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Contents

1. Introduction	1
2. Data and Descriptive Analysis	1
3. Empirical Specification	3
3.1. Effect of FDI on TFP	6
3.2. Robustness of Results	6
3.3. Treatment Effects by Technology Intensity	7
4. Analysis by Type of FDI	9
5. Discussion/Conclusion	10
References	13
A. Appendix	iii
A.1. Treatment by Technology Intensity	iii

List of Tables

1.	Frequency of FDI Types	1
2.	Summary Statistics of Categorical Covariates	2
3.	Summary Statistics of Continuous Covariates	3
4.	Difference in Pre-Treatment Covariate Means	3
5.	ATE of FDI on TFP	6
6.	Robustness of Results	8
7.	ATE by Technology Intensity of Industry	9
8.	ATE by Type of FDI	10

1. Introduction

2. Data and Descriptive Analysis

Our analysis is based on observational firm-level data ranging from 2015 to 2017. The dataset comprises 11,323 firms, of which 4,460 received FDI in 2016. The FDI can be divided into three subcategories. Table 1 shows the frequencies of each type of FDI in our sample. Among the recipients of FDI, most firms (1,965) received domestic market seeking FDI. 1,555 firms received technology intensive FDI and the remaining 640 firms received exports oriented FDI. The outcome variable TFP was measured in 2017 after the treatment. We standardize the outcome variable to a mean of zero and a standard deviation of one, to make the interpretation more intuitive.

Table 1: Frequency of FDI Types

FDI type	Abs. Freq.	Rel. Freq.
No FDI	6,863	61%
Exports oriented FDI	940	8%
Technology intensive FDI	1,555	14%
Domestic market seeking FDI	1,965	17%
Total	11,323	100%

A set of categorical and continuous control variables was measured in 2015, one year prior to the firms receiving FDI. Table 2 provides an overview of the categorical variables and the frequencies of each category in our sample. The categorical variables are included as factor variables in the subsequent analysis. The port variable indicates whether a firm has access to a port within 500km. The legal ownership of a firm is captured in the ownership variable. The technology intensity of the industry the respective firm is operating in, is measured in four categories from low- to high-tech. The R&D dummy indicates whether a firm has invested in Research and Development in 2015.

The summary statistics of the continuous variables, i.e. wages, total-factor productivity (TFP), firm size¹, debts and the firms' export intensity are displayed in Table 3. The variables wages, employment and, to a lesser extent, debts show large differences between their mean and median values, hinting at the existence of outliers in the sample. Taking

¹Since the original variable is only available in logarithmic form and lacks an indicator for the unit of measurement we presume it is measured in number of employees.

Table 2: Summary Statistics of Categorical Covariates

	Abs. Freq.	Rel. Freq.
Port^a		
No	7,366	65.05
Yes	3,957	34.95
Ownership		
Listed company	909	8.03
Subsidiary	2,630	23.23
Independent	4,593	40.56
State owned	3,191	28.18
Technology Intensity		
Low-tech	4,194	37.04
Medium low-tech	1,685	14.88
Medium high-tech	3,539	31.25
High-tech	1,905	16.82
R&D^b		
No	9,951	87.88
Yes	1,372	12.12

^a Indicates whether a firm has access to a port within 500km.

^b Indicates whether a firm has invested in R&D in 2015.

the logarithm of the skewed variables is an easy way of reducing the influence of extreme values.

However, during placebo estimation with a different outcome it became clear that using the untransformed employment variable yields better covariate balance in all models. Noting an extreme value in this variable (see Figure 1) we added a robustness check that excluded this observation.

To further motivate the use of propensity scores in estimating the effect of FDI on a firm's TFP, we show the differences in means between the firms that received FDI and the firms that did not in Table 4. The t-tests show significant differences in all observable characteristics, meaning that there is in fact selection into treatment.

Table 3: Summary Statistics of Continuous Covariates

	Mean	Median	Sd	Min	Max
Wages	1,967 ^a	1,538	50,990 ^a	0.00065	5,519,000 ^a
TFP	3.041	3.032	2.047	-5.359	11.36
Employment	7,111	81.39	117,155	0.00197	8,824 ^a
Debt	1.762	1.649	0.634	0.819	3.668
Export intensity	0.159	0.154	0.0798	0.0103	0.483

Note: All variables in levels.

