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

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Abstract

Mutual fund managers with degrees from elite universities tend to outperform their counterparts from less elite universities. We show that the better performance of elite graduates is generated from their better connections with underwriters that facilitate allocations to underpriced initial public offerings (IPOs). Indeed, we find that the funds outperform *only* in months when they are connected to underwriters issuing IPOs. A strategy of buying mutual funds in months when they are connected to underwriters scheduled to issue IPOs generates significant abnormal returns, as high as 4.08% per annum in hot markets.

I. Introduction

Since the seminal work of Jensen (1968), researchers have explored the possibility that some mutual fund managers generate better performance than others. Although the original Jensen (1968) study failed to detect abnormal performance, the evidence presented by Grinblatt and Titman (1989) and others suggests that

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some mutual fund managers have special skills or information.[1] A natural question is whether mutual fund managers who are in some sense better trained or more talented achieve consistent superior performance.

The research in this article is motivated by Chevalier and Ellison (1999), who document that mutual fund managers who attended more selective schools outperform those who did not.[2] The question we ask is whether this relation between mutual fund performance and elite education, which also exists in our more recent and longer time series, reflects the superior ability and training of the elite graduates or, alternatively, the broader social network that these elite schools provide. In other words, is their superior performance generated by *who they know or what they know?*

To better understand the benefits of superior connections, we examine the initial public offering (IPO) allocations of mutual funds. Given the evidence of IPO underpricing,[3] being allocated (especially hot) IPOs is a potential source of the observed superior 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 who underwrote 1,636 IPO deals during our sample period (Jan. 1992–Mar. 2012). We find that mutual funds managed by elite graduates are indeed allocated more IPOs, indicating that this is likely to be one source of their superior performance.

To explore the link between educational connections and IPO allocations, we categorize the relation between a mutual fund and an underwriter with an upcoming IPO along two dimensions. The first dimension is whether or not the mutual fund is managed by an individual who attended the same university as one of the officers of the bank underwriting the IPO, and the second dimension is whether the mutual fund was allocated shares in the underwriter's previous deal. As we show, both dimensions are important, and the combination is a good predictor of whether a mutual fund is allocated a future IPO. A mutual fund with an educational tie to the underwriter as well as an allocation in its previous deal, what we are calling an effectively connected (EC) mutual fund, is approximately five times as likely to be allocated an IPO in its next IPO compared with other mutual funds.

Mutual funds that are effectively connected in a given month outperform other mutual funds, but only in the months in which the funds are effectively connected to an underwriter taking a firm public. Moreover, after we control for whether or not a mutual fund is effectively connected, being managed by elite graduates does not significantly influence the probability of being allocated an

[1]More recently, Kacperczyk, Sialm, and Zheng (2005) find that funds with higher industry concentration generate annual abnormal returns, Kacperczyk, Sialm, and Zheng (2008) find that funds that outperform in one period using their return gap measure outperform in the following year, and Cremers and Petajisto (2009) report that funds with higher active shares outperform.

[2]Li, Zhang, and Zhao (2011) find similar results using a hedge fund sample.

[3]Ibbotson, Sindelar, and Ritter (1988) document a large initial day return of 16.4% for firms going public between 1960 and 1987. The updated statistics on Ritter's Web site (https://site.warrington.ufl.edu/ritter/ipo-data/) show that the average first-day return of IPOs was 7.2% in the 1980s, 14.8% from 1990 to 1998, and 13.3% from 2001 to 2013 (it surged to 64.5% during the Internet bubble period of 1999–2000).

IPO and, in addition, does not significantly influence a mutual fund's performance. In other words, mutual funds managed by elite graduates do not generate significant abnormal performance in months in which they are unlikely to be allocated underpriced IPOs.

If effective connections with IPO underwriters subsume the elite graduate effect, then mutual fund portfolio strategies that exploit these connections should do even better than those that focus on elite education. We find that this is indeed the case. Our panel regressions indicate that after controlling for various fund characteristics, effectively connected mutual funds outperform the unconnected funds by approximately 1.34% on an annualized basis. Moreover, as indicated earlier, this superior performance occurs *only* in the months in which the funds are connected to underwriters who allocate IPOs, suggesting that most, if not all, of the superior performance can be attributed to these connections. Indeed, a strategy that holds mutual funds only when they are connected to issuers of upcoming IPOs generates annual excess returns (relative to 3- and 4-factor models) of 2.28% on average and 4.08% in hot IPO markets.

This article contributes to a large and growing literature that explores the importance of connections in the finance industry. Our research is particularly 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 perform significantly better than their nonconnected counterparts. However, their estimates indicate that the total impact of these connections on mutual fund performance is only approximately 2 basis points (bps) per year on average, which is not large enough to explain the Chevalier and Ellison (1999) elite graduate effect. The relatively modest effect is likely due to the fact that mutual fund managers tend to be connected to relatively few firms with favorable information, and they are constrained to hold relatively small stakes in each individual firm. In contrast, as we illustrate with a simple "back of the envelope" calculation, the high frequency of IPOs and their large initial day returns are in fact sufficient to materially influence mutual fund returns.

There are a number of other contributors to the literature on the benefits of connections in other parts of the finance industry. Noteworthy contributions include Hochberg, Ljungqvist, and Lu (2007), (2010), who find that better-networked venture capital (VC) firms face less competition and experience significantly better fund performance; Hwang and Kim (2009), who study the connection between chief executive officers (CEOs) and directors and find that independent directors are not necessarily socially independent; Cohen, Frazzini, and Malloy (2010), who find that analysts outperform by up to 6.60% per year on their stock recommendations when they have an educational link to the company; Shue (2013), who studies how the alumni networks of executives affect corporate policies; Engelberg, Gao, and Parsons (2013), who examine the impact of social connection between CEOs and outside firm executives and find that CEOs with larger social networks have higher compensation; and Engelberg, Gao, and Parsons (2012), who show that informal connections between firms and banks can lower a firm's borrowing costs.

Our article is similar to that of Engelberg et al. (2012) in that we observe the educational background of the top executives of the banks rather than the background of the relevant decision makers (in their case, the lending officer; in our case, the underwriter). It is interesting that in both cases these more indirect links explain behavior. One possibility is that the top executives in these banks do in fact influence lending decisions and IPO allocations. A second possibility is that the educational backgrounds of top executives at banks are in fact pretty good proxies for the educational backgrounds of the lower-level managers or in some other way influence the culture of the bank. However, in contrast to other articles in the social network literature, the exact channel linking education to IPO allocations is not important for our argument. We are simply documenting the fact that the superior returns of mutual funds managed by elite graduates come about because of these allocations. Specifically, selecting mutual funds based on connections to the underwriters of upcoming IPOs rather than by elite education substantially increases the magnitude of the returns.

We are also not the first to examine the allocation of IPOs to mutual funds. Most notably, Reuter (2006) previously showed how the connections of mutual funds facilitate IPO allocations. However, the connections examined by Reuter are linked to the brokerage commissions paid to the IPO underwriters. Although we do not have data on brokerage commissions, we do observe that mutual funds with higher turnover tend to be allocated more IPOs, which supports Reuter's finding. In addition, Gaspar, Massa, and Matos's (2006) study of mutual fund allocations within fund families suggests that in large fund families, IPOs are allocated strategically, so individual mutual fund managers in large families may not always benefit as much from their individual connections as our analysis suggests. Finally, Massa, Reuter, and Zitzewitz (2010) observe that some of the mutual funds in large families have named managers, whereas some do not, and those with named managers tend to receive more IPO allocations and have higher return gaps. It should be noted that by construction, all of the managers in our sample have named managers, and when we take out fund-family fixed effects, we do not find evidence of preferential treatment for those managers with an elite education, but we do find evidence of educational connections mattering for within-fund family allocations.[4]

Our research is also related to the literature that explores the high and growing level of compensation in the finance industry. The relevant stylized facts are that relative wages in finance have risen (Kaplan and Rauh (2010), Philippon and Reshef (2012), (2013)), that a higher proportion of elite graduates have joined the finance industry (Goldin and Katz (2008), Oyer (2008)), and that the return to elite education is especially high in the finance industry (Célérier and Vallée (2015)). One interpretation of these observations is that because of increases in the complexity of financial contracts, the finance industry requires higher-skilled workers. An alternative interpretation, suggested by the analysis in this article,

[4]Our discussions with managers at Fidelity confirm that at Fidelity, IPOs are allocated from the underwriters to the fund family, which then distributes the IPOs to the individual funds. We do not have evidence of any preferential treatment in the allocation of IPOs at Fidelity or at the other two large fund families.

is that an elite education provides superior networks and connections, which have recently become more important.

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, the rents associated with being better connected that we document are consistent with these models.

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

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 come from the Thomson Reuters Mutual Fund Database (TR MF) and the Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund Database (CRSP MF); the former includes information from the semiannual N-SAR filings that are mandatory for mutual funds,[5] whereas the latter provides fund characteristics such as their size, age, turnover ratio, expense ratio, and investment style at the share-class level. We also use factor portfolios from Ken French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) to calculate the monthly risk-adjusted returns (ALPHA) of the mutual funds. Specifically, we regress the monthly mutual fund returns (after fees, expenses, and brokerage commissions but before front-end and back-end loads) on the 4-factor portfolios, MKTRF, SMB, HML, and UMD, as detailed by Fama and French (1993) and Carhart (1997), over the whole sample period to obtain the respective factor loadings. The monthly ALPHA is then calculated as the difference between the mutual fund's monthly excess return over the risk-free rate and the sum of the products of the monthly factor returns and the estimated factor loadings.

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

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

Because we use common educational background to proxy for "connectivity," we rely on biographical information on mutual fund managers and executives at underwriter firms. We identify historical employment and educational information for 216 senior executives[6] working at 31 public lead underwriters (see Table A1 of the Appendix for a list of the underwriters), covering 1,636 IPO deals, or 30.45% of the deals population. We also identify similar information about 1,320 mutual fund managers, managing 35.30% (= 1,320/3,739) of the open-end equity funds in the sample. From our data on the education of the portfolio managers, we define a fund-level measure, ELITE_SCHOOL, which equals 1 if the portfolio manager attended (as either an undergraduate or graduate student) one of the top 10 universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution,[7] and 0 otherwise.

The educational information about the senior underwriter executives comes from ExecuComp, which contains information about Standard & Poor's (S&P) 1500 executives. During our sample period, the number of underwriting firms in the S&P 1500 ranges from 16 to 24. In addition to the ExecuComp data, we check and collect information about the executives' education from at least two public sources to ensure its accuracy. For example, from ExecuComp we learn that Paul C. Reilly was the CEO of Raymond James Financial in May 2010. We search his name on public Web sites and cross-reference the public biographies from three sources: the company's Web site, the Notable Names Database (NNDB),[8] and *Bloomberg Businessweek*. From this search, we learn that Reilly was born in 1954[9] and received both a bachelor's and a master of business administration (MBA) degree from the University of Notre Dame.[10] We take extra care when different people have identical names by keeping track of their employment history. The employment and educational information of mutual fund managers is obtained from Morningstar.[11]

For each IPO, we identify each of the lead underwriters and extract the educational information about its senior executives. We then evaluate the status of these executives' educational connections to all mutual fund managers in the sample during the same IPO month. Following the definition given by

[6]These are the top-compensated executives in underwriter firms, such as CEO, chief financial officer (CFO), chairman, and so forth.

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

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

[9]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, Doctor of Medicine (MD), Juris Doctor (JD), and Doctor of Philosophy (PhD).

[10]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.

[11]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 nonmatched 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.

