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Applied Microeconometrics

Group Project A

The Effect of FDI on Firm Productivity - A Propensity Score Estimation Approach

Spring Term 2020

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1. Introduction

The understanding of potential effects of Foreign Direct Investment (FDI) on a firm's productivity is of major concern to policy makers. FDI is commonly associated with higher firm productivity (Girma and Görg, 2007). Despite many efforts of researchers to identify the causal mechanisms underlying this correlation, it remains difficult to pin down the size and direction of the relationship. Most argue that foreign investment positively impacts firm productivity. However, it is also possible that foreign investors choose more productive firms (Arnold and Javorcik, 2009). In order to identify the causal effect of FDI on a firm's performance, and in particular on its total-factor productivity (TFP), one would need to know the counterfactual outcome. Although it is inherently unobservable, different methods can be used to avoid biases stemming from this missing data problem, e.g. randomization, Difference-in-Differences (DiD), as well as Instrumental Variable and Propensity Score methods (Karpaty, 2007). A common method in the economic literature combines DiD with Propensity Score-based estimators.

The propensity score matching estimator is used to compare treated to those untreated firms that are similar in their likelihood of receiving treatment, given a set of observable pre-acquisition characteristics (e.g. size, industry characteristics). DiD estimation on the other hand accounts for unobservable firm characteristics which are constant over time. Estimations combining both methods provide a robust Average Treatment Effect (ATE). Using this combination of methods, Arnold and Javorcik (2009) find a positive and persistent effect of FDI on firm productivity. Their analysis suggests a 13.5% increase in productivity for treated firms after three years. The same method is used by Karpaty (2007); Girma and Görg (2007) and Schiffbauer et al. (2017). Karpaty (2007) finds a positive effect of foreign acquisitions on productivity in Swedish manufacturing ranging between 7 and 8 percent for the DiD estimations. Moreover, it can take up to five years for productivity differences to occur. Girma and Görg (2007) use plant-level data for the UK for the electronic and food industries. The authors find substantial heterogeneity across industries, especially with respect to the onset of positive effects on TFP growth.

Koch and Smolka (2019) combine DiD with Inverse Propensity Score Weighting (IPW). They use Spanish firm level data from 1998 to 2013, providing evidence of an increase in output of ten percent which is explained almost entirely through skill upgrading caused by foreign acquisitions.

Using various Propensity Score estimators, we investigate the effect of FDI on TFP for a sample of 11,323 firms. In line with previous research, we are able to identify a significant effect of FDI on firm productivity, with an ATE of about 13 percent of a standard deviation. This result is robust to various model specifications, although there seems to be some heterogeneity of the effect across different levels of technology intensity. We also examine the effects of the specific types of FDI, but find no evidence of differences in their impact on firm productivity.

The remainder of this paper is organized as follows: The data and empirical specification are presented in sections 2 and 3 respectively. The results and robustness checks are shown in section 4. Section 5 concludes.

2. Data and Descriptive Analysis

Our analysis is based on observational firm-level data 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 2017after 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.

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.

