01
Δ Log $(\text{Output})_{t-1}$	0.13	0.05	0.14	0.14	0.14	0.86	2.05	0.53
Δ Log $(\text{Energy Expenditure/Output})_{t-1}$	0.02	0.03	0.81	0.02	0.02	0.60	1.93	0.15
Δ Log$(\text{Energy Use/Output})_{t-1}$	0.05	0.04	0.87	0.04	0.04	0.81	1.48	0.16
Δ Log$(\text{CO2 Emissions/Output})_{t-1}$	0.04	0.04	0.96	0.04	0.04	0.78	1.66	0.22
Δ Log$(\text{Energy Exp./Materials})_{t-1}$	0.08	-0.02	0.08	0.04	0.04	0.81	0.00	0.20

Note: CEM - coarsened exact matching; PSM - propensity score matching; IPW - inverse probability weighting procedure. The variables used in each matching procedure include lagged output, energy expenditure, energy use (in MBTUs) and CO_2 emission and the log difference on the last three variables.

Table D.2: Difference-in-differences estimates: Coarsened exact matching.

	Acquisition Year	1 Year Later	2 Years Later
		Log(Output)	
Post*Acquired	**1.392*** **	**1.499*** **	**1.530*** **
	(0.141)	**(0.144)**	**(0.148)**
R-sq. (within)	0.350	0.383	0.392
No. of Obs.	876	876	876
		Log (Energy Expenditure in Rps)	
Post*Acquired	**1.012*** **	**1.189*** **	**1.159*** **
	(0.140)	**(0.149)**	**(0.158)**
R-sq. (within)	0.221	0.248	0.253
No. of Obs.	871	868	868
		Log(Energy Use in MBTUs)	
Post*Acquired	**0.992*** **	**1.149*** **	**1.085*** **
	(0.145)	**(0.157)**	**(0.165)**
R-sq. (within)	0.209	0.232	0.229
No. of Obs.	871	868	868
		Log (CO_2 Emissions)	
Post*Acquired	**1.000*** **	**1.158*** **	**1.099*** **
	(0.145)	**(0.156)**	**(0.165)**
R-sq. (within)	0.214	0.240	0.234
No. of Obs.	871	868	868
		Log (Energy Expenditure/Output)	
Post*Acquired	**-0.372*** **	**-0.297** **	**-0.382*** **
	(0.113)	**(0.121)**	**(0.123)**
R-sq. (within)	0.059	0.054	0.048
No. of Obs.	871	868	868
		Log (Energy Use/Output)	
Post*Acquired	**-0.392*** **	**-0.336** **	**-0.456*** **
	(0.119)	**(0.133)**	**(0.134)**
R-sq. (within)	0.053	0.042	0.048
No. of Obs.	871	868	868
		Log (CO_2 Emissions/Output)	
Post*Acquired	**-0.383*** **	**-0.327** **	**-0.443*** **
	(0.119)	**(0.131)**	**(0.133)**
R-sq. (within)	0.051	0.039	0.045
No. of Obs.	871	868	868

Note: The table reflects the result of estimating equation 4 on the matched sample using CEM. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. *Post* dummy and plant fixed effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Appendix E Inverse Probability of Treatment Weighting (IPTW)

As mentioned in the main text, one major drawback of the one-to-one propensity score matching is that we are limiting our conclusion to a very few matched observations. This may post an issue on the validity of our estimate if the majority of the dropped plants with acquisition cases are systematically different in our outcome variables but are marginally different in the set of covariates that we chose in the matching procedure. Moreover, there are also studies suggesting that the finite sample properties of one-to-one propensity score matching are inferior to other matching techniques (see, for example, Guadalupe et al., 2012; Busso et al., 2014).

To address this concern, we employ inverse probability of treatment weighting to identify the appropriate controls for each acquired plant. In particular, we transform the same propensity score estimated from the set of covariates in our baseline matching procedure into weights, following (Guadalupe et al., 2012). We weight each treated firm by $(1/\hat{p})$ and each control firm by $(1/(1-\hat{p}))$ where $\hat{p}$ is our estimated propensity score from the baseline matching procedure. We apply these weights for samples which includes acquired plants that we observe 2 and 5 years after acquisition case to test for the comparability of the estimated average effect effect (ATE) with our period-by-period baseline estimates.

