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

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A B S T R A C T

We compare the investment technology of foreign versus domestic investors with a focus on decomposing outcomes attributable to asset allocation and security selection. We document significant differences in exposure to systematic asset pricing factors between foreign and domestic investors. A quasi-experimental strategy is introduced, for comparing security selection after controlling for differences in asset allocation. Our results show that foreign investors in India fare poorly at security selection, while domestic investors fare well.

1. Introduction

Policy debates about financial globalisation are closely connected to the investment technology of foreign investors in emerging markets. On one hand, it is argued that foreign investors bring capital to good projects. At the same time, there are concerns that foreign investors are afflicted with weaknesses of information and analysis, which yields problems such as home bias, misallocation of capital, pro-cyclicality of capital flows, and vulnerability to sudden stops.

The home bias literature has shown that foreign investors often invest in only a small set of firms in an emerging market. As an example, 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 portfolio formation adopted by foreign investors? Do foreign investors possess a strong investment technology, through which their capital is channelled into good projects?

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Numerous papers have been written in this literature, with often contradictory results. The key innovation of this paper lies in disentangling asset allocation and security selection in understanding the investment technology of foreign investment. The distinction between asset allocation and security selection has been a central organising principle in the analysis of fund performance from the mid-1960s. Portfolio returns can be decomposed into exposure to systematic asset pricing factors, such as size or book-to-market, as opposed to returns from security selection. Differences in asset allocation reflect the portfolio strategy of the investor, and there can be legitimate reasons for differences in exposures to asset pricing factors. In contrast, performance in security selection unambiguously reflects investment technology.

We analyse the behaviour of foreign versus domestic institutional investors in India and find substantial differences in asset allocation. In some respects, foreign investors take on more risk, and should therefore obtain higher expected returns. In other respects, this operates in reverse; foreign investors take on reduced risk.

We then turn to the question of security selection. After controlling for differences in asset allocation, do foreign investors do well in choosing securities? Specifically, do firms chosen by foreign investors exhibit superior stock market returns? We look beyond the emphasis on returns in the finance perspective to also examine firm fundamentals. Do the firms chosen by foreign investors do better on growth in output, and growth of productivity?

This analysis of security selection contains 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 have a causal impact upon improved firm performance?* We pursue the reduced form outcome, and make no attempt to disentangle selection from treatment effects.

We devise a quasi-experimental strategy for measuring the ability of foreign or domestic investors to do security selection, after controlling for differences in asset allocation. This involves identifying and addressing numerous threats to validity. Differences between firms in systematic asset pricing factors, such as size, B/P and β, are correlated with future outcomes. As an example, high β firms are likely to see high output growth in a business cycle expansion. In order to measure security selection, firms with high foreign institutional investment (but not domestic institutional 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 identifies the security selection process, without being confounded by differences in asset allocation.

Our results may be summarised as follows. The firms chosen by foreign investors 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 weak stock market returns when compared with the controls.

In contrast, the firms chosen by domestic institutional investors appear to deliver superior returns, and superior productivity growth, in the years after measurement date. This suggests that domestic institutions possess a valuable investment technology.

The methodology and the results of this paper have many implications. The literature on investment technology of foreign versus domestic investors, which has generally emphasised reduced form portfolio returns, has inconclusive results. We would emphasise that differences in overall portfolio returns reflect a combination of differences in asset allocation and differences in security selection, which may explain how different researchers have obtained different results on the superiority of the investment technology of foreign investors. For foreign investors in India, these results suggest that the returns drag associated with poor security selection could be avoided by achieving the desired asset allocation through index funds that express systematic asset pricing factors. The methodology of this paper can be easily extended to other countries, since the data requirements are met in all emerging markets.

The remainder of this paper is organised as follows. Section 2 describes the dataset used in the paper. Section 3 sketches the questions and the measurement strategy. Section 4 examines the asset allocation choices of foreign and domestic institutional investors and finds substantial differences between the two. Section 5 measures the security selection process, after controlling for differences in asset allocation. Section 6 undertakes a series of modifications to the analysis in order to gauge the sensitivity of the results. Finally, Section 7 concludes.

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Table 1
Industry composition.

	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

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 155 information technology firms in 2001, which went up to 206 in 2011.

2. Data description

Many papers in this literature have observed the behaviour of individual fund managers. Our work in this paper utilises standard disclosures at the *firm* level. For each firm, we observe the structure of shareholding, which includes information about the ownership by domestic institutional investors and the ownership by foreign institutional investors. Certain firms have substantial investment by foreign institutional investors. The paper is an empirical exploration of the question: Do these firms fare better?

The dataset for our analysis is drawn from the CMIE Prowess database about firms in India, from 2001 to 2011. This is a rich database where a wide array of information about large firms is observed.[1] The industry structure of the dataset is shown in Table 1. As this table shows, the firms in our dataset are drawn from a diverse array of industries, and include many services firms also. Table 2 shows summary statistics about the firms in the dataset.

One simple measure of productivity is obtained by differentiating the Cobb-Douglas production function: $\dot{w} = \dot{y} - \alpha_l \dot{l} - (1 - \alpha_l)\dot{k}$ where $\dot{w}$ is the productivity growth, y is log output, k is log capital, l is log wages and α_l is the share of labour i.e. the ratio of wages to sales.

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 cannot be done for services firms which do not buy raw materials. Hence, when we analyse productivity using the Levinsohn-Petrin measure, this is limited to manufacturing firms.

Most firms in India have a dominant manager/shareholder, which is typically a family, which retains strategic control of the firm in the long run. 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.

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 (Shah and Patnaik, 2007). Once registration is done, the investment process is fairly

[1] 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 employees was not observed.

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Table 2
Summary statistics.

Variable	Units	Mean	SD	Min	25th	Median	75th	Max
Sales	Rs. million	7153.61	63,329.24	1.00	141.65	645.50	2655.40	3,574,219.80
Gross Fixed Assets	Rs. million	4255.86	36,627.87	1.00	96.90	371.30	1486.70	2,212,519.70
Total Assets	Rs. million	7943.24	55,635.54	1.00	180.50	695.00	2892.00	2,849,003.50
Employees	Number	1227.04	5,342.23	1.00	35.57	183.07	790.70	159,999.57
Wage bill	Rs. million	337.15	2,669.62	0.10	6.50	30.20	130.10	134,173.50
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	49,088.80
TFP (Levinsohn Petrin)		21.25	8.25	1.00	18.70	20.68	22.49	186.55

Some features of the dataset are shown in the table.

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.

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 the FII holding to 50%. That is, for this firm, FIIs own half the shares traded in the public market.

The median firm in the dataset has no foreign institutional investor (FII) shareholding. DII ownership is more widely prevalent: the 75th percentile of DII ownership stands at 13.48 per cent while the corresponding value for FII ownership is just 0.36 per cent.

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.

In our data, in contrast, there are striking differences between FIIs and DIIs along certain dimensions of firm characteristics. Table 3 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 4 shows that DIIs appear to have a lower shareholding for firms with bottom quintile values for insider shareholding. This suggests that FIIs and DIIs differ strongly in their choices of firms.

In order to explore these relationships, we wish to estimate linear models explaining FII and DII ownership in terms of firm characteristics. The estimation results cannot be taken too seriously as there is no causal interpretation. However, this analysis is a valuable part of data description. Many firms have zero values for either FII or DII or both. 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. Summary statistics about some firm characteristics of interest are shown in Table 5.

