The impact of outbound FDI on domestic investment

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Abstract

When a firm becomes a multinational, what does this do to its pace of growth of domestic assets? In contrast to the evidence for US multinational companies, where foreign and domestic investment are seen to be complements, we find evidence that for Indian MNCs, significant levels of outbound FDI have a negative impact on the growth in domestic investment. We conjecture that this is related to special features of capital controls against foreign borrowing, and to a difficult institutional environment faced in doing domestic investment.

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Contents

1 Introduction

Expansion of economic activity by multinational companies raises concerns about the loss of business at home. Particularly in developed countries, there have been fears that once a firm builds a production platform in a low wage country, future investments and job creation would focus on foreign subsidiaries, and growth at home of jobs or assets would subside. Economic theory does not yield a clear prediction about the impact of foreign investment on domestic activity. The empirical evidence on this impact has been found to be mixed.

When a firm in a low-wage country becomes a multinational, the conventional wisdom holds that a global platform is created for sales and distribution, and then work is moved to the home country where wages are low. This has raised fears about potential job loss in developed countries when local firms are purchased by developing country multinationals.

In this paper, we explore data about Indian multinationals. A rigorous causal analysis is undertaken, based on matching and difference-in-differences analysis. Our main finding is that across an array of statistical estimation strategies, once an Indian firm becomes a multinational with significant assets abroad, the pace of growth of domestic assets goes down. This result does not hold for firms which place only a small fraction of their balance sheet abroad: this limited scale FDI seems to be an element of enabling increased home production for the purpose of exports.

Given that wages in India are amongst the lowest in the world, this result is a puzzle. We may offer two elements of an explanation, without establishing their statistical validity or causal impact. The first concerns peculiar features of capital controls in India, where firms are able to obtain low-cost foreign debt capital if this would be used to grow offshore assets, but not if this would be used to invest domestically. This drives a wedge between the cost of capital for domestic versus foreign expansion. The second explanation may be related to the difficulties of the institutional environment in India, on issues such as land acquisition, the lack of a nationwide VAT system that is integrated with international trade, etc., which may impede the extent to which global firms find it efficient in India.

The remainder of this paper is organised as follows. Section 2 presents the theoretical and empirical background that motivates this paper. Section 3 describes the empirical methodology of the matching technique combined with the difference-in-differences approach adopted in this paper. Section

4 describes the data. Section 5 presents the matching techniques used and shows the balance achieved through various balance tests. Section 6 discusses our results. Section 7 concludes.

2 Foreign and domestic investment

An intuitive framework for analysing the relationship between outward foreign direct investment and the domestic capital stock would be to start from the multinational's production function as in Desai *et al.* (2005b). Let the global production be given by the function $Q(K_d, K_f, x, z)$, where K_d is the level of domestic input, K_f foreign input, x consists of factors that influence domestic production, and z represents factors that influence foreign production. We extend the model to allow differential prices of labour and capital between the home country and the rest of the world, so as to model the unique Indian situation of cheap labour (which encourages home production) alongside a wedge in the cost of capital between domestic and foreign investment (which encourages offshore expansion). Let the overall cost be $\lambda(K_d, K_f, x, z)$. This induces a profit function:

$$\pi \quad = \quad Q(K_d, K_f, x, z) - \lambda(K_d, K_f, x, z) \tag{1}$$

Firms choose K_d and K_f jointly to maximize π, hence it is necessary to specify carefully how foreign operations affect domestic operation. A change in the foreign specific factor (z) may impact K_f, which could in turn impact K_d. Desai *et al.* (2005a) looks at some such cases.

Abstracting from tax effects on investment and other complications, the optimal level of domestic capital maximizing the firm's profit would satisfy the first-order condition:

$$\frac{\partial Q(K_d, K_f, x, z)}{\partial K_d} = \frac{\partial \lambda(K_d, K_f, x, z)}{\partial K_d} \tag{2}$$

Clearly, from Equation 2 foreign capital can affect domestic capital through two channels, the cost of capital (λ), and the derived production function. This may take any of a number of forms but the final impact is either of *substitution*, whereby firms substitute domestic capital with foreign capital, or *complementarity* in which foreign operations complement domestic ones.

Looking at the cost factor which is determined by the market conditions and government policies, if firm resources are fixed then any addition in foreign capital will cause a reduction in domestic capital. However, as MNE's usually finance themselves through multiple world markets the cost factor could have a complementary affect. For example, MNE's affiliates borrow from local sources, as found by Desai *et al.* (2004) for US MNE's and (Du and Girma, 2008) for MNE affiliates based in China.

In the Indian case, financial sector policy and capital controls come together to imply that domestic debt is expensive, foreign debt is cheaper, and foreign debt can be undertaken for the purpose of offshore expansion but not for domestic expansion. This could encourage multinational firms to invest abroad, rather than at home.

If the financial resources are not fixed, the primary source of interaction between the domestic and foreign capital is the sign of the expression $\frac{\partial^2 Q(K_d,K_f,P)}{\partial K_d \partial K_f}$. Economic theory provides conflicting predictions, depending on the motive of FDI, the industry is question and income differentials between source and destination countries.

$\frac{\partial^2 Q(K_d,K_f,P)}{\partial K_d \partial K_f} > 0$ indicates that K_d and K_f are complementary, that is greater foreign capital stimulates higher levels of domestic activity. Whereas, $\frac{\partial^2 Q(K_d,K_f,P)}{\partial K_d \partial K_f} < 0$ indicates that K_d and K_f are substitutes, that is an increase in K_f will cause a fall in K_d.

