UNIVERSITY OF CALIFORNIA,
IRVINE

Technology, Trade and the Environment

DISSERTATION

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for the degree of

DOCTOR OF PHILOSOPHY

in Economics

by

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DEDICATION

To my parents, Ron and Mary Stroik, and to my close friends. Your unconditional love, encouragement, and stalwart support has made this work possible.

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ABSTRACT OF THE DISSERTATION

Technology, Trade and the Environment

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Doctor of Philosophy in Economics

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The three chapters in this dissertation use firm-level data from Vietnam, Chile, and a set of Eastern-European countries to understand the importance of foreign direct investment in technology diffusion and subsequent environmental implications of changes in the production process. Chapter 1 investigates whether increased within-firm or within-industry foreign exposure, or foreign exposure from domestic downstream industry increases technology adoption. Chapters 2 and 3 look beyond technology spillovers of foreign investment, considering whether increased foreign investment affects domestic firm energy intensities. Chapter 2 studies whether domestic Vietnamese firms that become suppliers of domestic foreign-owned firms experience differential technology adoption and changes in energy intensity. Chapter 3 studies whether increased within-firm or within-industry foreign exposure, or foreign exposure from domestic downstream industry in Chile affects firm-level energy intensities.

Studying manufacturing and service firms in Eastern-European countries, Chapter 1 finds that technology gains from domestic foreign exposure differ between lower-income and higher-income countries. In higher-income countries, increased within-industry foreign exposure and increased foreign exposure from downstream industries on average increases technology adoption.

Studying Vietnamese manufacturing firms, Chapter 2 finds that firms that become suppliers of domestic foreign firms are on average more likely to have innovated than their non-supplier peers. These technology gains are found not to translate into short-run changes in energy intensity.

Studying Chilean manufacturing firms, Chapter 3 finds as firms experience increased within-firm foreign investment, they on average increase their electricity intensity. Moreover, increased within-industry foreign exposure on average increases electricity intensity for all firms, and fuel intensity for firms in "dirty" industries.

Chapter 1

Increased Multinational Presence in Developing Countries Increases Technology Adoption for Domestic Firms

1.1 Introduction

Developing countries try to attract foreign direct investment (FDI) through incentives such as tax holidays, lower income taxes, subsidies for infrastructure, and import duty exemptions (Aitken and Harrison, 1999). One reason developing countries spend money to attract FDI is to speed up the transfer of technology from developed countries to developing countries (Heillener, 1989). From an economic efficiency perspective, subsidization of technology transfer to any domestic firm is justified when the transfered technology spreads to other domestic firms that do not compensate any firm for the new technology.

Unfortunately data on technology, such as patents or research and development spending, is often not observed. What is instead used to measure technology is total factor productivity (TFP). TFP is the result of subtracting from output the contributions of inputs into a production process, such as labor and capital. The idea is that any unexplainable change in output is viewed as coming from "technology."

Much of the work trying to identify the effect of FDI on domestic firm technology adoption has used the TFP approach in firm-level analysis in a single country. One consistent finding across studies on Venezuela, Lithuania, and Indonesia, is that increased within-industry multinational presence, a proxy variable for foreign exposure, does not increase domestic firm productivity. A second consistent finding across the same studies is that increases in downstream foreign exposure from domestic multinationals increases domestic firm productivity (Aitken and Harrison, 1999; Blalock and Gertler, 2008; Javorcik, 2004).

Using the TFP approach to identify technology spillovers can introduce measurement error and potential biases, as appropriate data on production inputs and outputs is typically unavailable (Keller, 2010). This point is made clearer in Beveren (2012), which points out that omitted price bias and bias from not accounting for firms being multi-product firms are not corrected by typical TFP estimation techniques such as that proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003). Moreover, previous studies use economy-wide input-output tables to determine industry-level downstream foreign exposure. This aggregate measure of downstream foreign exposure may result in estimation bias if multinationals do not source their inputs similarly to domestic firms (Keller, 2010).

This paper provides a fresh look at whether increases in FDI in developing countries increases the spread of technology to firms in developing countries. The analysis uses cross-country data on 23 countries in 9 industries from the 2002 and 2005 Enterprise Surveys collected by the World Bank and the European Bank of Reconstruction and Development (EBRD). Novel to this literature is the fact that from the EBRD dataset I observe whether a firm has recently upgraded a product, introduced a new product, or introduced a new production process, and I am able to construct a firm-level measure of downstream foreign exposure.

I present two main results. First, I find domestic non-exporting firms in higher-income developing countries that receive more downstream foreign exposure through competitors are on average more likely to have recently introduced a new product. Second, I find that these same firms are on average more likely to have recently adopted a new production process. These empirical results are in line with Pack and Saggi's (2001) theoretical result that multinationals are more likely to transfer technology to suppliers in industries with a higher likelihood for technology spillovers.

The increased likelihood of technology adoption comes not from supplying multinationals directly, but instead competing with firms increasingly supplying multinationals. This result provides more plausible confirmation of technology "spillovers" than found in previous works that cannot distinguish between these two channels (Blalock and Gertler, 2008; Javorcik, 2004).

1.2 Technology Spillover Channels and Evidence

Technology spillovers from domestic multinationals to domestic firms occur when the entry or presence of multinationals results in the spread of technology to domestic firms, and multinationals are not fully compensated for the value of the technology transfer. Technology spillovers from multinationals to domestic firms can occur in many ways, including the following: domestic firms copying multinational technology; domestic firms using resources more efficiently or searching for new technologies due to multinational competition; and domestic firms using newly available domestic services now in existence due to multinational competition, e.g. accounting firms, consulting firms, and international trade brokers (Blalock and Gertler, 2008; Javorcik, 2004).

The spread of technology to domestic firms has typically been looked at along *horizontal* and *vertical* relations. Horizontal relations are those of domestic firms with their multinational competitors. Vertical relations are those of domestic firms with their multinational suppliers or multinationals they supply. Multinationals have little incentive to allow technology to spread horizontally as doing so allows for more competition. Multinationals may have an incentive to allow technology to spread vertically, as they can benefit from improved performance of input suppliers (Javorcik, 2004; Pack and Saggi, 2001). Moreover, multinationals that diffuse their technology to one specific input supplier would become more vulnerable to hold-up. To reduce hold-up risk, the multinational can encourage technology diffusion to the input supplier industry as a whole (Blalock and Gertler, 2008).

The evidence of technology transfer through horizontal relations to date is mixed. Several papers examine the existence of horizontal FDI spillovers in developing countries by estimating the relationship between increases in industry-level inward FDI and domestic industry productivity (Blalock and Gertler, 2008; Aitken and Harrison, 1999; Javorcik, 2004). These papers all find either small positive or negative effects on productivity from increases in horizontal FDI. There exist additional papers examining horizontal FDI spillovers in developed countries, which find positive effects on productivity from increases in horizontal FDI (Haskel et al., 2007; Keller and Yeaple, 2009). Further discussion of the work done on this topic, along with the pitfalls and strengths of each work can be found in Keller (2010).

Domestic firms have an incentive to attract workers from domestic multinationals. Former domestic multinational employees may transfer knowledge about technologies used at multinationals to domestic firms that hire them. Evidence consistent with this form of technological spillover is observed in Javorcik (2004) in regressions including a five-year difference of foreign presence. Additional evidence consistent with technology diffusion from multinational employees moving to domestic firms is observed in Norwegian and Brazilian firms (Balsvik, 2011; Poole, 2013).[1]

The evidence on vertical technology transfer is more consistent and positive (Blalock and Gertler, 2008; Javorcik, 2004;). Evidence in favor of vertical FDI spillovers in developing countries is established by estimating a positive relationship between increases in industry output sold to domestic multinationals and domestic industry productivity. However, these estimated positive effects come from models that do not control for the potential that some suppliers of multinationals are selected based on their current or expected future productivity (Javorcik and Spatareanu, 2009). Controlling for multinational supplier selection, Javorcik and Spatareanu (2009) find that suppliers of multinationals in the Czech Republic do learn from their relationships with multinationals.

1.3 Data and Methodology

1.3.1 Data

The dataset used in this study is an unbalanced panel firm-level dataset collected by the World Bank and the European Bank of Reconstruction and Development (EBRD) in 2002 and 2005.[2] Since a full year of data is not available in the data-collection year, each collection year gathers data from the previous year. For example, all questions asked in 2002 refer to firm data from 2001.

[1] Balsvik finds that previous multinational employees working at domestic Norwegian manufacturing firms contribute 20% more to productivity of their plant than workers without this experience. Using Brazilian employee-employer data, Poole finds that when domestic firms hire workers from multinationals, the wages of the colleagues of the newly hired worker on average rise.

[2] The formal title of the dataset is the EBRD-World Bank Business Environment and Enterprise Performance Survey (BEEPS) II-III.

The original dataset consists of 27 countries,[3] and 45 two-digit ISIC manufacturing and service industries.[4] The countries included, along with their observational weights indicated by darker shades of green, are displayed in Figure 1.1. The survey methodology in 2005 minimized changes from the 2002 methodology to maintain comparability as best as possible.[5]

The original dataset contains a total of 15,251 firm-year observations. There are 6,153 observations in 2002, and 9,098 in 2005. The number of observations is reduced through the deletion of observations with missing values of foreign exposure or other main variables discussed in the methodology section. Moreover, the constructed measures of foreign exposure from multinational competitors and foreign exposure from within-industry suppliers of domestic multinationals require calculating an average for each industry in each country in each year. To get what I believe is a more representative average, I perform my analysis using only firms in country-industry blocks that have at least 10 observations in both the 2002 and 2005 surveys. All these deletions reduced the sample size to 4,281 (1,777 in 2002, and 2,504 in 2005). They also reduced the number of countries included to 23, and the number of industries included to 9.

The dataset contains information on revenue, foreign ownership, share of total sales to domestic firms, share of domestic sales to multinationals, and responses to several questions on firm-level innovation. Descriptive statistics from these variables and several other firm-level outcomes are provided in Table 1.1.

The innovation questions that were asked to each firm and that this paper studies are the following: "Has your company undertaken any of the following initiatives in the last

[3]Countries included are the following: Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Georgia, Hungary, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, MacedoniaFYR, Moldova, Montenegro, Poland, Romania, Russia, Serbia, Slovakia, Slovenia, Tajikistan, Ukraine, and Uzbekistan.

[4]Data available free from the World Bank at `https://www.enterprisesurveys.org/portal` Datasets used are titled "Eastern Europe & Central Asia Panel Data 2002, 2005, 2009" and "Standardized data 2002-2005".

[5]In 2005 survey methodology, available at `http://ebrd-beeps.com/data/` by accessing year 2005.

Figure 1.1: Enterprise Survey Countries Studied

three years?: 1)Developed a major new product line; 2) Upgraded an existing product line; 3)Introduced new technology that has substantially changed the way that the main product is produced."[6]

Table 1.1: Descriptive Statistics by Domestic and Foreign Firms, 2002 and 2005

	Obs	Mean	Std. Dev.	Min	Max
Horizontal FDI	4,281	15.05	18.77	0	88.06
Backward FDI	4,281	2.94	11.66	0	100
% Foreign Ownership in Firm	4,281	8.45	25.80	0	100
% Domestic Sales	4,281	94.95	16.17	1	100
% Multinational Sales	4,281	3.44	12.91	0	100
Competition (1 = none, 4 = strong)	4,281	2.72	1.12	1	4
Revenue	4,281	1,982,480	9,325,894	1,000	440,235,000
Labor	4,281	69.85	207.31	2	6,500
% of Inputs Imported	4,281	26.36	36.49	0	100
% Workers > 12 Years Education	4,281	27.52	28.69	0	100

Horizontal FDI is the output-weighted percentage of equity which is foreign owned at the two-digit ISIC level. Backward FDI is the product of the % of firm sales that are domestic, and the % of firm domestic sales that are made to multinationals. Revenue is in thousands of US dollars.

Considering the benefits of the dataset that this study uses, e.g. the ability to measure direct and indirect vertical technology spread, and the usage of firm-reported innovation activity, the dataset has two major drawbacks. The first drawback is the representativeness of industries in each country. This worry is mitigated by documentation that survey teams in each country went through steps to try and maintain representativeness of each industry, however they cannot be guaranteed due to the requirement that certain quotas of firm types be sampled.[7] I believe that by considering only industry-country blocks that have at least 10 firms surveyed in each year, I have best controlled for representativeness while still maintaining enough observations to control for country-by-industry-by-year differences.

[6]Following the same question format, each firm was also asked about discontinuing product lines, opening new plants, closing plants, agreeing to new joint ventures, obtaining license agreements, outsourcing production, and insourcing production.

[7]Sampling information comes from the "Report on sampling and information" available from the European Bank of Reconstruction and Development http://ebrd-beeps.com/wp-content/uploads/2013/09/beeps2005r1.pdf. Last accessed 01/23/2015.

The second drawback is the small sample size of the data relative to previous papers. Extending the dataset to include earlier and/or later years of survey results does not mitigate this problem, because an important question on vertical foreign presence exposure was only asked in 2002 and 2005.[8] Due to the small sample size, only two-digit industry classification codes are used, instead of more disaggregate industry classification codes.

1.3.2 Methodology

To test for technology spillovers from domestic multinationals to domestic developing-country firms, I estimate a probit model of a firms' decision to adopt new technology. I assume each firm has a linear technology adoption function that is dependent upon domestic multinational presence in the following form:

$$\begin{aligned} A^*_{ijct} = \beta_1 HorizontalComp_{ijct} + \beta_2 MNESupplier_{ijct} + \beta_3 Backward_{ijct} \\ + \beta_4 HorizontalSupp_{ijct} + \beta_5 \mathbf{X}_{ijct} + u_{ijct} \end{aligned} \quad (1.1)$$

where A^*_{ijct} is the unobserved decision rule the firm uses to adopt a new technology. Due to their difficulty of introduction, the independent variables are not explained immediately. For this technology adoption function, the probability that firm i innovates is:

$$\begin{aligned} Pr(A_{ijct} = 1) = Pr(u_{ijct} > -\beta_1 HorizontalComp_{ijct} - \beta_2 MNESupplier_{ijct} \\ - \beta_3 Backward_{ijct} - \beta_4 HorizontalSupp_{ijct} - \beta_5 \mathbf{X}_{ijct}) \end{aligned} \quad (1.2)$$

[8] Firms were not asked the share of domestic sales to multinationals outside of the 2002 and 2005 survey waves. Questionnaires verifying this are available at http://ebrd-beeps.com/data/ by accessing years 1999 and 2009.

where A_{ijct} equals one if a firm has recently adopted a new technology, and zero if not.

A_{ijct} differs over the following three dependent variables of technological progress: whether a firm has adopted a new product in the past three years; whether a firm has adopted a new production process in the past three years; and whether a firm has upgraded a product in the past three years.

$HorizontalComp_{ijct}$ measures exposure to domestic multinationals through domestic multinational competition to firm i in industry j in country c in year t. $HorizontalComp_{ijct}$ is the percentage of domestic competitors' revenue attributed to foreign ownership,[9] and is calculated as follows:

$$HorizontalComp_{ijct} = \frac{\left(\sum_{\forall k \in j; k \neq i} ForeignShare_{kjct} * Y_{kjct}\right)}{\sum_{\forall k \in j} Y_{kjct}}. \tag{1.3}$$

As the amount of foreign ownership in any firm k except firm i in industry j in country c in year t increases, or as foreign-owned firms' revenue increases relative to their non-foreign peers, the level of domestic multinational competition to firm i increases.

$MNESupplier_{ijct}$ measures exposure to domestic multinationals through supplying domestic multinationals. $MNESupplier_{ijct}$ is a binary variable, and equals one for firms supplying domestic multinationals, and zero otherwise.

$Backward_{ijct}$ measures the intensity of exposure to domestic multinationals through supplying domestic multinationals. $Backward_{ijct}$ equals the percentage of total output sold to domestic multinationals.

[9] This definition is similar to that used by Aitken and Harrison (1999), Blalock and Gertler (2008), and Javorcik (2004).

$HorizontalSupp_{ijct}$ measures exposure to domestic multinationals through domestic competitors that supply multinationals. $HorizontalSupp_{ijct}$ is the percentage of domestic competitors' revenue from sales to domestic multinationals, and is calculated as follows:

$$HorizontalSupp_{ijct} = \frac{\left(\sum_{k;\forall k \in j; k \neq i} Backward_{ijct} * Y_{ijct}\right)}{\sum_{k;\forall k \in j; k \neq i} Y_{ijct}}. \tag{1.4}$$

As the percentage of sales to domestic multinationals from any firm except firm i in industry j in country c in year t increases, the level of exposure to domestic multinationals through domestic competitors for firm i increases.

$\mathbf{X}_{ijct}$ is a vector containing firm-specific factors that also contribute to the likelihood that a firm adopts a new technology. The following are controlled for by variables contained in $\mathbf{X}_{ijct}$: firm size (log of revenue), age (and its square), foreign ownership, exporting and importing behavior, market competition, workforce education, and governmental ownership.[10]

Equation 3.5 is estimated using maximum likelihood, with standard errors clustered at the industry-by-country-by-year level. Additionally, each regression includes country-by-industry-by-year fixed effects.

Since multinationals have an incentive to provide their suppliers with technology (Pack and Saggi, 2001), positive coefficient estimates for $MNESupplier_{ijct}$ or $Backward_{ijct}$ will not be inferred as evidence of technology spillovers, but rather evidence of direct technology transfer. Only positive coefficient estimates for $HorizontalComp_{ijct}$ or $HorizontalSupp_{ijct}$ will be inferred as evidence of technology spillovers, as competing firms have an incentive to withhold technology from their competitors (Aitken and Harrison, 1999).

[10]Most of the inspiration for these additional covariates comes from Almeida and Fernandes (2008).

1.4 Results

Prior work finds differences in technology "spillovers" in high-income and low-income countries (Aitken and Harrison, 1999; Blalock and Gertler, 2008; Haskel et al., 2007; Javorcik, 2004; Keller and Yeaple, 2009b). Therefore, each equation is estimated for firms in higher-income and lower-income developing countries separately. Higher-income developing countries are defined as: Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Russia (2005), Slovakia, Slovenia. Low-income developing countries are defined as: Albania, Armenia, Belarus, Bosnia, Bulgaria, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Romania, Russia (2002), Tajikistan, Uzbekistan. Due to the separation of higher-income and lower-income countries, as well as some firms not reporting on all innovation outcomes, every set of estimates will come from smaller groups of observations than the 4,281 mentioned in the data section.

Tables 2 through 7 present the estimation results described in the methodology section, with columns 1 through 3 indicating results from different samples of firms. Only the coefficient estimates from the foreign exposure variables are included for simplicity.[11] For coefficient discussion purposes, all coefficient estimates from column 3 will be discussed, as they come from regressions including only firms with the least opportunity for other sources of multinational exposure (domestic non-exporting firms).