Cohen et al. (2008), our connection indicator equals 1 if both the fund manager and the underwriter involved in the IPO attended the same college and 0 otherwise. We then aggregate the connection measure from the person–person level to the deal–fund level; that is, our connection dummy is set to 1 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's portfolio managers and 0 otherwise. Because attending the same tertiary institution does not necessarily mean the individuals know each other, we refine the connection measure to create an enhanced version, EC (effectively connected), which is an indicator variable that takes a value of 1 if the fund and deal underwriter are currently connected (i.e., one of the incumbent fund managers and underwriter firm executives attended the same school) and, in addition, if the fund received at least one IPO allocation from the same underwriter in the past and 0 otherwise. It should be emphasized that mutual funds managed by elite graduates are more likely to be effectively connected. In our sample, the correlation between EC and ELITE_SCHOOL is approximately 0.37.

Finally, we follow Gaspar et al. (2006) to roughly identify the mutual funds' IPO allocations. Specifically, we identify whether a fund reports, in its quarterly holdings statements, the stock of a firm that went public during the prior quarter, setting the allocation dummy, ALLOCATED, equal to 1 if the fund holds the IPO stock at the end of the issuance quarter and 0 otherwise. This, of course, is a noisy measure because some funds sell the IPO stock prior to the quarter's end, and others acquire the IPO stocks on the market.

B. Fund Characteristics

There are 1,320 unique open-end equity funds in the sample, amounting to approximately 35.30% of the domestic open-end equity fund population during the sample period. Table 1 reports descriptive statistics for our sample. Compared

TABLE 1

Fund Characteristics

Table 1 reports the fund–month level summary statistics for the 76,794 fund–month observations in the sample. 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. The variable RET is the monthly return net of fees, expenses, and brokerage commissions but before front-end and back-end loads. The variable ELITE_SCHOOL is a binary indicator variable for funds with top-school-graduated managers, which equals 1 if the portfolio manager has attended one of the top 10 universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and 0 otherwise. We report statistics for all open-end equity funds in the intersection of the Center for Research in Security Prices (CRSP) and Thomson Reuters mutual fund databases in column 1, for the sample funds in column 2, for those funds managed by elite graduates in column 4, and for those managed by non-elite graduates in column 5. The *p*-value of the difference between the sample funds and non-sample funds is reported in column 3, and that between the elite and non-elite sample funds is reported in column 6.

Variable	All Funds 1	Sample Funds 2	*p*-Value of Difference 3	ELITE_SCHOOL 4	Non-ELITE_SCHOOL 5	*p*-Value of Difference 6
TNA ($millions)	1,297.646	1,938.250	<0.001	2,718.743	1,168.095	<0.001
EXPENSE_RATIO (%)	1.226	1.118	<0.001	1.159	1.194	<0.001
TURNOVER_RATIO (%)	92.558	88.016	<0.001	72.098	103.211	<0.001
AGE	12.756	14.168	<0.001	16.064	12.350	<0.001
RET (%)	1.011	1.096	<0.001	1.101	1.092	0.802

with all funds, funds in our sample tend to be larger, as measured by total net assets (TNA); they have lower turnover; and they are older, as measured by AGE in years. They also have higher returns (RET), suggesting that there may be a selection issue, but there is no survival bias because we do not require our sample fund to be surviving funds. The univariate results in Table 1 also suggest that ELITE_SCHOOL funds on average are larger, have lower turnover, and are older as measured by AGE in years, but they have similar returns as non-ELITE_SCHOOL funds.

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 et al. (1994),[12] is the percentage of deals that are priced above the midpoint of the original file price range. We define a binary indicator variable HOT_MKT, which equals 1 if the "hotness" value falls above the median value over the 1980–2012 period, and 0 otherwise. Given this definition, we have 1,042 deals that take place in a hot market and 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.

TABLE 2
IPO Characteristics

Table 2 presents summary statistics on the 1,636 initial public offerings (IPOs) in our sample. The variable IR, or initial return, is the difference between the first-trading-day closing price and the offer price, divided by the offer price. SIZE is the market value of equity of IPO firms at the month-end following the IPO, expressed in millions of dollars. PROCEEDS is the dollar size of the offering, excluding over-allotment shares and expressed in millions of dollars. ELITE_SCHOOL funds are funds with at least one portfolio manager who graduated from one of the top 10 universities ranked by the average SAT score of the freshmen. EC funds are the effectively connected funds. These funds had at least one fund manager who graduated from a university that an underwriter executive attended and, in addition, received at least one IPO allocation from the underwriter in the past. NC funds are those that are not effectively connected. 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 U.S. market for a given IPO deal. The variable PROB_ALLOCATED_TO_EC_(ELITE_SCHOOL)_FUNDS_PER_DEAL is the number of EC (ELITE_SCHOOL) funds that get allocation for a given deal divided by the total number of EC (ELITE_SCHOOL) 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 PROB_OF_ALLOCATION_WITH_(W/O)_EXPERIENCE_FROM_THE_SAME_UW represents the probability that a mutual fund is allocated shares with (without) past allocation experience from the same underwriter. 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 by Ibbotson, Sindelar, and Ritter (1994): the percentage of deals that are priced above the midpoint of the original file price range. The binary indicator variable HOT_MKT equals 1 if the "hotness" is greater than the sample median over the 1980–2012 period, and 0 otherwise.

Variable	All Markets	Hot Markets	Cold Markets	*p*-Value of Difference
No. of deals	1,636.000	1,042.000	594.000	—
IR (%)	31.524	40.013	16.305	<0.001
SIZE ($millions)	903.326	999.658	727.187	0.029
PROCEEDS ($millions)	138.061	115.815	177.670	0.017
%_SHARES_ALLOCATED_TO_SAMPLE_FUNDS_PER_DEAL	15.044	15.826	13.650	0.153
PROB_ALLOCATED_TO_ELITE_SCHOOL_FUNDS_PER_DEAL	0.017	0.017	0.015	0.014
PROB_ALLOCATED_TO_NON_ELITE_FUNDS_PER_DEAL	0.012	0.012	0.011	0.031
PROB_OF_ALLOCATION_WITH_EXPERIENCE_FROM_THE_SAME_UW	0.044	0.046	0.042	0.674
PROB_OF_ALLOCATION_W/O_EXPERIENCE_FROM_THE_SAME_UW	0.006	0.006	0.005	0.030
PROB_ALLOCATED_TO_EC_FUNDS_PER_DEAL	0.051	0.056	0.045	0.001
PROB_ALLOCATED_TO_NC_FUNDS_PER_DEAL	0.012	0.012	0.012	0.240
#_OF_IPOS_PER_MONTH	11.265	12.639	8.855	<0.001

[12]These data are available at Jay Ritter's Web site (http://bear.warrington.ufl.edu/ritter/IPOdata.htm).

Our sample deals typically have one identifiable lead underwriter per IPO firm, and the average underpricing (initial return (IR), calculated as the difference between the first-trading-day closing price and the offer price divided by the offer price) is approximately 31.52%. The average post-issue market capitalization is approximately $903.33 million, and the average proceeds are approximately $138.06 million. Among the offered shares, the percentage of shares allocated to our sample funds is approximately 15.04% per deal, which is less than half of the 34% allocation to all open-end equity funds reported by Ritter and Zhang (2007).[13]

The univariate summary statistics indicate that past allocations predict future allocations and that being a graduate of an elite school is associated with more IPO allocations. The probability that a particular IPO is allocated to an elite-school managed fund is approximately 2%, whereas the probability that a particular IPO is allocated to a non-elite-school managed fund is only approximately 1%. In addition, mutual funds receive allocations for 4.4% of the IPOs underwritten from banks that allocated IPOs to them in the past, which compares to 0.6% of the IPOs underwritten by banks with which they had no previous relation. For funds that are effectively connected (EC), that is, that have a previous relation as well as an educational connection, the probability of an IPO allocation is approximately 5%, which can be compared to the probability that a particular IPO is allocated to a non-EC (NC) fund, which is approximately 1%.

The last three columns of Table 2 present a 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 due to the fact that smaller issues choose to go public in hot markets. The percentage allocated to our sample funds is indistinguishable in the two markets. The probability of getting an allocation is higher for EC funds in hot markets, which we explore in greater depth in Section IV.

D. Connection Characteristics

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 5, and the median number of portfolio managers per fund is 1. In terms of our key connection variable of interest in this article, 12.56% of funds are effectively connected every month. The variable #_OF_EFFECTIVE_CONNECTIONS_PER_FUND_MONTH indicates that, unconditionally, a fund is effectively connected to 0.40 deals per month on average and that, conditioned on being connected in a particular month, a fund is effectively connected to approximately 3 deals (#_OF_EFFECTIVE_CONNECTIONS_PER_EC_FUND_MONTH). The average mutual fund is effectively connected 13.74% of the time (%_EFFECTIVELY_CONNECTED_MONTHS_PER_FUND), but elite-school funds are effectively connected

[13]The discrepancy arises because we only include open-end equity funds for which we have educational information about their portfolio managers.

TABLE 3
Connection Characteristics

Table 3 provides connection- and education-related statistics. In Panel A, the variable #_OF_EXECUTIVES_PER_UNDERWRITER_YEAR refers to the number of executives with educational information at the underwriter for a given year. The variable #_OF_PORTFOLIO_MANAGERS_PER_FUND_YEAR is the number of mutual fund managers with educational information per fund in a given year. The variable %_EFFECTIVELY_CONNECTED_FUNDS_PER_MONTH denotes the percentage of funds that are effectively connected each month. 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_MONTH is the number of effectively connected underwriters per fund per month conditional on being a fund with an effective connection (EC). The variable %_EFFECTIVELY_CONNECTED_MONTHS_PER_FUND is the number of effectively connected months divided by the total number of months in the sample for a given fund, and %_EFFECTIVELY_CONNECTED_MONTHS_PER_ELITE_SCHOOL_FUND is the number of effectively connected months divided by the total number of months in the sample for a fund with a manager or managers who graduated from an elite school. The variables %_EFFECTIVELY_CONNECTED_MONTHS_PER_CONNECTED_FUND and %_EFFECTIVELY_CONNECTED_MONTHS_PER_CONNECTED_ELITE_SCHOOL_FUND are identical to the previous two variables except that they are conditioned on having effective connection experience. The variable %_EFFECTIVELY_CONNECTED_FUNDS_PER_IPO represents the number of effectively connected funds out of the total number of funds associated with an initial public offering (IPO) in a given month. ELITE_SCHOOL funds are funds with at least one portfolio manager who graduated from one of the top 10 universities ranked by the average SAT score of the freshmen. EC funds are the effectively connected funds. These funds had at least one fund manager who graduated from a university that an underwriter executive attended and, in addition, received at least one IPO allocation from the underwriter in the past. Panel B lists the five universities most commonly attended by underwriter executives and portfolio managers.