The results of this estimation are shown in Table 6. 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 public sector corporations. They favour

Table 3
Institutional ownership by asset tangibility.

	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

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 14.05%, while in the top quintile, this has a median value of 96.02%. In each quintile, we report the median value of FII and DII ownership. The median DII ownership is much higher (20.33%) in the top quintile.

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Table 4
Institutional ownership by insider holding.

	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

This table breaks down the dataset into quintiles by insider shareholding. Bottom quintile companies, by insider shareholding, have a median insider shareholding of 25.57%. Top quintile companies, by insider shareholding, have a median insider shareholding of 73.46%.
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.

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 omitted 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 load up more on illiquid stocks while FIIs do not care about it. 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 FIIs favour firms with reduced tangible assets. Finally, DIIs invest more in low R&D companies and avoid firms that spend more on 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. However, in undertaking these comparisons, we have to be conscious of differences in asset allocation and control for these.

3. 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. They 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,

Table 5
Firm characteristics that may influence FII and DII ownership.

Variable	Mean	SD	Min	25th	Median	75th	Max	IQR	Observations
Yield	1.92	3.29	0.00	0.00	0.00	2.68	16.73	2.68	25,402
Global beta	0.64	0.66	−6.47	0.29	0.63	0.95	7.61	0.67	15,250
Total risk	0.85	0.47	0.26	0.56	0.72	0.96	2.86	0.40	20,251
Export-Sales ratio	15.97	26.50	0.00	0.00	1.68	19.38	100.00	19.38	28,155
Age	25.95	18.03	1.00	15.00	20.00	30.00	148.00	15.00	30,773
Tangibility	63.13	43.77	1.27	32.38	56.69	84.51	244.94	52.12	29,101
R and *D* intensity	0.23	0.89	0.00	0.00	0.00	0.00	6.77	0.00	28,243

This table shows summary statistics about firm characteristics that may influence FII and DII ownership. 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. Global beta is estimated using S&P 500. IQR stands for the interquartile range.

Table 6
Tobit models that explain FII and DII ownership.

	FII	*t*	DII	*t*
Insider holding	−0.13	−7.16	−0.02	−1.74
Log mktcap	7.14	30.01	3.88	22.05
Turnover ratio	0.39	1.14	−1.36	−5.48
Yield	−0.29	−3.25	−0.09	−1.36
Domestic beta	3.39	4.61	−0.49	−0.97
Global beta	0.74	1.77	−0.17	−0.51
Total risk	−4.92	−2.80	−0.43	−0.35
Export to sales	0.01	1.11	−0.01	−0.81
Age	−0.11	−5.72	0.16	9.39
Is public sector	−6.00	−2.76	10.32	4.52
Tangibility	−0.03	−2.94	0.08	9.06
Low *R* and *D*	−0.33	−0.59	1.74	3.43
High *R* and *D*	0.99	1.64	−1.55	−2.66

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 two (separate) 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 −7.16) for the FII tobit, while it is −0.02 (with a *t* statistic of −1.74) for the DII tobit.

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.

These questions are important to the policy debates about financial globalisation (Patnaik and Shah, 2012). If foreign investors suffer from asymmetric information and thus possess an inferior investment technology, their decisions could induce misallocation. Some of the pathologies identified by the international finance literature, such as 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 et al. (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 et al. (2009) argue that the returns-chasing behaviour of US investors can be attributed to superior information, not inferior knowledge or trend-following.

The mainstream finance literature on these questions has focused on investment technology in the sense of returns forecasting. We broaden the analysis to also evaluate forecasts of 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.

3.1. Differences in asset allocation

The first challenge is that of distinguishing information processing about securities as opposed to portfolio formation strategies. If foreign and domestic institutional investors have divergent portfolio strategies, in the sense of exposures to systematic asset pricing factors, this fact will in itself induce

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differences in portfolio performance. The investors who accept a greater exposure to risk factors, such as investment in high beta, low size, and high B/P firms, will obtain superior expected returns. This difference in returns should be interpreted as returns to asset allocation, and not related to information processing or forecasting about emerging market firms.

Indeed, given that asset allocation is often largely determined by the investment mandate, to a substantial extent, differences in asset allocation between foreign and domestic investors should not be attributed to differences in the investment technology of foreign or domestic investors. 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.

These issues arise when evaluating other measures of firm performance also. 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 skills in *security selection* during a business cycle expansion. Before skills in security selection can be assessed, we have to control for differences in asset allocation.

Our first objective is thus to measure the asset allocation of domestic versus foreign investors. The empirical asset pricing literature suggests that the Fama-French factors – size, B/P, and β – explain the bulk of the variation in portfolio performance. In our sensitivity analyses, we will also explore liquidity and momentum as potentially important asset pricing factors.

3.2. Differences in security selection

Our analysis of asset allocation (in Section 4) shows that foreign and domestic investors differ in their choices on size, B/P and β.[2] 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 relationship is likely to be nonlinear, resulting in misspecification of conventional linear models and (b) When there is a lack of match balance, conventional linear models involve extrapolation, which is fraught with estimation risk.

Hence, we embark on a matching process, where each firm that was chosen by FIIs, but not DIIs (or by DIIs, but not FIIs) 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 and β. If a high quality match is not obtained, the firm is deleted from the dataset. This ensures a high quality design which gives us the ability to focus on security selection without being confounded by differences in asset allocation.

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 fare well in forecasting future stock market returns and thus pick winners? Do the firms that they choose experience high growth in output and productivity?

If the question under analysis were purely about treatment effects, then 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.[3]

[2] Before we examine the security selection of foreign investors, two possibilities need to be ruled out. One possibility involves foreign investors investing primarily in index funds. In this case, their returns would reflect exposure to systematic asset pricing factors and the returns to security selection would be zero. Another possibility involves foreign and domestic investors choosing alike. In this case, there would be no discernable difference between the security selection of foreign versus domestic investors. Our preliminary analysis in Section 2 has ruled out both these possibilities.

[3] 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. Focusing on high export companies may be a valuable part of the investment technology. If FIIs select firms for investment using export intensity, and if this yields high quality investments, this phenomenon would not be captured by a comparison of treatment and control through propensity score matching.

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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?

3.3. *The problems of comparing institutional investors against domestic individual investors*

Most foreign investment in emerging markets is done by institutional investors, while most domestic 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 comparisons between foreign institutional investors against domestic individual investors, we compare the behaviour of foreign institutional investors (FII) against domestic institutional investors (DII).

3.4. *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.

3.5. *Summary of methodology for measuring security selection*

In summary, our strategy for measuring capabilities in security selection, after controlling for differences in asset allocation, works in 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. Drop firms that have high FII and high DII investment.
2. For each firm in the High FII or High DII sets, identify a matched control 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. 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.

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Table 7
Summary statistics about asset pricing characteristics.

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	15,882
Log book-to-price	0.11	1.19	−7.06	−0.66	0.14	0.89	4.61	1.55	22,989
Size	5.82	2.41	−1.14	4.00	5.55	7.35	15.07	3.35	25,402
Log momentum	1.59	0.09	−0.12	1.56	1.61	1.62	2.43	0.06	28,523
Turnover ratio	0.22	0.56	0.00	0.01	0.04	0.16	3.97	0.15	24,916

This table shows summary statistics about firm characteristics of interest. As an example, log market capitalisation ranged from −1.14 to 15.07 with a median value of 5.55.

