Is it Who You Know or What You Know? Evidence from IPO Allocations and Mutual Fund Performance*

Chuan-Yang Hwang

Nanyang Business School

Nanyang Technological University

cyhwang@ntu.edu.sg

Sheridan Titman

McCombs School of Business

The University of Texas at Austin

titman@mail.utexas.edu

Yuxi Wang

Nanyang Business School

Nanyang Technological University

wang0672@e.ntu.edu

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Abstract

Consistent with Chevalier and Ellison (1999), we find that mutual fund managers with degrees from elite university tend to outperform their less elite counterparts. The superior performance of elite graduates can be characterized as "fast performance," the stock's they select realize excess returns only in the quarter the stock is purchased, and this fast performance is largely due to the elite graduates having better access to IPO underwriters. Indeed, mutual funds managed by elite graduates realize superior performance *only* in months in which they have connections with underwriters issuing IPOs. We further show that investors can generate excess returns with a strategy of buying mutual funds in months when they are connected to underwriters scheduled to issue IPOs.

JEL classification: G23, G24

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Since the seminal work of Jensen (1968), researchers have explored the possibility that some mutual fund managers generate better performance than others. Efficient markets and zero abnormal performance is the obvious null in these performance studies and a plausible alternative is that smarter and better connected individuals outperform others. While Jensen (1968) failed to find evidence of abnormal performance, relatively weak evidence in Grinblatt and Titman (1989) and others suggest that some mutual fund managers have special skills or information.[1]

The research in this paper is motivated by Chevalier and Ellison (1999) who document that mutual fund managers who attended more selective schools outperform those who did not. As these authors note, this evidence is consistent with the idea that these elite graduates are either smarter or are better trained than their competitors. However, as the authors also note, these better performing portfolio managers may also benefit from the broader social network that these elite schools provide. In other words, superior performance may be generated by *who you know rather than what you know.*

To better understand the relation between elite education and mutual fund performance we start by decomposing mutual fund performance into what we characterize as its slow and fast components. The slow component is measured by the future performance of the mutual funds' end of quarter portfolio holdings. More specifically, we follow Grinblatt and Titman (1989, 1993), Daniel, Grinblatt, Titman and Wermers (1997) and others who measure mutual fund

[1] For example, Kacperczyk, Sialm and Zheng (2005) find that the most industry concentrated funds earn an annual abnormal return of about 2.12 percent over 1984 to 1999. Kacperczyk, Sialm and Zheng (2008) document a 3.41 percent of return difference between the top and bottom decile portfolios based on their return gap measure during the sample period of 1984 to 2003. Cremers and Petajisto (2009) report a return difference of 2.55 percent per year between the highest and lowest active share quintile.

performance by examining the excess returns of a hypothetical portfolio that holds, for one quarter, the end of quarter holdings of the mutual funds. This measure captures excess returns that can potentially occur as long as six months following the initiation of a position. To capture the fast component of performance we take the difference between the actual mutual fund return and this hypothetical return. This difference, which was examined previously in Grinblatt and Titman (1989) and Kacperczyk, Sialm and Zheng (2008), measures excess returns that are realized within the same quarter the positions are initiated.

The hypothesis we will be testing is that *what you know* is more important for generating the slow component of performance, but *who you know* is more important for the fast component. The idea is that obtaining information a little bit faster than others can clearly be facilitated by having a better placed network of contacts. Moreover, as we will show, a better network of contacts can also facilitate access to under-priced IPOs, which also contributes to the fast component of performance.

We start by documenting that the relation between mutual fund performance and elite education, shown in Chevalier and Ellison (1999), also exists in our more recent and longer time series. As in Chevalier and Ellison, the magnitude of the effect is not particularly large (about 60 basis points per year) and the level of significance is pretty weak (the t-statistic is 1.52). Moreover, our decomposition reveals no evidence of a relation between the education of the portfolio manager and the slow component of performance. There is, however, a reliably positive relation between the fast component of performance and whether or not the portfolio manager attended an elite institution, which is consistent with the idea that these portfolio managers benefit from their superior connections.

To more deeply examine the relative benefits of superior connections we examine the IPOs that are allocated to mutual funds. Given the evidence of IPO under-pricing,[2] getting allocated (especially hot) IPOs is a potential source of the observed fast performance of the mutual funds managed by elite graduates. Specifically, we examine data on the education of 1,420 portfolio managers working at 1,320 open-end equity mutual funds along with the education of 216 firm executives that underwrote 1,636 IPO deals during our sample period (January 1992 to March 2012). We find that mutual funds managed by elite graduates are indeed allocated more IPOs, and that these better allocations are related to school ties.

Next we study the allocations of what we describe as *EC* funds, which are funds that are *effectively connected* to an underwriter taking a firm public. An *EC* fund has a portfolio manager that attended the same tertiary institutions as one of the top executives at the underwriter and in addition, was allocated shares in one of its previous IPOs. We find that these *EC* funds get favorable allocations in terms of both probability and deal quality. Specifically, the probability of an *EC* fund getting an IPO allocation is measured about six times that for an *NC* (not connected) fund. Moreover, for the deals with the higher initial returns, the evidence of more favorable allocations to *EC* funds is even stronger. Similarly, we find that the connected funds have a higher probability of receiving IPO allocation in what we characterize as hotter markets.

Our evidence indicates that IPO allocations explain a significant portion of the fast performance as well as the total performance of portfolio managers who are graduates of elite universities. The benefits of these connections are characterized by a significant 1.68 percent

[2]Ibbotson, Sindelar and Ritter (1988) show that there is a large initial day return (16.4 percent) of IPO between 1960 and 1987. The updated statistics on Ritter's website show that the average first-day return on initial public offerings (IPOs) was 7.2 percent in the 1980s, 14.8 percent from 1990 to 1998, and 13.3 percent from 2001 to 2013 (it surged to 64.5 percent during the internet bubble period of 1999-2000).

difference between the average annualized returns of *EC* and *NC* funds after controlling for month fixed effects and various fund characteristics. This superior performance, however, is apparent *only* in the months in which the funds are connected to underwriters that allocate IPOs. When we examine the performance of mutual funds that previously benefited from connections, we find no evidence that formerly, but not currently connected mutual funds experience superior performance. To further illustrate this observation, we calculate the returns of a strategy that holds mutual funds only when they are connected to issuers of upcoming IPOs. This strategy generates excess returns (relative to 3 and 4 factor models) of 2.28 percent on average, and 4.08% in hot IPO markets.

As we mentioned at the outset, our results build on and extend the previous literature on networks and mutual fund performance. We confirm Chevalier and Ellison (1999) findings that mutual fund managers who graduated from elite institutions outperform, but show that after accounting for the fact that elite funds are more connected and hence benefited from better IPO allocations, the elite school fund manager performance is no longer reliably different than the performance of their non-elite counterparts.

This research is also related to Cohen, Frazzini and Malloy (2008) who find that mutual fund managers tilt their portfolios toward firms with which they are connected through school ties, and the connected holdings of these funds performed significantly better than their non-connected counterparts. However, since mutual fund managers are connected to relatively few firms, the total impact of these connections on fund performance is only about 2 basis points per year, which is too small to explain the Chevalier and Ellison (1999) findings. It should also be noted that the Cohen, Frazzini and Malloy (2008) methodology only picks up the slow component of performance, and may thus miss out on more important benefits of connections.[3]

Finally, it should be noted that our analysis is tangentially related to the book building literature, which suggests that underpricing arises because of information asymmetries between issuers and portfolio managers. As described in models by Benveniste and Spindt (1989) and Benveniste and Wilhelm (1990), the relationship between asset managers and underwriters is quite important for the pricing of IPOs. Because the book-building process relies in part on trust, there are plausible economic rationales for underwriters to allocate IPOs to a network of individuals they know well. Indeed, within the context of these models there are rents associated with being better connected.

The remainder of the paper is organized as follows. In section II, we explain how our sample is constructed and present descriptive statistics. In section III through VI, we explore the relation between elite school graduates and fund performance in more detail and explain sources of the possible relation. We provide additional robustness checks in section VII and conclude in section VIII.

[3] There is a growing literature on social connections. For example, Hwang and Kim (2009) study the CEO-director connection and find that independent directors are not necessarily socially independent; Shue (2013) studies how the alumni networks of executives affect corporate policies; Engelberg, Gao and Parsons (2013) examine the impact of social connection between CEOs and outside firm executives and find that CEOs with larger social networks have higher compensation. Engelberg, Gao and Parsons (2012) show that informal connections between firms and banks can lower a firm's borrowing costs.

II. Data

A. Sample construction

Our study examines data on mutual fund returns and holdings, IPO data, and connection-related data. The mutual fund data comes from the Thomson Reuters Mutual Fund Database and the CRSP Survivor-Bias-Free US Mutual Fund Database (CRSP MF); the former includes information from the semi-annual N-SAR filings that are mandatory for mutual funds,[4] while the latter provides fund characteristics such as their size, age, turnover ratio, expense ratio, and investment style at the share class level. To measure fund performance, we employ net returns (*Ret*) extracted from CRSP MF; i.e., returns after fees, expenses and brokerage commissions but before front-end and back-end loads.

We use the Securities Data Company (SDC) New Issues database to identify initial public offerings. Following Loughran and Ritter (2002), we exclude unit offerings, closed end funds, real estate investment trusts (REITs), partnerships and American depository receipts (ADRs), as well as all IPOs with a file price below $5.00 per share. There are 5,372 IPOs that meet the above-mentioned criteria during the sample period of January 1992 to March 2012.

Since we use common educational background to proxy for "connectivity," we rely on biographical information on mutual fund managers and top executives in IPO lead underwriter firms. We identify historical employment and educational information for 216 senior executives,[5] working at 31 public lead underwriters, (see Appendix, Table A.1, for a list of the underwriters), covering 1,636 IPO deals, or 30.5 percent of the deals population. We also

[4] Wermers (2000) observes that over 80% of the funds voluntarily report their portfolio holdings on a quarterly basis.

[5] These are the top-compensated executives in underwriter firms such as CEO, CFO, Chairman, etc.

identify similar information about 1,420 mutual fund managers, managing 35 percent (=1,320 / 3,739) of the open-end equity funds in the sample.