Panel A. Connection Characteristics

Variable	Median	Mean	Std. Dev.
#_OF_EXECUTIVES_PER_UNDERWRITER_YEAR	5.000	4.509	1.938
#_OF_PORTFOLIO_MANAGERS_PER_FUND_YEAR	1.000	1.535	1.114
%_EFFECTIVELY_CONNECTED_FUNDS_PER_MONTH	13.294	12.563	5.889
#_OF_EFFECTIVE_CONNECTIONS_PER_FUND_MONTH	0.000	0.398	1.294
#_OF_EFFECTIVE_CONNECTIONS_PER_EC_FUND_MONTH	2.000	3.299	2.463
%_EFFECTIVELY_CONNECTED_MONTHS_PER_FUND	0.000	13.735	24.054
%_EFFECTIVELY_CONNECTED_MONTHS_PER_ELITE_SCHOOL_FUND	13.512	26.923	30.014
%_EFFECTIVELY_CONNECTED_MONTHS_PER_CONNECTED_FUND	35.052	38.695	25.772
%_EFFECTIVELY_CONNECTED_MONTHS_PER_CONNECTED_ELITE_SCHOOL_FUND	42.308	45.006	26.291
%_EFFECTIVELY_CONNECTED_FUNDS_PER_IPO	6.130	6.141	5.027

Panel B. Top-Five Most-Attended Institutions

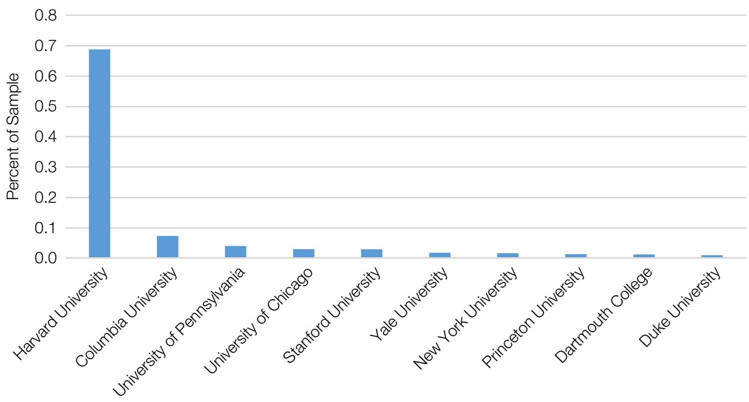
By Underwriter Executives		By Portfolio Managers	
Harvard	60	Harvard	45
Stanford	19	Pennsylvania	45
Pennsylvania	16	New York	35
Yale	14	Chicago	33
Columbia	14	Columbia	31

26.92% of the time (%_EFFECTIVELY_CONNECTED_MONTHS_PER_ELITE_SCHOOL_FUND).

Panel B of Table 3 lists the five universities most attended by the number of underwriter firm executives and the number of portfolio managers. The most popular universities among underwriter executives are Harvard University, attended by 60 underwriter executives in our sample, followed by Stanford University, the University of Pennsylvania, Yale University, and Columbia University. Harvard University also leads in the number of portfolio managers graduated (45), followed by the University of Pennsylvania, New York University, the 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, Harvard is dominant, with approximately 68.80% of the observations with connections. This is because Harvard graduates are highly represented in both top-executive positions in investment banking, approximately 23.63% of our sample of executives, as well as

FIGURE 1
Top 10 Most Connected Universities



in the portfolio manager positions in our mutual funds, approximately 8.1% of our sample of portfolio managers.

III. Elite Education and Mutual Fund Performance Revisited

We start our analysis 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. Specifically, we run panel regressions of a fund's risk-adjusted excess return in month t (ALPHA in Table 4) on a dummy indicating whether or not the fund is managed by an elite graduate, along with fund characteristics that include age, assets under management, turnover, expense ratio, and investment style, all of which can plausibly influence performance.

Table 4 reports the results. Column 1, which reports the panel regression over all calendar months in the sample period, shows that elite-school funds significantly outperform their non-elite counterparts by 4.6 bps per month, or 0.55% per year. The magnitude of the excess performance, which is consistent with Chevalier and Ellison (1999), is roughly equivalent to typical mutual fund management fees. When we further separate the sample in columns 2 and 3 by months with and without IPOs, we find that the ELITE_SCHOOL dummy is significant only in the subsample with IPO months. However, because we have very few months with no IPOs, we cannot reject the hypothesis that the coefficients of the ELITE_SCHOOL dummy in the two subsamples are equal.[14]

[14]We also ran regressions over two subsamples using the median value of the number of IPOs (NIPO) as the cut-off, and we still did not find the ELITE_SCHOOL dummy to be significantly different between the two subsamples.

TABLE 4
Do Elite School Mutual Fund Managers Outperform?

In Table 4 we report regressions of mutual fund risk-adjusted return (ALPHA) on an elite-school dummy and other control variables over the Jan. 1992–Mar. 2012 sample period. ALPHA, expressed in percentage, is calculated as $\text{ALPHA}_{it} \equiv r_{it} - rf_t - X_t\hat{\beta}_{it}$, where X_t is a vector of realized returns in month t for each of the 4-factor portfolios (MKTRF, SMB, HML, and UMD), and $\hat{\beta}_{it}$ represents fund-specific factor loadings obtained from the whole-sample time-series regression of fund excess return over market portfolio on the Carhart (1997) 4 factors. The key independent variable ELITE_SCHOOL is the binary indicator variable for funds with top-school-graduated managers, which equals 1 if the portfolio manager has attended one of the top 10 universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and 0 otherwise. Control variables of fund characteristics throughout the regressions include investment-style fixed effects; the natural logarithm of fund size (ln(TNA)) and fund age (ln(AGE)); EXPENSE_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, which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month total net assets (TNA) of the fund. In column 1 we run regressions over all the calendar months in our sample period, in column 2 we restrict the regressions to the 222 months that have initial public offering (IPO) activities, and in column 3 we restrict the regressions to the 21 sample months that do not have any IPO activities. All fund characteristics are obtained at the end of month $t-1$. Robust standard errors (White (1980)) are used and are clustered at the month level. t-statistics are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: ALPHA		
Variable	1	2	3
ELITE_SCHOOL	0.046***	0.049***	0.008
	(2.862)	(2.918)	(0.131)
ln(TNA)	−0.010	−0.007	−0.059
	(−1.144)	(−0.963)	(−1.365)
ln(AGE)	0.020	0.015	0.081
	(0.897)	(0.720)	(0.660)
EXPENSE_RATIO × 100	0.096	−0.418	3.677*
	(0.226)	(−1.168)	(1.849)
TURNOVER_RATIO	0.008	0.016	−0.064*
	(0.607)	(1.204)	(−2.027)
Constant	0.098	0.113	−0.031
	(0.554)	(0.609)	(−0.057)
No. of obs.	84,879	76,794	8,085
R^2	0.002	0.003	0.015
Style fixed effects	Yes	Yes	Yes
Sample	All months	IPO months	Non-IPO months

IV. Elite Education, Connections, and IPO Allocations

The evidence reported in the preceding section confirms Chevalier and Ellison's (1999) finding that elite-school funds outperform in our longer and more recent sample period. As we mentioned in the Introduction, a possible explanation is that elite graduates benefit from their connections. 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 the connections of elite graduates increase the number of their IPO allocations as well as the quality of their IPO allocations.

A. Elite Education and IPO Allocations

We first estimate logit regressions of the binary indicator variable ALLOCATED on the ELITE_SCHOOL dummy, deal characteristics, and fund characteristics. These regressions examine whether or not a particular mutual fund was allocated a particular IPO, so the dependent variable in the regression, ALLOCATED, equals 1 if the fund holds the stock of any firm that went public in the prior quarter, and 0 otherwise. As we previously noted, this is a noisy signal of whether or not a fund receives an IPO allocation because funds can sell their allocations before the end of the quarter and can purchase IPOs they are not allocated in the secondary market. If this noise is uncorrelated with the education of the portfolio manager, it will generate a bias against finding a significant relation.[15]

Our first connection measure, CONNECTED, designated as a type I connection by Cohen et al. (2008),[16] is a dummy variable that equals 1 if the fund manager and at least one of the underwriter executives attended the same tertiary institution, and 0 otherwise. We also define ALLOCATED_BEFORE, which equals 1 if the fund was previously allocated an IPO from the bank underwriting the current deal and 0 otherwise, to capture the past allocation history. As we will show, both variables, that is, a common educational experience and a past IPO allocation, predict IPO allocations. In addition, the interaction between these variables is quite important. In particular, past allocations are much better indicators of future allocations if they are accompanied by common school ties. We say that a fund is *effectively connected* (EC) if both dummy variables equal 1.

Panel A of Table 5 presents a set of logit regressions that estimate the relation between whether or not an IPO is allocated to a particular mutual fund and the education of the mutual fund manager, whether the mutual fund manager has an educational connection with the IPO underwriter, and whether the mutual fund was allocated an IPO from the underwriter in the past. In addition to these education and connection variables, the regressions also include control variables that describe characteristics of the mutual funds and the IPOs. These variables show, for example, that mutual funds are more likely to be allocated shares in larger offerings (because there are more shares to allocate). 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, as described by Reuter (2006).

The positive coefficient of CONNECTED reported in column 1 of Table 5 shows that having an educational connection increases the odds of receiving IPO allocations. Column 2 shows that a fund's past allocation history, ALLOCATED_BEFORE, is the most important indicator of future IPO allocation decisions, which is not surprising because the past-allocation history essentially captures the effect of all the factors that influence IPO allocations, including CONNECTED. Column 2 also shows a strong positive interaction between CONNECTED and ALLOCATED_BEFORE, indicating that the positive impact of a fund's allocation

[15]We do not have either evidence or theory about how education will affect the tendency of mutual funds to flip shares after an allocation.

[16]Cohen et al. (2008) also adopt the more restrictive definition of connections that requires connected individuals to attend the same colleges at the same time or to attend the same schools or departments in the colleges. Because we are considering a relatively small number of underwriters rather than the entire sample of corporations, these more restrictive criteria generate very few connections. Our less restrictive definition captures the connections developed outside of classrooms, such as alumni functions that graduates may attend. It is also likely that affinity between individuals who attended the same university influences decisions. For example, job recruiters may show favoritism to alums in their hiring decisions. We conduct a robustness check with a more restrictive definition of connections in a later section.

history on the odds of receiving a current allocation is larger when the fund has an educational connection with the underwriter.

TABLE 5
What Determines IPO Allocations?

In Panel A of Table 5, we run logit regressions of the binary indicator variable ALLOCATED on the CONNECTED dummy, deal characteristics, and fund characteristics in column 1. The dependent variable ALLOCATED equals 1 if the fund holds the initial public offering (IPO) stock at the end of the quarter of its issuance, and 0 otherwise. The key independent variable CONNECTED in column 1 is built in the same way as described by Cohen et al. (2008) and, in our case, equals 1 if the fund manager and one of the underwriter executives attended the same tertiary institution, and 0 otherwise. As the name suggests, the independent variable ALLOCATED_BEFORE in column 2 represents the existence of previous allocation experience from the same underwriter; that is, it equals 1 if the fund has received an allocation from the same underwriter in the past, and 0 otherwise. ALLOCATED_BEFORE × CONNECTED is the interaction term between ALLOCATED_BEFORE and CONNECTED, and it is our key independent variable of effective connection (EC) in column 3 when both ALLOCATED_BEFORE and CONNECTED are equal to 1. The key independent variable EC in columns 3 and 5 is the effective connection indicator denoting that the fund manager and underwriter executive attended the same school and the fund received at least one IPO allocation from the same connected underwriter in the past. In column 4 the key independent variable ELITE_SCHOOL is the binary indicator variable for funds with top-school-graduated managers, which equals 1 if the portfolio manager has attended one of the top 10 universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and 0 otherwise. The binary indicator variable AWC in column 6 equals 1 if the fund has obtained IPO allocation through the same underwriter in the past and was not educationally connected then, and 0 otherwise. Throughout the table, we control for the deal characteristics of the natural logarithm of dollar proceeds (ln(PROCEEDS)). Fund characteristics include investment-style fixed effects; the natural logarithm of fund size (ln(TNA)) and fund age (ln(AGE)); EXPENSE_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, which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month total net assets (TNA) of the fund. In Panel B we construct a 2×2 probability table that displays the probabilities of allocation for funds with and without connections and with and without an allocation in past deals. We compute probabilities with the same set of control variables as in column 2 of Panel A, held at the mean and with the fund style being small-cap funds. In Panel C we construct a 2×2 table that displays the mean initial return of IPO deals for funds with and without connections and with and without an allocation in past deals. We restrict to the subsample of funds with current IPO allocation. In Panel D we employ a subsample of funds whose fund family can be identified and run the same regression as those in columns 3–5 of Panel A with additional family fixed effects. Standard errors are heteroscedasticity robust and clustered at the month level. Z-statistics are shown in parentheses. The sample period is Jan. 1992–Mar. 2012. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Dependent Variable: ALLOCATED