Looking first at the development of new products (Tables 1.2 & 1.3), I find that firms in higher-income developing countries (column 3, Table 1.2) that experience more competition from suppliers of domestic multinationals ($HorizontalSupp_{ijct}$) are on average more likely to have developed a major new product line in the last three years. This result does not hold for lower-income developing country firms (column 3, Table 3). Together, these results

[11] Complete estimation results can be obtained from the author on request.

provide evidence in support of technology spillovers occurring in higher-income developing countries, but not in lower-income developing countries.

Table 1.2: Impact of Foreign Presence on New Product Development - Higher-income Countries

Dependent Variable: New Product	(1)	(2)	(3)
H Competitors	-0.0077	0.0016	0.9783
	(0.0095)	(0.2022)	(0.5997)
MNE Supplier	0.2459*	0.2577*	0.3031
	(0.1351)	(0.1536)	(0.2097)
Backward (Direct Vertical)	0.0009	0.0094	-0.0019
	(0.0101)	(0.0123)	(0.0067)
H Suppliers (Indirect Vertical)	-0.0001	0.0284	0.1553**
	(0.0266)	(0.0283)	(0.0776)
Sample Restrictions			
All Firms	x		
Domestic Firms		x	
Domestic Non-Exporting Firms			x
Observations	1,904	1,651	1,304

Dependent variable equals 1 if a firm has developed a major new product line in the past 3 years, and 0 otherwise. H Competitors is the percentage of industry revenue attributed to local multinationals (1 = 1%). Backward (Direct Vertical) is the percentage of firm revenue from local multinationals (1 = 1%). H Suppliers (Indirect Vertical) is the percentage of industry revenue from sales to local multinationals. Each regression includes controls for firm size, age, foreign ownership, exporting and importing behavior, market competition, workforce education, and governmental ownership. Each regression includes country-by-industry-by-year fixed effects. Standard errors clustered at the industry-country-year level in parentheses. High-income developing countries are defined as: Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Russia (2005), Slovakia, Slovenia.
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Now looking at product upgrading (Tables 1.4 & 1.5), I find that suppliers of domestic multinationals ($MNESupplier_{ijct}$) in both higher-income and lower-income developing countries are on average more likely to have upgraded a product in the last three years. This result is difficult to interpret, as many stories can explain this positive coefficient estimate (direct

Table 1.3: Impact of Foreign Presence on New Product Development - Lower-income Developing Countries

Dependent Variable: New Product	(1)	(2)	(3)
H Competitors	0.0217*	0.0087	0.0027
	(0.0113)	(0.0552)	(0.0553)
MNE Supplier	0.1393	0.2088	0.2985
	(0.1661)	(0.1908)	(0.2071)
Backward (Direct Vertical)	0.0053	0.0243	-0.0019
	(0.0111)	(0.0154)	(0.0057)
H Suppliers (Indirect Vertical)	-0.0153	-0.0123	-0.0071
	(0.0335)	(0.0557)	(0.0559)
Sample Restrictions			
All Firms	x		
Domestic Firms		x	
Domestic Non-Exporting Firms			x
Observations	2,280	2,040	1,840

Dependent variable equals 1 if a firm has developed a major new product line in the past 3 years, and 0 otherwise. H Competitors is the percentage of industry revenue attributed to local multinationals (1 = 1%). Backward (Direct Vertical) is the percentage of firm revenue from local multinationals (1 = 1%). H Suppliers (Indirect Vertical) is the percentage of industry revenue from sales to local multinationals. Each regression includes controls for firm size, age, foreign ownership, exporting and importing behavior, market competition, workforce education, and governmental ownership. Each regression includes country-by-industry-by-year fixed effects. Standard errors clustered at the industry-country-year level in parentheses. Low-income developing countries are defined as: Albania, Armenia, Belarus, Bosnia, Bulgaria, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Romania, Russia (2002), Tajikistan, Uzbekistan.
$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

technology transfer, technology spillover, and multinationals selecting more productive suppliers). Therefore, I find I am unable to conclude which of these factors explains this positive coefficient estimate.

Still considering the upgrading of a product (Table 1.5), I find that lower-income developing country firms are less likely to have upgraded a product in the last three years when they face more multinational competition ($HorizontalComp_{ijct}$). This result is in line with multinational competition having a negative effect on local firm productivity due to lower economies of scale achieved by local firms (Aitken and Harrison, 1999).

Turning finally to the adoption of a new production process (Tables 1.6 & 1.7), I find that firms in higher-income developing countries (column 3, Table 6) that experience more competition from suppliers of domestic multinationals ($HorizontalSupp_{ijct}$) are on average more likely to have adopted a new production process in the last three years. This result does not hold for lower-income developing country firms (column 3, Table 1.7). Together with the results of Tables 1.2 & 1.3, these results provide further evidence in support of technology spillovers occurring in higher-income developing countries, but not in lower-income developing countries.

The effect of increases in multinational competition ($HorizontalComp_{ijct}$) on the likelihood a firm adopts a new production process mirrors the results of earlier research on horizontal spillovers. Higher-income developing-country firms with more multinational competition are on average more likely to adopt a new production process in the last three years, while lower-income developing country firms with more multinational competition are on average less likely to adopt a new production process in the last three years.

Table 1.4: Impact of Foreign Presence on Product Upgrading - Higher-income Countries

Dependent Variable: Upgraded Product	(1)	(2)	(3)
H Competitors	0.0062	-0.1528	0.0138
	(0.0086)	(0.2491)	(0.3536)
MNE Supplier	0.0641	0.1278	0.3279*
	(0.1237)	(0.1422)	(0.1713)
Backward (Direct Vertical)	0.0247***	0.0305***	0.0055
	(0.0077)	(0.0109)	(0.0054)
H Suppliers (Indirect Vertical)	-0.0355	-0.0269	-0.0026
	(0.0315)	(0.0330)	(0.0461)
Sample Restrictions			
All Firms	x		
Domestic Firms		x	
Domestic Non-Exporting Firms			x
Observations	1,997	1,774	1,436

Dependent variable equals 1 if a firm has upgraded a product in the past 3 years, and 0 otherwise. H Competitors is the percentage of industry revenue attributed to local multinationals (1 = 1%). Backward (Direct Vertical) is the percentage of firm revenue from local multinationals (1 = 1%). H Suppliers (Indirect Vertical) is the percentage of industry revenue from sales to local multinationals. Each regression includes controls for firm size, age, foreign ownership, exporting and importing behavior, market competition, workforce education, and governmental ownership. Each regression includes country-by-industry-by-year fixed effects. Standard errors clustered at the industry-country-year level in parentheses. High-income developing countries are defined as: Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Russia (2005), Slovakia, Slovenia.
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 1.5: Impact of Foreign Presence on Product Upgrading - Lower-income Developing Countries

Dependent Variable: Upgraded Product	(1)	(2)	(3)
H Competitors	0.0035	-0.0827*	-0.0934*
	(0.0122)	(0.0496)	(0.0537)
MNE Supplier	0.3538**	0.3350*	0.4150**
	(0.1689)	(0.1885)	(0.1996)
Backward (Direct Vertical)	0.0044	0.0095	-0.0036
	(0.0117)	(0.0144)	(0.0047)
H Suppliers (Indirect Vertical)	-0.0142	0.0618	0.0695
	(0.0270)	(0.0503)	(0.0542)
Sample Restrictions			
All Firms	x		
Domestic Firms		x	
Domestic Non-Exporting Firms			x
Observations	2,278	2,038	1,832

Dependent variable equals 1 if a firm has upgraded a product in the past 3 years, and 0 otherwise. H Competitors is the percentage of industry revenue attributed to local multinationals (1 = 1%). Backward (Direct Vertical) is the percentage of firm revenue from local multinationals (1 = 1%). H Suppliers (Indirect Vertical) is the percentage of industry revenue from sales to local multinationals. Each regression includes controls for firm size, age, foreign ownership, exporting and importing behavior, market competition, workforce education, and governmental ownership. Each regression includes country-by-industry-by-year fixed effects. Standard errors clustered at the industry-country-year level in parentheses. Low-income developing countries are defined as: Albania, Armenia, Belarus, Bosnia, Bulgaria, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Romania, Russia (2002), Tajikistan, Uzbekistan.

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table 1.6: Impact of Foreign Presence on New Production Process - Higher-income Countries

Dependent Variable: New Production Process	(1)	(2)	(3)
H Competitors	0.0027	0.0807	2.7592**
	(0.0092)	(0.3233)	(1.3044)
MNE Supplier	0.0662	0.1898	0.2859
	(0.1423)	(0.1680)	(0.1982)
Backward (Direct Vertical)	0.0003	-0.0110	0.0037
	(0.0110)	(0.0112)	(0.0059)
H Suppliers (Indirect Vertical)	-0.0220	0.0339	0.3845**
	(0.0370)	(0.0421)	(0.1690)
Sample Restrictions			
All Firms	x		
Domestic Firms		x	
Domestic Non-Exporting Firms			x
Observations	1,914	1,681	1,342

Dependent variable equals 1 if a firm has adopted a new production process in the past 3 years, and 0 otherwise. H Competitors is the percentage of industry revenue attributed to local multinationals (1 = 1%). Backward (Direct Vertical) is the percentage of firm revenue from local multinationals (1 = 1%). H Suppliers (Indirect Vertical) is the percentage of industry revenue from sales to local multinationals. Each regression includes controls for firm size, age, foreign ownership, exporting and importing behavior, market competition, workforce education, and governmental ownership. Each regression includes country-by-industry-by-year fixed effects. Standard errors clustered at the industry-country-year level in parentheses. High-income developing countries are defined as: Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Russia (2005), Slovakia, Slovenia.
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Table 1.7: Impact of Foreign Presence on New Production Process - Lower-income Countries

Dependent Variable: New Production Process	(1)	(2)	(3)
H Competitors	0.0179	0.0209	-0.2387***
	(0.0110)	(0.0638)	(0.0242)
MNE Supplier	0.2832	0.1946	0.1122
	(0.1941)	(0.2235)	(0.2669)
Backward (Direct Vertical)	0.0091	0.0118	-0.0028
	(0.0118)	(0.0173)	(0.0068)
H Suppliers (Indirect Vertical)	-0.0514	-0.0365	-0.0307
	(0.0376)	(0.0648)	(0.0626)
Sample Restrictions			
All Firms	x		
Domestic Firms		x	
Domestic Non-Exporting Firms			x
Observations	2,256	1,983	1,775

Dependent variable equals 1 if a firm has adopted a new production process in the past 3 years, and 0 otherwise. H Competitors is the percentage of industry revenue attributed to local multinationals (1 = 1%). Backward (Direct Vertical) is the percentage of firm revenue from local multinationals (1 = 1%). H Suppliers (Indirect Vertical) is the percentage of industry revenue from sales to local multinationals. Each regression includes controls for firm size, age, foreign ownership, exporting and importing behavior, market competition, workforce education, and governmental ownership. Each regression includes country-by-industry-by-year fixed effects. Standard errors clustered at the industry-country-year level in parentheses. Low-income developing countries are defined as: Albania, Armenia, Belarus, Bosnia, Bulgaria, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Romania, Russia (2002), Tajikistan, Uzbekistan.
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

1.5 Conclusion

Utilizing firm-level data on different forms of technology adoption, this is the first work to show that firms with indirect exposure to local multinationals benefit by experiencing technology spillovers from those local multinationals. This result strengthens the previous findings of vertical technology spillovers, as the channel through which technology spreads is not through operating as a domestic multinational supplier, but rather as a competitor of domestic multinational suppliers.

These results are of interest to the literature on the environment and trade. Grossman and Krueger (1993) identify three effects on pollution and the rate of depletion of environmental resources from changes in trade and foreign investment policy. Of relevance to the topic of technology spread, is the technique effect. That is, pollution per unit of output does not need to stay the same after foreign investment occurs. One reason pollution per unit of output may fall in a developing country, is that foreign producers may spread (voluntarily and involuntarily) more modern technologies that are typically cleaner due to growing global awareness of environmental concerns (Zarsky, 1999).

Although my results say nothing directly about the change in the pollution per unit of output when developing-country firms experience increased exposure to multinational firms, there is evidence that foreign firms are significantly more energy efficient and use cleaner forms of energy (Eskeland and Harrison, 2003). Therefore, a combination of the results from this paper and that of Eskeland and Harrison (2003) provide suggestive evidence that the technique effect exists and is negative (increase in multinational firm presence decreases pollution through technology transfer). Some suggestive evidence of such ”environmental spillovers” already exists (Albornoz et al., 2009). Further work should consider the direct relation of multinational firm presence and pollution per unit of output of domestic firms.

Chapter 2

No Cleaner Than the Rest: Supplying Domestic Foreign Firms Yields No Environmental Gain for Domestic Vietnamese Firms

2.1 Introduction

Trade liberalization has the potential for positive and negative environmental effects for developing countries. Some have argued freer trade and foreign investment may result in worse environmental outcomes for developing countries (Durbin, 1993; Kelly and Kamp, 1991). Decreased environmental quality may come through increased global production as a result of freer trade, i.e. a scale effect. Decreased environmental quality may also come from developed nations shifting polluting industry to countries with lax regulation, i.e. a composition effect. Others have argued foreign investment may serve as a conduit for cleaner developing-country environmental outcomes through the proliferation of cleaner, more efficient technology (Albornoz et al., 2009; Grossman and Krueger, 1993; Zarsky, 1999), i.e. a technique effect.

Developing-country evidence of the technique effect is sparse. Knowing the sign and magnitude of the technique effect aids in understanding expected environmental changes in developing countries from free-trade agreements, and thus how free-trade agreements should be structured if pursuing sustainable development.

The technique effect of trade liberalization has two main mechanisms. First, trade liberalization increases real wealth as reduced tariffs imply reduced import costs and lower final goods costs. Since environmental quality is a normal good, increased wealth increases demand for tougher environmental standards, bringing forth cleaner production technology, having an *environment-demand* effect. The environment-demand effect is likely to take many years to occur, and is best viewed as solely a long-run effect. Second, trade liberalization lowers production costs in developing countries, making them more appealing to foreign investors. Foreign investors may transfer modern, cleaner, technologies to developing countries, having an *environment-supply* effect. Foreign investors need not transfer cleaner production techniques to developing countries for morale reasons. Cleaner production techniques may simply increase firm profit by utilizing inputs more efficiently and minimizing firm costs.

The environment-supply effect has two main components. First, transfer of cleaner production technologies to firms that receive foreign investment is a *direct environment-supply* effect. Some evidence for the direct environment-supply effect exists, as Blackman and Wu (1998) and Eskeland and Harrison (2003) find foreign firms have on average cleaner production processes than domestic peers in developing countries.[1] Second, transferred cleaner production technologies can spill over to firms that have contact with the firm that received

[1] Blackman and Wu study electricity generators in China in the late 1990s, while Eskeland and Harrison study several industries in Côte d'Ivoire, Mexico, and Venezuela primarily over the 1980s.

foreign investment, or *environment-spillover* effects. Environment-spillover effects are either vertical, for example to suppliers of foreign firms, or horizontal, to competitors of foreign firms. Little evidence exists on horizontal and vertical environment-spillover effects (Albornoz et al., 2009; Chudnovsky et al., 2005), however the vertical effect is more likely to exist in the short run, as this channel has been found empirically and theoretically to support short-run technology spillovers in developing countries, while the horizontal channel does not (Aitken and Harrison, 1999; Blalock and Gertler, 2008; Javorcik, 2004; Pack and Saggi, 2001).[2]

The purpose of this paper is to verify the existence of the conditions for the vertical environment-spillover effect and estimate the short-run vertical environment-spillover effect in a developing-country context. The existence and magnitude of this effect influences trade-policy design for attaining sustainable development in developing countries. If the vertical-environment-spillover effect decreases environmental footprints of domestic developing-country firms and is large, environmental policy may not be necessary to maintain or improve environmental quality with economic development supported through trade agreements. Conversely, if the vertical-environment-spillover effect increases environmental footprints of domestic developing-country firms or is nonexistent, environmental policy may be necessary to maintain or improve environmental quality with economic development supported through trade agreements.

The existence of the vertical-environment-spillover effect has been studied by Albornoz et al. (2009) using Argentinean firm data. The authors find that foreign-firm suppliers are more likely to report engaging in environmental management activities, providing evidence in support of a positive vertical-environment-spillover effect. This work, however, is constrained by the available data. Albornoz et al. (2009) are forced to infer environmental

[2]Even though Aitken and Harrison (1999), Javorcik (2004), and Blalock and Gertler (2008) find no evidence of short-run productivity spillovers horizontally to peers of foreign firms, some evidence of labor mobility from foreign firms to domestic firms has been found to result in productivity spillovers (Balsvik, 2011; Poole, 2013).

quality improvements from firms reporting engaging in environmental management activities, instead of a more direct and quantifiable measure, such as pollution intensity or energy intensity. Additionally, Albornoz et al. (2009) are unable to control for unobserved time-invariant industry and firm factors, which biases their estimates in favor of finding a positive vertical-environment-spillover effect if cleaner Argentinean industries or firms are more likely to supply foreign firms. For example, more productive industries and firms may be selected as suppliers by foreign firms, and productivity may be positively correlated with cleaner production processes.[3]

To determine the existence of the vertical environment-spillover effect, I estimate changes in innovation adoption and energy intensities from Vietnamese manufacturers that become domestic-foreign-firm suppliers between 2006 and 2012. I employ estimation techniques that control for observable selection-into-treatment variables (regression control and propensity score matching), as well as unobserved selection-into-treatment variables (regression control with firm fixed effects and instrumental variables). Consistent with existing literature on innovation spillovers, I provide evidence in support of the existence of innovation spillovers from foreign firms to domestic suppliers in developing countries.

When domestic Vietnamese firms become suppliers of domestic foreign firms, I find that they are on average 7-11 percentage points more likely to have recently upgraded their products. However, I find these same firms to experience no change in environmentally-linked input intensity as proxied by energy intensity. When domestic firms become suppliers of domestic foreign-firms they experience no significant changes in electricity or fuel intensities. Early-stage developing-country domestic firms may on average learn from the domestic foreign firms they supply, but they on average do not receive significantly cleaner production processes than their non-supplier peers as a result.

[3] Or more productive industries and firms are the only ones that can afford paying fixed costs associated with becoming part of supplying a foreign market (Melitz, 2003).

