Three essays on finance

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2016

Wang, Y. (2016). Three essays on finance. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/69399>

<https://doi.org/10.32657/10356/69399>

**NANYANG
TECHNOLOGICAL
UNIVERSITY**

THREE ESSAYS ON FINANCE

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2016

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A thesis submitted to the Nanyang Technological University

in partial fulfilment of the requirement for the degree of

Doctor of Philosophy

2016

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my supervisor, Professor **Hwang Chuan Yang**. He has been supportive since my first day as a graduate student. He has taught me, both consciously and unconsciously, what it takes to be an independent researcher. I deeply appreciate all his contributions of time, ideas, funding and most importantly moral support, without which my PhD journey would not have been possible. Sometimes he feels like a father to me, being strict yet caring and helpful. His encouraging words, enthusiasm and hard work in research are what guided me through during the difficult times. I am also thankful for the excellent example he has put up as a successful researcher and professor.

I express my gratitude to Associate Professor **Gao Huasheng, Stephen G. Dimmock**, with whom I have had many enlightening discussions. Stephen has shared with me numerous programming advices, empirical skills as well as career development advices. Huasheng has motivated me with his bright research ideas and his efficiency in research projects. I am also grateful to my thesis committee members Associate Professor **Luo Jiang, Zhang Huai** and Assistant Professor **Chen Zhanhui** for being my thesis readers and provide constructive and valuable advices on how to improve my papers. Besides, Zhanhui has also inspired me immensely during his asset pricing course and informal gatherings in terms of how to choose wisely in life. I would like to thank Assistant Professor **Chen Tao** for sharing his hand collected data generously and the many productive discussions we have had when we work together. I am also thankful for all the faculty members who share insightful comments at the divisional presentations.

Looking back, the entire doctoral process is a rough road to travel, but my fellow peers in the PhD office have made it much more pleasant. We share countless days and nights together. We work side by side and cheer each other up. I am especially grateful for my peers **Huang Xiaoran, Liu Na, Ma Yujing** and **Yang Bowen** who stuck it out with me. I express my sincere gratitude to my seniors and juniors: **Cai Yu, Deng Xin, Luo Juan, Li Bing, Wang Ying, He Zhongda, Pang Caiji, Yao Jiaquan, Fu Kangkang, Kim Jungmin, Qiao Zheng, Xu Limin, Li Lingwei, Xia Chongwu**, and **Yang Endong** for the amazing guidance they have shared with me, the willingness to listen and, of course, for our enjoyable badminton time. I could never think of a better companion than my friends at the PhD office.

I owe my thanks to the ladies: Ms **Karen Barlaan**, Ms **Hu Tsai Ting**, Ms **Amarnisha Mohd**, and Ms **Quek Bee Hua** at the PhD office who organize all the unforgettable gatherings and who are always there to help with all the conference claims, coordination of recommendation letters, and all the forms to fill and who take such a good care of each of us.

At the very end I would like to express my deepest appreciation to my parents for their constant support and unconditional love. I am greatly indebted to my best friend, lifelong partner, the most interesting teacher, the tenderest listener, my most beloved husband. Rainy or shine, he is always there holding my hands. I thank him for all those joyful and tearful moments we spend together and all the wonderful bedtime stories he has told. Without him, I would never have the courage to embark on the doctoral journey.

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Introduction

In chapter one, we find that 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 connections with underwriters that facilitate allocations to underpriced 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 percent per annum in hot markets.

In chapter two, I show that there are greater occurrences of fraud committed by elite school graduates even after taking into account the fact that there are more CEOs graduated from such schools. The firm-level analysis further reveals that there is a stronger peer effect of fraud in elite schools, suggesting that frauds are more contagious among elite school graduates. Furthermore, elite school CEOs are no more likely than non-elite school graduates to commit fraud if it were not for peer effect. Using school endowment as a proxy for the tightness of the alumni network, I find evidence suggesting that there is an elite school culture that promotes tighter school network, which, in turn, enhances the peer effect. An instrumental variable approach provides consistent evidence of causality. I further examine the possible channels, and document that the performance of peer firms positively influences the peer effect of fraud, which is consistent with the “keeping up with Joneses” argument. My paper sheds light on the costs of educational connection in the context of financial misconduct.

In chapter three, we document a negative cross-sectional relationship between the ownership of smart investors (high return gap mutual funds) and future stock returns controlling for total institutional ownership. We interpret this result as an attenuation of cost of capital by smart investors, which is further corroborated by a similar relation between smart investor ownership and implied cost of capital estimated from various models. Our finding is consistent with the predictions from the noisy rational expectation models like Easley and O'hara (2004) that when there are more informed investors in a firm and/or when the private signals they receive are more precise, uninformed investors face lower information risk, which leads to lower cost of capital. These predictions are further supported by evidence from natural experiments including brokerage closure and the passage of Reg. FD.

Chapter 1

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

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 connections with underwriters that facilitate allocations to underpriced 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 percent per annum in hot markets.

JEL classification: G23, G24

Keywords: Social connection, IPO allocation, mutual fund performance, mutual funds

1. Introduction

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

The research in this paper is motivated by Chevalier and Ellison (1999) who document that mutual fund managers who attended more selective schools outperform those who did not.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 IPO allocations of mutual funds. Given the evidence of IPO under-pricing,³ being allocated (especially hot) IPOs is a potential source of the observed superior performance of the

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 (2012) find similar results using a hedge fund sample.

³ Ibbotson, Sindelar and Ritter (1988) document a large initial day return of 16.4 percent for firms going public between 1960 and 1987. The updated statistics on Ritter's website show that the average first-day return of IPOs was 7.2 percent in the 1980s, 14.8 percent from 1990 to 1998, and 13.3 percent from 2001 to 2013 (it surged to 64.5 percent during the internet bubble period of 1999-2000).

mutual funds managed by elite graduates. Specifically, we examine data on the education of 1,420 portfolio managers working at 1,320 open-end equity mutual funds along with the education of 216 firm executives that underwrote 1,636 IPO deals during our sample period (January 1992 to March 2012). We find that mutual funds managed by elite graduates are indeed allocated more IPOs, 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 both an educational tie and an allocation in the previous deal, what we are calling an effectively connected (*EC*) mutual fund, is about five times as likely to be allocated an IPO in a deal than other mutual funds. Effectively connected mutual funds also outperform other mutual funds, and this outperformance occurs only in the months in which the funds are effectively connected to an underwriter taking a firm public. 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 IPO and in addition, does not significantly influence a mutual fund's performance.

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 about 1.34 percent on an annualized basis. It should be noted that this superior performance occurs *only* in the months in which the funds are connected to underwriters that allocate IPOs. Indeed, the returns of 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 percent on average, and 4.08 percent in hot IPO markets.

We are not the first to illustrate the benefits of educational networks in the finance industry. Cohen, Frazzini and Malloy (2008) find that mutual fund managers tilt their portfolios toward firms with which they are connected through school ties, and the connected holdings of these funds performed significantly better than their non-connected counterparts. Cohen, Frazzini and Malloy (2008) estimate the total impact of the connection between fund managers and firm executives is only about 2 basis points per year, 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 envelop” 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 social connections in the finance industry. Noteworthy contributions include Hochberg, Ljungqvist and Lu (2007, 2010), who find that better-networked VC firms face less

competition and experience significantly better fund performance, Hwang and Kim (2009), who study the CEO-director connection 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 percent 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 paper is similar to Engelberg, Gao and Parsons (2012) in that we observe the educational background of top executives of the banks rather than the background of the relevant decision maker (in their case the lending officer and 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 background of top executives at banks are in fact pretty good proxies for the educational backgrounds of the lower level managers, or in some other ways influence the culture of the bank. However, in contrast to other papers 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. Indeed, if one selects mutual funds based on connections to the underwriters of upcoming IPOs rather than by elite education, the magnitude of the returns are substantially greater.

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 (2006) 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 (2006) study of mutual fund allocations within fund families suggest that in large fund families, IPOs are allocated strategically, so that 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 and 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 to those managers with 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) and Philippon and Reshef (2012, 2013)), a higher proportion of elite graduates have joined the finance industry (Goldin

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.

and Katz (2008) and 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 paper, 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, rents associated with being better connected that we empirically observe are consistent with these models.

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

2. Data

2.1. Sample construction

Our study examines data on mutual fund returns and holdings, IPO data, and connection-related data. The mutual fund data comes from the Thomson Reuters Mutual Fund Database (TR MF) and the CRSP Survivor-Bias-Free US Mutual Fund Database (CRSP MF); the former includes information from the semi-annual N-SAR filings that are mandatory for mutual funds,⁵ while 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 website 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 four factor portfolios, MKTRF, SMB, HML and UMD as detailed in 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 initial public offerings. Following Loughran and Ritter (2002), we exclude unit offerings, closed end funds, real estate investment trusts (REITs), partnerships and American depository receipts (ADRs), as well as all IPOs with a file price below \$5.00 per share.

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

There are 5,372 IPOs that meet the above-mentioned criteria during the sample period of January 1992 to March 2012.

Since we use common educational background to proxy for “connectivity,” we rely on biographical information on mutual fund managers and executives at underwriter firms. We identify historical employment and educational information for 216 senior executives,⁶ working at 31 public lead underwriters, (see Appendix, Table AI, for a list of the underwriters), covering 1,636 IPO deals, or 30.45 percent of the deals population. We also identify similar information about 1,320 mutual fund managers, managing 35.30 percent ($=1320/3739$) 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, *EliteSchool*, which equals one if the portfolio manager attended (as either an undergraduate or graduate student) one of the top ten universities ranked by the average SAT score of the freshmen at the portfolio managers’ tertiary institution,⁷ and zero otherwise.

The educational information about the senior underwriter executives comes from ExecuComp, which contains information about 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 executive’s 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-

⁶ These are the top-compensated executives in underwriter firms such as CEO, CFO, Chairman, etc.

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

reference the public biographies from three sources: the company's website, NNDB,⁸ and Bloomberg Businessweek. From this search we learned that Reilly was born in 1954⁹ and received both a bachelor's and an MBA degree from 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 in Cohen, Frazzini and Malloy (2008), our connection indicator equals one if both the fund manager and the underwriter involved in the IPO attended the same college. We then aggregate the connection measure from the person-person level to the deal-fund level, i.e., our connection dummy (*Connected*) is set to one for a mutual fund if any of the top executives from one of the lead underwriters attended the same tertiary institution as any one of the mutual fund's portfolio managers. Since 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

⁸ NNDB is an intelligence aggregator that tracks the activities of people that 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, MD, JD and 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 non-matched funds. Second, for the remaining fund names with a spelling distance greater than 20, we use the fund ticker to obtain the match and manually check its accuracy.

a value of one 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, the fund received at least one IPO allocation from the same underwriter in the past. 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 *EliteSchool* is about .37.

Finally, we follow Gaspar, Massa and Matos (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*, to one if the fund holds the IPO stock at the end of the issuance quarter. This, of course, is a noisy measure since some funds sell the IPO stock prior to the quarter's end, and others acquire the IPO stocks on the market.

2.2. Fund characteristics

There are 1,320 unique open-end equity funds in the sample, amounting to about 35.30 percent of the domestic open-end equity fund population during the sample period. Table 1 reports descriptive statistics for our sample. Compared with all funds, funds in our sample tend to be larger, as measured by total net assets (*TNA*), they have lower turnover, and are older as measured by *Age* in years. They do have higher returns (*Ret*), suggesting that there may be an selection issue, but there is no survival bias as we don't require our sample fund to be surviving funds. The univariate results in Table 1 also suggest that *EliteSchool* funds on average are larger, have lower turnover, and are older as measured by *Age* in years, but have similar returns as *Non-EliteSchool* funds.

[Insert Table 1 here]

2.3. Deal characteristics

There are 1,636 IPOs in our sample period, and of these, 1,303 allocated IPO shares to mutual funds in our sample. The variable capturing the “hotness” of the IPO market, taken from Ibbotson, Sindelar and Ritter (1994),¹² is the percentage of deals that are priced above the midpoint of the original file price range. We define a binary indicator variable *HotMkt*, which equals one if the “hotness” value falls above the median value over the 1980 to 2012 period, and zero otherwise. Given this definition, we have 1,042 deals that take place in a hot market and 594 in a cold market. In Table 2, we present summary statistics for all IPO firms as well as for those issued in hot and cold markets.

[Insert Table 2 here]

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

¹² This data is available at Jay Ritter’s website: <http://bear.warrington.ufl.edu/ritter/IPOdata.htm>.

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

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 about 2 percent, while the probability that a particular IPO is allocated to a non-elite-school managed fund is only about 1 percent. In addition, mutual funds receive allocations for 4.4 per cent of the IPOs underwritten from banks that allocated IPO to them in the past, which compares to the 0.6 per cent of the IPOs underwritten by banks for which they had no previous relation. For funds that are effectively connected (*EC*), i.e., they have a previous relation as well as an educational connection, the probability of an IPO allocation is about 5 percent, which can be compared to the probability that a particular IPO is allocated to an *NC* fund (a fund which is not *EC*), which is about 1 percent.

The last three columns present the comparison of deal characteristics in different market conditions: as the market conditions for IPOs become hotter, we see more deals per month, higher average first-day returns, and lower proceeds per deal. The lower proceeds are 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.

2.4. Connection characteristics

[Insert Table 3 here]

This section provides descriptive statistics about the educational connections between underwriters and mutual funds. As Panel A of Table 3 shows, the median

number of senior executives per underwriter is 5 and the median number of portfolio managers per fund is 1. 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, a fund is connected to about 3 deals (*# of effective connections per EC fund-month*). The average mutual fund is effectively connected 13.74 percent of the time (*% effectively connected months per fund*), but elite-school funds are effectively connected 26.92 percent of the time (*% effectively connected months per elite school fund*).

Panel B 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, University of Pennsylvania, Yale University and Columbia University. Harvard University also leads in the number of portfolio managers graduated (45), followed by University of Pennsylvania, New York University, University of Chicago and Columbia University.

When we aggregate the connections of individuals from the various universities we find that individuals from Harvard, Columbia, Pennsylvania, Chicago and Stanford are the most connected. As shown in Figure 1, Harvard is dominant, with about 68.80 percent of the observation with connections. This is because Harvard graduates are highly represented in both top executive positions in investment banking, about 23.63 percent of our sample of executives, as well as in the portfolio manager positions in our mutual funds, about 8.1 percent of our sample of portfolio managers.

[Insert Figure 1 here]

3. 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.

[Insert Table 4 here]

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 basis points per month, or 0.55 percent 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 column (2) and (3) by months with and without IPOs we find that the superior performance is concentrated in months with IPOs.

4. Elite education, connections, and IPO allocations

The evidence reported in the preceding section confirms Chevalier and Ellison (1999)'s finding that elite school funds outperform in our longer and more recent sample period. One interpretation of this evidence is that the excess returns come from the superior connections rather than the superior analytic ability of the elite graduates that manage the funds. In this section we consider a potential channel that can enable elite

graduates to benefit from their connections; the allocation of IPOs. We examine whether connections of elite graduates increase the number of their IPO allocations as well as the quality of their IPO allocations.

4.1. *Elite education and IPO allocations*

We first estimate logit regressions of the binary indicator variable *Allocated* on the *EliteSchool* 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 one if the fund holds the stock of any firm that went public in the prior quarter, and zero otherwise. As we previously noted, this is a noisy signal of whether or not a fund receives an IPO allocation, since funds can sell their allocations before the end of the quarter and can purchase IPOs they are not allocated in the secondary market. If this noise is uncorrelated with the education of the portfolio manager it will generate a bias against finding a significant relation.¹⁴

Our first connection measure *Connected*, designed as in Cohen, Frazinni and Malloy (2008),¹⁵ is a dummy variable that equals one if the fund manager and at least one of the underwriter executives attended the same tertiary institution and zero otherwise. We also define *AllocatedBefore*, which equals one if the fund was allocated an IPO from the bank underwriting the current deal previously, to capture the past allocation history. As we will show, both variables, i.e., a common educational

¹⁴ We do not have either evidence or theory about how education will affect the tendency of mutual funds to flip shares after an allocation. As we mention in the introduction, education connections may be associated with IPO allocations because of the importance of personal relationships in this business, which can influence the tendency to flip the shares. See also footnote 17.

¹⁵ Cohen, Frazinni and Malloy (2008) also adopts more restrictive definitions of connections that requires connected individuals to attend the same colleges at the same time or that they attended the same schools or departments in the college. If we used these more restrictive definitions we would have very few matches.

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 will say that a fund is *effectively connected (EC)* if both dummy variables equal one.

[Insert Table 5 here]

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 (since 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 in Reuter (2006).

The positive coefficient of *Connected* reported in column (1) shows that having an educational connection increases the odds of receiving IPO allocations. Column (2) shows that the fund's past allocation history *AllocatedBefore* is a more important indicator of future IPO allocation decisions, which is not surprising since past allocation history essentially captures the effect of all variables, including *Connected*, that are

important in affecting IPO allocations. Column (2) also shows a strong positive interaction between *Connected* and *AllocatedBefore*, indicating that the positive impact of allocation history on the odds of allocation is larger when the fund has an educational connection with the underwriter.

Using the coefficients of Column (2), we can calculate the probability of receiving an IPO allocation for funds conditioned on their previous allocations and connections. As shown in Panel B of Table 5, we see that *EC* funds have the greatest probability of receiving allocations of the upcoming IPOs. In contrast, connected funds that were not allocated in the past are actually slightly less likely to be allocated future IPOs than their less connected counterparts, suggesting that many of the educational connections have no influence on allocations. Consequently, in Column (3) we re-estimate the regression in Column (2) but drop the individual variables, *Connected* and *AllocatedBefore* to focus on the impact of *EC* on the odds of IPO allocations. The R-squared of this regression is only slightly lower than the Column (2) R-squared, suggesting that the combined *EC* variable pretty well captures the notion of being connected to the underwriter.

The estimates reported in column (4), which includes the *EliteSchool* 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 *EliteSchool* 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* by its counterpart *AWC* (short for “Allocation Without Connection”), which is a dummy variable that takes the value of one for funds

that were previously allocated an IPO by the incumbent underwriter without the benefit of a school connection. *AWC* is slightly negatively correlated with *EliteSchool*, so as expected the inclusion of this variable does not affect the significance of the *EliteSchool* effect, providing further evidence of the importance of connections.

As we mentioned in the introduction, research by Gaspar, Massa, and Matos (2006) and Massa, Reuter, and Zitzewitz (2010) provide evidence that fund families may strategically allocate IPOs to favor some funds over others. To examine whether managers with an elite education receive favorable IPO allocations within their fund families, 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. The regressions reported in columns (1) and (3) of Panel C 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 do find (in columns (2) and (3)) that *EC* funds receive more IPO allocations than *NC* funds within families.

For the analysis that follows, our focus is on the *EC* classification. As the above regressions 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.

4.2. Are connected mutual funds allocated better IPOs?

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, *HotMkt*, which is an indicator variable measuring whether the IPO is issued in a hot market period.

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 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*HotMkt* indicates that the gains from connections is larger in hot markets,¹⁶ and the significantly negative coefficient of *HotMkt* 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.

[Insert Table 6 here]

We also run these regressions separately in hot and cold market subsamples, which we report in columns (3) and (4) respectively. The juxtaposition of these two columns provides a clearer picture: the significant coefficient of *EC* in both columns

¹⁶ In unreported tests, we explore various definitions of market conditions, including those based on monthly IPO volume and average underpricing. The results remain qualitatively the same as in column (3) and (4) of Table 6.

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.¹⁷

5. IPO connection and fund performance

Up to this point we have presented evidence that is consistent with the Chevalier and Ellison (1999) finding that mutual funds managed by graduates of elite universities outperform their counterparts from less prestigious universities. We considered one potential channel that could have generated these excess returns, the allocation of underpriced IPOs, and found that mutual funds managed by elite university 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 in Chevalier and Ellison (1999), but also include our measures of mutual fund connections. We also report Fama-MacBeth 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.

¹⁷ We should interpret this result with some caution since we observe end of quarter holdings rather than actual allocations. We are particularly concerned about potential biases that can arise if *EC* funds systematically flip IPOs more often when their initial returns are unfavorable.

5.1. Panel Regressions

Table 7 reports regressions that are similar to those reported in column (2) of Table 4, but the focus is 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 those months in which a mutual fund is connected to an underwriter doing an IPO, i.e., *EC*=1, the fund earns a 0.11 percent (*t*=3.76) higher risk adjusted return than its non-connected peers with the same investment style and characteristics.

[Insert Table 7 here]

The 0.11 percent monthly excess returns 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-envelope calculation with the following information obtained from Table 2: *IR*=31.52 percent; *prob. allocated to NC funds per deal* = 0.012; *prob. allocated to EC funds per deal* = 0.051; *# of IPOs per month* = 11.265. Then the average weight of IPO stocks in *EC* funds can be imputed as $\frac{0.11\%}{11.265 \times (0.051 - 0.012)} = 0.79\%$, which is of a similar magnitude as the average weight of 1.18 percent for the connected securities examined in Cohen, Frazzini and Malloy (2008). In other words, the magnitude of the estimated coefficient is consistent with the excess returns being generated by the IPO allocations.¹⁸

¹⁸ Alternatively, if we use the size-weighted initial return, which is 18 percent the back-of-envelope calculation generates an estimated weight of 1.31 percent.

In column (2) 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.

Column (5) in Table 7 simply reproduces column (2) from Table 4, which replicates the Chevalier and Ellison (1999) result, and column (6) adds *EC* to that regression. Our findings suggest that *EC*, which is statistically significant in this regression, substantially subsumes the effect of *EliteSchool*, which is not statistically significant in this specification. In column (7), we replace *EC* by its counterpart *AWC*, 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 coefficient of *AWC* is marginally significant in this regression, and in contrast to the regression reported in column (6), the coefficient of *EliteSchool* 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 *EliteSchool* 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.¹⁹

5.2. 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)*, *exp_ratio*, *turn_ratio* and fund styles are obtained at the end of month *t-1*.

[Insert Table 8 here]

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

5.3. 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

¹⁹ We have also estimated the regressions in this table with returns before fees and generated very similar results.

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 one month.

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

[Insert Table 9 here]

There are on average 55 *EC* funds and 348 *NC* funds per month in our sample. We have 1 *EC* fund and 84 *NC* funds in the first sample month, January 1992; 49 *EC* and 256 *NC* funds in January 2000; and 74 *EC* and 675 *NC* funds in January 2008. From Row “1” in the “All Markets” sections of Panels A through C, we find that investing in an *EC* portfolio generates a significant (at the 1 percent level) monthly abnormal return of about 0.25 percent ($t=2.70$), or an equivalent 3 percent annual return using the CAPM alpha; 0.19 percent ($t=2.80$), or about 2.28 percent annualized abnormal return using the three-factor model; and 2.28 percent ($t=2.85$) using the four-factor model. The insignificant alphas in row “0” of the CAPM, three-factor and four-factor models

indicate that investing in an *NC* portfolio will not yield an abnormal return. The difference between *EC* and *NC* portfolios is 1.92 percent ($t=2.53$), 2.40 percent ($t=4.11$), or 2.04 percent ($t=3.80$) per annum, depending on whether we use the CAPM, three-factor or four-factor model.

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

6. Robustness Tests and Extensions

It is likely that there are some funds that are both 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 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 one, if a fund belongs to a fund family ranked among the top three at the end of year 2000,²⁰ and zero otherwise and a *NYBoston* dummy, which takes the value of one if a fund is located in either New York or Boston and zero otherwise.

[Insert Table 10 here]

Panel A of Table 10 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 percent of the fund managers in the *Big3* families come from elite schools versus 44.53 percent in non-*Big3* families and 63.97 percent of the New York/Boston fund managers come from elite schools versus 43.21 percent in other cities. Similarly, 35.08 percent of *Big3* fund managers are connected to the underwriters that conduct IPO in a given month, versus 11.30 percent for those outside of the *Big3*. The corresponding numbers are 24.00 percent and 10.46 percent respectively for funds in New York/Boston versus other cities.

Panel B of Table 10 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

²⁰ The top three mutual fund families ranked by the asset under management at the end of year 2000 are Fidelity, Vanguard and American Funds.

and Boston appear to outperform by about 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) to (6) have the same specifications as those in column (1) to column (3) except that the *EC* dummy has been replaced by the *EliteSchool* dummy. We find that the elite effects in all columns are close to that reported in column (4) in Panel A of Table 4, suggesting that the results documented earlier are not driven by the fact that there are more elite graduates working for big fund families as well as in funds located in New York and Boston. Interestingly, we observe a significant negative interaction between *EliteSchool* 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 families,²¹ then we might expect the smarter but less connected portfolio managers to outperform.²²

²¹ We were able to confirm that this is indeed the case at Fidelity.