^a In Thousands

Table 4: Difference in Pre-Treatment Covariate Means

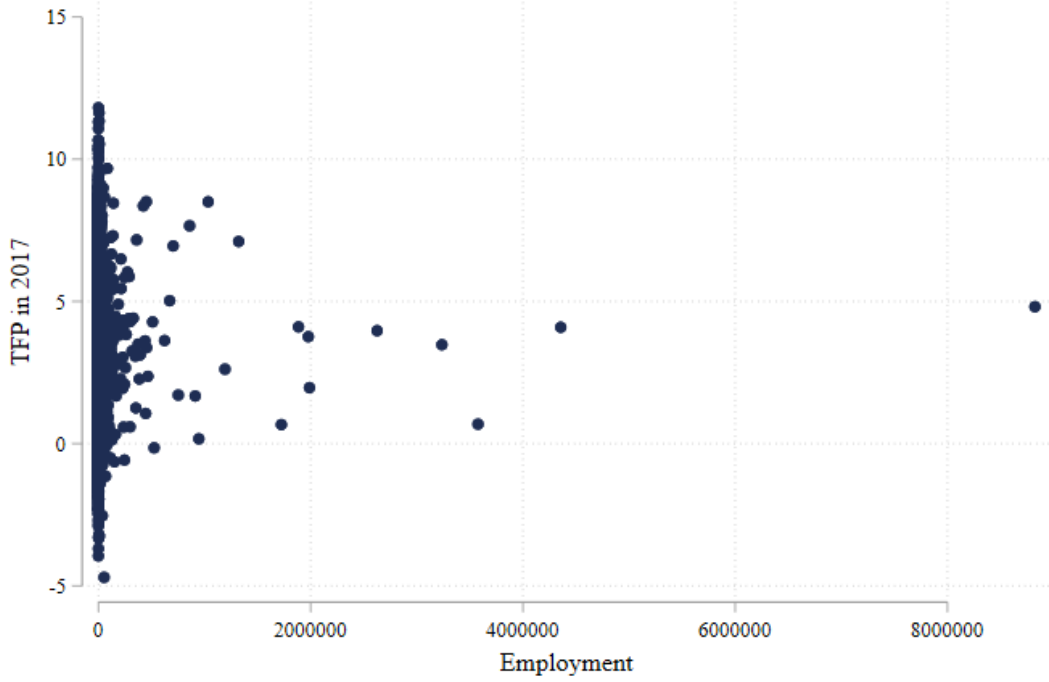
	(1) Control	(2) Treatment	T-test Difference (1)-(2)
Technology intensity	2.565 (0.014)	1.838 (0.015)	0.728***
Access to port	0.273 (0.005)	0.467 (0.007)	-0.194***
Log wages	7.529 (0.046)	7.031 (0.057)	0.498***
TFP	3.185 (0.025)	2.821 (0.030)	0.364***
Log employment	3.766 (0.037)	5.405 (0.041)	-1.639***
Log debts	0.511 (0.004)	0.493 (0.005)	0.019***
Export intensity	0.131 (0.001)	0.204 (0.001)	-0.073***
R&D dummy	0.117 (0.004)	0.128 (0.005)	-0.012*
Observations	6863	4460	

Notes: Columns (1) and (2) show the pre-treatment covariate means of the control and treatment group respectively. Standard errors are displayed in parentheses. The values displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

3. Empirical Specification

We have seen in Table 4 that firms which received FDI differ significantly from those that did not. This indicates that treatment was not randomly assigned to firms. Thus,

Figure 1: Outliers in Employment Variable



a simple comparison of treated and untreated firms will yield a biased treatment effect. Instead, we use propensity score estimation to compare the outcomes of similar firms. For this purpose we estimate the likelihood of treatment for each firm, i.e. the propensity score. It is based on a set of observable characteristics that influence both the outcome and the likelihood of treatment.

For the main model we use the nearest-neighbour matching estimator, which compares the outcomes of treated observations to the closest control observation in terms of propensity scores. We estimate matching models with one and five nearest neighbours, with replacement. For the latter model we add a caliper cutoff at 0.05.

We also fit inverse probability weighting models, which weigh observations by the inverse probability of being in their observed treatment group. Further we estimate the treatment effect using the augmented inverse probability weighting model, which adds covariate adjustment to the weighting. Thus, as long as either the propensity score or the covariate adjustment model is correctly specified the results are unbiased (Imbens and Rubin, 2015, p. 393).