To obtain educational information about senior executives at underwriter firms, we manually search the name of each corporate executive working at the one of the top 50 underwriters ranked by the number of deals underwritten; and check the information against at least two public sources to ensure the accuracy of their educational history and to make sure they are not just sitting on the board of the university or managing its endowment. For example, from ExecuComp, we know that Paul C. Reilly served as the CEO of Raymond James Financial in May 2010. We then search his name on public sites and cross-reference his public biography among three sources: the company's website, NNDB,[6] and Bloomberg Businessweek; this enables us to ascertain that Reilly was born in 1954[7] and received both a bachelor's and an MBA degree from University of Notre Dame.[8] We take extra care when different people have identical names by keeping track of their employment history. We then extract the employment information of the top executives from ExecuComp, which covers firms in the S&P 1500 universe and provides compensation and employment information for up to 9 executives per firm; hence, the doesn't include underwriters that are not members of the S&P 1500 firms. The employment and educational information of mutual fund managers is obtained from Morningstar.[9]

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[6] NNDB is an intelligence aggregator that tracks the activities of people that the general public has determined to be noteworthy, both living and dead.

[7] The graduation year of corporate executives is obtained by adding the average age at graduation for each one of the six degree types respectively: bachelor, master, MBA, MD, JD and PhD.

[8] The three public sources that we use to identify Paul C. Reilly's educational information are available at the following sites: http://www.raymondjames.com/profiles/reilly.htm, http://www.nndb.com/people/248/000170735/, and http://investing.businessweek.com/research/stocks/people/person.asp?personId=886856&ticker=RJF

[9] We match the Morningstar fund names and Thomson Reuters fund names first by restricting the spelling distance to be less than or equal to 20 and manually delete the non-matched funds. Second, for the remaining fund names with a spelling distance greater than 20, we use the fund ticker to obtain the match and manually check its accuracy.

The process of constructing our final sample is as follows: For each IPO, we identify each of its lead underwriters and extract the educational information about its senior executives. We then evaluate the status of these executives' connections to all mutual fund managers in the sample during the same IPO month; that is, for each incumbent executive employed at an underwriter, we determine the mutual fund managers he or she is connected to. Following the definitions in Cohen, Frazzini and Malloy (2008) our connection indicator equals to one if both the incumbent fund manager and executive at the underwriter firm attended the same college. We then aggregate the connection measure from the person-person level to the deal-fund level; i.e., our connection dummy (*Connected*) is set to one for a mutual fund if any of the top executives from one of the lead underwriters attended the same tertiary institution as any one of the mutual fund managers working for the fund. Since attending the same tertiary institution does not necessarily mean the individuals have a relationship, we refine the connection measure to create an enhanced version, *EC* (Effectively Connected), which takes a value of one if the fund and deal underwriter are connected (i.e., one of the incumbent fund managers and underwriter firm executives attended the same school) and the fund has received at least one IPO allocation from the same underwriter firm before, and zero otherwise. Note that we do not impose any constraints on current allocation status to define the status of effective connection.

Next, we define the fund level measure *EliteSchool* to be equal to one if the portfolio manager attended one of the top ten universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution[10], and zero otherwise.

[10] The top 10 universities ranked by average SAT score over the 2001 to 2008 period are California Institute of Technology, Harvard University, Massachusetts Institute of Technology, Princeton University, Yale University, Pomona College, Stanford University, Dartmouth College, Swarthmore College, and Columbia University.

Last but not least, we follow Gaspar, Massa and Matos (2006) to identify the mutual funds' IPO allocations. Since most of the holdings are reported at a quarterly frequency, we identify the IPO holdings of each fund at the end of the calendar quarter in which the IPO takes place, and we set the allocation dummy *Allocated* to one if the fund holds the IPO stock at the end of the issuance quarter. This, of course, is a noisy measure since some funds sell the IPO stock prior to the quarter's end, and others will acquire the IPO stocks on the market.

B. Fund characteristics

There are 1,320 unique open-end equity funds in the sample, amounting to about 35 percent of the domestic open-end equity fund population during the sample period. Table 1 reports descriptive statistics for our sample. We also summarize the fund characteristics based on *EliteSchool*. The univariate results suggest that *EliteSchool* funds on average are larger as measured by *TNA*, have slightly lower turnover, and are older as measured by *Age* in years.

[Insert Table 1 here]

C. Deal characteristics

There are 1,636 IPOs in our sample period, and of these, 1,303 allocated IPO shares to mutual funds in our sample. The variable capturing the "hotness" of the IPO market, taken from Ibbotson, Sindelar and Ritter (1994),[11] is the percentage of deals that are priced above the midpoint of the original file price range. We define a binary indicator variable *HotMkt,* which equals one if the "hotness" value falls above the median value over the 1980 to 2012 period, and zero otherwise. Given this definition, we have 1,042 deals that take place in a hot market, and

[11] This data is available at Jay Ritter's website: http://bear.warrington.ufl.edu/ritter/IPOdata.htm.

594 in a cold market. In Table 2, we present summary statistics for all IPO firms as well as for those issued in hot and cold markets.

[Insert Table 2 here]

On average, our sample deals have about one identifiable lead underwriter per IPO firm, and the average underpricing (*IR*, calculated as the difference between first trading day closing price and the offer price divided by offer price) is about 31.52 percent. The average post-issue market capitalization is about $903 million and the average proceeds are about $138 million. Among the offered shares, the *% shares allocated to sample funds,* or the proportion allocated to our sample fund is about 15 percent per deal, which is slightly less than half the 34 percent allocation to all open-end equity funds reported in Ritter and Zhang (2007).[12] We find that the probability that a particular IPO is allocated to an *EC* is about 6%, which contrasts to the probability that a particular IPO is allocated to an *NC* fund, which is about 1 percent. Relatedly, the probability that a particular IPO is allocated to an elite-school fund is about 2%, while the probability that a particular IPO is allocated to a non-elite-school fund is 1%; this is because elite-school funds are more likely to be connected as we will see later in Table 3.

The last three columns present the comparison of deal characteristics in different market conditions: as the market conditions for IPOs become hotter, we see more deals per month, higher average first-day returns, and lower proceeds per deal. The lower proceeds are possibly due to the fact that far more smaller-sized issues choose to do IPOs in hot markets. The market capitalization of deals is bigger for hot market deals. The percentage allocated to sample funds is indistinguishable in the two markets, and the percentage of shares offered out of total shares

[12] The discrepancy arises because we only include the open-end equity funds with educational information of portfolio managers.

outstanding is lower in hot markets. The probability of getting an allocation is higher for *EC* funds in hot markets. We will explore this result in greater depth in Section IV.

D. Connection characteristics

[Insert Table 3 here]

This section provides descriptive statistics about the educational connections between underwriters and mutual funds. As Panel A of Table 3 shows, the median number of senior executives per underwriter is 4 and the median number of portfolio managers per fund is 1. Our connection measure is first determined at the fund-underwriter-month level, and then we sum up the connection dummy (*EC*) to the fund-month level to facilitate the study of fund performance. When the fund-underwriter-month level observation is aggregated to the fund-month level, each fund is effectively connected to 0.4 deals on average (*# of effective connections per fund-month*), and 12.56% of the funds are effectively connected in an average sample month. Moreover, for an average *EC* fund, each is effectively connected to 4 deals (*# of effective connections per EC fund-month*). On average, each fund is effectively connected 14 percent of the time *(% effectively connected months per fund*); for elite-school funds, each fund is effectively connected 25 percent of the time *(% effectively connected months per elite school fund*), indicating that fund managers attended elite schools indeed are significantly better connected through their school ties.

Panel B lists the five universities most attended by underwriter firm executives and portfolio managers. The most popular universities among underwriter executives are Harvard University, Stanford University, University of Pennsylvania, Yale University and Columbia University, while the most popular universities for portfolio managers are Harvard University, University of Pennsylvania, New York University, University of Chicago and Columbia

University. When we aggregate the connections of individuals from the various universities we find that individuals from Harvard, Columbia, Pennsylvania, Chicago and Stanford are the most connected, as shown in Figure 1.[13]

[Insert Figure 1 here]

III. Elite education and mutual fund performance revisited

We start our analysis of mutual fund performance by revisiting the Chevalier and Ellison (1999) observation that mutual funds managed by elite portfolio managers outperform their counterparts who are educated at less elite institutions. We do this by regressing four different measures of mutual fund excess returns on a dummy indicating whether or not the fund is managed by an elite graduate along with the funds' turnover, age, assets under management, and its expense ratio to control for fund characteristics that can plausibly influence performance.

Our first measure of mutual fund excess return is the four-factor-adjusted alpha. We estimate four-factor alpha by first regressing the excess total return over risk free rate of the mutual fund on the four factor portfolios described in the last section over month *t-24* to *t-1* to compute beta loadings on respective factors and then calculate alpha as the difference of current month excess return and the respective product of factor loadings and factor returns in month *t*. We then decompose the mutual fund return into two components: The first component (*hypothetical return*) is what Grinblatt and Titman (1989) describe as the return that one could hypothetically achieve by buying the portfolio reported by the mutual funds in their quarterly filings. We calculate the four factor alpha as well as the Daniel, Grinblatt, Titman and Wermers

[13] Harvard connection seems to dominate our sample, therefore in unreported tests, we purge Harvard graduates from the sample and our main results still hold, i.e. *EC* funds are more likely to get allocation and earn significantly higher return.

(1997) DGTW selectivity measure to gauge the excess returns of this portfolio. The second component, referred to as the *return gap*, by Kacperczyk, Sialm and Zheng (2008), is the difference between the actual mutual fund return and the hypothetical return.

The first component, the excess hypothetical returns, measures how stocks selected in the prior quarter perform in the current quarter. As such, it measures the efficacy of relatively slow signals that are likely to be generated by the analysis of company fundamentals. In contrast, the return gap measures the performance of stocks within the quarter that they are selected, and thus measure the efficacy of fast signals along with the allocation of discounted stock, like IPOs. As we mentioned in the introduction, our conjecture is that while insights and intelligence clearly contribute to the efficacy of both fast and slow signals, that connections are especially important for the fast signals.

[Insert Table 4 here]

Table 4 reports regressions of the four performance measures on the *EliteSchool* dummy (henceforth elite dummy or elite fund dummy) and the four control variables. As we see in Column (1), the elite dummy has a coefficient of .05, indicating that the managers produce an excess return of about 60 bps per year, which is consistent with the magnitude found by Chevalier and Ellison (1999). However, the t-statistic is only 1.52, so the significance of this finding is pretty weak. Columns (2) and (3) report the excess hypothetical returns measured relative to the four factors and DGTW benchmarks. The elite dummy in these regressions are identical (.01 per month) and are not significantly different than zero, suggesting that none of the superior performance of the elite graduates can be attributed to the efficacy of their slow information. Finally, the regression reported in Column (4), with the return gap being the dependent variable, generates a coefficient of .04 for the elite dummy, indicating that the fast signals of the elite graduates enable them to generate a statistically significant excess return of about 50 bps per year.