In contrast to our baseline procedure and CEM, we find statistically significant mean difference between treated and control plants on some observable covariates (see Table D.1). However, we find balanced sample in the trends of our variables of interests, which is a key assumption in performing difference-in-differences. The results from performing this alternative matching procedure are fairly consistent with our baseline estimates, suggesting that our baseline results are robust to different matching procedure (see Table E.1).

Table E.1: Difference-in-differences estimates: Inverse probability of treatment weighting.

	Acquisition Year	1 Year Later	2 Years Later
		Log(Output)	
Post*Acquired	**1.659*** **	**1.763*** **	**1.906*** **
	(0.184)	**(0.218)**	**(0.221)**
R-sq. (within)	0.803	0.807	0.809
No. of Obs.	138750	138750	138750
		Log (Energy Expenditure in Rps)	
Post*Acquired	**1.353*** **	**1.421*** **	**1.399*** **
	(0.176)	**(0.199)**	**(0.220)**
R-sq. (within)	0.806	0.802	0.800
No. of Obs.	138011	138009	138008
		Log(Energy Use in MBTUs)	
Post*Acquired	**1.284*** **	**1.337*** **	**1.324*** **
	(0.172)	**(0.192)**	**(0.212)**
R-sq. (within)	0.805	0.798	0.795
No. of Obs.	138011	138009	138008
		Log (CO_2 Emissions)	
Post*Acquired	**1.359*** **	**1.400*** **	**1.395*** **
	(0.170)	**(0.192)**	**(0.211)**
R-sq. (within)	0.806	0.799	0.794
No. of Obs.	138010	138008	138007
		Log (Energy Expenditure/Output)	
Post*Acquired	**-0.324*** **	**-0.358*** **	**-0.516*** **
	(0.120)	**(0.133)**	**(0.159)**
R-sq. (within)	0.640	0.649	0.638
No. of Obs.	138011	138009	138008
		Log (Energy Use/Output)	
Post*Acquired	**-0.392*** **	**-0.443*** **	**-0.590*** **
	(0.129)	**(0.149)**	**(0.178)**
R-sq. (within)	0.643	0.642	0.625
No. of Obs.	138011	138009	138008
		Log (CO_2 Emissions/Output)	
Post*Acquired	**-0.318*** **	**-0.380*** **	**-0.519*** **
	(0.117)	**(0.134)**	**(0.165)**
R-sq. (within)	0.653	0.653	0.629
No. of Obs.	138010	138008	138007

Note: The table shows the results of estimating equation 4 on the full dataset using inverse propensity of treatment weighting. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. Year and plant fixed-effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Table E.2: Regression results using extended data (1983-2008).

	Acquisition Year	1 Year Later	2 Years Later	3 Years Later	4 Years Later	5 Years Later
			Log(Output)			
Post*Acquired	**0.872*** **	**0.897*** **	**0.911*** **	**1.079*** **	**1.048*** **	**0.988*** **
	(0.104)	**(0.111)**	**(0.110)**	**(0.119)**	**(0.121)**	**(0.130)**
R-sq. (within)	0.174	0.162	0.189	0.224	0.217	0.193
No. of Obs.	1050	1050	1050	1050	1050	1050
			Log (Energy Expenditure)			
Post*Acquired	**0.510*** **	**0.550*** **	**0.577*** **	**0.575*** **	**0.465*** **	**0.623*** **
	(0.115)	**(0.128)**	**(0.125)**	**(0.142)**	**(0.143)**	**(0.149)**
R-sq. (within)	0.089	0.080	0.105	0.091	0.091	0.115
No. of Obs.	1024	1024	1024	1024	1024	1024
			Log (Energy Expenditure/Output)			
Post*Acquired	**-0.353*** **	**-0.335*** **	**-0.320*** **	**-0.467*** **	**-0.549*** **	**-0.341*** **
	(0.101)	**(0.104)**	**(0.109)**	**(0.113)**	**(0.117)**	**(0.117)**
R-sq. (within)	0.024	0.020	0.017	0.037	0.045	0.018
No. of Obs.	1024	1024	1024	1024	1024	1024
			Log (Energy Expenditure/Materials)			
Post*Acquired	**-0.388*** **	**-0.382*** **	**-0.435*** **	**-0.506*** **	**-0.606*** **	**-0.416*** **
	(0.113)	**(0.116)**	**(0.130)**	**(0.135)**	**(0.143)**	**(0.145)**
R-sq. (within)	0.026	0.026	0.028	0.032	0.041	0.020
No. of Obs.	962	962	962	962	962	962