²² In unreported regressions (available on request) we replicate our analysis excluding data from the three largest mutual fund families and mutual funds from New York and Boston. Because a large fraction of the portfolio managers in our sample are Harvard graduates we also looked at a sample that excludes those funds managed by Harvard graduates. The estimates of these regressions are quite similar to the regressions for the full sample.

7. 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 distribution of analytical ability at elite universities and non-elite universities overlap, then mutual funds should be able to find individuals that match the abilities of elite graduates from say the top 1 percent 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, while we see no reason to expect portfolio managers from elite universities to have better analytic ability than their non-elite counterparts, the elite grads are likely to be better connected. Indeed, mutual funds may rationally hire elite graduates with less analytic ability, given the compensating benefits that can be generated by their connections.

The evidence in this paper suggests that the above characterization provides a 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 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 other mutual fund strategies that have been documented in the literature. Examples include Kacperczyk, Sialm and Zheng (2005), who find that the most concentrated funds earn an annual abnormal return of about 2.12 percent; Kacperczyk and Seru (2007) who document a performance gap of 2.16 percent between managers in top 30 percent and bottom 30 percent of their RPI measures; Kacperczyk, Sialm and Zheng (2008), who document a 3.41 percent return difference between the top and bottom decile portfolios based on their return gap measure; and Cremers and Petajisto (2009), who document a 2.55 percent excess return with their active share measure.

As we mentioned in the introduction, this paper 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, i.e., we observe the college attended by the issuing banks' top executives rather than 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 background of a bank's top executives are either pretty good proxies for the educational backgrounds of the lower level managers, or that the educational background of the executives influence the bank cultures 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 about two to three billion dollars in assets and realized risk adjusted excess returns of about 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.

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Appendix

Table AI List of underwriters in the sample

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

Permno	Bookrunner	Sdate	Edate	IsTop10
10071	Alex Brown & Sons Inc	-	29/8/1997	1
36469	First Union Capital Markets Group	-	31/12/2008	0
38703	Wells Fargo Bank NA	3/11/1998	31/12/2012	0
47159	Fleet Boston	20/4/1992	31/3/2004	0
47248	Westfield Financial Corporation	3/10/2001	-	0
47896	Chase Manhattan	2/1/2001	31/12/2012	1
48071	Morgan JP Co Inc	-	29/12/2000	1
50200	Wachovia Securities Inc	-	31/8/2001	0
54463	PaineWebber Inc	-	3/11/2000	0
59408	Banc of America Securities LLC	1/10/1998	-	0
63220	Dain Rauscher Wessels	-	10/1/2001	0
64995	KeyCorp/McDonald Investments	-	-	0
65330	Legg Mason & Co Inc	-	-	0
66157	US Bancorp Piper Jaffray Inc	2/5/1998	1/1/2004	0
68144	Robinson-Humphrey Co	-	-	0
68304	Bear Stearns & Co Inc	-	30/5/2008	0
69032	Morgan Stanley	-	-	1
69649	Raymond James & Associates Inc	-	-	0
70519	Citigroup	8/10/1998	-	0
72726	State Street Capital Markets Corp	-	-	0
72996	Stifel Nicolaus & Co Inc	-	-	0
77043	Southwest Securities Group Inc	11/10/1991	-	0
78946	Dean Witter Reynolds Inc	23/2/1993	30/5/1997	0
80599	Lehman Brothers	31/5/1994	17/9/2008	1
83823	Hambrecht & Quist Inc	9/8/1996	10/12/1999	1
85653	Friedman Billings Ramsey Group	23/12/1997	9/6/2009	0
85944	Tucker Anthony Inc	2/4/1998	31/10/2001	0
86868	Goldman Sachs & Co	4/5/1999	-	1
89195	Principal Financial Securities Inc	23/10/2001	-	0
89826	Texas Capital Securities Inc	13/8/2003	-	0
89968	Piper Jaffrey Cos	2/1/2004	-	0

Figure 1 Top 10 most connected universities

Table 1 Fund characteristics

This table 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 *EliteSchool* is a binary indicator variable for funds with top school graduated managers, which equals to one if the portfolio manager has attended one of the top ten universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and zero otherwise. We report statistics for all open-end equity funds in the intersection of CRSP and Thomson Reuters mutual fund database in column (1), the sample funds in column (2) and for those funds managed by elite graduates in column (4) and those managed by non-elite graduates in column (5) respectively. The p-values 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).

	All funds (1)	Sample funds (2)	p-Val. of Diff. (3)	EliteSchool (4)	Non-elite (5)	p-Val. of Diff. (6)
<i>TNA (\$mil)</i>	1297.646	1938.250	<0.001	2718.743	1168.095	<0.001
<i>Expense ratio (%)</i>	1.226	1.118	<0.001	1.159	1.194	<0.001
<i>Turnover (%)</i>	92.558	88.016	<0.001	72.098	103.211	<0.001
<i>Age</i>	12.756	14.168	<0.001	16.064	12.350	<0.001
<i>Ret (%)</i>	1.011	1.096	<0.001	1.101	1.092	0.802

Table 2 IPO characteristics

This table presents summary statistics on the 1,636 IPOs in our sample. The variable *IR*, or initial return, is the difference between the first trading day closing price and 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* are the dollar size of the offering, excluding over-allotment shares and expressed in millions of dollars. *EliteSchool* funds are funds with at least one portfolio manager who graduated from one of the top ten universities ranked by the average SAT score of the freshmen. *EC* funds are the effectively connected funds. These funds had at least one fund managers who graduated from a university in which an underwriter executive attended, and in addition, received at least one IPO allocation from the underwriter in the past. *NC* funds are those which are not *EC*. The variable *% shares allocated to sample funds per deal* is the number of shares allocated to sample funds, divided by the total number of primary shares offered in the US market for a given IPO deal. The variables *prob. allocated to EC (EliteSchool) funds per deal* is the number of *EC (EliteSchool)* funds that get allocation for a given deal divided by the total number of *EC (EliteSchool)* funds in a given month; similarly, *prob. allocated to NC (Non-Elite) funds per deal* is the number of *NC (Non-Elite)* funds that get allocation for a given deal divided by the total number of *NC (Non-Elite)* funds in a given month. The variables *prob. of allocation with (w/o) experience from the same UW* represent the probability a mutual fund is allocated shares with (without) past allocation experience. The variable *# of IPOs per month* is the number of new offerings per month in the sample. Market conditions are defined based on the monthly measure of the "hotness" of the IPO market used in Ibbotson, Sindelar and Ritter (1994): the percentage of deals that are priced above the midpoint of the original file price range. The binary indicator variable *HotMkt* equals one if the "hotness" is greater than the sample median over the 1980 to 2012 period, and zero otherwise.

	All Markets	Hot Market	Cold Market	p-Val. of Diff.
<i>Number of deals</i>	1636.000	1042.000	594.000	-
<i>IR (%)</i>	31.524	40.013	16.305	<0.001
<i>Size (\$ mil)</i>	903.326	999.658	727.187	0.029
<i>Proceeds (\$ mil)</i>	138.061	115.815	177.670	0.017
<i>% shares allocated to sample funds</i>	15.044	15.826	13.650	0.153
<i>prob. allocated to EliteSchool funds per deal</i>	0.017	0.017	0.015	0.014
<i>prob. allocated to Non-Elite funds per deal</i>	0.012	0.012	0.011	0.031
<i>prob. of allocation with experience from the same UW</i>	0.044	0.046	0.042	0.674
<i>prob. of allocation w/o experience from the same UW</i>	0.006	0.006	0.005	0.030
<i>prob. allocated to EC funds per deal</i>	0.051	0.056	0.045	0.001
<i>prob. allocated to NC funds per deal</i>	0.012	0.012	0.012	0.240
<i># of IPOs per month</i>	11.265	12.639	8.855	<0.001

Table 3 Connection characteristics

This table provides connection- and education-related statistics. In Panel A, the variable *# of executives per underwriter* refers to the number of executives with educational information at the underwriter for a given year. *# of portfolio managers per fund* is the number of mutual fund managers with educational information per fund in a given year. The variable *% 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* is the number of effectively connected underwriters per fund per month conditional on being an *EC* fund. *% effectively connected months per fund* is the number of effectively connected months divided by the total number of months in sample for a given fund, and *% effectively connected month per elite school fund* is the number of effectively connected months divided by the total number of months in sample for a fund with manager(s) who graduated from an elite school. *% effectively connected 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. *% effectively connected funds per IPO* represents the number of effectively connected funds out of the total number of funds associated with an IPO in a given month. *EliteSchool* funds are funds with at least one portfolio manager who graduated from one of the top ten 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 in which 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.

<i>Panel A Connection characteristics</i>			
	Median	Mean	Std. Dev.
<i># of executives per underwriter-year</i>	5.000	4.509	1.938
<i># of portfolio managers per fund-year</i>	1.000	1.535	1.114
<i>% effectively connected funds per month</i>	13.294	12.563	5.889
<i># of effective connections per fund-month</i>	0.000	0.398	1.294
<i># of effective connections per EC fund-month</i>	2.000	3.299	2.463
<i>% effectively connected months per fund</i>	0.000	13.735	24.054
<i>% effectively connected months per elite school fund</i>	13.512	26.923	30.014
<i>% effectively connected months per connected fund</i>	35.052	38.695	25.772
<i>% effectively connected months per connected elite school fund</i>	42.308	45.006	26.291
<i>% effectively connected funds per IPO</i>	6.130	6.141	5.027

<i>Panel B Top 5 most attended institutions</i>			
<i>By underwriter executives</i>		<i>By portfolio managers</i>	
Harvard	60	Harvard	45
Stanford	19	Pennsylvania	45
Pennsylvania	16	NYU	35
Yale	14	Chicago	33
Columbia	14	Columbia	31

Table 4 Do elite school mutual fund managers outperform?

We report regressions of mutual fund risk adjusted return (*Alpha*) on an elite school dummy and other control variables over the January 1992 to March 2012 sample period. *Alpha*, expressed in percentage, is calculated as $Alpha_{it} \equiv r_{it} - rf_t - X_t \hat{\beta}_{it}$, where X_t is a vector of realized returns in month t for each of the four factor portfolios (MKTRF, SMB, HML, and UMD) and $\hat{\beta}_{it}$ are fund-specific factor loadings obtained from a the whole-sample time series regression of fund excess return over market portfolio on Carhart (1997) four factors. The key independent variable *EliteSchool* is the binary indicator variable for funds with top school graduated managers, which equals to one if the portfolio manager has attended one of the top ten universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and zero otherwise. Control variables of fund characteristics throughout the regressions include investment style fixed effects, natural logarithm of fund size ($\ln(TNA)$) and fund age ($\ln(Age)$), expense ratio (*exp_ratio*) which is the annual ongoing operating expenses shareholders pay for the mutual fund, expressed as percentage of total investment by shareholders and turnover ratio (*turn_ratio*) which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month *TNA* of the fund. In column (1) we run regressions over all the calendar months in our sample period and in column (2) we restrict to the 222 months that have IPO activities and column (3) we restrict 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 month level. T-stats are shown in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level respectively.

Dependent variable: <i>Alpha</i>			
	(1)	(2)	(3)
<i>EliteSchool</i>	0.046*** (2.862)	0.049*** (2.918)	0.008 (0.131)
$\ln(TNA)$	-0.010 (-1.144)	-0.007 (-0.963)	-0.059 (-1.365)
$\ln(Age)$	0.020 (0.897)	0.015 (0.720)	0.081 (0.660)
<i>exp_ratio</i> ×100	0.096 (0.226)	-0.418 (-1.168)	3.677* (1.849)
<i>turn_ratio</i>	0.008 (0.607)	0.016 (1.204)	-0.064* (-2.027)
Constant	0.098 (0.554)	0.113 (0.609)	-0.031 (-0.057)
Observations	84,879	76,794	8,085
R-squared	0.002	0.003	0.015
Style FE	Yes	Yes	Yes
Sample	All months	IPO months	Non-IPO months

Table 5 What determines IPO allocations?

Panel A

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 to one if the fund holds the IPO stock at the end of the quarter of its issuance, and zero otherwise. The key independent variable *Connected* in column (1) is built in the same way as described in Cohen, Frazinni and Malloy (2008), which in our case, equals one if the fund manager and one of the underwriter executives attended the same tertiary institution and zero otherwise. As the name suggests, the independent variable *AllocatedBefore* in column (2) represents the existence of previous allocation experience from the same underwriter, i.e. it equals one if the fund has received allocation from the same underwriter in the past, and zero otherwise. *AllocatedBefore*×*Connected* is the interaction term between *AllocatedBefore* and *Connected* and it is indeed our key independent variable *EC* in column (3) when both *AllocatedBefore* and *Connected* equal to one. The key independent variable *EC* in column (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) key independent variable *EliteSchool* is the binary indicator variable for funds with top school graduated managers, which equals one if the portfolio manager has attended one of the top ten universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and zero otherwise. The binary indicator variable *AWC* in Column (6) equals one if the fund has obtained IPO allocation through the same underwriter in the past and not educationally connected then, and zero 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, natural logarithm of fund size (*ln(TNA)*) and fund age (*ln(Age)*), expense ratio (*exp_ratio*) which is the annual ongoing operating expenses shareholders pay for the mutual fund, expressed as percentage of total investment by shareholders and turnover ratio (*turn_ratio*) which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month *TNA* of the fund. Standard errors are heteroskedasticity robust and clustered at the month level. Z-stats are shown in parentheses. The sample period is from January 1992 to March 2012. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

<i>Panel A All funds</i>						
Dependent variable: <i>Allocated</i>						
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Connected</i>	0.284*** (7.831)	-0.400*** (-6.931)				
<i>AllocatedBefore</i>		0.966*** (15.143)				
<i>AllocatedBefore</i> × <i>Connected (EC)</i>		0.522*** (6.172)	1.077*** (23.717)		1.062*** (22.377)	
<i>AWC</i>						1.118*** (32.194)
<i>EliteSchool</i>				0.272*** (7.602)	0.034 (0.870)	0.397*** (11.537)
<i>ln(Proceeds)</i>	0.145*** (6.257)	0.135*** (5.830)	0.144*** (6.247)	0.140*** (6.101)	0.144*** (6.243)	0.131*** (5.659)
<i>ln(Size)</i>	0.351*** (15.013)	0.345*** (14.513)	0.340*** (14.303)	0.364*** (15.608)	0.340*** (14.299)	0.358*** (15.154)
<i>ln(TNA)</i>	0.318*** (22.985)	0.279*** (20.467)	0.287*** (20.790)	0.311*** (22.515)	0.286*** (20.931)	0.273*** (19.748)
<i>ln(Age)</i>	-0.239*** (-8.186)	-0.296*** (-9.981)	-0.272*** (-9.199)	-0.236*** (-8.158)	-0.272*** (-9.213)	-0.268*** (-9.179)
<i>exp_ratio</i> × 100	1.377* (1.911)	0.645 (0.901)	0.635 (0.891)	1.284* (1.807)	0.599 (0.840)	0.529 (0.731)
<i>turn_ratio</i>	0.027*** (4.125)	0.017** (2.553)	0.021*** (3.268)	0.029*** (4.383)	0.021*** (3.280)	0.031*** (4.657)
Constant	-5.199*** (-23.984)	-5.119*** (-23.825)	-5.161*** (-24.101)	-5.306*** (-24.240)	-5.182*** (-23.947)	-5.735*** (-25.832)
Observations	457,592	457,592	457,592	457,592	457,592	457,592
Pseudo R-squared	0.091	0.109	0.103	0.091	0.103	0.114
Style FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B

In Panel B we construct a 2x2 probability tables that displays the probabilities of allocation for funds with and without connections and with and without an allocation on the past deals. We compute probabilities with the same set of control variables as in column (2) of Panel A held at mean and fund style being small cap funds.

<i>Panel B Prob. of IPO allocations</i>			
		<i>AllocatedBefore</i>	
		0	1
<i>Connected</i>	0	2.58%	6.50%
	1	1.74%	7.28%

Panel C

In Panel C 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 heteroskedasticity robust and clustered at the month level. Z-stats are shown in parentheses. The sample period is from January 1992 to March 2012. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

<i>Panel C Funds with families</i>			
<i>Dependent variable: Allocated</i>			
	(1)	(2)	(3)
<i>EliteSchool</i>	-0.125** (-2.353)		-0.247*** (-4.536)
<i>EC</i>		0.462*** (8.492)	0.545*** (9.782)
<i>ln(Proceeds)</i>	0.118*** (7.395)	0.123*** (7.686)	0.122*** (7.638)
<i>ln(Size)</i>	0.224*** (15.695)	0.200*** (13.346)	0.203*** (13.549)
<i>ln(TNA)</i>	0.111*** (6.744)	0.097*** (5.985)	0.105*** (6.413)
<i>ln(Age)</i>	0.048 (1.388)	0.018 (0.511)	0.026 (0.792)
<i>exp_ratio</i> ×100	0.282 (0.352)	-0.638 (-0.769)	-0.039 (-0.048)
<i>turn_ratio</i>	-0.228*** (-5.710)	-0.235*** (-5.962)	-0.208*** (-5.246)
Constant	4.164*** (15.945)	4.079*** (20.593)	4.307*** (18.705)
Observations	34,178	34,178	34,178
Pseudo R-squared	0.371	0.377	0.380
Style FE	Yes	Yes	Yes
Fund Family FE	Yes	Yes	Yes

Table 6 Are connected mutual funds allocated better IPOs?

This table reports logit regressions of the binary indicator variable *Allocated* on the *EC* dummy, initial return of deals, deal characteristics and fund characteristics. The dependent variable *Allocated* equals one if the fund is found to hold IPO stock within the first quarter of its issuance, and zero otherwise. The independent variable, *EC*, is the effective connection indicator, which equals one 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 *HotMkt* and its interaction with *EC* in column (2). The market condition, i.e., the "hotness" of the IPO market, is measured in the way proposed by Ibbotson, Sindelar and Ritter (1994), i.e., the percentage of deals that are priced above the midpoint of the original file price range. The binary indicator variable *HotMkt* as equal to one if the "hotness" is greater than the sample median over the 1980 to 2012 period, and zero otherwise. The deal characteristics include the natural logarithm of dollar proceeds (*ln(Proceeds)*) and log IPO size measured at the end of IPO month (*ln(Size)*). Fund characteristics include investment style fixed effects, the natural logarithm of fund size (*ln(TNA)*) and fund age (*ln(Age)*), expense ratio (*exp_ratio*), which is the annual ongoing operating expenses expressed as percentage of total investment by shareholders, and turnover ratio (*turn_ratio*), which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month *TNA* of the fund. We repeat the logit regression in column (1) in hot and cold IPO market subsamples in columns (3) and (4), respectively. Standard errors are heteroskedasticity robust and clustered at the month level. Z-stats are shown in parentheses. The sample period is from January 1992 to March 2012. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Dependent variable: <i>Allocated</i>				
	(1)	(2)	(3)	(4)
			Hot Market	Cold Market
<i>EC</i>	1.071*** (24.910)	0.969*** (13.590)	1.110*** (21.258)	1.007*** (13.930)
<i>IR_adj</i>	-0.010 (-0.253)		-0.108*** (-2.823)	0.471*** (4.639)
<i>EC</i> × <i>IR_adj</i>	0.135*** (3.486)		0.178*** (3.938)	0.029 (0.291)
<i>HotMkt</i>		-0.039 (-0.746)		
<i>EC</i> * <i>HotMkt</i>		0.179** (1.980)		
<i>ln(Proceeds)</i>	0.154*** (5.852)	0.144*** (6.279)	0.102*** (3.567)	0.285*** (5.208)
<i>ln(Size)</i>	0.328*** (11.920)	0.339*** (14.074)	0.350*** (10.833)	0.227*** (4.181)
<i>ln(TNA)</i>	0.288*** (20.802)	0.287*** (20.894)	0.306*** (17.031)	0.260*** (12.171)
<i>ln(Age)</i>	-0.276*** (-9.298)	-0.273*** (-9.207)	-0.273*** (-7.118)	-0.282*** (-5.966)
<i>exp_ratio</i> ×100	0.678 (0.952)	0.635 (0.894)	1.035 (1.124)	0.052 (0.046)
<i>turn_ratio</i>	0.021*** (3.292)	0.021*** (3.314)	0.023*** (3.209)	0.024* (1.852)
Constant	-5.183*** (-23.801)	-5.133*** (-23.479)	-5.281*** (-21.847)	-4.982*** (-11.876)
Observations	453,823	457,592	274,448	177,258
Pseudo R-squared	0.103	0.103	0.103	0.107
Style FE	Yes	Yes	Yes	Yes

Table 7 Connections, elite education, and fund performance

These regressions examine the effect of connections and education on mutual fund performance. We define effective connection (*EC*) as a binary variable that equals one if the fund is connected in month t and has received IPO allocation from the same connected underwriter at least once prior to month t . The variable *NCnow_ECbefore* is a binary indicator variable that takes a value of one if the fund was effectively connected before but is not connected in the current month, and zero otherwise. *EliteSchool* is the binary indicator variable for funds with top school graduated managers, which equals to one if the portfolio manager has attended one of the top ten universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and zero otherwise. The binary indicator variable *AWC* in column (7) equals to one if the fund has obtained IPO allocation through the same underwriter in the past and not educationally connected then, and zero otherwise. The following fund characteristics controls are included in the regression but are not reported in the table: $\ln(TNA)$, the natural logarithm of *TNA* of a fund, $\ln(Age)$, the natural logarithm of (1+ fund age), *exp_ratio*, the annual ongoing operating expenses of the mutual fund, *turn_ratio*, the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month *TNA* of the fund. The dependent variable *alpha* is calculated as $Alpha_{it} \equiv r_{it} - r_{ft} - X_t \hat{\beta}_{it}$, where X_t is a vector of the realized returns in month t for each of the four factor portfolios (MKTRF, SMB, HML, and UMD) and $\hat{\beta}_{it}$ are fund-specific factor loadings estimated from the time series regression of fund excess returns on the four factors over the entire sample period. The sample period is from January 1992 to March 2012. Robust standard errors (White (1980)) are used and are clustered at the month level and t-statistics are shown in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level respectively.