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

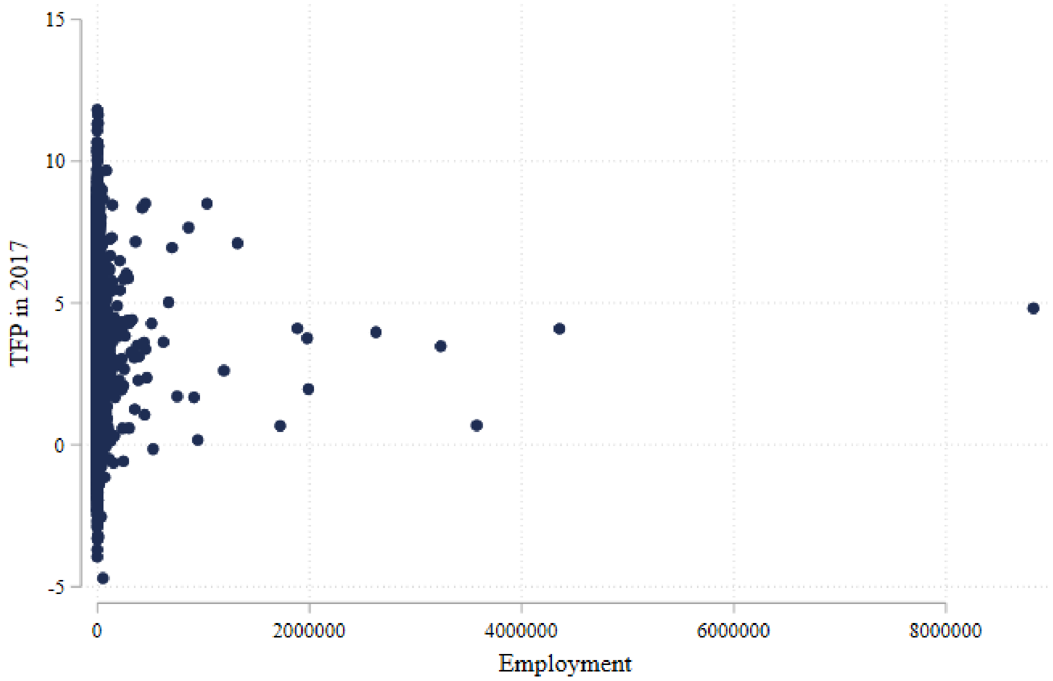
Note: All variables in levels.
[a] In Thousands

The summary statistics of the continuous variables, i.e. wages, total-factor productivity (TFP), firm size[1], 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

[1] Since 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.

their mean and median values, hinting at the existence of outliers in the sample. Taking the logarithm of the skewed variables is an easy way of reducing the influence of extreme values. However, including the log transformed employment variable deteriorates the covariate balance in all estimated models. We therefore include the untransformed employment variable for the estimation of our models, despite noting at least one extreme value in this variable (see Figure 1). To rule out any bias due to outliers, we test the robustness of our models to the exclusion of observations with extreme values in the employment variable in section 4.

Figure 1: Outliers in Employment Variable



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.

Table 4: Difference in Pre-Treatment Covariate Means

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

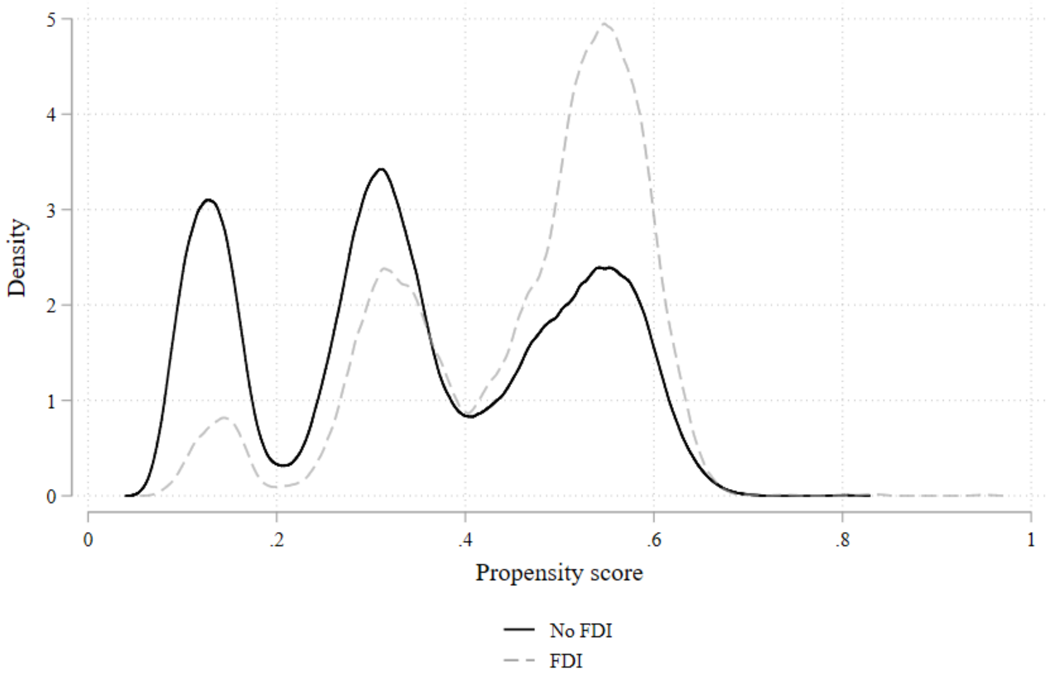
We have seen that FDI was not randomly assigned to firms. Thus, a simple comparison of treated and untreated firms will yield a biased treatment effect. Instead, we use propensity score estimation to compare the outcomes of similar firms. For this purpose we estimate the likelihood of treatment for each firm, i.e. the propensity score. It is based on a set of observable characteristics influencing both the outcome and the likelihood of treatment. We assume that conditional on these confounders, the treatment is independent of the potential outcome, i.e. the Conditional Independence Assumption (CIA) is satisfied.