4. The asset allocation of FIIs and DIIs

The empirical asset pricing literature has emphasised three factors: size (market capitalisation), book-to-price and β (Fama and French, 1993). The expected returns of a portfolio tend to be higher when it tilts towards high β, low size and high book-to-price firms. Summary statistics for these firm characteristics are shown in Table 7.[4]

Table 8 repeats the Tobit analysis of Table 6, 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.

We then compute the asset pricing characteristics of the representative FII and the representative DII as a weighted average of firm characteristics.[5] These calculations are made for each year, and the median across all years is shown in Table 9. This shows substantial differences across the asset allocation of these two investors. As an example, the weighted average value of log B/P for the representative FII, −1.37, differs substantially from the value of −0.8 for the representative DII.

Fig. 1 shows values for each year. Table 9 shows the median values across the time-series that are reported in Fig. 1. Apart from two years (2002 and 2006), the beta of the FII portfolio is always higher. FIIs have invested in larger firms through all years other than the recent three years. FIIs have had a lower value of B/P in all years other than the recent four years.

This analysis demonstrates that there are systematic differences in the asset allocation of FIIs and DIIs:

Beta Higher beta is likely to be associated with greater expected returns, and we find that FIIs take on higher beta exposure: in the univariate analysis of Table 9, after controlling for other asset pricing factors in the tobit model in Table 8 and after controlling for other firm observables in the tobit model in Table 6. This is consistent with rational portfolio formation under segmented markets, where domestic investors are averse to non-diversifiable risk while foreign investors see a significant part of domestic beta risk as being diversifiable.

Size The home bias literature has generally found that foreign investors favour large firms, and our results strongly agree with this in Table 9 (univariate analysis), Table 8 (tobit with asset pricing factors) and Table 6 (tobit with other observables). However, smaller firms are likely to be associated with greater expected returns. Here, it is the DIIs that take on the risk of owning smaller firms and presumably obtain superior expected returns as a consequence.

Liquidity Liquidity is expected to be associated with a liquidity premium. In an international context, an argument could be made that domestic investors supply liquidity while foreign investors demand it (Campbell et al., 2009). Our results in Table 6 show that after controlling for other observables, it is the DIIs that are holding more illiquid stocks, after controlling for size. This issue is addressed in more detail in Section 6.3.1 ahead.

[4] We estimate the stock β for all firms using weekly returns data for the latest two years.

[5] As an example, consider a two-firm world, where the FII ownership in the two firms is w_1 and w_2, if the market capitalisation is m_1 and m_2, and the firm betas are b_1 and b_2. The weight of each firm in the portfolio of the representative FII is $x_1 = w_1m_1/(w_1m_1 + w_2m_2)$. The portfolio beta of the representative FII is $x_1b_1 + x_2b_2$.

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Table 8
Tobit model based on empirical asset pricing characteristics.

	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

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. Year fixed effects are present. In each case, the bottom quartile is the excluded dummy variable. The results show that FIIs and DIIs differ strongly in their asset pricing exposures. As an example, FIIs load strongly on Low beta (which stands for second quartile by beta), with a coefficient of +4.63 with a *t* statistic of 7.51. DIIs, in comparison, are largely indifferent to the domestic beta.

Value The measure of value used in Table 6 is dividend yield. This shows that FIIs avoid value stocks. Strong differences in value investing are also seen in Tables 8 and 9, which suggests that DIIs should earn higher expected returns through exposure to the HML factor.

There is no simple mapping from these differences in asset allocation to their implications for expected return. For the purpose of the present analysis, we do not pursue the impact of these divergent choices in asset allocation upon expected returns. It suffices to demonstrate that FIIs and DIIs are dissimilar in their asset allocation. This shapes our analysis of security selection.

5. The security selection of 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 control 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.

In each year, we assign a firm to the following groups based on the median ownership of firms by FIIs and DIIs, in the class of firms for which non-zero investment was present. These median values prove to be 5 per cent for FIIs and 6 per cent for DIIs.

We define a ‘High FII’ group as one where FII ownership was above median, but DII ownership was below median. These are the firms favoured by FIIs but disfavoured by DIIs. Similarly, we define a ‘High DII’ group where DII ownership was above median, but FII ownership was below median. Finally, a control pool termed ‘None’ is constructed of firms where FII ownership was below its median value and DII ownership was below its median value. 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
Median exposure to asset pricing factors.

	Beta	Size	Log book-to-price
FII	0.93	11.05	−1.37
DII	0.73	9.17	−0.80
Difference	0.20	1.88	−0.58

We report median values across the years of the characteristics of the representative FII and the representative DII portfolio. As an example, the representative FII has firms with size 11.05, which is larger than the corresponding value of 9.17 for the firms in the portfolio of the representative DII.

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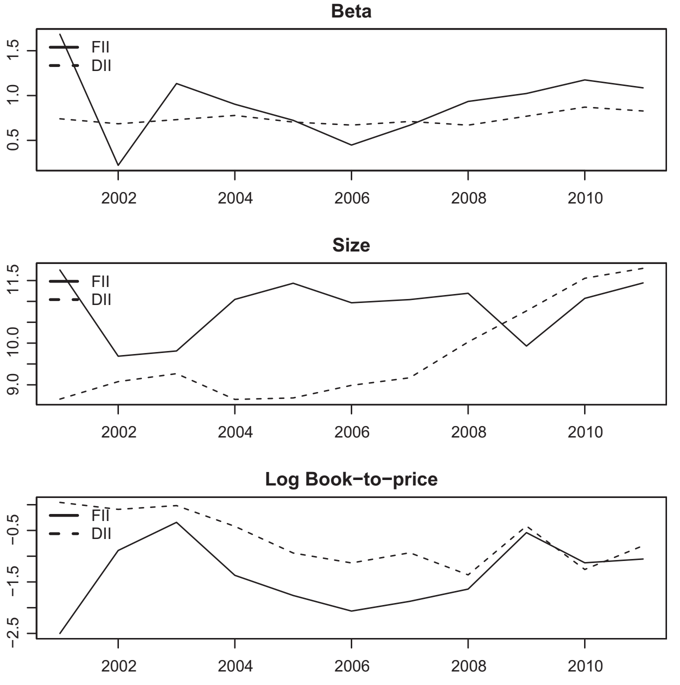

Fig. 1. Exposure to asset pricing factors. We examine the FII and DII exposure to systematic asset pricing factors in this figure. The exposure is calculated as the weighted sum of the asset pricing factor, where the weight is equal to the funds allocated to a security as a percentage of the portfolio.

Table 10 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 'High DII' firms and 274 'High FII' firms. There were a large number of firms in 'None', which is our control pool. A key insight of our quasi-experimental strategy lies in not utilising information for firms that lie in the set 'Both', as the effects of interest are not identified.

Table 11 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.

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

$$y_{i,t+j} - y_{i,t-k} = \beta_0 + \beta_1 \text{size}_{i,t} + \beta_2 \text{book/price}_{i,t} + \beta_3 \text{beta}_{i,t} + \gamma' D_{i,t} + e_{it}$$

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

Table 10
Number of firms in each category.

	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

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).

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Table 11
Transition probabilities across the four groups of firms.

