The investment technology of foreign and domestic institutional investors in an emerging market

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Abstract

The home bias literature has demonstrated that foreign investors only invest in a small set of firms in the typical emerging market. We explore the extent to which firms chosen by foreign institutional investors (FIIs) obtain superior returns, output growth, and productivity growth in following years. We propose a quasi-experimental measurement strategy that addresses numerous threats to validity. Our findings suggest that FIIs do not posses a valuable investment technology: while their chosen firms have high growth in output, there is little evidence of improved productivity and the stock market returns tend to be negative. Domestic institutional investors (DIIs) appear to often invest in distressed firms. These chosen firms appear to obtain productivity growth and deliver superior stock market returns.

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1 Introduction

The policy analysis of capital controls in emerging markets is closely connected to the investment technology of foreign investors. Do foreign investors contribute capital to good projects, and thus enhance the functioning of the financial system? Or are foreign investors afflicted with weaknesses of information and analysis, which could then lead to misallocation of capital, pro-cyclicality of capital flows, and vulnerability to sudden stops?

As has been observed in the home bias literature, foreign investors often invest in only a small set of firms in an emerging market. As an example, the data analysed in this paper shows that while there are over 5000 listed firms in India, in 2011 there were only 703 firms where foreign investors owned above 5 per cent of the publicly traded (i.e. 'floating') market value. This raises questions about these chosen firms. What is the process of security selection adopted by foreign investors? Do they possess a strong investment technology, through which these firms go on to obtain high stock market returns?

Turning away from financial returns to firm fundamentals, do the firms chosen by foreign investors achieve superior growth in output and productivity? This reflects a mix of a selection process (do foreign investors forecast well, and manage to identify firms that are going to do well?) and a treatment effect (does the decision by a foreign investor to buy shares in a company help the company do better?). In this paper, we pursue the reduced form outcome, and make no attempt to disentangle selection from causal impact.

In this paper, we devise a strategy for measuring the ability of foreign investors to do security selection, and apply it for Indian data. This involves identifying and addressing numerous threats to validity.

Most foreign investment is by institutional investors, while most domestic share ownership is by individuals. The literature on institutional investors and on individual investors has highlighted unique features of both groups. In order to compare like to like, we compare foreign institutional investors (FIIs) against domestic institutional investors (DIIs).

While many firms have investments by neither FIIs nor DIIs, many firms have investment by both. In order to identify the distinct effects, we construct two groups of firms: those with high FII investment (but low DII investment) and those with high DII investment (but low FII investment). The comparison of outcomes for these two groups will identify investment technology.

The investment mandate or portfolio strategy of foreign investors may involve certain choices on systematic asset pricing factors, i.e. size, B/P and β.

These are correlated with future outcomes. As an example, high β portfolios are likely to see high output growth in a business cycle expansion. In order to focus on security selection, we undertake a matching strategy. Firms with high FII investment (but not DII investment) are matched against firms which got neither. Controls are identified which have similar size, B/P and β to the chosen firms. The comparison of outcomes would then identify security selection without being confounded by differences in asset allocation.

Our results, for India, may be summarised as follows. The firms chosen by FIIs are those that have experienced high growth of capital (when compared with the control) prior to the observation date. They continue to obtain high growth of capital after the observation date. There is some evidence of superior output growth. However, the chosen firms have inferior productivity growth, and deliver inferior stock market returns when compared with the controls. FIIs do not possess a valuable investment technology.

In contrast, the firms chosen by DIIs appear to deliver superior returns in the years after measurement date. This suggests that DIIs possess a valuable investment technology. The firms chosen by DIIs appear to be distressed firms. They tend to have reduced growth of capital both prior to observation date and in the years thereafter. The chosen firms appear to have superior productivity growth in the years after observation date.

The contribution of this paper lies in two respects. First, these results illuminate the role of foreign and domestic institutional investors in one large emerging market, India. Second, many elements of the measurement strategy used in this paper are applicable more generally.

The remainder of this paper is organised as follows. Section 2 sketches the questions and the measurement strategy. Section 3 describes the dataset used in the paper. Section 4 shows reduced form models explaining FII and DII ownership, which helps us obtain greater intuition into the phenomena at work. We see that there are systematic differences between FIIs and DIIs in size, B/P and β. The main results of the paper are presented in Section 5. Section 6 undertakes three sensitivity analyses, using size weights, using a more extreme definition for high FII and high DII sets, and using momentum as an additional empirical asset pricing factor. Finally, Section 7 concludes.

2 Questions and methodology

The presence of home bias is a well established fact in the international finance literature: foreign investors hold relatively low weights in emerging markets. Turning to the evidence at the firm level, foreign investors tend to invest in large and liquid firms with international visibility and better corporate governance.

One strand of this literature has asked the question: Do foreign investors perform well? The presence of home bias, which suggests limitations in the information processing of foreign investors, may imply inferior investment performance by foreign investors. If the investment technology of foreign investors has difficulties, this could encourage investment in index funds that give exposure to emerging markets without engaging in security selection. It could also exacerbate home bias.

These questions are important to the policy debates about financial globalisation. If foreign investors suffer from asymmetric information and thus possess an inferior investment technology, they could be associated with misallocation. Some of the pathologies identified by the international finance literature, such the pro-cyclical behaviour of foreign investment or the phenomena of sudden stops and capital flow reversals, could be attributed to poor information processing by foreign investors.

This motivates a careful examination of the investment technology of foreign investors. The existing literature does not have a single unifying model and methodology; a series of papers have obtained diverse datasets, and each has fashioned a methodology suited to the dataset at hand. Dvořák (2005) utilises transaction data from the Jakarta Stock Exchange, and finds that clients of local brokerage firms do well in the short run, but clients of foreign brokerage firms do better in the long run. Choe, Kho, and Stulz (2005) find that foreign investors suffer higher transactions costs in Korea. Froot and Ramadorai (2008) harness a unique identification opportunity by juxtaposing closed-end country fund NAV returns and home country returns. They argue that institutional cross-border flows are based on sound information processing about country fundamentals. Albuquerque, H Bauer, and Schneider (2009) argue that the returns-chasing behaviour of US investors can be attributed to superior information, not inferior knowledge or trend-following.

In this paper, we broaden the analysis away from the investment returns in the short run to firm fundamentals. A recent paper which has embarked on similar questions with the same dataset is Petkova (2012). As the home bias literature has demonstrated, foreign investors invest in only a small set of firms in an emerging markets. How well does this selectivity process work? Do the firms chosen by foreign investors do well in terms of growth of output and productivity?

While these questions are interesting and important, the analysis faces numerous threats to validity which need to be factored in while constructing a measurement strategy.

2.1 A mix of selectivity and treatment effects

The questions of interest involve a complex interplay between selectivity effects and treatment effects. Foreign investment is not a treatment in the sense of the literature on treatment effects. When a foreign investor buys shares on the secondary market, in some respects, the firm is unaffected. Further, foreign investors can flit in and out of ownership of the company. From this viewpoint, the phenomenon of interest is *selection*: Do foreign investors do well in forecasting future stock market returns and thus pick winner? Do the firms that they choose experience high growth in output and productivity?

If the question under analysis were about treatment effects, then the conventional strategy of propensity score matching would have been appropriate. However, to the extent that the mechanism of selection is the phenomenon of interest, propensity score matching is inappropriate. As an example, consider a firm characteristic X (e.g. export intensity) that is used by FIIs in identifying firms to invest in. If X is present in the logit model used for propensity score matching, then the matched control will have similar values for X. However, this may obscure the phenomenon of interest. If FIIs select firms for investment using export intensity, and if this yields high quality investments, this phenomenon would not be captured by propensity score matching.

At the same time, there may also be an element of a casual impact of foreign investment upon the firm. Foreign investors might get involved in corporate governance and thus improve the functioning of the firm. In a model of imperfect capital market integration such as Merton (1987), the entry of foreign investors into a firm may be associated with enhanced stock prices, and may enable improved access to equity and debt financing which may fuel growth of capital. If firms are financially constrained, this might make it possible for them to take up good quality projects and thus obtain sharp improvements in output and productivity.

In this paper, we recognise that both selection and treatment effects are present, and make no attempt to disentangle them. We focus on the reduced form question: Regardless of whether this is owing to selection or treatment effects, do the firms chosen for investment by foreign investment fare well in the future, in terms of growth in output, productivity and stock market returns?

2.2 The problems of comparing institutional investors against domestic individual investors

Most foreign investment in emerging markets is done by institutional investors, while most investors in emerging markets are individuals. An extensive literature in financial intermediation has emphasised the unique decision problems of institutional investors. A more recent household finance literature has identified unique features of the behaviour of individual investors.

In order to avoid comparisions between foreign institutional investors against domestic individual investors, we compare the behaviour of foreign institutional investors (FII) against domestic institutional investors (DII).

2.3 Identifying FII vs. DII

The simplest estimation strategy would involve running regressions explaining an outcome (e.g. output growth) from time t to time $t+k$ on ownership structure at time t. This would suffer from the problem that many firms have both domestic and foreign institutional investment. The phenomena of interest are not identified for these firms.

Hence, we devise a quasi-experimental strategy by identifying two groups of firms: Those with high FII investment but not DII investment, and vice versa. The former set is the firms chosen by FIIs for investment but shunned by DIIs, and the latter is the firms chosen by DIIs for investment by shunned by FIIs. The comparison of performance by these firms would highlight the differences in information processing (and potential treatment effects) by FIIs vs. DIIs.

2.4 Asset allocation versus security selection

In this comparison, we encounter problems of distinguishing information processing about securities as opposed to portfolio formation strategies. As an example, the investment mandate or chosen portfolio strategy of a foreign investor may require investment in firms with a market capitalisation of above $1 billion. The security selection by this investor must then be judged by comparisons against similar sized firms that were not chosen for investment. Similarly, high beta firms would tend to obtain high growth in a business cycle expansion. This would make it appear that an investor with a high beta asset allocation possesses high quality security selection during a business cycle expansion.