2.2 Trade Openness, Income, and Environmental Quality

Ever since Grossman and Krueger's (1993) discussion of the effect of the North American Free Trade Agreement on environmental quality, economists recognize that changes in environmental quality from increased trade openness are due to scale, composition, and technique effects. Scale refers to increased production and pollution following trade liberalization due to an expansion of economic activity. Composition refers to changes in location of production and its associated pollution following trade liberalization as firms relocate to other countries due to changes in competitive advantage. Technique refers to changes in production methods following trade liberalization.

Early work on the effect of trade liberalization on environmental quality took an aggregate approach, estimating the relationship between per-capita income and pollution instead of estimating the magnitudes of the scale, composition, and technique effects.[4] Out of this work came the environmental Kuznets curve (EKC); an inverted-U relationship between per-capita income and pollution concentrations. Much work has been done to determine the uniform turning point of the environmental Kuznets curve, with little consistency, as the turning point depends greatly on what states or countries are used in the analysis.[5]

Regardless of where the EKC turning point is, looking at the correlation between per-capita income and pollution concentrations gives us little understanding of the important factors associated with trade liberalization, and how those factors affect environmental quality. Building on the intuition of the scale, composition, and technique effects provided by Grossman and Krueger (1993), Antweiler et al. (2001) and Cole and Elliott (2003) estimate elasticities

[4] For example, Andreoni and Levinson (2001), Cole et al. (1997), Grossman and Krueger (1993, 1995), Harbaugh et al. (2002), List and Gallet (1999), Panayotou (1997), Stern (2004), Stern and Common (2001), and Torras and Boyce (1998).

[5] Stern (2004) provides a review of how much the estimated turning points differ and why they differ.

of each effect from a model created by Antweiler et al. (2001). Both papers find a positive scale elasticity, a negative composition elasticity, and a negative technique elasticity of pollution concentrations or intensities. Both papers conclude that their mean or median country experiences environmental improvements from trade liberalization if it increases output and per-capita income proportionately.

The works of Antweiler et al. (2001) and Cole and Elliott (2003) are by design not able to pick up both components of the technique effect pointed out in Grossman and Krueger (1993). The first technique-effect component is that trade liberalization increases real wealth as reduced import costs lower final goods costs. Since environmental quality is a normal good, increased wealth increases demand for tougher environmental standards, bringing forth cleaner production technology; an environment-demand effect. The environment-demand effect is the sole component of the technique effect whose elasticity both Antweiler et al. (2001) and Cole and Elliott (2003) estimate.

The second technique-effect component is that trade liberalization lowers production costs in developing countries, making them more appealing to foreign investors. Foreign investors may transfer modern, cleaner, technologies to developing countries, having a direct environment-supply effect. Those transferred cleaner technologies may additionally spread to other firms in the same country, having an environment-spillover effect.

The environment-spillover effect has been investigated to date by two papers, Chudnovsky et al. (2005) and Albornoz et al. (2009). Both papers used 1998-2001 Argentinean manufacturing firm data, and both papers find evidence of positive environment-spillover effects. Chudnovsky et al. (2005) find evidence of a positive horizontal environment-spillover effect to competitors conditional on "absorptive capability";[6] domestic Argentinean firms with higher than the median absorptive capability and higher levels of competition with domestic

[6]Absorptive capability is the capability of firms to take advantage of foreign technologies. See Chudnovsky et al. (2005) for their construction of a measure of absorptive capability.

foreign firms that adopt environmental management activities are on average more likely to adopt environmental management activities. Albornoz et al. (2009) find evidence of the vertical-environment-spillover effect to suppliers conditional on exporting; domestic Argentinean firms that export and have higher levels of industry output supplied to domestic foreign firms are on average more likely to adopt environmental management activities.

These earlier environment-spillover-effect studies suffer from three limitations due to the constraints of the available data. First, both Chudnovsky et al. (2005) and Albornoz et al. (2009) are forced to infer environmental quality improvements from firms reporting engaging in environmental management activities,[7] instead of a more direct and quantifiable measure, such as pollution or energy intensity. Second, both studies are unable to control for unobserved time-invariant industry and firm factors, which biases their estimates in favor of finding positive environment-spillover effects if cleaner industries or cleaner firms are more likely to compete with or supply domestic foreign firms. Third, both papers study Argentina, which by the World Bank definition is an upper-middle-income country during the time period studied. Positive environment-spillover effects may be a result specific to Argentina or countries in the upper-middle-income range, and not generalizable to all developing countries.

To address these problems of earlier environment-spillover work, I employ a new panel dataset of biennial survey results from 2006-2012 of Vietnamese manufacturing firms. With this dataset, I measure changes in environmental quality using firm-level energy intensity. I control for unobserved time-invariant industry and firm factors, as I use a firm-level measure of downstream foreign exposure instead of an industry-level measure, which is used in all prior environment- and productivity-spillover work. Finally, by looking at Vietnam I am able

[7]The environmental management activities that firms reported engaging in are the following: 1) Used systems and equipment for the treatment of residuals and effluents; 2) Taken actions for the purposes of environmental remediation; 3) Improve efficiency of the use of water, energy and other inputs; 4) Replaced or modified pollution processes; 5) Replaced inputs that are pollution intensive; 6) Developed environmentally friendly products; 7) Established internal or external recycling procedures; 8) Obtained any environmental certification; 9) None of ones listed.

to discuss the generality of the earlier positive results to a developing country transitioning from a low-income to a lower-middle-income country.

2.3 Vietnam and Foreign Investment History

Vietnam is an attractive setting for research on foreign investment, technology transfer, and environmental spillovers for several reasons. First, contributions such as Vietnam making several foreign-investment law reforms since 1987, joining the Association of Southeast Asian Nations (ASEAN) in 1995, and signing on to many free-trade agreements,[8] have helped Vietnam increase the amount of foreign investment dramatically in recent years (Figure 2.1). Second, most research on the effects of foreign investment investigates upper-middle-income countries or high-income countries. Being a country transitioning between low-income and lower-middle-income status between 2006 and 2012, Vietnam gives us perspective on the effects of foreign investment for countries at earlier stages of development. Third, Vietnam has firm-level panel data that not only allows researchers to control for unmeasured confounding effects of time, industry, and time-invariant firm-specific effects, but also contains data that allows researchers to construct foreign-firm supplier and energy-intensity variables. Many other developing countries have collected firm-level data over several years,[9] however they do not contemporaneously collect information on the degree to which domestic firms supply domestic foreign firms and energy expenses. This information is essential for study-

[8]List of international trade organizations and agreements according to Athukorala (2006) and the Asian Development Bank with effective dates in parentheses: ASEAN Free Trade Area member (1995), Vietnam-US Bilateral Trading Agreement (2002), ASEAN-People's Republic of China Comprehensive Economic Cooperation Agreement (2005), ASEAN-[Republic of] Korea Comprehensive Economic Cooperation Agreement (2007), WTO accession (2007), ASEAN-Japan Comprehensive Economic Partnership (2008), Japan-Vietnam Economic Partnership Agreement (2009), ASEAN-Australia and New Zealand Free Trade Agreement (2010), ASEAN-Indea Comprehensive Economic Cooperation Agreement (2010), Chile-Vietnam Free Trade Agreement (2012).

[9]For example: Ethiopia, Ghana, and Tanzania - all performed by the Centre for the Study of African Economies at the University of Oxford.

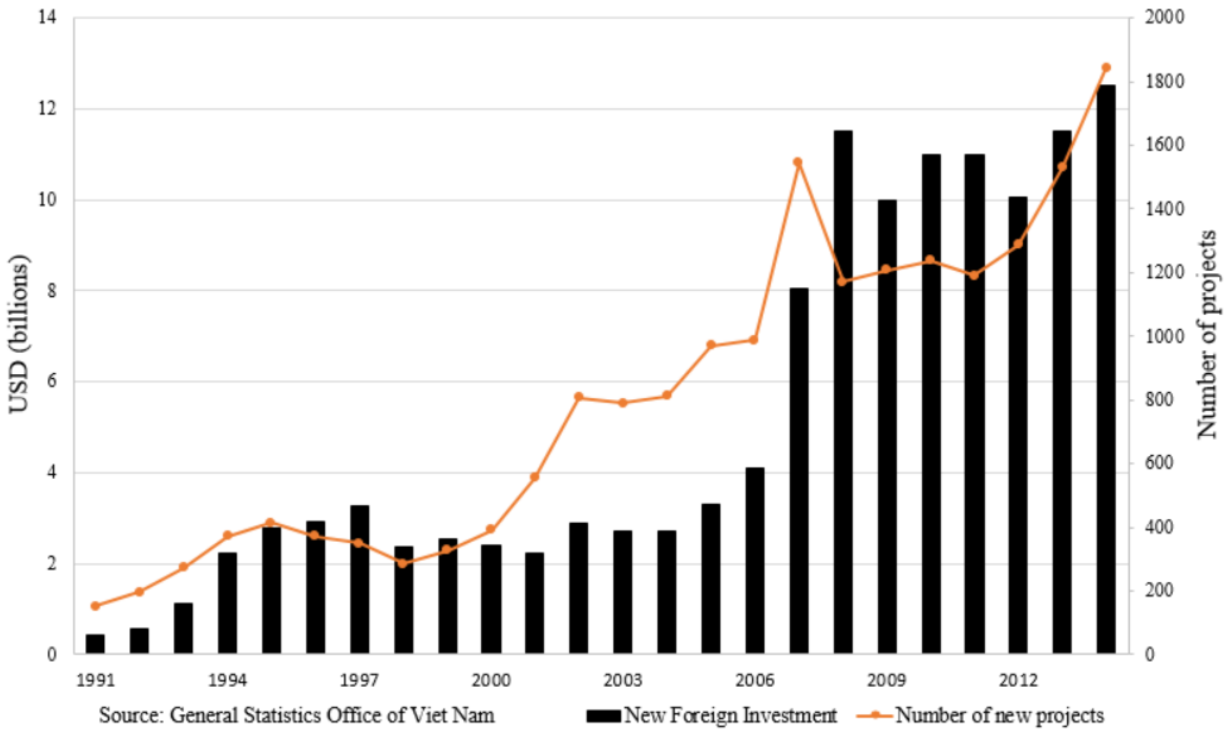

Figure 2.1: Vietnamese Foreign-Investment Inflow and Number of Projects

ing technology diffusion from domestic foreign firms to domestic non-foreign firms and any subsequent environmental spillovers.

The Vietnamese economy and manufacturing sector grew substantially from 1990 to 2012. Vietnam experienced 6-7% average annual gross domestic product growth, as compared to 2.5% in the United States. Much of this economic growth was driven by manufacturing which expanded from 25% of gross domestic product to 39% (General Statistics Office of Viet Nam (GSO) Statistical Yearbooks 2005-2011 and 2013). The increase in manufacturing output was driven by foreign investment, as annual manufacturing output from foreign-invested firms rose from 9% to 43% (GSO Statistical Yearbooks 2005-2011 and 2013).

Over the past 30 years, government regulation has shifted from policies antagonistic to foreign investment to policies encouraging it (Arkadie and Mallon, 2003). Following reunification of North and South Vietnam in 1976, the Vietnamese government nationalized many South Vietnamese private firms, particularly in areas where ethnic Chinese, who opposed socialist transformation, owned businesses. Weak property rights and socialistic rhetoric kept foreign investment low from the late 1970s to the late 1980s (Arkadie and Mallon, 2003).

Gradual reforms began in 1986 as part of *Doi Moi* (renovation) policy (Athukorala, 2006), with many reforms being made in the late 1980s and early 1990s (Arkadie and Mallon, 2003). By 1989, price reforms ended the attempt to operate a centrally planned "command economy." Moreover, the Law on Foreign Investment of 1987 created a legal framework to attract foreign investment to Vietnam. Vietnam "...gradually relaxed the restrictions on foreign trade, regulations on registration procedures, access to land, capital and foreign exchanges, and tax measures to promote a greater presence of foreign-invested enterprises" (Vo and Nguyen, 2012).

The recent history of foreign-investment inflows into Vietnam can be seen in Figure 2.1 (GS0). Foreign investment inflow increases in the mid-1990s stemmed predominantly from expectations of the economic potential of a newly opened economy (Vo and Nguyen, 2012). Foreign investment inflows fell in the late-1990s, likely due to the East-Asian Financial Crisis, as historically more than 50% of foreign investment came from east asian nations as shown in Figure 2.2 (GSO).[10] Foreign-investment inflows increased remarkably in 2007, following Vietnam's accession to the World Trade Organization (WTO). Foreign investment is dispersed throughout the Vietnamese provinces, with most of it settling in firms in Ha Noi and Ho Chi Minh City (Figure 2.3).

[10] At the writing of this work, the Vietnam GSO provided FDI data by country going back to 2005. In 2005, the three countries with the most new projects invested in in Vietnam were South Korea (24%), Japan (19%), and Taiwan (12%).

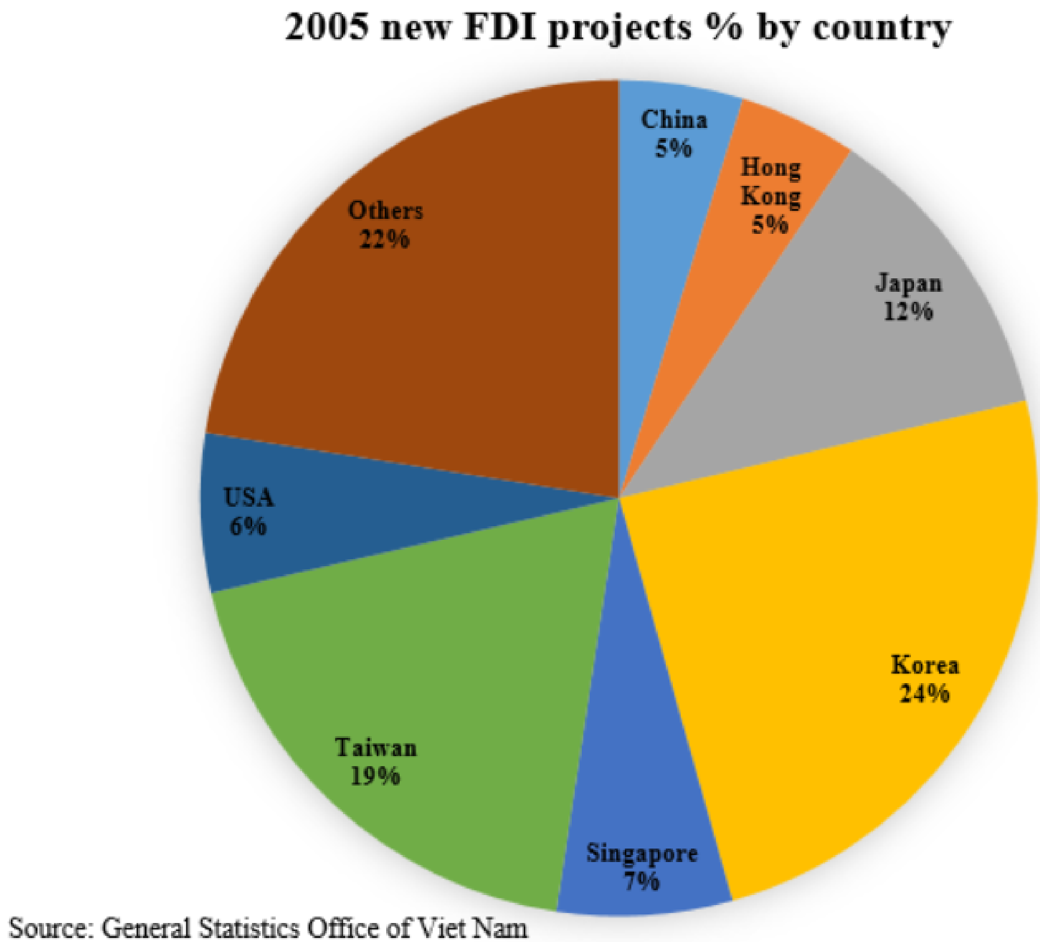

Figure 2.2: 2005 New FDI Projects % by Country

2.4 Data

2.4.1 Data Explanation

The analysis is based primarily on data from the Survey of Small and Medium Scale Manufacturing Enterprises (SMEs) in Vietnam, provided and maintained by the Development Economics Research Group (DERG) of the University of Copenhagen.[11] According to the Vietnamese governmental decree No. 90/2001/CP-ND, small and medium scale enterprises

[11]Several waves available at http://www.econ.ku.dk/derg/links/vietnam/. The remaining waves were acquired by request through the Vietnamese Enterprise Data contact official. The surveys are performed in cooperation with two Vietnamese institutions: 1) the Central Institute for Economics Management (CIEM), and the Institute for Labour Science and Social Affairs (ILSSA).

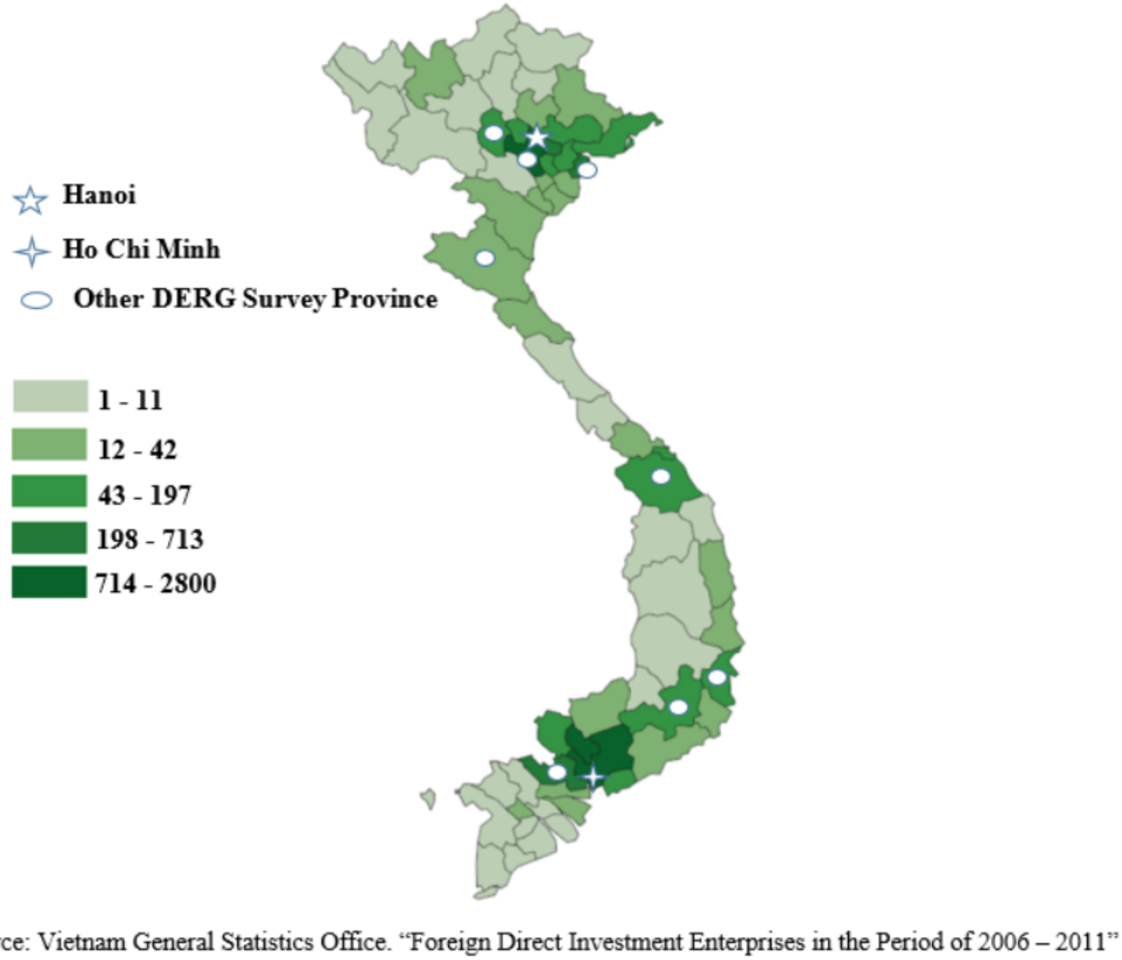

Figure 2.3: 2011 Foreign Investment Distribution by Province

are those with either less than 300 employees, or less than approximately 680,000 2001 USD.[12] In this paper I refer to "enterprises" as "firms," as they are referred to as firms in the survey questionnaire.