	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

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'. For a firm that is in 'High FII' in time t, there is a 18.46% chance of it falling back to 'None' at time $t+1$.

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 $t+j$.

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.[6] 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:

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

This utilises 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, the results obtained here would differ from the previous tobit regressions, since the design matrix here is a more carefully constructed one.

Table 12 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 13. 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.

[6] 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 four marginal distributions (of size, log book-to-market and β) are approximately normally distributed. 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.

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Table 12
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 14 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 15. The null of equality of distributions is always rejected in the raw data and is never rejected after matching.

A similar analysis for the firms with high DII investment (but low FII investment) is shown in Tables 16 and 17. 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. This ensures that we are focused on the security analysis by FIIs and DIIs, without being clouded by their asset allocation strategies. The fact that the raw data has poor match balance in both cases (High FII and High DII), and that match balance is only achieved after matching, is a reminder that we should be skeptical about the usefulness of conventional econometrics when applied to the raw data.

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 18. 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 0.23 on a horizon of three years. All these 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

Table 13
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

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Table 14
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 15
Kolmogorov Smirnov test for FII. *P*-values are reported in the brackets.

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

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 0.15 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 significantly greater than the control. On a three year horizon, there is evidence of improved output when compared with the control.

The simple productivity measure as described above yields negative estimates which are not statistically significant. For manufacturing firms, we are able to compare TFP using Levinsohn-Petrin estimates. On a one year horizon, there is some evidence of inferior TFP growth by the firms chosen by FIIs.

Finally, we look at stock market returns. Firms chosen by FIIs show inferior returns without strong statistical significance.

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 reflect a combination of forecasts of high growth by the FII, or a causal effect of the purchase of shares by FIIs.

The remaining efftects are lukewarm. Firms chosen by FIIs have positive estimates of employment growth, but this is not statistically significant. Output growth for the chosen firms is better, and on a three year horizon this difference is statistically significant. Firms chosen by FIIs seem to get higher output growth on a three year horizon through a strongly capital-intensive strategy. There is some evidence of inferior productivity growth. In terms of stock market returns, FIIs do worse, though the results are not statistically significant.

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 19. In the years prior to the measurement date, the firms selected by DIIs had *lower* growth in fixed assets and in total assets.

Table 16
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 17
Kolmogorov Smirnov test for DII. *P*-values are reported in the brackets.

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

In the years after measurement date, their growth of capital is not statistically significantly different from the control.

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

When we examine the simple measure of productivity growth on a three year horizon, the firms chosen by DIIs outperform the controls by a factor of 0.08, which is statistically significant at a 95 per cent level. However, this result is not present when using the Levinsohn-Petrin measure of TFP (which applies for manufacturing firms only).

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

Table 18
Outcomes for firms chosen by FIIs but not DIIs.

	Log gross fixed assets			Log total assets	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.08 (0.033)*	0.11 (0.036)**	$X_t - X_{t-2}$	0.15 (0.036)***	0.1 (0.027)***
$X_t - X_{t-1}$	0.04 (0.02)*	0.06 (0.021)**	$X_t - X_{t-1}$	0.1 (0.02)***	0.05 (0.014)***
$X_{t+1} - X_t$	0.06 (0.021)**	0.06 (0.018)**	$X_{t+1} - X_t$	0.08 (0.019)***	0.05 (0.014)**
$X_{t+2} - X_t$	0.08 (0.033)*	0.14 (0.039)***	$X_{t+2} - X_t$	0.11 (0.031)***	0.1 (0.029)**
$X_{t+3} - X_t$	0.12 (0.044)**	0.23 (0.057)***	$X_{t+3} - X_t$	0.13 (0.043)**	0.15 (0.047)**
	Log employment			Log sales	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.17 (0.044)***	0.1 (0.038)*	$X_t - X_{t-2}$	0.04 (0.033)	0.03 (0.042)
$X_t - X_{t-1}$	0.11 (0.025)***	0.05 (0.022)*	$X_t - X_{t-1}$	0.03 (0.018).	0.02 (0.024)
$X_{t+1} - X_t$	0.02 (0.024)	0.03 (0.022)	$X_{t+1} - X_t$	0.06 (0.021)**	0.03 (0.025)
$X_{t+2} - X_t$	0.07 (0.047)	0.07 (0.044)	$X_{t+2} - X_t$	0.11 (0.041)**	0.04 (0.046)
$X_{t+3} - X_t$	0.07 (0.067)	0.11 (0.069)	$X_{t+3} - X_t$	0.2 (0.064)**	0.16 (0.07)*
	Cobb Douglas productivity growth			TFP (Log LP estimate)	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.05 (0.033)	−0.06 (0.027)*	$X_t - X_{t-2}$	−0.01 (0.016)	0 (0.01)
$X_t - X_{t-1}$	0.09 (0.056)	−0.11 (0.045)*	$X_t - X_{t-1}$	0 (0.008)	0 (0.006)
$X_{t+1} - X_t$	0.01 (0.028)	−0.03 (0.03)	$X_{t+1} - X_t$	−0.01 (0.01)	−0.01 (0.007)
$X_{t+2} - X_t$	0.05 (0.049)	−0.09 (0.055)	$X_{t+2} - X_t$	0.01 (0.012)	−0.01 (0.012)
$X_{t+3} - X_t$	0.07 (0.069)	−0.05 (0.075)	$X_{t+3} - X_t$	0.01 (0.013)	0 (0.016)
				Log adjusted closing price	
				OLS	Matching
$X_t - X_{t-2}$				0.21 (0.092)*	−0.05 (0.057)
$X_t - X_{t-1}$				0.19 (0.06)**	−0.01 (0.035)
$X_{t+1} - X_t$				0.01 (0.07)	−0.04 (0.038)
$X_{t+2} - X_t$				−0.08 (0.106)	−0.11 (0.069)
$X_{t+3} - X_t$				−0.09 (0.128)	−0.12 (0.103)

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 0.15, with a standard error of 0.047.

significant: 7 per cent on a one year horizon (with a standard error of 2.3 percentage points), 12 per cent on a two year horizon (with a standard error of 3.8 percentage points) and 18 per cent on a three year horizon (with a standard error of 5.7 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 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 not on a high growth trajectory. 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.

1. Size weights
2. More extreme definitions of FII and DII
3. Alternative choices of asset pricing factors

Table 19
Outcomes for firms chosen by DIIs but not FIIs.