Variable	1	2	3	4	5	6
CONNECTED	0.284***	−0.400***				
	(7.831)	(−6.931)				
ALLOCATED_BEFORE		0.966***				
		(15.143)				
ALLOCATED_BEFORE × CONNECTED (EC)		0.522***	1.077***		1.062***	
		(6.172)	(23.717)		(22.377)	
AWC						1.118***
						(32.194)
ELITE_SCHOOL				0.272***	0.034	0.397***
				(7.602)	(0.870)	(11.537)
ln(PROCEEDS)	0.145***	0.135***	0.144***	0.140***	0.144***	0.131***
	(6.257)	(5.830)	(6.247)	(6.101)	(6.243)	(5.659)
ln(SIZE)	0.351***	0.345***	0.340***	0.364***	0.340***	0.358***
	(15.013)	(14.513)	(14.303)	(15.608)	(14.299)	(15.154)
ln(TNA)	0.318***	0.279***	0.287***	0.311***	0.286***	0.273***
	(22.985)	(20.467)	(20.790)	(22.515)	(20.931)	(19.748)
ln(AGE)	−0.239***	−0.296***	−0.272***	−0.236***	−0.272***	−0.268***
	(−8.186)	(−9.981)	(−9.199)	(−8.158)	(−9.213)	(−9.179)
EXPENSE_RATIO × 100	1.377*	0.645	0.635	1.284*	0.599	0.529
	(1.911)	(0.901)	(0.891)	(1.807)	(0.840)	(0.731)
TURNOVER_RATIO	0.027***	0.017**	0.021***	0.029***	0.021***	0.031***
	(4.125)	(2.553)	(3.268)	(4.383)	(3.280)	(4.657)
Constant	−5.199***	−5.119***	−5.161***	−5.306***	−5.182***	−5.735***
	(−23.984)	(−23.825)	(−24.101)	(−24.240)	(−23.947)	(−25.832)
No. of obs.	457,592	457,592	457,592	457,592	457,592	457,592
Pseudo-R^2	0.091	0.109	0.103	0.091	0.103	0.114
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

(continued on next page)

TABLE 5 (continued)
What Determines IPO Allocations?

Panel B. Probability of IPO Allocations

		ALLOCATED_BEFORE	
		0	1
CONNECTED	0	2.58%	6.50%
	1	1.74%	7.28%

Panel C. Initial Returns

		ALLOCATED_BEFORE	
		0	1
CONNECTED	0	33.18%	29.59%
	1	28.80%	43.73%

Panel D. Funds with Families

	Dependent Variable: ALLOCATED		
Variable	1	2	3
ELITE_SCHOOL	−0.125**		−0.247***
	(−2.353)		(−4.536)
EC		0.462***	0.545***
		(8.492)	(9.782)
ln(PROCEEDS)	0.118***	0.123***	0.122***
	(7.395)	(7.686)	(7.638)
ln(SIZE)	0.224***	0.200***	0.203***
	(15.695)	(13.346)	(13.549)
ln(TNA)	0.111***	0.097***	0.105***
	(6.744)	(5.985)	(6.413)
ln(AGE)	0.048	0.018	0.026
	(1.388)	(0.511)	(0.792)
EXPENSE_RATIO × 100	0.282	−0.638	−0.039
	(0.352)	(−0.769)	(−0.048)
TURNOVER_RATIO	−0.228***	−0.235***	−0.208***
	(−5.710)	(−5.962)	(−5.246)
Constant	4.164***	4.079***	4.307***
	(15.945)	(20.593)	(18.705)
No. of obs.	34,178	34,178	34,178
Pseudo-R^2	0.371	0.377	0.380
Style fixed effects	Yes	Yes	Yes
Fund-family fixed effects	Yes	Yes	Yes

In column 3 of Table 5 we estimate the column 2 regression without the individual components of EC, CONNECTED, and ALLOCATED_BEFORE. The R^2 of this regression is only slightly lower than the column 2 R^2, suggesting that the combined EC variable captures the notion of being connected to the underwriter as well as the individual components.

The estimates reported in column 4 of Table 5, which include the ELITE_SCHOOL dummy but no connection variables, indicate that mutual funds managed by elite graduates are indeed more likely to be allocated IPOs than their non-elite counterparts. However, as illustrated in the column 5 regression, the effect of ELITE_SCHOOL is completely subsumed by EC, suggesting that elite-school graduates receive better IPO allocations because they are more likely to be connected to an underwriter. To further corroborate this conclusion, the regression in column 6 replaces EC with its counterpart, allocation without connection (AWC). Because AWC is slightly negatively correlated with ELITE_SCHOOL, the inclusion of this variable does not affect the significance of the ELITE_SCHOOL effect, providing further evidence of the importance of school connections.

To glean more intuition from these coefficient estimates, one can use the coefficients reported in column 2 of Table 5 to calculate the probabilities of receiving an IPO allocation for funds conditioned on their previous allocations and their educational connections. As shown in the 2×2 classification reported in Panel B of Table 5, EC funds, that is, those with ALLOCATED_BEFORE and CONNECTED taking values of 1, have the greatest probability, 7.28%, of receiving allocations of the upcoming IPOs. This probability is larger than the 6.50% probability of receiving a current allocation if the fund is classified as AWC; that is, ALLOCATED_BEFORE takes a value of 1, and CONNECTED takes a value of 0. It should also be noted that CONNECTED funds that were not allocated IPOs in the past are actually slightly less likely to be allocated future IPOs than their less connected counterparts. This observation, which suggests that many of the educational connections have no influence on allocations, was our motivation for combining past allocations and educational connections into a single EC measure.

Although the difference in the probability of IPO allocation between EC funds and AWC funds is small, the difference in the quality of the IPOs, measured as first-day return (IR), is significantly larger. As shown in Panel C of Table 5, EC funds are allocated IPOs with greater initial returns on average (43.73%) than those allocated to AWC funds (29.59%). This could reflect the possibility that connections are more important for being allocated the hottest IPOs or, alternatively, that portfolio managers are better positioned to evaluate the IPOs underwritten by bankers with common educational backgrounds and thus are better positioned to aggressively seek the better IPOs.[17] In any event, this observation is important for understanding the superior performance of EC funds relative to AWC funds.

Finally, Panel D of Table 5 reports regressions that include fund-family fixed effects. In particular, we add family fixed effects to the regressions reported in columns 3, 4, and 5 of Panel A and estimate the regressions on the subsample of funds that are part of an identified fund family. These regressions, which allow us to examine whether managers with an elite education receive favorable IPO allocations within their fund families, is motivated by Gaspar et al. (2006) and Massa et al. (2010), who show that fund families may strategically allocate IPOs to favor some funds over others. The regressions reported in columns 1 and 3 of Panel D are inconsistent with the idea that fund families preferentially allocate IPOs to those funds managed by elite graduates. Indeed, the evidence suggests that they do the opposite. However, we find (in columns 2 and 3) that EC funds do receive more IPO allocations than NC funds within families.

B. Are Connected Mutual Funds Allocated Better IPOs?

As the regressions described in the previous subsection illustrate, EC is a strong predictor of whether or not a mutual fund is allocated an IPO, and importantly, when we control for EC, elite education does not predict IPO allocations. Hence, when we examine mutual fund returns, controlling for EC should subsume the elite-education effect if it is indeed the IPO channel that generates the excess returns of those mutual funds managed by elite graduates. However, before reevaluating mutual fund returns, we will document that EC mutual funds are even more likely to be allocated the better-quality IPOs.

[17] We thank the referee for proposing this alternative interpretation.

To estimate whether connected funds are more likely to be allocated the 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 an indirect proxy, HOT_MKT, which is an indicator variable measuring whether the IPO is issued in a hot-market period, as defined earlier in Table 2.

To estimate how these quality variables influence IPO allocations, we interact them with our EC variables in the regressions that predict IPO allocations. As shown in column 1 of Table 6, the coefficient of EC × IR_ADJ (the interactive term between EC and IR_ADJ) is positive and significant, indicating that EC funds

TABLE 6

Are Connected Mutual Funds Allocated Better IPOs?

Table 6 reports logit regressions of the binary indicator variable ALLOCATED on the effective connection (EC) dummy, initial return of deals, deal characteristics, and fund characteristics. The dependent variable ALLOCATED equals 1 if the fund is found to hold initial public offering (IPO) stock within the first quarter of its issuance, and 0 otherwise. The independent variable, EC, is the effective connection indicator, which equals 1 if the fund manager and underwriter executive attended the same school and the fund received at least one IPO allocation from the underwriter in the past. In column 1 we control for the 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 HOT_MKT and its interaction with EC in column 2. The market condition, that is, the "hotness" of the IPO market, is measured in the way proposed by Ibbotson et al. (1994), that is, the percentage of deals that are priced above the midpoint of the original file price range. The binary indicator variable HOT_MKT is equal to 1 if the "hotness" is greater than the sample median over the 1980–2012 period, and 0 otherwise. The deal characteristics include the natural logarithm of dollar proceeds (ln(PROCEEDS)) and log IPO size measured at the end of the IPO month (ln(SIZE)). Fund characteristics include investment-style fixed effects; the natural logarithm of fund size (ln(TNA)) and fund age (ln(AGE)); EXPENSE_RATIO, which is the annual ongoing operating expenses expressed as percentage of total investment by shareholders; and TURNOVER_RATIO, which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month total net assets (TNA) of the fund. We repeat the logit regression in column 1 in the subsamples of hot and cold IPO markets in columns 3 and 4, respectively. Standard errors are heteroscedasticity robust and clustered at the month level. Z-statistics are shown in parentheses. The sample period is Jan. 1992–Mar. 2012. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: ALLOCATED			
			Hot Market	Cold Market
Variable	1	2	3	4
EC	1.071***	0.969***	1.110***	1.007***
	(24.910)	(13.590)	(21.258)	(13.930)
IR_ADJ	−0.010		−0.108***	0.471***
	(−0.253)		(−2.823)	(4.639)
EC × IR_ADJ	0.135***		0.178***	0.029
	(3.486)		(3.938)	(0.291)
HOT_MKT		−0.039		
		(−0.746)		
EC × HOT_MKT		0.179**		
		(1.980)		
ln(PROCEEDS)	0.154***	0.144***	0.102***	0.285***
	(5.852)	(6.279)	(3.567)	(5.208)
ln(SIZE)	0.328***	0.339***	0.350***	0.227***
	(11.920)	(14.074)	(10.833)	(4.181)
ln(TNA)	0.288***	0.287***	0.306***	0.260***
	(20.802)	(20.894)	(17.031)	(12.171)
ln(AGE)	−0.276***	−0.273***	−0.273***	−0.282***
	(−9.298)	(−9.207)	(−7.118)	(−5.966)
EXPENSE_RATIO × 100	0.678	0.635	1.035	0.052
	(0.952)	(0.894)	(1.124)	(0.046)
TURNOVER_RATIO	0.021***	0.021***	0.023***	0.024*
	(3.292)	(3.314)	(3.209)	(1.852)
Constant	−5.183***	−5.133***	−5.281***	−4.982***
	(−23.801)	(−23.479)	(−21.847)	(−11.876)
No. of obs.	453,823	457,592	274,448	177,258
Pseudo-R^2	0.103	0.103	0.103	0.107
Style fixed effects	Yes	Yes	Yes	Yes

are more likely to be allocated IPOs with higher first-day returns, and the coefficient of IR_ADJ is insignificant, suggesting that the allocation to NC funds is not affected by deal quality. Similarly, as shown in column 2, the positive and significant coefficient on EC × HOT_MKT indicates that the gains from connections are larger in hot markets,[18] and the significantly negative coefficient of HOT_MKT 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.