The SME survey was carried out in 1991, 1997, 2002, and biennially from 2005 to 2013. Due to pre-2005 waves not being "owned" by DERG and to changes in industry classifications between waves 2005 and 2007, only the four biennial waves from 2007 to 2013 are used in this

[12]Official wording is 10 billion VND, http://www.unido.org/fileadmin/import/40748_DecreeSME2001.pdf. According to the World Bank World Development Indicators the exchange rate is 1 USD to approximately 14,725 VND. New firms of up to 400 employees were allowed to be surveyed, and no employee limit was put on surveying repeat enterprises.

study. Each wave asks about firm information in the year prior, along with financial data in the two years prior. Thus the firm data used in this study covers 2006 to 2012 biennially.[13]

Enterprises across 10 regions are surveyed in each wave (Figure 2.3 - stars and ovals): Ha Noi, Phu Tho, Ha Tay, Hai Phong, Nghe An, Quang Nam (including nearby Da Nang), Khanh Hoa, Lam Dong, Ho Chi Minh City, and Long An. A list of two-digit manufacturing industries included in this study is provided in Table 1. Column 3 of Table 1 lists the percentage of observations in the 2006-2012 DERG data by industry.

Columns 4 and 5 provide information on how representative the DERG data is of the Vietnamese manufacturing sector. Column 4 is the percentage of manufacturing revenue by industry in 2012 in the DERG data. Column 5 is the percentage of manufacturing revenue by industry in 2012 from the manufacturing census data from the General Statistics Office of Viet Nam. The more similar column's 4 and 5 are, the more likely the DERG data is representative of the Vietnamese manufacturing sector, and the more confidence I have that the ensuing results extend to the Vietnamese manufacturing sector. Outside of a few industries, column's 4 and 5 line up within three percent of one another. Therefore, I am fairly confident that the results of this work are representative for the Vietnamese manufacturing sector.

As additional evidence on the representativeness of the DERG dataset, I show in Figure 2.4 the percentage of DERG firms in each year that supply domestic foreign firms. Concurrent with Vietnamese foreign-investment inflows rising between 2004 and 2012, the percentage of firms supplying domestic foreign firms grew from 2% in 2004 to about 5% in 2012, with a spike following their 2007 accession to the WTO.

[13]2015 data is available, however questions necessary for outcome variables of this study were not asked. For example, firms are not asked their annual expenditure on electricity, fuel, or water.

Table 2.1: Observation and Revenue Percentages in 2012 DERG Vietnam Data and Revenue Percentages from GSO Census Data by 2-Digit Industry

VSIC (1)	Manufacturing industry (2)	N % (3)	N 2012 Rev % (4)	2012 GSO Rev % (5)
10	Food products	28	21	19
11	Beverages	2	2	2
13	Textiles	4	4	4
14	Wearing apparel	5	5	5
15	Leather and related products	2	1	4
16	Wood and of products of wood and cork (no furniture)	11	8	2
17	Paper and paper products	3	8	3
18	Printing and reproduction of recorded media	3	2	1
19	Coke and refined petroleum products	0	0	4
20	Chemicals and chemical products	1	5	5
21	Pharmaceuticals, medicinal chemical and botanical products	0	1	2
22	Rubber and plastics products	5	13	5
23	Other non-metallic mineral products	5	6	6
24	Basic metals	0	1	5
25	Fabricated metal products, except machinery and equipment	17	11	7
26	Computer, electronic and optical products	0	0	8
27	Electrical equipment	1	4	3
28	Machinery and equipment not elsewhere classified	1	2	1
29	Motor vehicles; trailers and semitrailers	1	0	3
30	Other transport equipment	0	1	4
31	Furniture	7	4	4
32	Other manufacturing	1	1	1

VSIC stands for Vietnam Standard Industrial Classification. Column 3 lists the percentage of observations in the 2006-2012 DERG data by industry. Column 4 is the percentage of manufacturing revenue by industry in 2012 in the DERG data. Column 5 is the percentage of manufacturing revenue by industry in 2012 from the manufacturing census data from the General Statistics Office of Viet Nam taken from the 2013 GSO Statistical Yearbook.

The SME surveys were conducted by the Vietnamese Institute of Labour Studies and Social Affairs, and the Department of Economics at the University of Copenhagen. According to Rand and Tarp (2012):

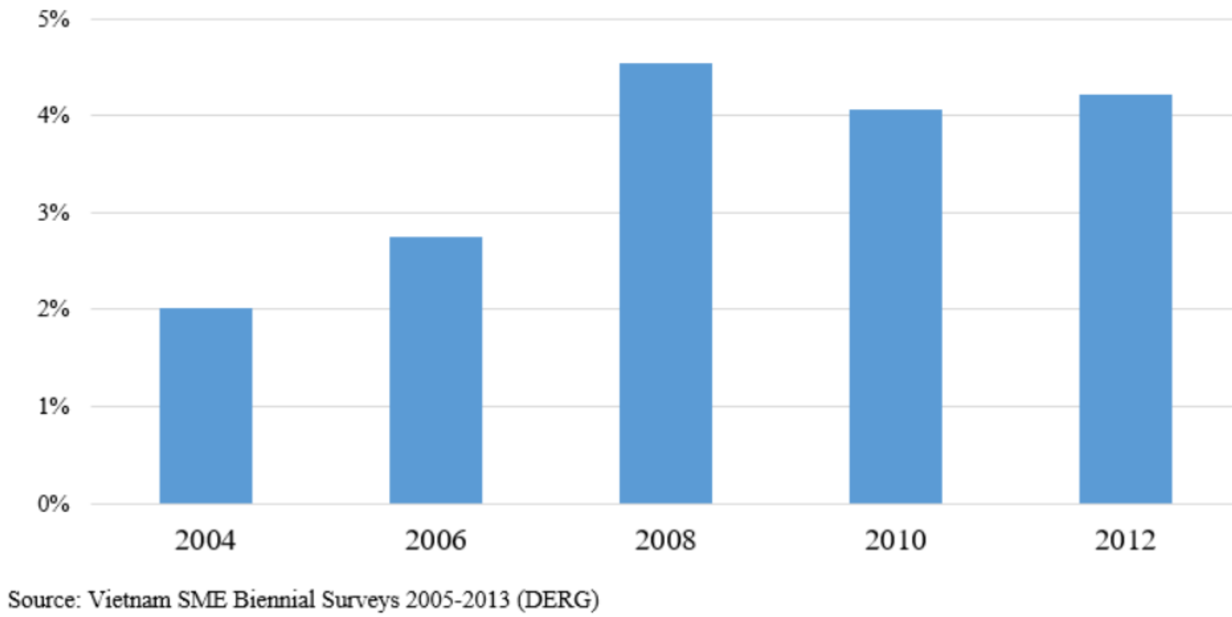

Figure 2.4: Share of Foreign-Firm Suppliers in SME Survey Data

> ...samples were stratified by ownership form to ensure that all types of non-state enterprises, including both officially registered (with a business registration license) formal household, private, cooperative, limited-liability, joint-stock enterprises, and nonofficial (informal) household firms, were represented. For reasons of implementation, the surveys were confined to specific areas in each province/city. Subsequently, stratified random samples were drawn from a consolidated list of formal enterprises and an onsite random selection of informal firms. While the sampling was adjusted over time to accommodate the rapidly changing business environment in Vietnam, other aspects, including the questionnaires, were maintained virtually identical.

One benefit of the DERG Vietnam dataset is that a wide variety of questions are asked each wave. 142 questions were asked in 2007 covering the following subjects: general enterprise characteristics; enterprise history; household characteristics of owner/manager; production characteristics; sales structure and export; indirect costs, raw materials, and services; fees, taxes, and informal payments; employment; investments, assets, liabilities, and credit; environment; networks; economic constraints and potentials. The variables in the DERG dataset that are useful for this study are the following: electricity, fuel, and water expenses; value of production; recent innovation activity; percent of output sold to foreign-invested companies;

assets; labor (total employment); value of raw materials used; percent of output exported; percent of raw materials imported; region classification (10 regions); industry classification (4-digit Vietnamese Standard Identification Codes, or VSICs); and firm identifiers.

Surveys were conducted in person. The preferred interviewed candidate was the person who retains effective control of the firm.[14] Respondents were informed their responses are confidential and only used for statistical purposes. Interviewers are told to make extensive efforts to obtain quality responses and to complete the questionnaire for all firms in the sample.[15]

2.4.2 Variable Creation

To examine how supplying domestic foreign firms affects innovation adoption and energy intensity, I construct several variables from the DERG Vietnam dataset.

First, I construct electricity, fuel, and water "intensities" as the following:

$$S = \frac{P_E Q_E}{P_Y Q_Y} = \frac{\text{Annual energy cost}}{\text{Annual revenue}}.$$

Admittedly, this energy "intensity" measure is not ideal, as energy intensity is the quantity of energy used, e.g. kilowatt-hour, divided by the associated quantity produced, e.g. one t-shirt, exclusive of energy and output prices. Unfortunately the DERG dataset only contains biennial energy expenses and annual revenue. I am unaware of data on Vietnamese energy

[14]Either the owner or manager. Larger firms are allowed to have one or several senior managerial staff assist.

[15]Interviewers are asked to make "every effort" to obtain final book figures, and when not available, to get the respondent's best estimate. If firms are temporarily closed and reopen while the interviewer is in the area, he/she has to return when the firm opens. If the firm will not open while the interviewer is in the area, and the owner/manager lives in the neighborhood, they are required to try and contact the owner/manager at home to complete the questionnaire.

prices at any disaggregate enough level to confidently convert annual energy cost into annual energy used.[16]

Second, domestic "foreign-firm" suppliers are firms reporting selling a positive amount to "foreign-invested companies." Conversation with the DERG Vietnam data contact official verified that "foreign-invested companies" are domestic firms with a majority being 100% foreign owned, and all are at least majority foreign owned.[17] Formally, a domestic foreign-firm supplier is defined as follows:

$$FFsupplier = I(\text{Sales to domestic foreign-invested firm} > 0\%)$$

where $I(\cdot)$ is an indicator function equal to one for firms that supply at least one foreign-invested firm, and zero otherwise. The results of this work are robust to the inclusion of linear, squared, and cubic terms of the percentage of sales to domestic foreign-invested firms.

Third, I construct real capital following Javorcik (2004). Real capital is defined as the value of fixed assets at the end of the year, deflated by the simple average price for five two-digit VSIC industries: computers, electronic and optical products; electrical equipment; machinery and equipment not elsewhere classified; motor vehicles, trailers, and semitrailers; other transport equipment. The simple average price for a given year is calculated by summing the reported average prices of all firms surveyed in the above two-digit industries in a given year, and dividing by the total number of firms surveyed in those two-digit industries in a given year.

Fourth, I construct real materials. Real materials is defined as the value of raw materials used by the end of the year, deflated by an intermediate-input price calculated for each industry based on the input-output matrix and reported average prices for the relevant industries.[18]

[16] Inability to construct energy intensity is common for firm-level survey and census datasets (Eskeland and Harrison, 2003; Cole et al., 2008; Batrokova et al., 2012.

[17] Email with John Rand on 10/23/2015, "foreign-invested companies" have at least 50% foreign ownership share.

[18] 2007 input-output values were used for every wave. Refer to the "Instrument Data and Construction" section for how I got this data.

For a given industry j in year t, the intermediate-input price is defined as the following:

$$IIP_{jt} = \sum_{k} \alpha_{jk} \bar{P}_{kt}$$

where α_{jk} is the cost share of industry k's output in industry j's total costs. This is taken from the 2007 input-output matrix at the three-digit VSIC level, and $\bar{P}_{kt}$ is the simple average price for industry k in year t. Put simply, the intermediate-input price is the weighted average input price, weighted by the cost share of each input in good j.[19]

Real capital and materials are not included in any estimation explicitly. They are only used to show differences between suppliers of domestic foreign firms and non-suppliers, and to ensure balance between treated and control firms in the later explained propensity-score matching estimation.

Finally I construct an instrument for the likelihood of becoming a foreign-firm supplier. The instrument is two-year lagged industry tariffs.

Tariff and import data was gathered from the World Bank World Integrated Trade Solution (WITS) database. Tariff and import data is stored at the 6-digit Harmonized System level, while data from the Vietnamese DERG dataset is stored at the 3-digit Vietnamese Standard Industrial Classification (VSIC) industry level. Therefore, I converted 6-digit Harmonized System tariffs to 3-digit VSIC tariffs using concordance tables available from WITS and the United Nations Statistics Division. To aggregate 6-digit Harmonized System tariffs to 3-digit VSIC industries I calculated the weighted-average 3-digit industry tariff, weighted by the import share of each 6-digit Harmonized System industry within a 3-digit VSIC industry. This was enough information to construct the 2-year lagged industry tariffs.

[19]For example, suppose industry j is beer brewing and has two input (k) industries, water and hops. Suppose that the inputs of water and hops are defined such that for one bottle of beer, water is responsible for one-third of the input costs and hops are responsible for two-thirds of the input costs. Also suppose that the price of a unit of water is \$2 and the price of a unit of hops is \$1. The calculation of the intermediate-input price for the beer brewing industry would yield \$1.33=0.33(\$2.0)+0.66(\$1.0).

2.4.3 Summary Statistics

In an ideal experiment, treatment status of supplying a domestic foreign firm would be applied randomly across the Vietnamese manufacturing sector. In this ideal experiment differences in simple averages of any outcome between foreign-firm suppliers and non-foreign-firm suppliers would provide the causal average marginal effect of becoming a domestic foreign-firm supplier on that outcome. However, the forced random assignment of Vietnamese suppliers to domestic foreign firms appears an experimentalist pipe dream.

Table 2.2 provides variable descriptions of all the main variables included, and Table 2.3 provides summary statistics for all main variables separated into suppliers of domestic foreign firms and non-suppliers. Table 2.3 shows suppliers of foreign firms differ from non-suppliers across several systematic dimensions. It is important to control for these dimensions to perform as close of an, "apples to apples," comparison in estimating any causal effect of supplying a domestic foreign firm.

Looking at the outcome variables of energy intensities and innovation activity, foreign-firm suppliers' average electricity, fuel, and water intensities do not differ from firms that do not supply foreign firms, with averages ranging between zero and 0.02. For interpretation's sake, an electricity intensity of 0.02 means that for every dollar earned, two cents go towards paying for electricity. Foreign-firm suppliers are on average 19 percentage points more likely to have recently upgraded a product and 14 percentage points more likely to have adopted a new process innovation or technology. These averages give an initial sign that domestic foreign-firm suppliers might be receiving more technology as a result of supplying domestic foreign firms over their non-supplier peers, however they do not appear to also immediately decrease any of their energy intensities.

Turning to other firm characteristics, foreign-firm suppliers are on average larger than non-foreign-firm suppliers. They have on average more capital, more employees, and use more

Table 2.2: Variable Definitions

Variable	Description
Electricity intensity	Annual electricity cost divided by annual production value.
Fuel intensity	Annual fuel cost divided by annual production value.
Water intensity	Annual water cost divided by annual production value.
Product Innovation	Indicator that equals one for firms that have introduced a new product.
Product Upgrade	Indicator that equals one for firms that have made major improvements to existing products or changed specification.
Process Innov/New Tech	Indicator that equals one for firms that have introduced new production processes/new technology in the last two years.
FF Supplier	Indicator equal to one for firms supplying domestic foreign firms.
Age	Age of the firm in years.
Exports	Indicator variable equal to one if a firm exports any percentage of output.
Imports	Indicator variable equal to one if a firm imports any percentage of raw materials.
VA/Employee	Value added per employee in 2005 USD.
Employees	Total labor force (paid and unpaid).
Capital	Value of year-end fixed assets (land, buildings, machinery, transportation equipment) deflated by the simple average price for five two-digit industries: computers, electronic and optical products; electrical equipment; machinery and equipment not elsewhere classified; motor vehicles, trailers, and semitrailers; other transport equipment.
Materials	Annual value of raw materials used, deflated by an intermediate input price calculated for each industry based on the input-output matrix and survey-reported average prices for the relevant industries.

materials. Foreign-firm suppliers are on average more productive than their non-supplier peers, as they have on average higher average capital-to-labor ratios, and value added per worker. Foreign-firm suppliers are on average two years younger than their non-supplier peers, as well as on average eight percentage points more likely to export their output and 15 percentage points more likely to import raw materials.