IV. Elite education, connections, and IPO allocations

The evidence reported in the preceding section indicates that the superior performance of mutual funds managed by elite graduates is generated almost exclusively from what we describe as fast components. One interpretation of this evidence is that the excess returns come from the superior connections rather than the superior ability of the elite graduates that manage the funds. In this section we consider a potential channel that can enable elite graduates to benefit from their connections; the allocation of IPOs. We examine whether connections of elite graduates increase the number of their IPO allocations as well as the quality of their IPO allocations.

A. Elite education and the odds of IPO allocations

We first estimate logit regressions of the binary indicator variable *Allocated* on the *EliteSchool* dummy, deal characteristics and fund characteristics. The dependent variable *Allocated* equals one if the fund holds the stock of any firm that went public in the prior quarter and zero otherwise. It should be noted that this is a noisy signal of whether or not a fund receives an IPO allocation, since funds can sell their allocations before the end of the quarter and can purchase IPOs they are not allocated in the secondary market. This noise is unlikely to be related to the education of the portfolio manager, and if anything, should bias us against finding a significant relation.

[Insert Table 5 here]

Column (1) of Table 5 reports the results of this regression. As expected, graduates of elite schools are allocated more IPOs. While this is not the focus of our paper, the coefficients of some of the control variables are also of interest. As expected, mutual funds are more likely to be allocated IPOs in bigger deals (larger proceeds). It should also be noted that bigger funds are allocated more IPOs, but after controlling for size, older funds are allocated fewer IPOs. Finally, higher turnover is associated with more IPO allocations, which is consistent with the idea that IPO allocations are used to reward mutual funds that generate large trading commissions.

To test if the positive relation of elite school education and allocation is driven by past allocation experience, we include an indicator variable for past allocation not through connection in Column (2). Specifically, we define a dummy variable *AllocatedBeforeNTC* that equals one if the fund in the past has received at least one IPO allocation not through educational connection from the same underwriter who conducts IPO in current month, and zero otherwise. The coefficient of *EliteSchool* remains positive and significant after controlling for *AllocatedBeforeNTC* suggests that while past allocation experience is important in affecting IPO allocation, it is likely the past allocation experience *through educational connection* that explains the predicting power of *EliteSchool* in IPO allocation. As the past allocation experience through connection will be very similar to our *EC*[14] measure which we will study next, we omit reporting the results for "past allocation through connection".

In Column (3), we estimate the logit regression reported in Column (1), but replace the *EliteSchool* dummy with the indicator variable *EC,* which measures whether or not the mutual fund's portfolio manager graduated from the same university as one of the underwriters. The

[14] According to the definition of *EC*, a fund is effectively connected to an underwriter if the portfolio manager attended the same university as the underwriter executives and has received at least one allocation from the same underwriter in the past. It will be identical to "past allocation through connection" if the fund manager and underwriter executives do not change.

regression reveals a strong relation between *EC* and IPO allocations. The estimated coefficient of *EC*, 1.07, indicates that all else equal, connected funds are about three times as likely to be allocated shares in a new issue as non-connected funds. The other control variables are virtually unchanged.

Column (4) includes both the *EliteSchool* and the *EC* indicator variables in the regression. The coefficient of *EliteSchool* becomes insignificant. This result is in sharp contrast with Column (2), indicating that at least for the allocations of IPOs, the benefits of an elite education comes entirely from educational connections.

B. Are connected mutual funds allocated better IPOs?

To estimate whether connected funds get allocations to better quality IPOs we consider two proxies for quality. The first is a direct proxy, *IR_adj*, which is the demeaned first-day IPO return. The second is indirect proxy, whether the IPO is offered in hot market period. We interact these variables with our EC variables in the regressions that predict IPO allocations. The results are reported in Table 6. In Column (2), the positive and significant coefficient of *EC*IR_adj* (the interactive term between *EC* and *IR_adj*) indicates that *EC* funds are more likely to be allocated IPOs that are more underpriced, or, in other words, IPOs with higher adjusted first-day returns, while the insignificant coefficient on *IR_adj* means that the probability of allocation to *NC* funds is not affected by deal quality.

[Insert Table 6 here]

Next we examine whether allocations depend on market conditions. In particular, we include the market condition indicator *HotMkt* and its interaction with *EC* to test if the preferential allocation of IPOs to *EC* funds depends on market conditions. The significantly negative coefficient of *HotMkt* in Column (3) indicates that *NC* funds are less likely to receive IPO allocations in hot markets than in cold markets. The positive and significant coefficient of *EC* indicates that *EC* funds have an edge in receiving allocations over *NC* funds even in cold markets, while the positive and significant coefficient on *EC*HotMkt* indicates that the gains from connections is even larger in hot markets.[15]

We also run these regressions separately in hot and cold market subsamples, which we report in Columns (4) and (5) respectively. The juxtaposition of these two columns provides a clearer picture: the significant coefficient of *EC* in both columns indicates that *EC* funds are more likely to get IPO allocations in both hot and cold markets, but the better allocation of high quality deals to *EC* funds *only* occurs in hot IPO markets, as indicated by the coefficients of *EC*IR_adj* in the hot and cold markets.

V. Do IPO allocations explain the superior performance of elite grads?

Up to this point we have presented evidence that is consistent with the Chevalier and Ellison (1999) finding that mutual funds managed by graduates of elite universities slightly outperform their counterparts from less prestigious universities. We have presented evidence that the superior performance comes solely from what we have characterized as the fast component, i.e., stock picks whose excess returns are realized within the quarter they are selected. Since these quickly realized excess returns can be generated from the allocation of underpriced IPOs we examined whether the connections of the elite university graduates lead to better IPO allocations and find that, indeed, they do.

[15] In unreported tests, we explore various definitions of market conditions, including those based on monthly IPO volume and average underpricing. The results remain qualitatively the same as in Column (3) of Table 4.

In this section, we "connect the dots" and examine the extent to which the return gap realized by the elite graduates can be attributed to their superior IPO allocations. We do this in two ways: we first run regressions to estimate the extent to which the return gap (the difference between the mutual fund return and returns of the beginning of quarter holdings) is due to IPO allocations. We then provide a "back of the envelope" calculation to approximate the gain due to IPO allocations based on our estimates of allocations and average one day returns on the IPO issuance date.

In Panel B of Table 4, we regress the fast component on the elite dummy, the *Allocated* dummy and their interaction term. In Column (1), we observe a large and significant coefficient on the *Allocated* dummy, indicating that an extra 10 basis points are earned by non-elite funds in months that they are allocated IPOs. The significant *EliteSchool* dummy indicates that elite-school funds generate an additional 4 basis point return gap over their non-elite counterparts in the months that they are not allocated IPOs. This observation suggests that fast performance generated by elite graduates may not come exclusively from IPO allocations. However, it is important to remember that our *Allocated* dummy is measured with error and that we may miss months where the elite graduates are allocated IPOs that are sold before the end of the quarter.

To investigate this possibility, Column (2) and Column (3) reports the same Fama-MacBeth regressions as in Column (1), but separately for High IR and Low IR months, where High IR (Low IR) month is defined as the month when the average first day return (IR) in that month is above (below) the median IR of all IPOs in the whole sample period. If the significant coefficient of the elite dummy in model (1) is related to unobserved IPO allocations, we should observe a larger coefficient of elite dummy in the high IR months. As we see in Columns (2) and (3), the coefficient of the elite dummy is significant only in the high IR months, indicating that the excess returns of the elite fund managers are likely to be IPO related even in the months where we cannot verify that they were allocated IPOs. In other words, the results from Panel B of Table 4, show the superior fast performance of elite fund managers can be fully explained by better IPO allocations.

A "back of envelope" calculation confirms that the magnitude of our estimates make sense. Note that from Column (1), compared with non-allocated/non-elite funds, allocated/elite funds have 11 (10+4-3) basis points higher fast returns. Conditioned on being allocated, elite funds receive 1.42 deals per month; and the mean first-day return of the allocated deals is 28.82 percent. If we assume the 11 basis point difference in the fast component all comes from IPOs, it would imply a portfolio weight of 0.27% (11/(2882*1.42)), which is very close to the observed portfolio weight of 0.29% for IPO stocks.

VI. IPO connection and fund performance

In this section we examine the returns that the holders of the mutual funds could have received from an implementable portfolio strategy. Specifically, we will be regressing mutual fund monthly returns *Mret*, on our *EC* indicator variable, measured at the beginning of each month *t*. The regression includes a number of fund characteristics, *ln(TNA)*, *ln(Age)*, *expense ratio* and *turnover ratio*, which change over time, we adopt White (1980) heteroskedasticity-robust standard errors with clustering at the month level to account for the cross-sectional dependence of fund returns; t-statistics are shown in parentheses.

$$Mret_{i,t} = \alpha + b_1 EC_{i,t} + cFund\ characteristics_{i,t-1} + u_i + v_t + \varepsilon_{i,t} \qquad (1)$$

Table 7 reports the estimates from the above regression.

[Insert Table 7 here]

Note that the observation unit in this regression is a fund-month, so *EC* is aggregated from fund-deal-month level as in Table 5 to fund-month level, which takes the value of 1 if a particular fund is effectively connected to *any* underwriters who conduct IPO in month *t* and 0 otherwise. The point estimate b_1 on our key variable of interest, *EC* in Column (1), suggests that in a given month, a mutual fund that is connected to an underwriter doing an IPO in that month earns a 0.14 percent (t=4.49) higher return than its non-connected peers with the same investment style and characteristics.

Since past allocations are used to define *EC*, it is also interesting to ask whether allocation experience also predicts future returns. To examine this possibility we introduce a dummy variable *AllocatedBefore*, which equals one if the fund has past allocation experience, through connection or not, from the same underwriter as the current one. As shown in Column (2) the coefficient of *AllocatedBefore* is not significant once we control for *EC*, indicating that *EC* is more important than past allocation experience in explaining IPO allocations.