There are two kinds of FDI, Horizontal and Vertical based on motive. *Horizontal FDI* is largely motivated by replicating business in foreign countries in response to higer foreign output prices, lower trade costs or other frictions. In the initial stage of horizontal investment we would expect substitution of foreign capital by domestic exports. Once this investment is made, complementarity between domestic and foreign capital may materialise as synergies between headquarters and foreign operations emerge. In the non-tradable sector it is reasonable to expect a complementary relation from the start as there are no domestic exports.

Vertical FDI is made by MNEs that geographically fragment stages of their production process and optimise globally (Ekholm and Markusen, 2002). Other reasons could be lower foreign input prices or improved investment opportunities abroad. Initially the splitting up of the production process is likely to lead to substitutability between domestic and foreign capital. After the split and over time, the vertical FDI could lead to an increased demand of domestic goods (Brainard and Riker, 1997), hence increasing the demand for domestic capital. The decision of what to produce where is made on the basis of factor intensities. The firm may choose to shift labour-intensive stages of production abroad to exploit differential lower unit labour costs. In the case of a low labour cost economy like India, it may be due to availability of skilled labour, rather than cost.

Keeping in mind the theoretical background and Indian scenario, there are a few opposing forces at play. Availability of cheap labour in the domestic market which could cause domestic capital to rise, higher cost of capital domestically could push Indian firms to do FDI, and as Chari *et al.* (2009) points out that emerging-market firms could enter new markets to acquire new technology and brand equity. Also, as we have seen that different stages of investment cause different affects on domestic capital. The substitution and complementarity affects can happen for different firms at different times making this a matter of empirical resolution.

Finally it is helpful to note that the relationship between domestic and foreign capital has been analysed at three different levels: macro, industry and firm level studies with each having its benefits and drawbacks.

Macro level studies rely on time series techniques based on aggregate domestic and capital stocks to get a handle on the casual relationship between K_d and K_f. Feldstein (1995) for OECD countries, Herzer and Schrooten (2008) for Germany and Sauramo (2008) for Finland find a negative relationship between K_d and K_f Desai *et al.* (2005b) report that K_d and K_f are complementary for the USA. Arndt *et al.* (2007) highlights the main advantage of industry level studies and using panel cointegration technique, concludes that the positive relationship between German OFDI and domestic FDI which is driven by intra-industry effects.

Firm level studies minimise the risk of aggregation bias, allow for heterogeneous investment behaviours and provide the oppertunity to control for potential endogeneity between K_d and K_f. Using data on US MNEs, Desai *et al.* (2005b) report a positive relationship between K_d and K_f. Several firm level studies focus on the domestic employment/output effects of K_f producing mixed results. To mention a few examples, Feenstra and Hanson (1996) for the US; Lipsey *et al.* (2000) for Japan; Braconier and Ekholm (2001)for Sweden and Navaretti and Castellani (2004) for Italy, document evidence that expansion abroad results in additional domestic job creation. On the other hand, Brainard and Riker (1997)for the US and Braconier and Ekholm (2001) for Sweden, amongst others, found a substitution effect between foreign affiliates expansion and domestic employment growth.

3 Empirical methodology

The aim of the paper is to analyse whether there is a causal effect from outbound foreign investment of a domestic firm on domestic investment of the firm. The empirical modelling problem is the evaluation of the causal effect of foreign investment on y, where y represents domestic investment of the firm.

Some firms, hence called the OFDI (outbound foreign investment) firms engage in outbound foreign direct investment, through acquision or joint venture, or green field investment. Their investment at home can be affected by their foreign investment. We do not observe what would have been the growth in domestic investment of the OFDI firms had they not invested abroad.

In the microeconometric evaluation literature this question has been viewed as a missing-data problem. Following (Heckman *et al.*, 1998; Dehejia and Wahba, 2002), we define the average effect of the 'treatment', in this case, investment abroad, on the OFDI firms as the difference between the counterfactual and the observed outcome. The counterfactual is constructed by choosing a set of firms with similar characteristics.

The challenge here is an accurate construction of the counterfactual. This is done through the selection of a well chosen control group. We employ matching techniques to do so. The purpose of matching is to pair each firm that invests abroad with one or more firms that do not do so, based on observable pre-treatment characteristics such as age, size, wages etc. The microeconometric evaluation literature suggests that it is desirable to perform the matching exercise on the basis of a single index that captures all the information from these 'covariates'. We adopt the method of propensity score matching due to (Rosenbaum and Rubin, 1983) , which suggests the use of the probability of receiving treatment conditional on those characteristics, to reduce the dimensionality problem.

We identify the probability (or propensity score) of investing abroad using a logit model. We then choose two sets, the treated, from those who invested abroad, and the control, from those who did not, based on the distance between their propensity scores. We drop firms from the treatment group which cannot be matched as the propensity of the firm to invest abroad is too high, or outside the common support, to find a good match in the control group. From the set of firms that did not invest abroad we choose for the control group, firms which are closest in terms of their propensity to invest abroad based on observable characteristics.

We can now use the two differences between domestic investment of the two groups, treated and control, to assess the causal impact of investment abroad on domestic investment. The limitation of this approach is that it ignores the unobserved time-invariant differences between the firms who self-select themselves into investing abroad and those who do not. Following the microeconometric evaluation literature, and given that we have the necessary longitudinal data to do so, we use a difference-in-differences (DID) approach

Table 1 Number of firms doing OFDI each year

	No OFDI	OFDI firms	High OFDI	Low OFDI
2000	1731	27	4	23
2001	1726	93	22	71
2002	1707	150	41	109
2003	1750	174	44	130

Table 2 Number of firms doing OFDI sector wise for 2003

	No OFDI	OFDI firms	High OFDI	Low OFDI
Chemicals	356	30	4	26
Diversified	23	4	0	4
Electricity	13	0	0	0
Food	138	6	1	5
Machinery	215	15	0	15
Metals	141	8	0	8
Mining	17	0	0	0
MiscManuf	81	1	0	1
NonMetalMin	82	5	0	5
Serv.Construction	91	1	0	1
Serv.IT	94	78	36	42
Serv.Other	215	19	3	16
Textiles	185	5	0	5
TransportEq	99	2	0	2