Table 2.3: Descriptive Statistics

	Foreign-Firm Suppliers (N = 403)		Non-Foreign-Firm Suppliers (N= 9,277)	
	Mean	Standard deviation	Mean	Standard deviation
Electricity Intensity	0.02	0.04	0.02	0.03
Fuel Intensity	0.01	0.02	0.02	0.04
Water Intensity	0.00	0.00	0.00	0.01
Product Innovation (1=yes)	0.05	0.23	0.03	0.17
Product Upgrade (1=yes)	0.54	0.50	0.35	0.48
Process Innov/New Tech (1=yes)	0.27	0.44	0.12	0.32
Capital	244.94	426.61	90.24	429.12
Employees	48.90	60.78	16.34	50.27
Materials	100.45	298.03	44.92	1,438.65
Capital/Employee	9.82	20.95	7.86	23.46
Value Added/Employee	4,534.54	5,068.60	2,441.88	3,336.71
Age (Years)	12.00	9.04	14.43	10.53
Exports (1=yes)	0.11	0.32	0.03	0.18
Imports (1=yes)	0.18	0.39	0.03	0.16

Electricity, fuel, and water intensities are measured as increases in Vietnamese Dong spent on each energy source per Vietnamese Dong earned. Product Innovation, Product Upgrade, and Process Innov/New Tech are indicators equal to one for firms that have introduced a new product, made major improvements to existing products or changed specification, and introduced new production processes/new technology in the last two years. Value added per worker is in 2005 USD. Age of the firm is in years. Exports is an indicator equal to one for firms that export. Imports is an indicator equal to one for firms that import raw materials.

2.5 Research Design

2.5.1 Energy Intensity and Innovation

To identify the extent foreign-investment inflows result in vertical environmental spillovers in Vietnam, I prefer to study how becoming a supplier of domestic foreign firms affects supplying-firm pollution intensity. However, similar to other studies investigating cleanliness of domestic and foreign firms in developing countries,[20] firm-level pollution information is not available in Vietnam.

[20]Batrakova and Davies (2012), Cole et al. (2008), and Eskeland and Harrison (2003).

Due to lacking firm-level emissions intensity, I proxy for emissions intensity with electricity and fuel intensity. The quality of a proxy variable depends on its correlation with the variable for which it proxies.

Electricity is a good proxy for emissions due to it being primarily generated from fossil-fuel sources. Historically, Vietnam's electricity production was heavily skewed towards hydro-electric power (Figure 2.5).[21] Over the period of this study (2006-2012), over 50% of the electricity produced in Vietnam came from fossil-fuel sources, with on average 20% coming from coal and 41% coming from oil and natural gas. Moreover, the International Atomic Energy Agency projects over 60% of Vietnamese electricity production to continue coming from fossil-fuel sources annually from 2015-2030, shifting heavily towards coal.[22] Since over 50% of electricity produced in Vietnam between 2006-2012 came from burning fossil fuels, which are inherently polluting (e.g. sulfur dioxide, nitrogen oxide, particulate matter, carbon dioxide, etc.), increased electricity usage is expected to increase pollution in Vietnam.

Fuel expenses reported in the DERG dataset come from "...[l]iquid fuel, solid fuel and gas water." Correspondence with the Vietnamese Institute for Labour Science and Social Affairs (ILSSA) determined that examples of fuel reported in this expense information are gasoline, oil, and firewood.[23] Using the same argument that burning fossil fuels for electricity is an inherently polluting process, burning fossil fuels and wood on site is an inherently polluting process. Therefore, increased fuel usage is expected to increase pollution in Vietnam.

On top of estimating how becoming a supplier of domestic foreign firms affects electricity and fuel intensities, I estimate how becoming a supplier of domestic foreign firms affects domestic-firm water intensity and innovation activity. Although increased water usage does

[21] Based on International Energy Agency data from Viet Nam Statistics ©OECD/IEA accessed 5/2016, www.iea.org/statistics. License: www.iea.org/t&c; as modified by Paul Stroik.

[22] The International Atomic Energy Agency projects much larger shares of Vietnamese energy production to come from coal. According to the U.S. Energy Information Administration, electricity produced using coal emits more carbon monoxide, sulfure dioxide, nitrogen dioxide, etc. per unit of heat energy generated than natural gas or oil, except for formaldehyde (EIA, 1998).

[23] Email correspondence with Nguyen Hai Ninh of the ILSSA on July 25th, 2015.

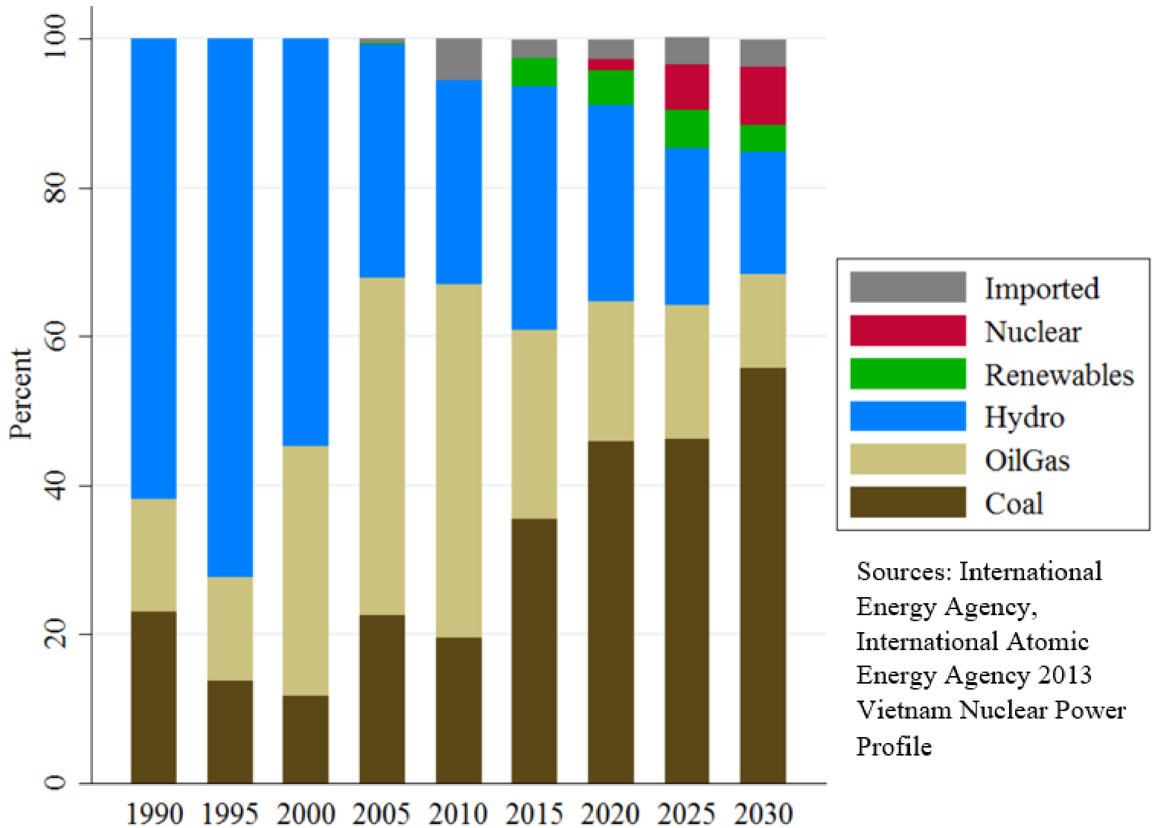

Figure 2.5: Vietnam Electricity Production

not guarantee increased pollution, it could show firms switching inputs between different resources and different pollution mediums, for example water instead of air.[24] Estimating how becoming a supplier of domestic foreign firms affects innovation activity verifies whether or not changes in electricity or fuel intensities are driven by new technology adoption.

2.5.2 Empirical Framework

The framework for estimating the effect that supplying domestic foreign firms has on domestic firm energy intensity is based on the potential outcomes model (Angrist and Pischke,

[24]One example of firms substituting between pollution mediums comes from Gibson (2015), where he finds in response to air pollution regulation, firms substitute their pollution activities away from air pollution to water pollution.

2009).[25] I assume there are two states of a firm to which a domestic Vietnamese firm can be assigned: a supplier of at least one domestic foreign firm, or a supplier of no domestic foreign firms. Let $D_{ijpt} = 1$ if firm i in industry j in province p is a first-time supplier of at least one domestic foreign firm in year t (i.e., the firm is "treated"), and $D_{ijpt} = 0$ if it is not a supplier of at least one domestic foreign firm and has never supplied a domestic foreign firm as reported in the DERG dataset (i.e., the firm is "untreated"). Potential outcomes $Y_{ijpt}(1)$ and $Y_{ijpt}(0)$ denote annual firm-level energy intensity or reported technology adoption conditional on supplying domestic foreign firms for the first time and never supplying, respectively.

The observed difference in each outcome between treated and untreated firms is the following:

$$\begin{aligned} E[Y_{ijpt'}(1)|D_{ijpt'} = 1] - E[Yijpt'(0)|D_{ijpt'} = 0] = & \underbrace{E[Y_{ijpt'}(1) - Y_{ijpt'}(0)|D_{ijpt'} = 1]}_{\text{Average treatment effect on the treated}} \\ & + \underbrace{E[Y_{ijpt'}(0)|D_{ijpt'} = 1] - E[Y_{ijpt'}(0)|D_{ijpt'} = 0]}_{\text{Selection bias}} \end{aligned} \tag{2.1}$$

where t' represents the first year a domestic firm reports supplying at least one domestic foreign firm.

I am primarily interested in estimating the average treatment effect on the treated (ATT), as I am interested in knowing how supplying new domestic foreign firms brought to developing countries through increased trade liberalization is likely to affect those firms that through market forces become suppliers of domestic foreign firms. I am less interested in the average treatment effect, as it provides the expected outcome change for becoming a supplier of a domestic foreign firm for the average firm, many of which are expected to never become suppliers of domestic foreign firms.

[25] The potential outcomes idea is also referred to as the Rubin [causal] model in Holland (1986).

Energy intensity at both treated and similar untreated firms is observed prior to when a firm becomes a supplier of a domestic foreign firm, and in the year a firm becomes a supplier of a domestic foreign firm. This information allows for the identification of $E[Y_{ijpt'}(1)|D_{ijpt'} = 1]$. However, $[Y_{ijpt'}(0)|D_{ijpt'} = 1]$, the outcome a "treated" firm would have were it not given the treatment, is not observed. I construct estimates of these counterfactual outcomes using firms that in year t' do not supply domestic foreign firms, and have no indication through the DERG survey of past supplying to domestic foreign firms.

The simplest estimate of an ATT of becoming a domestic foreign firm supplier is the average difference in an outcome variable between treated and untreated firms. This estimator is biased if factors related to firm-level outcomes and the likelihood of becoming a supplier of domestic foreign firms vary significantly across treated and untreated groups. In order to reduce any bias due to differences across firms that become suppliers of domestic foreign firms and those that do not, I employ two strategies that condition on observable covariates; regression control and propensity-score matching. I also employ two identification strategies that attempt to control for unobservable firm differences that are correlated with the likelihood of treatment and outcome variables. These identification strategies are regression control using a within model, in which all values are demeaned, thus removing observed and unobserved time-invariant firm-level factors, and instrumental variables, which controls for all forms of unobservable differences between treated and untreated firms.

Methods and Assumptions in Estimating Causal Effects

Regression Control. – Ordinary least squares (OLS) can control for covariates that are correlated with treatment status and outcomes such as energy intensity and technology adoption. OLS estimates of the ATT can be interpreted as causal, so long as the *Conditional Independence Assumption* (CIA) holds. The CIA states that conditional on observed characteristics,

X_{ijpt}, there is no selection bias. Formally the CIA states:

$$\{Y_{ijpt}(1), Y_{ijpt}(0)\} \perp D_{ijpt} | X_{ijpt} \tag{2.2}$$

where $\perp$ denotes the independence relation. The CIA holds if differences in outcomes between treated and untreated groups have already controlled for all the covariates that are correlated with becoming a supplier of domestic foreign firms and energy intensity or technology adoption.

Ensuring the CIA holds requires controlling for those covariates that are correlated with becoming a supplier of domestic foreign firms and energy intensity or technology adoption. I view becoming a supplier of domestic foreign firms as similar to becoming an exporter, in that there are up-front fixed costs a firm pays when entering a foreign market, be it locally or internationally. Javorcik and Spatareanu (2009), Melitz (2003), and Ranjan and Raychaudhuri (2011) have shown that firm productivity and firm size are positively correlated with becoming an exporter or a supplier of domestic foreign firms.[26] Therefore, I estimate the following linear model using OLS:

$$Y_{ijpt'} = \beta_0 + \beta_1' X^1_{ijpt} + \beta_2' X^2_{ijpt'} + \alpha D_{ijpt'} + \varepsilon_{ijpt'} \tag{2.3}$$

where β_0 is a single coefficient for all observations, β_1 and β_2 are column vectors of coefficients, X^1_{ijpt} is a column vector of observable firm-level covariates in year t, $X^2_{ijpt'}$ is a column vector of observable firm-level covariates in the following observed year t', α is the average effect of becoming a supplier of domestic foreign firms, and $\varepsilon_{ijpt'}$ is an error term. This approach assumes the covariates in X^1_{ijpt} and $X^2_{ijpt'}$ are exogenous to treatment status $D_{ijpt'}$.

[26] Javorcik and Spatareanu (2009) provide a further discussion of why suppliers of domestic foreign firms may be inherently different than their non-supplier peers.

X^1_{ijpt} includes lagged productivity measured in terms of value added per worker, lagged firm size measured as firm-specific total workforce (paid and unpaid), and lagged main sales industry measured at the three-digit level. $X^2_{ijpt'}$ includes firm age, the year in which the firm answered the survey, and the province in which the firm operates. Inclusion of these controls ensures that differences in outcomes are between firms that were similar before one firm became treated, in that they are of similar age, province, lagged productivity, lagged size, and lagged industry. Conditional on these covariates, the error term $\varepsilon_{ijpt'}$ is assumed to be independent of treatment status.

There are a couple possible problems with the regression control approach of estimating causal effects. First, if overlap in the distributions of X^1_{ijpt} and $X^2_{ijpt'}$ across treated and untreated groups is limited and/or functional-form assumptions are incorrect, missing outcomes will be imputed incorrectly leading to biased estimates. Second, estimates can be biased if control observations are not properly reweighted to control for differences in the distributions of X^1_{ijpt} and $X^2_{ijpt'}$ over regions common to the treated and untreated groups. In order to mitigate these potential biases, I implement a semi-parametric matching estimator, i.e. propensity score matching.

Propensity-Score Matching. – Just like regression control, propensity-score matching provides causal estimates of being treated under a specific assumption. That assumption is that conditional on the propensity score, or the likelihood of being treated, treated and untreated outcomes are independent of treatment status. More formally, propensity-score-matching estimates of treatment effects are causal under the following assumption:

$$\{Y_{ijpt'}(1), Y_{ijpt'}(0)\} \perp D_{ijpt'} | Pr(D_{ijpt'} = 1) \tag{2.4}$$

where $Pr(D_{ijpt'} = 1)$ is the estimated propensity score.

As made clear in Angrist and Pischke (2009, p.80), the identifying assumptions of regression control and propensity-score matching are the exact same. After controlling for the correct covariates, treated and untreated outcomes are independent of treatment.

The benefit of propensity-score matching is not using a different identifying assumption, but rather correcting for potential biases from regression control. These potential biases are a lack of overlap in the distributions of X^1_{ijpt} and $X^2_{ijpt'}$ across treated and untreated groups, as well as reweighting control observations for differences in the distributions of X^1_{ijpt} and $X^2_{ijpt'}$ over regions common to the treated and untreated groups.

The first bias is corrected by matching treatment and control firms based on their likelihood of being treated, i.e. their propensity score. Given a good estimate of the propensity score, treated and untreated groups will have no significant differences in the distributions of X^1_{ijpt} and $X^2_{ijpt'}$ across treated and untreated groups. Since propensity-score estimation uses only independent variables, there is no theoretical issue with searching for the covariates used in estimating the propensity score that result in no significant differences in the distributions of X^1_{ijpt} and $X^2_{ijpt'}$ across treated and untreated groups.

The second bias is corrected by weighting control firms on their "closeness" to treated firms, as measured by the propensity score. Several methods exist to reweight the control firms based on their "closeness" to treated firms. I utilize the nearest neighbor matching algorithm, and match treated observations with the average of their three nearest untreated observations within a 0.02 range of the propensity score.[27]

The propensity score, or likelihood of being treated, I estimate is the following:

$$Pr(D_{ijpt'} = 1) = \Phi(X^3_{ijpt}, t', p) \tag{2.5}$$

[27]Estimates using 1, 3, and 5 nearest neighbors all produce similar results.

where Φ stands for the standard Gaussian cumulative distribution function, and X^3_{ijpt} contains lagged productivity, lagged total employment, the squares of lagged productivity and lagged employment, and lagged main sales industry. t' is the year in which the firm answered the survey, and p is the province in which the firm operates.

Propensity-score estimates are calculated in the following manner:

$$\widehat{\alpha_{PSM}} = \frac{1}{N_1} \sum_{h \in I_1} \{Y_{ijpt'}(1) - w_{hk} \sum_{k \in I_0} Y_{ijpt'}(0)\} \tag{2.6}$$

where I_1 indicates the set of treated firms, I_0 indicates the set of untreated firms, and N_1 is the number of firms in the treated group. Treated firms are indexed by h; untreated firms are indexed by k. The weight on firm k when constructing the counterfactual estimate for treated firm h is w_{hk}. Due to using nearest neighbor matching with three nearest neighbors in constructing each treated firm's counterfactual, the weight w_{hk} equals $\frac{1}{3}$ for the untreated firms identified as nearest neighbors of treated firm h, and 0 for untreated firms not identified as nearest neighbors of treated firm h.

One problem that will result in both regression control and propensity-score matching providing biased estimates is if selection into treatment is driven by any unobserved factor that is also correlated with the outcome variables of interest. In order to try and mitigate this worry, I first include regression control within estimates that control for time-invariant unobserved firm-specific effects.

Within Model. – Within estimates provide causal effects so long as time-invariant firm-specific factors effect both the likelihood a firm becomes a supplier of domestic foreign firms, and the outcome variable of interest. This issue is clearer by considering the following formulation of the earlier linear model:

$$Y_{ijpt'} = \beta_0 + \beta_1' X^1_{ijpt} + \beta_2' X^2_{ijpt'} + \alpha D_{ijpt'} + c_i + u_{ijpt'} \tag{2.7}$$

where c_i is an unobserved firm-specific effect and $u_{ijpt'}$ is an idiosyncratic error term. If c_i is correlated with treatment status $D_{ijpt'}$ and an outcome variable of interest $Y_{ijpt'}$, then OLS estimates of a linear model without controlling for the unobserved firm-specific effects will be biased. In this case OLS estimates from the within-model, which takes every observation and subtracts from it the firm-specific mean value, will be unbiased.

One problem that will result in within estimates being biased is if selection into treatment is driven by any time-varying unobserved factor that is correlated with the outcome variables of interest. In order to try and mitigate this worry, I include instrumental variable estimates that control for both time-invariant and time-varying unobserved firm-specific effects.

