Peer Effects in Investment Manager Selection: Evidence from University Endowments

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Abstract

This is the first paper to provide evidence that the behaviour of peer institutions plays a role in decisions of external investment manager appointments and terminations in the institutional investor space. Using unique data on university endowments, I explore the characteristics of their manager selection. I show that endowments' similar external manager appointments can be explained by commonalities in their institutional attributes, that endowments follow their peers in the frequency of external manager hiring and firing, and respond faster to the specific appointment and termination decisions of endowments in their peer groups. Overall, this study suggests that institutional investor herding effects are prevalent not only in decisions about their financial assets, but also in decisions about the external investment managers of their portfolios.

Keywords: Investment manager selection, peer effects, herding, university endowments

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1 Introduction

This paper examines peer effects as a determinant of external investment manager selection in the institutional investor space. The literature has previously focused on peer effects and herding in security or asset class selection of individual and institutional investors, as well as in strategic firm decisions and corporate policy. This study is the first to address peer effects when institutional investors choose which external investment managers to delegate their portfolio to. Such an analysis is enabled through a novel hand-collected dataset on university endowment manager appointments that spans over 30 years.

University endowments are entities that manage nonprofit assets. Endowments are substantial investors with very long-term horizons, are run by experienced professionals, and have served as investment role-models for many individual and institutional investors[1]. Each endowment has an investment office that decides on investment policy and can choose to manage the funds itself (internally) or to delegate management to external asset management firms. Outsourcing the investment management of endowment portfolios has become quite prevalent in recent years. Regarding this trend, Mr Narv Narvekar, CEO of Harvard Management Company (HMC), has noted in a memo to the university in 2017 that "in the past, HMC's unique approach of investing in internally-managed portfolios generated superior returns. In recent years, however, the tremendous flow of capital to external managers has created a great deal of competition for both talent and ideas, therefore making it more difficult to attract and retain the necessary investment expertise while also remaining sufficiently nimble to exploit rapidly changing opportunities". All endowments in my sample in 2008 adopt the external management approach (at least for part of their portfolio) and delegate mandates to investment managers expecting them to deliver performance. If they do not, then they are often fired.

I investigate external manager hiring and firing decisions by endowments which compete against each other on investment performance and inputs such as students and faculty (Acharya and Dimson (2007)). Since they effectively participate in a tournament, their investment strategies and external manager hiring and firing decisions are likely to be influenced by the behavior of their peers. Furthermore, since some endowments appear able to pick skilled managers (Lerner et al. (2008)), I

[1]The 2016 total market value of non-profit U.S. endowments was \$0.7 trillion (Dahiya and Yermack (2018)).

consider whether others are able to follow their decisions through peer networks.

More specifically, this paper studies the influence of the network of university peers in external manager hiring and firing decisions. In particular, I examine the following three research questions: (i) what are the determinants of the commonalities in external manager selection among endowments; (ii) whether endowments follow their peers in the frequency of manager appointments and terminations; and (iii) what influences how fast endowments respond to hiring and firing decisions of other institutions.

First, I show that similarities in endowment characteristics between pairs of endowments can explain commonalities in manager appointments. I find that the more similar the endowments are (especially in terms of Carnegie Classification, location and market value), the more likely they are to hire the same managers. Second, I find that endowments are more likely to hire and fire managers if their peers hired or fired managers with greater frequency. More specifically, I show that a higher average number of past hirings and firings by peers has a positive effect on the number of manager hiring and firing events by an endowment during the following year. In separate regressions, the number of manager hiring and firing events also rises when peer endowments are hiring or firing more managers on average than the whole sample of institutions (isolating the decisions of peers from the general trend). Finally, I show that endowments respond faster to hiring and firing decisions of other endowments when their institutional characteristics are similar. Looking at the managers hired by two or more institutions, I track the time interval between pairs of endowments appointing the same manager and find that when differences in characteristics are smaller, the interval between appointments or terminations of the same manager is shorter. This suggests that endowments track more closely the specific manager hiring and firing behaviour of endowments similar to them. Overall, the results provide evidence that peer effects play a significant role in the choice of external investment managers by university endowments.