In our analysis we distinguish between high versus low foreign investment. We define a *cutoff* value which divides OFDI firms into two groups: ones doing OFDI greater than the cutoff (defined as *high OFDI*), and ones doing OFDI less than the cutoff, but higher than one percent (defined as *low OFDI*). The cutoff is defined so that the top 25 percent of firms are defined as the *high OFDI* firms. This figure, in 2003, is 12.3 percent indicating that the top 25 percent firms in terms of the ratio of OFDI to total assets have assets worth 12.3 percent of their total assets outside India. So we define *high OFDI* firms as those with foreign assets above this ratio, the *low OFDI* firms as those with less than 12.3 percent of assets abroad. Figure 1 shows the density plot of the ratio of OFDI to total assets for the year 2003.

Table 2 shows the number of firms doing OFDI, high OFDI,and low OFDI sector wise for 2003. *Service IT* has the most number of firms doing OFDI by a long way, followed by the Chemicals sector.

Figure 1 Density plot of OFDI

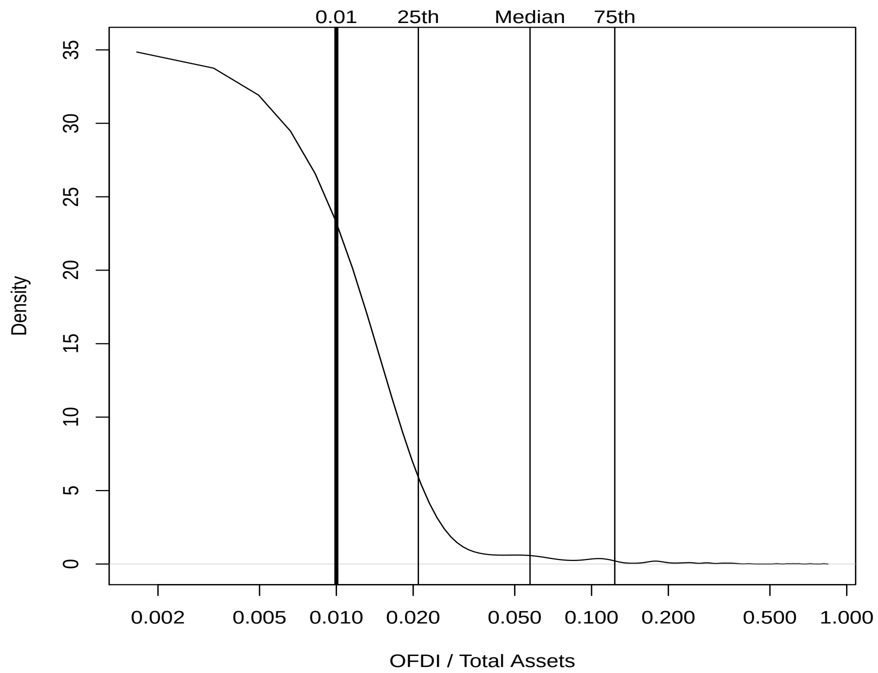

Table 3 Propensity score estimation

Panel A: Low OFDI

	Estimate	Standard Error	z-value	p-value
Intercept	-3.15	0.43	-7.40	0.00
Total assets	5.47	3.23	1.70	0.09
Age	-0.02	0.01	-3.68	0.00
Wages	0.45	0.12	3.78	0.00
Sales	-0.36	0.12	-2.93	0.00
Domestic assets	-5.08	3.22	-1.58	0.11
Panel B: High OFDI				
Intercept	-0.42	0.64	-0.66	0.51
Total assets	8.86	5.12	1.73	0.08
Age	-0.10	0.02	-4.42	0.00
Wages	1.04	0.20	5.31	0.00
Sales	-0.69	0.18	-3.81	0.00
Domestic assets	-8.99	5.09	-1.77	0.08

5 Matching method

We match firms using the nearest neighbour matching method. Nearest neighbor matching selects the best control matches for each individual in the treatment group (excluding those discarded such those those outside the common support). Matching is done using a logit model. Matches are chosen for each treated unit one at a time. At each matching step we choose the control unit that is not yet matched, but is closest to the treated unit on the distance measure. Total assets, domestic assets, sales and wages are measured in logs.

Firms in each of the groups are matched, dropping the firms in the treated group that could not be matched if they are outside the common support. The matched firms are thus within the common support. In the case of *low OFDI* firms, 16 firms were dropped from the matched sample, and in the case of *high OFDI*, 10 firms are dropped from the analysis.

Table 3 shows the results from the logit model estimation for the propensity score for the low and high OFDI cases.

We now show that the matching done by the above method results in good matches.

Table 5 and Table 5 provide us the summary statistics of the treated and control groups before and after matching. The means of all the variables

Table 4 Sample size after matching firms

	Control	Treated
Low FDI		
All	1572	116
Matched	100	100
Unmatched	1472	0
Discarded	0	16
High FDI		
All	1650	38
Matched	28	28
Unmatched	1622	0
Discarded	0	10

should become closer for the treated and control groups after matching, if the matching is good. This can also be seen as the mean difference after matching getting closer to zero. The last three columns give the median, mean, and maximum value of difference in the empirical quantile functions for each covariate. We would expect these values to be moving closer to zero or at least reducing after matching. As the tables show, the matching procedure improves the match.