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 cut-off 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 to ensure that the investigated effect is robust to the use of different estimation methods.

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 also do not include the port variable for the same reason.

Our matching model is thus a logit regression of the treatment 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 2 shows evidence of sufficient propensity score overlap for a matching analysis. The covariate balance of the different models is discussed in more detail below.

Figure 2: Propensity Score Overlap in Main Model



4. Results

4.1. Effect of FDI on TFP

The main findings of this paper are displayed in Table 5. It reports the Average Treatment Effectsof FDI on TFP. Across different 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.Had all firms in our sample received FDI, the TFP would have increased by 13 percent of a standard deviation on average. Slightly lower results are obtained from propensity score matching with five nearest neighbours and a caliper of 0.05 in column (2). The caliper cut-off excluded five observations. The estimate of the IPW in column (3) is also somewhat below that of the one in column (1). The estimate of the doubly robust AIPW-estimator is slightly larger than that of the first model, but all estimates differ by no more than 3 percent of a standard deviation.

Table 5: ATE of FDI on TFP

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

Note: This table reports the standardized coefficients of several matching estimators. All matching was done with replacement. Columns (1) and (2) show the coefficients of the one and five nearest neighbour propensity score matching respectively. For the NN5 matching, a caliper was set to .05. Columns (3) and (4) display the coefficients of the inverse probability and augmented inverse probability matching estimators respectively. The covariate adjustment model specification is the same as that of the propensity score model. Standard errors are displayed in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Checking the covariate balances of our models, the standardized differences and variance ratios are within a very good range for all models. We prefer the one-to-one propensity score matching as it gives us the best covariate balance of all the estimators. The maximum standardized difference among all covariates is 4 percent and the largest variance ratio is 1.7, with all others being close to 1 (see Table in Appendix A).

4.2. Robustness of Results

Alternative Specifications

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 throughout all specifications, confirming our main results that foreign investment 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 practised to improve covariate balance (Caliendo and Kopeinig, 2008). However, the covariate balance of our model does not show notable improvements. In fact, the covariate balance of the included interaction terms is not within an acceptable range, 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.

As we decided not to log transform the employment variable, our results could further be biased by its outliers (see Figure 1). We are concerned about two observations with extreme values: one firm with over eight million employees, and another one that, according to the data, 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. Although one could argue that having access to a port might increase productivity e.g. by facilitating market access, we find no evidence of this. Column (3) reports only a small change of 0.5 percent of a standard deviation when including the port dummy in our set of covariates. Column (4) reports the Average Treatment Effect on the Treated (ATT) of the propensity score matching with one neighbour and replacement. While the ATE measures the average effect of FDI for the hypothetical case that all firms had received FDI, the ATT estimates the effect only for those firms that have actually been treated. Because it is assumed that selection into treatment is non-random, we might find different effects of treatment on the treated. It could for example be higher if those firms receiving treatment are also the ones benefiting more from it in terms of productivity. However, our estimate in column (4) reports an ATT that is very similar to the average treatment effect. This suggests that despite potential selection into treatment, the effect size would be very similar in the absence of such selection.

Effects by Technology Intensity

FDI flows vary strongly between different sectors (see, for example, 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 target 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] There is in fact empirical evidence for heterogeneity of the effect of FDI on firm productivity depending on a firm's technology intensity. 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,

[2] The same holds true when interacting only dummy variables, only continuous variables or all variables.
[3] See Appendix ??.