The rest of the paper is organised as follows. Section 2 discusses the relevant literature on peer effects and networks, investment manager selection and endowment investing. Section 3 describes the data sources and matching, the final sample and its trends. Section 4 presents the empirical results of the manager selection and peer effects analysis, and Section 5 concludes and discusses the scope for further research.

2 Related Literature

This paper examines the influence of peer institutions on the external manager selection and termination by university endowments. Therefore, it lies in the intersection of the literature on networks and peer effects, institutional investor manager selection, and endowment investing.

This paper relates to the extensive literature on institutional and individual investors that explores herding and tournament effects. Early work on herding has shown that managers tend to “go with the flow” and invest similarly to other managers in their peer groups. Lakonishok et al. (1992), in their empirical investigation of U.S. pension fund data, note that "Managers are evaluated against each other. To avoid falling behind a peer group by following a unique investment strategy, they have an incentive to hold the same stocks as other money managers”. Examining manager incentives, Maug and Naik (1995) show that fund managers tend to ignore their own information and adjust their portfolio allocation to that of their peers. Grinblatt et al. (1995) examine the tendency of mutual funds to get into similar positions in the same stocks at the same time, while Hong et al. (2005) claim that a mutual fund manager is more likely to buy (or sell) a particular stock if other managers in the same city are buying (or selling) that same stock. More recently, Jiang and Verardo (2018) show a negative relationship between herding behaviour and skill in mutual funds, while other papers examine herding behaviour in different types of institutional investors (such as pension funds (Blake et al. (2017)) or passive funds (Fisch et al. (2018))) and markets (such as futures (Boyd et al. (2016)), bonds (Cai et al. (2019)), or global assets (Clare et al. (2016))). This literature explores herding in the selection of financial assets, while this is the first paper to address herding in the selection of external investment managers. While endowments differ considerably from other institutional investors in terms of structure and goals, their investment committees operate in a competitive market where good performance (and survival) is rewarded. This analysis becomes possible with my novel data on the external managers hired by a cross-section of endowments over an extended period.

Moreover, social learning and peer effects have gained increased attention in many areas of economics and finance and have been investigated in recent studies of firms, individual and institutional investors. Social networks play a significant role in identifying information transfers in the security markets. Ozsoylev et al. (2014) claim that information diffusion influences investor trading behaviour and returns, and that central to the network investors earn higher returns and trade earlier than peripheral investors. Hochberg et al. (2007) look at networks of venture capital firms and find that better-networked firms experience significantly better performance (IPO exits), Rossi et al. (2018) suggest that network centrality of equity managers of U.K. pension plans is positively related to risk-adjusted performance and growth in assets under management, while Li and Schürhoff (2019) find that dealers in the over-the-counter municipal bond market form trading networks with other dealers to mitigate search frictions. In the field of corporate boards and governance, Kuhnen (2009) finds that directors tend to hire advisory firms that they have worked with in the past, while Nguyen (2012) finds that a CEO well-connected with the board of directors does not get fired easily after bad performance and is more likely to find a good job later. In addition, Cohen et al. (2008) connect mutual fund managers and corporate board members and find that portfolio managers place larger bets and generate significantly better performance on firms they are connected to[2]. The aforementioned studies measure network connections in an indirect way (for example, through shared attributes such as educational background), as direct connections between fund managers (or between managers and corporate CEOs) are generally informal and undocumented. This paper examines peer effects in the institutional investor space and identifies peer institutions in a unique way, as classified by the universities themselves.