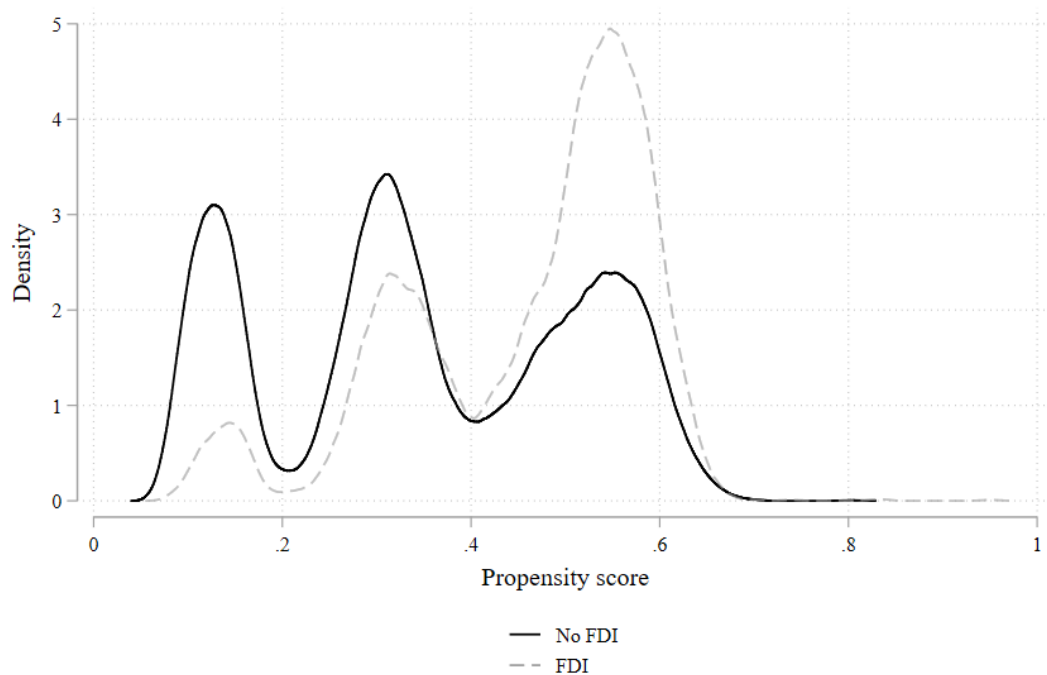
The point of using multiple estimators is mainly to show their convergence of estimates

given our large sample size. As long as results are reasonably close to each other we can take this as an indicator that the selection bias has been eliminated. (CITATION NEEDED)

We use the same specification of covariates for the matching, weighting and regression adjustment models, unless stated otherwise. We do not include the export variable as a matching covariate, since only covariates that influence the likelihood of treatment and the outcome of interest should be included. Although there is some debate about the direction of causality between exports and productivity, in his literature review Wagner (2007) argues that productivity increases exports, but not the other way around. The exclusion of the export variable significantly improves covariate balance. We do not include the port variable for the same reason.

Our matching model is thus a logit regression of the dummy that is equal to one if the firm received FDI in 2016 on ownership, technology intensity, a Research&Development dummy, the logarithm of wages, TFP, employment and debts in 2015. Figure ?? shows evidence of sufficient overlap for a matching analysis. The covariate balances are discussed in more detail below.

Figure 2: Overlap in Main Model



3.1. Effect of FDI on TFP

The main findings of this paper are displayed in Table 5. It reports the Average Treatment Effects for FDI on TFP. Across estimators, we find large and highly significant coefficients, showing that receiving FDI increases TFP of companies on average. The reported coefficients differ only slightly in magnitude. Column (1) shows the results of a one-to-one propensity score matching with replacement. Receiving FDI increases factor productivity by 13 percent of a standard deviation for the average company. Slightly lower results are obtained from a propensity score matching with five nearest neighbors and a caliper of 0.05 in column (2) as well as for the inverse IPW in column (3). The caliper cutoff excluded five observations. The estimate of the doubly robust AIPW-estimator is slightly larger than that of the main model, but all estimates differ by no more than 3 percent of a standard deviation.

Table 5: ATE of FDI on TFP

	NN1	NN5 ^a	IPW	AIPW
	(1)	(2)	(3)	(4)
FDI2016	0.130*** (0.015)	0.114*** (0.011)	0.122*** (0.007)	0.142*** (0.003)
PO Means			-0.068*** (0.010)	-0.057*** (0.009)
Observations	11,323	11,318	11,323	11,323

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Note: Covariates include, unless otherwise specified: Ownership, Technology Intensity, Research&Development, logarithm of wages, Total Factor Productivity, Employment and Debts.