The empirical asset pricing literature has identified four factors that explain the bulk of portfolio performance: size, B/P, β and momentum. The evidence offered ahead shows that FIIs and DIIs differ strongly in their choices on size, B/P and β. Traditional regression analysis would attempt to control for these differences by running regressions where size, B/P and β are present as controls. However, such analysis suffers from two key problems: (a) The true relationships may be nonlinear and (b) When there is a lack of match balance, conventional regression involves extrapolation, which is fraught with estimation risk.

Hence, we embark on a matching process, where each firm that was chosen by FIIs (or DIIs) is matched against a partner that got neither FII nor DII investment, where the chosen firm and the partner have similar values for size, B/P, β and (in a robustness check) momentum. If a high quality match is not obtained, the firm is deleted from the dataset. This ensures a high quality design. Through this, we focus on security selection and are not confounded by asset allocation.

2.5 Summary

The measurement strategy pursued in this paper thus consists of three steps:

1. At each year, identify a 'High FII' set of firms, with high FII investment but low DII investment, and a 'High DII' set of firms, with high DII investment but low FII investment. A third set of firms of interest is 'None', where there is neither FII nor DII investment.
2. For each firm in these two sets, identify a partner from the set None that has similar size, B/P and β. Reject chosen firms where a high quality match cannot be obtained.
3. This leaves us holding a dataset containing N firms with high FII investment (but not DII investment) and another N firms with neither FII investment nor DII investment, where the two sets are matched by size, B/P and β. Observations across many years are pooled into this dataset. This permits regressions of the form $y_{i,t+k} - y_{i,t} = a_0 + a_1 D + e_{i,t}$ where the growth in y is explained using the dummy variable D which denotes high FII investment. Clustered and heteroscedasticity-robust standard errors are reported.

3 Data description

The dataset for our analysis is drawn from the CMIE Prowess database, from 2000 to 2011. This is a rich database where a wide array of information about large firms in India is observed. The industry structure of the dataset is shown in Table 1. As this table shows, the firms in our dataset are drawn

Table 1 Industry Composition

This table shows the number of firms in each major industry group, in each year, of the dataset under examination. In addition to manufacturing firms, we also observe many services firms. As an example, there were 180 information technology firms in 2001, which went up to 299 in 2011.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Chemicals	482	509	551	516	522	506	578	574	578	570	571
Diversified	33	34	34	31	34	38	40	42	42	42	42
Electricity	11	12	12	13	15	17	17	21	22	23	24
Food	193	211	223	210	210	208	247	252	251	246	252
Machinery	254	273	264	268	267	265	287	288	284	279	283
Metals	179	199	203	202	204	204	244	249	249	241	243
Mining	18	21	22	20	22	23	26	26	28	29	32
MiscManuf	101	108	106	104	102	111	136	137	138	141	139
NonMetalMin	114	127	132	125	124	121	135	135	138	137	142
Serv.Construction	109	116	112	110	116	124	141	160	166	175	191
Serv.IT	155	151	167	153	154	154	182	195	195	200	206
Serv.Other	460	480	479	444	455	475	544	543	529	537	578
Textiles	248	274	285	272	266	264	307	305	298	292	299
TransportEq	90	95	92	90	98	100	113	113	117	117	115
Sum	2447	2610	2682	2558	2589	2610	2997	3040	3035	3029	3117

Table 2 Summary Statistics

Some features of the dataset are shown in the table.

Variable	Units	Mean	SD	Min	25th	Median	75th	Max
Sales	Rs. million	7153.61	63329.24	1.00	141.65	645.50	2655.40	3574219.80
Gross Fixed Assets	Rs. million	4255.86	36627.87	1.00	96.90	371.30	1486.70	2212519.70
Total Assets	Rs.million	7620.04	54514.44	0.00	151.10	625.55	2699.40	2849003.50
Employees	Number	1227.04	5342.23	1.00	35.57	183.07	790.70	159999.57
Wage bill	Rs. million	337.15	2669.62	0.10	6.50	30.20	130.10	134173.50
FII ownership	Per cent	4.05	10.85	0.00	0.00	0.00	0.36	89.29
DII ownership	Per cent	9.60	15.66	0.00	0.00	1.22	13.48	100.00
Promoter ownership	Per cent	49.01	20.01	0.00	35.64	50.03	63.27	99.83
Adjusted Closing Price	Rs.	68.85	378.85	0.01	4.00	12.35	45.35	49088.80
TFP (Levinsohn Petrin)		18.46	6.71	1.00	16.08	18.07	19.88	55.36

from a diverse array of industries, and include many services firms also. Table 2 shows summary statistics about the firms in the dataset.

Not all firms in the CMIE database disclose the number of employees. In this paper, we have used data within a given industry within a year, to compute the average wage using firms where the number of employees was observed. This was used to impute the number of employees for observations where the overall wages was observed but the number of firms was not observed.

One simple measure of productivity is the change in output - change in inputs. In the estimation of firm productivity, Levinsohn and Petrin (2003) argued that there is an endogeneity problem owing to the correlation between unobservable productivity shocks and the input levels. They propose using intermediate inputs (raw material expenditure) as a proxy for the purpose of estimation. We implement their procedure using their Stata code. This procedure cannot be implemented for services firms which do not buy raw materials. Hence, when we analyse productivity using the Levinsohn-Petrin measure, we lose data for services firms.

Finally, we turn to describing categories of institutional investors observed in this dataset. Indian capital controls only permit registered 'foreign institutional investors' (FIIs) to invest in the equity market. Once registration is done, the investment process is fairly unconstrained. Three kinds of domestic institutional investors (DIIs) are present – banks, mutual funds and insurance companies. We focus on the ownership by FIIs and by DIIs.

Most firms in India have a dominant manager/shareholder, which is typically a family, which retains strategic control of the firm for very long time horizons. In the Indian parlance, this shareholder is termed 'the promoter'. As Table 2 shows, the median firm has promoter ownership of 50.03 per cent, i.e. full control.

Institutional investors can only choose to hold shares which are not held by the dominant shareholder. Hence, we rescale the observed shareholding by FIIs and DIIs by the total outsider shareholding. As an example, if the promoter owns 60%, and if FIIs own 20%, then we rescale this to 50%. That is, for this firm, FIIs own half the shares traded in the public market.

The striking feature of this dataset, that motivates this paper, is the ownership by foreign and domestic institutional investors. The median firm in the dataset has no foreign institutional investor (FII) shareholding. At the 75th percentile, FII ownership is at 0.36%. Most firms appear to be shunned by foreign investors. The median firm has just 1.22% of ownership by DIIs. At the 75th percentile, we see DII shareholding of 13.48 per cent. While this is bigger than the 75th percentile ownership of FIIs, it remains a small number. For three quarters of the firms, DIIs own below 13.48 per cent of the shares relinquished by insiders.

Table 3 Summary statistics about asset pricing characteristics

This table shows summary statistics about the asset pricing factors. As an example, log market capitalisation ranged from -1.14 to 15.07 with a median value of 5.55.

Variable	Mean	SD	Min	25th	Median	75th	Max	IQR	Observations
Domestic Beta	0.82	0.50	-2.50	0.54	0.80	1.07	5.31	0.53	15882.00
Log Book-to-Price	0.11	1.19	-7.06	-0.66	0.14	0.89	4.61	1.55	22989.00
Size	5.82	2.41	-1.14	4.00	5.55	7.35	15.07	3.35	25402.00
Momentum	-0.05	0.47	-4.11	-0.23	0.00	0.05	6.37	0.28	28523.00

This raises questions about institutional ownership. What firms are chosen by FIIs and DIIs? How effective is the process of selection employed by these investors? Are institutional investors able to identify the firms with the best prospects, who would achieve high growth and stock market returns in the future? We explore these questions in the remainder of this paper.

The empirical asset pricing literature has emphasised three factors: size (log of market capitalisation), book-to-price and beta (Fama and French, 1993). We estimate the stock β for all firms using weekly returns data for the latest two years. As a robustness check, we also explore a fourth factor: momentum (Desai, Ramesh, Thiagarajan, and Balachandran, 2002), which is calculated as the six-month stock return for each firm year. Summary statistics for these firm characteristics are shown in Table 3.

4 The selection process of FIIs and DIIs

The first exploration that we must embark on is to examine the process of security selection of FIIs and DIIs. If, hypothetically, we find that FIIs and DIIs behave similarly, then there is no need for further exploration. As an example, Dahlquist and Robertsson (2001) find that in Sweden, while there are differences between foreign investment and domestic investment, these derive primarily through the fact that most foreign investment is institutional. When foreign institutional investors are compared against Swedish institutional investors, their preferences for firms are largely alike.

The first question that we address is that of identifying empirical regularities about the ownership by FIIs and DIIs. The data appears to have some striking features in this regard. As an example, Table 4 shows that DIIs have a much bigger shareholding in top quintile companies by asset tangibility, while no strong pattern is visible with FIIs. Similarly, Table 5 shows that DIIs appear to have a lower shareholding for firms with bottom quintile values for insider shareholding.

In order to explore these relationships, we wish to estimate linear models explaining FII and DII ownership in terms of firm characteristics. Summary

Table 4 Institutional ownership by asset tangibility

This table breaks down the dataset into quintiles by asset tangibility, defined as the fraction of total assets which are tangible assets. In the bottom quintile, this has a median value of 14.60%, while in the top quintile, this has a median value of 101.01%. In each quintile, we report the median value of FII and DII ownership. The median DII ownership is much higher (20.09%) in the top quintile.

	Q1	Q2	Q3	Q4	Q5
Tangibility	14.05	34.74	51.10	69.32	96.02
FII	0.00	0.00	0.00	0.00	0.89
DII	0.76	0.27	1.39	2.92	20.33

Table 5 Institutional ownership by insider holding

This table breaks down the dataset into quintiles by insider shareholding. Bottom quintile companies, by insider shareholding, have a median insider shareholding of 25.16%. Top quintile companies, by insider shareholding, have a median insider shareholding of 73.29%. In all quintiles, the median value of FII ownership is 0. In the case of DIIs, the median value is lower for Q1 when compared with the other quintiles, i.e. DIIs appear to shun companies where a dominant shareholder has a relatively small shareholding.

