UNIVERSITY OF NOTTINGHAM

APPLIED MICROECONOMETRICS

GROUP PROJECT A

Insert Title

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Since (I guess) we will be focussing on ATE rather than ATT, we need to satisfy the following two assumptions:

1. Assumption: **Unconfoundedness (CIA)**
   "*[G]iven a set of observable covariates X which are not affected by treatment, potential outcomes are independent of treatment assignment*" (**?**, p. 35)

2. Assumption: **Overlap**
   "*persons with the same X values have a positive probability of being both participants and nonparticipants*" **?**, p. 35

–> if Assumption 1 holds, all biases due to observable components can be removed by conditioning on the propensity score (Imbens, 2004).

Binary Treatment

Difference between logit and probit lies in the link function. Logit assumes a log-distribution of residuals, probit assumes a normal distribution. Heteroskedastic probit models can account for non-constant error variances –> Check for heteroskedasticity?

Multiple Treatments

The multinomial probit model is the preferable option compared to logit. Alternatively, just run several binary ones (more complicated but also more robust to errors).

Variable selection

- outcome variable must be independent of treatment conditional on the pscore (CIA)

- Only variables that influence simultaneously the participation decision and the outcome variable should be included (based on theory and empirical findings)

- variables should either be fixed over time or measured before participation (include only variables unaffected by participation)

- choice of variables should be based on economic theory and previous empirical findings

Tests for variable selection

Strategies for the selection of variables to be used in estimating the propensity score:

3 Data and Descriptive Analysis

Our analysis is based on observational firm-level data. The dataset comprises 11,323 firms, of which 4,460 received FDI in 2016. The FDIs are categorized into three different types: Exports-oriented, technology intensive and domestic market seeking FDI. The outcome variable TFP was measured in 2017. The baseline variables were measured in 2015 (one year prior to receiving FDI) and comprise information on:

- Ownership (listed company, subsidiary, independent or state owned)

- Technology intensity (low, medium low, medium high or high-tech industries)

- Access to a port

- Wages (as log variable)

- Total Factor Productivity (TFP)

- Firm size (measured in number of employees, log variable)

- Debt (as log variable)

- Export intensity

- Whether the firm has invested in Research and Design

4 Empirical Specification

4.1 Effect of FDI on TFP

5 Analysis by Type

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. Doing so we can test

Table 1: Impact of FDI on TFP-Standardized

VARIABLES	NN1 ATE	NN1 ATT	NN5 ATE	NN5 ATT	IPW ATE	IPW POmean	IPW ATET	IPW POmean	AIPW ATE	AIPW POmean
r1vs0.FDI2016	0.125***	0.147***	0.119***	0.133***	0.119***		0.179***		0.142***	
	(0.019)	(0.020)	(0.013)	(0.011)	(0.006)		(0.006)		(0.003)	
0.FDI2016						-0.071***		-0.199***		-0.057***
						(0.010)		(0.016)		(0.009)
Observations	11,323	11,323	11,321	11,321	11,323	11,323	11,323	11,323	11,323	11,323

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

Table 2: Impact of FDI on TFP

VARIABLES	NN1 ATE	NN1 ATT	NN5 ATE	NN5 ATT	IWP ATE	IPW ATT	AIWP ATE
r1vs0.FDI2016	0.257***	0.302***	0.246***	0.273***	0.245***	0.367***	0.292***
	(0.038)	(0.040)	(0.028)	(0.022)	(0.013)	(0.013)	(0.006)
0.FDI2016							
P0 Means					3.510***	3.247***	3.540***
					(0.020)	(0.033)	(0.020)
Observations	11,323	11,321	11,321	11,323	11,323	11,323	11,323

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

the possibility that one specific type of Investment drives our previous results. From the data we can distinguish between three different types of FDI: (i) exports-oriented FDI, (ii) technology intensive FDI and (iii) domestic market seeking FDI. Table 5 shows their absolute and relative frequencies. It is possible, that for example only exports-oriented increased factor productivity while the other two types had little or no impact.

To test for this possibility we estimate IPW and augmented IPW models with multi-valued treatment effects. The matching covariates are the same as in the previous model and the regression adjustment model is the same as that for propensity score estimation. The covariate balance is good in both models,

In table 6 results from IPW and AIPW regressions are shown, where the treatment model is a Multinomial Logit with FDI types as unordered outcomes. The results show that all three types of FDI have positive and significant effects, so all types of FDI have a positive and significant effect on TFP. The effect sizes of the AIPW in table six are

Table 3: 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%

very close to those from the single valued treatment in table 4. Relative to the potential outcome mean of 3.5, the different types of FDI increase Factor productivity by 14% of a standard deviation at at the 99% level of significance. The potential outcomes mean for receiving no FDI is 5.7% below the sample mean.

The Inverse Probability Weighting Model gives us somewhat bigger differences in effect sizes between the types. The difference between the bigger effect of Exports oriented FDI and the smaller effect of Technology intensive FDI amounts to 4% of a standard deviation. Including interaction terms between continuous and categorical regressors

With the AIPW being a doubly robust estimators and rather small differences in the IPW estimator we take these results to suggest that all types of FDI have similar positive impacts on factor productivity.

Table 4: Multinomial Logits

VARIABLES	(1) AIPW	(2) IPW
Exports-oriented FDI	0.141***	0.155***
	(0.006)	(0.028)
Technology intensive FDI	0.139***	0.114***
	(0.005)	(0.016)
Domestic market seeking FDI	0.143***	0.123***
	(0.004)	(0.010)
PO Means	-0.057***	-0.071***
	(0.009)	(0.010)
Observations	11,323	11,323

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To account for the possibility that the choice of the FDI type does not satisfy the IIA assumption we further estimate separate logit models for the two estimator types. The results, reported in table 7, are very similar to those obtained from a multinomial specification, suggesting that the IIA assumption holds.

6 Discussion/Conclusion

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Table 5: Seperate Logits for FDI Type

VARIABLES	Export AIPW	Export IPW	Technology AIPW	Technology IPW	Domestic AIPW	Domestic IPW
ATE	0.136***	0.110***	0.139***	0.078***	0.143***	0.095***
	(0.007)	(0.037)	(0.005)	(0.020)	(0.004)	(0.012)
PO Mean	-0.013	-0.014	-0.025**	-0.028***	-0.017	-0.022**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	7,803	7,803	8,418	8,418	8,828	8,828

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

?

(**?**, p. 35)

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?

3. Might depend on firm size (see Aitken & Harrison 1999 → will include citation): 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)

6. Propensity Score matching might not be the best approach for given data as CIA could be violated

Appendix