Instrumental Variable. – Instrumental variable estimates provide causal effects so long as the instrument used is *excludable* and *relevant*. An instrument is excludable from a model if it is uncorrelated with unobserved shocks to the outcome variable of that model. An instrument is relevant so long as it is "highly" correlated with the endogenous variable it is instrumenting, which in my case is an indicator variable equal to one for domestic firms in their first reported year of supplying a domestic foreign firm.

The instrument I employ is the two-year lagged weighted three-digit-industry tariff. Excludability of any instrument cannot be directly tested, and must be argued. Trefler (2004) shows that industry tariffs for U.S. and Canadian industries are endogenous, however industry tariffs for U.S. and Canadian firms are exogenous. For the excludability restriction to hold, I assume the tariff result for the U.S. and Canada holds in Vietnam.

Relevance of an instrument can be tested, and is usually done by reporting the F-statistic comparing the regression of the instrumented variable on the instrument(s) and exogenous covariates to the regression of the instrumented variable on the exogenous covariates excluding the instrument(s). The F-statistic using two-year lagged weighted three-digit-industry tariff is 7.092.[28] Comparing the Kleibergen-Paap F-statistics to Cragg-Donald F-statistic critical values provided in Stock and Yogo (2005), it is possible two-year lagged weighted three-digit-industry tariffs might be a weak instrument, because the range of reported critical values for a single instrument are 5.53 to 16.38.[29]

I use two-stage least squares estimation to provide instrumental variables estimates. When using a single instrument that is weak, estimating an instrumental variables model with two-stage least squares or limited information maximum likelihood is expected to yield similar results as they are both median-unbiased (Angrist and Pischke, 2009).

The benefit of instrumental variable estimates is that they are unbiased in the face of time-invariant and time-varying unobserved factors that select firms into being treated; a potential source of bias for which regression control, with and without firm fixed effects, and propensity score matching methods cannot control. However, if the excludability assumption is not valid, all sense of causality of the treatment variable is lost. Moreover, if the instrument is weak in that the relevance of the instrument is questionable, the instrumental variable estimate is biased away from the true causal effect and towards the OLS estimate.

[28]This is the Kleibergen-Paap F-statistic. The Kleibergen-Paap F-statistic is appropriate when errors are not assumed to be independent and identically distributed (i.i.d.) within each firm, which I assume.

[29]Javorcik and Spatareanu (2009b) provide several potential instruments for the likelihood of becoming a supplier of domestic foreign firms. Lagged 3-digit-industry tariff had the highest first-stage F statistic of all their recommended instruments available in the DERG data. Adding further recommended instruments only produced lower first-stage F statistics.

2.6 Results

In this section, I present my estimates of the average treatment effect on the treated of becoming a supplier of domestic foreign firms. The outcomes of interest are the firm-level likelihood of technology adoption (product upgrading, process innovation, product innovation), and firm-level energy intensities (electricity, fuel, and water). I report energy intensity results using both levels and log-transformed data. Using log-transformed data, estimates of the average treatment effect on the treated are in percentage terms. The control group for year t' is always firms that have never reported supplying a domestic foreign firm up to year t'.

Due to providing ATT for many outcomes, the following tables only provide ATT results and their respective standard errors, clustered at the three-digit industry level to allow for correlation between firm-specific estimation error in the same industry over province and time. More detailed estimation results for all identification strategies are available from the author upon request.

2.6.1 Regression Control Estimates

I first use a simple linear regression framework to show average outcome differences between treated and untreated firms, controlling only for sets of province indicators, year of operation indicators, and lagged three-digit-industry indicators. I then provide multivariate linear regressions results, where indicator variables of technology adoption and energy intensities in levels and logs are independently regressed on firm-specific lagged value added per worker, total employment, age, and sets of province indicators, year of operation indicators, and lagged three-digit-industry indicators.

Column 1 of Table 2.4 shows that the simple linear regression estimates of the effect of becoming a supplier of domestic foreign firms are significant at the 1% level for two measures of technology adoption, and the 10% level for water intensity. Simple average comparisons of treated and control groups provide evidence that becoming a supplier of domestic foreign firms increases the probability of technology adoption (15 percentage points for product upgrading, and 12 percentage points for process innovation), and decreases water intensity (for every 10,000 dollars earned annually, new suppliers of domestic foreign firms spend 12 dollars less on water).

Column 2 of Table 2.4 provides estimates from regressions similar to column 1, except they additionally control for firm age and selection-into-treatment variables; lagged firm value added per worker and lagged firm size. In general, controlling for selection-into-treatment variables decreases all point estimates in an absolute sense, while no changes in statistical significance occur. Results from these regressions provide evidence that becoming a supplier of domestic foreign firms increases the probability of technology adoption (13 percentage points for product upgrading, and 10 percentage points for process innovation), and decreases water intensity (for every 10,000 dollars earned annually, new suppliers of domestic foreign firms spend 11 dollars less on water).

2.6.2 Propensity-Score Matching Estimates

The prior estimates are derived from fully parametric estimation techniques. It is possible that the parameterization is incorrect, leading still to biased estimates. In order to check the robustness of the parametric estimates, I provide results from a semi-parametric estimation technique; specifically propensity-score (P-score) matching. Propensity-score matching is parametric only in the matching treated and control firms stage. Estimating the ATT is done taking a simple difference in observed values, and no additional parameter estimation.

Table 2.4: Effect of Foreign-Firm Supplier Status by Outcome Variable and Identification Strategy

	Model/Identification				
Outcome Variable	Simple (1)	Control (2)	P-score (ATT) (3)	Firm FE (4)	IV (2SLS) (5)
Product Upgrade	0.1496***	0.1261***	0.1064**	0.0677	n/a
	(0.0297)	(0.0296)	(0.0438)	(0.0495)	
Process Innovation	0.1189***	0.0996***	0.0680*	-0.0126	n/a
	(0.0238)	(0.0224)	(0.0376)	(0.0526)	
Product Innovation	0.0219	0.0173	0.0139	-0.0220	n/a
	(0.0146)	(0.0149)	(0.0178)	(0.0297)	
Electricity Intensity	-0.0023	-0.0021	0.0000	-0.0007	0.0162
	(0.0033)	(0.0032)	(0.0035)	(0.0032)	(0.0380)
Electricity Intensity (%Δ)	-0.0024	-0.0022	-0.0002	-0.0005	0.0095
	(0.0028)	(0.0027)	(0.0030)	(0.0030)	(0.0345)
Fuel Intensity	-0.0015	-0.0013	-0.0011	0.0034	-0.1941
	(0.0023)	(0.0023)	(0.0020)	(0.0023)	(0.1807)
Fuel Intensity (%Δ)	-0.0012	-0.0011	-0.0009	0.0032	-0.1823
	(0.0020)	(0.0021)	(0.0019)	(0.0020)	(0.1715)
Water Intensity	-0.0012***	-0.0011***	-0.0011	-0.0001	-0.0238
	(0.0004)	(0.0003)	(0.0007)	(0.0004)	(0.0169)
Water Intensity (%Δ)	-0.0012***	-0.0011***	-0.0011	-0.0001	-0.0235
	(0.0004)	(0.0003)	(0.0007)	(0.0004)	(0.0166)
Observations	7,502	7,502	191/6,799	7,502	7,502
					[F = 7.092]

IV results have two-digit-industry clustered standard errors in parentheses. All other results have three-digit-industry clustered standard errors in parentheses. P-score matching output includes observations split, with treated first, and untreated second. P-score matching estimates require treated and untreated firms to only match when within 0.02 propensity-score units. All estimates control for or match on year, province, and lagged industry effects (2-digit industry for IV estimates, 3-digit industry for all other estimates). All estimates except for those in the "Simple" column additionally control for or match on firm-level lagged value added per worker, lagged total employment, and age. The P-score matching estimates were additionally matched on the square of lagged firm-level value added per worker and lagged total employment. IV estimation output includes the Kleibergen-Paap first-stage F statistic, providing evidence that lagged 3-digit industry tariff may be a weak instrument. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

The propensity-score matching estimator constructs the counterfactual estimate for each treated firm using untreated firms that most closely resemble treated cases. I match firms based on year, province, 2-year lagged main sales industry, age, 2-year lagged value added per worker, and 2-year lagged total employment. P-score matching estimates require treated and untreated firms to only match when within 0.02 propensity-score units.

Column 3 of Table 2.4 provides estimates of the ATT from propensity-score matching. In general, using propensity-score matching to control for selection-into-treatment variables decreases all point estimates relative to regression control in an absolute sense. Results from these regressions provide evidence that becoming a supplier of domestic foreign firms increases the probability of technology adoption (11 percentage points for product upgrading, and 7 percentage points for process innovation). None of the energy-intensity inputs are found to experience statistically significant changes by becoming a supplier of domestic foreign firms. However, ignoring the reduction in precision, the point estimates imply that becoming a supplier of domestic foreign firms decreases domestic firms' fuel and water intensities.

2.6.3 Within Estimates

Column 4 of Table 2.4 provides within-firm estimates that control for similar covariates as column 2, however now time-invariant firm-specific effects are controlled for due to all outcome and covariate variables being demeaned. Controlling for time-invariant firm-specific effects results in loss of conventional levels of significance for all estimates that previously were found to be statistically significantly different from zero. The loss in significance is due to both coefficient estimates generally falling towards zero, and the estimates becoming generally less precise. Discounting the loss in precision, there is still evidence of firms that become suppliers of domestic foreign firms being more likely to innovate through product upgrading (6.8 percentage points).

2.6.4 Instrumental Variable Estimates

Column 5 of Table 2.4 provides instrumental variable estimates that control for similar covariates as column 2, however the treatment variable of becoming a supplier of domestic foreign firms is instrumented with two-year lagged weighted three-digit-industry tariff. Furthermore, I only control for two-year lagged two-digit-industry fixed effects, as controlling at the three-digit-industry level implies identifying variation of the ATT comes only from firms becoming a supplier of domestic foreign firms as a result of switching three-digit industry. This variation misses all the firms that become suppliers of foreign firms but do not switch three-digit industry.

IV estimates are not provided for any of the technology adoption outcomes, as two-stage least squares estimation provided estimates outside theoretically plausible ranges (e.g. first-time suppliers of domestic foreign firms being 304 percentage points less likely to report upgrading a product than their non-supplier peers).[30]

Again ignoring the loss in precision between the IV estimates and the P-score estimates, there is evidence of short-run decreases in fuel intensity (for every 10,000 dollars earned annually, new suppliers of domestic foreign firms spend 1,921 dollars less on fuel) and water intensity (for every 10,000 dollars earned annually, new suppliers of domestic foreign firms spend 243 dollars less on fuel), and short-run increases in electricity intensity (for every 10,000 dollars earned annually, new suppliers of domestic foreign firms spend 103 dollars more on electricity). The point estimates imply that becoming a supplier of domestic foreign

[30]Traditional methods of combining instrumental variables in a probit model are designed for when the endogenous variable being instrumented is continuous (Lewbel et al., 2012). In the case of a discrete outcome and an endogenous instrumented variable, Dong and Lewbel (2015) suggest implementing their "special regressor" method. Implementing this method is left for future work.

firms decreases domestic firms' fuel and water intensities, while increasing their electricity intensity.

The difference in IV estimates from all the other estimates is primarily due to controlling for industry at the two-digit level instead of the three-digit level. Hausman test for systematic differences between IV estimates and similarly specified OLS estimates for all outcome variables of interest all find no systematic differences in coefficient estimates. Due to the potential of using a weak instrument, it is hard to know whether the lack of finding systematic differences between OLS and IV estimates is due to the actual lack of systematic differences or due to the weak instrument biasing IV estimates towards the OLS estimates.

2.7 Conclusion

In this paper I compare the outcomes of domestic Vietnamese firms that become suppliers of domestic foreign firms to their non-supplier peers. This work brings new evidence to bear on two important questions. First, does starting supplying domestic foreign firms lead to more technology transferring to domestic firms than would have happened without their new foreign-firm interaction? Second, does starting supplying domestic foreign firms lead to short-run environmental intensity reductions for domestic firms? If so, then entrance of foreign firms from further trade openness may actually increase environmental quality.

My results indicate that on average more technology is transferred as a result of supplying domestic foreign firms. I find relatively robust evidence that new suppliers of domestic foreign firms are 7-11 percentage points more likely to have recently upgraded a product, and weak evidence of being seven percentage points more likely to have recently made a process innovation.

I find little to no evidence that new suppliers of domestic foreign firms are less environmentally intensive as a result of supplying domestic foreign firms. I find weak evidence that becoming a supplier of domestic foreign firms decreases water intensity in the short run.

Although I find little to no evidence of reduction in environmentally-linked input intensities (electricity and fuel), environmental gains from modern technology spreading in developing countries that further open to trade may still be found by looking at other dimensions and channels. First, it is possible that the environmental effects of becoming a supplier of domestic foreign firms are long run in nature. Second, technology that cuts on environmentally-linked input intensities may only spread horizontally to competitors of domestic foreign firms instead of vertically to their suppliers. Third, the entrance of new, less environmentally intensive foreign firms into developing countries may push out dirtier domestic developing-country firms.

Chapter 3

Environmental Spillovers from Domestic Foreign Investment to Chilean Manufacturing Firms

3.1 Introduction

Economists have been estimating the environmental effects from trade openness at least since the early 1990s when the potential existence of environmental effects of the North American Free Trade Agreement entered policy discussion (e.g. Grossman and Krueger, 1993; Levinson, 2002; Stern, 2004; Torras and Boyce, 1998).[1] In their seminal work, Grossman and Krueger (1993) decompose changes in environmental quality from increased trade openness into scale, composition, and technique effects. Scale refers to increased production and pollution following trade liberalization due to an expansion of economic activity. Composi-

[1]In 1993, Friends of the Earth put on record the following statement in front of the House Ways and Means Subcommittee on Trade: "Many crucial environmental issues are not addressed at all in the [North American Free Trade Agreement] side agreement. For example, the agreement: ...does not deter companies from relocating to countries with weaker or non- enforced environmental standards."

tion refers to changes in location of production and its associated pollution following trade liberalization as firms relocate to other countries due to changes in competitive advantage. Technique refers to changes in pollution brought about by changes in production methods following trade liberalization.

Most of the work on the environmental effects of trade has focused on scale and composition effects, with little work focusing on identifying firm-level of the technique effect, or changes in production processes from trade openness. The existing literature on all these effects is discussed in Chapter 2. The purpose of this work, therefore, is to provide further firm-level evidence of the technique effect, specifically through increased foreign investment.

Earlier firm-level work on the technique effect (Albornoz et al., 2009; Chudnovsky et al., 2005; and Chapter 2 of this work) is unable to estimate the effects of foreign investment and within-industry foreign exposure on environmental quality while controlling for lagged selection variables and time-invariant firm factors that may explain why firms receive foreign-exposure changes. If firms receive more foreign investment or more foreign exposure due to observed time-varying pre-existing factors or time-invariant firm-specific factors that are also correlated with environmental quality, then coefficient estimates from models lacking these controls are biased.[2]

Furthermore, existing literature proxies for environmental quality with either firm reports of adoption of environmental management activities (e.g. recycling, obtaining an environmental certification, replacing pollution intensive inputs, etc.), or energy intensity as measured by the ratio of annual energy usage over annual revenue. Firm reports of adoption of environmental management activities do not guarantee environmental improvements. Energy intensity as measured by annual energy expenditure over annual revenue might be correlated

[2]This is a worry for Chudnovsky et al. (2005), and Albornoz et al. (2009). Chapter 2 of this work is unable to even estimate these coefficients due to lacking firm-level foreign ownership information.

with foreign exposure, but through changes in output or energy prices, and not through actual changes in physical energy intensity.

To address these problems of earlier environment-spillover work, I use an annual panel dataset of Chilean manufacturing firms from a Chilean census covering 1995-2006. Using this dataset allows me to control for unobserved time-invariant firm factors and observed time-varying pre-existing factors that may be correlated with foreign exposure and firm-level environmental intensity.

I measure changes in environmental quality using firm-level energy intensity. My dataset contains the physical units of energy used by each firm rather than only energy expenses. Therefore, my measure of energy intensity is the physical unit of energy over deflated annual revenue.

Contrary to the environmental spillover work of Chudnovsky et al. (2005) and Albornoz et al. (2009), I find that increases in foreign exposure result in increased energy intensities, which are consistent with decreased environmental quality. Controlling for time-invariant firm-specific effects, I find that a one-percentage-point increase in within-firm foreign investment on average increases electricity intensity by 1.10 kilowatt hours across all firms in the short run. Moreover, I find that a one-percentage-point increase in within-industry foreign exposure on average increases electricity intensity by 4.60 kilowatt hours across all firms in the short run, and fuel oil and diesel fuel intensity by 139.50 cubic meters across "dirty"-industry firms in the short run.

3.2 Data

3.2.1 Data Explanation

The analysis is based primarily on data from the Encuesta Nacional Industrial Annual (ENIA) between 1995 and 2006. The ENIA data is from an annual census covering all formal Chilean manufacturing plants with more than 10 employees.[3] The dataset is an unbalanced panel that includes an average of about 5,400 plants per year. Contained within the dataset is comprehensive accounting information such as sales, intermediate materials, energy, employment, and investment, as well as region and 4-digit International Standard Industrial Classification (ISIC) industries. I refer to plants as firms throughout this work, as an overwhelming majority of the observations are from single-plant firms.[4]

A list of two-digit manufacturing industries included in this study is provided in Table 3.1, along with their respective frequency in the trimmed dataset. The full dataset contains 65,182 observations. The dataset was trimmed down to 59,684 observations for two main reasons, along with general outlier checks. The first main reason firms were removed was for changing industry throughout the survey. Many firms sell multiple products, so shifting four-digit-industries is not necessarily indicative of a change in production process. The second main reason was for firms having inconsistent reporting of foreign capital ownership and ownership type.

[3] The ENIA is carried out by the National Statistics Institute of Chile (INE) http://www.ine.cl/. The ENIA has been performed since 1979, however data prior to 1995 are only provided by the INE in paper format on site in Santiago, Chile. At the writing of this work, waves 1995-2013 are available from the National Statistics Institute of Chile (INE). Waves 2008-2013 are not used due to firm IDs being recoded every year starting in 2008 to further ensure confidentiality of firm data. 2007 data is not used due to lacking information on fuel usage.

[4] Fernandes and Paunov (2012) obtained information from INE that 91.7% of plants are single-plant firms on average from 1997-2003.