Dependent variable: <i>Alpha</i>							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Hot mkt	Cold mkt			
<i>EC</i>	0.112*** (3.761)		0.144*** (3.670)	0.084* (1.875)		0.099*** (3.063)	
<i>NCnow_ECbefore</i>		-0.026 (-0.752)					
<i>EliteSchool</i>					0.049*** (2.918)	0.026 (1.409)	0.054*** (3.210)
<i>AWC</i>							0.064* (1.853)
Constant	0.127 (0.681)	0.147 (0.793)	0.142 (0.533)	0.097 (0.386)	0.113 (0.608)	0.113 (0.609)	0.079 (0.423)
Observations	76,794	76,794	38,915	37,879	76,794	76,794	76,794
R-squared	0.003	0.002	0.009	0.009	0.003	0.003	0.003
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

This table replicates some of the regressions in Table 7 with Fama-MacBeth regressions (Fama and MacBeth (1973)). The dependent variable $Alpha$ and the independent variable EC for fund i are obtained at month t ; fund characteristics such as $\ln(TNA)$, $\ln(Age)$, exp_ratio , $turn_ratio$ and fund styles are obtained at the end of month $t-1$. Market conditions are defined based on the monthly measure of the "hotness" of the IPO market used in Ibbotson, Sindelar and Ritter (1994): the percentage of deals that are priced above the midpoint of the original file price range. We define the binary indicator variable $HotMkt$ as equal to one if the "hotness" is greater than the sample median over the 1980 to 2012 period, and zero otherwise. The dependent variable $alpha$ is calculated as $Alpha_{it} \equiv r_{it} - rf_t - X_t \hat{\beta}_{it}$, where X_t is a vector of the realized returns in month t for each of the four factor portfolios (MKTRF, SMB, HML, and UMD) and $\hat{\beta}_{it}$ are fund-specific factor loadings estimated from the time series regression of fund excess returns on the four factors over the entire sample period. The cross-section estimation is performed using the Fama-MacBeth method over the 222 IPO months during the sample period of January 1992 to March 2012; the results appear in column (1). Columns (2) and (3) present the Fama-MacBeth regression results for the hot and cold IPO market subsamples. The means of coefficients are presented with t-statistics in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Dependent variable: $Alpha$			
	(1) Full Sample	(2) Hot Mkt	(3) Cold Mkt
EC	0.070** (1.971)	0.109** (2.163)	0.021 (0.443)
$\ln(TNA)$	-0.001 (-0.174)	0.006 (0.527)	-0.011 (-0.976)
$\ln(Age)$	0.005 (0.359)	-0.011 (-0.551)	0.026 (1.254)
$exp_ratio \times 100$	-0.095 (-0.241)	0.598 (1.031)	-0.940* (-1.864)
$turn_ratio$	-0.026 (-1.149)	-0.015 (-0.412)	-0.041 (-1.504)
Constant	0.147 (0.886)	0.271 (1.094)	-0.004 (-0.017)
Observations	76,794	38,915	37,879
R-squared	0.395	0.402	0.387
Style FE	Yes	Yes	Yes

Table 9 Trading strategy based on effective connection

This table 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 *EC*; then, for the test month *t*, we compute the monthly average excess return for the two portfolios and regress the excess return on the monthly market risk factor, as well as the Fama and French (1993) and Carhart (1997) factors. The table presents the intercepts from these regressions, alphas, and coefficients on the respective risk factors, as well as the t-statistics (in parentheses). Rows 1 and 0 display the results for *EC* and *NC* portfolios; the “Difference” row presents the result of regressing the hedged return of a long/short portfolio of *EC* and *NC* portfolios on risk factors. Panels A, B and C present results for the CAPM, three-factor and four-factor regressions, respectively. Market conditions are defined based on monthly measure of “hotness” of the IPO market used in Ibbotson, Sindelar and Ritter (1994): the percentage of deals that are priced above the midpoint of the original file price range. We define the binary indicator variable *HotMkt* as equal to one if the “hotness” is greater than the sample median over the 1980 to 2012 period, and zero otherwise. We then use this variable to separate the sample into hot and cold market subsamples. The sample period is from January 1992 to March 2012. Robust standard errors (White (1980)) are used. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

<i>Panel A CAPM alpha</i>			
Effective Connection		Alpha	RMRF
All Markets	1	0.252*** (2.696)	1.030*** (41.974)
	0	0.091 (1.386)	0.956*** (47.163)
	Difference	0.157** (2.533)	0.074*** (4.005)
Hot Markets	IPO 1	0.468*** (3.301)	1.001*** (24.096)
	0	0.201** (2.169)	0.927*** (30.790)
	Difference	0.259*** (2.715)	0.075** (2.413)
Cold Markets	IPO 1	0.017 (0.142)	1.047*** (37.689)
	0	-0.019 (-0.214)	0.976*** (36.371)
	Difference	0.034 (0.430)	0.070*** (3.179)

<i>Panel B Three-factor alpha</i>					
Effective Connection		Alpha	RMRF	SMB	HML
All Markets	1	0.190*** (2.803)	0.988*** (52.642)	0.271*** (8.074)	0.045* (1.666)
	0	-0.011 (-0.245)	0.954*** (70.706)	0.191*** (9.217)	0.132*** (6.877)
	Difference	0.203*** (4.106)	0.035*** (2.641)	0.080*** (3.279)	-0.089*** (-3.933)
Hot IPO Markets	1	0.329*** (3.473)	0.976*** (31.120)	0.272*** (7.054)	0.058 (1.464)
	0	0.035 (0.510)	0.930*** (43.703)	0.187*** (7.832)	0.141*** (5.235)
	Difference	0.296*** (4.114)	0.048** (2.188)	0.084** (2.547)	-0.088** (-2.428)
Cold IPO Markets	1	0.034 (0.329)	0.990*** (39.980)	0.265*** (3.939)	0.022 (0.598)
	0	-0.048 (-0.744)	0.968*** (54.255)	0.201*** (4.257)	0.123*** (4.163)
	Difference	0.081 (1.207)	0.021 (1.343)	0.063** (2.213)	-0.101*** (-3.750)

Panel C Four-factor alpha						
Effective Connection		Alpha	RMRF	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)

Table 10 Robustness checks: the influence of big family and NY/ Boston on fund performance

We test the robustness of the relationship between *EliteSchool/EC* and *Alpha* in this table. Panel A presents the descriptive statistics of the percentage of *EliteSchool/EC* fund-month observations in the biggest three families ranked by the total net asset at the end of 2000, the rest of the families, funds that are located in New York or Boston, and funds that are in the rest of the US cities separately, together with an overall statistic in the whole sample. The dependent variable *alpha* is calculated as $Alpha_{it} \equiv r_{it} - rf_t - X_t \hat{\beta}_{it}$, where X_t is a vector of the realized returns in month t for each of the four factor portfolios (MKTRF, SMB, HML, and UMD) and $\hat{\beta}_{it}$ are fund-specific factor loadings estimated from the time series regression of fund excess returns on the four factors over the entire sample period. The key independent variable *EliteSchool* is the binary indicator variable for funds with top school graduated managers, which equals to one if the portfolio manager has attended one of the top ten universities ranked by the average SAT score of the freshmen at the portfolio managers' tertiary institution, and zero otherwise. The other independent variable *EC* is the effective connection indicator denoting that the fund manager and underwriter executive attended the same school and the fund has received at least one IPO allocation from the same connected underwriter in the past. The variable *Big3* is an indicator variable that takes the value of unity if the fund belongs to one of the biggest three fund families ranked by total asset at the end of 2000, and zero otherwise. The dummy variable *NYBoston* equals to one if the fund family is either located in New York City or Boston, and zero otherwise. Control variables of fund characteristics include investment style fixed effects, natural logarithm of fund size ($\ln(TNA)$) and fund age ($\ln(Age)$), expense ratio (*exp_ratio*) which is the annual ongoing operating expenses shareholders pay for the mutual fund, expressed as percentage of total investment by shareholders and turnover ratio (*turn_ratio*) which is the minimum of aggregated sales or aggregated purchases of securities, scaled by the average 12-month *TNA* of the fund. Robust standard errors (White (1980)) are used and are clustered at month level. T-stats are shown in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level respectively.

<i>. Panel A Percentage of Elite/EC fund-month by category</i>					
	Big3	Non-Big3	NYBoston	Non-NYBoston	Overall
<i>% of EliteSchool fund-month</i>	80.606	44.529	63.968	43.209	48.228
<i>% of EC fund-month</i>	35.081	11.296	24.003	10.461	13.735

<i>Panel B Pooled regression</i>						
Dependent variable: <i>Alpha</i>						
	(1)	(2)	(3)	(4)	(5)	(6)
<i>EC</i>	0.120*** (3.555)	0.115*** (3.424)	0.121*** (3.376)			
<i>EC</i> × <i>Big3</i>	-0.057 (-0.945)		-0.050 (-0.798)			
<i>EC</i> × <i>NYBoston</i>		-0.033 (-0.679)	-0.022 (-0.447)			
<i>EliteSchool</i>				0.059*** (3.609)	0.042** (2.345)	0.049*** (2.779)
<i>EliteSchool</i> × <i>Big3</i>				-0.193*** (-2.718)		-0.189*** (-2.669)
<i>EliteSchool</i> × <i>NYBoston</i>					-0.004 (-0.097)	0.021 (0.567)
<i>Big3</i>	0.040 (0.927)		0.017 (0.360)	0.183*** (2.762)		0.158** (2.338)
<i>NYBoston</i>		0.078*** (3.073)	0.075*** (2.783)		0.076** (2.328)	0.058* (1.726)
Constant	0.122 (0.658)	0.097 (0.525)	0.096 (0.517)	0.109 (0.584)	0.086 (0.461)	0.084 (0.450)
Observations	76,794	76,794	76,794	76,794	76,794	76,794
R-squared	0.003	0.003	0.003	0.003	0.003	0.003
Style FE	Yes	Yes	Yes	Yes	Yes	Yes

Chapter 2

Fraud Connection: Are Frauds More Contagious Among Elite School Graduates?

ABSTRACT

There are greater occurrences of fraud committed by elite school graduates even after taking into account the fact that there are more CEOs graduated from such schools. The firm-level analysis further reveals that there is a stronger peer effect of fraud in elite schools, suggesting that frauds are more contagious among elite school graduates. Furthermore, elite school CEOs are no more likely than non-elite school graduates to commit fraud if it were not for peer effect. Using school endowment as a proxy for the tightness of the alumni network, I find evidence suggesting that there is an elite school culture that promotes tighter school network, which, in turn, enhances the peer effect. An instrumental variable approach provides consistent evidence of causality. I further examine the possible channels, and document that the performance of peer firms positively influences the peer effect of fraud, which is consistent with the “keeping up with Joneses” argument. My paper sheds light on the costs of educational connection in the context of financial misconduct.

JEL classification: I23, K22, M41, G34

Keywords: corporate fraud, financial misconduct, peer effects, CEO characteristics

1. Introduction

There is evidence that the educational background of key decision makers such as chief executive officers (CEOs) and mutual fund managers impinge on respective corporate and fund performances. For example, Malmendier and Tate (2005) document that the degree type of CEOs matters for firm's investment cash flow sensitivity¹. Chevalier and Ellison (1999) show that mutual fund managers' elite education has value in terms of better risk-adjusted fund performance. However, less is known about the dark side of elite education. In this paper, I address the question: are CEOs equipped with elite tertiary education in the past more likely to commit financial misconduct?

To answer this question, I make use of an annual panel of the Boardex firms merged with financial misconduct incidences identified by the Stanford Security Class Action Clearinghouse (SSCAC) and supplemented by Audit Analytics. The sample period is from the year 2000 to 2012.

I find that even after controlling for the cluster size, financial misconducts do occur 31% more frequently in elite universities, defined on either the historical US News ranking or the ranking of freshmen SAT scores. Moreover, such *elite effect* cannot be explained by the observable university characteristics or the average attributes of firms with CEOs graduated from such schools.

This naturally raises the follow-up question: what is the cause of the *elite effect*? In other words, why is fraud more clustered in elite universities? Following the classical Manski (1993, 2000) framework that studies the interpretations for the common

¹ In the management literature, Zahra, Priem and Rasheed (2005) state that the individual characteristics, education in particular, may contribute to the propensity of managerial misconduct. This is consistent with the finding in Kelley, Ferrell and Skinner (1990), Frank, Gilovich and Regan (1993) and Williams, Barrett and Brabston (2000) that business degree graduates exhibit less moral standards.

behavior of a selected population, three possible explanations surface. First, the *endogenous (peer) effects* whereby an agent's behavior varies with the behavior of the peer group. Second, the *exogenous (genetic) effects* wherein the agent's behavior varies with some exogenous characteristics of the group. Last but not least, the *correlated (contextual) effects* wherein agents of the same group behave similarly because they are subject to the same environment.

An example may help to illustrate the distinctions. Consider the tendency to commit fraud by the CEO of a particular firm. If all else equal, the individual's fraud decision tends to vary with the average rate of fraud by CEOs belonging to the same reference group, or the same alumni network in my context, there is an endogenous peer effect. There is an exogenous or genetic effect if the fraud decision is likely to vary with the exogenous characteristics of the reference group—the quality of the university measured by the fraction of total applicants that is admitted by the university for instance. Correlated effects arise when the CEOs from the same alumni network tend to behave alike because they face similar incentives and/or are subject to common economic shocks.

Empirically, I define the binary indicator for financial misconduct by the “violation period” when the actual damage of the misconduct begins to accumulate. This is consistent with Christopher, Sulaeman and Titman (2016) and Dimmock and Gerken (2012). Examples of such misconducts may include misrepresenting earnings, concealing material information from the investors, trading on proprietary information, etc.

I begin by investigating the expected frequency of financial misconduct across different school years in a standard Poisson regression model and find that after

normalizing the number of associated CEOs per school, or the network size, the expected frequency of elite-school-CEO financial misconduct is about 1.31 times that of non-elite school ones for a typical school-year observation. More importantly, the impact of network size is greater for elite schools. This points to the peer effect channel because neither of the exogenous effect or contextual effect would yield such prediction regarding the network size.

I employ various university demographic variables to capture the exogenous school characteristics that may affect the outcome variable. In an attempt to take care of the contextual effect, I control for the average firm characteristics of the constituent firms in each alumni network to capture the extent to which they face similar incentives. After including these characteristics, the coefficient on elite effect and peer effect do not change much, which at least rules out the exogenous effects arising from the observable school characteristics and contextual effects that are driven by the common incentives that can be explained by firm attributes.

To further examine the peer effect at CEO level, I run the firm level probit regressions that model the firm's propensity to commit financial misconduct as a function of its peer fraud rate and other firm and industry characteristics. After controlling for industry dynamics, industry fixed effect, state fixed effects and firm fundamentals, the significant coefficient on peer fraud rate indicates that there is marginal peer effect of a CEO's alumni network. Furthermore, I find that the peer effect, or contagion effect, is stronger in elite schools.

I uncover a novel finding that the contagion increases with network size, suggesting that CEO is influenced by the number of fraud cases rather than merely the average fraud rate of the reference group. However, after controlling for the network

size and its impact on the peer effect, I find that the elite schools still have an active peer effect, suggesting that there is some cultural aspect of the elite school other than network size that contributes to the heightened contagion effect among elite schools. Moreover, elite school graduates are no more likely than non-elite school ones to commit fraud if it were not for peer effect.

One possible explanation for the cultural aspect is that if there is more intensive social interactions amongst the alumni group or the inter-personal tie is stronger, the peer effect will be stronger. In the sociology literature, the social attachment to one's alma mater grows with the prestige of the school (Mael and Ashforth (1992)). Put differently, the social interaction in elite schools is more active; therefore we expect to see a more pronounced contagion effect. Since alumni donation is believed to be financial backbone of US university endowment (Bakal (1979)) and the alumni involvement is far from homogenous, the dollar value of the endowment reflects the degree of alumni attachment to their alma mater and is, therefore, a reasonable measure of the tightness of the alumni network. I make use of a historical-cross section of the dollar value of university endowment fund to proxy for the tightness of the alumni network. I find that the peer effect is indeed more pronounced in tighter networks measured by the natural logarithm value of endowment size and such relationship concentrates only in elite schools. This implies that one possible explanation for the observed phenomenon of more contagious fraud in elite schools is the closer interpersonal ties in these schools.

Subsequently, I shed light on a possible source underlying the peer effect. One possible explanation is the “keeping up with Joneses” argument whereby an agent's decision is determined by both his own behavior as well as the average

contemporaneous behavior of the reference group.² Indeed, I document a positive sensitivity of firm j 's fraud propensity to the interaction of the contemporaneous peer fraud rate and peer performance. This implies that the contagion effect is more intensive when the performance of the peer firms appears to be better.

As pointed out by Manski (1993, 2000), one of the greatest challenges in empirical peer effect studies is the *reflection problem*. The key to addressing this concern is to use an idiosyncratic and exogenous variation of peer firms that is unrelated to the contextual or exogenous characteristics of the peer group so that the only effective channel is through peer effect. I follow the conceptual framework of Bartik (1991) test recently implemented by Parsons, Sulaeman and Titman (2015) and use the shocks to the firms in the dominant city-industry pair but outside the alumni network of interest as an instrumental variable to the fraud rate of firms in the dominant industry-city pairs that share the same alumni network with the rest of the firms that are not in the dominant industry-city pair. The instrumental variable approach suggests that the contextual or exogenous effects do not drive the results.

The findings in this paper are subject to several limitations. First, as prevalent in the financial misconduct literature, only *detected* fraud is included in the sample. Although I include the state fixed effects to eliminate any inherent heterogeneity in strength of law enforcement across states and firm characteristics to account for the attributes that are known to affect the firm's incentive to engage in dishonest behaviors, I cannot rule out the possibility that there are other unobservable factors contributing to the fraud decision and therefore the observed fraud is a biased estimation. Second, I cannot pin down the exact means and contents of the intra-network communication due

² See for example GÓMez, Priestley and Zapatero (2009), and Bursztyn, Ederer, Ferman and Yuchtman (2014).

to the nature of the data. Third, a firm's engagement in fraudulent activities is a complex process involving considerable within-firm coordination, focusing on CEO alone may not be adequate to describe the whole picture of the process as other senior executives, say CFO, and board members may play crucial roles. However, the confounding influences from other senior executives or board members may bias against me finding any significant relation and moreover, CEO is the ultimate decision maker of the firm and his personal traits may shape the culture of the firm profoundly.

The paper proceeds as follows. Section 2 reviews the related literature. Section 3 describes the relevant datasets used in the paper. Section 4 tests the relationship between CEO education and the frequency of fraud. Section 5 explains the relationship. Section 6 deals with the identification challenge, followed by robustness tests and tests on an alternative story in Section 7. Section 8 concludes the paper.

2. Related research

There is extensive corporate finance literature on certain CEO personal traits or experiences that may have imprints on various corporate policies and performances. In terms of managerial education background, Malmendier and Tate (2005) find that CEO education is related to firm's investment cash flow sensitivity and Miller and Xu (2016) find that MBA CEOs are more likely to engage in self-serving behaviors. Bertrand and Schoar (2003) and Kaplan, Klebanov and Sorensen (2012) consider different aspects of CEO's personal traits and their impacts on different type of corporate activities. Malmendier, Tate and Yan (2011) and Benmelech and Frydman (2015) analyse CEO early-life experience and corporate outcomes. Custódio and Metzger (2013, 2014) and Dittmar and Duchin (2016) focus on managerial work. Except for Miller and Xu (2016), relatively little is known about the cost of the CEO educational background.

I fill the gap of the literature by documenting the evidence that there are disproportionately more elite school CEOs committing financial misconduct and such elite effect is likely to be attributable to the endogenous peer effect within the alumni network, which contributes to the growing literature of social network and finance.

Most of the evidences in the broader social network literature show the benefit of social networks in facilitating information flow. For example, Cohen, Frazzini and Malloy (2008) find that mutual fund managers tilt their portfolios toward firms with which they are connected through school ties, and the connected holdings performed significantly better than their non-connected holdings. Hochberg, Ljungqvist and Lu (2007, 2010) demonstrate that better-networked venture capitalist firms face less competition and experience significantly better fund performance, Engelberg, Gao and Parsons (2012) show that informal connections between firms and banks can lower a firm's borrowing costs. Engelberg, Gao and Parsons (2013) examine the impact of social connection between CEOs and outside firm executives and find that CEOs with larger social networks have higher compensation.

To the best of my knowledge, this paper is the first one that studies the alumni peer effect and corporate fraud. The evidence presented in this paper is consistent with Shue (2013) that demonstrates that the alumni peer effect is an important determinant of managerial decision making. The result also contributes to the literature of other types of peer effects and corporate policy studies that investigate the same-industry peers (Leary and Roberts (2014)), same-city peers (Parsons, Sulaeman and Titman (2015)) and same-firm peers (Dimmock, Gerken and Graham (2015)).

Extant research on the managerial incentives for fraud can be largely classified into two strands. The former emphasizes on internal factors while the latter stresses

external factors. With respect to the internal determinants of fraud, firm characteristics emerges. For example, growth firms are more likely to commit fraud due to a greater flexibility in reporting earnings (Crutchley, Jensen and Marshall (2007)), larger firms are more prone to fraud because of a potentially larger settlement (Francis, LaFond, Olsson and Schipper (2005)). Contract arrangement may shape the way the manager views short-term earnings and therefore his/her decision to boost earnings dishonestly (Bergstresser and Philippon (2006); Burns and Kedia (2006); Denis, Hanouna and Sarin (2006); Efendi, Srivastava and Swanson (2007); Peng and Röell (2008)). CEO overconfidence is also believed to affect his/her propensity to commit fraud (Schrand and Zechman (2012)). Moreover, if CEO develops more internal executive social ties, it may reduce the costs associated with fraud and therefore increases the risk of fraud (Khanna, Kim and Lu (2015)).

External mechanisms that contribute to firm's incentive of financial misconduct include industry characteristics (Biddle and Seow (1991)), business conditions (Povel, Singh and Winton (2007), Wang, Winton and Yu (2010)), product market competition (Wang and Winton (2012)) and the regulators' presence and attention (Kedia and Rajgopal (2011)).

Apart from the existing managerial incentives for fraud, this paper adds to the external factor of financial misconduct by showing that the CEO's alumni peer effect is a first-order determinant of a firm's propensity to engage in fraudulent activities and is in the same magnitude of the industry effect. That peer effect predicts financial misconduct has important implications for the regulators as well as the academics.

3. Data

The data employed in this paper consists of four parts: event level financial misconducts, annual firm characteristics, CEO biographical background information and university demographics.

3.1 Financial misconduct

I collect the corporate misconduct data from two sources: 1) the major data source is from the litigation filings of the Stanford Law School Securities Class Action Clearinghouse (SSCAC) and 2) I supplement it with the litigation data set from Audit Analytics (AA) for the period of 2000 to 2012.

The former is an online database of all security class actions filed in US Federal Court since the passage of the Private Securities Litigation Reform Act of 1995. Because the law firms specializing in class actions have automated filing system that react to any negative shock to stock prices, it is unlikely that any value-relevant fraud would not end up in a class action suit (Choi, Nelson and Pritchard (2009)). Therefore SSCAC has a comprehensive coverage of all the class actions against large public firms. Besides security class actions, AA covers SEC actions and material federal civil litigation filed after January 2000. In the combined dataset, the dominant type of the cases filed is violation of Rule 10b-5, related to security fraud³ involving either material misrepresentation or misstated financial results. This type of cases are clearly alleged attempts to manipulate the stock price.

³ Detailed statistics on the classifications of cases can be found in the annual report series by Cornerstone Research (<http://securities.stanford.edu/clearinghouse-research.html>). Example of academic studies that make use of SSCAC include Denis, Hanouna and Sarin (2006), Dyck, Morse and Zingales (2010), etc.

An example of such fraud would be an ongoing class action lawsuit brought against American Express Company (AmEx) on July 30, 2015. AmEx, the credit card company, was alleged to conceal the financial impact of its co-branding relationships with Costco Wholesale Corp. AmEx failed to disclose the status of its negotiation to renew its co-branding agreement with Costco which was about to expire in March 2016. According to the complaint, after AmEx announced that it had lost the Costco deal on February 12, 2015 its share price plunged by 6.4 percent, the largest one-day percentage decline since August 2011. As a result, investors were alleging that AmEx was responsible for billions of dollars in lost market capitalization. The plaintiff sought to establish a class of investors who purchased AmEx shares between October 16, 2014 and February 11, 2015, the so-called “*class period*” and to recover compensatory damages to be determined at trial.

[Insert Figure 1 here]

This example also outlines the typical timeline of a financial misconduct event. The “*violation period*” begins when the fraudulent activity actually takes place and economic losses are incurred; this corresponds to the *class period* recorded in the class action filings. The “*revelation period*” starts from the date when the fraud becomes public. To be consistent with the convention in Parsons, Sulaeman and Titman (2015) and Dimmock and Gerken (2012), I focus on the violation period to identify fraudulent firm-year observations, i.e. I define the binary indicator variable *Fraud* to be equal to one if the firm commits fraud in year t , and zero otherwise. The typical episode lasts about 1-3 years before it is resolved.

3.2 CEO and firm characteristics

Next, I obtain data of CEO employment and educational information from Boardex which starts from 1999. I keep the most recent identifiable degree and alma mater of a given CEO since this is probably the social tie formed that is closest to his/her work relationship and therefore the most effective one. Given one of the data sources for financial misconduct starts in year 2000, I constrain the sample period of this paper to be between 2000 to 2012 and to US firms only. Firm attributes are merged from Compustat and stock return information is from CRSP. I restrict the sample to US firms with non-missing CEO educational information and further restrict the tertiary institution to be an US one. The final sample consists of 16,036 firm-year observations during 2000 to 2012.

[Insert Table 1 here]

Evidenced in Panel A of Table 1, a typical sample firm has an average probability of fraud of about 3.3%, an annual return of 16.9%, a Tobin's Q of about 2.0, a log value total asset at about 6.4, cash flow over total asset at about 0.07, ROA of about -0.8% and CEO's percentage non-cash compensation of about 74.5%. I identify 306 cases of fraud with 546 fraud-year observations.

3.3 University demographics

The primary source of university demographics is the historical statistics of the Integrated Postsecondary Education Data System (IPEDS), a dataset of annual college/university level survey compiled by National Center for Educational Statistics (NCES).⁴ All colleges/universities that participate in the federal student financial aid

⁴ IPEDS data is publicly available at <http://nces.ed.gov/ipeds/datacenter/InstitutionByGroup.aspx>

programs are required to provide information to NCES that covers basic characteristics of institutions, enrollments, completions and completers, graduation rates and other outcome measures, faculty and staff, finances, institutional prices, student financial aid, admissions and academic libraries. I supplement university attributes with a historical cross-section of endowment data from the National Association of College and University Business Officers website for the year prior to the first sample year.⁵

[Insert Table 2 here]

As presented in Panel B of Table 1, a typical university as about 12,483 applicants and among them, 59.4% gets the admission letter and 2,478 finally accept the offer. There are 52.3% female students on average and the mean freshmen SAT score is 1,184. It is also evidenced in Table 2 that there is considerable variation in school level fraud rate, from 0.6% to 13.5% among the 25 elite universities defined in the sample.