Table 5 Summary Statistics: *Low OFDI*

	Means Treated	Means Control	SD Control	Mean Difference	eQQ Median	eQQ Mean	eQQ Max
Before matching							
Distance	0.12	0.07	0.06	0.05	0.04	0.05	0.49
Total assets	5.38	4.34	1.61	1.05	1.17	1.07	1.71
Age	22.29	22.90	19.88	-0.60	1.00	1.54	39.00
Wages	2.35	1.19	1.93	1.16	1.26	1.21	2.15
Sales	4.92	4.04	1.84	0.88	1.01	0.95	2.62
Domestic assets	5.38	4.34	1.61	1.04	1.17	1.07	1.72
After matching							
Distance	0.11	0.11	0.07	0.00	0.00	0.00	0.01
Total assets	5.43	5.25	1.66	0.18	0.25	0.27	1.14
Age	23.42	20.95	15.44	2.47	2.00	2.67	35.00
Wages	2.30	2.21	1.95	0.10	0.15	0.25	1.79
Sales	4.99	4.74	1.94	0.25	0.31	0.33	2.20
Domestic assets	5.43	5.25	1.66	0.17	0.23	0.26	1.14

SD: Standard deviation.
eQQ: Empirical quantile quantile.

Table 6 Summary Statistics: *High OFDI*

	Means Treated	Means Control	SD Control	Mean Difference	eQQ Median	eQQ Mean	eQQ Max
	Before Matching						
Distance	0.13	0.02	0.04	0.11	0.04	0.10	0.61
Total assets	4.05	4.42	1.64	-0.36	0.38	0.45	2.44
Age	10.71	23.14	19.92	-12.43	7.00	14.18	99.00
Wages	1.47	1.26	1.95	0.20	0.44	0.55	2.93
Sales	3.49	4.11	1.86	-0.62	0.56	0.71	4.65
Domestic assets	4.02	4.42	1.64	-0.40	0.42	0.48	2.44
	After Matching						
Distance	0.07	0.07	0.06	0.00	0.00	0.00	0.00
Total assets	4.62	3.83	1.59	0.79	0.80	0.79	1.52
Age	11.86	10.75	7.49	1.11	3.00	2.61	12.00
Wages	1.77	1.37	1.56	0.40	0.68	0.68	1.72
Sales	4.02	3.74	1.73	0.29	0.23	0.38	1.58
Domestic assets	4.62	3.83	1.58	0.79	0.80	0.79	1.52

SD Control - Standard Deviation of Control group
eQQ - empirical quantile quantile functions

Table 7 Balance Improvement

Low OFDI	Mean Difference	eQQ Median	eQQ Mean	eQQ Max
Distance	99.93	99.88	99.17	98.03
Total assets	82.73	78.51	75.30	33.10
Age	-308.62	-100.00	-73.03	10.26
Wages	91.76	88.19	79.07	16.69
Sales	72.10	69.65	65.76	16.05
Domestic assets	83.28	80.26	75.52	33.59
High OFDI				
Distance	99.87	99.83	99.69	99.61
Total assets	-116.10	-109.47	-76.81	37.71
Age	91.09	57.14	81.62	87.88
Wages	-96.30	-53.60	-24.10	41.39
Sales	53.53	58.36	46.08	66.02
Domestic assets	-98.59	-91.76	-64.78	37.71

Table 7 gives us the balance improvement between the before and after matched units, defined as

$$100((|a| - |b|)/|a|)$$

where a is the balance before and b is the balance after matching. Clearly, it is best to get a balance improvement close to 100, and negative values would imply that the post matching outcome difference has increased. We have good balance improvement for the distance measure. The covariates used are age, total assets and sales as a proxy of size of a company, wages and domestic assets.

Next we perform the Hotelling's T-squared test on all observations of our matched set. We see in Table 8 that balance is maintained by this test. Thus, the null hypothesis of mean differences equal to zero for the whole sample is not rejected.

6 Difference-in-differences estimates

We follow the microeconometric evaluation literature and use a difference-in-differences(DID) approach to evaluate the Average Treatment Effect (ATE)

Table 8 Hotelling's T-squared test

	T-squared stat	p-value
Low OFDI		
Matched sample	1.91	0.10
High OFDI		
Matched sample	1.93	0.11

on the firms that invested abroad. This requires longitudinal data, which we have. To measure the ATE we estimate the counterfactual following Blundell (2000); Girma and Gorg (2007) and using MatchIt and Zelig packages in R (Ho *et al.*, 2007, 2009).

Using this approach we first fit a linear model to the treatment group. We then conduct a simulation procedure in order to impute the counterfactual outcome for the control group using the model parameters of the treated group. These are a proxy for the missing data, that is, what would have been the domestic investment by the treated group had they not invested abroad. We then compute the difference between observed and the counterfactual or expected values for the OFDI group. This gives us the average treatment effect of investing abroad on growth in domestic investment.

6.1 Sensitivity analysis: Other matching methods

In addition to the neighbour neighbour matching method, we test our hypothesis using other matching methods.

6.1.1 Optimal matching

The nearest neighbor matching method is a greedy match, where the closest control match for each treated unit is chosen one at a time, without trying to minimize a global distance measure. In contrast, optimal matching and the matched samples with the smallest average absolute distance across all the matched pairs. Gu and Rosenbaum (1993) find that greedy and optimal matching approaches generally choose the same sets of controls for the overall matched samples, but optimal matching does a better job of minimizing the distance within each pair. In addition, optimal matching can be helpful when there are not many appropriate control matches for the treated units (Hansen (2004).

6.1.2 Full matching

Full matching is a particular type of subclassification that forms the subclasses in an optimal way (Rosenbaum (2002);Hansen (2004)). A fully matched sample is composed of matched sets, where each matched set contains one treated unit and one or more controls (or one control unit and one or more treated units). As with subclassification, the only units not placed into a subclass will be those discarded because they are outside the range of common support. Full matching is optimal in terms of minimizing a weighted average of the estimated distance measure between each treated subject and each control subject within each subclass.