Table 3.1: Industry Distribution in 1995-2006 ENIA Dataset by Two-Digit Industry

ISIC	Manufacturing Industry	# obs
15	Food products and beverages	18,522
17	Textiles	3,084
18	Wearing apparel; dressing and dyeing of fur	3,677
19	Tanning and dressing of leather; luggage, handbags, saddlery, harness and footwear	2,039
20	Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials	4,152
21	Paper and paper products	1,639
22	Publishing, printing and reproduction of recorded media	2,375
23	Coke, refined petroleum products and nuclear fuel	11
24	Chemicals and chemical products	3,357
25	Rubber and plastics products	3,602
26	Other non-metallic mineral products	3,187
27	Basic metals	1,328
28	Fabricated metal products, except machinery and equipment	4,242
29	Machinery and equipment not elsewhere classified	2,693
30	Office, accounting and computing machinery	10
31	Electrical machinery and apparatus not elsewhere classified	959
32	Radio, television and communication equipment and apparatus	94
33	Medical, precision and optical instruments, watches and clocks	329
34	Motor vehicles, trailers and semi-trailers	811
35	Other transport equipment	5,541
36	Furniture; manufacturing not elsewhere classified	3,019

ISIC stands for International Standard Industrial Classification Revision 3. Column 3 lists the number of observations in the 1995-2006 ENIA trimmed data by two-digit industry.

3.2.2 Variable Creation

To examine how domestic foreign exposure affects energy intensity, I construct several variables from the ENIA dataset.[5]

First, I construct electricity, fuel, and water intensity as the following, where E is used for each energy input individually:

$$S^E_{ijrt} = \frac{Q^E_{ijrt}}{P^Y_{ijr,1992} Q^Y_{ijrt}} = \frac{\text{Annual energy used}}{\text{Deflated annual revenue}}.$$

[5]Construction of foreign exposure variables follow Blalock and Gertler (2008), and Javorcik (2004).

where i indicates firm, j indicates four-digit-industry, r indicates Chilean region, t indicates year, Q^E is the quantity of energy used, Q^Y is the quantity of output produced, and $P^Y_{ijr,1992}Q^Y_{ijrt}$ is deflated annual revenue. The publicly available ENIA data reports firm annual revenue, instead of product-specific production. Therefore, I deflate revenue by annual three-digit-industry price deflators with 1992 as the base year.[6] So long as firm-specific prices do not vary much within industry over time, then changes in my measure of energy intensity are reflective of changes in physical energy intensity (e.g. kilowatt-hours used per roll of carpet produced).

Second, I construct firm-specific within-industry foreign exposure, hereafter termed "Horizontal," as peer output attributed to foreign ownership as a share of total industry-region output. Peers are defined as firms in the same four-digit-industry and region.

$$Horizontal_{ijrt} = \frac{\left(\sum\limits_{\forall h \in j; h \neq i} ForeignShare_{hjrt} * Y_{hjrt}\right)}{\sum\limits_{\forall h \in j} Y_{hjrt}}. \tag{3.1}$$

Firm-specific within-industry foreign exposure increases as the amount of foreign ownership in firm h in industry j in region r in year t increases. Horizontal also increases as output from foreign-invested firms increases, holding all other within-industry output constant.

Third, I construct industry-region-specific foreign exposure from downstream industry, hereafter termed "Downstream," as industry-region output attributed to domestic downstream foreign ownership as a share of total industry-region output.

$$Downstream_{jrt} = \sum_{\forall k} \alpha_{jk} Horizontal_{krt}, \tag{3.2}$$

[6] 1979-2007 three-digit-industry price deflators were provided to me by Roberto Espinoza, and come from Bergoeing and Repetto (2005b). Four-digit-industry price deflators exist through INE, but only cover years 2009 and beyond.

where α_{jk} is the share of output from industry j to industry k taken from the 1996 Chilean three-digit-industry input-output matrix.[7] $Horizontal_{krt}$ is the share of output attributed to foreign ownership for industry k in region r in year t. $Horizontal_{krt}$ is calculated in the same manner as $Horizontal_{ikrt}$, except that firm i's foreign output contribution is included.

Increases in downstream foreign exposure to industry j in region r in year t can occur for two reasons, holding everything else constant. Either through increased industry j average sales to domestic foreign-invested firms in region r, or through increased foreign investment in domestic firms already being supplied by industry j in region r.

Fourth, since firms report annual investment instead of the value of their capital stock, I construct real capital using the perpetual inventory method (PIM) following Fernandes and Paunov (2012). First, annual deflated net investment is calculated as the sum of deflated net investment flows for each type of capital in the ENIA survey: buildings, machinery and equipment, transport equipment, and land. Net investment flows are the sum of purchased new capital, used capital, and improvements to capital, minus the sales of capital. These net investment flows are deflated by an investment price deflator, which I construct as the ratio of current gross capital formation to constant gross capital formation from the World Bank World Development Indicators with base year 2008.

Once annual deflated net investment is calculated, I construct real capital as the sum of the four types of real capital. For each capital type, I apply the PIM formula $K_{it+1} = (1-\delta)K_{it}+I_{it}$, where I_{it} is deflated net investment flow and δ is a capital-specific depreciation rate. Due to the lack of detailed studies of Chilean depreciation rates, I use the following rates recommended by Pombo (1999) for the same type of capital goods in Colombia: 3% for buildings, 7% for machinery and equipment, 11.9% for transport equipment, and 0% for land (land is assumed not to depreciate). The initial capital stock needed to properly use

[7] Obtained from Ana Fernandes, Senior Economist with The World Bank, on 3,17,2016.

the PIM formula is taken as the deflated book value of each capital type respectively in the first year a firm is in the ENIA sample.

Fifth, I construct real materials. Real materials is defined as the value of raw materials used by the end of the year, deflated by a three-digit-industry intermediate-input price deflator calculated for each industry based on the 1996 Chilean input-output matrix and three-digit-industry price deflators. For a given industry j in year t, the intermediate-input price deflator is defined as the following:

$$IIP_{jt} = \sum_{k} \sigma_{jk} P_{kt}$$

where σ_{jk} is the cost share of industry k's output in industry j's total costs. P_{kt} is the price deflator for industry k in year t. Put simply, the intermediate-input price deflator is the weighted average input price deflator, weighted by the cost share of each input in industry j.[8]

Sixth, I estimate firm-level productivity, also known as total factor productivity (TFP). I estimate TFP using the Levinsohn and Petrin (2003) method that controls for simultaneity bias between input decisions and econometrician unobserved firm-specific productivity shocks. The Levinsohn-Petrin method traditionally utilizes materials to proxy for unobserved productivity. I also experimented using electricity to proxy for unobserved productivity as is done in Fernandes and Paunov (2012), which had no significantly different effect on the estimation of TFP using materials.

[8]For example, suppose industry j is beer brewing and has two input (k) industries, water and hops. Suppose that the inputs of water and hops are defined such that for one bottle of beer, water is responsible for one-third of the input costs and hops are responsible for two-thirds of the input costs. Also suppose that the price deflator for water is 2 and the price deflator for hops is 1. The calculation of the intermediate-input price deflator for the beer brewing industry would yield 1.33=0.33(2.0)+0.66(1.0).

3.3 Research Design

3.3.1 Quality of Energy Intensity as a Proxy for Environmental Intensity

To identify the extent foreign-investment inflows result in environmental spillovers in Chile, I prefer to study how changes in foreign-investment inflows affect domestic-firm pollution intensity. However, similar to other studies investigating cleanliness of domestic and foreign firms in developing countries,[9] firm-level pollution information is not available in Chile.

Due to lacking firm-level emissions intensity, I proxy for emissions intensity with electricity and fuel intensity. The quality of a proxy variable depends on its correlation with the variable for which it proxies.

Admittedly, the quality of electricity as a good proxy for emissions in Chile is not clear. Historically, Chile's electricity production was heavily skewed towards hydroelectric power (Figure 3.1).[10] For example, in 1992 about 80% of electricity available in Chile came from hydroelectric power.

However, over the period of this study (1995-2006), on average 45% of the electricity available in Chile came from fossil-fuel sources, with on average 20% coming from coal and 25% coming from oil and natural gas. Looking to years after this study (2007-2013), on average 58% of electricity available in Chile came from fossil-fuel sources, with 29% coming separately from coal and oil and natural gas separately.[11]

[9]Batrakova and Davies (2012), Cole et al. (2008), Eskeland and Harrison (2003).

[10]Based on International Energy Agency data from Chile Statistics ©OECD/IEA accessed 7/2016, www.iea.org/statistics. License: www.iea.org/t&c; as modified by Paul Stroik.

[11]According to the U.S. Energy Information Administration, electricity produced using coal emits more carbon monoxide, sulfur dioxide, nitrogen dioxide, etc. per unit of heat energy generated than natural gas or oil, except for formaldehyde (EIA, 1998).

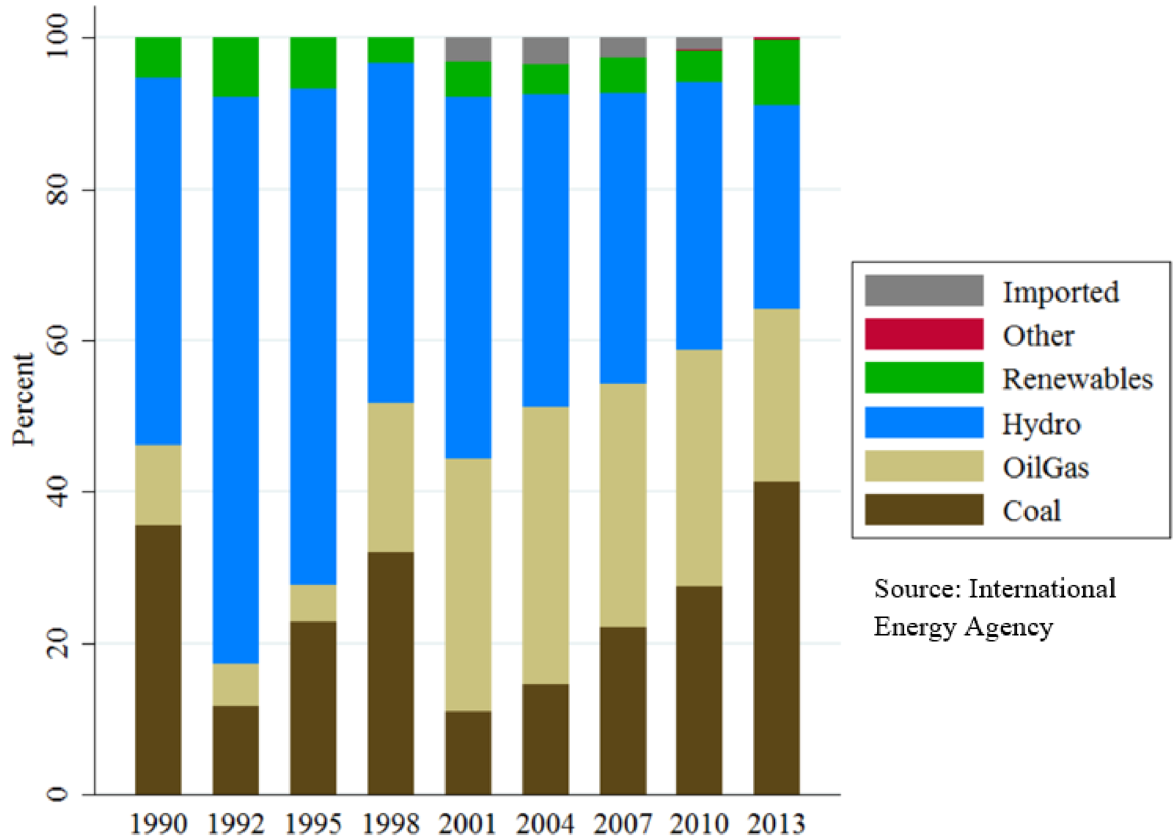

Figure 3.1: Chile Electricity Sourcing

The fuel reported in the ENIA dataset that I use in this work is diesel and fuel oil. This fuel is only recorded if it is being used in the production of energy or heat. Therefore changes in fuel intensity represent changes in fuel burned per unit produced at a firm. Haneke (2003) shows that the burning of fuel oil emits several air pollutants, such as carbon monoxide, nitrogen oxide, sulfur dioxide, volatile organic compounds, and particulate matter.

Given the above information, holding all else equal, increases (decreases) in fuel intensity guarantee poorer (better) air quality. Changes in electricity intensity are less clear. If the annual composition of Chilean electricity generation represents the source of an average unit of electricity, then we can also expect, holding all else equal, increases (decreases) in electricity intensity to provide poorer (better) air quality. These changes in air quality will not be as strong as would occur in an economy with generation coming more heavily from fossil-fuel sources. However, since electricity is likely generated outside of dense population centers, increased electricity intensity, if paired with reduced fuel intensity, can be a sign of better air quality with firms shifting polluting activities away from their production facilities to electricity generation facilities.

On top of estimating how becoming a supplier of domestic foreign firms affects electricity and fuel intensities, I estimate how becoming a supplier of domestic foreign firms affects domestic-firm water intensity. Although increased water usage does not guarantee increased pollution, it could show firms switching inputs between different resources and different pollution mediums, for example water instead of air.[12]

3.3.2 Empirical Framework

The framework for estimating the effect that domestic foreign exposure has on domestic firm energy intensity is based on the potential outcomes model (Angrist and Pischke, 2009).[13] I assume there are a continuous number of states of a firm to which a domestic Chilean firm can be assigned, with each state varying in its domestic foreign exposure. Let $F_{ijrt} = f$ stand for one measure of foreign exposure equaling f for firm i in industry j in region r in year t (i.e., the firm is "treated"), and $F_{ijrt} = f - 1$ if firm i had one less unit of foreign exposure, equaling $f - 1$ (i.e., the firm is "untreated"). Potential outcomes $Y_{ijrt}(f)$ and $Y_{ijrt}(f-1)$ denote annual firm-level energy intensity conditional on having foreign exposure levels f and $f - 1$ respectively.

[12]One example of firms substituting between pollution mediums comes from Gibson (2015), where he finds in response to air pollution regulation, firms substitute their pollution activities away from air pollution to water pollution.

[13]The potential outcomes idea is also referred to as the Rubin [causal] model in Holland (1986).

The observed difference in each outcome between treated and untreated firms is the following:

$$E[Y_{ijrt}(f)|F_{ijrt}=f]-E[Y_{ijrt}(f-1)|F_{ijrt}=f-1] = \underbrace{E[Y_{ijrt}(f)-Y_{ijrt}(f-1)|F_{ijrt}=f]}_{\text{Average treatment effect on the treated}} + \underbrace{E[Y_{ijrt}(f-1)|F_{ijrt}=f]-E[Y_{ijrt}(f-1)|F_{ijrt}=f-1]}_{\text{Selection bias}} \tag{3.3}$$

I am primarily interested in estimating the average treatment effect on the treated (ATT), as I am interested in knowing how increased domestic foreign exposure brought to developing countries through increased trade liberalization is likely to affect those firms that through market forces experience increased domestic foreign exposure. I am less interested in the average treatment effect, as it provides the expected outcome change for experiencing increased domestic foreign exposure for the average firm, many of which may never experience increased domestic foreign exposure.

I observe energy intensity at both treated and similar untreated firms prior to when a firm experiences changes in domestic foreign exposure, and in the year a firm experiences changes in domestic foreign exposure. This information allows me to identify $E[Y_{ijrt}(f)|F_{ijrt}=f]$. However, $[Y_{ijrt}(f-1)|F_{ijrt}=f]$, the outcome a "treated" firm would have were it not given the treatment, is not observed. I construct estimates of these counterfactual outcomes using firms that in year t have foreign exposure level $f-1$.

The simplest estimate of an ATT of changes in domestic foreign exposure is the average difference in an outcome variable between treated and untreated firms. This estimator is biased if factors related to firm-level energy intensity and the likelihood of experiencing increased domestic foreign exposure vary significantly across treated and untreated groups. In order to reduce any bias due to differences across firms that experience increased domestic foreign exposure and those that do not, I employ one strategy that controls for observable firm differences; regression control. I also employ one identification strategy that controls for unobservable firm differences that are correlated with the likelihood of treatment and outcome variables; regression control using a within model, in which all values are demeaned, removing observed and unobserved time-invariant firm-level factors.

3.3.3 Methods and Assumptions in Estimating Causal Effects

Regression Control. – Ordinary least squares (OLS) can control for covariates that are correlated with treatment status and outcomes such as various energy intensities. OLS estimates of the ATT can be interpreted as causal, so long as the *Conditional Independence Assumption* (CIA) holds. The CIA states that conditional on observed characteristics, X_{ijrt}, there is no selection bias. Formally the CIA states:

$$\{Y_{ijrt}(f), Y_{ijrt}(f-1)\} \perp F_{ijrt} | X_{ijrt} \tag{3.4}$$

where $\perp$ denotes the independence relation. The CIA holds if differences in outcomes between treated and untreated groups have already controlled for all covariates correlated with domestic foreign exposure and energy intensity.

Ensuring the CIA holds requires controlling for those covariates that are correlated with increased domestic foreign exposure and energy intensity. Therefore, I estimate the following linear model using OLS for each energy intensity:

$$S^E_{ijrt} = \gamma_0 + \Gamma_1' F_{ijrt} + \Gamma_2' X_{ijr(t-1)} + \eta_{jrt} + \varepsilon_{ijrt}, \tag{3.5}$$

where γ_0 is a single coefficient for all observations representing average energy intensity, Γ_1 and Γ_2 are column vectors of coefficients, F_{ijrt} is a column vector of foreign exposure variables in year t, $X_{ijr(t-1)}$ is a column vector of observable firm-level covariates in year $t-1$, η_{jrt} is a linear combination of industry, region, year, industry-year, and region-year fixed effects, and ε_{ijpt} is an error term. Γ_1 contains the coefficients of interest, i.e. the coefficients that represent the average marginal effect that changes in domestic foreign exposure have on energy intensity. This approach assumes the covariates in $X_{ijr(t-1)}$ and η_{jrt} are exogenous to foreign exposure F_{ijrt}.

Due to their likely correlation with both foreign investment and energy intensity, the following one-year-lagged covariates are in $X_{ijr(t-1)}$: firm size and high-skill worker availability (labor separated by skilled and unskilled), capital, productivity, and export and import status (Ablov, 2015; Batrakova and Davies, 2012; Cole et al., 2008; Garavito et al., 2014).[14]

The industry, region, year, industry-year, and region-year fixed effects in η_{jrt} control for average factors that are both correlated with foreign exposure and energy intensity. Although each fixed effect may control for multiple biasing factors, I list one potentially biasing factor for each type of fixed effect to motivate its inclusion. Industry fixed effects control for specific industries being consistently more productive. Region fixed effects control for local supplier industries being consistently more productive. Year fixed effects control for specific years having country-wide energy price shocks. Industry-year fixed effects control for industries having growing productivity or expected productivity growth. And region-year fixed effects control for supplier industries having growing productivity or expected productivity growth.