All reported coefficients are normalized for better interpretation.

^a We use the Propensity Score Matching method with five nearest neighbours and replacement as well as a 0.05 caliper.

Checking the covariate balances of our models, we prefer the one-to-one propensity score matching as it gives us the best covariate balance of all the estimators *see Appendix*.

3.2. Robustness of Results

In order to test for the sensitivity of our main findings to alternative model specifications, we perform several robustness checks for the nearest-neighbour matching estimator with one neighbour. The results are reported in Table 6. The positive and significant effect of

FDI on TFP persists through all specifications, confirming our main results that foreign equity participation increases the productivity of domestic firms.

In column (1), we add interaction terms of the dummy variables with the continuous regressors to our set of covariates. This is widely practiced to improve covariate balance (Caliendo and Kopeinig, 2008). However, the covariate balance of our model does not improve with the inclusion of interaction terms, suggesting that interactions do not increase the quality of matching.² The estimated ATE of FDI on productivity slightly increases by 0.022 standard deviations compared to the effect reported in Table 5.

Our results could further be biased by outliers of the employment variable (see Figure 1). While most of the firms' employee numbers are concentrated around the mean of 7,111, we are concerned about two observations with extreme values: one firm with over eight million employees, and another one that apparently employed more than four million people in 2015. To check whether these outliers influence our main findings, we restrict the sample to firms with less than four million employees. The results reported in column (2) show no significant change in the treatment effect when excluding the two extreme observations. Besides, we have assumed that the presence of a port within 500 km of the firm does not influence productivity. Column (3) reports a small change of 0.005 standard deviations when including the dummy variable port in our set of covariates. Column (4) reports the average treatment effect on the treated (ATT) of the propensity score matching with one neighbor and replacement. While the ATE measures the average effect of FDI for the hypothetical case that all firms have received FDI, the ATT only considers those firms that have actually been treated. Because it is assumed that selection into treatment is non-random, we might find stronger effects of treatment on the treated. This would be the case if those firms receiving treatment are also the ones benefiting more from it. However, our estimate in column (4) reports an ATT that is very similar to the average treatment effect. This suggests that although there was selection into treatment, the effect size would be very similar in the absence of such selection.

3.3. Treatment Effects by Technology Intensity

FDI flows vary strongly between different sectors (see, for example, Smarzynska Javorcik (2004); Keller and Yeaple (2009); Haskel et al. (2007)). In our sample, firms are divided into four industry groups, ranging from low-tech to high-tech industries. While foreign investors targeted only 13 percent of firms in high-tech industries, more than half of the observations in low-tech industries have received FDI in 2016.³ This selection can have

²The same holds true when interacting only dummy variables, only continuous variables or all variables.

³See Appendix A.1.

Table 6: Robustness of Results

	Including Interactions ^a (1)	Excluding Outliers ^b (2)	Including Port ^c (3)	Effect on the Treated (4)
ATE	0.152*** (0.016)	0.127*** (0.015)	0.125*** (0.019)	
ATT				0.127*** (0.017)
Observations	11,323	11,321	11,323	11,323

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Note: All specifications use the Propensity Score Matching method with one nearest neighbor and replacement. Covariates include, unless otherwise specified: Ownership, Technology Intensity, Research&Development, logarithm of Wages, Total Factor Productivity, Employment and Debts.

^a Interacting dummy variables (Ownership, Technology Intensity, Research & Development) with continuous variables (Logarithm of wages, Total Factor Productivity, Employment and Debts).

^b Two observations with extreme values of Employment 2015 above four million are excluded.

^c Adding a dummy variable indicating whether a port lies within 500km of the firm to the set of covariates.

several reasons that we do not discuss in further detail. Instead, we focus on the change in the ATE when analyzing industries separately. For instance, Keller and Yeaple (2009) find a strong effect of FDI on the productivity of domestically owned firms in the high-tech sector but only a very small, if any, effect on low-tech industries. In Table 7, we report the estimates for the ATE of FDI on productivity separately for each industry. Standard errors have increased slightly, but the results are still highly significant. The impact of FDI does indeed vary across industries. Our estimates support the finding of Keller and Yeaple (2009) that firms in high-tech industries benefit the most, as FDI increases productivity of these firms by 18 percent of a standard deviation, five percentage points more than our results for the full sample suggest. Somewhat surprising is that the estimates for the low-tech industry are also higher than in our main specification. The medium low-tech industry instead does not benefit as much as the other industries do. It experiences an increase in TFP of only 8.6 percent when receiving FDI.