	Q1	Q2	Q3	Q4	Q5
Insider holding	25.57	40.99	50.96	59.99	73.46
FII	0.01	0.02	0.02	0.00	0.00
DII	0.74	3.53	4.24	3.55	2.60

Table 6 Firm characteristics that may influence FII and DII ownership

This table shows summary statistics about firm characteristics that may influence FII and DII ownership. Turnover ratio is the latest 12 month turnover expressed as a ratio of market capitalisation. The largest value, of 3.45, denotes turnover which is 3.45 times the market capitalisation. Yield is the dividend yield expressed in per cent. Total risk is the standard deviation of daily returns. Age is measured in years. Asset tangibility is the tangible assets expressed as per cent of total assets. R&D intensity is the expense on R&D expressed as per cent of sales.

Variable	Mean	SD	Min	25th	Median	75th	Max	IQR	Observations
Turnover Ratio	0.18	0.48	0.00	0.00	0.02	0.11	3.45	0.11	30794.00
Yield	1.92	3.29	0.00	0.00	0.00	2.68	16.73	2.68	25402.00
Global beta	0.64	0.66	-6.47	0.29	0.63	0.95	7.61	0.67	15250.00
Total Risk	0.85	0.47	0.26	0.56	0.72	0.96	2.86	0.40	20251.00
Export-Sales ratio	15.97	26.50	0.00	0.00	1.68	19.38	100.00	19.38	28155.00
Age	25.95	18.03	1.00	15.00	20.00	30.00	148.00	15.00	30773.00
Tangibility	63.13	43.77	1.27	32.38	56.69	84.51	244.94	52.12	29101.00
R and D intensity	0.23	0.89	0.00	0.00	0.00	0.00	6.77	0.00	28243.00

Table 7 Tobit models that explain FII and DII ownership

We wish to explore the relationships between FII and DII ownership, and firm characteristics. Many firms have zero values for FII or DII investment (or both). Hence, we estimate Tobit models. Correlations within firm are addressed by clustered standard errors. Macroeconomic effects are controlled by having year fixed effects.
The table shows estimation results for a tobit model explaining FII ownership and another tobit model explaining DII ownership. Both models use the identical set of explanatory variables.
As an example, the coefficient of insider shareholding is -0.13 (with a t statistic of -7.15) for the FII tobit, while it is -0.03 (with a t statistic of -1.80) for the DII tobit.

	FII	t	DII	t
Insider holding	-0.13	-7.15	-0.03	-1.80
Log mktcap	7.13	29.99	3.89	22.09
Turnover ratio	0.45	1.23	-1.49	-5.53
Yield	-0.29	-3.27	-0.09	-1.36
Domestic beta	3.41	4.66	-0.48	-0.96
Global beta	0.71	1.71	-0.20	-0.62
Total Risk	-4.82	-2.77	-0.30	-0.24
Export to sales	0.01	1.11	-0.01	-0.80
Age	-0.11	-5.70	0.16	9.39
Is public sector	-6.00	-2.75	10.30	4.51
Tangibility	-0.03	-2.95	0.08	9.12
Low R and D	-0.33	-0.59	1.75	3.44
High R and D	1.00	1.65	-1.55	-2.66

statistics about firm characteristics of interest are shown in Table 6. Many firms have zero values for either or both of these. Hence, we resort to Tobit models. Clustered standard errors are reported to reflect the fact that a given firm can often be observed in many years.

The results of this estimation are shown in Table 7. In the case of FIIs, we find strong results where FIIs favour firms with reduced shareholding by insiders, bigger size, a high domestic beta, a high beta against a global index, low total risk and lower age. They avoid the dummy variable for public sector corporations. They favour reduced asset tangibility. Firms are broken into three groups by R&D expenses – None, low and high – and three dummy variables are constructed. Of these, 'None' is the ommitted category. FIIs appear to weakly favour firms with high R&D expenses.

The results for DIIs are strikingly different. While FIIs avoid firms with a high inside shareholding, this does not influence DIIs. The coefficient for size is much weaker: DIIs invest in smaller firms than FIIs. DIIs strongly avoid illiquid stocks while FIIs do not care about stock market liquidity. While FIIs favour domestic β exposure, DIIs are not influenced by it, or by the global β. While FIIs avoid total risk, DIIs are not concerned about it.

Like FIIs, DIIs are not influenced by the exports/sales ratio. They strongly favour older companies, in contrast to FIIs who favour young companies.

DIIs own much more public sector companies, while FIIs systematically avoid them. DIIs strongly favour firms with more tangible assets, while DIIs favour firms with reduced tangible assets. Finally, DIIs invest more in low R&D companies and avoid firms that do more R&D.

If we believe that dynamic companies are young, private, with low tangible assets, and high R&D, then it appears that FIIs systematically favour these firms while DIIs shun them. While it may be obvious that young or private or high R&D companies are good, they may not achieve high stock market returns or growth in the future. The information processing capabilities of an investor must be evaluated by examining the performance of firms in the period after investment date. The investment technology of an institutional investor can be evaluated in two ways: by comparing stock market returns in the future, and also by comparing the economic performance of firms in the future.

This suggests an exploration of firm performance in the future, after an investment is observed. However, there are important concerns that impede the interpretation of these results. There are two parts to the behaviour of an institutional investor. On one hand, the portfolio strategy of an institutional investor involves choices about systematic asset price factors. As an example, a certain institutional investor may favour small firms, while another might favour high beta firms. The second dimension is security analysis, where FIIs and DIIs analyse individual firms, and make forecasts about their future performance.

Differences in systematic asset price factors may merely derive from the investment mandate of a fund, and may be correlated with future performance. As an example, high beta firms may do well in a business cycle expansion and vice versa. If FIIs favour high beta companies, they will appear to outperform in good times and vice versa.

Tabel 8 repeats the Tobit analysis, where the explanatory variables are quartile dummies for the size, B/P and β. The results differ strongly, which suggests that FIIs and DIIs differ strongly in their exposure to empirical asset pricing factors. These differences need to be controlled for when examining the future performance of firms.

5 Measuring the security selection by FIIs and DIIs

We would like to judge the investment technology of FIIs and DIIs by evaluating the performance of firms in the future, after the date on which the shareholding pattern is observed. At the same time, we would like to con-

Table 8 Tobit model based on empirical asset pricing characteristics

This table shows Tobit models explaining FII and DII ownership based on empirical asset pricing factors. For each of the three factors – size, B/P and β – we construct four quartile dummies. The results show that FIIs and DIIs differ strongly in their asset pricing exposures.

	FII	t	DII	t
Intercept	-8.75	-16.81	5.41	19.81
Small size	30.49	24.35	20.10	25.95
Med size	6.92	9.44	4.71	9.32
Large size	1.38	2.78	1.50	3.99
Low Book-to-Price	1.56	2.47	5.56	9.14
Med Book-to-Price	4.99	10.23	2.74	6.52
High Book-to-Price	-0.42	-1.14	-0.03	-0.10
Low beta	4.63	7.51	-0.15	-0.33
Med beta	-0.85	-1.80	-0.10	-0.27
High beta	-0.01	-0.02	0.47	1.51

Table 9 Number of firms in each category

The table shows the number of firms in each year, which fall into the four categories 'Both' (investment by both FIIs and DIIs that is above-median), 'High DII' (above-median investment by DIIs but below-median investment by FIIs), 'High FII' (above-median investment by FIIs but below-median investment by DIIs) and 'None' (below-median investment by both FIIs and DIIs).

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Both	181	141	134	185	241	375	442	495	416	421	428
High DII	927	980	962	807	708	598	635	572	593	539	483
High FII	35	41	38	63	97	141	207	246	262	236	274
None	1319	1466	1560	1508	1547	1496	1719	1732	1769	1838	1937
Sum	2462	2628	2694	2563	2593	2610	3003	3045	3040	3034	3122

trol for differences in exposures to empirical asset pricing factors. This would help us assess the security selection by FIIs and DIIs, without being confounded by differences in asset allocation, i.e. systematic asset pricing factors.

We assign firm years to the following groups based on the median ownership of firms by FIIs and DIIs. We define a 'High FII' group as one where FII ownership was above 5%, and DII ownership was below 6%. These are the firms favoured by FIIs but disfavoured by DIIs. Similarly, we define a 'High DII' group where DII ownership was above 6%, but FII ownership was below 5%. Finally, a control pool is constructed of firms where neither FII nor DII ownership was above their median values (i.e. 5% for FII ownership and 6% for DII ownership). We would like to compare the future performance of a High FII company against a similar company from 'None', and the future performance of a High DII company against a similar company from 'None'.

Table 9 shows the number of firms falling into the four categories ('Both', 'High DII', 'High FII' and 'None') in each year. In 2011, there were 483

Table 10 Transition probabilities across the four groups of firms

Each row of this table shows probabilities for where a firm would be in year $t+1$ given that it is in a certain category in year t. As an example, a firm which is classified as 'None' at time t would stay in that state in year $t+1$ with a probability of 94.98%. There is a 2.26% per cent chance that it would jump up to 'High FII' and a 2.13% chance that it would jump up to 'High DII'. Once it goes into 'High FII' in time t, there is a 18.46% chance of it falling back to 'None'.

	Both	High DII	High FII	None
Both	80.50	10.68	6.81	2.00
High DII	5.86	82.54	0.91	10.69
High FII	12.33	1.72	67.49	18.46
None	0.63	2.13	2.26	94.98

'High DII' firms and 274 'High FII' firms. There was a large number of firms in 'None', the control pool.

Table 10 shows transition probabilities on a one year horizon across these four categories. We observe that DII investment is sticky, but FIIs change portfolio frequently. There is a strong possibility of dropping back to 'None' in year $t+1$ after being in either 'High DII' or 'High FII' category at time t. Once a firm is in 'High FII' category, there is an 18.46% chance that it will drop into 'None' in the next year, but there is a 12.33% chance that it will go up to 'Both' in the next year by gaining high DII investment also.

Figure 1 juxtaposes kernel density plots for size, B/P and β for the three groups of firms. This shows substantial differences across the three groups. This confirms the earlier argument, that these differences need to be controlled for when examining the future performance of stock returns or firm fundamentals; these may diverge owing to asset allocation and not security selection.