6.1.3 Subclassification

When there are many covariates (or some covariates can take a large number of values), finding sufficient exact matches will often be impossible. The goal of subclassification is to form subclasses, such that in each the distribution (rather than the exact values) of covariates for the treated and control groups are as similar as possible. Various subclassification schemes exist, including the one based on a scalar distance measure such as the propensity score estimated.

6.2 Summary of the key results

Table 9 gives us the ATE values for the outcomes obtained by the Nearest Neighbour matching, Optimal, Full and Subclassification matching methods. Table 9 shows the average treatment effect on the outcome variable, i.e. the growth in domestic assets from the year 2000 to the years 2005 and 2006 for both low and high OFDI firms. The column head ATE (after 2 years) shows the difference two years after treatment i.e in 2005 and ATE (after 3 years) shows the growth in domestic assets over the three year period 2003-2006.

The results show that for the *low OFDI* firms the impact of investing abroad on growth in domestic assets after 2 years is negative and insignificant by the nearest neighbour method. This result is not supported by the three other methods of matching. While the optimal matching method gives a positive and insignificant result, the full method gives a positive and significant, the subclassification method shows a positive and not significant impact. The impact on domestic investment after three years for *low OFDI* firms is seen

Table 9 ATE using various Matching Methods

Low OFDI	ATE (after 2 years)	t-stat (2 years)	ATE (after 3 years)	t-stat (3 years)
Nearest	-0.03	-0.10	0.02	0.06
Optimal	0.07	1.93	0.14	3.04
Full	0.13	5.37	0.19	6.82
Subclassification	0.04	1.69	0.11	3.79
High OFDI				
Nearest	-0.57	-3.14	-0.59	-2.48
Optimal	-0.26	-2.12	-0.40	-2.67
Full	-0.19	-2.73	-0.29	-3.51
Subclassification	-0.38	-14.97	-0.48	-15.14

to be positive and insignificant by the nearest neighbour method and positive and significant by the other methods. We can conclude that the results support no immediate impact of OFDI of low levels and a small complimentarity of investing abroad with growth in domestic assets, after a lag of three years. This is consistent with the hypothesis that small investment abroad can be used to support marketing networks and act as export platforms.

For the *high OFDI* firms we find that all methods at both the two year and the three year lag suggest that there is subsititutability between foreign investment by a domestic firm and the growth in its domestic investment. This effect is significant and robust across different matching methods.

There is a distinct difference between the results for low and high OFDI firms. The results for the high OFDI firms support the substitutability hypothesis for all the matching methods employed, and are significant for the three year horizon. In contrast, the results for low OFDI firms suggest complementarity, though the impact is not as robust and significant.

7 Conclusion

In this paper we have studied the impact of outbound FDI by firms from an emerging economy on their domestic activity. Evidence suggests that while low levels of foreign investment bring in more business for the firm at home, which then invests more at home, once a firm becomes a serious investor in the foreign market, this effect reverses. High levels of foreign investment are associated with lower growth in domestic assets. This result is in contrast with that for US multinationals. There are a number of factors that can influence the decisions of firms to invest domestically after investing abroad such as vertical or horizontal OFDI, time horizon of the study, and the desire to diversify, and the higher cost of capital in an emerging economy in the context of segmented financial markets and capital controls. Further analysis of what shaped the decisions of Indian OFDI firms in greater detail can help understand some of the causes of our observations.

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A Appendix

To look at the matching balance we look at three types of plots: Q-Q plots of each covariate, jitter plots of the distance measure, and histograms of the distance measure. If the Q-Q plots,Figure **??**, lie on the 45 degree line this would imply that the treated and control groups have the same empirical distributions, as is the case here. The jitter plots, Figure 9, shows the overall distribution of propensity scores in the treated and control groups.

The above analysis establishes that we have we have well matched treatment and control groups.