4. Are financial misconduct more likely to occur in elite schools?

In this section, I develop an empirical framework to test if there is any differences in the frequency of financial misconduct between firms with CEOs graduated from elite schools and firms with CEOs graduated from non-elite schools.

$$count = e^{\beta_0 + \beta_1 \ln(n) + \beta_2 EliteSchool + \beta_3 Controls}$$

(1)

In Table 3, I estimate a series of Poisson regressions to model occurrence of financial misconducts within a given school-year observation as shown in Equation (1).

⁵ Data is available at: http://www.nacubo.org/Research/NACUBO-Commonfund_Study_of_Endowments/Public_NCSE_Tables/Total_Market_Value_of_Endowments.html

The dependent variable is the number of financial misconduct events per school-year. I include the natural logarithm of the total number of firms per school-year pair, $\ln(NFirm)$, in the independent variable to explicitly control for the potential exposure to fraud, i.e. the more number of firms at risk, the more number of financial misconducts that we expect to observe for a school-year observation. The independent variable of interest in column (1) is the binary indicator variable *EliteSchool* that equals one if the university ranks among the top 25 universities by a historical US News Ranking in 2007.⁶

[Insert Table 3 here]

As expected, the coefficient on $\ln(NFirm)$ is positive and highly significant due to the mechanical relation that the more firms there are at risk, the greater the number of incidences of financial misconduct observed. What is intriguing, however, is the coefficient on the *EliteSchool* indicator. The positive and significant coefficient of 0.270 ($t=3.156$) means that for a given number of CEOs graduated from a given school, being an elite school increases the log of expected count of fraud-year observations by 0.270. It may be easier to interpret the coefficient in terms of incidence rate ratio. The 1.31 ($=e^{.270}$) incidence rate ratio indicates that holding other variables constant, the expected count of fraud events for elite schools is 1.31 times that of non-elite schools. This is termed “*elite effect*” hereafter.

I include an interaction term of *EliteSchool* and the network size variable $\ln(NFirm)$ in column (2) and the positive and significant coefficient on the interaction term reveals that the impact of network size on the occurrences of fraud is not

⁶ I tried different cut-offs, such as the top 10, top 20, top 50 universities and the historical ranking at other years such as 1983, 1985, 1990, 2000 to define the *EliteSchool* indicator, the results are similar.

homogeneous across school—it is stronger for elite school. Since elite school network is hypothesized to be tighter and that peer effect is related to the size of network, this suggest the existence of peer effect which we will investigate in greater detail later on.

An alternative explanation for the elite school effect could be attributed to the exogenous factors such as school quality or contextual factors such as common incentives faced by firms. For example, elite schools graduates are “smarter” and more knowledgeable about how to push the envelope, or firms with elite school managers tend to be larger firms, which are known to have a higher rate of financial misconduct because of larger settlement. I control for a battery of observable school characteristics as well as school-level average firm attributes in an attempt to capture the genetic and contextual differences between CEOs with certain alma mater.

The school-level average firm attributes that I control for include firm size measured in log value of total asset, its return on asset, Tobin’s Q, cash flow over asset and leverage ratio. All of the firm characteristics variables are measured at the end of last fiscal year end. University demographics include its geographical location (*State*), the natural logarithm of total number of students that accept the offer ($\ln(TotalAccept)$), fraction of admission (*FracAdmission*), that is, the number of applicants who get admission letter in a given year divided by the total number of applicants, the average SAT score of freshmen (*FreshmenSAT*) and fraction of female students (*FracFemale*). The $\ln(TotalAccept)$ proxies for the size of the university and *FreshmenSAT* and *FracAdmission* provide a rough measure of the intellectual capability of its graduates and the quality of the university as used in Dimmock (2012). In addition, I control for year fixed effect to remove any time-series trend in financial misconduct.

A comparison of column (2) and (3) indicates that the demographical differences do not explain the elite school effect. In fact, except for firm size and Tobin's Q, none of the rest of the characteristics variable is statistically significant and the including them do not seem to contribute much to the overall model fit. In short, it seems that the observable demographical differences cannot explain the elite school effect and elite effect is more likely to be due to the endogenous peer effect.

5. Can elite effect be explained by peer effect?

5.1 Peer effect and financial misconduct

While the previous section provides school level evidence, I study peer effect in more detail from an individual firm's perspective in the framework of Manski (1993)'s "linear-in-mean" model in this section. Specifically, I estimate a standard probit model that regress the propensity to commit fraud on various peer effect measures together with firm, industry and market level controls. In other words, I test whether peer interactions among college alumni networks affect financial misconduct.

$$\Pr(\text{Fraud}_{j,t}^{i,c} | \mathbf{X}) = \Phi(\mathbf{X}^T \boldsymbol{\beta}) = \Phi(\beta_1 \text{FMRate}_t^{-i,c} + \beta_2 \text{FMRate}_{-j,t}^{i,c} + \beta_3 \text{FMRate}_t^{i,-c} + \beta_4 \text{Controls}_{t-1}). \quad (2)$$

[Insert Table 4 here]

In Equation (2), the dependent variable is the probability of firm j in a given year t that belongs to the Fama-French 12 industry i and school cluster c being investigated for financial misconduct. Subscript i refers to Fama-French 12 industry classification and c denotes a university cluster. Φ is the cumulative distribution function of the standard normal distribution. The key peer fraud rates are $\text{FMRate}_t^{-i,c}$

and $FMRate_{-j,t}^{i,c}$, where I distinguish between the peer fraud rate of same-school, different industry peers ($FMRate_t^{-i,c}$) and same-school, same-industry peers excluding firm j itself ($FMRate_{-j,t}^{i,c}$). Therefore the coefficient β_1 on $FMRate_t^{-i,c}$ captures whether at any given year t , firm j is more likely to commit financial misconduct as the average fraud rate of a portfolio consisting of the same-school firms outside its primary industry ($-i$) is higher. Likewise the coefficient β_2 captures whether fraudulent behavior of the same-school and same-industry peers would have any impact on the propensity to commit fraud for firm j . According to Leary and Roberts (2014), adopting contemporaneous measures of average peer outcome is to limit the time for firms to respond to one another as well as to mitigate the scope for confounding effects. Taken together, these coefficients capture the marginal peer effect of the extent to which a firm's time-varying same-school peers' behavior influences the chances it engages in financial fraud.

I also control for $FMRate_t^{i,-c}$, the annual average fraud rate for firms in the same industry (i) but outside the school cluster ($-c$). The annual fluctuations in $FMRate_t^{i,-c}$ capture industry dynamics, suggesting that any school peer effects are identified net of these and can therefore be interpreted as marginal peer effects.

The main advantage of this approach is the flexibility to control for a series of firm characteristics that may affect the manager's incentive to engage in financial fraud and that may at the same time be correlated with the CEO's educational cluster. For instance, firms with negative past return and high leverage ratio are likely to be firms that are financially distressed and may find fraud more tempting than firms with brighter outlooks. Fraud are more likely to occur in larger firms. Growth firms, or firms with less tangible asset have more flexibility in financial reporting and more scope for financial

misconduct. To capture the possible firm characteristics that affect fraud propensity, I control for the lagged attributes including 12-month stock return, leverage ratio, firm size measured in natural logarithm of total assets, its accounting performance measured in ROA, Tobin's Q and cash flow over total asset. Since the CEO compensation variable from ExecuComp is only available for a subgroup of firms, I control for it in only one of the regressions.

Throughout the regressions in Table 4, I control for the time-series average rate of school level financial misconduct rate to take out the overall school level financial misconduct rate. In all the regressions in Panel B of Table 4, I include state fixed effects to mitigate the concern of differential likelihood of detection caused by the regional differences in law enforcements. In addition, I control for industry fixed effects to account for the inherent industry attributes that are related to financial misconduct. It's worth noting that the incidental parameter problem in nonlinear models reviewed in Lancaster (2000) is not a problem in my context. Incidental parameter problem arises when the number of fixed effects grows with number of observations, which is clearly not the case for state and industry fixed effects (Woolridge (2002)), i.e. the number of states and industries stays fixed no matter how large the sample size grows to.

Let's consider the results presented in Table 4. The coefficients β_1 and β_2 capture whether firm j 's industry and non-industry peers would predict firm j 's fraudulent activities after controlling for firm j 's fundamentals, the industry dynamics and state, school and industry fixed effects. In the first two columns, the estimate of β_1 is 9.130 with a z-statistic of 10.339 and that on β_2 is 6.321 with a z-statistics of 24.276. This implies that an increase of 1% in the contemporaneous financial misconduct rate of a firm's same-school, non-industry peers increases the probit index of it committing

fraud by about 9.1%; an increase in the contemporaneous financial misconduct rate of a firm's same-school, same-industry peers increases the probit index by about 6.3%.

In terms of the economic significance, it is more helpful and straightforward to consider the marginal effects. Take the coefficient β_1 for example, suppose there is a one-standard-deviation increase in the fraud rate of non-industry, same school peers ($FMRate_t^{-i,c}$) from its mean value, the predicted probability of financial misconduct for firm j increases from 1.87% to 4.41%, holding other variables at their means. Similarly, the predicted probability of fraud behavior in any given year for firm j increases from 1.00% to 3.54%, a more than 200% increase, as the fraud rate of same-industry, same school peers ($FMRate_{-j,t}^{i,c}$) sees a one-standard deviation increase from its mean value. To benchmark the magnitude of peer effect and industry effect, I control for the annual average fraud rate of the same-industry different-school peers in column (3). As the industry fraud rate increases by one standard deviation from its mean value, the predicted probability of fraud rises from 2.13% to 4.05%, a less than 100% increase. The magnitude of school peer effects is on the same order as industry effect. Further, the same-industry, same school rate $FMRate_{-j,t}^{i,c}$ has the largest impact on the propensity to commit financial misconduct.

In column (4) and (5), I control for school peer effect together with industry effect and both the non-industry and same-industry school peer effect remain significant. In column (6) the significance of non-industry, same-school peers is subsumed by the same-industry, same-school peers; therefore I control for the same-industry, same school rate $FMRate_{-j,t}^{i,c}$ together with industry effect $FMRate_t^{i,-c}$ in the subsequent regressions and label column (5) as the *baseline regression* and refer to the same-industry and same-school peer as the reference group for peer effect.

In column (7), I introduce an interaction term of the peer effects and network size, measured in the natural logarithm of the number of firms in school c , industry i and year t . The positive and significant coefficient on the interaction term suggests that the peer effect is stronger in larger networks.

Although not my main focus of this paper, the control variables are largely consistent with prior literature. Larger firms are more likely to end up in a fraud litigation as the settlement amount is expected to be larger. Growth firms are more likely to be prosecuted for fraud because they have more discretion over the accounting of earnings. I add to the firm-level controls the percentage of non-cash compensation paid to the CEO in the last column. Since the compensation variables from ExecuComp is only available for a subsample of firms, I control for it in only one of the regressions. The insignificant coefficient on it implies that the compensation incentive does not have additional explanatory power of the firm's fraud propensity.

Including state and industry fixed effects in Panel B barely changes the results⁷. This suggests that first, the peer effect is unlikely to be caused by the exogenous characteristics of the law enforcement environment in different states that happen to be correlated with different educational clusters. Second, the peer influences cannot be explained by the inherent differences across various industries.

5.2 Peer effect, elite effect and network size

In this section, I examine whether the elite school effect can be explained by peer effect in firm level analysis. The regression set up is identical to the baseline regression except that I include a dummy variable *EliteSchool* in column (1) of Table 5.

⁷ The number of observations dropped in regressions with fixed effects because the observation is dropped when there is no variation in the response group within a fixed effect group.

The positive and significant coefficient on *EliteSchool* implies that for a particular CEO, his/her tendency to engage in fraudulent activities is significantly higher if he/she graduated from an elite institution after controlling for the same-school, same-industry peer fraud rate and the different-school, same-industry average fraud rate. In column (2), the significance on *EliteSchool* increases slightly after controlling for state and industry fixed effects.

[Insert Table 5 here]

In column (3), I introduce the interaction term of *EliteSchool* and the same-industry, same-school peer fraud rate ($FMRate_{-j,t}^{i,c}$) to test the conjecture that the contagion effect is more pronounced in elite schools. Consider the economic interpretation of coefficients in column (3), in non-elite schools, suppose the peer fraud rate increases from its median to mean value, the probability of fraud for firm j increases from 0.40% to 0.67%; whereas in elite schools the same change in peer fraud rate would increase the propensity for firm j to engage in financial misconduct from 0.67% to 1.16%, nearly doubles the probability increase for non-elite schools.

In the last two columns, I control for network size ($\ln(NFrim)$), together with the interaction term of peer fraud rate and network size ($FMRate_{-j,t}^{i,c} \times \ln(NFrim)$). The significant coefficient on the interaction term $FMRate_{-j,t}^{i,c} \times EliteSchool$ implies that the fraud is more contagious among elite school graduates even after control for the stronger peer effect due to network size we uncover previously. This indicates that there is some culture in elite school that enhance the peer effect of fraud that is beyond the fact that elite school having a larger network size. It is also interesting to see the coefficient of elite is no longer significant, suggesting the elite graduate is no more likely to commit fraud than the non-elite one after controlling for peer effect.

5.3 Peer effect and network tightness

Given the prevalent endowment funding culture in the US and the fact that alumni donation is one of the major sources of university endowments, the size of university endowment is a reasonable proxy for the social identification of the alumni to their alma mater. In other words, the stronger the attachment to their alma mater, the larger the endowment amount. Thus, I employ a historical cross-section of the dollar value of university endowments at the beginning of the sample period in an attempt to capture the tightness of the alumni network. In addition, apart from the set of control variables in the baseline regression, I also control for the size category of the university to make sure that the value of the endowment is not merely driven by the size of the student body.

[Insert Table 6 here]

The positive and significant coefficient on the interaction term between the peer fraud rate and the natural logarithm of endowment size ($FMRate_{-j,t}^{i,c} \times \ln(Endowment)$) in column (1) indicates that the contagion of fraud is more intensive in tighter networks measured by a larger endowment size, holding the size of the student body and other firm fundamentals constant. In column (2) and (3), I separate the sample into elite and non-elite school subsamples. The positive and significant result in column (2) and the insignificant one in column (3) indicate that the tightness of network is an important determinant of the contagion effect of fraud among elite schools, conditional on the endowment size being a good proxy for network tightness.

In column (4), I include the interaction term between peer fraud rate and the elite school dummy ($FMRate_{-j,t}^{i,c} \times EliteSchool$). The coefficient on the interaction term of peer fraud rate and the elite school dummy is positive and significant; and that on peer

fraud rate and the endowment size is insignificant. This implies that either *EliteSchool* is a more precise measure of network tightness and/or there is some cultural aspects in elite school, tighter network being one of them, that enhance the fraud contagion.

5.4 Mechanism of peer effect

Having documented the existence and magnitude of the contagion effect of the same-school, same-industry peers, I investigate on the possible mechanisms underlying the peer effect in this sub-section. One possible explanation is the “keeping up with Joneses” argument whereby an agent’s decision is determined over both his own behavior as well as the contemporaneous average behavior of the reference group.⁸ In my context, the “keeping up with Joneses” explanation would predict a positive sensitivity of firm j ’s fraud probability to the interaction of the contemporaneous peer fraud rate and peer performance. This means that the contagion effect is more intensive when the performance of the peer firms appears to be better.

[Insert Table 7 here]

I implement the test by introducing interaction terms between the key peer fraud rate measure $FMRate_{-j,t}^{i,c}$ and various peer firm performance measures including the average return on asset ($ROA_{-j,t}^{i,c}$), return on equity ($ROE_{-j,t}^{i,c}$) and return on sales ($ROS_{-j,t}^{i,c}$) respectively. Two out of the three interaction terms are positive and significant at 1%. The positive and significant interaction terms between the peer fraud rate and peer firm performance are consistent with the “keeping up with Joneses” story

⁸ See for example Abel (1990), GÓMez, Priestley and Zapatero (2009), and Bursztyn, Ederer, Ferman and Yuchtman (2014).

that the contagion effect from peer firms is stronger when the peers appear to be performing better as measured by either a higher ROE or higher ROS.

6. Identification

In peer effect studies, the primary identification challenge arises from the presence of peer fraud rate as a regressor in equation (1). Intuitively, if firm j 's propensity to engage in financial misconduct is influenced by its peer firms, the propensity of financial misconduct for firm k , another firm in the peer group, is affected by firm j vice versa. Such simultaneity indicates that the peer fraud rate is an endogenous regressor. This is the so-called *reflection problem* discussed in Manski (1993).

In Leary and Roberts (2014)'s framework that examines the peer effect of capital structure, the key to address the *reflection problem* is to use an idiosyncratic and exogenous variation of peer firms that is unrelated to the contextual or exogenous characteristics of the peer group. This serves as an instrument for the capital structure of peer firms; and given the exogeneity, the only channel that the instrument can have an effect is through the endogenous peer effect. In the context of this paper, the aim is to identify an exogenous shock that is uncorrelated with the contextual or exogenous characteristics of educational peer group and at the same time is correlated with the peers' financial misconduct rate. I borrow from the economic literature and follow the method in Bartik (1991) and recently implemented in Parsons, Sulaeman and Titman (2015).⁹ The tests employ non-local shock as an instrument for some, but importantly not all, firms of a city.

⁹ Other recent employment of the same approach can be found in Autor and Duggan (2003) that examines the spillover effects of disability insurance and Luttmer (2005) which studies relative consumption effects.

Building on the evidence in Parsons, Sulaeman and Titman (2015) that documents the importance of city and industry effect as determinants of financial misconduct, I use the financial misconduct rate of firms in the dominant city-industry pair (e.g. New York City- Finance industry) outside an educational cluster to instrument for the average fraud rate of peer firms within this cluster. The dominant city-industry pair is useful because both city and industry are known channels that financial misconducts propagate, and through these channels I can use variation in the firms outside an educational cluster to impose a shock on some firms within the educational cluster without affecting the rest of firms that are not in the dominant city-industry.

It may be more straightforward to illustrate with a graphical example. To identify the dominant city-industry pair, I first compute the time-series average of the total number of CEOs graduated from each university that belong to a particular industry and city. For each school, I identify the most dominant industry-city pair, New York City-Finance for Harvard and Houston-Energy for University of Texas (UT) for example. Among all the schools, I identify the single most concentrated city-industry pair as the one that produces the greatest number of CEOs each year on average over the sample period, i.e. New York City-Financial. I then label the dominant school-city-industry triplet as the Dominant City-Industry by identifying universities with New York City-Financial as its most dominant city-industry pair. This results in 9 out of 201 universities in the sample. The rest of the school-city pairs are the non-dominant ones, UT-Houston-Energy for instance. I instrument the propensity to commit fraud of Harvard financial firms that are located in the New-York City by UT financial firms whose headquarters are in the New York City. The fact that I use no Harvard specific information to proxy for the propensity to commit fraud by Harvard financial firms in New York City means that any time-varying, Harvard specific contextual effects cannot explain any contagion

to other Harvard firms outside the dominant city-industry pair, e.g. technology firms in San Francisco whose CEO graduates from Harvard. The only channel that UT NYC Financial firms can have any impact on the Harvard San Francisco Technology firm is through the endogenous peer effect within Harvard.

[Insert Figure 2 here]

Specifically, I run an instrumental variable probit model with a continuous endogenous regressor $FMRate_t^{Dom,c}$, the average fraud rate of peer firms in the dominant city-industry pair. The model is identical to the baseline regression except two changes. First, the sample in the second stage probit regression is restricted to the non-dominant firms within the nine universities that have NYC-Financial as the dominant city-industry pair. Second, I use $FMRate_t^{Dom,-c}$, the average rate of financial misconduct of firms in the dominant city-industry pair but outside the educational cluster, to instrument for $FMRate_t^{Dom,c}$ in the first stage regression. The first column of Table 8 displays the first stage results. The highly significant coefficient on $FMRate_t^{Dom,-c}$ indicates that the annual fluctuations in the fraud rate for each dominant city-industry pair is strongly correlated when measured outside the university of interest. This precludes the weak instrument concern.

[Insert Table 8 here]

In the second stage shown in column (2), the positive and significant coefficient on the instrumented variable implies a large sensitivity 2.14 (t=4.637). Since the estimate is based solely on the shocks outside the university cluster, any within-school environmental influences cannot explain the effect, be it related to the common

economic conditions or common incentives faced by CEOs of a particular university. This effectively rules out the contextual effect channel.

7. Placebo test of random peer group assignment

In this section, I implement a placebo test to randomize peer group assignment and examine the possibility that the results are purely driven by chance. To be specific, I randomly assign a university identifier to each firm-year observation based on the proportion of the number of firm-year observations associated with each university and form peer group with industry and the assigned university. Since the assigned university is not (or very unlikely to be) the CEO's true alma mater, I designate the peer group formed in this approach the *pseudo peer group*. I then re-estimate the coefficient on $FMRate_{-j,t}^{i,c}$ from the baseline regression with the key variables determined on the *pseudo peer group*.

[Insert Figure 3 here]

I repeat the above practice for 5,000 times and plot the distribution of regression coefficient in Figure 3. The actual coefficient on $FMRate_{-j,t}^{i,c}$ of 6.104 (see column (5) of Panel B of Table 4) is more than twenty times standard deviations (0.268) above the mean (0.109) of the distribution and is even larger than the maximum coefficient estimate (1.155). The result indicates that our baseline result is highly unlikely to be driven by chance.

8. Robustness tests and alternative explanations

8.1 *Excluding frivolous cases*

As pointed out in Dyck, Morse and Zingales (2010), the biggest problem in using the SSCAC data is the possible inclusion of frivolous cases. I apply a firm size filter as the one adopted in Dyck, Morse and Zingales (2010) to address this concern. Operationally, I restrict to large domestic firms with total asset greater than \$750 million in the year prior to the violation period to ensure that the firms have sufficient assets and insurance to incentivize the law firms to initiate the suit.

[Insert Table 9 here]

The regression specification replicates the main regressions in Table 4 except that I require the firms to have at least \$750 million in total assets. Despite dropping a significant number of observations and fraudulent cases, the significance and magnitude of coefficients remain virtually unchanged compared to those in Table 4.

8.2 *CEO overconfidence and peer effect*

The peer effect of fraud that I uncover in this paper may be driven by the possibility that elite school CEOs are more overconfident; and according to Schrand and Zechman (2012), overconfident CEOs are more likely to engage in financial misconduct. To investigate on this possibility, I first test if the overconfidence is contagious among CEOs within a peer group, and if so, whether the contagion is able to explain the elite effect.

[Insert Table 10 here]

Consistent with prior literature (Malmendier and Tate (2005) and Phua, Tham and Wei (2016) for example), the overconfidence measure is constructed based on the extent to which CEO is holding vested in-the-money options. It is a dummy variable that equals to one if the ratio of the average value per option to the average strike price is at least 67% in the money for at least two incidences in the past five years. The regression setup is similar to the baseline regression except that in column (1) of Table 10, I replace the peer fraud rate by the mean percentage of overconfident CEOs in the peer group ($Overconfidence_{-j,t}^{i,c}$) and the dependent variable by the binary indicator variable ($Overconfidence$) for overconfidence of the CEO of firm j . The insignificant coefficient on the variable $Overconfidence_{-j,t}^{i,c}$ indicates that there is no contagion effect of CEO overconfidence within the peer group. Further, the insignificant coefficient on the interaction term ($EliteSchool \times Overconfidence_{-j,t}^{i,c}$) and the significant one on the variable $EliteSchool$ in column (2) imply that the overconfidence story cannot explain the elite effect.

8.3 Peer effect and earnings management

I explore a possible extension of the results in this subsection. In particular, earnings management occurs when managers use discretion in the financial reporting to window-dress and mislead users of financial statements (Healy and Wahlen (1999)). In fact, earnings management becomes fraud when the firm intentionally provides materially misstated information. If my conjecture in this paper is true that there is contagion of financial misconduct among alumni networks, we would expect to see the contagion effect of earnings management practices among the same network since CEOs have great discretion on the decision to “manage” earnings.