While these kernel plots show significant differences between the three groups, they also suggest that there is common support. It will be possible to find firms in 'None' which are similar to those seen in 'High FII' and 'High DII' groups, so as to undertake comparisons.

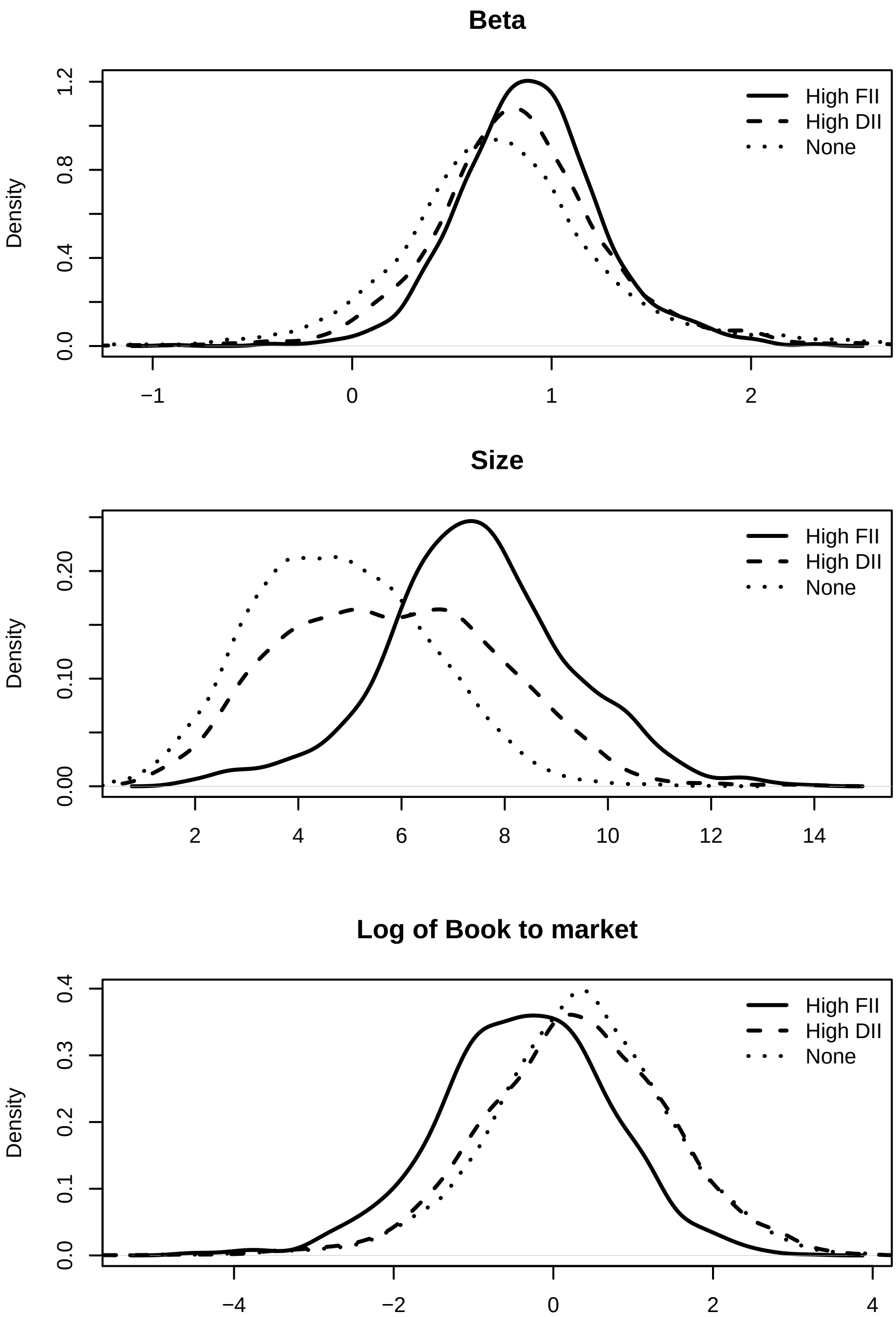
At the simplest, an OLS model explaining an outcome of interest y_{it} (such as stock market returns or sales growth or productivity) could control for size, B/P and β:

$$y_{i,t+j} - y_{i,t-k} = \beta_0 + \beta_1 size_{i,t} + \beta_2 book/price_{i,t} + \beta_3 beta_{i,t} + \gamma' D_{i,t} + e_{it}$$

Year fixed effects are present in order to control for macroeconomic fluctuations. In this regression, we are interested in the coefficients γ about membership in the group 'High FII' or 'High DII' in year $t-1$. Differences between firms in size, B/P and β would be controlled for. We utilise information about the investment characteristics at time t in order to make

Figure 1 Asset pricing factors by firm category

We examine kernel density plots for size, B/P and β for the three groups of firms. Substantial differences are visible.



statements about the growth of an outcome variable y from year $t-k$ to year $t+j$.

This traditional regression strategy suffers from certain weaknesses (Stuart, 2010). The impact of size, B/P and β upon y might not be linear. When the design matrix involves some firms in 'None' and some firms in 'High FII', and their characteristics differ, the OLS regression relies upon linear extrapolation to overcome these differences. This extrapolation is fraught with difficulties. A design matrix constructed with all observations may be a poor path to sound estimates of γ.

In order to address these problems, we propose a matching-based strategy. For each firm in the 'High FII' or 'High DII' categories, we use Mahalanobis distance matching in order to find a matched partner from the 'None' category, aiming to match on size, B/P and β.[1] For each of these categories, this would yield a balanced design. A caliper is used, to delete observations where the match quality is poor. Matched pairs from all years are pooled to construct the dataset where OLS estimation is done:

$$y_{i,t+j} - y_{i,t-k} = \beta_0 + \gamma D_{i,t} + e_{i,t}$$

Year fixed effects are present, in order to control for macroeconomic fluctuations. We utilise information about the investment characteristics at time t in order to make statements about the growth of an outcome variable y from year $t-k$ to year $t+j$.

The design here is a series of matched pairs. For the firm with 'High FII', we have $D = 1$, while its matched partner (which has neither high FII nor high DII investment), $D = 0$. The coefficient γ thus reports on the extent to which selection by FIIs at time t impacts upon the outcome y.

It is also interesting to look *backwards* into time. The left hand side variable $y_{i,t}$ can pertain to conditions that prevailed *before* date t. In this case, the results of the regression give us insights into the process of selectivity by FIIs or DIIs. At the same time, results would be different, when compared with those obtained through the tobit regressions above, since the design matrix here is a more carefully constructed one.

[1] Mahalanobis distance matching in a vector of characteristics x is most appropriate when x is multivariate normal. While the joint distribution of size, B/P and β is not exactly multivariate normal, the three marginal distributions (of log size, log book-to-market and β) are approximately normally distributed as seen in Figure 1. While this departure from normality is a blemish, the entire matching scheme is a means to an end: that of achieving match balance in x. As we show in this paper, our matching scheme (Mahalanobis distance matching with a calipers) succeeds in the sense of achieving high quality match balance.

Table 11 Number of matched pairs for high FII

	Low FII, Low DII	High FII, Low DII	Matched pairs
2002	1466	41	14
2003	1560	38	10
2004	1508	63	34
2005	1547	97	63
2006	1496	141	59
2007	1719	207	91
2008	1732	246	127
2009	1769	262	182
2010	1838	236	179
2011	1937	274	199

Table 12 Number of matched pairs for high DII

	Low FII, Low DII	High DII, Low FII	Matched pairs
2002	1466	980	407
2003	1560	962	322
2004	1508	807	236
2005	1547	709	208
2006	1496	598	204
2007	1719	635	220
2008	1732	572	219
2009	1769	593	286
2010	1838	539	266
2011	1937	483	244

Table 11 shows the results of this matching process for firms with high FII investment. As an example, in 2002, there were 41 firms with high FII investment but low DII investment, and 1466 firms with low FII investment and low DII investment. However, Mahalanobis distance matching based on size, B/P and β yielded only 14 matches. Overall, we see that a fairly large dataset of matched pairs is assembled using this process.

The same strategy, applied to high DII investment firms (with low FII investment) yields matched pairs as shown in Table 12. Here, a much larger number of matched pairs is obtained.

5.1 Match balance

The first question that has to be addressed is about the extent to which this quasi-experimental strategy achieves match balance.

Table 13 shows standardised differences of size, B/P and β for firms with high FII investment (but low DII investment). The matching process has worked well; the standardised differences have dropped to near zero. This is reinforced by Kolmogorov-Smirnoff tests shown in Table 14. The null of equality of distributions is always rejected in the raw data and is never

Table 13 Standardised Difference for FII

	Before Matching	After Matching
Size	1.46	0.05
Book-to-Price	-0.75	-0.02
Beta	0.30	0.05

Table 14 Kolmogorov Smirnov Test for FII

	Before Matching	After Matching
Size	0.5716	0.048
	(0)	(0.2194)
Book-to-Price	0.3061	0.0303
	(0)	(0.7724)
Beta	0.1905	0.0438
	(0)	(0.316)

rejected after matching.

A similar analysis for the firms with high DII investment (but low FII investment) is shown in Table 15 and 16. In the raw data, there are serious problems of match balance, but after matching, the standardised differences are near zero, and the null in the K-S test is not rejected.

For both kinds of institutional investors, this analysis persuades us that the matching process has resulted in a sound design. That is, we will be comparing a firm chosen by an FII or a DII against one that was not chosen by either, while ensuring that there are no systematic differences in size, B/P and β. As emphasised earlier, this ensures that we are focused on the security analysis by FIIs and DIIs, without being clouded by their asset allocation strategies.

5.2 Firms that got high FII but low DII investment

We now analyse the future outcomes for firms that got high FII investment, but low DII investment. These results are shown in Table 17. While conventional OLS results with all data are also shown, we focus on the quasi-experimental design obtained through matching.