In corporate policy, Leary and Roberts (2014) show that peer firms play a very important role in determining corporate capital structures and financial policies. Kaustia and Rantala (2015) find that firms are more likely to split their stocks if their peer firms have recently done so and Matsumoto et al. (2018) show that the likelihood that a firm voluntarily provides an earnings forecast is sensitive to the extent to which other firms in the same geographic area provide earnings forecasts. With respect to portfolio similarities of investment funds, Antón and Polk (2014) look at commonalities in stock ownership by mutual fund investors and show that the degree of shared ownership forecasts cross-sectional variation in return correlation, while Getmansky et al. (2018) show that insurers with more similar portfolios have larger subsequent common sales. This paper looks at endowment similarities regarding pools of external managers, explores their manager hiring and firing decisions

[2]Other related papers that fall into the social networks literature are Hong et al. (2004) who suggest that measures of sociability are linked to increased stock market participation, Gaspar and Massa (2011) who find that personal connections between divisional managers and the CEO increase the bargaining power of the connected managers and decrease the efficiency of decisions within the organisation, and Kaustia and Knüpfer (2012) who show that investors are more likely to enter the stock market after their neighbors have enjoyed above than average portfolio returns.

and the determinants of commonalities in these choices.

With regards to manager selection and termination decisions in the institutional investor space, Heisler et al. (2007) suggest that plan sponsors screen for managers that beat benchmarks while not necessarily considering the magnitude by which they beat them, while Goyal and Wahal (2008) show that the performance of the fired managers is no different than the performance of the newly hired ones. So, the expertise of plan sponsors in delegating assets to institutional investment management firms does not generate excess returns. In a related study, Cornell et al. (2017) claim that it is more profitable to evaluate a manager's strategy and firm characteristics than to make decisions based on historical performance. Last, Brown et al. (2016) show that the amount of private information that institutional investors acquire from hedge funds influences their decisions to invest. This paper closely examines the external manager hiring and firing decisions of endowments including another factor that can play a critical role in their decision-making, namely competition and information-sharing with peer institutions.

Finally, the focus of this paper is university endowments, which operate in a highly competitive environment. The U.S. endowment model, often attributed to Yale University, is an investment approach relying on diversification, active management, equity orientation and illiquid assets (Chambers and Dimson (2015), Chambers and Dimson (2013), Chambers et al. (2015)). The prior literature has commended endowment investment decisions and performance, suggesting that U.S. university endowments might have the ability to outperform other types of investors, which makes their investment manager decisions important to explore. Lerner et al. (2008), who investigate the factors of university endowment success, attribute the dramatic growth in endowment size to high investment returns related to the quality of student body and use of alternative assets, and document that Ivy League schools managed their commitments to alternative investments much better than non-Ivy League schools. Endowments have also been successful in their security selection process, especially in terms of venture capital partnerships (Lerner et al. (2007)), and seem to directly benefit from having experts in alternative investments serving on university boards (Binfarr et al. (2018)). Literature has also shown that endowments are adjusting their asset allocations to catch up with competing institutions (Goetzmann and Oster (2012)), which suggests that other investment decisions might also be influenced by their peer groups.

All the above suggest that, in the institutional investor space, external manager selection is an important strategic decision and make it reasonable to expect that peer effects play a critical role in manager hirings and firings. This paper provides evidence towards this.

3 Data on Endowments and External Managers

I employ a novel dataset of university endowments and their external investment managers across all asset class mandates for 1978-2008. The main sources of endowment managers are the NACUBO reports, which stopped including managers after 2008. From this novel panel data set, I am able to infer all manager hiring and firing events each year from annual changes in the lists of managers employed by each endowment. This data is supplemented by existing datasets on endowment characteristics (NACUBO), university characteristics (IPEDS) and separate account investment manager characteristics (PSN Enterprise, Broadridge Marketplace, Nelson's Directory of Investment Managers).

3.1 Data Sources

NACUBO[3]

The endowment managers data is hand-collected from a series of annual reports by NACUBO[4]. NACUBO distributes yearly surveys to university endowments since 1970 with questions regarding their investment practices. From 1977-2008, endowments list their investment managers in a section of the NACUBO report which was discontinued from 2009 onwards. To the best of my knowledge, this section of the NACUBO reports has not been tabulated and exploited in the past. Therefore, I use this data as the base to create a novel dataset on external investment manager appointments.