I adopt four earnings management (quality) measures in the empirical test. EQ1, EQ2 are based on discretionary accruals and discretionary current accruals in Dechow, Sloan and Sweeney (1995). EQ3, EQ4 are based on cash flow from operations in Dechow and Dichev (2002). The positive and significant coefficient on the peer effect of earnings management terms $EQ1_{-j,t}^{i,c}$, $EQ2_{-j,t}^{i,c}$, $EQ3_{-j,t}^{i,c}$, $EQ4_{-j,t}^{i,c}$ indicate that there does exist contagion effect of earnings management practices regardless of which measure is used.

9. Conclusion

The primary objective of this paper is to document the systematic differences in the frequencies of corporate financial misconducts between firms with elite school CEOs and those with non-elite school ones. I develop an empirical framework that quantifies the disproportionate occurrence of elite-school frauds and the extent to which it can be explained by the endogenous peer effect among the alumni network. I find that the elite school graduates are more likely to commit fraud because fraud is more contagious among the elite graduates. I uncover a novel finding that the peer effect, or contagion effect, increases with the network size, suggesting that CEO is influenced by the number of fraud cases rather than just the rate of fraud of the peer group. Moreover, the tightness of the network matters for the peer effect in addition to the network size. The elite school graduates are no more likely to commit fraud if not for peer effect.

Understanding whether and how peer effect predicts financial misconduct has important implications for regulators, auditors as well as the academics. The possible consequences, such as extreme corporate events like forced CEO turnover or bankruptcy may worth exploring in future research.

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Figure 1 A typical timeline of an ongoing security class action

Figure 2 A visual illustration of the instrumental variable approach

Figure 3 Placebo test

Table 1 Firm and school characteristics

This table presents the summary statistics at firm-year level in Panel A and school-year level in Panel B. In Panel A, *Fraud* is a binary indicator variable that equals to one if the firm commits fraud in year t , and zero otherwise. $FMRate_t^{-i,c}$ is the annual average fraud rate of firms in the same education cluster (same school) and different industry. $FMRate_{-j,t}^{i,c}$ is the annual average fraud rate of firms in the same education cluster and same industry, and excluding firm j itself. $FMRate_t^{i,-c}$ is the annual average fraud rate of firms in the same industry and different school. Past return is the annual return over the past one year. The variable $\ln(AT)$ is natural logarithm of total asset. *Cash Flow/AT* is the cash flow scaled by total asset. *Leverage Ratio* is the long term debt to equity ratio calculated using the market value of equity. *ROA* is calculated as the net income plus interest divided by the mean value of the current total asset and the lagged value of total asset. *Non-cash compensation* is the percentage of CEO compensation that is not base salary. In Panel B, firm characteristics are averaged at school-year level. *TotalApplication* is the total number of students that apply the school and *TotalAccept* is the total number of students that accept the offer. *FracAdmission* is the number of applicants who get admission letter in a given year divided by the total number of applicants. *FreshmenSAT* is the average SAT score of freshmen and *FracFemale* is the fraction of female students. The sample period is from 2000 to 2012.

Panel A By Firm-Year						
	N	Mean	SD	P25	P50	P75
<i>Fraud</i>	16,036	0.033	0.179	0.000	0.000	0.000
$FMRate_t^{-i,c}$	16,036	0.031	0.040	0.000	0.199	0.049
$FMRate_{-j,t}^{i,c}$	16,036	0.031	0.086	0.000	0.000	0.000
$FMRate_t^{i,-c}$	16,036	0.033	0.025	0.017	0.025	0.043
<i>Past Return</i>	16,036	0.169	0.654	-0.213	0.076	0.378
<i>Tobin's Q</i>	16,036	2.005	1.507	1.093	1.485	2.294
$\ln(AT)$	16,036	6.443	2.148	4.870	6.377	7.908
<i>Cash Flow/AT</i>	16,036	0.072	0.161	0.0317	0.087	0.149
<i>Leverage Ratio</i>	16,036	0.363	0.814	0.0000	0.102	0.359
<i>ROA</i>	16,036	-0.008	0.203	-0.016	0.049	0.087
<i>Non-cash Compen.</i>	8,910	0.745	0.206	0.675	0.809	0.886

Panel B By School-Year						
	N	Mean	SD	P25	P50	P75
<i>Fraud</i>	2,308	0.055	0.151	0.000	0.000	0.038
$\ln(AT)$	2,308	7.705	1.715	6.770	7.827	8.737
<i>ROA</i>	2,308	-0.004	0.472	-0.050	0.011	0.055
<i>Tobin's Q</i>	2,308	1.912	0.923	1.355	1.726	2.212
<i>Leverage Ratio</i>	2,308	0.733	4.033	0.157	0.315	0.572
<i>Cash Flow/AT</i>	2,308	0.054	0.105	0.026	0.065	0.101
<i>TotalApplicant</i>	2,308	12,483	8,740	5,212	10,651	17,917
<i>FracAdmission</i>	2,308	0.594	0.207	0.460	0.656	0.748
<i>TotalAccept</i>	2,308	2,478	1,787	1,080	1,967	3,583
<i>FracFemale</i>	2,308	0.523	0.081	0.492	0.534	0.574
<i>FreshmanSAT</i>	2,308	1,184	134.4	1,080	1,173	1,277

Table 2 Distribution of fraud rate across elite schools

This table reports the time-series average of number of firms and the fraud rate for each of the 25 elite universities defined by a historical US News ranking. The sample period is from 2000 to 2012.

	NFirms	Fraud Rate				
		Mean	P25	P50	P75	SD
Princeton University	15.769	0.027	0.000	0.000	0.056	0.030
Harvard University	204.846	0.038	0.030	0.035	0.047	0.018
Yale University	20.923	0.038	0.000	0.000	0.067	0.046
Stanford University	85.154	0.032	0.013	0.023	0.056	0.028
Massachusetts Institute of Technology	36.077	0.026	0.000	0.000	0.030	0.042
California Institute of Technology	3.462	0.135	0.000	0.000	0.000	0.300
University of Pennsylvania	81.154	0.030	0.011	0.013	0.054	0.032
Duke University	14.923	0.046	0.000	0.056	0.063	0.055
University of Chicago	47.077	0.061	0.043	0.064	0.077	0.021
Columbia University	50.692	0.032	0.018	0.022	0.040	0.023
Dartmouth College	19.692	0.018	0.000	0.000	0.000	0.036
Cornell University	30.154	0.041	0.031	0.036	0.061	0.023
Washington University	11.231	0.013	0.000	0.000	0.000	0.046
Northwestern University	43.692	0.053	0.022	0.036	0.059	0.048
Brown University	3.385	0.058	0.000	0.000	0.000	0.151
Johns Hopkins University	4.692	0.044	0.000	0.000	0.000	0.083
Rice University	5.154	0.038	0.000	0.000	0.000	0.073
Vanderbilt University	13.154	0.007	0.000	0.000	0.000	0.025
Emory University	9.538	0.046	0.000	0.000	0.100	0.064
University of Notre Dame	11.077	0.006	0.000	0.000	0.000	0.023
University of California, Berkeley	24.077	0.034	0.000	0.000	0.059	0.046
Georgetown University	14.692	0.046	0.000	0.059	0.071	0.050
University of Michigan	34.615	0.025	0.000	0.025	0.032	0.031
University of Virginia	24.769	0.026	0.000	0.000	0.042	0.033
UCLA	24.769	0.032	0.000	0.037	0.053	0.030

Table 3 Inter-school differences in frequencies of financial misconducts

This table reports a series of Poisson regressions in the first three columns and a probit regression in the last column. The dependent variable is the number of financial misconduct events per school-year. The independent variable of interest in column (1) is the binary indicator variable *EliteSchool* that equals one if the university ranks among the top 25 universities by a historical US News Ranking in 2007. The variable $\ln(NFirm)$ is the natural logarithm of the total number of firms per school-year pair. The school-level average firm attributes at measured at the end of year t-1, they include firm size measured in log value of total asset ($\ln(AT)$), return on asset (*ROA*), Tobin's Q, cash flow over asset (*Cash Flow/AT*) and leverage ratio. University demographics include its geographical location (*State*), the annual observation of the natural logarithm of total number of students that accept the offer ($\ln(TotalAccept)$), fraction of admission (*FracAdmission*), that is, the number of applicants who get admission letter in a given year versus the total number of applicants, the average SAT score of freshmen (*FreshmenSAT*) and fraction of female students (*FracFemale*). The sample period is from 2000 to 2012.

	NFraud		
	(1)	(2)	(3)
$\ln(NFirm)$	0.863*** (23.268)	0.675*** (13.125)	0.666*** (7.766)
<i>EliteSchool</i>	0.270*** (3.156)	-0.912*** (-3.664)	-0.932** (-2.510)
<i>EliteSchool</i> × $\ln(NFirm)$		0.375*** (5.188)	0.353*** (3.447)
$\ln(AT)$			0.133*** (4.555)
<i>ROA</i>			-0.042 (-0.215)
<i>Tobin's Q</i>			0.131*** (2.755)
<i>Cash Flow/AT</i>			0.406 (0.785)
<i>Leverage Ratio</i>			0.004 (0.326)
$\ln(TotalAccept)$			-0.007 (-0.105)
<i>FracAdmission</i>			0.006 (0.014)
<i>FracFemale</i>			0.495 (0.737)
<i>FreshmanSAT</i>			-0.000 (-0.175)
Constant	-3.092*** (-31.074)	-2.644*** (-20.945)	-4.184*** (-3.486)
Observations	2,308	2,308	2,308
Year FE	No	No	Yes
State	No	No	Yes
Pseudo R-squared	0.220	0.226	0.277

Table 4 Peer fraud rate and propensity of financial misconduct

This table reports a series of probit regressions that relates the firm level propensity of financial misconduct to various peer fraud rate. In Panel A, the dependent *Fraud* is a binary indicator variable that equals to one if the firm commits fraud in year t , and zero otherwise. The independent variable $FMRate_t^{-i,c}$ is the annual average fraud rate of firms in the same education cluster (same school) and different industry. $FMRate_{-j,t}^{i,c}$ is the annual average fraud rate of firms in the same education cluster and same industry, and excluding firm j itself. $FMRate_t^{i,-c}$ is the annual average fraud rate of firms in the same industry and different school. All firm characteristic are measured at the end of year $t-1$. Past return is the annual return over the past one year. The variable $\ln(NFirm)$ is the natural logarithm of the total number of firms per industry-school cluster. *Non-cash compensation* is the percentage of CEO compensation that is not base salary. Past return is the annual return over the past one year. The variable $\ln(AT)$ is natural logarithm of total asset. *Cash Flow/AT* is the cash flow scaled by total asset. *Leverage Ratio* is the long term debt to equity ratio calculated using the market value of equity. *ROA* is calculated as the net income plus interest divided by the mean value of the current total asset and the lagged value of total asset. I include school level average fraud rate over the sample period in all regressions. Panel B is identical to Panel A except that I include state fixed effects and industry fixed effects. The industries are defined on the Fama-French 12 industry classification. The sample period is from 2000 to 2012. The standard errors are clustered at industry level and robust z-statistics are shown in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level respectively.

Panel A Without fixed effects								
Dependent Variable: <i>Fraud</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$FMRate_t^{-i,c}$	8.864*** (9.777)			7.800*** (11.103)		-0.274 (-0.527)		
$FMRate_{-j,t}^{i,c}$		6.012*** (34.094)			5.779*** (38.261)	5.828*** (28.210)	5.812*** (22.221)	6.170*** (28.447)
$FMRate_t^{i,-c}$			11.391*** (10.874)	8.427*** (9.124)	4.213*** (3.417)	4.269*** (3.473)	1.992** (2.028)	3.337 (1.593)
$FMRate_{-j,t}^{i,c} \times \ln(NFirm)$							1.159*** (3.194)	
$\ln(NFirm)$							0.204*** (6.431)	
<i>Non-cash Compensation</i>								0.220 (0.833)
<i>Past Return</i>	0.024 (0.414)	0.034 (0.676)	0.014 (0.273)	0.018 (0.310)	0.032 (0.624)	0.032 (0.618)	0.034 (0.616)	0.043 (0.763)
<i>Tobin's Q</i>	0.115*** (6.120)	0.113*** (7.245)	0.104*** (5.669)	0.104*** (5.847)	0.107*** (6.783)	0.107*** (6.763)	0.107*** (6.118)	0.100*** (5.328)
$\ln(AT)$	0.149*** (10.514)	0.145*** (7.603)	0.134*** (10.516)	0.146*** (13.255)	0.144*** (7.959)	0.144*** (7.901)	0.164*** (15.595)	0.105** (2.414)
<i>Cash Flow/AT</i>	0.583** (2.024)	0.565*** (3.199)	0.374** (2.007)	0.490** (2.228)	0.548*** (3.046)	0.547*** (3.058)	0.713*** (3.407)	0.430 (0.592)
<i>Leverage Ratio</i>	0.015 (0.483)	0.022 (0.677)	0.020 (0.733)	0.011 (0.337)	0.020 (0.596)	0.020 (0.597)	0.016 (0.435)	0.041 (0.929)
<i>ROA</i>	-0.659*** (-5.088)	-0.541** (-2.308)	-0.332** (-2.448)	-0.482*** (-3.961)	-0.479** (-2.044)	-0.477** (-2.013)	-0.466 (-1.583)	-0.884 (-1.214)
Constant	-3.637*** (-29.213)	-3.769*** (-22.220)	-3.875*** (-29.921)	-3.929*** (-29.872)	-3.913*** (-23.493)	-3.913*** (-23.438)	-4.347*** (-29.959)	-3.717*** (-10.971)
Observations	16,036	16,036	16,036	15,478	16,036	16,036	16,036	8,275
Pseudo R-squared	0.169	0.401	0.196	0.220	0.405	0.405	0.434	0.411
State FE	No	No	No	No	No	No	No	No
Industry FE	No	No	No	No	No	No	No	No
School fraud rates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B With fixed effects								
Dependent Variable: <i>Fraud</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$FMRate_t^{-i,c}$	9.130*** (10.339)			8.017*** (11.255)		-0.798 (-1.518)		
$FMRate_{-j,t}^{i,c}$		6.321*** (24.276)			6.104*** (24.497)	6.257*** (19.861)	6.103*** (17.257)	6.827*** (19.472)
$FMRate_t^{i,-c}$			13.060*** (17.096)	8.888*** (9.318)	5.555*** (7.103)	5.820*** (6.806)	3.645*** (6.190)	4.364*** (2.577)
$FMRate_{-j,t}^{i,c} \times \ln(NFirm)$							1.179*** (3.117)	
$\ln(NFirm)$							0.200*** (6.212)	
<i>Non-cash Compensation</i>								0.203 (0.803)
<i>Past Return</i>	0.028 (0.457)	0.055 (1.026)	0.025 (0.476)	0.027 (0.452)	0.055 (1.052)	0.054 (1.053)	0.054 (0.937)	0.079 (1.308)
<i>Tobin's Q</i>	0.098*** (6.397)	0.099*** (7.520)	0.098*** (5.526)	0.095*** (5.488)	0.096*** (6.723)	0.096*** (6.703)	0.098*** (5.508)	0.068*** (4.107)
$\ln(AT)$	0.154*** (11.952)	0.158*** (9.707)	0.148*** (9.948)	0.157*** (11.934)	0.161*** (10.234)	0.161*** (10.094)	0.185*** (14.925)	0.101*** (2.653)
<i>Cash Flow/AT</i>	0.323 (1.234)	0.270 (1.225)	0.255 (1.113)	0.330 (1.373)	0.304 (1.331)	0.296 (1.295)	0.465** (2.451)	-0.366 (-0.497)
<i>Leverage Ratio</i>	0.015 (0.590)	0.030 (1.213)	0.024 (0.973)	0.011 (0.393)	0.029 (1.133)	0.029 (1.159)	0.022 (0.729)	0.050 (1.434)
<i>ROA</i>	-0.355*** (-5.593)	-0.325** (-2.069)	-0.279*** (-3.609)	-0.348*** (-5.439)	-0.336** (-2.213)	-0.328** (-2.125)	-0.327* (-1.736)	-0.009 (-0.013)
Constant	-4.500*** (-16.849)	-4.618*** (-13.136)	-4.896*** (-17.254)	-4.889*** (-16.348)	-4.875*** (-12.457)	-4.886*** (-12.425)	-5.273*** (-10.123)	-4.367*** (-16.851)
Observations	15,478	15,478	15,478	15,478	15,478	15,478	15,478	7,882
Pseudo R-squared	0.200	0.424	0.151	0.220	0.430	0.430	0.455	0.454
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School fraud rates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5 Elite effect and peer effect

This table reports a series of probit regressions that relates the firm level propensity of financial misconduct to various peer fraud rate and the elite school effect. The dependent *Fraud* is a binary indicator variable that equals to one if the firm commits fraud in year t , and zero otherwise. The independent variable *EliteSchool* is a dummy variable that equals one if the university ranks among the top 25 universities by a historical US News Ranking in 2007 and zero otherwise. $FMRate_{-j,t}^{i,c}$ is the annual average fraud rate of firms in the same education cluster and same industry, and excluding firm j itself. $FMRate_t^{i,-c}$ is the annual average fraud rate of firms in the same industry and different school. All firm characteristic are measured at the end of year $t-1$. Past return is the annual return over the past one year. The variable $\ln(NFirm)$ is the natural logarithm of the total number of firms per industry-school cluster. Past return is the annual return over the past one year. The variable $\ln(AT)$ is natural logarithm of total asset. *Cash Flow/AT* is the cash flow scaled by total asset. *Leverage Ratio* is the long term debt to equity ratio calculated using the market value of equity. *ROA* is calculated as the net income plus interest divided by the mean value of the current total asset and the lagged value of total asset. I include school level average fraud rate over the sample period in all regressions. The even numbered columns are identical to the odd ones except that I include state fixed effects and industry fixed effects. The industries are defined on the Fama-French 12 industry classification. The sample period is from 2000 to 2012. The standard errors are clustered at industry level and robust z-statistics are shown in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level respectively.

Dependent variable: <i>Fraud</i>						
	(1)	(2)	(3)	(4)	(5)	(6)
<i>EliteSchool</i>	0.293*** (4.507)	0.342*** (5.512)	0.180** (2.381)	0.204*** (2.930)	-0.043 (-0.489)	-0.031 (-0.348)
$FMRate_{-j,t}^{i,c} \times EliteSchool$			0.820** (2.530)	1.001*** (3.749)	0.874** (2.066)	0.988** (2.419)
$FMRate_{-j,t}^{i,c} \times \ln(NFirm)$					0.980** (2.359)	0.971** (2.245)
$\ln(NFirm)$					0.214*** (5.241)	0.206*** (4.931)
$FMRate_{-j,t}^{i,c}$	6.035*** (28.483)	6.408*** (21.152)	5.724*** (30.325)	6.039*** (20.043)	5.664*** (25.999)	5.953*** (18.241)
$FMRate_t^{i,-c}$	3.721*** (3.113)	4.878*** (6.588)	3.460*** (2.953)	4.555*** (6.124)	1.727* (1.724)	3.335*** (5.500)
<i>Past Return</i>	0.035 (0.673)	0.055 (1.039)	0.035 (0.667)	0.055 (1.012)	0.034 (0.608)	0.053 (0.903)
<i>Tobin's Q</i>	0.104*** (6.955)	0.094*** (6.859)	0.104*** (7.089)	0.095*** (6.996)	0.107*** (6.325)	0.097*** (5.686)
$\ln(AT)$	0.137*** (7.583)	0.153*** (9.838)	0.137*** (7.618)	0.154*** (9.985)	0.161*** (14.214)	0.182*** (13.863)
<i>Cash Flow/AT</i>	0.501*** (2.892)	0.287 (1.211)	0.508*** (2.931)	0.288 (1.188)	0.697*** (3.293)	0.449** (2.137)
<i>Leverage Ratio</i>	0.019 (0.562)	0.029 (1.104)	0.014 (0.421)	0.023 (0.906)	0.010 (0.280)	0.016 (0.558)
<i>ROA</i>	-0.429* (-1.905)	-0.313** (-2.057)	-0.428* (-1.920)	-0.309** (-2.100)	-0.452 (-1.608)	-0.318* (-1.830)
Constant	-4.005*** (-26.953)	-5.065*** (-12.007)	-3.949*** (-28.650)	-5.035*** (-11.699)	0.771 (0.387)	-5.291*** (-10.222)
Observations	16,036	15,478	16,036	15,478	16,036	15,478
Pseudo R-squared	0.411	0.437	0.412	0.438	0.436	0.457
Industry FE	No	Yes	No	Yes	No	Yes
State FE	No	Yes	No	Yes	No	Yes
School fraud rates	Yes	Yes	Yes	Yes	Yes	Yes

Table 6 Heterogeneous tightness of alumni network

This table examines the impact of peer effect in networks with heterogeneous tightness proxied by endowment size. The dependent *Fraud* is a binary indicator variable that equals to one if the firm commits fraud in year t , and zero otherwise. $FMRate_{-j,t}^{i,c}$ is the annual average fraud rate of firms in the same education cluster and same industry, and excluding firm j itself. The variable $\ln(Endowment)$ is the log value of the endowment size measured at year 1999. The variable *EliteSchool* is a dummy variable that equals one if the university ranks among the top 25 universities by a historical US News Ranking in 2007 and zero otherwise. $FMRate_t^{i,-c}$ is the annual average fraud rate of firms in the same industry and different school. All firm characteristic are measured at the end of year $t-1$. Column (1) and (4) are full sample regressions and column (2) is the subsample regression of elite schools and column (3) is the subsample regression of non-elite schools. Past return is the annual return over the past one year. Past return is the annual return over the past one year. The variable $\ln(AT)$ is natural logarithm of total asset. *Cash Flow/AT* is the cash flow scaled by total asset. *Leverage Ratio* is the long term debt to equity ratio calculated using the market value of equity. *ROA* is calculated as the net income plus interest divided by the mean value of the current total asset and the lagged value of total asset. I include school level average fraud rate over the sample period in all regressions. The industries are defined on the Fama-French 12 industry classification. The sample period is from 2000 to 2012. The standard errors are clustered at industry level and robust z-statistics are shown in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level respectively.

Dependent variable: <i>Fraud</i>				
	(1)	(2)	(3)	(4)
$FMRate_{-j,t}^{i,c}$	1.538 (0.871)	-11.691*** (-3.273)	5.047** (2.068)	3.795*** (2.308)
$FMRate_{-j,t}^{i,c} \times \ln(Endowment)$	0.384*** (3.017)	1.316*** (5.170)	0.119 (0.596)	0.199 (1.549)
$\ln(Endowment)$	0.095*** (2.804)	0.046 (1.274)	0.026 (0.360)	0.132** (3.975)
$FMRate_{-j,t}^{i,c} \times EliteSchool$				0.634** (1.973)
<i>EliteSchool</i>				-0.102 (-1.017)
$FMRate_t^{i,-c}$	3.595*** (4.210)	3.852*** (4.346)	1.426* (1.832)	3.279*** (4.568)
<i>Past Return</i>	0.052 (0.862)	0.061 (0.620)	0.047 (0.818)	0.051 (0.874)
<i>Tobin's Q</i>	0.098*** (8.627)	0.092*** (4.189)	0.110*** (3.254)	0.099*** (9.453)
$\ln(AT)$	0.155*** (9.485)	0.176*** (5.290)	0.145*** (4.691)	0.155*** (10.065)
<i>Cash Flow/AT</i>	0.447** (2.188)	0.968*** (3.935)	-0.032 (-0.082)	0.453** (2.253)
<i>Leverage Ratio</i>	0.031 (1.151)	-0.013 (-0.314)	0.106** (2.061)	0.030 (1.096)
<i>ROA</i>	-0.362** (-2.079)	-0.621** (-2.236)	-0.132 (-0.439)	-0.367** (-2.287)
Constant	-6.545*** (-8.516)	-7.931*** (-10.135)	-5.788*** (-4.202)	-7.649*** (-4.767)
Observations	14,398	7,403	6,611	14,398
Pseudo R-squared	0.442	0.394	0.534	0.440
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
University Size FE	Yes	Yes	Yes	Yes
School fraud rates	Yes	Yes	Yes	Yes

Table 7 The influences of peers' performance

This table explores the source of peer effect. The dependent *Fraud* is a binary indicator variable that equals to one if the firm commits fraud in year t , and zero otherwise. $FMRate_{-j,t}^{i,c}$ is the annual average fraud rate of firms in the same education cluster and same industry, and excluding firm j itself. Peer firm performance measures include $ROA_{-j,t}^{i,c}$, $ROE_{-j,t}^{i,c}$ and $ROS_{-j,t}^{i,c}$, which are the average return on asset, return on equity and return on sales of peer firms from the same school and same industry except for the firm itself respectively. $FMRate_t^{i,-c}$ is the annual average fraud rate of firms in the same industry and different school. All firm characteristic are measured at the end of year $t-1$. Past return is the annual return over the past one year. Past return is the annual return over the past one year. The variable $\ln(AT)$ is natural logarithm of total asset. *Cash Flow/AT* is the cash flow scaled by total asset. *Leverage Ratio* is the long term debt to equity ratio calculated using the market value of equity. *ROA* is calculated as the net income plus interest divided by the mean value of the current total asset and the lagged value of total asset. I include school level average fraud rate over the sample period in all regressions. The industries are defined on the Fama-French 12 industry classification. The sample period is from 2000 to 2012. The standard errors are clustered at industry level and robust z-statistics are shown in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level respectively.