The first outcome variable that we analyse is log gross fixed assets. When we look *back* in time, we see that the firms where $D = 1$, i.e. the firms with high FII investment (but not high DII investment) got faster growth in fixed assets in the one and two years prior to observation date. In other words, FIIs appear to be choosing firms which have experienced high growth in fixed assets. Looking into the future, the firms chosen by FIIs had a change in log fixed assets that was larger than the control by 0.06 on a horizon of one year, 0.14 on a horizon of two years and 0.24 on a horizon of three years. All these

Table 15 Standardised Difference for DII

	Before Matching	After Matching
Size	0.50	0.03
Book-to-Price	-0.07	0.00
Beta	0.13	-0.01

Table 16 Kolmogorov Smirnov Test for DII

	Before Matching	After Matching
Size	0.2342	0.0337
	(0)	(0.1031)
Book-to-Price	0.0513	0.0191
	(0)	(0.7249)
Beta	0.0973	0.0257
	(0)	(0.3566)

differences are strongly statistically significant. This suggests that the firms chosen by FIIs increased their fixed assets strongly in the period following selection by FIIs. This could either reflect selectivity by FIIs (i.e. FIIs chose firms which were likely to grow well) and it could reflect a causal effect as well (the purchase of shares on the secondary market by FIIs impacted upon the growth of the firm).

Similar results are obtained for log total assets. FIIs chose firms where the balance sheet grew faster in the preceding one and two years. After the measurement date, the firms chosen by FIIs had a change in log total assets that was larger than the control by 0.05 on a horizon of one year, 0.1 on a horizon of two years and 0.16 on a horizon of three years. All these differences were strongly statistically significant.

Turning to employment growth, the firms chosen by FIIs had weakly superior employment growth in the years prior to measurement date. After the measurement date, their employment growth was only slightly greater than the control. The firms chosen by FIIs thus appear to have pursued capital-intensive growth strategies in the years after measurement date.

Despite strong increases in capital, and slight increases in employment, on a horizon of one and two years after measurement date, output growth by selected firms was not different from the control. It was only on a three year horizon that a statistically significantly different coefficient of 0.16 is found.

A simple productivity measure is output growth - input growth. This yields striking and negative estimates. The firms chosen by FIIs were inferior compared with the control in the two years prior to measurement date and in the three years thereafter. This reflects the combination of high growth of capital but weak growth in output.

For manufacturing firms, we are able to compare TFP using Levinsohn-

Table 17 Outcomes for firms chosen by FIIs but not DIIs

The dataset is a series of matched pairs, where $D = 1$ is a firm with high FII investment (but low DII investment), and $D = 0$ is a matched partner which got neither FII nor DII investment. Matching has been done on size, B/P and β, and there is high quality match balance. OLS estimates for $y_{i,t} = \beta_0 + \gamma D_{i,t-j} + e_{i,t}$ are estimated for various outcomes of interest y, for values of j, and the estimated $\hat{\gamma}$ is reported in each case. Clustered robust standard errors are reported. While the main focus is on the matching-based estimates, conventional OLS estimates using unfiltered data are also reported.
As an example, consider an outcome of interest: log total assets. The matching based estimate shows that the firms chosen by FIIs have a change in log total assets over a three year horizon that is larger than that observed for controls by 0.16, with a standard error of 0.047.

Log Gross Fixed Assets

	OLS	Matching
$X_t - X_{t-2}$	0.07 (0.034) *	0.11 (0.036) **
$X_t - X_{t-1}$	0.04 (0.02) *	0.06 (0.021) **
$X_{t+1} - X_t$	0.06 (0.021) **	0.06 (0.018) **
$X_{t+2} - X_t$	0.08 (0.033) *	0.14 (0.039) ***
$X_{t+3} - X_t$	0.12 (0.043) **	0.24 (0.057) ***

Log Total Assets

	OLS	Matching
$X_t - X_{t-2}$	0.15 (0.035) ***	0.1 (0.027) ***
$X_t - X_{t-1}$	0.09 (0.02) ***	0.05 (0.014) ***
$X_{t+1} - X_t$	0.08 (0.019) ***	0.05 (0.014) **
$X_{t+2} - X_t$	0.12 (0.031) ***	0.1 (0.029) ***
$X_{t+3} - X_t$	0.14 (0.043) **	0.16 (0.047) ***

Log Employment

	OLS	Matching
$X_t - X_{t-2}$	0.17 (0.044) ***	0.1 (0.039) *
$X_t - X_{t-1}$	0.1 (0.025) ***	0.05 (0.022) *
$X_{t+1} - X_t$	0.03 (0.024)	0.03 (0.022)
$X_{t+2} - X_t$	0.08 (0.046)	0.07 (0.044) .
$X_{t+3} - X_t$	0.08 (0.066)	0.12 (0.069) .

Log Sales

	OLS	Matching
$X_t - X_{t-2}$	0.04 (0.033)	0.03 (0.042)
$X_t - X_{t-1}$	0.03 (0.018) .	0.02 (0.023)
$X_{t+1} - X_t$	0.06 (0.021) **	0.03 (0.025)
$X_{t+2} - X_t$	0.11 (0.04) **	0.04 (0.046)
$X_{t+3} - X_t$	0.21 (0.063) **	0.16 (0.069) *

Output Growth - Input Growth

	OLS	Matching
$X_t - X_{t-2}$	-0.05 (0.039)	-0.12 (0.033) ***
$X_t - X_{t-1}$	-0.04 (0.069)	-0.21 (0.057) ***
$X_{t+1} - X_t$	0 (0.033)	-0.07 (0.036) *
$X_{t+2} - X_t$	-0.01 (0.057)	-0.17 (0.067) *
$X_{t+3} - X_t$	-0.01 (0.074)	-0.2 (0.09) *

TFP (LP estimate)

	OLS	Matching
$X_t - X_{t-2}$	0 (0.02)	0 (0.012)
$X_t - X_{t-1}$	0.01 (0.01)	0 (0.008)
$X_{t+1} - X_t$	-0.01 (0.013)	-0.02 (0.009) .
$X_{t+2} - X_t$	0.01 (0.014)	-0.01 (0.015)
$X_{t+3} - X_t$	0.01 (0.016)	0 (0.019)

Log Adjusted Closing Price

	OLS	Matching
$X_t - X_{t-2}$	0.23 (0.09) **	-0.05 (0.056)
$X_t - X_{t-1}$	0.2 (0.057) ***	-0.01 (0.035)
$X_{t+1} - X_t$	0.05 (0.05)	-0.04 (0.037)
$X_{t+2} - X_t$	-0.04 (0.09)	-0.11 (0.07)
$X_{t+3} - X_t$	-0.06 (0.118)	-0.09 (0.094)

Petrin estimates. This shows no statistically significant difference between the firms chosen by FIIs and the controls.

Finally, we look at stock market returns. There is no statistically significant difference between the firms chosen by FIIs and the controls.

To summarise, these results suggest that the firms chosen by FIIs are on a trajectory of capital deepening. In the period after measurement date, there is strong growth of capital when compared with the control, which could either reflect forecasts of high growth by the FII, or a causal effect of the purchase of shares by FIIs. There is weak evidence of increased employment. However, the impact of output, productivity and stock market returns is surprisingly weak. On horizons of one, two and three years, it is hard to suggest that the firms chosen by FIIs fared better than the controls, either in terms of returns or in terms of growth in output and employment.

5.3 Firms that got high DII but low FII investment

We now turn to the firms chosen by DIIs but not FIIs, where results are in Table 18. In the years prior to the measurement date, the firms selected by DIIs had *lower* growth in fixed assets and in total assets. In the years after measurement date, their growth of capital is not statistically significantly different from the control. This may be interpreted as investing in distressed companies.

With employment and output, there is no difference between the firms chosen by DIIs and the controls, either in the period before measurement date or after.

When we examine the simple measure of productivity growth – output growth - input growth – on a three year horizon, the firms chosen by DIIs outperform the controls by a factor of 0.1, which is statistically significant at a 95 per cent level. However, when this is repeated within manufacturing firms only using the Levinsohn-Petrin measure of TFP, the differences in productivity are not statistically significant.

The most interesting results are found with stock market returns. On horizons of one, two and three years, the firms chosen by DIIs outperform the controls. The superior returns are economically significant: 7 per cent on a one year horizon (with a standard error of 2.2 percentage points), 9 per cent on a two year horizon (with a standard error of 3.7 percentage points) and 10 per cent on a three year horizon (with a standard error of 5 percentage points).

The firms chosen by DIIs yield superior stock market returns when compared with controls, while the firms chosen by FIIs do not. This suggests

Table 18 Outcomes for firms chosen by DIIs but not FIIs

The dataset is a series of matched pairs, where $D = 1$ is a firm with high DII investment (but low FII investment), and $D = 0$ is a matched partner which got neither FII nor DII investment. Matching has been done on size, B/P and β, and there is high quality match balance. OLS estimates for $y_{i,t} = \beta_0 + \gamma D_{i,t-j} + e_{i,t}$ are estimated for various outcomes of interest y, for values of j, and the estimated $\hat{\gamma}$ is reported in each case. Clustered robust standard errors are reported. While the main focus is on the matching-based estimates, conventional OLS estimates using unfiltered data are also reported.
As an example, consider an outcome of interest: log total assets. The matching based estimate shows that the firms chosen by DIIs have a change in log total assets over a three year horizon that is larger than that observed for controls by -0.01, with a standard error of 0.025.