Table 1 shows the variables included in the NACUBO reports under the "Investment Managers" section each year. External investment manager names are reported since 1977, and asset class breakdown is reported from 1978 onwards. For a smaller part of the sample, the asset class mandates are further refined with the manager's geographic orientation since 1988, and NACUBO's "Type" and "Style" asset classifications since 2002. More specifically, "Geography" represents the location of the portfolio investments (Domestic, International or Foreign), "Type" represents mandates such

[3]I thank Ken Redd of NACUBO for help in accessing the data.

[4]The National Association of College and Business Officers (NACUBO) is an advocacy organization devoted to improving management practices in the higher education industry.

as large or small for public equities, hedge funds or private equity for alternative investments, and "Style" represents mandates such as growth or value for equities, short or long-term for fixed income. Last, for 1995-2005, the "% of pool" represents the percentage of the investment portfolio that is delegated to each manager[5].

The NACUBO data also contains yearly cross-sectional characteristics of the endowment portfolios such as market values, asset allocation and nominal returns[6]. This part of the NACUBO data has already been used in several prior studies of endowment investing, including Lerner et al. (2008), Brown et al. (2010) and Barber and Wang (2013). The NACUBO data are not backfilled, and are virtually free of survivorship and reporting bias (Barber and Wang (2013)). Lastly, the NACUBO study has a very high annual rate of compliance by endowments (Goetzmann and Oster (2012)).

IPEDS

I source the characteristics of the universities the endowments support from IPEDS[7]. The data includes university-specific variables such as the name of the university, Zip Code, state, Carnegie Classification[8], public or private university status, age since the university was founded, total university income, costs, assets and debt, tuition and appropriations, total applicants and applicants admitted, and full-time equivalent (FTE) students. Providing information through IPEDS is mandatory for all U.S. post-secondary institutions, and institutions that fail to provide information are barred from accessing federal funding (Brown et al. (2012)).

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[5]The asset class categories and mandates are sometimes reported differently throughout my sample. Therefore, to keep the sample consistent through time and make sure that the hiring/firing events I am capturing are not affected by yearly differences in mandate reporting, I classify the different asset classes in reasonable groups that stay constant over time (Table 9 of the Appendix). These transformations provide broad and uniform classifications of asset types, which are particularly useful as classification of assets differs not only from year to year but also from endowment to endowment (for example, a hedge fund investing in distressed commercial mortgages might be defined as a marketable alternative strategy for one endowment, a distressed debt fund for another endowment, or even as a private equity real estate fund for a different endowment (Ang et al. (2018))). Grouping assets minimizes these reporting biases. Last, in cases of introductions or discontinuations of asset classes (for example, introduction of a balanced mandate in the portfolio instead of separate stock and bond mandates), I identify the manager hirings and firings using only the names of the endowment managers.

[6]A more detailed description of this part of the NACUBO data is provided by Brown et al. (2010).

[7]Integrated Postsecondary Education Data System, data submitted to the National Center for Education Statistics (NCES), available since 1984

[8]The Carnegie Classification of Institutions of Higher Education classifies educational institutions with respect to the degrees they offer. Such classifications include doctoral (offering PhDs), masters, bachelor, associate, theology, medical and specialty colleges. For more information, see: http://carnegieclassifications.iu.edu/.

Chronicle of Higher Education

I identify university peers through a 2012 study of 1,595 U.S. universities and colleges conducted by the Chronicle of Higher Education. Each year colleges submit "comparison groups" to the U.S. Department of Education to get feedback on how their institution compares to other universities in terms of finances, enrollment, and other measures tabulated in IPEDS. The groups sometimes represent a college's actual peers but more often reveal their aspirations (Fuller (2012)). The Chronicle's study reports the following information about each university: a list of the universities it considers to be its peers, a list of the universities that consider it as a peer and the overlap of these two lists[9]. This data provides a helpful indication of peer relationships or aspirations of peer classifications among U.S. universities, as reported by the universities themselves.