Note: The table reflects the result of estimating equation 4 on the matched sample described in Section 4 but extending the period up to 2008. The dependent variables are as listed in each panel. Expenditure on energy and materials and output are deflated using consumer price index (2014=100). Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Heteroskedasticity-robust standard errors are in parentheses. *Post* dummy and plant fixed effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Appendix F Extended data: 1983-2008

Table F.1: Balancing tests between domestic and acquired plants: Extended data (1983-2008).

Variables	Matched sample (pre-acquisition, N=816)		
	Treated	Control	p-value
Used in matching			
Log (Output)$_{t-1}$	12.58	12.55	0.869
Log (Energy expenditure/output)$_{t-1}$	-3.70	-3.66	0.626
Log (Output)$_{t-2}$	12.43	12.51	0.519
Log (Energy expenditure/output)$_{t-2}$	-3.69	-3.70	0.915
Not used in matching			
Log (Energy expenditure)$_{t-1}$	8.88	8.90	0.871
Log(Energy exp./materials exp.)$_{t-1}$	-2.79	-2.90	0.317
Δ Log (Energy expenditure)$_{t-1}$	0.14	0.09	0.461
Δ Log (Energy expenditure/output)$_{t-1}$	-0.01	0.05	0.334
Δ Log(Energy exp./materials exp.)$_{t-1}$	-0.04	0.01	0.407

Note: Acquired and treated plants are those that were previously domestic and remained acquired for at least two years after the acquisition case. Domestic plants are those plants that had no acquisition case, while control plants are those year-plant observations that had foreign equity below the threshold for four consecutive years.
Source: Indonesian Census of Manufacturing

Table F.2: Regression results using inverse probability of treatment weighting: Extended data (1983-2008).

	Acquisition Year	1 Year Later	2 Years Later
	Log(Output)		
Post*Acquired	**1.355*** **	**1.473*** **	**1.625*** **
	(0.133)	**(0.150)**	**(0.141)**
R-sq. (within)	0.814	0.818	0.825
No. of Obs.	229790	229790	229790
	Log (Energy Expenditure)		
Post*Acquired	**1.156*** **	**1.256*** **	**1.305*** **
	(0.138)	**(0.157)**	**(0.156)**
R-sq. (within)	0.800	0.787	0.792
No. of Obs.	228842	228842	228844
	Log (Energy Expenditure/Output)		
Post*Acquired	**-0.170***	**-0.218** **	**-0.315*** **
	(0.091)	**(0.103)**	**(0.112)**
R-sq. (within)	0.667	0.655	0.648
No. of Obs.	228840	228840	228842

Note: The table shows the results of estimating equation 4 on the extended dataset (1983-2008) using inverse propensity of treatment weighting. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. Year and plant fixed-effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Table F.3: Regression results on fuel and electricity expenditure, use and intensities.