	Log gross fixed assets			Log total assets	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	−0.1 (0.02)***	−0.05 (0.02)*	$X_t - X_{t-2}$	−0.1 (0.018)***	−0.06 (0.015)***
$X_t - X_{t-1}$	−0.05 (0.011)***	−0.02 (0.01)	$X_t - X_{t-1}$	−0.04 (0.01)***	−0.01 (0.008)
$X_{t+1} - X_t$	−0.03 (0.01)*	−0.01 (0.012)	$X_{t+1} - X_t$	−0.01 (0.01)	−0.01 (0.009)
$X_{t+2} - X_t$	−0.05 (0.02)**	−0.02 (0.023)	$X_{t+2} - X_t$	−0.02 (0.018)	−0.02 (0.017)
$X_{t+3} - X_t$	−0.05 (0.031)	−0.04 (0.033)	$X_{t+3} - X_t$	−0.01 (0.026)	−0.02 (0.025)
	Log employment			Log sales	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	−0.06 (0.024)**	−0.02 (0.021)	$X_t - X_{t-2}$	−0.05 (0.021)*	0 (0.025)
$X_t - X_{t-1}$	−0.03 (0.013)*	0 (0.013)	$X_t - X_{t-1}$	−0.02 (0.012)	0.01 (0.015)
$X_{t+1} - X_t$	−0.03 (0.015)	0.01 (0.013)	$X_{t+1} - X_t$	0.01 (0.015)	0 (0.017)
$X_{t+2} - X_t$	−0.03 (0.026)	−0.02 (0.024)	$X_{t+2} - X_t$	0.03 (0.028)	0.01 (0.032)
$X_{t+3} - X_t$	−0.01 (0.036)	−0.04 (0.035)	$X_{t+3} - X_t$	0.05 (0.04)	0.06 (0.044)
	Cobb Douglas productivity growth			TFP (Log LP estimate)	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.02 (0.018)	0.02 (0.016)	$X_t - X_{t-2}$	0 (0.007)	0 (0.006)
$X_t - X_{t-1}$	0.05 (0.03)	0.04 (0.026)	$X_t - X_{t-1}$	0 (0.005)	0 (0.004)
$X_{t+1} - X_t$	0.03 (0.018)	0 (0.017)	$X_{t+1} - X_t$	0.01 (0.005)	0 (0.004)
$X_{t+2} - X_t$	0.09 (0.031)**	0.03 (0.031)	$X_{t+2} - X_t$	0.02 (0.006)*	0.01 (0.006)
$X_{t+3} - X_t$	0.13 (0.043)**	0.08 (0.042)*	$X_{t+3} - X_t$	0.01 (0.008)	0.01 (0.01)
			Log adjusted closing price		
			OLS		Matching
$X_t - X_{t-2}$			0.05 (0.052)		0.03 (0.035)
$X_t - X_{t-1}$			0.06 (0.03)		0.04 (0.021)
$X_{t+1} - X_t$			0.17 (0.034)***		0.07 (0.023)**
$X_{t+2} - X_t$			0.25 (0.053)***		0.12 (0.038)**
$X_{t+3} - X_t$			0.26 (0.066)***		0.18 (0.057)**

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 γ 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 two years prior to measurement date that is larger than that observed for controls by −0.06, with a standard error of 0.015.

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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 22 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. However, this is associated with inferior productivity growth. The coefficients at all horizons are negative but not statistically significant. 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 23 in the appendix. These are also qualitatively similar to the main results. These firms have experienced declining total assets for the years prior to measurement date and both one and three years after measurement date. Employment and output growth appear to be no different from the control prior to measurement date, though they are significantly lesser than the control firm over a horizon of two and three years. However, there is strong evidence of superior productivity growth. There is also strong evidence of superior stock market returns by 15% on a one year horizon and 21% on a two year horizon. This suggests that DIIs have an 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. We define a High FII group as one where FII ownership was above 12.5% (i.e. 66th percentile of the distribution of FII investment), and DII ownership was below 1.35% (i.e. 33rd percentile of the distribution of DII investment). Similarly, we define a High DII group where DII ownership was above 18.6%, but FII ownership was below 3.23%. The control group is constructed of firms where neither FII nor DII ownership was above their 33rd percentile values.

Table 24, 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 productivity measures show that the chosen firms have inferior productivity growth when compared with the controls. 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. The magnitudes involved are large: stock returns are inferior by 29% on a two year horizon and 38% on a three year horizon.

Turning to the firms chosen for high investment by DIIs (but not FIIs), the results (Table 25 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 three years. Output growth is no different from the controls. The stock market returns are strongly superior: a superiority of 14% on a two year horizon and a superiority of 24% on a two year horizon.

6.3. Alternative choices of asset pricing factors

The main results of the paper were based on matching the securities selected by FIIs and DIIs on the basis of the three asset pricing factors: Size, B/P, and β. Below, we redo the calculations by matching firms on two additional variables: Liquidity of the stock measured by the turnover ratio, and momentum measured as the six month return of the stock. Turnover ratio is the latest 12 month turnover expressed as a ratio of market capitalisation.

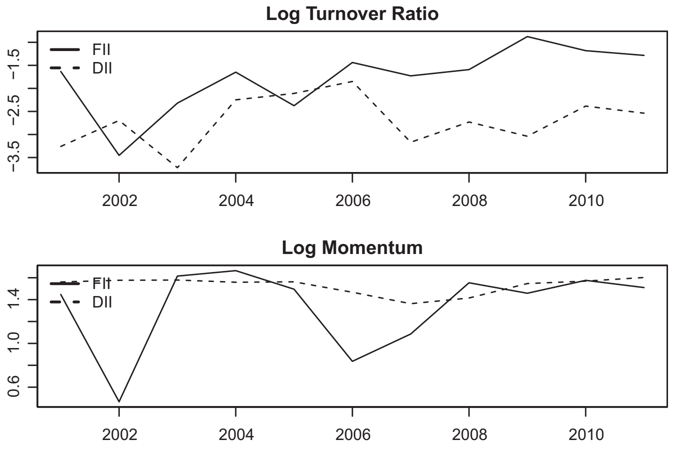

Fig. 2. Exposure to Turnover Ratio and Momentum. This figure shows the FII and DII exposure in terms of turnover ratio and momentum. The calculation is done as described in Fig. 1.

6.3.1. Liquidity

Fig. 2 and Table 20 show that FIIs invest in more liquid stocks as compared to DIIs. The median FII exposure is greater by 1.06 points than the median DII exposure, further highlighting the difference in asset allocation by these two types of investors.

To incorporate liquidity in the analysis, the matching is done on four parameters – size, beta, book-to-market and liquidity. Table 26 in the appendix, shows the results for firms with high FII investment (but low DII investment). 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 not significantly different from the controls, but output growth over a horizon of three years is higher than the controls. However, the simple measure of productivity shows that the chosen firms have inferior productivity growth when compared with the controls prior to measurement date. The stock market returns obtained by these firms is lesser than that obtained by the controls but are not statistically significant.

Table 27 in the appendix, shows the results for firms with high DII investment and low FII investment. DIIs choose firms where total assets have declined over the recent two years. Employment growth and output growth are no different from the controls. However, both the measures of productivity show that the firms chosen by DIIs have superior productivity growth over a horizon of three years. The stock market returns of firms chosen by DIIs are sharply superior to that obtained by the controls over a horizon of one, two and three years. Thus the results with controlling for liquidity are qualitatively similar to the main results of the paper.

6.3.2. Momentum

Momentum is an important idea in the asset pricing literature (Jegadeesh and Titman, 1993; Desai et al., 2002). As Fig. 2 shows, there is no important difference between FIIs and DIIs on the momentum factor. The median difference in exposure is only 0.07 as shown in Table 20. Hence, the analysis of

Table 20
Median exposure to turnover ratio and momentum.

	Log momentum	Log turnover ratio
FII	1.50	−1.63
DII	1.56	−2.70
Difference	−0.07	1.06

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Table 21
Summary of results.