We also run these regressions separately in subsamples of hot and cold markets, which we report in columns 3 and 4 of Table 6, 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. IPO Connection and Fund Performance

Up to this point we have presented evidence that is consistent with the finding of Chevalier and Ellison (1999) that mutual funds managed by graduates of elite universities outperform their counterparts from less prestigious universities. We consider one potential channel that could have generated these excess returns, the allocation of underpriced IPOs, and find that mutual funds managed by elite-school graduates are indeed allocated more IPOs.

In this section, we "connect the dots" and examine the extent to which the excess mutual fund returns realized by the elite graduates can be attributed to their superior IPO allocations. We start with panel regressions that more closely resemble the regressions estimated by Chevalier and Ellison (1999) but also include our measures of mutual fund connections. We also report Fama–MacBeth (1973) regressions that address the same issues. Finally, we present the returns of an implementable portfolio strategy that uses connected mutual funds to indirectly exploit the underpricing of IPOs.

A. Panel Regressions

Table 7 reports regressions that are similar to those reported in column 2 of Table 4, but the focus is on the relation between EC and excess returns. The observation unit in this regression is the fund-month, so EC takes a value of 1 if a particular fund is effectively connected to *any* of the underwriters who conduct an IPO in month t, and 0 otherwise. As the regression in column 1 indicates, in months in which a mutual fund is connected to an underwriter doing an IPO (i.e., EC = 1), the fund earns a 0.11% ($t = 3.76$) higher risk-adjusted return than its nonconnected peers with the same investment style and characteristics.[19]

[18] 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 columns 3 and 4 of Table 6.

[19] As shown in the Supplementary Material, the Table 7 results are robust to clustering the standard errors at the level of mutual fund investment style.

TABLE 7
Connections, Elite Education, and Fund Performance

The regressions in Table 7 examine the effect of connections and education on mutual fund performance. We define effective connection (EC) as a binary variable that equals 1 if the fund is connected in month t and has received an initial public offering (IPO) allocation from the same connected underwriter at least once prior to month t. The variable NCNOW_ECBEFORE is a binary indicator variable that takes a value of 1 if the fund was effectively connected before but is not connected in the current month, and 0 otherwise. ELITE_SCHOOL is a binary indicator variable for funds with top-school-graduated managers, which equals 1 if the portfolio manager has attended one of the top 10 universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and 0 otherwise. The binary indicator variable AWC in columns 5 and 8 equals 1 if the fund has obtained an IPO allocation through the same underwriter in the past and was not educationally connected then, and 0 otherwise. The following fund-characteristic controls are included in the regression but are not reported in the table: ln(TNA), the natural logarithm of the total net assets (TNA) of a fund; ln(AGE), the natural logarithm of (1 + fund age); EXPENSE_RATIO, the annual ongoing operating expenses of the mutual fund; and TURNOVER_RATIO, the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month total net assets (TNA) of the fund. The dependent variable ALPHA is calculated as $\text{ALPHA}_{it} \equiv r_{it} - rf_t - X_t\hat{\beta}_{it}$, where X_t is a vector of the realized returns in month t for each of the 4-factor portfolios (MKTRF, SMB, HML, and UMD), and $\hat{\beta}_{it}$ represents fund-specific factor loadings estimated from the time-series regression of fund excess returns on the 4 factors over the entire sample period. The sample period is Jan. 1992–Mar. 2012. Robust standard errors (White (1980)) are used and are clustered at the month level, and t-statistics are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: ALPHA							
			Hot Market	Cold Market				
Variable	1	2	3	4	5	6	7	8
EC	0.112***		0.144***	0.084*	0.108***		0.099***	
	(3.761)		(3.670)	(1.875)	(3.780)		(3.063)	
NCNOW_ECBEFORE		−0.026						
		(−0.752)						
ELITE_SCHOOL						0.049***	0.026	0.054***
						(2.918)	(1.409)	(3.210)
AWC					0.055			0.064*
					(1.625)			(1.853)
Constant	0.127	0.147	0.142	0.097	0.100	0.113	0.113	0.079
	(0.681)	(0.793)	(0.533)	(0.386)	(0.535)	(0.608)	(0.609)	(0.423)
No. of obs.	76,794	76,794	38,915	37,879	76,794	76,794	76,794	76,794
R^2	0.003	0.002	0.009	0.009	0.003	0.003	0.003	0.003
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The 0.11% monthly excess return of EC funds is more than twice as high as the previously estimated excess return of funds managed by elite graduates. To help us interpret the plausibility of the magnitude of this effect, we provide a simple back-of-the-envelope calculation that uses the observed quarterly holdings of the mutual funds, along with an assumption about the probability that mutual funds that are allocated shares in IPOs flip the shares prior to the quarter's end.

Specifically, we posit that

$$\begin{aligned}\text{Monthly return of funds due to IPOs} \quad &= \\ \text{mean IR} \times \frac{\text{observed probability of allocation}}{(1 - \text{probability of flipping})} \\ \times \text{size of IPO allocation} \times \text{number of IPO allocations per month.}\end{aligned}$$

Assuming that both EC funds and NC funds flip 50% of their IPOs, we can calculate that the monthly excess return of EC funds due to allocated IPOs = 43.73% × (7.28%/0.5) × 0.28% × 11.265 = 20 bps and that the monthly return of NC funds due to allocated IPOs = 32.31% × (2.39%/0.5) × 0.45% × 11.265 = 8 bps. The probability of an allocation for EC funds (7.28%) is obtained from

Panel B of Table 5. The probability of an allocation for NC funds (2.39%) is obtained by the weighted average of the probabilities of the other three cells in Panel B of Table 5 with the weight being the number of observations in each cell. The initial returns of EC funds (43.73%) and NC funds (32.31%) are obtained in a similar fashion from Panel C of Table 5. Given these numbers, EC funds generate excess returns from IPO allocations that exceed the NC funds' excess returns from IPO allocations by approximately 12 bps, which is close to the 11 bps we estimated from Table 7.[20]

In column 2 of Table 7, we include a dummy variable NCNOW_ECBEFORE that captures the subsample of funds that are not currently connected but were effectively connected previously. The insignificant coefficient of NCNOW_ECBEFORE implies that mutual funds do not outperform in month t if they are not connected to an underwriter that conducts an IPO in month t. In other words, EC funds outperform NC funds *only* in months in which they are connected to underwriters taking firms public. This finding indicates that the superior performance of connected funds is in fact generated by connections to underwriters rather than unobserved mutual fund characteristics. Further evidence is revealed in the regressions reported in columns 3 and 4, which separately examine hot and cold markets. A comparison of the EC coefficient estimates in these columns reveals that being effectively connected is more important in hot-market periods when the IPOs are more underpriced; however, we cannot reject the hypothesis that these two coefficients are equal.[21]

In column 5 of Table 7, we introduce the variable AWC, which is the binary variable that indicates whether the mutual fund received a previous allocation from an underwriter taking a firm public in the upcoming month without the benefit of an educational connection. The introduction of this variable does not have a material effect on the coefficient of EC, and the coefficient of AWC is approximately half the size of the coefficient of EC and is not statistically significant. The difference in the magnitudes of these coefficients (0.108% for EC funds and 0.055% for AWC funds) is noteworthy because higher AWC is also associated with greater IPO allocations. However, as we showed in Table 5, the IPOs allocated to funds without educational connections tend to have substantially lower initial returns (29.59% for AWC funds vs. 43.73% for EC funds). The magnitude

[20]Note that this derivation ignores the possibility that firms flip part of their IPO allocation. To account for partial flipping we can modify the previous equation as follows:

$$\begin{aligned}\text{Monthly return of funds due to IPOs} \quad = \quad & \text{mean IR} \times \frac{\text{observed probability of allocation}}{(1-\text{probability of flipping})}\\ & \times \frac{\text{observed IPO holding}}{(1-\text{degree of partial flipping})}\\ & \times \text{number of IPO allocations per month.}\end{aligned}$$

If we set the probability of flipping and the degree of partial flipping at 0.3, we get very similar results.

[21]An alternative definition of hot markets, defined by IPO volume, provides similar point estimates for hot and cold markets. These point estimates do turn out to be statistically different from each other.

of this difference in initial returns is roughly consistent with the difference in the magnitude of the coefficients.[22]

Column 6 in Table 7 simply reproduces column 2 from Table 4, which replicates the Chevalier and Ellison (1999) result, and column 7 adds EC to that regression. Our findings suggest that EC, which is statistically significant in this regression, substantially subsumes the effect of ELITE_SCHOOL, which is not statistically significant in this specification. In column 8, we replace EC with its counterpart, AWC. The coefficient of AWC is marginally significant in this regression, and in contrast to the regression reported in column 7, the coefficient of ELITE_SCHOOL remains positive and significant. These regressions are consistent with the pattern observed in the Table 5 regressions that examine characteristics that predict IPO allocations, reinforcing the observation that school connection is critical to the explanation of the ELITE_SCHOOL effect. Furthermore, a comparison of the two tables reveals that combinations of variables that predict IPO allocations also predict returns, suggesting that the excess returns are indeed generated by the IPO allocations.[23]

B. Fama–MacBeth Regressions

This subsection estimates similar regressions using the Fama and MacBeth (1973) methodology. The results are reported in Table 8. The dependent variable ALPHA and the independent variable EC for fund i are obtained at month t, and fund characteristics such as ln(TNA), ln(AGE), EXPENSE_RATIO, TURNOVER_RATIO, and fund styles are obtained at the end of month $t-1$.

The results in column 1 of Table 8 are consistent with the panel regressions in Table 7. The Fama–MacBeth (1973) coefficient of EC is positive and significant, but the magnitude is slightly smaller than that of our panel regression estimate. We also note that the superior performance generated by having an effective connection is greater in hot IPO markets, as evidenced by the significant coefficient on EC in column 2 and the insignificant coefficient in column 3. These results reinforce our earlier findings in columns 3 and 4 of Table 7.[24]

[22]Column 5 of Table 7 shows that the excess return of EC over AWC is $0.108\% - 0.055\% = 0.53\%$. Because the observed IPO probability is similar for EC and AWC funds (about 7%), the key difference is the IPO first-day return (43.73% vs. 29.59%), which is mainly responsible for the difference in fund performance for EC funds and AWC funds. The following back of the envelope calculation suggests that the difference in excess returns of EC and AWC funds is roughly consistent with the difference in the first-day returns of the IPOs they are allocated:

$$\begin{aligned}&(\text{IR of EC} - \text{IR of AWC}) \times \text{number of IPOs per month}\\&\qquad \times \text{actual probability of IPO allocation} \times \text{average size of IPO allocation}\\&= \quad (43.73\% - 29.59\%) \times 11.265 \times [0.07/(1-0.5)] \times 0.3\% \quad = \quad 0.07\%.\end{aligned}$$

[23]To estimate the robustness of this regression we considered a number of alternative specifications. Specifically, we estimated the regressions in Table 7 with returns before fees, alphas estimated with time-varying betas calculated over the previous 36 months, and alphas calculated with factor models that also include the Pástor and Stambaugh (2003) and Sadka (2006) liquidity factors. These regressions generate results that are very similar to those reported.