Figure 2 QQ plots for each covariate in the full and matched sample: *Low OFDI*

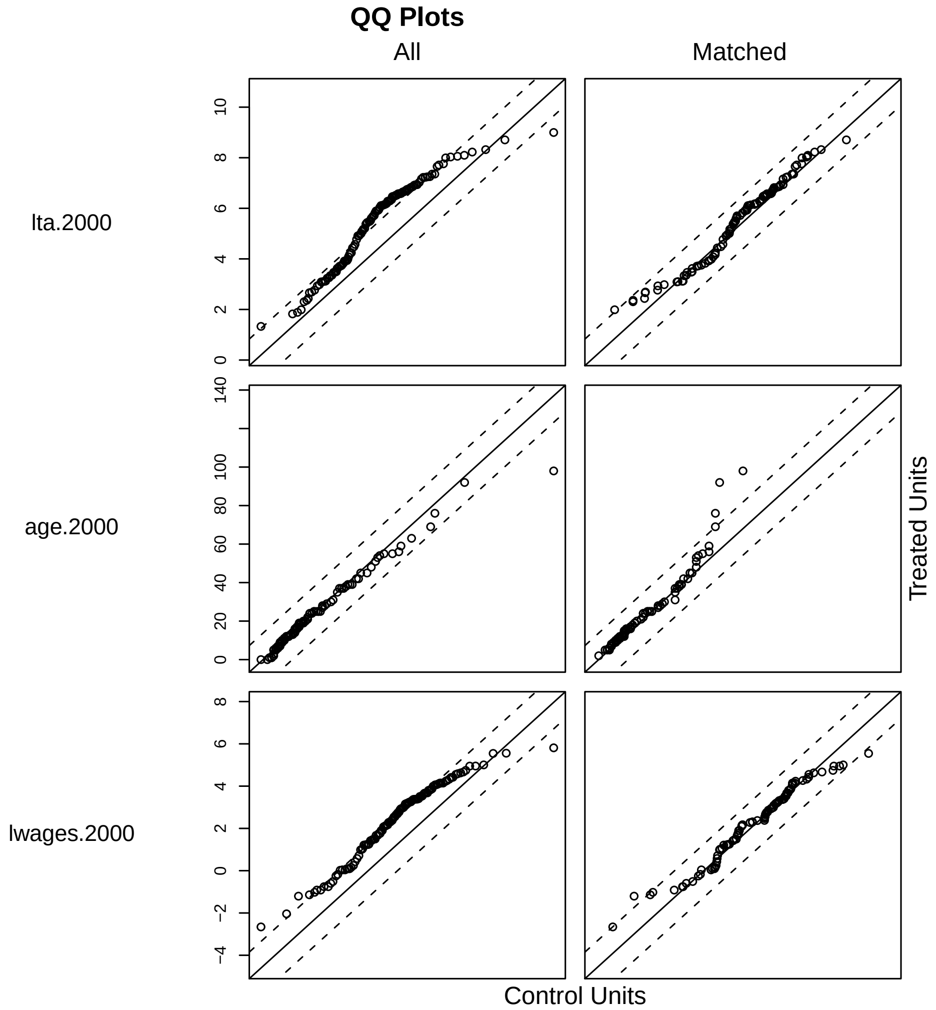

Figure 3 QQ plots for each covariate in the full and matched sample: *Low OFDI* (continued)