	Baseline		Size wts		Extreme defn		With liq.	
	FII	DII	FII	DII	FII	DII	FII	DII
Fixed assets	0.23***	−0.04	0.16*	−0.12*	0.27**	−0.08	0.17**	−0.02
Employment	0.11	−0.04	−0.01	−0.1	0.03	−0.1*	0.06	−0.04
Sales	0.16*	0.06	0.24**	0.15	0.02	−0.01	0.12	0.04
CD prod.	−0.05	0.08*	0.1	0.24**	−0.22	0.04	−0.05	0.07
LP prod.	0.00	0.01	0.01	0.06**	0.01	0.01	0	0.02*
Price	−0.12	0.18**	−0.11	0.24	−0.38**	0.24**	−0.1	0.18**

This table summarises the results of the paper. In all cases, coefficient estimates on a predictive horizon of three years are reported. Baseline refers to the main results reported in the paper. 'Size wts' weights observations by size. 'Extreme defn' uses more extreme cutoffs for defining the 'High FII' and 'High DII' sets. 'With liq.' refers to results based on matching on four factors where the fourth factor is the turnover ratio.
In all cases, six coefficients are reported: log gross fixed assets, log employment, log sales, Cobb-Douglas productivity, Levinsohn–Petrin productivity and adjusted closing price (in logs).

security selection after controlling for four asset pricing factors – B/M, size, beta, momentum – would be no different from the analysis with the three Fama-French factors as shown in Section 5.

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 stock market returns, and also 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 skill in security selection.

Table 21 summarises the results across alternative designs. In all cases, the coefficients reported pertain to a three year predictive horizon.

Firms that are chosen by FIIs experience strong growth of gross fixed assets. In contrast, firms chosen by DIIs experience either zero or somewhat negative growth of assets. The growth of employment seems to be zero with the firms chosen by FIIs and is slighly negative with the firms chosen by DIIs. The firms chosen by FIIs have some output growth while the firms chosen by DIIs have low or zero output growth.

Across the two productivity measures, the firms chosen by FIIs appear to have zero or negative productivity growth while the firms chosen by DIIs have positive productivity growth.

In terms of stock market returns, firms chosen by FIIs experience somewhat negative performance while the firms chosen by DIIs do very well.

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

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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 numerous other settings. Extending the strategy of this paper 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.

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Appendix

Table 22
Outcomes for firms chosen by FIIs but not DIIs: size weighted.

	Log gross fixed assets			Log total assets	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.28 (0.169)	0.2 (0.05)***	$X_t - X_{t-2}$	0.3 (0.074)***	0.15 (0.031)***
$X_t - X_{t-1}$	0.2 (0.149)	0.12 (0.03)***	$X_t - X_{t-1}$	0.14 (0.046)**	0.07 (0.017)***
$X_{t+1} - X_t$	0.15 (0.089)	0.09 (0.031)**	$X_{t+1} - X_t$	0.1 (0.031)**	0.07 (0.016)***
$X_{t+2} - X_t$	0.06 (0.121)	0.16 (0.046)***	$X_{t+2} - X_t$	0.14 (0.051)**	0.11 (0.043)**
$X_{t+3} - X_t$	0.06 (0.173)	0.16 (0.066)*	$X_{t+3} - X_t$	0.17 (0.066)**	0.13 (0.066)*
	Log employment			Log sales	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.22 (0.116)	0.37 (0.199)	$X_t - X_{t-2}$	−0.16 (0.099)	0.08 (0.047)
$X_t - X_{t-1}$	0.12 (0.039)**	0.25 (0.154)	$X_t - X_{t-1}$	0.11 (0.109)	0.01 (0.044)
$X_{t+1} - X_t$	0.01 (0.028)	0.07 (0.023)**	$X_{t+1} - X_t$	0.05 (0.054)	0.06 (0.026)*
$X_{t+2} - X_t$	0.01 (0.063)	0.04 (0.059)	$X_{t+2} - X_t$	−0.01 (0.054)	0.13 (0.055)*
$X_{t+3} - X_t$	−0.03 (0.077)	−0.01 (0.084)	$X_{t+3} - X_t$	0.04 (0.109)	0.24 (0.075)**
	Cobb Douglas productivity growth			TFP (Log LP estimate)	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.09 (0.037)*	−0.11 (0.063)	$X_t - X_{t-2}$	−0.01 (0.019)	−0.02 (0.022)
$X_t - X_{t-1}$	0.2 (0.08)*	−0.14 (0.083)	$X_t - X_{t-1}$	−0.01 (0.014)	−0.02 (0.017)
$X_{t+1} - X_t$	0.02 (0.034)	−0.05 (0.038)	$X_{t+1} - X_t$	0 (0.013)	−0.02 (0.015)
$X_{t+2} - X_t$	0.02 (0.074)	−0.03 (0.078)	$X_{t+2} - X_t$	0.01 (0.015)	−0.02 (0.025)
$X_{t+3} - X_t$	0.08 (0.099)	0.1 (0.121)	$X_{t+3} - X_t$	0.02 (0.022)	0.01 (0.028)
	Log adjusted closing price				
	OLS				Matching
$X_t - X_{t-2}$	0.45 (0.133)***				0.15 (0.108)
$X_t - X_{t-1}$	0.26 (0.099)**				0.04 (0.051)
$X_{t+1} - X_t$	0.01 (0.109)				0.01 (0.059)
$X_{t+2} - X_t$	−0.07 (0.24)				0.05 (0.115)
$X_{t+3} - X_t$	−0.21 (0.301)				−0.11 (0.166)

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Table 23
Outcomes for firms chosen by DIIs but not FIIs: size weighted.

	Log gross fixed assets			Log total assets	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	−0.05 (0.04)	−0.24 (0.169)	$X_t - X_{t-2}$	−0.03 (0.045)	−0.07 (0.024)**
$X_t - X_{t-1}$	−0.03 (0.022)	0 (0.017)	$X_t - X_{t-1}$	−0.01 (0.028)	−0.04 (0.015)**
$X_{t+1} - X_t$	−0.04 (0.023)	−0.01 (0.015)	$X_{t+1} - X_t$	−0.01 (0.023)	−0.04 (0.017)*
$X_{t+2} - X_t$	−0.17 (0.098)	−0.05 (0.037)	$X_{t+2} - X_t$	−0.04 (0.035)	−0.06 (0.032)
$X_{t+3} - X_t$	−0.21 (0.15)	−0.12 (0.059)*	$X_{t+3} - X_t$	−0.04 (0.048)	−0.1 (0.049)*
	Log employment			Log sales	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	−0.01 (0.058)	0.13 (0.134)	$X_t - X_{t-2}$	−0.24 (0.148)	−0.3 (0.252)
$X_t - X_{t-1}$	−0.01 (0.019)	0.14 (0.109)	$X_t - X_{t-1}$	−0.01 (0.018)	−0.01 (0.023)
$X_{t+1} - X_t$	−0.03 (0.025)	0.12 (0.123)	$X_{t+1} - X_t$	0.02 (0.024)	0.01 (0.017)
$X_{t+2} - X_t$	−0.07 (0.042)	−0.07 (0.035)	$X_{t+2} - X_t$	0 (0.075)	0.09 (0.051)
$X_{t+3} - X_t$	−0.06 (0.057)	−0.1 (0.051)	$X_{t+3} - X_t$	−0.08 (0.143)	0.15 (0.078)
	Cobb Douglas productivity growth			TFP (Log LP estimate)	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.09 (0.037)*	−0.11 (0.063).	$X_t - X_{t-2}$	0.01 (0.012)	0 (0.009)
$X_t - X_{t-1}$	0.2 (0.08)*	−0.14 (0.083).	$X_t - X_{t-1}$	0.01 (0.008)	0 (0.006)
$X_{t+1} - X_t$	0.02 (0.034)	−0.05 (0.038)	$X_{t+1} - X_t$	0.02 (0.011)*	0 (0.009)
$X_{t+2} - X_t$	0.02 (0.074)	−0.03 (0.078)	$X_{t+2} - X_t$	0.04 (0.013)**	0.03 (0.014)*
$X_{t+3} - X_t$	0.08 (0.099)	0.1 (0.121)	$X_{t+3} - X_t$	0.04 (0.013)**	0.06 (0.02)**