Investment Manager Datasets

For part of the analysis, I match the endowment managers to the Informa PSN Enterprise database on institutional managers, which is free from survivorship bias[10]. This dataset is used by investment product managers for performance comparison to their peers and by plan sponsors and consultants to identify candidate investment managers (Heisler et al. (2007)). I source variables for investment managers such as assets under management (AUM), firm age and performance of products. I match each endowment manager name to the PSN manager name of the same mandate[11]. I also source other management firm characteristics such as the fund location (state and Zip Code), the date that the company was founded, the total asset size, the total number of accounts per product, the firm name changes and their corresponding dates. I supplement the PSN data with other existing datasets, such as the Broadridge Marketplace and the Nelson's Directory of Investment Managers.

The matching procedure results in a loss of data. One of the reasons for this is the absence

[9]The network of peers as identified from the Chronicle of Higher Education study can be found at: https://www.chronicle.com/interactives/peers-network

[10]PSN has data on long-only portfolios managed on behalf of accredited investors. Product performance information starts in 1979, while AUM figures are available from 1984. See Busse et al. (2010) for more details on the data.

[11]PSN has various products under the same investment manager firm and mandate. Therefore, I create composite characteristics (such as composite performance, AUM, etc.) of the products of a particular asset class (equity/fixed income and their subcategories) and match this performance to the corresponding endowment manager. I create the composites because the variation in the performance of the products of the same manager under the same mandate is low.

of some endowment managers from the databases[12]. Moreover, the way endowment managers are reported might inhibit the identification of specific manager names. For example, endowments might report external managers with names such as “various managers” or “10 managers”. Lastly, I can only match the PSN investment managers to equity and fixed income endowment managers.

3.2 Manager Selection Characteristics

Table 2 presents summary statistics for universities and their endowments for 1978-2008. The sample involves a large cross section of institutions ranging from 110 to 722 in number that exhibit high dispersion in terms of market values. For example, in 2008 Harvard was managing US$36 billion while Georgia Perimeter College was managing only around US$600,000. Moreover, about 30% of the universities belong to the “Doctoral” Carnegie classification (they offer PhD degrees). Overall, the sample consists of 1,386 unique universities employing around 5,800 investment managers spanning various asset class categories (equities, bonds, alternative assets, real estate, cash and subcategories of the above) over 30 years.

The average endowment has dramatically increased the number of external managers it employs since 1978, as seen in Figure 1. This outsourcing of the management of the endowment to multiple investment managers has become very prevalent, and Sharpe (1981) refers to it as “decentralized investment management”[13]. Figure 1 classifies institutions into “Ivy League” schools, “Doctoral” Carnegie classification schools, and the rest of the institutions. I use the “Doctoral” classification as a proxy for prestigious institutions, as the “Ivy league” schools stop reporting their managers after 1998. These prestigious institutions have been consistently employing more managers on average than the rest of the universities, a pattern that is also similar in terms of endowment size - on average, large institutions employ more managers than smaller ones (about 30 vs 15 managers on average in 2008) [14]. Moreover, Table 3 shows that endowments, on average, delegate a very large percentage (more than 90%) of their portfolio to external managers.

I break down the rise in the average number of managers employed by asset class in Figure 2. In

[12]Data checks confirm that the endowments whose managers can be identified through PSN are no different in terms of characteristics than the ones whose managers cannot be identified, so there is no selection bias.

[13]Blake et al. (2013) also discuss the tendency towards decentralized investment management in pension funds that move from balanced to specialist managers and from single to multiple managers in each asset class. In this way, pension funds can diversify the skills of specialist active managers having superior knowledge of a particular asset class (Sharpe (1981), Van Binsbergen et al. (2008)).

[14]The size classifications of the endowments and the relevant Figure 4 can be found in the Appendix.

the beginning of the period, university endowments employed investment managers in only two asset classes, namely domestic equities and domestic fixed income. Gradually, they started introducing managers to balanced mandates, cash and alternative investments. Most notably, the increase in the average number of investment managers mainly comes from the increase in the number of managers in equity and alternative assets. A similar pattern in the asset allocation to equities (1970-1980s) and alternative assets (1990-2000s) has already been reported in Lerner et al. (2008) and Brown et al. (2010), and can be analysed next to the number of investment firms employed to manage these asset classes.