The weighted average of these estimates yields an ATE of FDI on TFP of 0.158 standard

deviations.⁴ This effect slightly differs from our main result due to the fact that matching is performed within industry only now. Although matched neighbours might be more 'distant' regarding other covariate values, we can ensure that each treated firm is allocated to a control observation with the same technology intensity. The covariate balances remain very good.

Table 7: ATE by Technology Intensity of Industry

	Low-Tech Industry (1)	Medium Low-Tech Industry (2)	Medium High-Tech Industry (3)	High-Tech Industry (4)
FDI2016	0.160*** (0.020)	0.086*** (0.028)	0.172*** (0.019)	0.180*** (0.054)
Observations	4,194	1,685	3,539	1,905

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4. Analysis by Type of FDI

To further test the robustness of our results, we continue our analysis by looking at potential heterogeneity of the treatment effect across types of FDI. Recall the three types of FDI from table 1 as Exports oriented, Technology intensive and Domestic market seeking, with the latter being most common and the first being least common. We test the possibility that one specific type of investment single handedly drives our previous results. It is possible, that for example only exports-oriented increases factor productivity while the other two types have little or no impact.

We estimate an augmented IPW model with multi-valued treatment effects. The matching covariates are the same as in the previous model and the regression adjustment specification is the same as that for propensity score estimation. The covariate balance is good, but the variance ratio of employment (unlogged) is a borderline case.⁵

We further estimate an IPW model to check if it yields similar estimates without regression adjustment. The covariate balance in this model is practically the same. Finally, we specify a set of AIPW models where we restrict the sample to one type of

⁴Weights are allocated according to relative sample size.

⁵Unfortunately an AIPW model with any interactions did not converge, so it was impossible to try and improve the balance this way.

treatment each. This allows for the IIA assumption to be relaxed which is required for the multinomial logit models. The separate models have worse covariate balance than the first two but are borderline acceptable. The overlap assumption is satisfied for all treatment levels as can be seen in graph ??.

In Table 8 the results from the type-wise analysis are shown. In the AIPW Multinomial specification the ATE of different types of FDI are within half a percent of each other. This suggests, that all types of FDI increase factor productivity by essentially the same margin. The estimated effect size is close to the one estimated for FDI in table 2. In the IPW specification the differences slightly larger but still within 5% of a standard deviation of each other. The separate logit models also yield essentially the same effect sizes as the multinomial specification. Since the AIPW estimator is doubly robust (assuming correctly specified regression adjustment models) models (1) and (3) provide us with strong evidence of homogenous effects.

Table 8: ATE by Type of FDI

	(1) AIPW Mlogit	(2) IPW Mlogit	(3) AIPW Logit	(4) AIPW Logit	(5) AIPW Logit
Exports-oriented FDI	0.144*** (0.006)	0.157*** (0.032)	0.140*** (0.007)		
Technology intensive FDI	0.139*** (0.005)	0.112*** (0.018)		0.139*** (0.005)	
Domestic market seeking FDI	0.143*** (0.004)	0.134*** (0.011)			0.143*** (0.004)
PO Means	-0.057*** (0.009)	-0.068*** (0.010)	-0.012 (0.011)	-0.025** (0.011)	-0.017 (0.011)
Observations	11,323	11,323	7,803	8,418	8,828