[24]One cannot introduce interaction terms in the Fama–MacBeth regression presented in Table 8. We do, however, test for a difference between the EC coefficient in hot and cold IPO markets and cannot reject the hypothesis that the coefficients are equal.

TABLE 8
IPO Connection and Fund Performance

Table 8 replicates some of the regressions in Table 7 with Fama and MacBeth (1973) regressions. The dependent variable ALPHA and the independent variable EC for fund i are obtained at month t; fund characteristics such as ln(TNA), ln(AGE), EXPENSE_RATIO, and TURNOVER_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 initial public offering (IPO) market used by Ibbotson et al. (1994): the percentage of deals that are priced above the midpoint of the original file price range. We define the binary indicator variable HOT_MKT as equal to 1 if the "hotness" is greater than the sample median over the 1980–2012 period, and 0 otherwise. The dependent variable ALPHA is calculated as $\text{ALPHA}_{it} \equiv r_{it} - rf_t - X_t\hat{\beta}_{it}$, where X_t is a vector of the realized returns in month t for each of the 4-factor portfolios (MKTRF, SMB, HML, and UMD), and $\hat{\beta}_{it}$ represents fund-specific factor loadings estimated from the time-series regression of fund excess returns on the 4 factors over the entire sample period. The cross-sectional estimation is performed using the Fama–MacBeth method over the 222 IPO months during the sample period of Jan. 1992–Mar. 2012; the results appear in column 1. Columns 2 and 3 present the Fama–MacBeth regression results for the subsamples of hot and cold IPO markets. The means of coefficients are presented with t-statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: ALPHA		
	Full Sample	Hot Market	Cold Market
Variable	1	2	3
EC	0.070**	0.109**	0.021
	(1.971)	(2.163)	(0.443)
ln(TNA)	−0.001	0.006	−0.011
	(−0.174)	(0.527)	(−0.976)
ln(AGE)	0.005	−0.011	0.026
	(0.359)	(−0.551)	(1.254)
EXPENSE_RATIO × 100	−0.095	0.598	−0.940*
	(−0.241)	(1.031)	(−1.864)
TURNOVER_RATIO	−0.026	−0.015	−0.041
	(−1.149)	(−0.412)	(−1.504)
Constant	0.147	0.271	−0.004
	(0.886)	(1.094)	(−0.017)
No. of obs.	76,794	38,915	37,879
R^2	0.395	0.402	0.387
Style fixed effects	Yes	Yes	Yes

C. Daily Returns and Placebo Tests

If the excess returns of connected funds arise exclusively from IPO allocations, they should be observed only on the first day that the IPOs trade. To test this, we repeat Table 8 with daily alphas.

To identify the day the IPO starts to trade, we rely on both CRSP and SDC Platinum data. There is potentially some ambiguity regarding the IPO date because the date given in SDC Platinum is generally, but not always, 1 day before the first trading date in the CRSP data. When there is ambiguity, we sum the mutual fund returns on the date identified by the SDC and the following date. In column 1 of Table 9, we regress the daily fund alphas on the IPO dates on EC and other control variables. The highly significant coefficient of EC reveals that connected funds outperform their nonconnected counterparts by 2 bps on the IPO dates. On average, there are 4.61 IPO days per month in our sample period, so the 2-bps daily premium of an EC fund would translate to a 9.2-bps monthly premium, which is close to the 11 bps we report in Table 7.

Columns 2–4 of Table 8 present placebo tests that use the fund alphas from 2 to 4 days after the IPO dates as the dependent variables. If the excess returns of the connected funds arise exclusively from IPO allocations, the coefficient of EC should only be significant on the IPO dates. Consistent with the hypothesis, the coefficients of EC in columns 2–4 are not reliably different from 0.

TABLE 9

IPO Connection and Daily Fund Performance

Table 9 presents Fama and MacBeth (1973) regressions of daily mutual fund ALPHA on EC and other control variables. The dependent variable ALPHA is calculated as $\text{ALPHA}_{it} \equiv r_{it} - rf_t - X_t\hat{\beta}_{it}$, where X_t is a vector of the realized returns on date t for each of the 4-factor portfolios (MKTRF, SMB, HML, and UMD), and $\hat{\beta}_{it}$ represents fund-specific factor loadings estimated from the time-series regression of daily fund excess returns on the daily 4 factors over the sample period of Oct. 1998–Mar. 2012. The starting date of the daily mutual fund return series is Oct. 1, 1998. The regressions are estimated on initial public offering (IPO) days and the 4 subsequent days. We use the first trading date that appears in the Center for Research in Security Prices (CRSP) data as the IPO day. We then take the mutual fund daily alpha, ALPHA_{it}, from that particular date, expressed in percentage, as the dependent variable in column 1. In column 2, we extract fund daily alphas (expressed in percentage) 1 trading day subsequent to an IPO day, and we exclude observations when the IPO + 1 day is an IPO date itself. Similar treatments are used in columns 3–5, whereby daily alphas on the 2–4 trading days following the IPO date are taken as dependent variables, respectively, and observations are excluded if the IPO + 2 to IPO + 4 day is an IPO date. We define effective connection (EC) as the type of connection when the fund manager and underwriter executive attended the same school and the fund received at least one IPO allocation from the underwriter in the past. We therefore aggregate effective connection to the date level to form the EC indicator variable (i.e., EC equals 1 if the fund is effectively connected to at least one of the underwriters on a particular day, and 0 otherwise). We control for fund characteristics such as ln(TNA), ln(AGE), EXPENSE_RATIO, and TURNOVER_RATIO and fund styles that are obtained at the end of the month prior to IPO. In Panel A, the cross-sectional estimation is performed using the Fama–MacBeth method over the 680 IPO days during the sample period of Oct. 1998–Mar. 2012. In Panels B and C, we run regressions for subsamples based on market conditions. We define the binary indicator variable HOT_MKT as equal to 1 if the "hotness" is greater than the sample median over the 1980–2012 period, and 0 otherwise. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: ALPHA				
	IPO Day	IPO + 1	IPO + 2	IPO + 3	IPO + 4
Variable	1	2	3	4	5
Panel A. All IPO Days					
EC	0.019***	0.006	0.004	0.004	−0.006
	(2.983)	(0.950)	(0.786)	(0.615)	(−1.018)
ln(TNA)	0.002	−0.002	0.001	−0.002	−0.004**
	(1.630)	(−1.494)	(0.567)	(−1.312)	(−2.567)
ln(AGE)	−0.000	0.003	−0.003	−0.001	0.003
	(−0.018)	(1.309)	(−1.419)	(−0.375)	(1.343)
EXPENSE_RATIO × 100	0.077	−0.079	−0.061	−0.079	−0.163**
	(1.402)	(−1.271)	(−1.023)	(−1.322)	(−2.466)
TURNOVER_RATIO	−0.001	−0.003*	−0.001	0.000	0.001
	(−0.548)	(−1.817)	(−0.487)	(0.234)	(0.363)
Constant	0.001	0.034*	0.002	0.031	0.009
	(0.038)	(1.661)	(0.089)	(1.515)	(0.426)
No. of obs.	271,384	271,384	271,384	271,384	271,384
R^2	0.308	0.315	0.312	0.315	0.308
Style fixed effects	Yes	Yes	Yes	Yes	Yes
Panel B. Hot IPO Markets					
EC	0.022**	0.009	0.009	−0.007	−0.010
	(2.533)	(1.071)	(1.242)	(−0.859)	(−1.120)
ln(TNA)	0.002	−0.002	0.000	−0.002	−0.005***
	(1.215)	(−1.217)	(0.129)	(−0.801)	(−2.606)
ln(AGE)	−0.002	0.003	−0.003	−0.002	0.005
	(−0.552)	(0.927)	(−1.044)	(−0.748)	(1.564)
EXPENSE_RATIO × 100	0.150*	−0.003	−0.002	−0.069	−0.160*
	(1.929)	(−0.029)	(−0.023)	(−0.789)	(−1.707)
TURNOVER_RATIO	0.001	−0.001	0.001	0.001	0.003
	(0.525)	(−0.608)	(0.355)	(0.439)	(1.253)
Constant	−0.004	0.020	0.002	0.038	−0.002
	(−0.151)	(0.773)	(0.061)	(1.410)	(−0.092)
No. of obs.	154,976	154,976	154,976	154,976	154,976
R^2	0.315	0.323	0.319	0.323	0.312
Style fixed effects	Yes	Yes	Yes	Yes	Yes

(continued on next page)

TABLE 9 (continued)
IPO Connection and Daily Fund Performance

	Dependent Variable: ALPHA				
	IPO Day	IPO + 1	IPO + 2	IPO + 3	IPO + 4
Variable	1	2	3	4	5
Panel C. Cold IPO Markets					
EC	0.014	0.000	−0.004	0.021**	−0.001
	(1.575)	(0.040)	(−0.539)	(2.580)	(−0.125)
ln(TNA)	0.002	−0.001	0.001	−0.002	−0.001
	(1.373)	(−1.015)	(1.224)	(−1.612)	(−0.456)
ln(AGE)	0.003	0.003	−0.003	0.002	−0.000
	(1.024)	(1.124)	(−1.137)	(0.628)	(−0.183)
EXPENSE_RATIO × 100	−0.044	−0.205***	−0.160**	−0.096	−0.168**
	(−0.632)	(−2.884)	(−2.130)	(−1.445)	(−2.051)
TURNOVER_RATIO	−0.004*	−0.005***	−0.004*	−0.001	−0.003
	(−1.734)	(−2.602)	(−1.677)	(−0.271)	(−1.387)
Constant	0.008	0.056*	0.002	0.020	0.028
	(0.262)	(1.728)	(0.070)	(0.626)	(0.805)
No. of obs.	116,408	116,408	116,408	116,408	116,408
R^2	0.296	0.301	0.299	0.301	0.303
Style fixed effects	Yes	Yes	Yes	Yes	Yes

We repeat the same test in hot and cold markets in Panels B and C and find that the connected funds benefit from IPO allocations only in hot markets.

The fact that evidence of superior performance is only observed on IPO dates provides further support for our conclusion that the outperformance of connected funds arises from favorable IPO allocations. It also provides further evidence that the methodology of using end-of-quarter holdings as a proxy for allocations, initially used by Gaspar et al. (2006), is a reasonable approximation.[25]

D. 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. The strategy exploits 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 1 month.

Table 10 compares the profits from this strategy to those of an equivalent strategy that invests in NC funds. For EC (row 1) and NC (row 0) portfolios, we regress the monthly excess return, that is, the equally weighted portfolio return in excess of the 1-month T-bill rate on the capital asset pricing model (CAPM) market risk factor, the Fama and French (1993) 3 factors, and the Carhart (1997) 4 factors. We report the alphas and the beta coefficients on each of the factors

[25]It should be noted that we also use end of quarter holdings to proxy for past allocation experience to define EC. However, unlike current allocation, past allocation experience is less likely to be measured with error consistently. For example, we would mistreat an EC fund consistently as NC fund only when this fund flips out all IPO shares by the end of the first quarter each time it is allocated IPO shares by its connected underwriters.