Having shown that past business dealing alone cannot explain the superior performance of *EC* funds, we further examine whether past *EC* experience is related to the return premium. In Column (3) we include a dummy variable *NCnow_ECbefore* to capture a subsample of funds that are currently non-connected and have been effectively connected before; this variable is equal to one if the fund is not effectively connected in month *t* but was effectively connected in the past. In this regression, the benchmark to be compared against is the return of *NC* funds that do that have any prior *EC* experiences. The coefficient on *EC* captures the excess returns of *EC* funds relative to the benchmark and the coefficient of *NCnow_ECbefore* represents the excess return of

NC funds that have been *EC* before but are not connected to the incumbent underwriters. The significant coefficient on *EC* and the insignificant coefficient on *NCnow_ECbefore* imply that *EC* funds earn significantly higher return *only* when they are connected in the current month. In other words, *EC* funds outperform *NC only* in months when their connected underwriters conduct IPO activities.

In Column (4) we estimate the extent to which the return premium earned by *EC* funds comes from getting underpriced IPOs. To do this we introduce an interaction variable *EC*IR* that scales *EC* by the average IPO return in the month. If the connected mutual funds achieve their abnormal returns from their allocations of underpriced IPOs the returns should be especially strong when the IPOs are especially underpriced. The results in Column (4) confirm that this is indeed the case.

Our result that connections can have a material effect on performance should be contrasted with the observation in Cohen, Frazzini and Malloy (2008), who find that fund managers selectivity is improved by their connections, however, their portfolio weights on stocks with which they are connected is not sufficient to materially affect fund performance. Similarly, Coval and Moskowitz (2001) show that when mutual funds select local stocks, the performance is better, but again, not enough to materially influence the overall mutual fund returns. These results are not particularly surprising given that mutual funds are required to be diversified and can thus hold only modest amounts in any one stock.

A. Can IPO connections explain the Chevalier and Ellison (1999) finding?

Our Table 4 results, described earlier, showed that elite graduates earn modest abnormal returns. In this section, we run similar regressions that use the pooled regression methodology used by Chevalier and Ellison (1999).

Column (5) in Table 7 confirms Chevalier and Ellison (1999) finding that elite school fund managers outperform their non-elite school counterparts using the pooled regression methodology they employ. The economic magnitude (4 basis points per month)[16] is similar to that obtained by Chevalier and Ellison (1999). In Column (6) we introduce the variable, *EliteSchoolEC,*[17] which is a subset of elite school managers who are connected to the incumbent underwriter in the current month (i.e., those who conduct IPOs in the current month). The coefficient of *EliteSchool* measures the performance difference of elite school graduates (relative to non-elite school graduates) who are not effectively connected to incumbent underwriters. The coefficient on *EliteSchoolEC* captures the additional impact of elite school graduates who are also connected to the incumbent underwriters on fund performance. In Column (6), we find the coefficient of the former is not significant, while that of the latter is positive and significant at the 1 percent level, indicating that elite school graduates deliver higher fund performance *only* in months when they are connected to underwriters associated with IPOs. This finding suggests that the explanatory power of having an elite school manager (*EliteSchool*) on fund performance comes from connections rather than from stock selection ability. If elite education also affects stock selection ability, we would expect elite school managers to outperform their non-elite counterparts even in the months when they are not effectively connected to IPO underwriters.

[16] Chevalier and Ellison (1999) give an example that a fund manager who attends the 4th highest SAT score school outperforms a manager from the mean school in their sample by about 1 percent per year.
[17] Note that the variable *EliteSchoolEC* is first computed as an interaction term between the underwriter-fund-month level connection variable *EC* and the fund-month level variable *EliteSchool* and then aggregated to fund-month level; therefore it is not a direct product of the fund-month level terms.

B. Fama-MacBeth regressions

In this subsection, we test the performance predicting power of *EC* using Fama-Macbeth regressions (Fama and MacBeth (1973)). The results are reported in Table 8. The dependent variable *Mret* and the independent variable *EC* for fund *i* are obtained at month *t*, and fund characteristics such as *ln(TNA)*, *ln(Age)*, *exp_ratio*, *turn_ratio* and fund styles are obtained at the end of month *t-1*. Factor loadings are estimated from regressions of fund *i* monthly returns in excess of the one-month T-bill rate on the return of Carhart (1997) factors during the 36-month period from *t*-36 to *t*-1. The estimation and test periods are rolling one month at a time. We present mean coefficients and *t*-statistics for the cross-sectional regressions over 222 IPO months during the sample period.

[Insert Table 8 here]

The results in Column (1) of Table 8 are consistent with those in Table 7 with fixed effect regression specifications: the mean coefficient of the cross-sectional regressions on *EC* is positive and significant at the 5 percent significance level, though the magnitude of the point estimate is slightly smaller. We also note that the superior performance generated by having an effective connection is concentrated in hot IPO markets, as evidenced by the significant coefficient on *EC* in Column (2) and the non-significant coefficient in Column (3). These results reinforce our earlier findings in Column (4) of Table 7, where the performance of connected funds increase with average *IR*, which tends to larger in hot market.

C. A trading strategy based on effective connection

The return premium of *EC* funds we document in Table 7 suggests a trading strategy that may allow retail investors to indirectly exploit underpricing in the IPO markets. Note that retail investors have access to public information about mutual fund holdings, the educational backgrounds of fund managers, most of the top executives from underwriter firms, and scheduled IPO dates. Using this information we can create a trading strategy that buys *EC* mutual funds at the beginning of every month and holds them for one month.

Table 9 compares the profits from this strategy to an equivalent strategy that invests in *NC* funds. For *EC* (Row "1") and *NC* (Row "0") portfolios, we regress the monthly excess return, i.e. the equally weighted portfolio return in excess of one-month T-bill rate on the CAPM market risk factor, the Fama and French (1993) three factors and the Carhart (1997) four factors. We report the alphas and the beta coefficients on each of the factors in Panels A, B and C respectively, as well as t-stats calculated with White (1980) robust standard errors. We also report the alphas and betas of the portfolio that takes a long position in the *EC* funds and a short position in the *NC* funds. These alphas and betas are also reported in hot and cold market conditions separately.

[Insert Table 9 here]

There are on average 55 *EC* funds and 348 *NC* funds per month in our sample. We have 1 *EC* fund and 84 *NC* funds in the first sample month, January 1992; 49 *EC* and 256 *NC* funds in January 2000; and 74 *EC* and 675 *NC* funds in January 2008. From Row "1" in the "All Markets" sections of Panels A through C, we find that investing in an *EC* portfolio generates a significant (at the 1 percent level) monthly abnormal return of about 0.25 percent (t=2.70), or an equivalent 3 percent annual return using the CAPM alpha; 0.19 percent (t =2.80), or about 2.28 percent annualized abnormal return using the three-factor model; and 2.28 percent (t =2.85) using the four-factor model. The insignificant alphas in row "0" of the CAPM, three-factor and four-factor models indicate that investing in an *NC* portfolio will not yield an abnormal return. The difference between *EC* and *NC* portfolios is 1.92 percent (t =2.53), 2.40 percent (t =4.11), or 2.04 percent (t =3.80) per annum, depending on whether we use the CAPM, three-factor or four-factor model.

The profits from this strategy arise exclusively from hot market periods. Using the same hot/cold market definition detailed in "Deal Characteristics," we find that in hot IPO markets, the strategy of buying *EC* funds yields an annualized abnormal return of 5.64 percent (t =3.30) for the CAPM model, 3.96 percent (t =3.47) for the Fama-French model, and 4.08 percent (t =3.68) for the Carhart four-factor model. In cold IPO markets the return from investing in an *EC* portfolio is not significantly different from zero regardless of the benchmark factor model adopted. Estimated loadings of the risk factors imply that compared to their *NC* peers, the *EC* funds tend to exhibit a tilt towards small, growth-oriented and momentum stocks. This is not surprising, since *EC* funds are more likely to be allocated IPOs, which tend to be small, growth firms.

VII. Robustness Tests and Extentions

A. How do large fund families and fund locations influence our results?

In some large fund families, such as Fidelity, IPOs are allocated first to the family and then allocated to individual funds within the family. In such a setting the connections of individual fund managers are likely to play a smaller role in the IPO allocations. On the other hand, the large fund families may be better connected at the fund level (because of their size) and they may also be hiring more elite graduates. It is possible that the relation between big fund families, IPO connections, and elite graduates may be spuriously generating our results.

Geography may also play an important role in the allocation of IPOs. In particular, funds located in New York and Boston, which are attractive locations for elite graduates, may be better connected with underwriters. Our concern is that the link between geography, education and connections could also be spuriously generating our results.

To address these concerns we define two dummy variables. A *Big3* dummy, which takes a value of one, if a fund belongs to a fund family ranked among the top three at the end of year 2000[18], and zero otherwise and a *NYBoston* dummy, which takes the value of one if a fund is located in either New York or Boston and zero otherwise. Panel A of Table 10 shows that elite graduates are indeed more prevalent in big fund families and in New York and Boston. Specifically, 80.61% of the fund managers in the *Big3* und families come from elite schools versus 44.53% in non-Big3 families and 63.97% of the New York/Boston fund managers come from elite schools versus 43.21% in other cities. Similarly, 35.08% of *Big3* fund managers are connected to underwriters who conduct IPO in a given month versus 11.30% outside of *Big3* .The corresponding numbers are 24% and 10.46% respectively for funds in New York/Boston versus other cities.

Panel B of Table 10 revisits the return gap results from Table 4. The results in Column (1) indicate that there is clearly a *Big3* effect as indicted by the significant positive coefficient of *Big3*—a fund belonging to a *Big3* family that is not connected to IPO underwriters realizes a 7 bps per month greater return gap than its counterpart in non-Big3 family. However, the coefficient of *EC* is still significant in this regression. Interestingly, there is a negative interactive effect of a similar magnitude (7 basis points) between *EC* and *Big3*, suggesting that

[18] The top three mutual fund families ranked by the asset under management at the end of year 2000 are Fidelity, Vanguard and American Funds.

within a *Big3* family, the *EC* funds have no advantage over *NC*. This makes senses since IPO allocations are determined within family, thus connections of fund managers with IPO underwriters play no role in these families. In Column (2), we observe a significant *NYBoston* effect—a fund located in New York City or Boston earns an additional 3 basis points per month, which is consistent with greater network opportunities in these cities. Note that the interactive effect between *EC* and *NYBoston* is insignificant, suggesting the benefit of connection with IPO underwrites in New York/Boston is the same as in other cities. We draw similar conclusions from the results in Column (3) where we control for *Big3* and *NYBoston* effects simultaneously. Columns (4) to (6) have the same specifications as those in Column (1) to Column (3) except that *EC* dummy has been replaced by *EliteSchool* dummy. We find that the elite effects in all columns are close to that reported in Column (4) in Panel A of Table 4, suggesting that the results documented earlier are not driven by the fact that there are more elite graduates working for big fund families or in big cities such as New York or Boston.