Log Gross Fixed Assets

	OLS	Matching
$X_t - X_{t-2}$	-0.09 (0.02) ***	-0.04 (0.02) *
$X_t - X_{t-1}$	-0.04 (0.011) ***	-0.02 (0.01)
$X_{t+1} - X_t$	-0.02 (0.011) *	0 (0.012)
$X_{t+2} - X_t$	-0.05 (0.02) **	-0.02 (0.024)
$X_{t+3} - X_t$	-0.06 (0.031) .	-0.03 (0.033)

Log Total Assets

	OLS	Matching
$X_t - X_{t-2}$	-0.07 (0.018) ***	-0.05 (0.015) ***
$X_t - X_{t-1}$	-0.03 (0.01) **	-0.01 (0.008)
$X_{t+1} - X_t$	-0.01 (0.01)	0 (0.009)
$X_{t+2} - X_t$	-0.03 (0.018)	-0.01 (0.017)
$X_{t+3} - X_t$	-0.03 (0.026)	-0.01 (0.025)

Log Employment

	OLS	Matching
$X_t - X_{t-2}$	-0.06 (0.025) *	-0.01 (0.021)
$X_t - X_{t-1}$	-0.03 (0.014) *	0 (0.013)
$X_{t+1} - X_t$	-0.03 (0.015) .	0.02 (0.013)
$X_{t+2} - X_t$	-0.02 (0.026)	-0.01 (0.024)
$X_{t+3} - X_t$	-0.01 (0.037)	-0.03 (0.035)

Log Sales

	OLS	Matching
$X_t - X_{t-2}$	-0.05 (0.022) *	0.01 (0.025)
$X_t - X_{t-1}$	-0.01 (0.013)	0.02 (0.015)
$X_{t+1} - X_t$	0.02 (0.015)	0.01 (0.017)
$X_{t+2} - X_t$	0.02 (0.028)	0.02 (0.032)
$X_{t+3} - X_t$	0.03 (0.04)	0.05 (0.043)

Output Growth - Input Growth

	OLS	Matching
$X_t - X_{t-2}$	0.05 (0.022) *	0.03 (0.021)
$X_t - X_{t-1}$	0.12 (0.038) **	0.06 (0.032) .
$X_{t+1} - X_t$	0.05 (0.02) *	-0.02 (0.02)
$X_{t+2} - X_t$	0.1 (0.034) **	0.02 (0.035)
$X_{t+3} - X_t$	0.11 (0.048) *	0.1 (0.047) *

TFP (LP estimate)

	OLS	Matching
$X_t - X_{t-2}$	0 (0.009)	0 (0.007)
$X_t - X_{t-1}$	0 (0.006)	0.01 (0.005)
$X_{t+1} - X_t$	0.01 (0.006)	0 (0.005)
$X_{t+2} - X_t$	0.02 (0.008) *	0.01 (0.007)
$X_{t+3} - X_t$	0.01 (0.009)	0.01 (0.012)

Log Adjusted Closing Price

	OLS	Matching
$X_t - X_{t-2}$	-0.03 (0.054)	0.02 (0.035)
$X_t - X_{t-1}$	0.03 (0.031)	0.04 (0.021) .
$X_{t+1} - X_t$	-0.01 (0.027)	0.07 (0.022) **
$X_{t+2} - X_t$	0.08 (0.046) .	0.09 (0.037) *
$X_{t+3} - X_t$	0.1 (0.061) .	0.1 (0.05) .

that DIIs possess a valuable investment technology while FIIs do not. While the firms that FIIs invest in experience exuberant growth, there are concerns about productivity, and superior stock market returns are not obtained. In contrast, DIIs appear to get involved in firms that are experiencing difficulties. However, there is some evidence of gains in productivity and strong evidence about superior stock market returns.

6 Sensitivity analyses

We assess the robustness of these results by undertaking three alternative estimations.

6.1 Size weights

The main results shown in the paper treated all firms as equal. This may give undue importance to a large number of small firms. Hence, we undertake the same analysis with size weights. Size is defined as the average of firm sales and firm total assets.

The results for firms with high FII investment (but not high DII investment) are presented in Table 19 in the appendix. As with the main results, firms chosen by FIIs (but not DIIs) experience rapid growth of capital, prior to the measurement year and after it. While there is improvement in employment growth on a horizon of one year, this does not take place over two and three year horizons. There is strong evidence of superior output growth. However, this is associated with inferior productivity growth. There is no evidence of superior stock market returns.

Size-weighted results for firms with high DII investment (but not high FII investment) are presented in Table 20 in the appendix. These are also qualitatively similar to the main results. These firms have experienced declining total assets for the one year prior to measurement date and the one year after measurement date. Employment and output growth appear to be no different from the controls. However, there is strong evidence of superior productivity growth. There is also strong evidence of superior stock market returns by 12% on a one year horizon and 14% on a two year horizon. This suggests that DIIs have impressive investment technology while FIIs do not.

6.2 More extreme definitions for FII and DII dummies

The main results of the paper were based on median values for FII and DII investment of five and six per cent respectively. That is, a "High FII investment" firm was defined as one with more than 5% ownership of non-promoter shares by FIIs.

We redo the calculations using a more extreme definition, using the 66th percentile of the distribution of FII investment (12.5%) and DII investment (18.6%).

Table 21, in the appendix, shows the results for firms with high FII investment (but low DII investment). These results are qualitatively similar to the main findings of the paper. The firms chosen by FIIs have experienced strong growth in capital prior to measurement date, and also see strong capital growth after measurement date. Employment growth is also superior, as is sales growth.

However, the simple productivity measure (output growth - input growth) shows that the chosen firms have inferior productivity growth when compared with the controls. When the Levinsohn-Petrin calculations are applied (to manufacturing firms only) the null of no difference in productivity changes cannot be rejected. The stock market returns obtained by these firms is sharply inferior to that obtained by the controls over horizons of one, two and three years.

Turning to the firms chosen for high investment by DIIs (but not FIIs), the results (Table 22 in the appendix) show that DIIs choose firms where total assets have declined over the recent two years. Employment growth is reduced over the horizons of two and three years. Output growth is no different from the controls. As a consequence, the simple productivity measure yields much superior productivity growth over a three year horizon. The null of no difference cannot be rejected for stock market returns and for the Levinsohn-Petrin productivity estimate.

6.3 A four-factor world including momentum

Finally, we consider matching on one additional factor: momentum. The results for firms chosen by FIIs (but not DIIs) are in Table 23 in the appendix. These firms have higher asset growth both before and after measurement date. There is also some evidence of superior employment growth. However, their output growth is not different from the controls. As a consequence, they deliver inferior productivity growth using the simple productivity measure of output growth - input growth. However, the null of no difference in productivity change between chosen firms and controls cannot be rejected when Levinsohn-Petrin estimates are computed using manufacturing firms only. On a two year and three year horizon, the stock market returns of the firms chosen by FIIs are inferior by 12 and 21 per cent respectively.

Turning to DIIs, (Table 24 in the appendix) the firms chosen by them are those that have experienced inferior growth of capital (compared with the control) in the one and two years prior to measurement date. In the period after measurement, their change in capital or labour is not different from the controls. However, they deliver superior output growth on a horizon of three years. Both productivity measures show superior gains in productivity when compared with the control. There is strong evidence of superior stock market returns.

7 Conclusions

This paper brings a fresh perspective in understanding the role of foreign and domestic institutional investors. The striking feature in the data is the fact that large numbers of firms obtain neither FII nor DII investment. There are strong differences between the characteristics of firms chosen by FIIs as opposed to the firms chosen by DIIs.

This encourages the question: Do FIIs and DIIs do well in choosing certain firms for investment? How do the chosen firms perform in the future, in terms of financial returns, and in terms of economic outcomes such as growth in output and productivity? A quasi-experimental opportunity to identify the differences between FIIs and DIIs is created by identifying firms which have high FII investment (but low DII investment) and vice versa. If either FIIs or DIIs have skills in identifying firms that will do well, or if their decision to invest in a firm has a causal impact upon the future trajectory of the firm, then the chosen firms will fare well in the future.

We emphasise the distinction between asset allocation and security selection. There are systematic differences between FIIs, DIIs and controls in the size, B/P and β. These differences in asset allocation need to be controlled for so as to focus on the investment technology of security selection. As an example, if FIIs systematically invest in high beta firms, and high beta firms do well in a business cycle expansion, it will appear that FIIs have the ability to pick winners under buoyant business cycle conditions.

We propose a matching-based strategy in order to address this problem. Each firm that is chosen by FIIs (but not DIIs) is matched to a control (that was chosen by neither FII nor DII) based on size, B/P and β. The comparison of future outcomes, between the firm that was chosen and the control, identifies the security selection prowess of the institutional investor.

The results suggest that the firms chosen by FIIs are those that have experienced high growth of capital (when compared with the control) prior to the observation date. They continue to obtain high growth of capital after the observation date. There is some evidence of superior output growth. However, the chosen firms appear to have inferior productivity growth, and deliver inferior stock market returns when compared with the controls. These results suggest that FIIs do not possess a valuable investment technology.

In contrast, the firms chosen by DIIs appear to deliver superior returns in the years after measurement date. This suggests that DIIs possess a valuable investment technology. The firms chosen by DIIs appear to be distressed firms. They tend to have reduced growth of capital both prior to observation date in the years thereafter. The chosen firms appear to have superior productivity growth in the years after observation date.

If large corporations in India were financially constrained, then firms with institutional investment would be expected to have sharp growth of assets, and to be able to deploy capital into high quality projects. However, the results show that firms chosen by DIIs do not increase capital, and while firms chosen by FIIs do experience capital growth, this may go with reduced productivity. The results are, thus, not consistent with the notion that large corporations in India have high quality projects but suffer from financing constraints.

The contribution of this paper lies in two respects. First, these results illuminate the role of foreign and domestic institutional investors in one large emerging market, India. Second, many elements of the measurement strategy used in this paper are applicable more generally. The distinction between asset allocation and security selection, and the quasi-experimental measurement strategy based on matching on size, B/P and β, could be applied in other settings. Extending this strategy to databases in other emerging markets would constitute one interesting area for future research.

Our results raise difficult questions. If FIIs do not possess a superior investment technology, would they be better off with investment strategies such as investing in index funds or in sub-contracting their investment process to DIIs? This raises questions about the incentives and contracts in financial intermediation that leads to foreign investment, which could be usefully explored in future research.