	Log adjusted closing price	
	OLS	Matching
$X_t - X_{t-2}$	0.17 (0.082)*	0.07 (0.049)
$X_t - X_{t-1}$	0.12 (0.056)*	−0.02 (0.046)
$X_{t+1} - X_t$	0.16 (0.075)*	0.15 (0.043)***
$X_{t+2} - X_t$	0.3 (0.121)*	0.21 (0.081)**
$X_{t+3} - X_t$	0.28 (0.166)	0.24 (0.129)

Table 24
Outcomes for firms chosen by FIIs but not DIIs: More extreme definitions of FII and DII ownership.

	Log gross fixed assets			Log total assets	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.06 (0.04)	0.1 (0.054)	$X_t - X_{t-2}$	0.17 (0.049)***	0.11 (0.04)**
$X_t - X_{t-1}$	0.04 (0.025)	0.05 (0.029)	$X_t - X_{t-1}$	0.11 (0.031)***	0.06 (0.021)**
$X_{t+1} - X_t$	0.05 (0.032)	0.11 (0.035)**	$X_{t+1} - X_t$	0.08 (0.026)**	0.07 (0.022)**
$X_{t+2} - X_t$	0.08 (0.048)	0.17 (0.067)*	$X_{t+2} - X_t$	0.1 (0.04)*	0.11 (0.043)**
$X_{t+3} - X_t$	0.13 (0.06)*	0.27 (0.096)**	$X_{t+3} - X_t$	0.1 (0.052)	0.13 (0.063)*
	Log employment			Log sales	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.13 (0.057)*	0.06 (0.058)	$X_t - X_{t-2}$	0.07 (0.043)	0.09 (0.059)
$X_t - X_{t-1}$	0.12 (0.034)***	0.04 (0.033)	$X_t - X_{t-1}$	0.05 (0.025).	0.04 (0.031)
$X_{t+1} - X_t$	0.01 (0.032)	0.02 (0.033)	$X_{t+1} - X_t$	0.06 (0.028)*	0 (0.039)
$X_{t+2} - X_t$	0.07 (0.06)	0.04 (0.066)	$X_{t+2} - X_t$	0.14 (0.052)**	0.01 (0.068)
$X_{t+3} - X_t$	0.1 (0.085)	0.03 (0.092)	$X_{t+3} - X_t$	0.16 (0.08)*	0.02 (0.097)
	Cobb Douglas productivity growth			TFP (Log LP estimate)	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.1 (0.05)	−0.04 (0.034)	$X_t - X_{t-2}$	0.02 (0.027)	0.02 (0.017)
$X_t - X_{t-1}$	0.18 (0.089)*	−0.06 (0.065)	$X_t - X_{t-1}$	0.01 (0.014)	0.01 (0.009)
$X_{t+1} - X_t$	−0.01 (0.039)	−0.11 (0.05)*	$X_{t+1} - X_t$	−0.01 (0.014)	−0.01 (0.009)

(continued on next page)

Table 24 (*continued*)

	Cobb Douglas productivity growth			TFP (Log LP estimate)	
	OLS	Matching		OLS	Matching
$X_{t+2} - X_t$	0.06 (0.068)	−0.15 (0.089).	$X_{t+2} - X_t$	0 (0.022)	0.01 (0.017)
$X_{t+3} - X_t$	0 (0.101)	−0.22 (0.114).	$X_{t+3} - X_t$	0.01 (0.022)	0.01 (0.024)

	Log adjusted closing price	
	OLS	Matching
$X_t - X_{t-2}$	0.19 (0.121)	−0.09 (0.078)
$X_t - X_{t-1}$	0.23 (0.078)**	−0.02 (0.048)
$X_{t+1} - X_t$	−0.05 (0.088)	−0.1 (0.057)
$X_{t+2} - X_t$	−0.14 (0.122)	−0.29 (0.099)**
$X_{t+3} - X_t$	−0.25 (0.145)	−0.38 (0.144)**

Table 25
Outcomes for firms chosen by DIIs but not FIIs: More extreme definitions of FII and DII ownership.

	Log gross fixed assets			Log total assets	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	−0.14 (0.029)***	−0.07 (0.033)*	$X_t - X_{t-2}$	−0.15 (0.023)***	−0.08 (0.022)***
$X_t - X_{t-1}$	−0.07 (0.016)***	−0.02 (0.018)	$X_t - X_{t-1}$	−0.06 (0.013)***	−0.03 (0.012)*
$X_{t+1} - X_t$	−0.04 (0.015)*	−0.02 (0.017)	$X_{t+1} - X_t$	−0.01 (0.014)	−0.01 (0.012)
$X_{t+2} - X_t$	−0.06 (0.027)*	−0.05 (0.032)	$X_{t+2} - X_t$	−0.01 (0.026)	−0.04 (0.023)
$X_{t+3} - X_t$	−0.06 (0.04)	−0.08 (0.045)	$X_{t+3} - X_t$	0 (0.037)	−0.04 (0.036)

	Log employment			Log sales	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	−0.1 (0.031)**	−0.05 (0.031)	$X_t - X_{t-2}$	−0.06 (0.028)*	−0.01 (0.036)
$X_t - X_{t-1}$	−0.04 (0.018)*	−0.02 (0.019)	$X_t - X_{t-1}$	−0.03 (0.019)	−0.02 (0.02)
$X_{t+1} - X_t$	−0.05 (0.022)*	−0.01 (0.021)	$X_{t+1} - X_t$	0 (0.023)	0 (0.027)
$X_{t+2} - X_t$	−0.06 (0.033).	−0.06 (0.036)	$X_{t+2} - X_t$	0.06 (0.039)	0 (0.042)
$X_{t+3} - X_t$	−0.03 (0.043)	−0.1 (0.048)*	$X_{t+3} - X_t$	0.08 (0.048)	0.01 (0.052)

	Cobb Douglas productivity growth			TFP (Log LP estimate)	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.04 (0.025)	0 (0.023)	$X_t - X_{t-2}$	0 (0.01)	0.01 (0.009)
$X_t - X_{t-1}$	0.08 (0.045)	0.05 (0.039)	$X_t - X_{t-1}$	0 (0.008)	0 (0.006)
$X_{t+1} - X_t$	0.03 (0.025)	0.01 (0.027)	$X_{t+1} - X_t$	0.01 (0.007)	−0.01 (0.007)
$X_{t+2} - X_t$	0.11 (0.04)**	0.02 (0.044)	$X_{t+2} - X_t$	0.02 (0.009)**	0.01 (0.01)
$X_{t+3} - X_t$	0.14 (0.055)*	0.04 (0.051)	$X_{t+3} - X_t$	0.03 (0.01)*	0.01 (0.015)