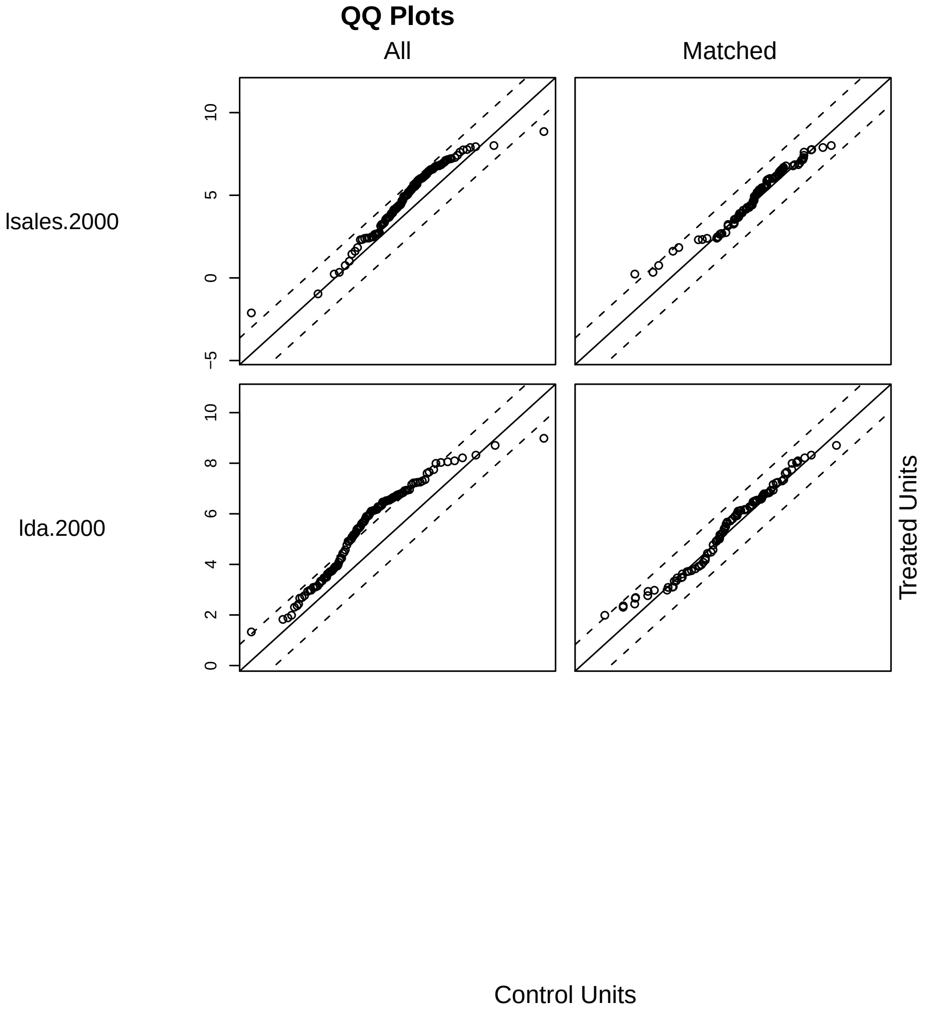

Figure 4 Histogram of Propensity Scores : *Low OFDI*

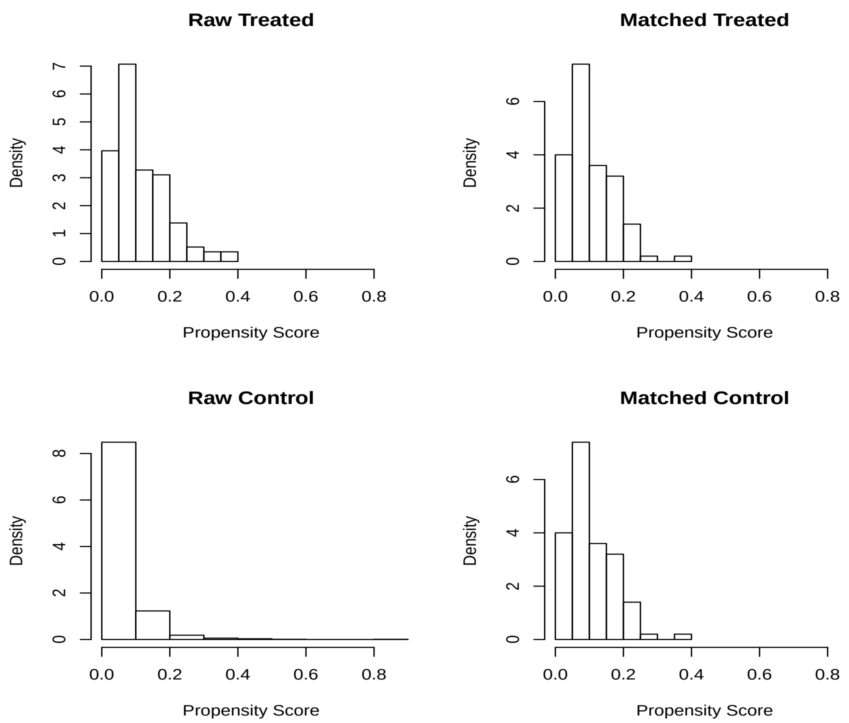

Figure 5 Jitter plots of the Distance Measure: *Low OFDI*

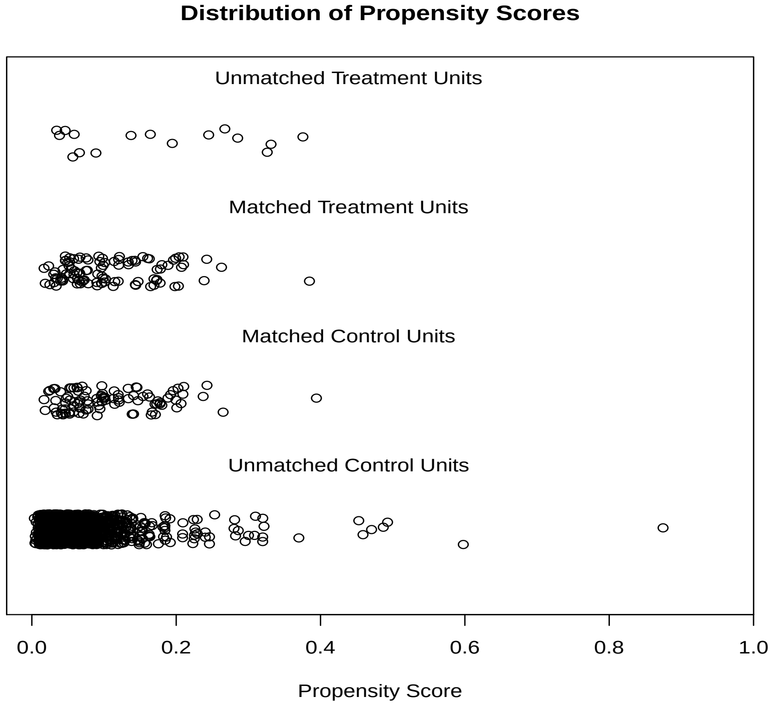

Figure 6 QQ plots for each covariate in the full and matched sample: *High OFDI*

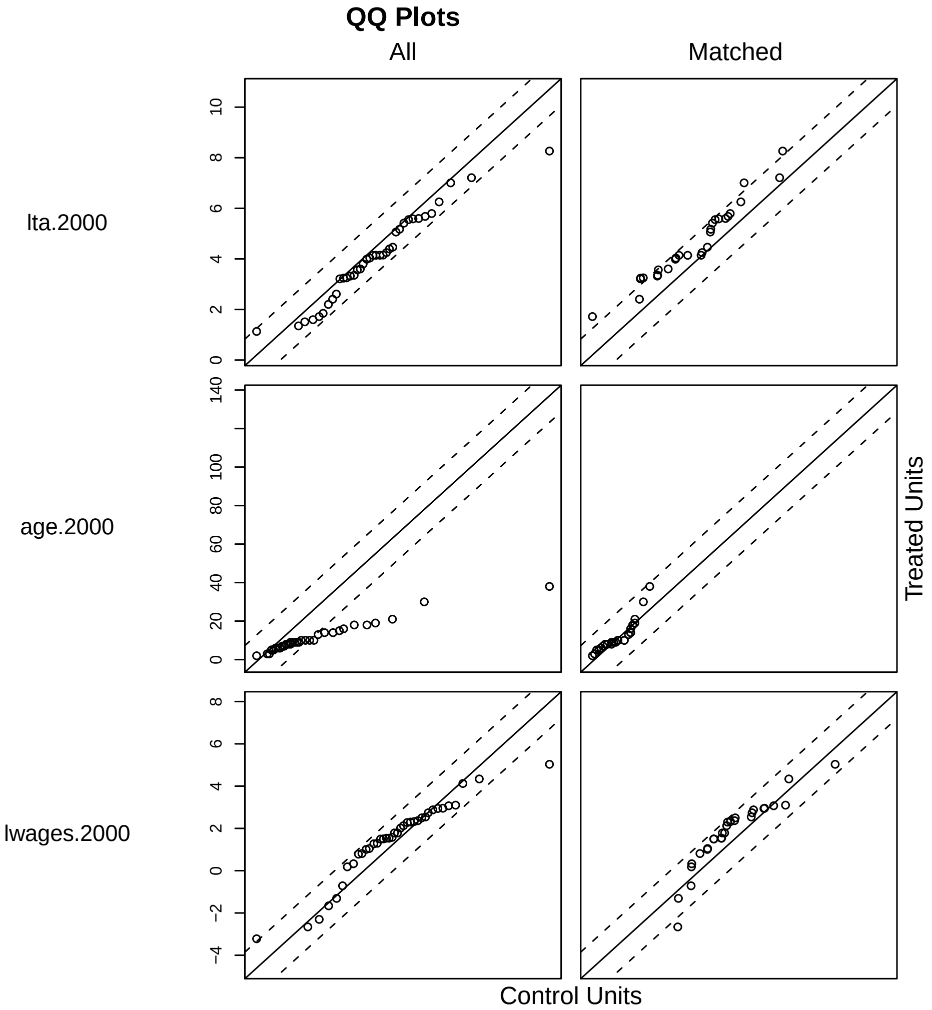

Figure 7 QQ plots for each covariate in the full and matched sample: *High OFDI* (continued)