TABLE 10

Trading Strategy Based on Effective Connection

Table 10 presents the alphas and betas of a trading strategy that exploits effective connections. Portfolios are formed by sorting all sample funds every month into one of two bins according to the value of effective connection (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, respectively; 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 capital asset pricing model (CAPM), 3-factor, and 4-factor regressions, respectively. Market conditions are defined based on a monthly measure of the "hotness" of the initial public offering (IPO) market used by Ibbotson et al. (1994): the percentage of deals that are priced above the midpoint of the original file price range. We define the binary indicator variable HOT_MKT as equal to 1 if the "hotness" is greater than the sample median over the 1980–2012 period, and 0 otherwise. We then use this variable to separate the sample into subsamples of hot and cold markets. The sample period is Jan. 1992–Mar. 2012. Robust standard errors (White (1980)) are used. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. CAPM ALPHA

Market Condition	EC	ALPHA	MKTRF
All markets	1	0.252***	1.030***
		(2.696)	(41.974)
	0	0.091	0.956***
		(1.386)	(47.163)
	Difference	0.157**	0.074***
		(2.533)	(4.005)
Hot IPO markets	1	0.468***	1.001***
		(3.301)	(24.096)
	0	0.201**	0.927***
		(2.169)	(30.790)
	Difference	0.259***	0.075**
		(2.715)	(2.413)
Cold IPO markets	1	0.017	1.047***
		(0.142)	(37.689)
	0	−0.019	0.976***
		(−0.214)	(36.371)
	Difference	0.034	0.070***
		(0.430)	(3.179)

Panel B. 3-Factor ALPHA

Market Condition	EC	ALPHA	MKTRF	SMB	HML
All markets	1	0.190***	0.988***	0.271***	0.045*
		(2.803)	(52.642)	(8.074)	(1.666)
	0	−0.011	0.954***	0.191***	0.132***
		(−0.245)	(70.706)	(9.217)	(6.877)
	Difference	0.203***	0.035***	0.080***	−0.089***
		(4.106)	(2.641)	(3.279)	(−3.933)
Hot IPO markets	1	0.329***	0.976***	0.272***	0.058
		(3.473)	(31.120)	(7.054)	(1.464)
	0	0.035	0.930***	0.187***	0.141***
		(0.510)	(43.703)	(7.832)	(5.235)
	Difference	0.296***	0.048**	0.084**	−0.088**
		(4.114)	(2.188)	(2.547)	(−2.428)
Cold IPO markets	1	0.034	0.990***	0.265***	0.022
		(0.329)	(39.980)	(3.939)	(0.598)
	0	−0.048	0.968***	0.201***	0.123***
		(−0.744)	(54.255)	(4.257)	(4.163)
	Difference	0.081	0.021	0.063**	−0.101***
		(1.207)	(1.343)	(2.213)	(−3.750)

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TABLE 10 (continued)
Trading Strategy Based on Effective Connection

Panel C. 4-Factor ALPHA

Market Condition	EC	ALPHA	MKTRF	SMB	HML	UMD
All markets	1	0.193***	0.987***	0.272***	0.044	−0.003
		(2.847)	(51.445)	(8.233)	(1.622)	(−0.177)
	0	0.020	0.943***	0.197***	0.121***	−0.030***
		(0.409)	(63.831)	(10.140)	(6.900)	(−2.740)
	Difference	0.176***	0.046***	0.073***	−0.079***	0.029**
		(3.796)	(3.461)	(2.924)	(−3.556)	(2.157)
Hot IPO markets	1	0.343***	0.971***	0.273***	0.048	−0.012
		(3.675)	(31.582)	(7.189)	(1.001)	(−0.559)
	0	0.098	0.910***	0.190***	0.103***	−0.048***
		(1.416)	(40.457)	(8.164)	(4.082)	(−3.700)
	Difference	0.251***	0.065***	0.080**	−0.058	0.038**
		(3.766)	(3.270)	(2.474)	(−1.419)	(2.041)
Cold IPO markets	1	0.011	0.994***	0.256***	0.019	0.025
		(0.109)	(41.335)	(3.728)	(0.464)	(0.583)
	0	−0.044	0.967***	0.203***	0.124***	−0.004
		(−0.685)	(57.016)	(4.763)	(3.842)	(−0.152)
	Difference	0.054	0.027	0.053	−0.105***	0.029
		(0.791)	(1.601)	(1.546)	(−4.067)	(1.345)

in Panels A, B, and C, respectively, as well as *t*-statistics 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 separately for hot and cold markets.

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, Jan. 1992; 49 EC and 256 NC funds in Jan. 2000; and 74 EC and 675 NC funds in Jan. 2008. From row 1 in the "All Markets" sections of Panels A–C, we find that investing in an EC portfolio generates a significant (at the 1% level) monthly abnormal return of approximately 0.25% ($t = 2.70$), or an equivalent 3% annual return using the CAPM alpha; 0.19% ($t = 2.80$), or approximately 2.28% annualized abnormal return using the 3-factor model; and 2.28% ($t = 2.85$) using the 4-factor model. The insignificant alphas in row 0 of the CAPM, 3-factor, and 4-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% ($t = 2.53$), 2.40% ($t = 4.11$), or 2.04% ($t = 3.80$) per annum, depending on whether we use the CAPM, 3-factor, or 4-factor model, respectively.

The profits from this strategy are generated exclusively in hot-market periods. Using the same definition of hot and cold markets 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% ($t = 3.30$) for the 1-factor model, 3.96% ($t = 3.47$) for the 3-factor model, and 4.08% ($t = 3.68$) for the 4-factor model. In cold IPO markets, the excess return from investing in an EC portfolio is not significantly different from 0 regardless of the factor model used, which is consistent with the excess return being generated from allocations of underpriced IPOs. Estimated loadings of the risk factors imply that compared with their NC peers, the EC funds tend to exhibit a tilt toward small, growth-oriented, and momentum stocks. This is not surprising because EC funds are more likely to be allocated IPOs, which tend to be small growth firms.

VI. Robustness Tests and Extensions

A. Alternative Sources of Connection

It is likely that there are some funds that are well connected for reasons other than the education of their portfolio managers, and these funds may also attract (or prefer) graduates from elite universities. In particular, because of their proximity to investment banks and Ivy League universities, one might expect mutual funds that are located in New York and Boston to employ more elite graduates and to also have more connections with IPO underwriters. One might also expect the largest fund families to be better connected and to be more attractive for elite graduates. Our concern is that a relation between big fund families, fund locations, IPO connections, and elite graduates may be spuriously generating our results.

To address this concern, we define two dummy variables: a BIG3 dummy, which takes a value of 1 if a fund belongs to a fund family ranked among the top three at the end of the year 2000,[26] and 0 otherwise, and a NYBOSTON dummy, which takes a value of 1 if a fund is located in either New York or Boston, and 0 otherwise.

Panel A of Table 11 shows that elite graduates are indeed more prevalent in the big fund families as well as in those funds located in New York and Boston. Specifically, 80.61% of the fund managers in the BIG3 families come from elite schools versus 44.53% in the non-BIG3 families, and 63.97% of the New York and Boston fund managers come from elite schools versus 43.21% in other cities. Similarly, 35.08% of BIG3 fund managers are connected to the underwriters that conduct IPOs in a given month, versus 11.30% for those outside of the BIG3. The corresponding numbers are 24.00% and 10.46%, respectively, for funds in New York and Boston versus other cities.

Panel B of Table 11 revisits the return results from Table 7. In the column 1 regression, which includes a BIG3 dummy, the coefficient of EC is still significant; the coefficient of BIG3 is insignificant, as is the coefficient of the EC and BIG3 interaction. The results in column 2 indicate that there is a significant NYBOSTON effect, as indicated by the significant positive coefficient of NYBOSTON: Mutual funds located in New York and Boston appear to outperform by approximately 7.8 bps per month; however, the coefficient of EC is still significant in this regression, and there is no significant interaction between EC and NYBOSTON, suggesting that the connections between IPO underwriters and mutual funds in New York and Boston are no different than they are in other cities. We draw similar conclusions from the regressions in column 3, which control for BIG3 and NYBOSTON effects simultaneously.

Columns 4–6 of Table 11 have the same specifications as those in columns 1–3 except that the EC dummy has been replaced with the ELITE_SCHOOL dummy. We find that the elite effects in all columns are close to the results reported

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

TABLE 11

Robustness Checks:
The Influence of Big Fund Family and New York or Boston Location on Fund Performance

In Table 11 we test the robustness of the relationship between ELITE_SCHOOL/EC and ALPHA. Panel A presents the descriptive statistics of the percentage of ELITE_SCHOOL/EC fund–month observations in the biggest three families ranked by total net assets (TNA) at the end of 2000, the rest of the families, the funds that are located in New York or Boston, and the funds that are in the rest of the U.S. cities separately, together with an overall statistic for the whole sample. The dependent variable ALPHA is calculated as $\text{ALPHA}_{it} \equiv r_{it} - rf_t - X_t\hat{\beta}_{it}$, where X_t is a vector of the realized returns in month t for each of the 4-factor portfolios (MKTRF, SMB, HML, and UMD), and $\hat{\beta}_{it}$ represents fund-specific factor loadings estimated from the time-series regression of fund excess returns on the 4 factors over the entire sample period. The key independent variable ELITE_SCHOOL is the binary indicator variable for funds with top-school-graduated managers, which equals 1 if the portfolio manager has attended one of the top 10 universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and 0 otherwise. The other independent variable is the effective connection (EC) indicator denoting that the fund manager and underwriter executive attended the same school and that 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 a value of 1 if the fund belongs to one of the biggest three fund families ranked by TNA at the end of 2000, and 0 otherwise. The dummy variable NYBOSTON equals 1 if the fund family is located in either New York City or Boston, and 0 otherwise. Control variables of fund characteristics include investment-style fixed effects; the natural logarithm of fund size (ln(TNA)) and fund age (ln(AGE)); EXPENSE_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, which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month TNA of the fund. Robust standard errors (White (1980)) are used and are clustered at the month level. t-statistics are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Percentage of ELITE_SCHOOL_(EC)_FUND_MONTH by Category

	Category				
Variable	BIG3	Non-BIG3	NYBOSTON	Non-NYBOSTON	Overall
%_OF_ELITE_SCHOOL_FUND_MONTH	80.606	44.529	63.968	43.209	48.228
%_OF_EC_FUND_MONTH	35.081	11.296	24.003	10.461	13.735

Panel B. Pooled Regression

	Dependent Variable: ALPHA					
Variable	1	2	3	4	5	6
EC	0.120***	0.115***	0.121***			
	(3.555)	(3.424)	(3.376)			
EC × BIG3	−0.057		−0.050			
	(−0.945)		(−0.798)			
EC × NYBOSTON		−0.033	−0.022			
		(−0.679)	(−0.447)			
ELITE_SCHOOL				0.059***	0.042**	0.049***
				(3.609)	(2.345)	(2.779)
ELITE_SCHOOL × BIG3				−0.193***		−0.189***
				(−2.718)		(−2.669)
ELITE_SCHOOL × NYBOSTON					−0.004	0.021
					(−0.097)	(0.567)
BIG3	0.040		0.017	0.183***		0.158**
	(0.927)		(0.360)	(2.762)		(2.338)
NYBOSTON		0.078***	0.075***		0.076**	0.058*
		(3.073)	(2.783)		(2.328)	(1.726)
Constant	0.122	0.097	0.096	0.109	0.086	0.084
	(0.658)	(0.525)	(0.517)	(0.584)	(0.461)	(0.450)
No. of obs.	76,794	76,794	76,794	76,794	76,794	76,794
R^2	0.003	0.003	0.003	0.003	0.003	0.003
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

in column 4 of Panel A in 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 as well as in funds located in New York and Boston. Interestingly, we observe a significant negative interaction between ELITE_SCHOOL and BIG3, suggesting that elite-school managers do relatively worse in the three big fund families. This evidence is consistent with the idea that mutual funds actually have a higher bar for the intellect of those hired from the less elite schools because they tend to contribute less in terms of connections. If this is the case, and if the IPO allocations are allocated centrally in the big fund families,[27] then we might expect the smarter but less connected portfolio managers to outperform.[28]

Finally, as we noted earlier, a large fraction of the effectively connected mutual fund managers are Harvard graduates. We were curious about whether a Harvard connection is better or worse than other connections and found that the probability of a connected Harvard graduate being allocated an IPO is somewhat less than the probability of a connected non-Harvard graduate being allocated an IPO. We conjecture that this is because the Harvard connections are much more prevalent than, say, connections between two Brown graduates, suggesting that the tie may not be as strong when they are connected. However, given the much greater number of connections, the Harvard degree still may be more valuable.