Dependent variable: <i>Fraud</i>			
	(1)	(2)	(3)
$FMRate_{-j,t}^{i,c}$	6.126*** (26.598)	6.143*** (28.855)	6.120*** (25.135)
$FMRate_{-j,t}^{i,c} \times ROA_{-j,t}^{i,c}$	0.640 (1.454)		
$ROA_{-j,t}^{i,c}$	-0.323*** (-3.081)		
$FMRate_{-j,t}^{i,c} \times ROE_{-j,t}^{i,c}$		0.543*** (2.901)	
$ROE_{-j,t}^{i,c}$		-0.192*** (-3.052)	
$FMRate_{-j,t}^{i,c} \times ROS_{-j,t}^{i,c}$			0.001*** (4.224)
$ROS_{-j,t}^{i,c}$			-0.000*** (-12.053)
$FMRate_t^{i,-c}$	5.473*** (7.349)	5.544*** (7.501)	5.583*** (7.239)
<i>Past Return</i>	0.056 (1.068)	0.055 (1.054)	0.055 (1.047)
<i>Tobin's Q</i>	0.095*** (6.702)	0.095*** (6.661)	0.096*** (6.696)
$\ln(AT)$	0.161*** (10.206)	0.161*** (10.205)	0.161*** (10.268)
<i>Cash Flow/AT</i>	0.292 (1.289)	0.293 (1.302)	0.307 (1.327)
<i>Leverage Ratio</i>	0.028 (1.083)	0.027 (1.030)	0.029 (1.133)
<i>ROA</i>	-0.273 (-1.645)	-0.290* (-1.662)	-0.335** (-2.213)
Constant	-4.863*** (-12.357)	-4.866*** (-12.500)	-4.875*** (-12.440)
Observations	15,478	15,478	15,478
Pseudo R-squared	0.430	0.430	0.430
Industry FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
School fraud rates	Yes	Yes	Yes

Table 8 Instrumental variable regression

This table reports two-stage IV probit regression. I restrict to a subsample of universities that have NYC-financial as the dominant city-industry pair to run the regression. In the first stage, I use the average fraud rate of firms from the dominant industry, different school to instrument for the average fraud rate of firms in the dominant industry, same educational cluster. The dependent variable $FM_{j,t}$ in the second stage is the dummy variable of financial misconduct for firm j in year t outside the dominant industry-city pair. Past return is the annual return over the past one year. Past return is the annual return over the past one year. The variable $\ln(AT)$ is natural logarithm of total asset. $Cash\ Flow/AT$ is the cash flow scaled by total asset. $Leverage\ Ratio$ is the long term debt to equity ratio calculated using the market value of equity. ROA is calculated as the net income plus interest divided by the mean value of the current total asset and the lagged value of total asset. I include school level average fraud rate over the sample period in all regressions. The industries are defined on the Fama-French 12 industry classification. The sample period is from 2000 to 2012. The standard errors are clustered at industry level and robust z-statistics are shown in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level respectively.

	(1) 1 st stage $FM\ Rate_t^{Dom,c}$	(2) 2 nd stage $FM_{j,t}$
<i>Instrumented $FM\ Rate_t^{Dom,c}$</i>		2.143*** (4.637)
<i>$FM\ Rate_t^{Dom,-c}$</i>	0.705*** (10.16)	
<i>Past Return</i>	0.00418 (0.646)	0.0772*** (3.481)
<i>Tobin's Q</i>	0.00413** (1.979)	0.0433*** (3.014)
<i>$\ln(AT)$</i>	0.00185 (1.100)	0.109*** (6.846)
<i>Cash Flow/AT</i>	0.00232 (0.0639)	1.410*** (3.604)
<i>Leverage Ratio</i>	-0.000827 (-0.528)	0.0108 (0.727)
<i>ROA</i>	-0.00521 (-0.153)	-0.823*** (-2.645)
Constant	-0.409*** (-7.410)	-2.533*** (-6.294)
Observations	4,359	4,359
State fixed effects	Yes	Yes
School fraud rates	Yes	Yes

Table 9 Eliminating frivolous cases

This table reports a series of probit regressions that relates the firm level propensity of financial misconduct to various peer fraud rate, which is identical to the main regressions in Table 4 except that I exclude firms with a total asset less than \$750 million to address the concern of frivolous cases. The dependent *Fraud* is a binary indicator variable that equals to one if the firm commits fraud in year t , and zero otherwise. The independent variable $FMRate_t^{-i,c}$ is the annual average fraud rate of firms in the same education cluster (same school) and different industry. $FMRate_{-j,t}^{i,c}$ is the annual average fraud rate of firms in the same education cluster and same industry, and excluding firm j itself. $FMRate_t^{i,-c}$ is the annual average fraud rate of firms in the same industry and different school. All firm characteristic are measured at the end of year $t-1$. Past return is the annual return over the past one year. The variable $\ln(NFirm)$ is the natural logarithm of the total number of firms per industry-school cluster. Past return is the annual return over the past one year. The variable $\ln(AT)$ is natural logarithm of total asset. *Cash Flow/AT* is the cash flow scaled by total asset. *Leverage Ratio* is the long term debt to equity ratio calculated using the market value of equity. *ROA* is calculated as the net income plus interest divided by the mean value of the current total asset and the lagged value of total asset. I include school level average fraud rate over the sample period in all regressions. I include state fixed effects and industry fixed effects. The industries are defined on the Fama-French 12 industry classification. The standard errors are clustered at industry level and robust z-statistics are shown in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level respectively.

Dependent variable: <i>Fraud</i>						
	(1)	(2)	(3)	(5)	(6)	(7)
$FMRate_t^{-i,c}$	9.136*** (8.770)			7.985*** (9.996)		
$FMRate_{-j,t}^{i,c}$		7.301*** (20.305)			7.073*** (21.396)	7.009*** (15.848)
$FMRate_t^{i,-c}$			13.171*** (9.696)	9.677*** (7.147)	5.254*** (3.655)	3.342*** (3.006)
$FMRate_{-j,t}^{i,c} \times \ln(NFirm)$						1.284* (1.693)
$\ln(NFirm)$						0.178*** (3.197)
<i>Past Return</i>	-0.091 (-1.020)	-0.127 (-1.236)	-0.073 (-0.767)	-0.084 (-0.890)	-0.117 (-1.146)	-0.147 (-1.380)
<i>Tobin's Q</i>	0.092*** (4.983)	0.107*** (4.836)	0.089*** (3.485)	0.071*** (3.160)	0.094*** (3.689)	0.097*** (3.939)
$\ln(AT)$	0.160*** (3.959)	0.164*** (2.906)	0.153*** (3.847)	0.161*** (3.976)	0.163*** (2.919)	0.192*** (3.348)
<i>Cash Flow/AT</i>	-1.317** (-2.539)	-2.068*** (-3.662)	-1.428*** (-3.327)	-1.256*** (-2.971)	-1.995*** (-4.097)	-1.468*** (-2.891)
<i>Leverage Ratio</i>	0.006 (0.251)	0.024 (1.041)	0.013 (0.577)	0.003 (0.121)	0.022 (1.021)	0.011 (0.571)
<i>ROA</i>	0.727 (1.082)	1.447** (2.323)	0.888* (1.871)	0.777* (1.728)	1.430*** (2.802)	1.176* (1.930)
Constant	-4.228*** (-12.561)	-4.303*** (-9.686)	-4.664*** (-14.180)	-4.629*** (-12.369)	-4.521*** (-9.613)	-4.945*** (-7.369)
Observations	6,964	6,964	6,964	6,964	6,964	6,964
Pseudo R-squared	0.199	0.460	0.159	0.225	0.464	0.486
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
School fraud rates	Yes	Yes	Yes	Yes	Yes	Yes

Table 10 Fraud and CEO overconfidence

This table tests the impact of CEO overconfidence and fraud propensity. The first dependent variable *Overconfidence* is constructed based on the extent to which CEO is holding vested in-the-money options. It is a dummy variable that equals to one if the ratio of the average value per option to the average strike price is at least 67% in the money for at least two incidences in the past five years. The second dependent variable *Fraud* is a binary indicator variable that equals to one if the firm commits fraud in year t , and zero otherwise. The independent variable $Overconfidence_{-j,t}^{i,c}$ is the number of overconfident CEOs in the peer group in year t excluding firm j itself. The variable *EliteSchool* is a dummy variable that equals one if the university ranks among the top 25 universities by a historical US News Ranking in 2007 and zero otherwise. The independent variable $FMRate_t^{-i,c}$ is the annual average fraud rate of firms in the same education cluster (same school) and different industry. $FMRate_{-j,t}^{i,c}$ is the annual average fraud rate of firms in the same education cluster and same industry, and excluding firm j itself. $FMRate_t^{i,-c}$ is the annual average fraud rate of firms in the same industry and different school. All firm characteristic are measured at the end of year $t-1$. Past return is the annual return over the past one year. The variable $\ln(NFirm)$ is the natural logarithm of the total number of firms per industry-school cluster. Past return is the annual return over the past one year. The variable $\ln(AT)$ is natural logarithm of total asset. *Cash Flow/AT* is the cash flow scaled by total asset. *Leverage Ratio* is the long term debt to equity ratio calculated using the market value of equity. *ROA* is calculated as the net income plus interest divided by the mean value of the current total asset and the lagged value of total asset. I include school level average fraud rate over the sample period in all regressions. I include state fixed effects and industry fixed effects. The industries are defined on the Fama-French 12 industry classification. The standard errors are clustered at industry level and robust z-statistics are shown in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level respectively.

Dependent variables:	<i>Overconfidence</i>	<i>Fraud</i>
	(1)	(2)
$Overconfidence_{-j,t}^{i,c}$	0.115 (0.708)	-0.102 (-0.426)
$EliteSchool \times Overconfidence_{-j,t}^{i,c}$		-0.106 (-0.310)
<i>EliteSchool</i>		0.439*** (4.399)
$FMRate_{-j,t}^{i,c}$		7.206*** (18.914)
$FMRate_t^{i,-c}$		4.599*** (2.794)
<i>Past Return</i>	-0.192*** (-9.029)	0.059 (0.876)
<i>Tobin's Q</i>	0.170*** (7.254)	0.064*** (3.733)
$\ln(AT)$	0.019 (1.345)	0.101*** (3.143)
<i>Cash Flow/AT</i>	-1.243*** (-3.892)	-0.348 (-0.514)
<i>Leverage Ratio</i>	-0.062* (-1.753)	0.046* (1.679)
<i>ROA</i>	1.973*** (5.580)	0.008 (0.014)
Constant	-1.978*** (-17.697)	-4.447*** (-11.064)
Observations	8,481	8,148
Pseudo R-squared	0.065	0.465

Table 11 Peer effect and earnings management

This table reports a series of probit regressions that relates earnings management to various peer fraud rate. The dependent variables are different earnings management measures. In particular, EQ1, EQ2 are accruals based measures as described in Dechow, Sloan and Sweeney (1995) and EQ3, EQ4 are cash flow from operation based measures as detailed in Dechow and Dichev (2002). $EQ_{-j,t}^{i,c}$ is the annual average fraud rate of firms in the same education cluster and same industry, and excluding firm j itself. $EQ_t^{i,-c}$ is the annual average earnings management measure of firms in the same industry and different school. All firm characteristic are measured at the end of year $t-1$. Past return is the annual return over the past one year. The variable $\ln(NFirm)$ is the natural logarithm of the total number of firms per industry-school cluster. The variable $\ln(AT)$ is natural logarithm of total asset. $Cash\ Flow/AT$ is the cash flow scaled by total asset. $Leverage\ Ratio$ is the long term debt to equity ratio calculated using the market value of equity. ROA is calculated as the net income plus interest divided by the mean value of the current total asset and the lagged value of total asset. I include school level average fraud rate over the sample period in all regressions. I include state fixed effects and industry fixed effects. The industries are defined on the Fama-French 12 industry classification. The sample period is from 2000 to 2012. The standard errors are clustered at industry level and robust z-statistics are shown in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level respectively.

	(1) EQ1	(2) EQ2	(3) EQ3	(4) EQ4
$EQ1_{-j,t}^{i,c}$	0.818*** (19.239)			
$EQ1_t^{i,-c}$	0.055 (1.151)			
$EQ2_{-j,t}^{i,c}$		0.800*** (22.019)		
$EQ2_t^{i,-c}$		0.036 (0.597)		
$EQ3_{-j,t}^{i,c}$			0.891*** (32.850)	
$EQ3_t^{i,-c}$			-0.010 (-0.243)	
$EQ4_{-j,t}^{i,c}$				0.806*** (16.599)
$EQ4_t^{i,-c}$				-0.226*** (-9.371)
Constant	0.028*** (15.901)	0.036*** (5.833)	0.025*** (8.749)	0.051*** (11.396)
Observations	11,249	11,264	10,240	10,185
R-squared	0.336	0.329	0.454	0.538
Firm Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Chapter 3

Smart Investor Ownership and the Cross-Section of Stock Returns

ABSTRACT

We document a negative cross-sectional relationship between the ownership of smart investors (high return gap mutual funds) and future stock returns controlling for total institutional ownership. We interpret this result as an attenuation of cost of capital by smart investors, which is further corroborated by a similar relation between smart investor ownership and implied cost of capital estimated from various models. Our finding is consistent with the predictions from the noisy rational expectation models like Easley and O'hara (2004) that when there are more informed investors in a firm and/or when the private signals they receive are more precise, uninformed investors face lower information risk, which leads to lower cost of capital. These predictions are further supported by evidence from natural experiments including brokerage closure and the passage of Reg. FD.

Keywords: cost of capital, mutual funds, institutional investor, information asymmetry

The role of institutional investors in equity returns has attracted extensive interest from both academia and practitioners. For example, Gompers and Metrick (2001) document a positive relation between institutional holding and stock returns and attribute it to temporal demand shock. Yet, no study has examined how the relation varies with institutional investors' informational advantage. In this paper, we ask the particular question that given a certain percentage of private information, whether uninformed investors face higher or lower information risk in a firm that has a greater percentage informed investor who are also smart sense that their private information are more precise. We find that firms with greater smart investor ownership have lower future returns and cost of capital, suggesting that the uninformed investors face lower information risk in these firms.

The possible relations between the holding by smart institutions and stock returns may not be self-evident. On the one hand, if future stock returns mainly reflect future performance and since smart institutional investors tend to have informational advantage and hence have superior stock picking skills, greater holding by smart investors should forecast higher stock returns. For example, Yan and Zhang (2009) report a positive relationship between the change in ownership by short-term institutions and stock returns. Baik, Kang and Kim (2010) argue that local institutional investors are more informed and consistent with this hypothesis they demonstrate a positive relation between the ownership of local institutional investors and stock returns. In other words, we have an *information* hypothesis that predicts a positive relation between smart investor ownership and future stock return.

On the other hand, if the future stocks return is viewed as the proxy of the expected return (the cost of capital), the relation between stock returns and smart investor ownership can be ambiguous. In the information risk literature, Wang (1993)

shows that the presence of informed investors would create information asymmetry between the informed and uninformed investors, the uninformed would ask for risk premium to compensate for the adverse selection problem when they trade with the informed. Similarly, Easley and O'Hara (2004) show that for a given amount of total information, a greater percentage of private information would increase the cost of capital. However, they also show that for a given proportion of private information, the cost of capital is smaller when percentage of the investors who are informed is large or when the precision of the private information is high. This is because in these situations, the informed investors trade more aggressively, which in turn makes the stock prices more informative, lowering the information risk faced by the uninformed investors. A greater smart investor ownership suggests not only a greater presence of informed investors in the firm, but more precise information possessed by them. Thus, controlling for the percentage of private information, Easley and O'Hara (2004) predict a negative relation between stock returns and smart investor ownership, which we refer to as *information risk* hypothesis.

To test the empirical predictions systematically in this paper, we first define *smart investors* as the actively managed mutual funds with persistent outstanding track record measured by return gap. Kacperczyk, Sialm and Zheng (2008) and Hwang, Titman and Wang (2015) argue that the return gap measure captures the abnormal return of mutual funds arising from the superior ability to process signals. Thus, when we sort all actively managed mutual funds with non-missing return gap measures based on the average return gap over the past 12 months into three groups, we are essentially ranking all mutual funds by the “quality” of information they acquire. We designate the mutual funds in the top tercile as *smart investors*.

Second, we compute smart investor ownership (*Smart IO*) as the number of shares held by the aforementioned smart investors divided by the total number of shares outstanding. We use the aggregate institutional ownership (total *IO*) to proxy for the fraction of private information in a firm, a key variable in Easley and O'Hara (2004). This is because information acquisition is not costless. Given a fixed component of information acquisition cost, an institution would only acquire information when the ownership stake is large enough, hence larger value of *IO* could simply proxy for the incentive to generate more information and keep a greater proportion of this information private (Boehmer and Kelley (2009)). We estimate the cost of capital with both future stock returns up to four quarters ahead as well as other prominent implied cost of capital measures.³² We test the cross-sectional relation of *Smart IO* and the stock returns in the setting of Gompers and Metrick (2001).

We find a strong negative relation between *Smart IO* and future stock returns as well as various implied cost of capital measures. It implies that a greater presence of *smart* investors is associated with a lower cost of capital. In particular, among stocks in the top tercile of total *IO* (total *IO* greater than 50%), the Carhart (1997) four factor alpha of high *Smart IO* portfolio is 2% lower than the low *Smart IO* portfolio per quarter. These results are consistent with models in the information risk literature including Admati (1985), Wang (1993), Easley and O'Hara (2004) and Hughes, Liu and Liu (2007). In these models, more informed investors with precise private signals would make stock price more informative through more aggressive trading by these investors, leads to a more a lower information risk, i.e., more effective resolution of uncertainty about asset payoffs and hence lower cost of capital.

³² The details of estimation can be found in Gebhardt, Lee, and Swaminathan (2001), Claus and Thomas (2001), and Gode and Mohanram (2003) and will be further elaborated in section 3.2.

We confirm that the positive relation between total *IO* and future stock return, first documented by Gompers and Metrick (2001), is also present in our longer sample period. Gompers and Metrick (2001) attribute the positive relation to the demand shock by treating future stock return as realized return. In this paper, we offer an alternative explanation by treating the future stock return as a proxy of expected return. In Easley and O'Hara (2004)'s formulation, the fact that some of the information is private and only available to informed investors, is the root cause of the information asymmetry. Thus, a great percentage of private information would exacerbate the information asymmetry and lead to higher cost of capital (expected return), which is consistent with the positive relation between total *IO* and stock return, when total *IO* is viewed as a proxy for the percentage of private information as we explained earlier. This explanation is further buttressed by the positive relation between total *IO* and various prominent implied cost of capital measures. To the best of our knowledge, we are the first to document these relations in the literature.

We find further supporting evidence of information risk hypothesis by conducting two natural experiments in which we examine the impact of smart investor ownership on the cost of capital when there are exogenous shocks to the information asymmetry. We first examine the exogenous increase in the information asymmetry of the firms caused by unexpected broker closure or merger (Kelly and Ljungqvist (2012), Hong and Kacperczyk (2010), Chen, Harford and Lin (2015)) and test the difference in difference (DiD) of expected returns between firms with smart investors and those without. The negative and significant coefficient on the DiD term suggests that the smart investors attenuate the information asymmetry by making the price more informative and mitigate the price impact of the sudden rise in information asymmetry.

We next examine the differential impact of smart investor ownership on expected returns before and after Regulation FD (Reg FD), an exogenous shock to a firm's information environment. In the post Reg FD period, the privileged access to managers are significantly curtailed; as a result, the precision of informed signals is greatly reduced in the post Reg FD period. Consistent with prediction from models like Easley and O'hara (2004), we find the beneficial effect of smart investor ownership in reducing the information risk premium decreases after the Reg FD. Specifically, we compare the cross-section regression of future return on smart investor ownership in the pre and post Reg FD period. We find the coefficient of smart investor ownership is only significant in the pre Reg FD period and the coefficient between the pre and post Reg FD period are significantly different.

Our paper is related to a series of papers on institutional ownership and future stock returns. In general, there is a positive relation between certain types of institutional ownership and stock returns in this line of research. For example, Nofsinger and Sias (1999) find that institutional trades predict next year's return positively. Gompers and Metrick (2001) document that the level of total institutional holding positively predicts stock returns. Yan and Zhang (2009) further attribute such relationship to short-term institutional investors. In addition, Baik, Kang and Kim (2010) provide empirical evidence of the return predictability by local investors. We confirm Gompers and Metrick (2001)'s finding in our work with a larger and more recent panel dataset from 1981 to 2013 that the total institutional holding is positively related to future stock returns up to four quarters ahead. To the best of our knowledge, we are the first paper to interpret the relation between institutional ownership and future stock return as the relation between institutional investor and cost of capital. As this relation also holds when we replace stock return by various implied cost of capital measures that are much

less likely to be driven by stock performance or change in temporal demand, our results strongly suggest *IO* increases cost of capital.

Our work also contributes to the growing literature of information risk. Easley and O'Hara (2004)'s model shows that information asymmetry is priced in asset returns. Lambert, Leuz and Verrecchia (2007) and Hughes, Liu and Liu (2007) come to the same conclusion that higher information asymmetry leads to higher cost of capital in a small economy when asset payoffs are idiosyncratic.

In the empirical literature of information risk, the focus has been on testing if the cost of capital increases with the percentage of private information, (i.e., the " α " in Easley and O'Hara (2004)'s model). Notably, Easley, Hvidkjaer and O'hara (2002) devise a structural microstructure model to estimate the probability of informed trading (PIN) and find that the cost of capital and PIN are positively related. However, Mohanram and Rajgopal (2009) shows that PIN is not a priced risk. Relatedly in the disclosure literature, it has been shown that better disclosure would lower the cost of capital, which is consistent with the fact that better disclosure reduces the fraction of private information (i.e., α) presumably by converting private information to public through disclosure (see for example Diamond and Verrecchia (1991), Leuz and Verrecchia (2000) and Christensen, de la Rosa and Feltham (2010)).

In contrast, our focus is on testing the seemingly counterintuitive predictions that the cost of capital decreases with the signal precision and fraction of informed investor (i.e., the " γ " and " μ " in Easley and O'Hara (2004)'s model), which few paper has tested. We show that at a given percentage of private information that we proxy by *IO*, the smart investor ownership would make stock prices more informative and mitigate the information asymmetry and hence lower the cost of capital.

Our paper also offers significant policy implications. As mentioned above, it has been shown that better disclosure leads to lower information asymmetry and cost of capital. However, disclosure has its cost too; loss of competitive edge comes to mind. Thus full disclosure may not be optimal. This paper shows that given certain amount of disclosure, (i.e., given a percentage of information being private) policies that encourage more traders to become informed and that enhance the precision of private signals such as curtailing insider trading and providing privileged access to firm managers would help lower the cost of capital. Consistent with these implications, Bhattacharya and Daouk (2002) and Fernandes and Ferreira (2009) find that initial enforcement of insider trading law is associated with lower cost of equity, because the profits of informed trading would be greater in the absence of insider trading. Higher informed trading profits motivate more traders to become informed and spend resources to increase the precision of their private signals (information). Our results from Reg FD also show that reducing privileged access has an undesirable consequence by decreasing the beneficial effect of informed trading. Given a certain fraction of information already being private, privileged access to managers can confirm or clarify the already private information and thereby increase the precision of information by informed investors. Greater precision of private information would make informed investors trade more aggressively, which in turn makes the stock price more informative and thereby lower the information risk and cost of capital.

Our paper is also loosely related to the strand of literature that assesses the mutual fund performance.³³ We use the outperformance measure, return gap (as

³³ In the mutual fund outperformance literature, examples include but not limited to the superior performance of low RPI funds demonstrated in Kacperczyk and Seru (2007), of high return gap funds documented in Kacperczyk, Sialm and Zheng (2008), and of high ActiveShare funds evidenced in Cremers and Petajisto (2009).

described in Kacperczyk, Sialm and Zheng (2008)) in particular, to define smart investors who are hypothesized to possess high quality private information. The strong and consistent results we document suggest that mutual fund managers are likely to derive higher return gap from information advantage.