Appendix

Table 19 Outcomes for firms chosen by FIIs but not DIIs: Size weighted

Log Gross Fixed Assets	OLS	Matching
$X_t - X_{t-2}$	0.31 (0.19)	0.19 (0.05) ***
$X_t - X_{t-1}$	0.24 (0.176)	0.12 (0.029) ***
$X_{t+1} - X_t$	0.12 (0.065) .	0.09 (0.028) **
$X_{t+2} - X_t$	0.02 (0.122)	0.16 (0.045) ***
$X_{t+3} - X_t$	0.02 (0.179)	0.17 (0.063) **

Log Total Assets	OLS	Matching
$X_t - X_{t-2}$	0.28 (0.072) ***	0.15 (0.032) ***
$X_t - X_{t-1}$	0.14 (0.046) **	0.07 (0.017) ***
$X_{t+1} - X_t$	0.11 (0.032) ***	0.07 (0.017) ***
$X_{t+2} - X_t$	0.15 (0.052) **	0.12 (0.045) **
$X_{t+3} - X_t$	0.19 (0.069) **	0.15 (0.071) *

Log Employment	OLS	Matching
$X_t - X_{t-2}$	0.23 (0.118) .	0.37 (0.191) .
$X_t - X_{t-1}$	0.12 (0.038) **	0.25 (0.153) .
$X_{t+1} - X_t$	0.02 (0.03)	0.07 (0.023) **
$X_{t+2} - X_t$	0.01 (0.064)	0.05 (0.059)
$X_{t+3} - X_t$	-0.02 (0.078)	0 (0.085)

Log Sales	OLS	Matching
$X_t - X_{t-2}$	-0.14 (0.108)	0.08 (0.05) .
$X_t - X_{t-1}$	0.12 (0.108)	0.02 (0.044)
$X_{t+1} - X_t$	0.06 (0.052)	0.06 (0.026) *
$X_{t+2} - X_t$	0.01 (0.059)	0.14 (0.055) *
$X_{t+3} - X_t$	0.03 (0.125)	0.26 (0.076) ***

Output Growth - Input Growth	OLS	Matching
$X_t - X_{t-2}$	0 (0.051)	-0.36 (0.209) .
$X_t - X_{t-1}$	0.03 (0.118)	-0.5 (0.264) .
$X_{t+1} - X_t$	0.04 (0.044)	-0.12 (0.044) **
$X_{t+2} - X_t$	0.04 (0.091)	-0.08 (0.116)
$X_{t+3} - X_t$	0.12 (0.124)	0.09 (0.172)

TFP (LP estimate)	OLS	Matching
$X_t - X_{t-2}$	-0.01 (0.023)	-0.01 (0.022)
$X_t - X_{t-1}$	-0.01 (0.016)	-0.02 (0.017)
$X_{t+1} - X_t$	0 (0.018)	-0.03 (0.016) .
$X_{t+2} - X_t$	0.01 (0.017)	-0.03 (0.027)
$X_{t+3} - X_t$	0.02 (0.026)	0 (0.03)

Log Adjusted Closing Price	OLS	Matching
$X_t - X_{t-2}$	0.48 (0.135) ***	0.15 (0.114)
$X_t - X_{t-1}$	0.28 (0.097) **	0.05 (0.055)
$X_{t+1} - X_t$	0.07 (0.086)	0.02 (0.06)
$X_{t+2} - X_t$	-0.02 (0.199)	0.04 (0.115)
$X_{t+3} - X_t$	-0.16 (0.264)	-0.02 (0.157)

Table 20 Outcomes for firms chosen by DIIs but not FIIs: Size weighted

Log Gross Fixed Assets

	OLS	Matching
$X_t - X_{t-2}$	-0.05 (0.037)	-0.2 (0.147)
$X_t - X_{t-1}$	-0.03 (0.021)	0.01 (0.019)
$X_{t+1} - X_t$	-0.04 (0.021) .	-0.01 (0.015)
$X_{t+2} - X_t$	-0.16 (0.088) .	-0.04 (0.037)
$X_{t+3} - X_t$	-0.2 (0.138)	-0.11 (0.059) .

Log Total Assets

	OLS	Matching
$X_t - X_{t-2}$	-0.01 (0.04)	-0.04 (0.024) .
$X_t - X_{t-1}$	0 (0.025)	-0.03 (0.014) *
$X_{t+1} - X_t$	-0.01 (0.022)	-0.03 (0.015) *
$X_{t+2} - X_t$	-0.04 (0.036)	-0.05 (0.033)
$X_{t+3} - X_t$	-0.04 (0.052)	-0.1 (0.05) .

Log Employment

	OLS	Matching
$X_t - X_{t-2}$	0 (0.05)	0.13 (0.117)
$X_t - X_{t-1}$	-0.01 (0.018)	0.13 (0.095)
$X_{t+1} - X_t$	-0.03 (0.025)	0.12 (0.109)
$X_{t+2} - X_t$	-0.06 (0.041)	-0.06 (0.036)
$X_{t+3} - X_t$	-0.06 (0.056)	-0.09 (0.05) .

Log Sales

	OLS	Matching
$X_t - X_{t-2}$	-0.24 (0.149)	-0.28 (0.233)
$X_t - X_{t-1}$	-0.02 (0.02)	0 (0.022)
$X_{t+1} - X_t$	0.02 (0.026)	0.01 (0.017)
$X_{t+2} - X_t$	-0.02 (0.071)	0.09 (0.05) .
$X_{t+3} - X_t$	-0.08 (0.136)	0.14 (0.075) .

Output Growth - Input Growth

	OLS	Matching
$X_t - X_{t-2}$	0.1 (0.038) **	-0.15 (0.127)
$X_t - X_{t-1}$	0.12 (0.066) .	-0.23 (0.216)
$X_{t+1} - X_t$	0.1 (0.039) **	-0.13 (0.124)
$X_{t+2} - X_t$	0.18 (0.05) ***	0.15 (0.068) *
$X_{t+3} - X_t$	0.2 (0.066) **	0.32 (0.091) ***

TFP (LP estimate)

	OLS	Matching
$X_t - X_{t-2}$	0.01 (0.014)	0 (0.01)
$X_t - X_{t-1}$	0.01 (0.009)	0 (0.006)
$X_{t+1} - X_t$	0.02 (0.011) .	0 (0.009)
$X_{t+2} - X_t$	0.04 (0.015) *	0.02 (0.013)
$X_{t+3} - X_t$	0.04 (0.016) *	0.05 (0.019) **

Log Adjusted Closing Price

	OLS	Matching
$X_t - X_{t-2}$	0.12 (0.09)	0.03 (0.054)
$X_t - X_{t-1}$	0.1 (0.062) .	-0.04 (0.051)
$X_{t+1} - X_t$	0.01 (0.046)	0.12 (0.037) **
$X_{t+2} - X_t$	0.16 (0.097)	0.14 (0.07) *
$X_{t+3} - X_t$	0.13 (0.15)	0.09 (0.114)

Table 21 Outcomes for firms chosen by FIIs but not DIIs: More extreme definitions of FII and DII ownership

Log Gross Fixed Assets		
	OLS	Matching
$X_t - X_{t-2}$	0.1 (0.028) ***	0.12 (0.029) ***
$X_t - X_{t-1}$	0.06 (0.017) ***	0.07 (0.018) ***
$X_{t+1} - X_t$	0.05 (0.018) **	0.07 (0.016) ***
$X_{t+2} - X_t$	0.07 (0.03) *	0.12 (0.026) ***
$X_{t+3} - X_t$	0.09 (0.04) *	0.15 (0.039) ***

Log Total Assets		
	OLS	Matching
$X_t - X_{t-2}$	0.15 (0.029) ***	0.15 (0.024) ***
$X_t - X_{t-1}$	0.1 (0.017) ***	0.07 (0.012) ***
$X_{t+1} - X_t$	0.07 (0.015) ***	0.06 (0.013) ***
$X_{t+2} - X_t$	0.09 (0.025) ***	0.1 (0.024) ***
$X_{t+3} - X_t$	0.11 (0.034) **	0.12 (0.037) **

Log Employment		
	OLS	Matching
$X_t - X_{t-2}$	0.15 (0.034) ***	0.14 (0.029) ***
$X_t - X_{t-1}$	0.08 (0.02) ***	0.06 (0.017) ***
$X_{t+1} - X_t$	0.05 (0.019) **	0.06 (0.017) ***
$X_{t+2} - X_t$	0.09 (0.033) **	0.11 (0.031) ***
$X_{t+3} - X_t$	0.11 (0.045) *	0.12 (0.045) **

Log Sales		
	OLS	Matching
$X_t - X_{t-2}$	0.07 (0.028) *	0.09 (0.033) **
$X_t - X_{t-1}$	0.04 (0.016) **	0.05 (0.019) *
$X_{t+1} - X_t$	0.05 (0.017) **	0.02 (0.018)
$X_{t+2} - X_t$	0.1 (0.033) **	0.04 (0.032)
$X_{t+3} - X_t$	0.15 (0.052) **	0.1 (0.048) *

Output Growth - Input Growth		
	OLS	Matching
$X_t - X_{t-2}$	-0.07 (0.032) *	-0.1 (0.026) ***
$X_t - X_{t-1}$	-0.09 (0.053)	-0.2 (0.041) ***
$X_{t+1} - X_t$	-0.03 (0.029)	-0.11 (0.027) ***
$X_{t+2} - X_t$	-0.06 (0.047)	-0.19 (0.044) ***
$X_{t+3} - X_t$	-0.08 (0.062)	-0.17 (0.067) **

TFP (LP estimate)		
	OLS	Matching
$X_t - X_{t-2}$	0.03 (0.018)	0 (0.011)
$X_t - X_{t-1}$	0.01 (0.009)	0 (0.007)
$X_{t+1} - X_t$	-0.01 (0.009)	-0.01 (0.008)
$X_{t+2} - X_t$	-0.01 (0.012)	0 (0.013)
$X_{t+3} - X_t$	0 (0.013)	0 (0.016)

Log Adjusted Closing Price		
	OLS	Matching
$X_t - X_{t-2}$	0.29 (0.072) ***	0.08 (0.049) .
$X_t - X_{t-1}$	0.26 (0.043) ***	0.05 (0.03)
$X_{t+1} - X_t$	-0.03 (0.037)	-0.08 (0.032) *
$X_{t+2} - X_t$	-0.12 (0.06) *	-0.17 (0.051) **
$X_{t+3} - X_t$	-0.22 (0.077) **	-0.2 (0.069) **

Table 22 Outcomes for firms chosen by DIIs but not FIIs: More extreme definitions of FII and DII ownership

Log Gross Fixed Assets	OLS	Matching
$X_t - X_{t-2}$	-0.09 (0.02) ***	-0.06 (0.021) **
$X_t - X_{t-1}$	-0.04 (0.012) **	-0.02 (0.011) .
$X_{t+1} - X_t$	-0.03 (0.012) *	-0.01 (0.012)
$X_{t+2} - X_t$	-0.06 (0.021) **	-0.03 (0.022)
$X_{t+3} - X_t$	-0.07 (0.031) *	-0.05 (0.031) .