Moreover, endowments seem to prefer local investment managers, which indicates home bias in a setting similar to Coval and Moskowitz (1999)[15]. Table 4 calculates the average distance of the endowment from the equity managers it selects compared to the managers on their benchmark (all available managers they could have selected). Table 4 shows that, on average, endowments are 1,120 to 1,578 miles away from the managers they choose to employ, and 1,542 to 1,665 miles away from their benchmark manager portfolio. Thus, the average endowment employs equity managers significantly closer to it than managers in its benchmark, a pattern which is also consistent over the long run.

As a preliminary indication of commonalities in manager appointments between endowments, Figure 3 depicts the number of managers hired by multiple endowments over 5-year rolling periods (I report every second year for brevity). The y axis depicts the number of managers included in each 5-year rolling window, and the columns break down this total figure to the number of managers hired by 1, 2-5, 6-10, and over 11 endowments. The figure shows that almost half of the managers are employed by more than one endowment. In the empirical analysis of the paper, I take this observation further and examine the drivers of this commonality in manager appointments.

[15]This result relates to a large literature that is concerned with home bias effects in investments and other strategic decisions of individuals and firms. Coval and Moskowitz (1999) document a "local bias" in equity investment within the U.S. market, whereby U.S. investment managers exhibit a strong preference for equities of local firms. Moreover, Portes and Rey (2005) show that investors not only overinvest in their home equity market but they also invest most heavily in markets that are close to them, while Sørensen et al. (2007) document a home bias in bond holdings. Home bias effects have also been prevalent in broader contexts such as in trade (Obstfeld and Rogoff (2000)), consumption (Lewis (2010)), and academic research (Karolyi (2016)).

4 Peer Effects in External Manager Selection

I examine the manager selection by looking at the individual manager appointments of each endowment in my sample. Endowments learn about the hiring and firing decisions of their peers through the NACUBO reports and through personal connections, and can be influenced by their choices. The long history of annual endowment reporting on NACUBO allows me to identify hiring and firing events of external managers in every year. I identify a hiring event of a manager in a year if, conditional on the university reporting managers in the Investment Managers section of the NACUBO report this year and the previous one, this manager was not employed during the previous year. Similarly, I identify a firing event if, conditional on the university reporting managers this year and the next one, this manager is not employed the following year. The hiring and firing events are of the order of 20% of the total number of appointments per year. Moreover, large endowments tend to hire more managers per year (as a percentage of total appointments) than small endowments, but do not tend to fire managers more frequently than the small ones.

In the following sections, I explore peer effects in manager appointments using three different specifications. First, I look at the determinants of the commonalities in manager appointments of endowment pairs per year. Second, I explore whether endowments follow peers in hiring and firing decisions in terms of the number of manager appointments and terminations per year. Third, I examine what influences how fast endowments respond to hiring and firing decisions of other institutions.

4.1 Manager Commonality

In this section, I identify the institutional characteristics that drive the commonality of managers employed by pairs of endowments at a particular point in time. The variable of interest is the number of common managers employed between each endowment pair, scaled by the sum of unique managers hired by both endowments:

$$\%\, of\, Manager\, Commonality_{i,j} = \frac{Common\, Managers_{i,j}}{Managers_i + Managers_j - Common\, Managers_{i,j}} \tag{1}$$

Table 5 reports summary statistics of the number of common managers and the percentage of manager commonality in endowment pairs. The average number of common managers across all pairs is almost one manager in 2008 but has a very high dispersion (ranges from 0 to 23 managers in some pairs). The percentage of manager commonality varies between 0 i.e. when there are no managers in common and 1 when all managers employed by the pair are common to them.

Next, I explore which institutional characteristics can determine these manager commonalities in endowment portfolios. Therefore, I calculate the distances in characteristics of each endowment pair in terms of endowment size, total assets, age, "status" (Carnegie Classification) and geographic location of the university. I calculate the geographic distances between pairs of universities using the NBER "Centroid" dataset from the ZIP Code Distance Database - ZIP Code Tabulation Area (ZCTA) Distance Database[16], which specifies the internal point latitude and longitude for all Zip Code tabulation areas in the United States. The data gathered from IPEDS also specify the Zip Codes of the universities in my sample. I match the university Zip Codes with the NBER "Centroid" dataset and, using the latitude and longitude of each area (converted from degrees to radians), I calculate the shortest distance in miles between any two university Zip Codes with the Haversine formula.