The remainder of the paper proceeds as follows: in Section 1, we revisit the theoretical framework in Easley and O'Hara (2004) and further elaborate on our empirical constructs. In Section 2, we discuss the sample of the empirical test and explain the steps in constructing our key variables. We test the cross-sectional relation between smart institutional ownership and expected returns in the first part of Section 3, followed by a portfolio approach test in the latter part of the section. We conduct a natural experiment of broker exit in Section 4 followed by a natural experiment on the Reg FD in Section 5 and conclude in the last section.

1. The model

We build our empirical work around Easley and O'Hara (2004)'s noisy rational expectation model with information asymmetry that examines the firm's information structure and its impact on the cost of capital in a setting with multiple risky assets. They demonstrate that in equilibrium the risk premium, which is the difference between future value v_k and stock price today p_k is given by the following equation:

$$E[v_k - p_k] = \frac{\delta \bar{x}_k}{\rho_k + (1 - \alpha_k)I_k \gamma_k + \mu_k \alpha_k I_k \gamma_k + (1 - \mu_k)\rho_{\theta k}} \quad (1)$$

The model yields several important implications: first, holding the total amount of information constant, the higher the private-to-public information ratio, the higher the risk premium. In other words, the cost of capital is positively related to the fraction

of information that is held private, that is, α_k in the model. The intuition behind is that informed investors tilt their portfolio more heavily than the uninformed towards stocks with positive private signals and against those with negative private signals and the uninformed are at an information disadvantage and such risk is not diversified away in a small economy. They therefore demand higher return to compensate higher information risk due to the information asymmetry.

Second, the risk premium is negatively associated with the precision of information γ_k and the fraction of informed traders μ_k and the amount of total information I_k . Specifically, when there are more information available and/or there are more informed traders and/or when the private signals are more precise, informed traders would trade more aggressively which, in turn, makes their private information partially revealed in the stock prices. In other words, stock prices become more informative which serves to lower the information risk faced by the uninformed traders. Hughes, Liu and Liu (2007) also come to the same conclusion in a small economy when asset payoffs are idiosyncratic (i.e. no systematic factor).

In our empirical setup, we control for the level of total institutional ownership of firm k . Holding IO constant implies that we are effectively holding the total amount of information (I_k) and the percentage total amount of information that can become private (α_k) constant. As explained earlier, greater institutional IO gives institutional investors greater incentive to spend resources to acquire information and keeping them private as best as they can, thus level of IO is positively correlated with both α_k and I_k . This implies the relationship between IO and cost of capital becomes an empirical question since α_k is positively correlated with the risk premium while I_k is negatively correlated with the risk premium.

At a given level of *IO*, a higher *Smart IO* is likely to arise from the possibility that either there are more informed investors (higher μ_k) and/or each informed investor has greater precision of information (higher γ_k), which is the reason why they have higher return gap. Given the negative relation of both parameters to the expected risk premium, we expect the level of smart ownership to negatively predict a firm's cost of capital under the *information risk hypothesis*.

Moreover, it can be easily shown that Easley and O'Hara (2004) model also predicts the beneficial effect of smart investor ownership in lowering the information

risk is larger when there is a greater information asymmetry (i.e., $\frac{\partial^2 E(v-p)}{\partial \alpha \partial \gamma} < 0$ and

$\frac{\partial^2 E(v-p)}{\partial \alpha \partial \mu} < 0$). This is because a greater information asymmetry would make

informed trades more profitable which in turn induces a more aggressive informed trade, making price more informative. Furthermore, as the profit of informed traders increase with the precision of the private information γ , the same intuition will lead to the prediction that the beneficial effect of smart institutional ownership in lowering the

information risk is larger when the precision is larger $\frac{\partial^2 E(v-p)}{\partial \gamma \partial \gamma} < 0$ and

$\frac{\partial^2 E(v-p)}{\partial \gamma \partial \mu} < 0$).

2. Data

We discuss the data source and variable construction in this section. The data of our main tests comes from the intersection of Thomson Reuters Institutional (13F) Holdings, CRSP stock files, COMPUSTAT annual file and I/B/E/S analyst forecasts. Thomson Reuters Institutional (13F) Holdings provide quarterly long equity positions

of all the 13F³⁴ institutions that are greater than 10,000 shares or \$200,000 in market value. They are used to compute the institutional ownership and smart institutional ownership. We extract stock return related information from CRSP monthly stock file and firm characteristics from COMPUSTAT annual file. We make use of the forecasted earnings and growth rate from I/B/E/S to derive various implied cost of capital measures. We will elaborate on the variable construction in detail in respective subsections.

2.1 Institutional ownership

As discussed earlier, we use the total institutional ownership to control for the total amount of information and the fraction of information that can become private. We compute *IO* as the number of shares held by all 13F institutions in Thomson Reuters Institutional Holdings dataset institutions divided by the number of shares outstanding at the end of each calendar quarter. We use the *IO* at previous quarter if there is a reporting gap.

2.2 Smart ownership

Not all institutional investors are equally informed. Among the institutional investors, there are some smart investors that are more agile and accurate in acquiring and processing information thereby achieving superior performances. Consequently, the signals produced by smart investors are more acute. In order to quantify the presence of such smart investors, we examine the ownership by actively managed equity mutual funds. Since mutual fund is the only type of institutional investor whose performance can be tracked by researchers timely and without the self-reporting bias, we confine the definition of smart investors to the context of mutual funds. According to Kacperczyk, Sialm and Zheng (2008) and Hwang, Titman and Wang (2015), the return gap measure,

³⁴ Form 13F is a mandatory SEC filing that requires all institutional investment managers with over \$100 million in qualifying assets disclose their holding quarterly.

or the difference between reported fund return and the hypothetical return that could be achieved by holding the portfolio formed at the start of the quarter, captures the extent to which the fund is able to obtain information faster than its peers and to process information in a more effective way. Such difference predicts fund's overall performances positively. Therefore we measure the "smartness" of mutual funds by the average return gap over the past year.

Specifically, we sort all open-end actively managed equity mutual funds into terciles based on the average return gap over the past 12 months (requiring the availability of at least six months of return gap variable to compute the sorting variable) every quarter and label them as "low-return-gap funds", "medium-return-gap funds", and "high-return-gap funds" respectively.³⁵ Thomson Reuters starts to report mutual fund stock holdings in year 1980 and we require prior one year hypothetical and actual fund return to calculate average return gap, so our sample period starts from year 1981 and ends at 2013.

[Table 1]

Panel A of Table 1 presents the time-series summary statistics for the mean return gap over the past 12 months for the low-return-gap, medium-return-gap and high-return-gap funds respectively. Consistent with the evidence in Kacperczyk, Sialm and Zheng (2008), the return gap variable is quite persistent over time. Moreover, the high-return-gap group is characterized by a positive return gap throughout the sample years, which indicates the superior ability to process the signal and achieve better short-term performance.

³⁵ In unreported tests, we sort all sample funds into two, four and five groups instead of three groups and the results are qualitatively similar.

Next, at firm level we compute the total ownership by the high-return-gap funds at a quarterly frequency and designate this as *smart institutional ownership* (*Smart IO*). The reference groups we use in later empirical tests is the ownership by other types of institutions (the 13F institutional investors in aggregate except smart investors). We exclude penny stocks with price lower than \$1, stocks with total institutional ownership greater than one and stocks with missing total institutional ownership to avoid data error. To sum up, the ownership by high-return-gap funds (*Smart IO*) proxies for the precision of signals by informed investors γ_k as well as the fraction of informed traders μ_k : the higher the level of *Smart IO*, the more precise the signal is and/or a greater fraction of the investors are informed.

In Panel B of Table 1, we present the firm level ownership by smart investors, i.e. what we define as “*Smart Ownership*”, or *Smart IO* and other firm level control variables which will be discussed in later sections. The summary statistics indicates that over the sample period of 1981 to 2013, the smart investors in aggregate hold about 2% of the market value of the firm, as opposed to the 34% held by all the institutions in aggregate.

2.3 Cost of capital

We examine the proxies for firms’ ex ante cost of capital used in both finance and accounting literature. To be consistent with the standard asset pricing models in finance, we define the cost of capital as the expected return.³⁶ In particular, we use quarterly stock returns up to one year ahead to proxy for the expected return to be consistent with the framework in Gompers and Metrick (2001).

³⁶ See, for example, Fama and Miller (1972), Fama and French (1992), Chordia, Subrahmanyam and Anshuman (2001), and Easley, Hvidkjaer, and O’Hara (2002), for example.

On the other hand, prior literature suggests that realized returns are noisy proxies for expected returns³⁷ and argues that estimates based on fundamentals are more accurate than those based on average stock returns (Claus and Thomas (2001), Fama and French (2002)). We do not intend to make a stand on which of the cost of capital measure is superior in this paper, therefore we present additional evidence based on the cost of capital inferred from fundamentals. We employ three of the widely used cost of capital measures: the measure developed by Gebhardt, Lee and Swaminathan (2001), Claus and Thomas (2001) and that developed by Ohlson and Juettner-Nauroth (2005) and implemented by Gode and Mohanram (2003).

The basic ideas behind the three models to estimate implied cost of capital are similar: they estimate cost of capital as a discount rate that equates the current stock price to the present value of expected future earnings obtained from analyst forecasts. The first two models are built on residual income model developed by Ohlson (1995), whereas the last one is based on the abnormal earnings growth valuation model in Ohlson and Juettner-Nauroth (2005). They differ in their assumption about the evolution of future earnings depending on the use of one-year ahead, two-year ahead earnings estimates and long-term growth estimates.

We follow the literature and exclude firms with less than five analysts following, firms that are smaller than \$100 million in market size, and we keep firms that have return information in CRSP and relevant accounting information in Compustat, firms that have positive one-year ahead and two-year ahead earnings forecast and that with

³⁷ See Elton (1999), Gebhardt, Lee and Swaminathan (2001) and Pastor, Sinha, and Swaminathan (2008) for a more detailed discussion of the matter.

five-year or long term growth rate estimate from I/B/E/S. We drop observations before year 1990 because there are too few firms with complete data.

To illustrate, we define the common variables used in the three models below, followed by elaborations of each model respectively.

P_0 = Current stock price. We use the price in June following the last fiscal year end obtained from CRSP.

B_0 = Book value of equity as of the most recent financial statement divided by the total number of shares outstanding. The data is obtained from COMPUSTAT's Industrial Annual Files.

EPS_t = Mean forecasted future earnings per share in period t from I/B/E/S or imputed earnings per share in period t .

DPR = Forecasted dividend payout ratio. We adopt the same procedure in Gebhardt, Lee, and Swaminathan (2001): if the current earnings (EPS_0) are positive, we divide the current dividend per share (DPS_0) by current earnings; otherwise, we divide DPS_0 by "normal earnings", which are assumed to be 6% of total assets.

Throughout the estimation process, we assume the clean surplus relation holds, that is, $B_{t+1} = B_t + EPS_{t+1} - DPS_{t+1}$, and the future dividend for period $t + 1$, DPS_{t+1} , is computed as the product of dividend payout ratio and future earnings (i.e., $DPS_{t+1} = DPR \times EPS_{t+1}$).

1. Gebhardt, Lee, and Swaminathan (2001)

$$P_0 = B_0 + \sum_{t=1}^{T-1} \frac{[ROE_t - r_{GLS}]B_{t-1}}{(1+r_{GLS})^t} + \frac{[ROE_T - r_{GLS}]B_{T-1}}{(1+r_{GLS})^{T-1}r_{GLS}} \quad (2)$$

We use $T=12$ as the paper. We obtain EPS_1 , EPS_2 and EPS_3 estimates directly from I/B/E/S to compute the forecasted ROE_1 to ROE_3 for the next three years as EPS_t/B_{t-1} . From ROE_4 onwards, we assume linear interpolation from ROE_4 to the equilibrium ROE , which is calculated as the 10-year, industry-specific ROE .³⁸ We then use numerical approximation algorithm to solve for r_{GLS} in Equation (2).

2. Claus and Thomas (2001)

$$P_0 = B_0 + \sum_{t=1}^5 \frac{[EPS_t - r_{CT}B_{t-1}]}{(1+r_{CT})^t} + \frac{[EPS_5 - r_{CT}B_4](1+g_{lt})}{(1+r_{CT})^5(r_{CT}-g_{lt})} \quad (3)$$

The numerator for the second term is the so-called “abnormal earnings” for period t and we assume it to grow at a constant long-term growth rate of g_{lt} from year 5 onwards. The long-term rate is assumed to be the difference between the contemporaneous risk-free rate (proxied by the yield on 10-year Treasury bonds) and 3%. We employ numerical approximation methods to solve for the discount rate r_{CT} in Equation (3).

3. Ohlson and Juettner-Nauroth (2005) model implemented by Gode and Mohanram (2003)

$$r_{OJN} = A + \sqrt{A^2 + \frac{EPS_1}{P_0}(g_2 - g_{lt})} \quad (4)$$

$$\text{where } A \equiv \frac{1}{2}(g_{lt} + \frac{DPS_1}{P_0})$$

The variable g_2 stands for short-term growth rate and it is estimated by the growth rate implied in the first two years’ analyst forecasts, i.e. $\frac{EPS_2 - EPS_1}{EPS_1}$. The

³⁸ We classify all firms into 48 industries based on Fama and French (1997) definition and follow the procedure in Botosan and Plumlee (2005) to compute industry ROE.

calculation of long-term growth rate g_{lt} is the same as the previous model: the risk free rate minus 3%.

We summarize the four annualized finance cost of capital measures (Ret_Q1 to Ret_Q4), three widely used accounting measures (r_{GLS} , r_{CT} , and r_{OJN}) and the mean value of the three accounting measures ($\bar{r}$) in Table 2.

[Table 2]

The mean value of various cost of capital measures ranges from 11% to 14% over the sample period. The values are largely consistent with what is reported in the literature. For instance, Claus and Thomas (2001) report an average 11.4% cost of capital over 1985 to 1998 while Gode and Mohanram report a 13.47% over similar sample period.

3. Smart ownership and the cost of capital

Based on our hypotheses, we expect that the level of the smart ownership to be negatively correlated with the firm's cost of capital after controlling for the total institutional ownership under the *information risk hypothesis* and we expect them to be positively correlated under the *information hypothesis*. We test these predictions formally in this section.

3.1 Cost of capital measured by expected return

We estimate Fama and MacBeth (1973) regressions to avoid cross-sectional dependence of returns. To be specific, for each quarter (or each year for accounting cost of capital measures), we run cross-sectional regression of the cost of capital measure (be it stock returns or accounting cost of capital measures) on smart ownership ($SmartIO$),

institutional ownership (IO) and other firm characteristics that are believed to affect stock returns and measured at the end of the quarter.

$$\text{cost of capital } (r) = \alpha + b\text{Smart}IO_{i,t} + cIO_{i,t} + \text{Firm Characteristics}_{i,t} + \varepsilon_{i,t}$$

(4)

We follow the literature of institutional ownership and stock returns (Gompers and Metrick (2001), Yan and Zhang (2009)) to include a battery of firm characteristics explained below:

- IO : total ownership by all S12 institutions computed as the total number of shares held by all S12 institutions divided by the number of shares outstanding of a given stock.
- ME : market equity computed as the number of shares outstanding times the stock price at the end of quarter t expressed in million dollars. The data is from CRSP monthly stock files.
- B/M : book value for the fiscal year ended before the most recent June 30th, divided by the market capitalization as of December 31st during that fiscal year.
- Age : firm age in months since the first appearance of the stock return in CRSP.
- $Turnover$: volume divided by total shares outstanding measured at the end of quarter t .
- $Volatility$: stock return variance computed over the past 24-month.
- $Price$: stock price at the end of quarter t .
- DIV : dividend yield calculated as the cash dividends for the fiscal year ended before the most recent June 30th, divided by market capitalization as of December 31st in that fiscal year.
- $Ret_{t-3,t}$: cumulative stock returns over the past three months.

- $Ret_{t-12,t-3}$: cumulative stock returns over month $t-12$ to $t-3$.
- SP500: binary indicator variable for S&P 500 membership.

Panel B of Table 1 reports the summary statistics of the firm characteristics variables. On average, the total institutional ownership of our sample firm is 34% over the sample period of 1981 to 2013. A typical sample firm has a market capitalization of \$1177 million, a per share price of \$16, an age of 167 months, a 2.6% dividend yield, 14% volatility, 1% turnover, 5% past three-month return and 14% cumulative return over month $t-12$ to $t-3$. We take the natural logarithm value of all independent variables except *Smart IO*, *IO*, *SP500*, $Ret_{t-3,t}$ and $Ret_{t-12,t-3}$.

The results for quarterly Fama-MacBeth (1973) regressions are reported in Table 3. To be specific, we run the cross-sectional regression of the one-quarter ahead stock returns on our key variable of interest, *Smart IO*, *IO*, and other firm characteristics every quarter and report the mean coefficient from the 131 cross-sectional regressions and associated t -statistics calculated from the time-series standard errors in column (1) of Table 3. Similarly, in column (2) to (4), we replace the dependent variable by two-quarter, three-quarter and four-quarter ahead stock returns respectively.

[Table 3]

First of all, consistent with Gompers and Metrick (2001) and Yan and Zhang (2009), we find strong evidence of return predictability by total institutional ownership and such predictability persists up to one year ahead. The average coefficient of *IO* in the first regression is 0.022 and it is significant at the 1% level. This is very close to the 0.019 coefficient estimate in Yan and Zhang (2009) with their sample period of 1980:Q3 to 2003:Q4. The positive and significant coefficient of *IO* has another layer of implication: since *IO* is positively related to the fraction of information that is held

private, the positive coefficient is empirically consistent with the prediction in Easley and O'Hara (2004) that the greater the private-to-public information ratio, the larger the expected return. The positive correlation resolves the uncertainty about the relationship between *IO* and risk premium that we discussed in Section 1: a higher level of *IO* is associated with a higher cost of capital through the higher proportional private information channel (rather than the greater number of signals that would decrease the risk premium).

More importantly, we find that the coefficient on smart ownership is negative and significant after controlling for total institutional ownership in all four regressions. This means that, take column (1) for example, holding the level of institutional ownership and other firm characteristics constant, a two standard deviation higher smart ownership would translate to a 0.33% lower quarterly expected return, or a 1.35% lower annually expected return in the cross section. The rest of the control variables are largely of expected sign as the previous literature (Gompers and Metrick (2001) and Yan and Zhang (2009)). Taken together, the negative and significant coefficient on *Smart IO* and the positive and significant coefficient on *IO* clearly reject the *information hypothesis* and support the *information risk hypothesis*: at a given level of information asymmetry as proxied by total institutional ownership, the higher the proportion of smart investors, the lower the cost of capital estimated by future stock returns.

3.2 Cost of capital inferred from fundamentals

To address the criticism in the literature that realized returns are noisy measures of expected return, we employ three of the widely used implied cost of capital measures inferred from fundamentals: that developed by Gebhardt, Lee, and Swaminathan (2001) (r_{GLS}), Claus and Thomas (2001) (r_{CT}), that developed by Ohlson and Juettner-Nauroth

(2005) and implemented by Gode and Mohanram (2003) (r_{OJN}) and the mean value of the three measures in column (1) through column (4) of Table 4 .

[Table 4]

We run the cross-sectional regression in Equation (4) annually and report the time-series statistics of the coefficients in Table 4. We include control variables from Table 3 but do not tabulate their coefficients. The control variables are obtained at the end of last year. Note that the number of observations is much smaller in Table 4 than Table 3. There are two reasons for the drop in observations: first, the Fama-MacBeth regression in Table 4 is at an annual frequency as opposed to the quarterly frequency in Table 3; second, the sample of Table 4 is an intersection of CRSP and I/B/E/S and we follow the literature to apply an additional set of firm filters as elaborated in Section 2.3 which further reduces the number of firms in the sample.

Out of the four implied cost of capital measures employed in Table 4, three of them are negatively correlated with *Smart IO* and the relationship is statistically significant. This further reinforces our belief that other things held constant, the presence of smart institutions is associated with a lower cost of capital in the cross-section.

Another important finding from Table 4 is that the coefficient on IO is positive and significant in three out of four regressions. Since the cost of capital measures inferred from firm fundamentals are much likely to be driven by stock performance or change in institutional demand as suggested in Gompers and Metrick (2001), we can safely conclude that our result provide empirical evidence that IO increases the cost of capital.

3.3 Portfolio approach

Having shown the cross-sectional dependence of cost of capital on the level of smart ownership, we utilize the portfolio approach to shed light on the economic magnitude of the extent of the reduced pricing of information asymmetry associated with smart investors in this section.

We first sort all sample firms based on the level of total institutional ownership (*IO*) into terciles every quarter, among each *IO* tercile, we further sort the firms into two groups based on the level of smart ownership. In the bottom *IO* tercile, the majority of firms have zero *Smart IO*, therefore sorting into two groups is not possible. We focus on the top two *IO* terciles. As a result, we form 2×2 portfolios based on the level of *IO* and *Smart IO*. The mean *IO* and *Smart IO* of each portfolio, as well as the number of firms to construct the portfolio are presented in Panel A of Table 5.

Next, we compute the equal weighted quarterly return and the Carhart (1997) four-factor adjusted return for each of the 4 portfolios, as well as for the hedging portfolio that long the high *Smart IO* group while short the low *Smart IO* group within each *IO* tercile. We report the portfolio raw returns and four-factor returns in Panel B and C of Table 5 respectively.

[Table 5]

Results in Table 5 suggest that among the high *IO* stocks, the high *Smart IO* portfolio has a significantly 0.8% ($t=3.31$) lower expected return than the portfolio of stocks with low smart ownership. The quarterly four-factor return of high *Smart IO* stock portfolio is 1.9% ($t=8.17$) lower among the high *IO* firms. It is interesting to note that the results are stronger in high *IO* stocks. This could be due to the possibility that at a higher level of *IO* and therefore information asymmetry, the attenuating effect of

Smart IO is stronger. However, our main point of this paper is not to determine the level of information asymmetry that affects expected return; rather what we emphasize is that given the level of information asymmetry proxied by total institutional ownership, a higher level of smart ownership is associated with a significantly lower expected return.

4. A natural experiment of brokerage exit

If smart investors release information to the market through their trading behavior, they will to some extent complement the information production role of analysts. We make use of the exogenous shock to the supply of information caused by the closure or merger of the brokerage house, or *broker exit* in short, in this section to further examine what roles the smart investors play in a firm's information environment.

According to Kelly and Ljungqvist (2012) and Hong and Kacperczyk (2010), broker exit provides an ideal source of exogenous increase in the information asymmetry of the firm due to the sudden loss of analyst coverage. Under such circumstances, Easley and O'Hara's (2004)'s model predicts an increased cost of capital due to the heightened information asymmetry. Furthermore as we explained in the model section, the benefit of smart IO in lowering the cost of capital is higher in an environment of greater information asymmetry. Thus, we expect the reduction of cost of capital due to smart IO would be greater after broker exit.

To implement the natural experiment empirically, we adopt the list of 54 closed brokerage houses or the targets of brokerage merger in the sample period of 2000 to 2010 compiled in Chen, Harford and Lin (2015). For each of the affected firms, we identify the quarter that the broker exit happens and the dummy variable *BrokerExit* equals to one only when there is a broker closure or merger event in a given quarter for the affected firm, and zero otherwise. We define an additional dummy variable

PosSmart IO to capture the presence of smart investors: it equals to one if a firm has positive level of smart ownership and zero otherwise. To study the change in cost of capital around the broker exit event, we take the difference of the one-quarter-ahead and one-quarter-prior return $\Delta Qret$ with respect to the broker exit quarter as the dependent variable. We also introduce the interaction term between *Smart IO* (*PosSmart IO*) and *BrokerExit* to capture the differential impact of smart investors on the cost of capital between firms that are affected by broker exit and firms that are not affected.

$$\Delta Qret = \alpha + bSmartOwn_{i,t} + cSmartOwn_{i,t} \times BrokerExit_{i,t} + dBrokerExit_{i,t} + eIO_{i,t} + Firm\ Characteristics_{i,t} + \varepsilon_{i,t} \quad (6)$$

[Table 6]

Table 6 reports the result of the Fama-MacBeth regression in Equation (6) in column (1). We replace *Smart IO* by *PosSmart IO* and repeat the same regression and document the result in column (2). We are mainly interested in the interaction term between *Smart IO* (or *PosSmart IO*) and the binary indicator variable *BrokerExit*, this term captures how the different influence of the level of smart ownership on the change in expected return for firms that suffer from termination in analyst coverage due to brokerage exit and those that are not affected. First, the positive and significant coefficient on *BrokerExit* in the two regressions means that there is indeed an unconditional increase in the expected return in the post broker exit period for the affected firms. Second and more importantly, the negative and significant coefficient on the interaction term, take that on *PosSmart IO*BrokerExit* for example, means that compared to the increase in expected returns in affected firms without any smart investor, the increase in affected firms with the presence of smart investors is 3.9% lower and the difference is significant at the 5% significance level. That is to say, the expected return

in firms with smart investors does still increase following the termination of analyst coverage; however, such increase is attenuated by the presence of smart investors. In short, the results imply that given the increased information asymmetry following an exogenous brokerage exit event, the expected returns increase unconditionally, supporting the hypothesis that information asymmetry is priced in asset returns; moreover, we show that the presence of smart investors reduce the pricing for information asymmetry in a clean identification strategy.