One problem that will result in regression control providing biased estimates of the foreign exposure coefficients in Γ_1 is if changes in foreign exposure are driven by unobserved factors that are correlated with energy intensity. In order to mitigate this worry, I include regression control within estimates that control for time-invariant unobserved firm-specific effects.

[14]Review of these works also leads me to want to include firm age, however firm age is not reported in the ENIA dataset. I do not construct firm age from length of firm in the panel, due to its opaqueness as a credible measure for firm age.

Within Model. – Within estimates provide causal effects so long as time-invariant firm-specific factors affect both the likelihood a firm experiences changes in domestic foreign exposure, and energy intensity. This issue is clearer in the following formulation of the earlier linear model:

$$S^E_{ijrt} = \gamma_0 + \Gamma_1' F_{ijrt} + \Gamma_2' X_{ijr(t-1)} + \eta_{jrt} + c_i + u_{ijrt}. \tag{3.6}$$

where c_i is an unobserved firm-specific effect and u_{ijrt} is an idiosyncratic error term. If c_i is correlated with domestic foreign exposure and energy intensity, then OLS estimates of a linear model without controlling for the unobserved firm-specific effects will provide biased estimates of the Γ_1 coefficients. In this case OLS estimates from the within-model, which takes every observation and subtracts from it the firm-specific mean value, will be unbiased.

3.4 Results

3.4.1 Average Energy Intensities: Foreign vs. Domestic

The belief that increased domestic foreign exposure is more likely to spread profitable production processes that economize on dirty inputs requires domestic foreign firms to have superior knowledge of production processes that economize on dirty inputs. Such evidence exists for several "dirty" industries in Côte d'Ivoire, Mexico, and Venezuela (Eskeland and Harrison, 2003), as well as electricity generators in China in the late 1990s (Blackman and Wu, 1998). To ensure that this pre-condition is likely in Chile, I first determine whether, on average, firms with higher foreign investment have lower energy intensities than similar firms. I follow Eskeland and Harrison (2003), and test whether this is the case for all manufacturing firms, and whether this is the case for their subset of "dirty" industries, which includes chemicals, petroleum refining, lumber and wood products, and nonelectrical machinery.[15]

Therefore, to determine whether foreign ownership is associated with cleaner production processes, I estimate the following linear model, the expanded form of Equation 3.5, using OLS, with standard errors clustered at the 4-digit industry level:

$$\begin{aligned} S^E_{ijrt} = &\beta_0 + \beta_{FS} ForeignShare_{ijrt} + \beta_{SL} SkilledLabor_{ijrt} + \beta_{UL} UnskilledLabor_{ijrt} \\ &+ \beta_K Capital_{ijrt} + \beta_M Materials_{ijrt} + \beta_{EX} Exports_{ijrt} + \beta_{IM} Imports_{ijrt} \\ &+ \alpha_t + \alpha_r + \alpha_j + \alpha_{jt} + \alpha_{rt} + \varepsilon_{ijrt}. \end{aligned} \tag{3.7}$$

The results in Table 3.2 indicate that firms with more foreign capital have on average lower electricity intensities, regardless of focusing on a subset of "dirty" industries or the entire manufacturing sector. The coefficient estimates for Foreign Share in Table 3.2 indicate that on average firms with one-percentage-point higher foreign investment relative to their peers have about two kilowatt hours lower electricity intensities.

Although little can be inferred about the environmental damages from water usage, on average firms with more foreign capital have lower water intensities when focusing on the "dirty" industry subset. The estimates of Table 3.2 indicate that on average firms with one-percentage-point higher foreign investment relative to their peers have about 0.07 cubic meters lower water intensities.

Therefore, the results of Table 3.2 are consistent with domestic foreign firms on average having production processes that economize on dirty inputs more than domestic firms.

[15]Eskeland and Harrison (2003) point out that only these U.S. industries have a statistically significant relationship between energy use and emissions.

Table 3.2: Foreign Investment Associated with Lower Average Electricity and Water Intensities

	(1)	(2)	(3)	(4)	(5)	(6)
	Electricity Intensity		Fuel Intensity		Water Intensity	
	All	Dirty	All	Dirty	All	Dirty
Foreign Share	-1.94*	-2.19**	-0.65	-31.81	-26.54	-0.07**
	(1.063)	(1.051)	(0.594)	(28.151)	(17.229)	(0.028)
Skilled Labor	2.53	0.09	1.47	0.66	22.36	0.01
	(1.972)	(0.213)	(1.293)	(3.045)	(19.666)	(0.009)
Unskilled Labor	1.75	0.07	1.18	-0.57	8.42	-0.01
	(1.841)	(0.168)	(1.257)	(1.613)	(9.296)	(0.008)
Capital	-0.00	0.00***	-0.00	0.00***	-0.00	-0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Materials	-0.00	0.00***	-0.00	0.00***	-0.00	-0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports	-404.23	-80.86*	-220.03	-713.02	-3,705.37	-3.80
	(320.361)	(42.064)	(211.650)	(454.564)	(2493.225)	(3.453)
Imports	-248.68	-153.31*	-106.02	-933.77**	-1,692.78**	0.46
	(150.830)	(78.442)	(100.430)	(388.370)	(836.064)	(2.707)
Observations	57,636	9,581	57,636	9,581	57,636	9,581
Adjusted R^2	0.02	0.06	0.01	0.09	0.01	0.05

Four-digit-industry clustered standard errors in parentheses. Each column indicates a separate regression. Electricity is recorded as kilowatt-hours, and fuel and water are recorded as cubic meters. Each energy intensity is the respective physical amount of energy recorded divided by annual revenue expressed in 1992 Chilean pesos. Each regression includes four-digit-industry, year, region, industry-year, and region-year fixed effects. Capital and materials are in 1,000s of 1992 Chilean pesos. “Dirty” industries include 1) lumber and wood (not furniture), 2) chemicals and allied products, 3) petrol refining and related products, and 4) nonelectrical machinery. All industries come from the manufacturing sector. Exports and Imports are indicator variables equal to one if a firm exports or imports respectively, and zero otherwise. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

3.4.2 Energy Efficiency Spillovers from Foreign Investment

Given that firms with more foreign ownership have on average lower energy intensities than their peers with more domestic ownership, does exposure to domestic firms with more foreign ownership cause domestic firms to also produce using lower energy intensities in the short run?

My first step in answering this question causally is taken by regressing each energy intensity independently on three measures of foreign exposure, and a set of variables that are correlated both with foreign exposure and energy intensity. The foreign exposure variables are the percentage of foreign ownership in a firm, the industry percentage of foreign production (Horizontal), and the industry percentage of domestic sales attributed to foreign ownership (Downstream). I discuss the construction of Horizontal and Downstream in section 3.2.2.

As motivated in the modeling section, the variables correlated with foreign exposure and energy intensity that I include in my linear model are the following (all one-year lags): firm size and high-skill worker availability (labor separated by skilled and unskilled), capital, productivity, and export and import status.[16]

Therefore, to determine whether foreign exposure on average changes the environmental intensity of Chilean firm production processes, I estimate the following linear model, the expanded form of Equation 3.6, using OLS, with standard errors clustered at the 4-digit

[16] Since these characteristics are believed to attract foreign investment and also be correlated with energy intensity, including them contemporaneously may provide biased estimates of the effects of foreign exposure, as changes in foreign exposure may be why changes in these variables occurred, thus attributing some of the total effect of foreign exposure on energy intensity to other factors. The interested reader can see this problem more generally in Angrist and Pitschke (2009), pp. 64–66 in the discussion of bad control variables.

industry level:

$$
\begin{aligned}
S^{E}_{ijrt} =& \gamma_0 + \gamma_1 ForeignShare_{ijrt} + \gamma_2 Horizontal_{ijrt} + \gamma_3 Downstream_{jrt} \\
& + \gamma_{SL} SkilledLabor_{ijr(t-1)} + \gamma_{UL} UnskilledLabor_{ijr(t-1)} + \gamma_K Capital_{ijr(t-1)} \\
& + \gamma_{TFP} TFP_{ijr(t-1)} \gamma_{EX} Exports_{ijr(t-1)} + \gamma_{IM} Imports_{ijr(t-1)} \\
& + \eta_t + \eta_r + \eta_j + \eta_{jt} + \eta_{rt} + \varepsilon_{ijrt},
\end{aligned} \tag{3.8}
$$

where TFP stands for total factor productivity, and $Exports$ and $Imports$ are indicator variables equal to one if a firm exports or imports respectively, and zero otherwise. Estimates of standard errors are clustered at the four-digit-industry level to allow for correlation between firm-specific estimation error in the same industry over region and time.

The results from this first-stage estimation are provided in Table 3.3. The coefficient estimates on Foreign Share indicate that a one-percentage-point increase in within-firm foreign investment on average decreases electricity intensity for all firms by 1.38 kWh and 3.52 kWh for dirty-industry firms. A one-percentage-point increase in within-firm foreign investment also on average decreases water intensity for "dirty" industry firms by 0.08 cubic meters.

The coefficient estimates on Horizontal indicate that a one-percentage-point increase in within-industry foreign exposure on average decreases electricity intensity by 16.21 kWh, fuel intensity by 201.52 cubic meters, and water intensity by 0.21 cubic meters for "dirty" industry firms. The coefficient estimates on Downstream indicate that a one-percentage point increase in foreign exposure from downstream intermediate-input customers on average increases electricity intensity by 47.17 kWh for "dirty" industry firms.

Taken together, these results are consistent with positive environmental spillovers occurring directly and horizontally from domestic foreign investment. However, they also indicate that there are negative environmental spillovers occurring vertically to suppliers of domestic foreign-invested firms.

Table 3.3: Environmental Spillovers of Domestic Foreign Exposure

	(1)	(2)	(3)	(4)	(5)	(6)
	Electricity Intensity		Fuel Intensity		Water Intensity	
	All	Dirty	All	Dirty	All	Dirty
Foreign Share	-1.38**	-3.52**	-29.13	-48.74	-0.04	-0.08***
	(0.605)	(1.453)	(19.811)	(36.336)	(0.030)	(0.027)
Horizontal	-2.09	-16.21***	-63.30	-201.52**	0.04	-0.21**
	(2.962)	(5.842)	(44.662)	(96.573)	(0.085)	(0.090)
Downstream	2.21	47.17**	45.23	559.87	-0.06	2.07
	(2.158)	(17.750)	(40.594)	(369.478)	(0.206)	(2.078)
Skilled Labor (t-1)	0.40**	0.13	16.77	2.29	0.03	-0.00
	(0.181)	(0.383)	(14.142)	(6.118)	(0.031)	(0.013)
Unskilled Labor (t-1)	0.03	0.05	0.57	-1.71	-0.01	-0.03**
	(0.061)	(0.254)	(0.985)	(2.314)	(0.008)	(0.011)
Capital (t-1)	0.00*	0.00**	0.00	0.00*	0.00**	0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TFP - LevPet (t-1)	-0.00***	-0.00***	-0.02***	-0.02***	-0.00**	-0.00
	(0.000)	(0.000)	(0.006)	(0.005)	(0.000)	(0.000)
Exports (t-1)	-87.77**	-76.14	-2,597.91	-237.93	-4.45	1.15
	(37.223)	(59.936)	(1669.951)	(511.224)	(4.027)	(5.893)
Imports (t-1)	-62.43**	-196.17*	148.62	-1,135.32***	1.05	-1.58
	(27.978)	(96.774)	(932.614)	(399.023)	(2.244)	(3.020)
Observations	46,868	7,753	46,868	7,753	46,868	7,753
Adjusted R^2	0.00	0.07	0.02	0.12	0.00	0.03

Four-digit-industry clustered standard errors in parentheses. Each column indicates a separate regression. Each regression includes four-digit-industry, year, region, industry-year, and region-year fixed effects. Capital and materials are in 1,000s of 1992 Chilean pesos. “Dirty” industries include 1) lumber and wood (not furniture), 2) chemicals and allied products, 3) petrol refining and related products, and 4) nonelectrical machinery. All industries come from the manufacturing sector. Horizontal is the share of an industry’s output attributed to foreign investment in Chile. Downstream is the share of an industry’s domestic sales attributed to being sold to foreign investors in Chile. Total Factor Productivity (TFP) is calculated using the Levinsohn and Petrin (2003) method with materials proxying for unobserved productivity shocks. Variable names including (t-1) indicate one year lagged values, controlling for selection into treatment of receiving more foreign exposure. Exports and Imports are indicator variables equal to one if a firm exports or imports respectively, and zero otherwise. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 3.4: Environmental Spillovers of Domestic Foreign Exposure Controlling for Time-Invariant Firm Factors

	(1)	(2)	(3)	(4)	(5)	(6)
	Electricity Intensity		Fuel Intensity		Water Intensity	
	All	Dirty	All	Dirty	All	Dirty
Foreign Share	1.10*	1.04	10.84	12.94	-0.09	0.02
	(0.568)	(1.368)	(11.232)	(19.775)	(0.076)	(0.054)
Horizontal	4.56*	4.50	33.61	139.50*	-0.30	-0.11
	(2.710)	(5.902)	(32.343)	(81.916)	(0.356)	(0.301)
Downstream	-0.07	-5.51	-41.84	706.45	1.00	1.68
	(2.765)	(41.553)	(25.451)	(532.865)	(1.040)	(2.931)
Skilled Labor (t-1)	-0.09	-2.07	12.89	10.23	0.02	-0.03
	(0.341)	(2.574)	(8.621)	(6.122)	(0.023)	(0.032)
Unskilled Labor (t-1)	-0.17	0.47	-9.65	3.15	-0.01	0.00
	(0.135)	(0.290)	(9.806)	(3.678)	(0.019)	(0.017)
Capital (t-1)	0.00	0.00	0.00	0.00	0.00	0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TFP - LevPet (t-1)	-0.00**	-0.00**	-0.02***	-0.01***	-0.00**	0.00
	(0.000)	(0.000)	(0.005)	(0.001)	(0.000)	(0.000)
Exports (t-1)	-61.26	31.24	-362.12	-643.85	-0.78	3.96
	(57.688)	(65.073)	(366.872)	(477.086)	(1.932)	(4.687)
Imports (t-1)	-3.17	-46.38	1,519.54	-863.16*	2.84	-4.05
	(29.616)	(54.710)	(1853.157)	(466.225)	(3.525)	(2.773)
Observations	46,868	7,753	46,868	7,753	46,868	7,753
Adjusted R^2	0.01	0.11	0.02	0.16	0.00	0.04

Four-digit-industry clustered standard errors in parentheses. Each column indicates a separate regression. Each regression includes four-digit-industry, year, region, industry-year, region-year, and firm fixed effects. Capital and materials are in 1,000s of 1992 Chilean pesos. "Dirty" industries include 1) lumber and wood (not furniture), 2) chemicals and allied products, 3) petrol refining and related products, and 4) nonelectrical machinery. All industries come from the manufacturing sector. Horizontal is the share of an industry's output attributed to foreign investment in Chile. Downstream is the share of an industry's domestic sales attributed to being sold to foreign investors in Chile. Variable names including (t-1) indicate one year lagged values, controlling for selection into treatment of receiving more foreign exposure. Exports and Imports are indicator variables equal to one if a firm exports or imports respectively, and zero otherwise. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

If the observable characteristics I controlled for are the only factors driving firm-level foreign investment and foreign investment at the industry level, then the estimates in Table 3.3 are the unbiased/causal effects of foreign exposure on each energy intensity respectively. However, time-invariant firm-average characteristics may be correlated with foreign exposure and energy intensity. For example, firm-specific constant management practices may attract more foreign investment, and those management practices may push a firm to be less or more energy intensive. To control for such time-invariant factors, I estimate the same models estimated in Table 3.3 but include firm fixed effects. Due to having vast amounts of firms, I opt for estimating the models with firm fixed effects using mean differencing, i.e. within estimation, instead of least-squares dummy variable estimation.[17]

Table 3.4 provides coefficient estimates from firm fixed-effects models using within estimation (the expanded form of Equation 6). The results from Table 3.4 point out the importance of controlling for firm fixed effects, and that much of the environmental-spillover story painted in Table 3.4 is due to time-invariant firm factors. This is because if time-invariant firm factors are all irrelevant variables with respect to the foreign exposure variables, theoretically we would expect no change in their coefficient estimates, and an increase in their standard errors. However, we observe changes in the coefficient estimates for all foreign exposure variables, changes in the sign of coefficient estimates, and several standard-error estimates fall relative to the model estimated without firm fixed effects.

The results from Table 3.4 contradict those of Table 3.3. The coefficient estimates on Foreign Share indicate that a one-percentage-point increase in within-firm foreign investment on average increases electricity intensity for all firms by 1.10 kWh. The coefficient estimates on Horizontal indicate that a one-percentage-point increase in industry sales for all firms attributed to domestic foreign investment on average increases electricity intensity by 4.56 kWh, and increases fuel intensity for "dirty"-industry firms on average by 139.50 cubic

[17] Within estimation is mathematically equivalent to least-squares dummy variable estimation (Wooldridge, 2010).

meters. I find that changes in Downstream, or foreign exposure from downstream firms, has no statistically significant effect on energy intensity.

The results of Table 3.4 are pessimistic in terms of positive environmental spillovers from increased trade openness leading to increased foreign exposure in developing countries. I find that increased foreign investment leads on average to increased environmentally-intensive input usage directly at the firm that receives foreign investment and to competitors of firms in industries that receive more foreign investment.

It is important to note that the effects measured in this study are short-run effects. These effects assume that changes in domestic foreign investment/exposure affect production processes of domestic firms only immediately, and they do not change domestic-firm production processes in later years.

3.5 Conclusion

In this paper I compare changes in energy intensities of Chilean firms that experience increased domestic foreign exposure through within-firm foreign investment, within-industry domestic foreign exposure, and foreign exposure through average industry supplier relations with domestic firms with foreign ownership. I find that a one-percentage-point increase in within-firm foreign investment on average across all firms increases electricity intensity by 1.10 kilowatt hours in the short run. Moreover, I find that a one-percentage-point increase in within-industry foreign exposure on average increases electricity intensity by 4.60 kilowatt hours across all firms in the short run, and increases fuel oil and diesel fuel intensity by 139.50 cubic meters across "dirty"-industry firms in the short run.

Future work on identifying the environmental effects of increased trade openness and foreign exposure could improve upon this paper's work in a few ways. First, product level information could be used to more accurately construct energy intensities. In this way, no estimation bias could arise from firms receiving different output prices relative to their industry average due to increased foreign exposure. Second, plant-level emissions data could be used to guarantee environmental quality changes, rather than inferring environmental quality changes from a proxy variable such as energy intensity. Third, further identification strategies that require more relaxed assumptions could be used to guarantee changes in foreign exposure are not endogenous to firm-specific time-varying factors.