In Table 11, we examine the robustness of the Table 5 results. In particular, we test if the result that the predictability of IPO allocations is due to connections generated from being in a large fund family or a financial center. To avoid relying on triple interactions, we repeat our tests in Table 5 on a sample of funds that are neither *Big3* nor *NYBoston*. We find that excluding *Big3* or *NYBoston* funds don't significantly affect our results and conclusions reached in Table 5. We also estimate the regressions from Table 7 on a sample that excludes *Big3* and *NYBoston* funds. The results are robust as reported in Table 12.

VIII. Conclusion

On average, graduates from elite universities have better analytical ability than those from less elite universities. This does not mean, however, that conditioned on being a mutual fund portfolio manager that a graduate from an elite university is likely to be smarter than his or her counterparts from less elite universities. If the distribution of analytical ability at elite universities and non-elite universities overlap, then mutual funds should be able to find equally smart managers from say the top 1% of the graduates of large state institutions. In contrast, given the concentration of talent at the elite schools, the distribution of connectivity at the elite and non-elite schools may overlap very little. As a result, while we see no reason to expect portfolio managers from elite universities to have better analytic ability than their non-elite counterparts, the elite grads may be better connected. Indeed, mutual funds may rationally hire elite graduates with less analytic ability, given the compensating benefits that can be generated by their connections.

The evidence in this paper suggests that the above characterization provides a fair description of the portfolio managers of active equity mutual funds. We replicate the Chevalier and Ellison (1999) finding that mutual fund managers from elite universities perform better and show that the better performance can be attributed to their better connections. Specifically, their performance is generated from their being allocated more underpriced IPOs.

As we show, retail investors, who may otherwise be shut out of the IPO market, can indirectly take advantage of IPO underpricing with a strategy that buys mutual funds that are managed by individuals who may be connected to the underwriters of upcoming IPOs. It is worth mentioning that the returns from this strategy are comparable to other mutual fund strategies that have been documented in the literature. Examples include Kacperczyk, Sialm and Zheng (2005), who find that the most concentrated funds earn an annual abnormal return of about 2.12 percent; Kacperczyk and Seru (2007) who document an performance gap of 2.16 percent between managers in top 30% and bottom 30% of their RPI measures; Kacperczyk, Sialm and Zheng (2008), who document a 3.41 percent return difference between the top and bottom decile portfolios based on their return gap measure; and Cremers and Petajisto (2009), who document a 2.55 percent excess return with their active share measure.

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Appendix

Table A.1 List of underwriters in the sample

This table provides a list of the underwriters included in the sample. We start with all of the underwriters involved in deals during the sample period of January 1992 to March 2012, and we extract the Permno for each underwriter firm from CRSP based on CUSIP. We then get the historical senior executive information from ExecuComp, which provides compensation and employment information for up to 9 executives per firm who file for the proxy statement, supplemented by Corporate Library from 2000. The sample of underwriters is further limited by the availability of relevant educational information; i.e., we keep only the senior executives we know graduated from US universities. The variable Sdate denotes the later of two dates: the date of the first IPO underwritten by the bookrunner during the sample period, or the start date of the Permno-bookrunner name link in CRSP. Edate represents the earlier of the date of the last IPO deal underwritten by the underwriter, or the end of the Permno-bookrunner link, which may happen when the underwriter goes bankrupt or is acquired by another bank. The "-" sign indicates that the start date is earlier than the start date of the sample period, or later than the end date of our sample period. The variable IsTop10 is a binary indicator variable that takes the value of one if the underwriter is among the top 10 underwriters that underwrite the greatest number of deals during the sample period.

Permno	Bookrunner	Sdate	Edate	IsTop10
10071	Alex Brown & Sons Inc	-	29/8/1997	1
36469	First Union Capital Markets Group	-	31/12/2008	0
38703	Wells Fargo Bank NA	3/11/1998	31/12/2012	0
47159	Fleet Boston	20/4/1992	31/3/2004	0
47248	Westfield Financial Corporation	3/10/2001	-	0
47896	Chase Manhattan	2/1/2001	31/12/2012	1
48071	Morgan JP Co Inc	-	29/12/2000	1
50200	Wachovia Securities Inc	-	31/8/2001	0
54463	PaineWebber Inc	-	3/11/2000	0
59408	Banc of America Securities LLC	1/10/1998	-	0
63220	Dain Rauscher Wessels	-	10/1/2001	0
64995	KeyCorp/McDonald Investments	-	-	0
65330	Legg Mason & Co Inc	-	-	0
66157	US Bancorp Piper Jaffray Inc	2/5/1998	1/1/2004	0
68144	Robinson-Humphrey Co	-	-	0
68304	Bear Stearns & Co Inc	-	30/5/2008	0
69032	Morgan Stanley	-	-	1
69649	Raymond James & Associates Inc	-	-	0
70519	Citigroup	8/10/1998	-	0
72726	State Street Capital Markets Corp	-	-	0
72996	Stifel Nicolaus & Co Inc	-	-	0
77043	Southwest Securities Group Inc	11/10/1991	-	0
78946	Dean Witter Reynolds Inc	23/2/1993	30/5/1997	0
80599	Lehman Brothers	31/5/1994	17/9/2008	1
83823	Hambrecht & Quist Inc	9/8/1996	10/12/1999	1
85653	Friedman Billings Ramsey Group	23/12/1997	9/6/2009	0
85944	Tucker Anthony Inc	2/4/1998	31/10/2001	0

86868	Goldman Sachs & Co	4/5/1999	-	1
89195	Principal Financial Securities Inc	23/10/2001	-	0
89826	Texas Capital Securities Inc	13/8/2003	-	0
89968	Piper Jaffray Cos	2/1/2004	-	0

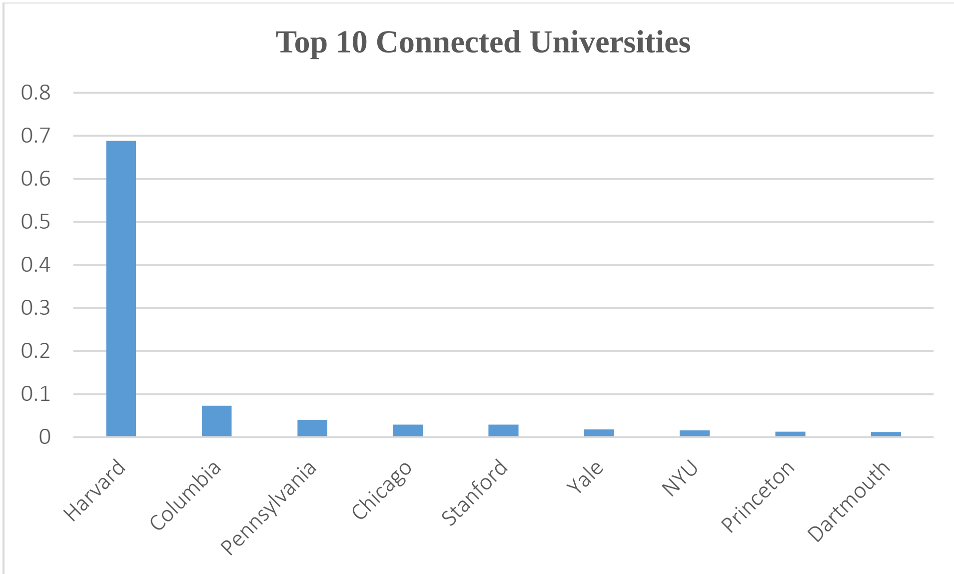

Figure 1 Top 10 most connected universities

Table 1 Fund characteristics

There are 82,739 fund-month observations in the sample. The table reports fund-month level summary statistics. *TNA* is the total net assets of a fund, or the closing market value of all securities owned by a fund plus all assets and minus all liabilities, in millions of dollars. *Expense ratio* is the annual ongoing operating expenses shareholders pay for a mutual fund, expressed as the percentage of total investment by shareholders. *Turnover ratio* is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month *TNA* of the fund. *Age* is the number of years since a fund's inception to the current date. *Hret* is the hypothetical buy-and-hold return in the return gap measure developed by Kacperczyk, Sialm and Zheng (2008). It is calculated as the weighted average of a hypothetical portfolio that invests in the most recent disclosed positions, where the weights are determined by the product of the number of shares held by the fund at the most recent reporting date and the stock prices at the end of month *t*-1 respectively. The variable *Mret* is the monthly return net of fees, expenses and brokerage commissions but before front-end and back-end loads. *Hret_DGTW* is characteristics adjusted buy-and-hold return, which is calculated by the weighted average of each stock's excess return over the DGTW (Daniel, Grinblatt, Titman, Wermers, 1997) benchmark in a mutual fund portfolio. The weight is determined in the same way as *Hret*. The variable *Hret_alpha* is the Carhart (1997) four-factor adjusted buy-and-hold return. The variable *RetGap* is calculated as the difference of fund reported return and hypothetical return net of expenses. We report statistics for the sample funds and for the elite school and non-elite school subsample of funds, and the p-values of the difference between the two.

	Sample funds	EliteSchool	Non-elite	p-Val. of Diff.
TNA ($mil)	1904	2687	1166	<0.001
Expense ratio (%)	1.18	1.16	1.19	<0.001
Turnover (%)	88.24	72.28	103.29	<0.001
Age	10.00	10.00	10.00	<0.001
Hret (%)	1.21	1.21	1.21	0.89
Mret (%)	1.09	1.10	1.08	0.68
Hret_DGTW(%)	0.05	0.06	0.04	0.17
Hret_alpha(%)	1.01	1.02	0.99	0.54
Mret_alpha(%)	0.88	0.90	0.85	0.20
RetGap	-0.02	-0.02	-0.03	0.35

Table 2 IPO characteristics

This table presents summary statistics at the IPO level. There are 1,636 IPOs in the sample. The variable *IR*, or initial return, is the difference between first trading day closing price and offer price, divided by offer price. *Size* is the market equity of IPO firms at the month-end following IPO, expressed in millions of dollars. *Proceeds* is the dollar size of the offering in the US market, excluding over-allotment shares and expressed in millions of dollars. The variable *% shares allocated to sample funds per deal* is the number of shares allocated to sample funds, divided by the total number of primary shares offered in the US market for a given IPO deal. The variables *prob. allocated to EC (EliteSchool) funds per deal* is the number of *EC (EliteSchool)* funds that get allocation for a given deal divided by the total number of *EC (EliteSchool)* funds in a given month; similarly, *prob. allocated to NC (Non-Elite) funds per deal* is the number of *NC (Non-Elite)* funds that get allocation for a given deal divided by the total number of *NC* (*Non-Elite)* funds in a given month. The variable *# of IPOs* per month is the number of new offerings per month in the sample. Market conditions are defined based on the monthly measure of the "hotness" of the IPO market used in Ibbotson, Sindelar and Ritter (1994): the percentage of deals that are priced above the midpoint of the original file price range. We define a binary indicator variable *HotMkt* as equal to one if the "hotness" is greater than the sample median over the 1980 to 2012 period, and zero otherwise. We then use this variable to divide the sample of deals into hot market deals and cold market deals.