Table 6: Robustness of Results

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

Note: All specifications are variations of our main model using the Propensity Score Matching method with one nearest neighbour and replacement. Covariates in the main model included: Ownership, Technology Intensity, Research&Development, logarithm of Wages, Total Factor Productivity, Employment and Debts. In column (1), the main model is augmented by interactions of the dummy variables (Ownership, Technology Intensity, Research & Development) with continuous variables (Logarithm of wages, Total Factor Productivity, Employment and Debts). The specification in column (2) excludes two observations with values of Employment 2015 above four million. In column (3) we include a dummy variable indicating whether a port lies within 500km of the firm as an additional covariate. Column (4) reports the average treatment effect on the treated. Standard errors are displayed in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

if any, effect on low-tech industries. To test for this possibility, we estimate the ATE of FDI on productivity separately for each industry and report the results in Table 7. 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 would 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, benefits much less than the other industries. It experiences an increase in TFP of only 8.6 percent of a standard deviation when receiving FDI.

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

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***	0.086***	0.172***	0.180***
	(0.020)	(0.028)	(0.019)	(0.054)
Observations	4,194	1,685	3,539	1,905

Note: The table reports the standardized ATE coefficients for subsamples of firms with different levels of technology intensity. Standard errors are displayed in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

dard deviations.[4] This effect slightly differs from our main result due to the fact that matching is now performed within industry only. 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. Despite the smaller sample sizes, the overall covariate balances remain good.

4.3. 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. 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 FDI increases factor productivity while the other two types have little or no impact. This would violate the Stable Unit Treatment Value Assumption (SUTVA), necessary for causal effect stability.

We estimate an augmented IPWmodel with multi-valued treatment effects. The matching covariates are the same as in the main model and the regression adjustment specification is the same as that of propensity score estimation. The model yields good covariate balance.

We further estimate an IPW model to check if it returns similar estimates without regression adjustment. The covariate balance in this model is practically the same. Finally, we specify a set of AIPW models, each comparing only one type of treatment to non-treated observations. This allows for the IIA assumptionto be relaxed which is

[4] Weights are allocated according to relative subsample size.

required for the multinomial logit models. The separate models have worse covariate balance than the first two but are still acceptable. The overlap assumption is satisfied for all treatment levels as can be seen in Figure 3.

In Table 8 the results of the type-wise analysis are shown. In the AIPW multinomial specification, the ATEs 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 5. In the IPW specification the differences are slightly larger but still within 5 percent 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 covariate adjustment models, the results in columns (1) and (3) provide us with strong evidence of homogeneous effects of FDI on TFP.