	Price-based measures			Physical Units		
	Acquisition Year	1 Year Later	2 Years Later	Acquisition Year	1 Year Later	2 Years Later
	Log(Total Fuel in Rps)			Log(Total Fuel in MBTUs)		
Post*Acquired	**0.392*** **	**0.596*** **	**0.543*** **	**0.343** **	**0.513*** **	**0.547*** **
	(0.149)	**(0.158)**	**(0.172)**	**(0.165)**	**(0.173)**	**(0.189)**
R-sq. (within)	0.044	0.069	0.058	0.028	0.045	0.045
No. of Obs.	812	815	805	812	815	806
	Log(Net Electricity in Rps)			Log(Net Electricity in MBTUs)		
Post*Acquired	**0.761*** **	**0.775*** **	**0.696*** **	**0.781*** **	**0.818*** **	**0.679*** **
	(0.204)	**(0.206)**	**(0.217)**	**(0.201)**	**(0.208)**	**(0.219)**
R-sq. (within)	0.092	0.115	0.118	0.099	0.137	0.142
No. of Obs.	714	713	711	714	713	711
	Log(Total Fuel/Output)			Log(Total Fuel/Output)		
Post*Acquired	**-0.422*** **	**-0.452*** **	**-0.429*** **	**-0.471*** **	**-0.535*** **	**-0.428** **
	(0.148)	**(0.153)**	**(0.160)**	**(0.164)**	**(0.171)**	**(0.182)**
R-sq. (within)	0.025	0.023	0.020	0.026	0.027	0.017
No. of Obs.	812	815	805	812	815	806
	Log(Net Electricity/Output)			Log(Net Electricity/Output)		
Post*Acquired	-0.103	**-0.343***	**-0.389***	-0.083	-0.300	**-0.406***
	(0.203)	**(0.202)**	**(0.213)**	(0.201)	(0.204)	**(0.219)**
R-sq. (within)	-0.001	0.011	0.015	-0.001	0.015	0.025
No. of Obs.	714	713	711	714	713	711

Note: The table reflects the result of estimating equation 4 on the matched sample described in Section 4. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Heteroskedasticity-robust standard errors are in parentheses. *Post* dummy and plant fixed effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Appendix G Energy Prices, Scale Economies and Other Outcomes

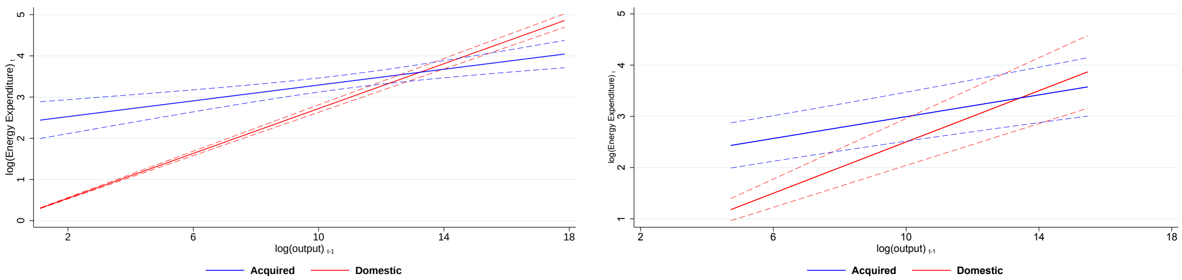
Table G.1: Difference-in-differences analysis on matched sample: Energy input prices in levels and logarithms.

	Acquisition Year	1 Year Later	2 Years Later
		Fuel price	
Post*Acquired	-0.080	0.021	-0.059
	(0.090)	(0.014)	(0.063)
R-sq. (within)	0.005	0.013	0.005
No. of Obs.	812	815	806
		Log(Fuel Price)	
Post*Acquired	0.049	0.083	0.014
	(0.057)	(0.054)	(0.057)
R-sq. (within)	0.004	0.008	0.001
No. of Obs.	812	815	805
	Acquisition Year	1 Year Later	2 Years Later
		Electricity Price	
Post*Acquired	-0.001	-0.003	0.006
	(0.003)	(0.003)	(0.007)
R-sq. (within)	0.001	0.026	0.004
No. of Obs.	714	713	711
		Log(Electricity Price)	
Acquired	-0.020	-0.043	0.016
	(0.040)	(0.044)	(0.051)
R-sq. (within)	0.002	0.038	0.045
No. of Obs.	714	713	711

Note: The table reflects the result of estimating equation 4 on the matched sample using PSM. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. Year and plant fixed-effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Figure G.1: Predicted energy expenditure and output.

(a) Unmatched sample　　　　(b) Matched sample



Note: The figures represent the estimated coefficient from regressing energy expenditure on foreign affiliate dummy (i.e. 1 if foreign-owned; 0 otherwise), lagged output and their interaction. Dashed lines represent 95-percent confidence intervals. Each variable is expressed in log.