	Log adjusted closing price	
	OLS	Matching
$X_t - X_{t-2}$	0.1 (0.07)	0.01 (0.054)
$X_t - X_{t-1}$	0.12 (0.041)**	0.04 (0.032)
$X_{t+1} - X_t$	0.25 (0.05)***	0.06 (0.035)
$X_{t+2} - X_t$	0.36 (0.077)***	0.14 (0.058)*
$X_{t+3} - X_t$	0.33 (0.093)***	0.24 (0.082)**

Table 26
Outcomes for firms chosen by FIIs but not DIIs: Using turnover ratio for matching,

	Log gross fixed assets			Log total assets	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.08 (0.033)*	0.1 (0.033)**	$X_t - X_{t-2}$	0.15 (0.035)***	0.08 (0.028)**
$X_t - X_{t-1}$	0.04 (0.02)*	0.06 (0.017)**	$X_t - X_{t-1}$	0.1 (0.02)***	0.04 (0.015)**

Table 26 (*continued*)

	Log gross fixed assets			Log total assets	
	OLS	Matching		OLS	Matching
$X_{t+1} - X_t$	0.06 (0.021)**	0.05 (0.018)**	$X_{t+1} - X_t$	0.08 (0.019)***	0.05 (0.015)**
$X_{t+2} - X_t$	0.08 (0.033)*	0.08 (0.037)*	$X_{t+2} - X_t$	0.11 (0.031)***	0.07 (0.03)*
$X_{t+3} - X_t$	0.12 (0.044)**	0.17 (0.059)**	$X_{t+3} - X_t$	0.13 (0.043)**	0.13 (0.048)**
	Log Employment			**Log Sales**	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.17 (0.044)***	0.05 (0.034)	$X_t - X_{t-2}$	0.03 (0.033)	0 (0.037)
$X_t - X_{t-1}$	0.1 (0.025)***	0.03 (0.02)	$X_t - X_{t-1}$	0.04 (0.018)	0.01 (0.021)
$X_{t+1} - X_t$	0.02 (0.024)	0.02 (0.023)	$X_{t+1} - X_t$	0.06 (0.021)**	0.03 (0.025)
$X_{t+2} - X_t$	0.07 (0.046)	0.02 (0.045)	$X_{t+2} - X_t$	0.11 (0.041)**	0.04 (0.047)
$X_{t+3} - X_t$	0.07 (0.067)	0.06 (0.065)	$X_{t+3} - X_t$	0.2 (0.064)**	0.12 (0.072)
	Cobb Douglas Productivity Growth			**TFP (Log LP estimate)**	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.05 (0.033)	−0.06 (0.023)*	$X_t - X_{t-2}$	0.21 (0.092)*	−0.07 (0.055)
$X_t - X_{t-1}$	0.09 (0.057)	−0.1 (0.042)*	$X_t - X_{t-1}$	0.19 (0.059)**	−0.03 (0.036)
$X_{t+1} - X_t$	0.01 (0.028)	−0.02 (0.029)	$X_{t+1} - X_t$	0.01 (0.07)	−0.05 (0.039)
$X_{t+2} - X_t$	0.05 (0.049)	−0.03 (0.051)	$X_{t+2} - X_t$	−0.08 (0.102)	−0.08 (0.068)
$X_{t+3} - X_t$	0.07 (0.069)	−0.05 (0.076)	$X_{t+3} - X_t$	−0.09 (0.124)	−0.1 (0.104)

	Log adjusted closing price	
	OLS	Matching
$X_t - X_{t-2}$	0.21 (0.092)*	−0.07 (0.055)
$X_t - X_{t-1}$	0.19 (0.059)**	−0.03 (0.036)
$X_{t+1} - X_t$	0.01 (0.07)	−0.05 (0.039)
$X_{t+2} - X_t$	−0.08 (0.102)	−0.08 (0.068)
$X_{t+3} - X_t$	−0.09 (0.124)	−0.1 (0.104)

Table 27
Outcomes for firms chosen by DIIs but not FIIs: Using Turnover ratio for matching,

	Log gross fixed assets			Log total assets	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	−0.1 (0.02)***	−0.04 (0.019).	$X_t - X_{t-2}$	−0.09 (0.018)***	−0.06 (0.015)***
$X_t - X_{t-1}$	−0.05 (0.011)***	−0.02 (0.011)	$X_t - X_{t-1}$	−0.04 (0.01)***	−0.02 (0.008)*
$X_{t+1} - X_t$	−0.02 (0.01)*	0 (0.012)	$X_{t+1} - X_t$	−0.01 (0.01)	−0.01 (0.009)
$X_{t+2} - X_t$	−0.05 (0.02)*	−0.01 (0.022)	$X_{t+2} - X_t$	−0.02 (0.018)	−0.01 (0.017)
$X_{t+3} - X_t$	−0.05 (0.03)	−0.02 (0.032)	$X_{t+3} - X_t$	−0.01 (0.026)	−0.02 (0.025)
	Log employment			**Log sales**	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	−0.06 (0.024)*	−0.01 (0.021)	$X_t - X_{t-2}$	−0.05 (0.021)*	0 (0.028)
$X_t - X_{t-1}$	−0.03 (0.013)*	0.02 (0.013)	$X_t - X_{t-1}$	−0.02 (0.012)	0.01 (0.016)
$X_{t+1} - X_t$	−0.03 (0.015)	−0.01 (0.013)	$X_{t+1} - X_t$	0.01 (0.015)	0.01 (0.017)
$X_{t+2} - X_t$	−0.03 (0.026)	−0.02 (0.024)	$X_{t+2} - X_t$	0.03 (0.027)	0.01 (0.031)
$X_{t+3} - X_t$	−0.01 (0.036)	−0.04 (0.034)	$X_{t+3} - X_t$	0.05 (0.039)	0.04 (0.042)
	Cobb Douglas productivity growth			**TFP (Log LP estimate)**	
	OLS	Matching		OLS	Matching
$X_t - X_{t-2}$	0.02 (0.019)	0.02 (0.016)	$X_t - X_{t-2}$	0 (0.007)	0 (0.006)
$X_t - X_{t-1}$	0.04 (0.031)	0.03 (0.028)	$X_t - X_{t-1}$	0 (0.005)	0 (0.003)

(*continued on next page*)

Table 27 (*continued*)

	Cobb Douglas productivity growth			TFP (Log LP estimate)	
	OLS	Matching		OLS	Matching
$X_{t+1} - X_t$	0.03 (0.017)	0 (0.018)	$X_{t+1} - X_t$	0.01 (0.004)	0 (0.004)
$X_{t+2} - X_t$	0.09 (0.03)**	0.02 (0.029)	$X_{t+2} - X_t$	0.02 (0.006)*	0.01 (0.006)*
$X_{t+3} - X_t$	0.11 (0.041)**	0.07 (0.041)	$X_{t+3} - X_t$	0.01 (0.008)	0.02 (0.009)*

	Log adjusted closing price	
	OLS	Matching
$X_t - X_{t-2}$	0.05 (0.052)	0.01 (0.036)
$X_t - X_{t-1}$	0.04 (0.03)	0.03 (0.021)
$X_{t+1} - X_t$	0.16 (0.034)***	0.06 (0.023)**
$X_{t+2} - X_t$	0.21 (0.053)***	0.1 (0.038)**
$X_{t+3} - X_t$	0.22 (0.066)***	0.18 (0.056)**

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