5. A natural experiment of Reg FD

On October 23, 2000, the SEC ratifies Regulation Fair Disclosure, or Reg FD, which mandates simultaneous disclosure of information to all investors by all public companies in the US. This single rule fundamentally transforms the way of communication from companies to its investors: selective disclosure becomes impossible. We make use of this exogenous event that applies to all sample firms as a natural experiment. Specifically, we examine the effect of *Smart IO* on expected returns separately before and after the effective date of Reg FD.

The exogenous shock to the information environment deprives the smart investors of the privileged access to information in the pre-Reg FD period, if any. Recall the prediction in the model section that the beneficial impact of smart IO in lowering the cost of capital is higher when the precision of private information is high. We expect a weaker impact of the presence of smart investors on the expected returns in the Post-reg FD period when precision of private information becomes lower. In Table 7 We run subsample regressions of Equation (4) in the pre- and post-Reg FD period respectively.

[Table 7]

The Fama-MacBeth (1973) regression results in Panel A of Table 7 clearly support our conjecture that the effect of *Smart IO* is only significant before Reg FD is adopted. This provides empirical support for the view that the private signals of smart investors come from the selective disclosure from management. Once the information channel is terminated, there is a sudden drop in private signal supply for smart investors and their trades are consequently not as informative as before. As we test the difference of coefficients on *Smart IO* before and after Reg FD. The coefficients are significantly different at 5% level in three out of four expected return measures.

6. Conclusion

In this piece of research we find a strong and persistent negative relation between the ownership by high return gap mutual funds and future stock returns, controlling for total institutional ownership and other firm characteristics that are believed to predict the cross-section of returns. We interpret the negative correlation as a mitigated pricing for information asymmetry due to the presence of smart investors. Further evidence on various cost of capital measures corroborates the negative correlation. The relation clearly contradicts the *information hypothesis* that mutual funds select into firms that are expected to have good news therefore the mutual fund holding should positively predict future stock return. Rather, it provides empirical support for the *information risk hypothesis* motivated by noisy rational expectation models like Easley and O'Hara (2004)--at a given level of information asymmetry, greater presence of investors with more precise signals makes the stock price more informative and hence lower information risk and the cost of capital.

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Table 1 Return gap, smart ownership and firm characteristics

Panel A of this table presents the annual mean of the mean return gap over the past 12 month sorted into terciles. Our sample consists of 4,678 actively managed open-end equity funds with non-missing return gap measures over the past 6 months. We sort all our sample funds into three groups every quarter based on the value of the mean return gap over past year. After getting the quarterly time-series of mean return gap for each of the three groups: low-return-gap, medium-return-gap and high-return-gap, we then summarize each group mean on an annual basis. Panel B presents the summary statistics for firm level ownership by smart investors and other firm characteristics. Our sample consists of 632,997 firm-quarter observations over the sample period of 1981 to 2013 involving 18,521 firms with stock price greater than \$1 and total institutional ownership not greater than one. The variable *Smart IO* is the number of shares held by the high-return-gap funds divided by the total number of shares outstanding of a given stock. The variable *IO* is the total ownership by all 13F institutions computed as the total number of shares held by all 13F institutions divided by the number of shares outstanding of a given stock. The variable *ME* is the market equity computed as the number of shares outstanding times the stock price at the end of quarter t expressed in million dollars. The variable *B/M* is obtained by book value for the fiscal year ended before the most recent June 30, divided by the market capitalization as of December 31 during that fiscal year. The *Age* variable is the firm age in months since the first appearance of the stock return in CRSP. Volume divided by total shares outstanding measured at the end of quarter t gives the variable *Turnover*. The variable *Volatility* is stock return variance computed over past 24-month *Price* is the stock price at the end of quarter t . The variable *DIV* represents dividend yield and is calculated as the cash dividends for the fiscal year ended before the most recent June 30, divided by market capitalization as of December 31 in that fiscal year. The two past return measures: $Ret_{t-3,t}$ denotes cumulative stock returns over the past three months and $Ret_{t-12,t-3}$ denotes cumulative stock returns over month $t-12$ to $t-3$ respectively. The indicator variable *SP500* equals to one if a firm is an S&P 500 member in quarter t and zero otherwise.

Panel A Mean return gap over the past year for all terciles: Summary statistics							
Year	Low	Medium	High	Year	Low	Medium	High
1981	-0.633	-0.058	0.371	1998	-0.571	-0.061	0.444
1982	-0.244	0.130	0.673	1999	-0.769	-0.028	0.680
1983	-0.921	-0.285	0.199	2000	-1.195	-0.086	0.905
1984	-0.261	0.076	0.544	2001	-0.595	0.073	1.137
1985	-0.562	-0.179	0.108	2002	-0.460	0.022	0.835
1986	-0.593	-0.183	0.212	2003	-0.563	-0.028	0.419
1987	-0.599	-0.121	0.276	2004	-0.614	-0.058	0.255
1988	-0.496	0.018	0.463	2005	-0.413	-0.021	0.257
1989	-0.550	-0.153	0.140	2006	-0.398	-0.024	0.252
1990	-0.316	0.054	0.506	2007	-0.359	-0.011	0.268
1991	-0.641	-0.132	0.297	2008	-0.363	0.056	0.555
1992	-0.481	-0.060	0.310	2009	-0.453	0.065	0.759
1993	-0.379	-0.046	0.321	2010	-0.561	-0.049	0.313
1994	-0.332	-0.005	0.344	2011	-0.426	-0.039	0.317
1995	-0.530	-0.107	0.241	2012	-0.383	-0.036	0.295
1996	-0.586	-0.123	0.373	2013	-0.443	-0.036	0.210
1997	-0.659	-0.137	0.310				

<i>Panel B Smart ownership and other firm characteristics: Summary statistics</i>				
	Mean	Median	Std Dev	N
<i>Smart IO</i>	.016	.002	.028	639149
<i>IO</i>	.336	.271	.274	639149
<i>ME</i> ($\times \$1\text{mil}$)	1177.247	123.256	3684.211	634530
<i>B/M</i>	.811	.620	1.005	576135
<i>Age</i> (in months)	166.960	115	172.963	639149
<i>Ret</i> _{<i>t-3,t</i>} (annualized)	.181	.071	1.309	624126
<i>Ret</i> _{<i>t-12,t-3</i>} (annualized)	.191	.070	1.029	588839
<i>Volatility</i>	.118	.140	.094	544801
<i>Turnover</i>	.005	.014	.032	623861
<i>Dividend yield</i>	.026	0	.097	639149
<i>Price</i>	10.350	16.185	19.160	634535
<i>SP500</i>	.118	0	.322	639149

Table 2 Cost of capital measures: Summary statistics

This table presents summary statistics for various cost of capital measures. The first four variables $Ret_{t,t+3}$, $Ret_{t+3,t+6}$, $Ret_{t+6,t+9}$, $Ret_{t+9,t+12}$ are one-quarter ahead, two-quarter ahead, three-quarter ahead and four-quarter ahead stock returns respectively. The next three variable r_{GLS} , r_{CT} and r_{OJN} are cost of capital measures developed by Gebhardt, Lee and Swaminathan (2001), Claus and Thomas (2001) and that developed by Ohlson and Juettner-Nauroth (2005) and implemented by Gode and Mohanram (2003). The last variable $\bar{r}$ is the mean value of the three accounting cost of capital measures.

	Mean	Median	N
$Ret_{t,t+3}$	.127	.052	621168
$Ret_{t+3,t+6}$	.131	.053	606476
$Ret_{t+6,t+9}$	.140	.058	591696
$Ret_{t+9,t+12}$	.142	.057	576656
r_{GLS}	.108	.097	29772
r_{CT}	.141	.090	37661
r_{OJN}	.130	.115	34540
$\bar{r}$	.127	.104	24302

Table 3 Smart ownership and future stock returns

This table presents the Fama-MacBeth (1973) regression of quarterly future stock returns on smart ownership. The dependent variable is one-quarter ahead to four-quarter ahead stock returns in column (1) through column (4). The key independent variable *Smart IO* is the number of shares held by the high-return-gap funds divided by the total number of shares outstanding of a given stock; *IO* is the total ownership by all 13F institutions computed as the total number of shares held by all 13F institutions divided by the number of shares outstanding of a given stock. The variable *ME* is the market equity computed as the number of shares outstanding times the stock price at the end of quarter *t* expressed in million dollars. The variable *B/M* is obtained by book value for the fiscal year ended before the most recent June 30, divided by the market capitalization as of December 31 during that fiscal year. The *Age* variable is the firm age in months since the first appearance of the stock return in CRSP. Volume divided by total shares outstanding measured at the end of quarter *t* gives the variable *Turnover*. The variable *Volatility* is stock return variance computed over past 24-month *Price* is the stock price at the end of quarter *t*. The variable *DIV* represents dividend yield and is calculated as the cash dividends for the fiscal year ended before the most recent June 30, divided by market capitalization as of December 31 in that fiscal year. The two past return measures: *Ret_{t-3,t}* denotes cumulative stock returns over the past three months and *Ret_{t-12,t-3}* denotes cumulative stock returns over month *t-12* to *t-3* respectively. The indicator variable *SP500* equals to one if a firm is an S&P 500 member in quarter *t* and zero otherwise. All the independent variables except for *Smart IO*, *IO*, *SP500*, *Ret_{t-3,t}* and *Ret_{t-12,t-3}* are expressed in natural logarithm forms. All the independent variables are measured at the end of quarter *t*. In all regressions, the quarterly cross-section estimation is performed using the Fama-MacBeth method. The time-series means of coefficients are presented with t-statistics in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

	(1) <i>Ret_{t,t+3}</i>	(2) <i>Ret_{t+3,t+6}</i>	(3) <i>Ret_{t+6,t+9}</i>	(4) <i>Ret_{t+9,t+12}</i>
<i>Smart IO</i>	-0.060** (-2.41)	-0.057** (-2.21)	-0.108*** (-4.11)	-0.077*** (-2.83)
<i>IO</i>	0.022*** (3.42)	0.027*** (4.07)	0.029*** (4.30)	0.028*** (4.17)
<i>ln(ME)</i>	0.002* (1.71)	0.002* (1.72)	0.002* (1.91)	0.002* (1.81)
<i>ln(B/M)</i>	0.005*** (2.84)	0.004** (2.39)	0.004** (2.24)	0.004** (2.27)
<i>ln(Age)</i>	0.001 (1.57)	0.001 (1.08)	0.001 (0.57)	0.001 (0.68)
<i>SP500</i>	0.001 (0.36)	0.002 (0.84)	0.002 (0.61)	0.003 (0.83)
<i>Ret_{t-3,t}</i>	0.010 (1.37)	0.026*** (4.22)	0.019*** (3.15)	0.014*** (2.67)
<i>Ret_{t-12,t-3}</i>	0.019*** (5.15)	0.003 (1.02)	-0.004 (-1.20)	-0.007*** (-2.64)
<i>ln(Volatility)</i>	-0.015*** (-2.72)	-0.004 (-0.77)	-0.002 (-0.30)	-0.000 (-0.07)
<i>ln(Turnover)</i>	-0.002 (-0.96)	-0.005*** (-3.49)	-0.005*** (-3.61)	-0.005*** (-3.79)
<i>ln(DIV)</i>	-0.004 (-0.33)	0.002 (0.19)	0.001 (0.102)	-0.001 (-0.11)
<i>ln(P)</i>	-0.021*** (-9.62)	-0.019*** (-9.00)	-0.020*** (-10.16)	-0.019*** (-9.98)
Constant	0.016 (0.53)	0.016 (0.51)	0.031 (1.00)	0.032 (1.00)
Observations	484,694	473,192	461,557	449,870
R-squared	0.073	0.069	0.065	0.063

Table 4 Smart ownership and implied cost of capital

This table presents the Fama-MacBeth (1973) regression of the ex-ante annual cost of capital measures on smart ownership. The dependent variable are cost of capital measures developed by Gebhardt, Lee and Swaminathan (2001), Claus and Thomas (2001) and that developed by Ohlson and Juettner-Nauroth (2005) and implemented by Gode and Mohanram (2003) in column (1) through column (3) and the mean value of the previous three measures in column (4). The key independent variable *Smart IO* is the number of shares held by the high-return-gap funds divided by the total number of shares outstanding of a given stock; *IO* is the total ownership by all 13F institutions computed as the total number of shares held by all 13F institutions divided by the number of shares outstanding of a given stock. The firm characteristics that we control for in this regression are identical to those in Table 3. The variable *ME* is the market equity computed as the number of shares outstanding times the stock price at the end of quarter *t* expressed in million dollars. The variable *B/M* is obtained by book value for the fiscal year ended before the most recent June 30, divided by the market capitalization as of December 31 during that fiscal year. The *Age* variable is the firm age in months since the first appearance of the stock return in CRSP. Volume divided by total shares outstanding measured at the end of quarter *t* gives the variable *Turnover*. The variable *Volatility* is stock return variance computed over past 24-month *Price* is the stock price at the end of quarter *t*. The variable *DIV* represents dividend yield and is calculated as the cash dividends for the fiscal year ended before the most recent June 30, divided by market capitalization as of December 31 in that fiscal year. The two past return measures: *Ret_{t-3,t}* denotes cumulative stock returns over the past three months and *Ret_{t-12,t-3}* denotes cumulative stock returns over month *t-12* to *t-3* respectively. The indicator variable *SP500* equals to one if a firm is an S&P 500 member in quarter *t* and zero otherwise. All the independent variables except for *Smart IO*, *IO*, *SP500*, *Ret_{t-3,t}* and *Ret_{t-12,t-3}* are expressed in natural logarithm forms. All independent variables are measured at the end of year *t*. In all regressions, the annual cross-section estimation is performed using the Fama-MacBeth method. The time-series means of coefficients are presented with t-statistics in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

	(1)	(2)	(3)	(4)
	r_{GLS}	r_{CT}	r_{OJN}	$\bar{r}$
<i>Smart IO</i>	-0.038** (-2.30)	-0.063 (-1.55)	-0.141** (-2.26)	-0.044** (-2.33)
<i>IO</i>	0.025*** (12.58)	0.017** (2.62)	0.004 (0.50)	0.013*** (3.92)
Constant	0.152*** (14.38)	0.146*** (9.87)	0.314*** (9.61)	0.182*** (21.30)
Firm Characteristics	Yes	Yes	Yes	Yes
Observations	27,507	34,106	31,068	22,643
R-squared	0.368	0.109	0.172	0.165

Table 5 Portfolio approach

This table presents summary statistics and return results for portfolio approach. We sort all sample firms into terciles based on *IO* every quarter, within each *IO* tercile, we further sort the firms into two groups based on the level of *Smart IO*. The sorting variable *IO* is the total ownership by all 13F institutions computed as the total number of shares held by all 13F institutions divided by the number of shares outstanding of a given stock and *Smart IO* is the number of shares held by the high-return-gap funds divided by the total number of shares outstanding of a given stock. Since the majority of firms in the low *IO* tercile has no Smart IO, we focus on the medium and high *IO* terciles. As a result, we form 2×2 portfolios sorted on *IO* and *Smart IO* every quarter and hold them for one quarter. The time-series average of mean *IO* and mean *Smart IO* as well as the number of firms of each portfolio are presented in Panel A of Table 5. Panel B displays the equal weighted quarterly return and the quarterly return adjusted for Carhart (1997) four factors for each of the 4 portfolios, as well as for the hedging portfolio that long the high *Smart IO* group while short the low *Smart IO* group within each *IO* tercile. We report the portfolio raw returns and four-factor returns in Panel B and C of Table 5 respectively.

<i>Panel A Portfolio IO and Smart IO: Summary statistics</i>				
IO Group No.	Smart IO Grp. No.	IO	Smart IO	N
2	1	27.43%	0.20%	921.38
2	2	32.69%	2.82%	810.68
3	1	59.44%	1.03%	858.33
3	2	64.57%	5.24%	870.98

<i>Panel B Quarterly Return</i>			
	Low Smart IO (1)	High Smart IO (2)	(2) - (1)
Medium IO	0.039*** (3.38)	0.033*** (2.93)	-0.006* (1.94)
High IO	0.039*** (4.12)	0.031*** (2.97)	-0.008*** (3.31)

<i>Panel C Four-factor Return</i>			
	Low Smart IO (1)	High Smart IO (2)	(2) - (1)
Medium IO	0.007** (1.98)	0.002 (0.73)	-0.017*** (-5.16)
High IO	0.007*** (3.64)	-0.001 (-0.42)	-0.019*** (-8.14)

Table 6 Broker exit and cost of capital

This table presents the results for difference-in-difference regressions around broker exit event. The broker exit events include the closure and merger of brokerage houses. We employ the list of 54 broker exit events compiled in Chen, Harford and Lin (2015) over the sample period of 2000 to 2010. The dependent variable, $\Delta Qret$ or change in quarterly returns is computed as the difference of the quarterly return between quarter $t+1$ and quarter $t-1$. The key independent variable *Smart IO* is the number of shares held by the high-return-gap funds divided by the total number of shares outstanding of a given stock. The indicator variable *BrokerExit* equals to one when there is a broker closure or merger event in quarter t and zero otherwise. The dummy variable *PosSmart IO* is defined to capture the presence of smart investors: it equals to one if a firm has positive level of smart ownership and zero otherwise. *Smart IO (PosSmart IO)*BrokerExit* is the interaction term between *Smart IO (PosSmart IO)* and *BrokerExit*. The firm characteristics controls are identical to that in Table 3. The variable *ME* is the market equity computed as the number of shares outstanding times the stock price at the end of quarter t expressed in million dollars. The variable *B/M* is obtained by book value for the fiscal year ended before the most recent June 30, divided by the market capitalization as of December 31 during that fiscal year. The *Age* variable is the firm age in months since the first appearance of the stock return in CRSP. Volume divided by total shares outstanding measured at the end of quarter t gives the variable *Turnover*. The variable *Volatility* is stock return variance computed over past 24-month *Price* is the stock price at the end of quarter t . The variable *DIV* represents dividend yield and is calculated as the cash dividends for the fiscal year ended before the most recent June 30, divided by market capitalization as of December 31 in that fiscal year. The two past return measures: $Ret_{t-3,t}$ denotes cumulative stock returns over the past three months and $Ret_{t-12,t-3}$ denotes cumulative stock returns over month $t-12$ to $t-3$ respectively. The indicator variable *SP500* equals to one if a firm is an S&P 500 member in quarter t and zero otherwise. All the independent variables except for *Smart IO*, *IO*, *SP500*, $Ret_{t-3,t}$, $Ret_{t-12,t-3}$, *BrokerExit* and the interaction terms are expressed in natural logarithm forms. All the independent variables are obtained at the end of quarter t . In all regressions, the quarterly cross-section estimation is performed using the Fama-MacBeth method. The time-series means of coefficients are presented with t-statistics in parentheses. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

<i>Dependent variable: $\Delta Qret = Qret_{qt+1} - Qret_{qt-1}$</i>		
	(1)	(2)
<i>Smart IO</i>	0.063 (0.80)	
<i>Smart IO*BrokerExit</i>	-0.320** (-2.31)	
<i>PosSmart IO</i>		0.026*** (4.06)
<i>PosSmart IO*BrokerExit</i>		-0.039** (-2.38)
<i>BrokerExit</i>	0.036*** (3.46)	0.058*** (2.93)
<i>IO</i>	0.123*** (5.33)	0.114*** (5.17)
Constant	0.058 (0.54)	0.059 (0.57)
Firm characteristics	Yes	Yes
Observations	136,581	136,581
R-squared	0.110	0.069

Table 7 Subsample tests before and after Reg FD

Panel A of this table presents the Fama-MacBeth (1973) regression of quarterly future stock returns on smart ownership in the subsamples pre and post Reg FD. The dependent variable is one-quarter ahead to four-quarter ahead stock returns in column (1) through column (8). The key independent variable *Smart IO* is the number of shares held by the high-return-gap funds divided by the total number of shares outstanding of a given stock; *IO* is the total ownership by all 13F institutions computed as the total number of shares held by all 13F institutions divided by the number of shares outstanding of a given stock. The variable *ME* is the market equity computed as the number of shares outstanding times the stock price at the end of quarter *t* expressed in million dollars. The variable *B/M* is obtained by book value for the fiscal year ended before the most recent June 30, divided by the market capitalization as of December 31 during that fiscal year. The *Age* variable is the firm age in months since the first appearance of the stock return in CRSP. Volume divided by total shares outstanding measured at the end of quarter *t* gives the variable *Turnover*. The variable *Volatility* is stock return variance computed over past 24-month *Price* is the stock price at the end of quarter *t*. The variable *DIV* represents dividend yield and is calculated as the cash dividends for the fiscal year ended before the most recent June 30, divided by market capitalization as of December 31 in that fiscal year. The two past return measures: *Ret_{t-3,t}* denotes cumulative stock returns over the past three months and *Ret_{t-12,t-3}* denotes cumulative stock returns over month *t-12* to *t-3* respectively. The indicator variable *SP500* equals to one if a firm is an S&P 500 member in quarter *t* and zero otherwise. All the independent variables except for *Smart IO*, *IO*, *SP500*, *Ret_{t-3,t}* and *Ret_{t-12,t-3}* are expressed in natural logarithm forms. All the independent variables are measured at the end of quarter *t*. The odd-numbered columns represent regressions in the pre-Reg FD period and the even-numbered columns represent regressions in the post-Reg FD period. In all regressions, the quarterly cross-section estimation is performed using the Fama-MacBeth method. The time-series means of coefficients are presented with t-statistics in parentheses. Panel B reports t-test of difference of coefficients on *Smart IO* and *IO* in the pre- and post-Reg FD period respectively. The t-statistic of the difference of coefficients is reported in parentheses followed by the p-value of difference in the row below. The symbols ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Panel A Subsample Fama-MacBeth regression								
	(1) <i>Ret_{t,t+3}</i>	(2) <i>Ret_{t,t+3}</i>	(3) <i>Ret_{t+3,t+6}</i>	(4) <i>Ret_{t+3,t+6}</i>	(5) <i>Ret_{t+6,t+9}</i>	(6) <i>Ret_{t+6,t+9}</i>	(7) <i>Ret_{t+9,t+12}</i>	(8) <i>Ret_{t+9,t+12}</i>
<i>Smart IO</i>	-0.090** (-2.443)	-0.015 (-0.530)	-0.102*** (-2.870)	0.014 (0.432)	-0.151*** (-4.208)	-0.041 (-1.133)	-0.116*** (-3.080)	-0.012 (-0.352)
<i>IO</i>	0.020** (2.392)	0.025** (2.465)	0.024*** (2.746)	0.031*** (3.106)	0.025*** (3.016)	0.036*** (3.068)	0.021** (2.480)	0.039*** (3.630)
Constant	0.005 (0.134)	0.033 (0.633)	0.017 (0.416)	0.015 (0.299)	0.043 (1.066)	0.013 (0.252)	0.035 (0.870)	0.026 (0.507)
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	296,804	187,890	291,534	181,658	286,016	175,541	280,401	169,469
R-squared	0.074	0.071	0.071	0.065	0.066	0.063	0.067	0.056
Post FD	No	Yes	No	Yes	No	Yes	No	Yes

Panel B T-test of difference of coefficients				
	(1) <i>Ret_{t,t+3}</i>	(2) <i>Ret_{t+3,t+6}</i>	(5) <i>Ret_{t+6,t+9}</i>	(7) <i>Ret_{t+9,t+12}</i>
<i>Smart IO</i>	(-1.619) 0.108	(-2.407)** 0.018	(-2.167)** 0.016	(-2.035)** 0.022
<i>IO</i>	(-0.411) 0.682	(-0.568) 0.571	(-0.738) 0.231	(-1.285) 0.202