Table G.2: Dependent Variable: Log(Energy Expenditure)

	All Sample		Matched Sample	
	(1)	(2)	(3)	(4)
Post*Acquired	**0.836****	**2.334*****	**0.997****	**1.931*****
	(0.329)	**(0.250)**	**(0.404)**	**(0.462)**
ln(Output)	**0.571*****		**0.621*****	
	(0.005)		**(0.040)**	
ln(Output)$_{t-1}$		**0.272*****		**0.250*****
		(0.005)		**(0.046)**
Post*Acquired*ln(Output)	**-0.060****		**-0.086****	
	(0.030)		**(0.038)**	
Post*Acquired*ln(Output)$_{t-1}$		**-0.176*****		**-0.144*****
		(0.022)		**(0.043)**
Firm fixed effect	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes
R-sq. (within)	0.261	0.097	0.389	0.134
No. of Obs.	255450	228733	2994	2571

Note: The table reflects the result of regressing the outcome variable on the unmatched sample. Each column in each panel is a separate regression. Heteroskedasticity-robust standard errors are in parentheses. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Table G.3: PSM-DID estimates on capital, employment and investments.

	Acquisition Year	1 Year Later	2 Years Later
		Log(Capital)	
Post*Acquired	**0.622*** **	**0.738*** **	**0.794*** **
	(0.147)	**(0.178)**	**(0.208)**
R-sq. (within)	0.109	0.099	0.082
No. of Obs.	658	644	627
		Log(Employment)	
Post*Acquired	**0.319*** **	**0.349*** **	**0.361*** **
	(0.050)	**(0.055)**	**(0.061)**
R-sq. (within)	0.153	0.152	0.109
No. of Obs.	840	840	840
		Log(Capital-Labor Ratio)	
Post*Acquired	**0.349** **	**0.406** **	**0.449** **
	(0.145)	**(0.174)**	**(0.201)**
R-sq. (within)	0.034	0.030	0.030
No. of Obs.	658	644	627
		Log(Investment in Machinery)	
Post*Acquired	**0.745*** **	**0.729*** **	**0.861*** **
	(0.178)	**(0.202)**	**(0.245)**
R-sq. (within)	0.087	0.070	0.067
No. of Obs.	650	637	620
		Log(Total Investment, 5 categories)	
Post*Acquired	0.324	0.449	-0.062
	(0.348)	(0.391)	(0.377)
R-sq. (within)	0.006	0.008	0.000
No. of Obs.	489	460	444

Note: The table reflects the result of estimating equation 4 on the matched sample using PSM. The dependent variables are as listed in each panel. Each column in each panel is a separate regression for a particular outcome variable covering two time periods: the year relative to acquisition (as listed in each column) and a year before foreign-owned plants were acquired. Heteroskedasticity-robust standard errors clustered at the plant level are in parentheses. Year and plant fixed-effects are included in all specifications. *, **, *** indicate statistical significance at 0.10, 0.05, and 0.01 level, respectively.

Appendix H Analysis of Channels: Additional Table

Table H.1: Balancing test for matched domestic and acquired plants, HHI<5%.

Variables	Unmatched sample (162 acquired vs 1,271 domestic)			Matched Sample (HHI<5%) (58 treated and 58 controls)		
	Acquired	Domestic	p-value	Treated	Control	p-value
Used in matching						
Log (Real output)$_{t-1}$	12.65	0.49	0.000	12.38	12.31	0.855
Log (Energy expenditure/output)$_{t-1}$	-3.97	0.00	0.000	-3.56	-3.49	0.777
Log (Real output)$_{t-2}$	12.79	0.00	0.000	12.10	12.27	0.649
Log (Energy expenditure/output)$_{t-2}$	-3.92	0.00	0.003	-3.51	-3.47	0.851
Unused in matching						
Log (Energy expenditure)$_{t-1}$	8.69	0.00	0.000	8.82	8.82	0.986
Log (predicted energy intensity, continuous)$_{t-1}$	-3.43	0.00	0.000	-3.45	-3.15	0.042
Log (predicted energy intensity, percentile)$_{t-1}$	3.82	0.00	0.001	3.85	4.01	0.089
Log (Employment)$_{t-1}$	5.24	0.00	0.000	4.82	4.90	0.743
Exporter dummy$_{t-1}$	1.49	0.00	0.000	1.63	1.82	0.191
Share of imported materials$_{t-1}$	0.27	0.00	0.000	0.27	0.14	0.028
Share of skilled workers$_{t-1}$	0.20	0.00	0.000	0.21	0.21	0.957
Log(Investment in machinery)$_{t-1}$	10.34	0.00	0.000	10.85	10.18	0.290
Log(Energy exp./materials exp.)$_{t-1}$	-3.16	0.00	0.000	-2.73	-2.67	0.831
Δ Log (Real output)$_{t-1}$	0.10	0.00	0.158	0.28	0.04	0.236
Δ Log (Energy expenditure)$_{t-1}$	0.11	0.00	0.872	0.22	0.02	0.351
Δ Log (Energy expenditure/output)$_{t-1}$	0.01	0.00	0.295	-0.05	-0.03	0.822
Δ Log(Energy exp./materials exp.)$_{t-1}$	-0.05	0.00	0.067	-0.22	0.01	0.174