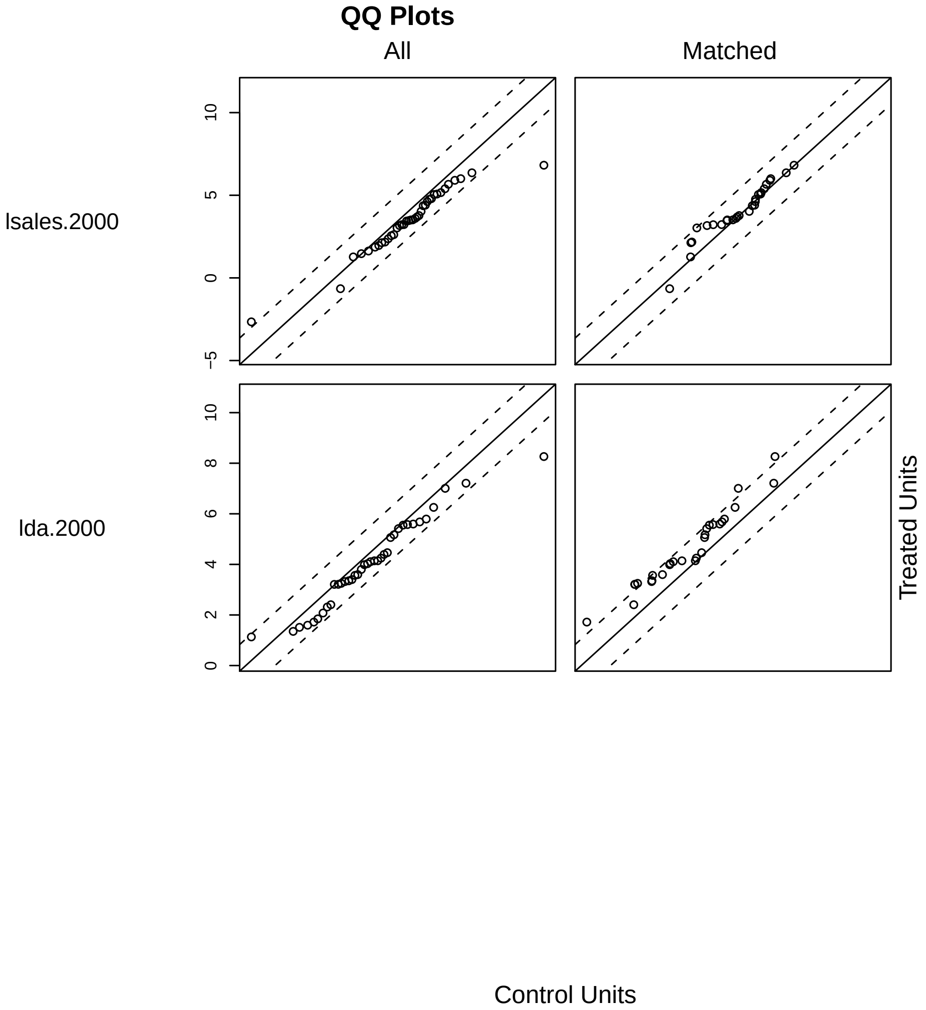

Figure 8 Histogram of Propensity Scores: *High OFDI*

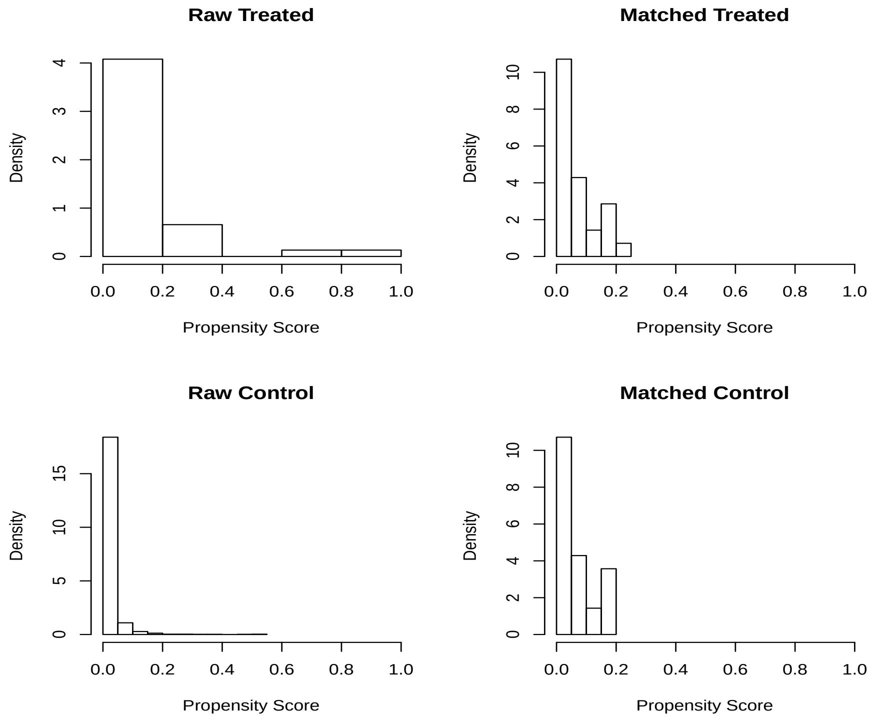

Figure 9 Jitter plots of the Distance Measure: *High OFDI*