	All Markets	Hot Market	Cold Market	p-Val. of Diff.
Number of deals	1,636	1,042	594	-
IR (%)	31.52	40.01	16.31	<0.001
Size ($ mil)	903.33	999.66	727.19	0.03
Proceeds ($ mil)	138.06	115.82	177.67	0.02
% shares allocated to sample funds	15.04	15.83	13.65	0.15
prob. allocated to EC funds per deal	0.06	0.07	0.05	0.08
prob. allocated to NC funds per deal	0.01	0.012	0.011	0.02
prob. allocated to EliteSchool funds per deal	0.02	0.02	0.01	0.01
prob. allocated to Non-Elite funds per deal	0.01	0.012	0.011	0.03
# of IPOs per month	11.27	12.64	8.86	<0.001

Table 3 Connection characteristics

This table provides connection- and education-related statistics. In Panel A, the variable *# of executives per underwriter* refers to the number of executives with educational information working at the underwriter for a given year. *# of portfolio managers per fund* is the number of mutual fund managers with educational information per fund in a given year. The variable *# of effective connections per fund-month* is the number of effectively connected underwriters per fund-month observation, and *# of effective connections per EC fund is the number of effectively connected underwriters per fund per month conditional on being an EC fund*. *% effectively connected months per fund* is the number of effectively connected months divided by the total number of months in sample for a given fund, and *% effectively connected month per elite school fund* is the number of effectively connected months divided by the total number of months in sample for a fund with manager(s) who graduated from an elite school. *% effectively connected funds per IPO* represents the number of effectively connected funds out of the total number of funds associated with an IPO in a given month. *% effectively connected funds per month* denotes the percentage of funds that are effectively connected each month. In Panel B, we present the five universities most commonly attended by underwriter firm executives and portfolio managers.

Panel A Connection characteristics

	Median	Mean	Std. Dev.
# of executives per underwriter-year	4.00	4.64	1.56
# of portfolio managers per fund-year	1.00	1.57	1.17
# of effective connections per fund-month	0	0.40	1.29
# of effective connections per EC fund-month	4.00	4.41	2.98
% effectively connected months per fund	0	13.74	24.05
% effectively connected months per elite school fund	13.23	25.41	28.83
% effectively connected funds per IPO	7.69	6.76	4.86
% effectively connected funds per month	13.29	12.56	5.89

Panel B Top 5 most attended institutions

	Average # of executives	% of sample executives		Average # of PMs	% of sample PMs
Harvard	60	12.56	Harvard	45	4.07
Stanford	19	4.03	Pennsylvania	45	4.07
Pennsylvania	16	3.32	NYU	35	3.17
Yale	14	2.84	Chicago	33	2.98
Columbia	14	2.84	Columbia	31	2.81

Table 4 Do elite school funds outperform?

We test the outperformance of elite school funds with Fama-MacBeth regressions (Fama and MacBeth (1973)) in Panel A and subsample regressions in Panel B. We employ four performance measures in Panel A: the first one based on the monthly reported fund returns (*Mret*), the middle two based on hypothetical buy-and-hold return (*Hret*) on a mutual fund portfolio that invests in the holdings disclosed previously, while the last one based on return gap (*RetGap*) as detailed in Kacperczyk, Sialm and Zheng (2008). In particular, the variable *Mret_alpha* is the monthly return net of fees, expenses and brokerage commissions and before front-end and back-end loads, adjusted for Carhart four factors. We use DGTW (Daniel, Grinblatt, Titman, Wermers, 1997) adjusted hypothetical return (*Hret_DGTW*) and Carhart (1997) four-factor adjusted hypothetical return (*Hret_alpha*) in the middle two columns. The variable *RetGap* is calculated as the difference of fund reported return and hypothetical return net of expenses. In Panel A, the dependent variables and the key independent variable *EliteSchool* for fund *i* are obtained at month *t* and the dependent variables are expressed in percentage terms. The key independent variable *EliteSchool* is the binary indicator variable for funds with top school graduated managers, which equals to one if the portfolio manager has attended one of the top ten universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and zero otherwise. Control variables of fund characteristics include investment style fixed effects, natural logarithm of fund size (*ln(TNA)*) and fund age (*ln(Age)*), expense ratio (*exp_ratio*) which is the annual ongoing operating expenses shareholders pay for the mutual fund, expressed as percentage of total investment by shareholders and turnover ratio (*turn_ratio*) which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month *TNA* of the fund. All fund characteristics are obtained at the end of month *t*-1. In Panel B we investigate whether the return gap is indeed due to IPO allocation. In Column (1) of Panel B, we make use of the same regression settings and the same control variables as the one in Column (4) of Panel A, with the dependent variable being return gap (*RetGap*). The additional independent variable *Allocated* equals to one if the fund is found to hold IPO stock within the first quarter of its issuance, and zero otherwise. In Column (2) and (3) we perform subsample tests based on the mean value of the IPO first-day returns, i.e. a month is classified as High IR month if the value of the mean IPO first-day return is greater than or equal to the sample median, and Low IR otherwise. For both panels, the estimation and test periods are rolling one month at a time. The cross-section estimation is performed using the Fama-MacBeth method over the 222 IPO months during the sample period of January 1992 to March 2012. The means of coefficients are presented with t-statistics in parentheses. The symbols ∗∗∗, ∗∗, and ∗ denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Panel A Fama-MacBeth regression

	(1) *Mret_alpha*	(2) *Hret_DGTW*	(3) *Hret_alpha*	(4) *RetGap*
EliteSchool	0.05	0.01	0.01	0.04***
	(1.52)	(0.48)	(0.15)	(2.92)
ln(TNA)	-0.02	-0.01	-0.02	0.00
	(-1.19)	(-0.67)	(-1.59)	(0.24)
ln(Age)	239.46	436.64**	411.27**	-185.97*
	(1.44)	(2.59)	(2.03)	(-1.78)
exp_ratio	1.64	1.66	6.08	4.60**
	(0.27)	(0.42)	(0.90)	(2.36)
turn_ratio	-0.01	-0.01	-0.01	0.01
	0.05	0.01	0.01	0.04***
Constant	0.80***	0.32	1.02***	-0.21***
	(2.95)	(1.49)	(3.60)	(-2.65)
Observations	68,015	74,481	67,838	82,739
R-squared	0.39	0.29	0.39	0.14
Style FE	Yes	Yes	Yes	Yes

Panel B Fama-MacBeth regression: High versus Low IR months			
Dependent Variable: *RetGap*			
	(1)	(2) High IR	(3) Low IR
EliteSchool	0.04***	0.06***	-0.00
	(2.85)	(3.37)	(-0.04)
*EliteSchool*Allocated*	-0.03	-0.07	0.02
	(-0.61)	(-1.05)	(0.31)
Allocated	0.10***	0.14***	0.06
	(2.62)	(2.64)	(1.04)
Constant	-0.21**	-0.35***	-0.09
	(-2.56)	(-2.90)	(-0.80)
Observations	82,739	41,461	41,278
R-squared	0.15	0.14	0.16
Fund controls	Yes	Yes	Yes
Style FE	Yes	Yes	Yes

Table 5 Are elite school funds more likely to receive allocation?

We run logit regressions of the binary indicator variable *Allocated* on the *EliteSchool* dummy, deal characteristics and fund characteristics in Column (1) and (2) of Table 5. The dependent variable *Allocated* equals to one if the fund is found to hold IPO stock within the first quarter of its issuance, and zero otherwise The key independent variable *EliteSchool* is the binary indicator variable for funds with top school graduated managers, which equals to one if the portfolio manager has attended one of the top ten universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and zero otherwise. The binary indicator variable *AllocatedBeforeNTC* equals to one if the fund has obtained IPO allocation through the same underwriter in the past and not educationally connected then, and zero otherwise. The other independent variable *EC* is the effective connection indicator denoting that the fund manager and underwriter executive attended the same school and the fund has received at least one IPO allocation from the same connected underwriter in the past. We control for the deal characteristics of the natural logarithm of dollar proceeds (*ln(Proceeds)*). Fund characteristics include investment style fixed effects, natural logarithm of fund size (*ln(TNA)*) and fund age (*ln(Age)*), expense ratio (*exp_ratio*) which is the annual ongoing operating expenses shareholders pay for the mutual fund, expressed as percentage of total investment by shareholders and turnover ratio (*turn_ratio*) which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month *TNA* of the fund. Standard errors are heteroskedasticity robust and clustered at the month level. Z-stats are shown in parentheses. The sample period is from January 1992 to March 2012. ∗∗∗, ∗∗, and ∗ denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Dependent variable: *Allocated*				
	(1)	(2)	(3)	(4)
EliteSchool	0.28***	0.39***		0.05
	(8.55)	(11.66)		(1.37)
AllocatedBeforeNTC		1.24***		
		(32.85)		
EC			1.07***	1.05***
			(24.27)	(22.31)
ln(Proceeds)	0.22***	0.23***	0.24***	0.24***
	(8.87)	(9.06)	(9.31)	(9.31)
ln(Size)	0.35***	0.33***	0.32***	0.32***
	(15.49)	(14.38)	(13.92)	(13.92)
ln(TNA)	0.27***	0.21***	0.24***	0.24***
	(22.09)	(17.63)	(20.34)	(20.26)
ln(Age)	-893.73***	-1,051.89***	-1,018.53***	-1,018.14***
	(-6.92)	(-8.58)	(-8.07)	(-8.06)
exp_ratio	77.87	-35.53	26.77	21.45
	(1.09)	(-0.49)	(0.38)	(0.30)
turn_ratio	0.04***	0.04***	0.03***	0.03***
	(5.56)	(5.64)	(4.54)	(4.56)
Constant	-5.42***	-5.86***	-5.29***	-5.32***
	(-24.90)	(-26.48)	(-24.70)	(-24.61)
Observations	480,817	480,817	480,817	480,817
Style FE	Yes	Yes	Yes	Yes

Table 6 Are connected mutual funds allocated better IPOs?