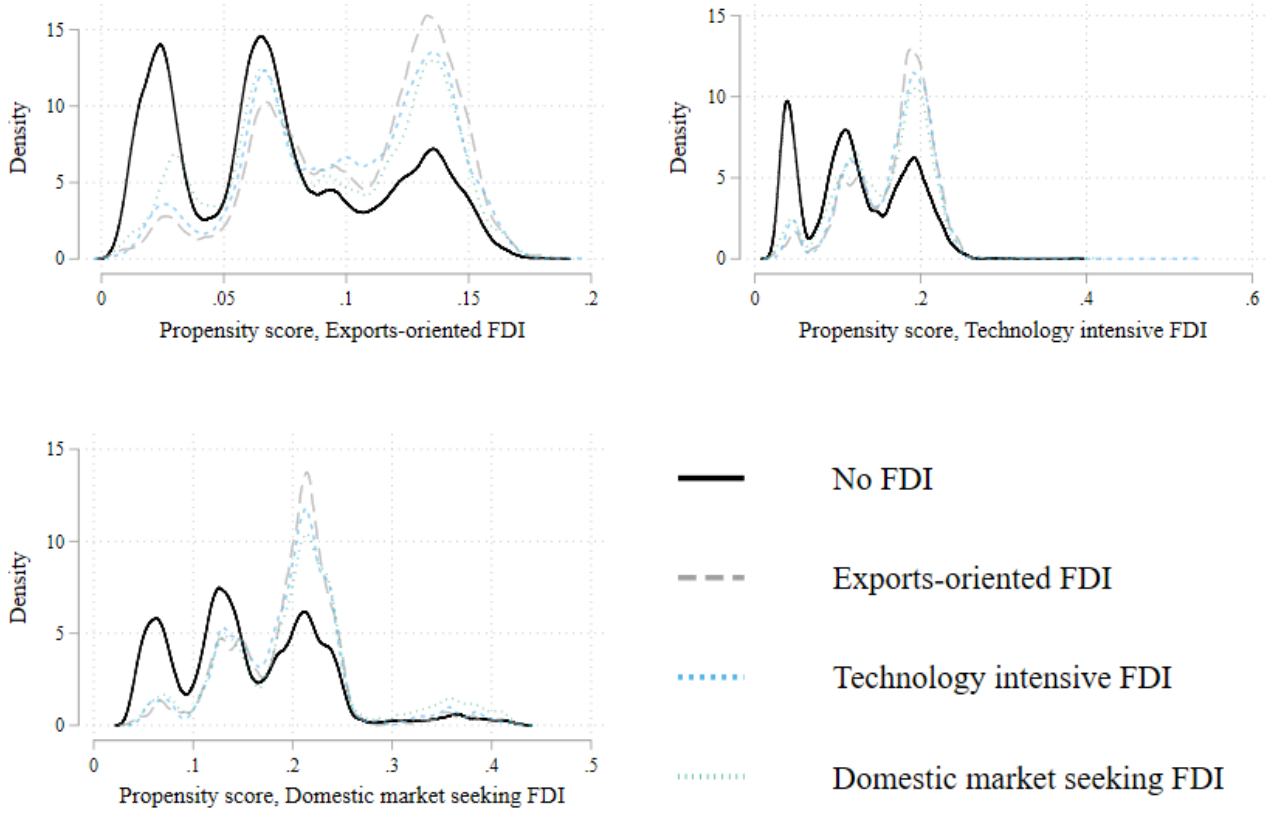
Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Discussion/Conclusion

Thoughts on what we could write for discussion/limits of our study:

1. Do not know much about the context of the treatment (so cannot really rule out anticipation-effects?)
2. Would have been interesting to extend the study to several years after the treatment. Do effects persist? Do they vanish?

Figure 3: Propensity Score by Treatment Level



3. Might depend on firm size (see Aitken and Harrison (1999)): find positive within-plant effects and spillover effects on TFP for small firms only (less than 50 employees)
4. Do not measure spillovers on plants that have not received FDI
5. Do not have sector-specific data → TECH variable has only 4 categories; e.g. in order to measure spillover effects from other firms in sector this would be necessary (i.e. if a foreign firm is more innovative)

One shortcoming of our analysis is the missing capability to explain the mechanisms behind the observed treatment effects. We do not distinguish between within-firm effects and spillover effects from firms receiving FDI to other firms. That is, the literature on spillover effects typically suggests spillovers within sectors rather than across sectors

(SOURCE) and higher spillover effects on nearby firms or firms that are trading factor inputs with foreign-owned companies (SOURCE). Due to the limited information on a firm's sector and location, we are unable to measure spillover effects.

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A. Appendix

A.1. Treatment by Technology Intensity

Technology intensity of industry	FDI in 2016					
	No.	No Col %	Cum %	No.	Yes Col %	Cum %
Low-tech	1869	44.6	27.2	2325	55.4	52.1
Medium low-tech	904	53.6	40.4	781	46.4	69.6
Medium high-tech	2432	68.7	75.8	1107	31.3	94.5
High-tech	1658	87.0	100.0	247	13.0	100.0
Total	6863	60.6		4460	39.4	