Figure 3: Propensity Score by Treatment Level

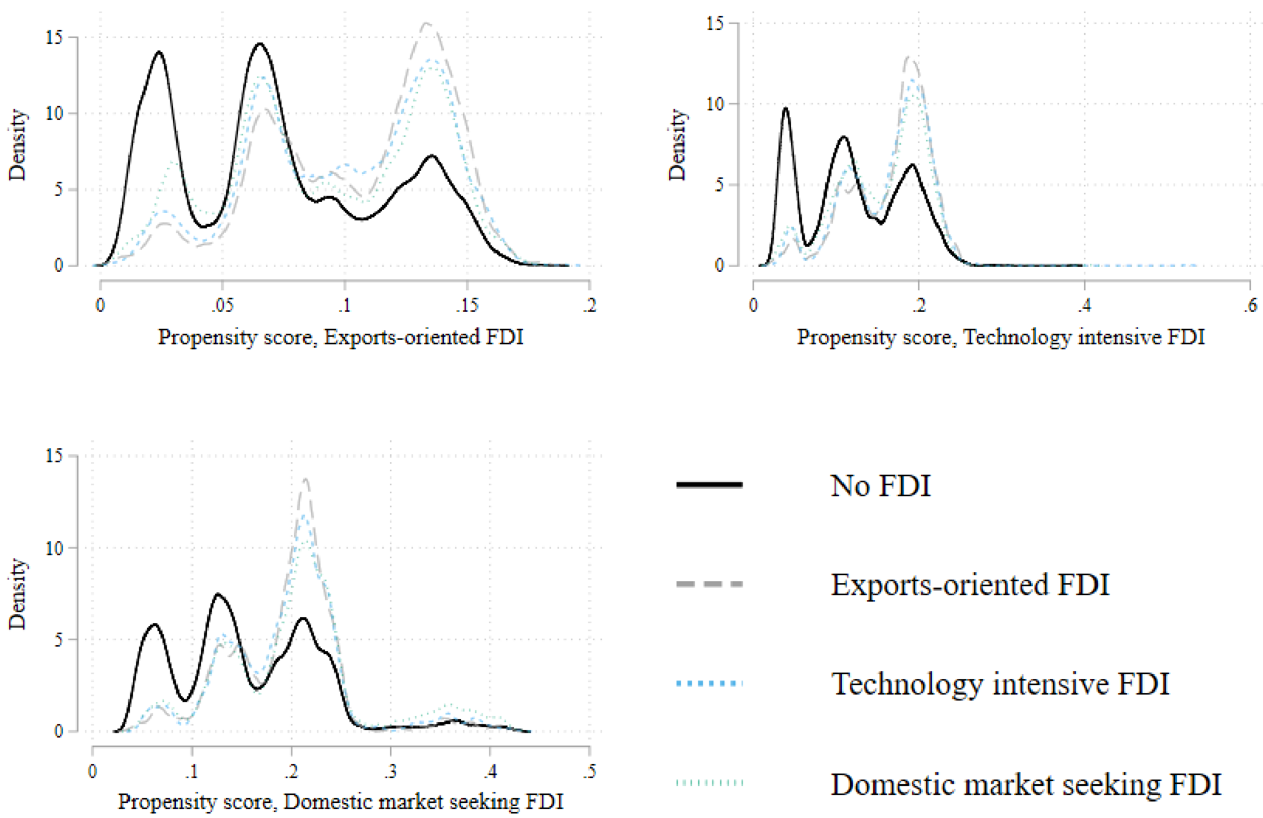


Table 8: ATE by Type of FDI

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

Note: Columns (1) and (2) report the coefficients of the multinomial augmented inverse probability and multinomial inverse probability matching estimators respectively. Columns (3)-(5) display the results of the augmented inverse probability matching estimator for subsamples of firms having received different types of FDI. Standard errors are displayed in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

5. Conclusion

Using Propensity Score-based estimators, we find a positive, economically and statistically significant effect of FDI on firm productivity. This effect is robust across various estimators as well as to different model specifications. However, we find evidence of heterogeneity across technology levels. In contrast to previous findings, this effect is not linearly increasing with technology intensity. Regardless of the type of FDI a firm receives, the effect remains positive and essentially the same size.

While our findings are broadly in line with the empirical literature, our ability to contextualize our results is limited by the lack of information about our data. For example, our dataset does not provide a detailed industry classification of our firms, or their geographical location. These variables might influence both treatment and outcome and should thus have been included in our analysis.

Moreover, we can only report estimates on the initial impact of FDI on TFP in the year after treatment. Thus we cannot make any claims about the persistence of the effect.As mentioned in the literature review, the effects of FDI seem to change over time. A DiD-Matching combination would have allowed us to control for the possible impact of unobservable characteristics, however, this would exceed the scope of our analysis.

Moreover, due to the limited information on a firm's sector and location, we are unable to account for spillover effects on nearby firms or on firms within an industry. This which may lead to an underestimation of the ATE.

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A. Appendix

Table A.1: Treatment by Technology Intensity

	Control Group			Treatment Group		
	(1) Abs.	(2) Rel.(%)	(3) Within(%)	(4) Abs.	(5) Rel.(%)	(6) Within(%)
Technology Intensity						
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**	

Note: This table reports firm technology intensity by treatment status. The first three columns respectively display the absolute and relative frequencies, as well as the within-group relative frequencies for the control group. The same parameters are reported in columns (4)-(6) for the group of firms that received FDI in 2016.

A.1. Stata Output