We run logit regressions of the binary indicator variable *Allocated* on the *EC* dummy, deal characteristics and fund characteristics in Column (1) and (2). The key independent variable *EC* is the effective connection indicator denoting that the fund manager and underwriter executive attended the same school and the fund has received at least one IPO allocation from the same connected underwriter in the past. The deal characteristics include the natural logarithm of dollar proceeds (*ln(Proceeds)*) and log IPO size measured at the end of IPO month (*ln(Size)*). Fund characteristics include investment style fixed effects, natural logarithm of fund size (*ln(TNA)*) and fund age (*ln(Age)*), expense ratio (*exp_ratio*) which is the annual ongoing operating expenses shareholders pay for the mutual fund, expressed as percentage of total investment by shareholders and turnover ratio (*turn_ratio*) which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month *TNA* of the fund. In Column (2) we control for adjusted first-day return of IPO deals, *IR_adj*, which is the demeaned version of *IR*, as well as the interaction between *EC* and *IR_adj*. We introduce the market condition indicator *HotMkt* and its interaction with *EC* in Column (3). Market conditions are defined based on the monthly measure of the "hotness" of the IPO market used in Ibbotson, Sindelar and Ritter (1994): the percentage of deals that are priced above the midpoint of the original file price range. We define the binary indicator variable *HotMkt* as equal to one if the "hotness" is greater than the sample median over the 1980 to 2012 period, and zero otherwise. We repeat the logit regression in Column (2) in hot and cold IPO market subsamples in Columns (4) and (5), respectively. Standard errors are heteroskedasticity robust and clustered at the month level. Z-stats are shown in parentheses. The sample period is from January 1992 to March 2012. ∗∗∗, ∗∗, and ∗ denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Dependent variable: *Allocated*					
	(1)	(2)	(3)	(4)	(5)
EC	1.07***	1.07***	0.96***	1.12***	0.97***
	(24.27)	(25.14)	(13.45)	(23.36)	(13.57)
IR_adj		-0.03		-0.13***	0.46***
		(-0.62)		(-3.34)	(4.31)
*EC*IR_adj*		0.13***		0.18***	-0.02
		(3.36)		(3.89)	(-0.22)
HotMkt			-0.15***		
			(-2.80)		
*EC*HotMkt*			0.19**		
			(2.15)		
ln(Proceeds)	0.24***	0.24***	0.23***	0.22***	0.32***
	(9.31)	(8.97)	(9.20)	(7.70)	(6.05)
ln(Size)	0.32***	0.31***	0.33***	0.33***	0.24***
	(13.92)	(12.37)	(14.40)	(11.73)	(4.47)
ln(TNA)	0.24***	0.24***	0.24***	0.27***	0.20***
	(20.34)	(20.19)	(20.58)	(16.33)	(12.74)
ln(Age)	-1,018.53***	-1,029.29***	-1,069.95***	-1,362.75***	-714.09***
	(-8.07)	(-7.97)	(-8.58)	(-9.17)	(-3.52)
exp_ratio	26.77	30.24	29.02	107.31	-87.74
	(0.38)	(0.43)	(0.41)	(1.20)	(-0.75)
turn_ratio	0.03***	0.03***	0.03***	0.03***	0.03**
	(4.54)	(4.57)	(4.66)	(4.29)	(2.49)
Constant	-5.29***	-5.32***	-5.21***	-5.49***	-5.06***
	(-24.70)	(-24.45)	(-24.09)	(-22.54)	(-12.18)
Observations	480,817	476,501	480,817	284,327	190,377
Style FE	Yes	Yes	Yes	Yes	Yes

Table 7 IPO connection, elite school funds, and fund performance

In this set of regressions, we explore the impact of effective connection on fund return. All regressions are controlled for month fixed effects and fund investment style fixed effects. We define effective connection (*EC*) as a binary variable that equals to one if the fund is connected in month *t* and has received IPO allocation from the same connected underwriter at least once prior to month *t*. The dummy variable *AllocatedBefore* is equal to one if the fund has received IPO allocation from the same underwriter before, regardless of its connection status in month *t*. The variable *NCnow_ECbefore* is a binary indicator variable that takes the value of one if the fund was effectively connected before but is not connected in the current month, and zero otherwise. The interaction term *EC*IR* is the interaction between *EC* and the monthly mean first day return of IPO deals. *EliteSchool* is the binary indicator variable for funds with top school graduated managers, which equals to one if the portfolio manager has attended one of the top ten universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and zero otherwise. The variable *EliteSchoolEC* is a subset of elite school managers who are connected to the incumbent underwriter in the current month (i.e., those who conduct IPOs in the current month). The dependent variable *Mret* is monthly return after fees, expenses and brokerage commissions but before front-end and back-end loads and expressed in percentage terms. The following fund characteristics controls are included in the regression but not shown in the table. *ln(TNA)* is the natural logarithm of *TNA* of a fund. *ln(Age)* is the natural logarithm of fund age. The variable *exp_ratio* is the annual ongoing operating expenses shareholders pay for the mutual fund, expressed as percentage of total investment by shareholders; *turn_ratio* is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month *TNA* of the fund. *MKTRF beta*, *SMB beta*, *HML beta* and *UMD beta* are regression coefficients from time-series regressions of monthly fund excess return on T-bill rate, on monthly Carhart (1997) four factors, using past three year return. All regressions are controlled for month fixed effects and fund investment style fixed effects. The sample period is from January 1992 to March 2012. Robust standard errors (White (1980)) are used and are clustered at month level. T-stats are shown in parentheses. The symbols ∗∗∗, ∗∗, and ∗ denote significance at the 1 percent, 5 percent, and 10 percent level respectively.

Dependent variable: *Mret*						
	(1)	(2)	(3)	(4)	(5)	(6)
EC	0.14***	0.12***	0.15***	-0.04		
	(4.49)	(3.95)	(4.89)	(-0.81)		
AllocatedBefore		0.04				
		(1.43)				
NCnow_ECbefore			0.03			
			(1.17)			
*EC*IR*				0.88***		
				(3.36)		
EliteSchool					0.04**	0.01
					(1.98)	(0.52)
EliteSchoolEC						0.10***
						(2.93)
Constant	1.06***	1.03***	1.04***	1.07***	1.03***	1.03***
	(5.12)	(4.95)	(5.08)	(5.19)	(4.52)	(4.51)
Observations	81,084	81,084	81,084	80,653	81,084	81,084
R-squared	0.73	0.73	0.73	0.73	0.73	0.73
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8 IPO connection and fund performance (Fama-MacBeth regressions)

We test the robustness of our key results in Table 7 with Fama-MacBeth regressions (Fama and MacBeth (1973)). The dependent variable *Mret* and the independent variable *EC* for fund *i* are obtained at month *t*; fund characteristics such as *ln(TNA), ln(Age), exp_ratio, turn_ratio* and fund styles are obtained at the end of month *t*-1. Market conditions are defined based on the monthly measure of the "hotness" of the IPO market used in Ibbotson, Sindelar and Ritter (1994): the percentage of deals that are priced above the midpoint of the original file price range. We define the binary indicator variable *HotMkt* as equal to one if the "hotness" is greater than the sample median over the 1980 to 2012 period, and zero otherwise. The dependent variable *Mret* is in percentage terms. Factor loadings (*mktrf_beta, smb_beta, hml_beta, umd_beta*) are estimated from regressions of fund *i* monthly return in excess of the one-month T-bill rate on returns of Carhart (1997) factors during the 36-month period from t-36 to t-1. The estimation and test periods are rolling one month at a time. The cross-section estimation is performed using the Fama-MacBeth method over the 222 IPO months during the sample period of January 1992 to March 2012; the results appear in Column (1). Column (2) and (3) present the Fama-MacBeth regression results for the hot and cold IPO market subsamples. The means of coefficients are presented with t-statistics in parentheses. The symbols ∗∗∗, ∗∗, and ∗ denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Dependent variable: *Mret*			
	(1) Full Sample	(2) Hot Mkt	(3) Cold Mkt
EC	0.09**	0.14**	0.02
	(2.11)	(2.11)	(0.55)
ln(TNA)	-0.01	-0.01	-0.01
	(-1.24)	(-0.54)	(-1.31)
ln(Age)	63.33	82.823	39.543
	(0.46)	(0.42)	(0.21)
exp_ratio	-0.87	3.30	-5.95*
	(-0.36)	(0.93)	(-1.86)
turn_ratio	-0.01	-0.01	-0.01
	(-0.54)	(-0.380)	(-0.39)
mktrf_beta	0.38	0.66*	0.03
	(1.47)	(1.98)	(0.08)
smb_beta	0.21	0.48*	-0.13
	(1.06)	(1.67)	(-0.51)
hml_beta	0.23	0.28	0.17
	(1.09)	(0.94)	(0.58)
umd_beta	0.07	-0.00	0.16
	(0.26)	(-0.01)	(0.44)
Constant	1.24***	1.58***	0.82
	(3.65)	(3.51)	(1.59)
Observations	81,084	40,701	40,383
R-squared	0.6033	0.5991	0.6084
Style FE	Yes	Yes	Yes

Table 9 Trading strategy based on effective connection

We present portfolio alpha and factor loadings in this table. Portfolios are formed by sorting all sample funds every month into one of two bins according to the value of *EC*; then, for the test month t, we compute the monthly average excess return for the two portfolios and regress the excess return on the monthly market risk factor, as well as the Fama and French (1993) and Carhart (1997) factors. The table presents the intercepts from these regressions, alphas, and coefficients on the respective risk factors, as well as the t-statistics (in parentheses). Rows 1 and 0 display the results for *EC* and *NC* portfolios; the "Difference" row presents the result of regressing the hedged return of a long/short portfolio of *EC* and *NC* portfolios on risk factors. Panels A, B and C present results for the CAPM, three-factor and four-factor regressions, respectively. Market conditions are defined based on monthly measure of "hotness" of the IPO market used in Ibbotson, Sindelar and Ritter (1994): the percentage of deals that are priced above the midpoint of the original file price range. We define the binary indicator variable *HotMkt* as equal to one if the "hotness" is greater than the sample median over the 1980 to 2012 period, and zero otherwise. We then use this variable to separate the sample into hot and cold market subsamples. The sample period is from January 1992 to March 2012. Robust standard errors (White (1980)) are used.