Note: Acquired and treated plants are those that were previously domestic and remained acquired for at least two years after the acquisition case. Domestic plants are those plants that had no acquisition case, while control plants are those year-plant observations that had foreign equity below the threshold for four consecutive years.
Source: Indonesian Census of Manufacturing

Appendix I Divestment: Additional Table

Table I.1: Balancing tests for matched and unmatched divested plants.

Variables	Unmatched sample (597 Divested vs 42,084 Foreign)			Matched sample (256 treated vs 256 controls)		
	Divested	Foreign	p-value	Treated	Control	p-value
Used in matching						
Log (Real output)$_{t-1}$	9.56	7.91	0.00	10.94	10.96	0.87
Log (Energy expenditure/output)$_{t-1}$	-4.04	-3.84	0.00	-4.21	-4.19	0.86
Log (Real output)$_{t-2}$	9.57	7.96	0.00	10.83	10.76	0.60
Log (Energy expenditure/output)$_{t-2}$	-3.97	-3.83	0.04	-4.13	-4.08	0.68
Unused in matching						
Log (Energy expenditure)$_{t-1}$	5.60	4.15	0.00	6.72	6.76	0.79
Log(Energy use)$_{t-1}$	8.51	7.11	0.00	9.66	9.69	0.80
Log (CO2 emission)$_{t-1}$	12.91	11.49	0.00	14.05	14.08	0.82
Log (Employment)$_{t-1}$	5.03	4.19	0.00	5.76	5.69	0.46
Exporter dummy$_{t-1}$	0.24	0.10	0.00	0.33	0.35	0.64
Share of imported materials$_{t-1}$	0.26	0.10	0.00	0.30	0.36	0.05
Share of skilled workers$_{t-1}$	0.20	0.14	0.00	0.22	0.21	0.39
Log(Investment in machinery)$_{t-1}$	7.79	5.66	0.00	8.84	8.96	0.55
Log(Energy use/output)$_{t-1}$	-1.13	-0.88	0.00	-1.28	-1.26	0.87
Log(CO2 emission/output)$_{t-1}$	3.27	3.51	0.00	3.11	3.13	0.89
Log(Energy exp./materials exp.)$_{t-1}$	-3.22	-3.00	0.00	-3.54	-3.37	0.19
Δ Log (Real output)$_{t-1}$	0.10	0.05	0.13	0.11	0.19	0.24
Δ Log (Energy expenditure)$_{t-1}$	0.03	0.06	0.49	0.03	0.08	0.51
Δ Log (Energy use)$_{t-1}$	0.03	0.08	0.23	0.02	0.10	0.40
Δ Log (CO2 emission)$_{t-1}$	0.03	0.08	0.23	0.02	0.10	0.43
Δ Log (Energy expenditure/output)$_{t-1}$	-0.06	0.01	0.09	-0.09	-0.11	0.78
Δ Log(Energy use/output)$_{t-1}$	-0.07	0.02	0.03	-0.09	-0.09	0.95
Δ Log(CO2 emission/output)$_{t-1}$	-0.07	0.03	0.03	-0.09	-0.10	0.91
Δ Log(Energy exp./materials exp.)$_{t-1}$	-0.05	0.01	0.21	-0.11	-0.13	0.77

Source of raw data: Indonesian Census of Manufacturing.