Log Total Assets	OLS	Matching
$X_t - X_{t-2}$	-0.09 (0.017) ***	-0.05 (0.017) **
$X_t - X_{t-1}$	-0.04 (0.009) ***	-0.02 (0.009) *
$X_{t+1} - X_t$	-0.01 (0.01)	-0.01 (0.009)
$X_{t+2} - X_t$	-0.03 (0.018)	-0.02 (0.017)
$X_{t+3} - X_t$	-0.03 (0.025)	-0.03 (0.025)

Log Employment	OLS	Matching
$X_t - X_{t-2}$	-0.08 (0.023) ***	-0.04 (0.023)
$X_t - X_{t-1}$	-0.03 (0.014) *	-0.01 (0.014)
$X_{t+1} - X_t$	-0.05 (0.015) **	-0.01 (0.013)
$X_{t+2} - X_t$	-0.08 (0.023) ***	-0.06 (0.023) **
$X_{t+3} - X_t$	-0.08 (0.03) **	-0.11 (0.032) ***

Log Sales	OLS	Matching
$X_t - X_{t-2}$	-0.04 (0.022) .	-0.01 (0.026)
$X_t - X_{t-1}$	-0.01 (0.014)	0 (0.016)
$X_{t+1} - X_t$	0 (0.016)	-0.02 (0.015)
$X_{t+2} - X_t$	0 (0.026)	-0.04 (0.026)
$X_{t+3} - X_t$	0 (0.036)	0 (0.035)

Output Growth - Input Growth	OLS	Matching
$X_t - X_{t-2}$	0.05 (0.023) *	0.02 (0.02)
$X_t - X_{t-1}$	0.13 (0.038) ***	0.09 (0.033) **
$X_{t+1} - X_t$	0.06 (0.023) *	-0.01 (0.023)
$X_{t+2} - X_t$	0.1 (0.031) **	0.04 (0.036)
$X_{t+3} - X_t$	0.13 (0.042) **	0.15 (0.048) **

TFP (LP estimate)	OLS	Matching
$X_t - X_{t-2}$	0 (0.008)	0 (0.007)
$X_t - X_{t-1}$	0 (0.006)	0 (0.005)
$X_{t+1} - X_t$	0.01 (0.006)	0 (0.006)
$X_{t+2} - X_t$	0 (0.008)	0 (0.009)
$X_{t+3} - X_t$	0.01 (0.009)	0.02 (0.012)

Log Adjusted Closing Price	OLS	Matching
$X_t - X_{t-2}$	0.02 (0.053)	-0.01 (0.039)
$X_t - X_{t-1}$	0.07 (0.031) *	0.04 (0.023)
$X_{t+1} - X_t$	-0.02 (0.029)	0.02 (0.025)
$X_{t+2} - X_t$	0.04 (0.048)	0.03 (0.041)
$X_{t+3} - X_t$	0.06 (0.061)	0.02 (0.054)

Table 23 Outcomes for firms chosen by FIIs but not DIIs: Four factors including momentum

Log Gross Fixed Assets	OLS	Matching
$X_t - X_{t-2}$	0.07 (0.034) *	0.1 (0.033) **
$X_t - X_{t-1}$	0.04 (0.02) *	0.05 (0.017) **
$X_{t+1} - X_t$	0.06 (0.021) **	0.05 (0.021) *
$X_{t+2} - X_t$	0.08 (0.033) *	0.1 (0.04) *
$X_{t+3} - X_t$	0.12 (0.043) **	0.12 (0.06) *

Log Total Assets	OLS	Matching
$X_t - X_{t-2}$	0.15 (0.035) ***	0.09 (0.027) ***
$X_t - X_{t-1}$	0.09 (0.02) ***	0.05 (0.014) ***
$X_{t+1} - X_t$	0.08 (0.019) ***	0.03 (0.015) *
$X_{t+2} - X_t$	0.12 (0.03) ***	0.06 (0.03) *
$X_{t+3} - X_t$	0.14 (0.042) **	0.08 (0.047) .

Log Employment	OLS	Matching
$X_t - X_{t-2}$	0.17 (0.044) ***	0.07 (0.033) *
$X_t - X_{t-1}$	0.1 (0.025) ***	0.03 (0.02)
$X_{t+1} - X_t$	0.02 (0.024)	0.05 (0.022) *
$X_{t+2} - X_t$	0.07 (0.046)	0.09 (0.047) .
$X_{t+3} - X_t$	0.07 (0.066)	0.1 (0.065)

Log Sales	OLS	Matching
$X_t - X_{t-2}$	0.06 (0.032) .	0.07 (0.04) .
$X_t - X_{t-1}$	0.05 (0.018) **	0.03 (0.021)
$X_{t+1} - X_t$	0.06 (0.021) **	0.04 (0.026)
$X_{t+2} - X_t$	0.11 (0.041) **	0.04 (0.046)
$X_{t+3} - X_t$	0.21 (0.063) **	0.08 (0.07)

Output Growth - Input Growth	OLS	Matching
$X_t - X_{t-2}$	-0.05 (0.039)	-0.07 (0.029) *
$X_t - X_{t-1}$	-0.04 (0.069)	-0.1 (0.049) *
$X_{t+1} - X_t$	0 (0.033)	-0.07 (0.038) .
$X_{t+2} - X_t$	-0.01 (0.057)	-0.16 (0.069) *
$X_{t+3} - X_t$	0 (0.074)	-0.12 (0.087)

TFP (LP estimate)	OLS	Matching
$X_t - X_{t-2}$	-0.01 (0.02)	0.01 (0.012)
$X_t - X_{t-1}$	0.01 (0.01)	0 (0.008)
$X_{t+1} - X_t$	-0.01 (0.013)	-0.01 (0.009)
$X_{t+2} - X_t$	0.01 (0.014)	-0.02 (0.014)
$X_{t+3} - X_t$	0.01 (0.016)	-0.02 (0.019)

Log Adjusted Closing Price	OLS	Matching
$X_t - X_{t-2}$	0.21 (0.077) **	-0.02 (0.056)
$X_t - X_{t-1}$	0.2 (0.057) ***	0.01 (0.036)
$X_{t+1} - X_t$	0.06 (0.05)	-0.05 (0.039)
$X_{t+2} - X_t$	-0.04 (0.09)	-0.12 (0.068) .
$X_{t+3} - X_t$	-0.05 (0.118)	-0.21 (0.096) *

Table 24 Outcomes for firms chosen by DIIs but not FIIs: Four factors including momentum

Log Gross Fixed Assets	OLS	Matching
$X_t - X_{t-2}$	-0.09 (0.02) ***	-0.05 (0.019) **
$X_t - X_{t-1}$	-0.04 (0.011) ***	-0.02 (0.012) *
$X_{t+1} - X_t$	-0.02 (0.011) *	-0.01 (0.01)
$X_{t+2} - X_t$	-0.05 (0.02) **	-0.02 (0.02)
$X_{t+3} - X_t$	-0.06 (0.031) .	-0.02 (0.033)

Log Total Assets	OLS	Matching
$X_t - X_{t-2}$	-0.07 (0.017) ***	-0.06 (0.016) ***
$X_t - X_{t-1}$	-0.03 (0.01) **	-0.02 (0.008) .
$X_{t+1} - X_t$	-0.01 (0.01)	-0.01 (0.009)
$X_{t+2} - X_t$	-0.03 (0.018)	-0.01 (0.017)
$X_{t+3} - X_t$	-0.03 (0.026)	-0.02 (0.026)

Log Employment	OLS	Matching
$X_t - X_{t-2}$	-0.06 (0.025) *	-0.03 (0.021)
$X_t - X_{t-1}$	-0.03 (0.014) *	-0.01 (0.013)
$X_{t+1} - X_t$	-0.02 (0.015) .	0.01 (0.013)
$X_{t+2} - X_t$	-0.02 (0.027)	0.01 (0.026)
$X_{t+3} - X_t$	0 (0.037)	-0.01 (0.035)

Log Sales	OLS	Matching
$X_t - X_{t-2}$	-0.04 (0.021) .	0 (0.024)
$X_t - X_{t-1}$	-0.01 (0.013)	0.01 (0.015)
$X_{t+1} - X_t$	0.02 (0.015)	0.01 (0.016)
$X_{t+2} - X_t$	0.03 (0.028)	0.05 (0.032)
$X_{t+3} - X_t$	0.04 (0.04)	0.1 (0.046) *

Output Growth - Input Growth	OLS	Matching
$X_t - X_{t-2}$	0.05 (0.022) *	0.03 (0.02)
$X_t - X_{t-1}$	0.12 (0.038) **	0.07 (0.03) *
$X_{t+1} - X_t$	0.04 (0.021) *	0 (0.02)
$X_{t+2} - X_t$	0.09 (0.035) **	0.05 (0.035)
$X_{t+3} - X_t$	0.11 (0.048) *	0.12 (0.049) *

TFP (LP estimate)	OLS	Matching
$X_t - X_{t-2}$	0 (0.009)	0.01 (0.007)
$X_t - X_{t-1}$	0 (0.006)	0.01 (0.005)
$X_{t+1} - X_t$	0.01 (0.006)	0 (0.005)
$X_{t+2} - X_t$	0.02 (0.008) *	0.01 (0.008)
$X_{t+3} - X_t$	0.01 (0.009)	0.02 (0.011) *

Log Adjusted Closing Price	OLS	Matching
$X_t - X_{t-2}$	0.01 (0.048)	0.01 (0.034)
$X_t - X_{t-1}$	0.03 (0.031)	0.02 (0.02)
$X_{t+1} - X_t$	-0.02 (0.027)	0.06 (0.023) *
$X_{t+2} - X_t$	0.08 (0.046) .	0.1 (0.037) **
$X_{t+3} - X_t$	0.09 (0.061)	0.13 (0.05) *

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