Panel A CAPM alpha

Effective	Connection	Alpha	RMRF
All Markets	1	0.25	1.03
		(2.70)	(41.97)
	0	0.09	0.96
		(1.39)	(47.16)
	Difference	0.16	0.08
		(2.53)	(4.01)
Hot IPO Markets	1	0.47	1.00
		(3.30)	(24.10)
	0	0.20	0.93
		(2.17)	(30.79)
	Difference	0.26	0.07
		(2.71)	(2.41)
Cold IPO Markets	1	0.02	1.05
		(0.14)	(37.69)
	0	-0.02	0.98
		(0.21)	(36.37)
	Difference	0.03	0.07
		(0.43)	(3.18)

Panel B Three-factor alpha

Effective	Connection	Alpha	RMRF	SMB	HML
All Markets	1	0.19	0.99	0.27	0.05
		(2.80)	(52.64)	(8.07)	(1.67)
	0	-0.01	0.95	0.19	0.13
		(0.25)	(70.71)	(9.22)	(6.88)
	Difference	0.20	0.04	0.08	-0.09
		(4.11)	(2.64)	(3.28)	(3.93)
Hot IPO Markets	1	0.33	0.98	0.27	0.06
		(3.47)	(31.12)	(7.05)	(1.46)
	0	0.04	0.93	0.19	0.14
		(0.51)	(43.70)	(7.83)	(5.23)
	Difference	0.30	0.05	0.08	-0.09
		(4.11)	(2.19)	(2.55)	(2.43)
Cold IPO Markets	1	0.03	0.99	0.26	0.02
		(0.33)	(39.98)	(3.94)	(0.60)

0	-0.05	0.97	0.20	0.12
	(0.74)	(54.25)	(4.26)	(4.16)
Difference	0.08	0.02	0.06	-0.10
	(1.21)	(1.34)	(2.21)	(3.75)

Panel C Four-factor alpha

Effective	Connection	Alpha	RMRF	SMB	HML	UMD
All Markets	1	0.19	0.99	0.27	0.04	-0.00
		(2.85)	(51.44)	(8.23)	(1.62)	(0.18)
	0	0.02	0.94	0.20	0.12	-0.03
		(0.41)	(63.83)	(10.14)	(6.90)	(2.74)
	Difference	0.17	0.05	0.07	-0.08	0.03
		(3.80)	(3.46)	(2.92)	(3.56)	(2.16)
Hot IPO Markets	1	0.34	0.97	0.27	0.05	-0.01
		(3.68)	(31.58)	(7.19)	(1.00)	(0.56)
	0	0.10	0.91	0.19	0.10	-0.05
		(1.42)	(40.46)	(8.16)	(4.08)	(3.70)
	Difference	0.25	0.07	0.08	-0.06	0.04
		(3.77)	(3.27)	(2.47)	(1.42)	(2.04)
Cold IPO Markets	1	0.01	0.99	0.26	0.02	0.02
		(0.11)	(41.34)	(3.73)	(0.46)	(0.58)
	0	-0.04	0.97	0.20	0.12	-0.00
		(0.68)	(57.02)	(4.76)	(3.84)	(0.15)
	Difference	0.05	0.03	0.05	-0.11	0.03
		(0.79)	(1.60)	(1.55)	(4.07)	(1.34)

Table 10 Robustness checks of big family and big city on fund performance

We test the robustness of the relationship between *EliteSchool/EC* and *RetGap* in this table. Panel A presents the descriptive statistics of the percentage of *EliteSchool*/*EC* fund-month observations in the biggest three families ranked by the total net asset at the end of 2000, the rest of the families, funds that are located in New York or Boston, and funds that are in the rest of the US cities separately, together with an overall statistic in the whole sample. The dependent variable *RetGap* in Panel B is calculated as the difference of fund reported return and hypothetical return net of expenses; they are obtained at month *t* and expressed in percentage terms. The key independent variable *EliteSchool* is the binary indicator variable for funds with top school graduated managers, which equals to one if the portfolio manager has attended one of the top ten universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and zero otherwise. The other independent variable *EC* is the effective connection indicator denoting that the fund manager and underwriter executive attended the same school and the fund has received at least one IPO allocation from the same connected underwriter in the past. The variable *Big3* is an indicator variable that takes the value of unity if the fund belongs to one of the biggest three fund families ranked by total asset at the end of 2000, and zero otherwise. The dummy variable *NYBoston* equals to one if the fund family is either located in New York City or Boston, and zero otherwise. Control variables of fund characteristics include investment style fixed effects, natural logarithm of fund size (*ln(TNA)*) and fund age (*ln(Age)*), expense ratio (*exp_ratio*) which is the annual ongoing operating expenses shareholders pay for the mutual fund, expressed as percentage of total investment by shareholders and turnover ratio (*turn_ratio*) which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month *TNA* of the fund. All fund characteristics are obtained at the end of month *t*-1. The estimation and test periods are rolling one month at a time. The cross-section estimation is performed using the Fama-MacBeth method over the 222 IPO months during the sample period of January 1992 to March 2012. The means of coefficients are presented with t-statistics in parentheses. The symbols ∗∗∗, ∗∗, and ∗ denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Panel A Percentage of Elite/EC fund-month by category

	Big3	Non-Big3	NYBoston	Non- NYBoston	Overall
% of EliteSchool fund-month	80.61	44.53	63.97	43.21	48.23
% of EC fund-month	35.08	11.30	24.00	10.46	13.74

Panel B Fama-MacBeth regression

Dependent variable: *RetGap*

	(1)	(2)	(3)	(4)	(5)	(6)
EC	0.06**	0.05**	0.06**			
	(2.44)	(2.06)	(2.30)			
*EC*Big3*	-0.07*		-0.06*			
	(-1.96)		(-1.78)			
*EC*NYBoston*		-0.00	-0.01			
		(-0.21)	(-0.35)			
EliteSchool				0.03***	0.03**	0.03**
				(2.65)	(2.45)	(2.33)
*EliteSchool*Big3*				-0.03		-0.03
				(-0.61)		(-0.54)
Big3	0.07***		0.06***	0.07		0.06
	(3.23)		(2.72)	(1.52)		(1.23)
NYBoston		0.03***	0.03***		0.02**	0.02*
		(3.46)	(3.07)		(2.44)	(1.71)
Constant	-0.16**	-0.18**	-0.17**	-0.18**	-0.21***	-0.19**
	(-2.09)	(-2.24)	(-2.22)	(-2.31)	(-2.77)	(-2.47)

Observations	82,739	82,739	82,739	82,739	82,739	82,739
R-squared	0.14	0.14	0.15	0.15	0.14	0.15
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11 Robustness checks of big family and big city on allocation

We test the robustness of Table 5 in this table. Specifically we run logit regressions of the binary indicator variable *Allocated* on the *EliteSchool* dummy, deal characteristics and fund characteristics and excluding the funds that belong to the biggest three fund families and funds that are located in either New York or Boston in each column. The dependent variable *Allocated* equals to one if the fund is found to hold IPO stock within the first quarter of its issuance, and zero otherwise The independent variable *EliteSchool* is the binary indicator variable for funds with top school graduated managers, which equals to one if the portfolio manager has attended one of the top ten universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and zero otherwise. In the other independent variable *EC* is the effective connection indicator denoting that the fund manager and underwriter executive attended the same school and the fund has received at least one IPO allocation from the same connected underwriter in the past. We control for the deal characteristics of the natural logarithm of dollar proceeds (*ln(Proceeds)*). Fund characteristics that we control for include investment style fixed effects, natural logarithm of fund size (*ln(TNA)*) and fund age (*ln(Age)*), expense ratio (*exp_ratio*) which is the annual ongoing operating expenses shareholders pay for the mutual fund, expressed as percentage of total investment by shareholders and turnover ratio (*turn_ratio*) which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month *TNA* of the fund. Standard errors are heteroskedasticity robust and clustered at the month level. Z-stats are shown in parentheses. The sample period is from January 1992 to March 2012. ∗∗∗, ∗∗, and ∗ denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Dependent variable: *Allocated*			
	(1)	(2)	(3)
EliteSchool	0.33***		0.06
	(8.05)		(1.19)
EC		1.29***	1.26***
		(23.27)	(19.54)
ln(TNA)	0.28***	0.24***	0.24***
	(20.28)	(17.64)	(17.70)
ln(Age)	-1,154.94***	-1,269.79***	-1,268.20***
	(-7.60)	(-8.44)	(-8.43)
exp_ratio	479.63***	435.33***	426.42***
	(8.65)	(7.41)	(7.24)
turn_ratio	0.03***	0.03***	0.03***
	(5.01)	(4.02)	(4.03)
ln(Proceeds)	0.42***	0.41***	0.41***
	(13.52)	(13.94)	(13.91)
Constant	2,261.37***	3,537.07***	2,469.94***
	(6.43)	(10.53)	(7.04)
Observations	461,707	406,887	461,707
Fund Controls	Yes	Yes	Yes
Style FE	Yes	Yes	Yes

Table 12 Robustness checks of big family and big city on fund performance

We test the robustness of results in Table 6 by excluding funds that belong to the biggest three families and funds that are located in big cities. The dependent variable *Mret* is the monthly return net of fees, expenses and brokerage commissions but before front-end and back-end loads and expressed in percentage terms. The dummy variable *EliteSchool* is the indicator variable for funds with top school graduated managers, which equals to one if the portfolio manager has attended one of the top ten universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and zero otherwise. The dummy variable *EC* is the effective connection indicator denoting that the fund manager and underwriter executive attended the same school and the fund has received at least one IPO allocation from the same connected underwriter in the past. Fund characteristics that we control for include investment style fixed effects, natural logarithm of fund size (*ln(TNA)*) and fund age (*ln(Age)*), expense ratio (*exp_ratio*) which is the annual ongoing operating expenses shareholders pay for the mutual fund, expressed as percentage of total investment by shareholders and turnover ratio (*turn_ratio*) which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month *TNA* of the fund. All regressions include month fixed effects. Standard errors are heteroskedasticity robust and clustered at the month level.

Dependent variable: *Mret*		
	(1)	(2)
EliteSchool	0.05**	0.03
	(2.27)	(1.15)
EliteSchoolEC		0.10**
		(2.23)
Constant	0.80***	0.80***
	(2.78)	(2.78)
Observations	56,923	56,923
R-squared	0.72	0.72
Month FE	Yes	Yes
Fund Controls	Yes	Yes
Style FE	Yes	Yes