B. Alternative Measures of Connection

To address the robustness of our results with respect to the definition of school connection, we explore more restrictive alternative definitions of school ties. Specifically, other than CONNECTED, the connection variable we have used up to now, we also define CONNECTED2, which equals 1 if CONNECTED equals 1 and, in addition, the fund manager attains the same degree as one of the underwriter executives, for example, an MBA and 0 otherwise. We also define CONNECTED3, which equals 1 if CONNECTED equals 1 and, in addition, the fund manager graduated at around the same time and 0 otherwise. Finally, we define CONNECTED4, which equals 1 if CONNECTED1, CONNECTED2, and CONNECTED3 each equal 1, and 0 otherwise. For the reason mentioned in footnote 15, the percentage of fund observations with these more restrictive connections drops significantly. The percentage of fund observations defined as connected based on CONNECTED is 43.50%, it drops to 36.61%, 15.70%, and 9.92% when the connection is based on CONNECTED2, CONNECTED3, and CONNECTED4, respectively.

Using these alternative measures, we repeat our main tests in the logit regression of IPO allocation in Panel A of Table 12 and the panel regression of mutual fund performance in Panel B. All of the four types of connections are significant in these two regressions in Panels A and B, but the precision of the estimates becomes less reliable with CONNECTED3 and CONNECTED4 because of the drop in the number of fund observations that are connected when we adopt the more restrictive definitions of connection.

VII. Conclusion

On average, graduates from elite universities have better analytical ability than those from less elite universities. This does not mean that, conditioned on being a mutual fund portfolio manager, a graduate from an elite university is likely to be smarter than his or her counterparts from less elite universities. If the

[27]We were able to confirm that this is indeed the case at Fidelity.

[28]In unreported regressions (available from the authors) we replicate our analysis excluding data from the three largest mutual fund families and mutual funds from New York and Boston.

TABLE 12

Robustness Checks: Alternative Measures of Educational Connection

In Panel A of Table 12, we test the four alternative measures of educational connection as described by Cohen et al. (2008) in the logit regression in Panel A of Table 5, and in Panel B we test these measures in the panel regression of Table 7. In Panel A, the dependent variable ALLOCATED equals 1 if the fund holds the initial public offering (IPO) stock at the end of the quarter of its issuance, and 0 otherwise; in Panel B, the dependent variable ALPHA is calculated as $\text{ALPHA}_{it} \equiv r_{it} - rf_t - X_t\hat{\beta}_{it}$, where X_t is a vector of the realized returns in month t for each of the 4-factor portfolios (MKTRF, SMB, HML, and UMD), and $\hat{\beta}_{it}$ represents fund-specific factor loadings estimated from the time-series regression of fund excess returns on the 4 factors over the entire sample period. The key independent variable CONNECTED1 in column 1 is built in the same way as described by Cohen et al. (2008) and, in our case, equals 1 if the fund manager and one of the underwriter executives attended the same tertiary institution, and 0 otherwise. Similarly, CONNECTED2 equals 1 if CONNECTED1 equals 1 and, in addition, the fund manager attains the same degree as one of the underwriter executives. CONNECTED3 equals 1 if CONNECTED1 equals 1 and, in addition, the fund manager graduated at approximately the same time. CONNECTED4 equals 1 if CONNECTED1, CONNECTED2, and CONNECTED3 all equal 1, and 0 otherwise. Throughout the table, we control for the deal characteristics of the natural logarithm of dollar proceeds (ln(PROCEEDS)). Control variables of fund characteristics include investment-style fixed effects; the natural logarithm of fund size (ln(TNA)) and fund age ln(AGE)); EXPENSE_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, which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month total net assets (TNA) of the fund. Robust standard errors (White (1980)) are used and are clustered at the month level. t-statistics are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variable	1	2	3	4
Panel A. Dependent Variable: ALLOCATED				
CONNECTED1	0.284***			
	(7.831)			
CONNECTED2		0.286***		
		(7.495)		
CONNECTED3			0.253***	
			(4.451)	
CONNECTED4				0.326***
				(4.778)
Constant	−5.199***	−5.155***	−5.138***	−5.130***
	(−23.984)	(−23.884)	(−23.886)	(−23.862)
No. of obs.	457,592	457,592	457,592	457,592
Fund controls	Yes	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Pseudo-R^2	0.0908	0.0906	0.0897	0.0898
Panel B. Dependent Variable: ALPHA				
CONNECTED1	0.079***			
	(3.200)			
CONNECTED2		0.085***		
		(3.146)		
CONNECTED3			0.057**	
			(2.193)	
CONNECTED4				0.064*
				(1.805)
Constant	0.110	0.118	0.135	0.140
	(0.586)	(0.634)	(0.724)	(0.753)
No. of obs.	76,794	76,794	76,794	76,794
R^2	0.003	0.003	0.003	0.003
Fund controls	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes

distribution of analytical ability at elite universities and non-elite universities overlap, then mutual funds should be able to find individuals who match the abilities of elite graduates from, say, the top 1% of the graduates of large state institutions. In contrast, given the concentration of talent at the elite schools, the typical elite graduate is likely to be better connected than even the most connected graduates of the lower-tier schools. As a result, although we see no reason to expect portfolio managers from elite universities to have better analytical ability than their non-elite counterparts, the elite grads are likely to be better connected. Indeed, mutual funds may rationally hire elite graduates with less analytical ability, given the compensating benefits that can be generated by their connections.

The evidence in this article suggests that the characterization just described provides a plausible 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 we show that the better performance can be attributed to their better connections. Specifically, their performance is generated from their being allocated more underpriced IPOs.

We also show that 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 those of other mutual fund strategies that have been documented in the literature. Examples include Kacperczyk et al. (2005), who find that the most concentrated funds earn an annual abnormal return of approximately 2.12%; Kacperczyk and Seru (2007), who document a performance gap of 2.16% between managers in the top 30% and bottom 30% of their RPI (reliance on public information) measures; Kacperczyk et al. (2008), who document a 3.41% 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% excess return with their active share measure.

As we mentioned in the Introduction, this article also contributes to a growing literature that studies the benefits of social connections in the finance industry. It should be noted that we find that educational ties explain IPO allocations even though our measure may be a very rough proxy for direct social connections; that is, we observe the colleges attended by the issuing banks' top executives rather than the colleges attended by the individuals who actually make the allocations. One possibility is that the top executives in these banks do in fact influence IPO allocations, and another possibility is that the educational backgrounds of a bank's top executives are either pretty good proxies for the educational backgrounds of the lower-level managers or that the educational backgrounds of the executives influence the bank culture in other ways. The exact channel by which these links influence behavior is beyond the scope of the current study; however, by linking these connections to mutual fund performance, we can very roughly quantify the value that connections can generate. For example, the typical mutual fund managed by an elite graduate had approximately \$2 to \$3 billion in assets and realized risk-adjusted excess returns of approximately 55 bps per year from their IPO allocations. Hence, their elite educations could conceivably generate several million dollars per year and may thus rationalize the very high return to "talent" in this industry.

Supplementary Material

Supplementary material for this article is available at https://doi.org/10.1017/S0022109018000534.

Appendix

TABLE A1
List of Underwriters in the Sample

Table A1 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 Jan. 1992–Mar. 2012 and extract the PERMNO for each underwriter firm from the Center for Research in Security Prices (CRSP) data based on the Committee on Uniform Securities Identification Procedures (CUSIP) number. We get the historical information on senior executives from ExecuComp, which provides compensation and employment information for up to nine executives per firm. This information is supplemented by the Corporate Library from 2000. The sample of underwriters is further limited by the availability of relevant educational information; that is, we keep only the senior executives we know graduated from U.S. 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 dash ("—") indicates that the start date is earlier than the start date of our sample period or later than the end date of our sample period. The variable IS_TOP_10 is a binary indicator variable that takes a value of 1 if the underwriter is among the top 10 underwriters, ranked by number of deals during the sample period, and 0 otherwise.

PERMNO	Bookrunner	SDATE	EDATE	IS_TOP_10
10071	Alex Brown & Sons Inc.	—	Aug. 29, 1997	1
36469	First Union Capital Markets Group	—	Dec. 31, 2008	0
38703	Wells Fargo Bank NA	Nov. 3, 1998	Dec. 31, 2012	0
47159	Fleet Boston	Apr. 20, 1992	Mar. 31, 2004	0
47248	Westfield Financial Corporation	Oct. 3, 2001	—	0
47896	Chase Manhattan	Jan. 2, 2001	Dec. 31, 2012	1
48071	Morgan JP Co. Inc.	—	Dec. 29, 2000	1
50200	Wachovia Securities Inc.	—	Aug. 31, 2001	0
54463	PaineWebber Inc.	—	Nov. 3, 2000	0
59408	Banc of America Securities LLC	Oct.1, 1998	—	0
63220	Dain Rauscher Wessels	—	Jan. 10, 2001	0
64995	KeyCorp/McDonald Investments	—	—	0
65330	Legg Mason & Co. Inc.	—	—	0
66157	US Bancorp Piper Jaffray Inc.	May 2, 1998	Jan. 1, 2004	0
68144	Robinson-Humphrey Co.	—	—	0
68304	Bear Stearns & Co. Inc.	—	May 30, 2008	0
69032	Morgan Stanley	—	—	1
69649	Raymond James & Associates Inc.	—	—	0
70519	Citigroup	Oct. 8, 1998	—	0
72726	State Street Capital Markets Corp.	—	—	0
72996	Stifel Nicolaus & Co. Inc.	—	—	0
77043	Southwest Securities Group Inc.	Oct. 11, 1991	—	0
78946	Dean Witter Reynolds Inc.	Feb. 23, 1993	May 30, 1997	0
80599	Lehman Brothers	May 31, 1994	Sept. 17, 2008	1
83823	Hambrecht & Quist Inc.	Aug. 9, 1996	Dec. 10, 1999	1
85653	Friedman Billings Ramsey Group	Dec. 23, 1997	June 9, 2009	0
85944	Tucker Anthony Inc.	Apr. 2, 1998	Oct. 31, 2001	0
86868	Goldman Sachs & Co.	May 4, 1999	—	1
89195	Principal Financial Securities Inc.	Oct. 23, 2001	—	0
89826	Texas Capital Securities Inc.	Aug. 13, 2003	—	0
89968	Piper Jaffray Cos	Jan. 2, 2004	—	0

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