For example, in 1997 Columbia University and Cornell University employed 4 common managers out of 68 in total (portfolio commonality at 0.06 for managers in all asset classes). In the same year, Columbia University was 111 years older (243 vs 174) and bigger in size by US$900mil (US$3bil vs US$2.1bil) than Cornell University. The universities were 0 Carnegie Classifications (both are Doctoral institutions) and about 173 miles apart (great-circle distance).

The regression specification is the following:

$$\begin{aligned} Manager\,Commonality_{i,j} = a + \beta_1 * MV\,Dist_{i,j} + \beta_2 * Age\,Dist_{i,j} + \\ + \beta_3 * Geographic\,Dist_{i,j} + \beta_4 * Status\,Dist_{i,j} + \varepsilon_{i,j} \end{aligned} \tag{2}$$

Table 6 reports contemporaneous regressions of the manager commonality measure in endowment portfolios regressed on differences in institutional characteristics. I estimate the regression for three representative years in the sample, namely 1984, 1997 and 2008. The negative coefficients of the distance explanatory variables show that the more similar the universities are in terms of characteristics, the more common managers they tend to employ for their portfolios. For example,

[16]NBER ZIP Code Distance Database: http://www.nber.org/data/zip-code-distance-database.html

if two universities in 1984 were 2,500 miles closer to one another, they would on average employ one additional common manager in a portfolio consisting of around 50 managers (holding everything else constant). Endowment characteristic similarities as determinants of manager portfolio commonality have also become more significant in more recent years. The characteristics that have stayed important over time are the geographic location, the market value of the endowment, as well as the Carnegie Classification ("Status").

In Table 10 of the Appendix, I also scale the differences of the market value and age characteristics using the percentile ranks of the variables in a way similar to Antón and Polk (2014)[17], and the baseline results seem to hold.

Overall, the regression analysis shows that similarities in manager appointments of endowments can be attributed to similarities in their institutional characteristics.

4.2 Peer effects in the frequency of appointments and terminations

In this section, I examine whether endowments tend to hire and fire managers with greater frequency if their peers have recently done so. I test this hypothesis using two types of specifications, in both of which the dependent variable of interest is the number of managers hired or fired per year by an endowment. The main explanatory variable is either the average number of managers hired/fired by the peer institutions in the past, or a dummy variable that resembles the one used in Kaustia and Rantala (2015)[18]. This dummy variable takes the value of one if the average number of managers hired by peers is larger than the average number of managers hired by all endowments, and zero otherwise. The use of the dummy variable isolates the differential effect of peer decisions from the general trend. I also include in the regression characteristics such as the lagged market value and return of the endowment, as well as the university's age. The specification is the following:

$$
\begin{aligned}
Number\,Managers\,Hired/Fired_{i,t} = {} & a + \beta * Peer\,Hiring/Firing\,Dummy_{i,t-1} \\
& + \gamma_1 \Delta\, MV_{i,t-1,t} + \gamma_2 log(Age)_{i,t-1} + \gamma_3 Return_{i,t-1} + \varepsilon_{i,t}
\end{aligned} \tag{3}
$$

[17] Antón and Polk (2014) measure stock similarities through differences in stocks' percentile rankings on particular firm characteristics.

[18] Kaustia and Rantala (2015) study the influence of peers in stock split decisions and use a dummy explanatory variable that is equal to one if the average number of splits announced by a firm's peers during the past year is higher than the corresponding NYSE average, and zero otherwise.

The data from the Chronicle of Higher Education is used to identify peer institutions on the baseline specification, as it contains the names of peer universities for every university, as reported by the institutions themselves. Therefore, I consider this to be the most accurate representation of the peer network. As a robustness check in the Appendix, I also explore different definitions of peers with respect to characteristics such as Carnegie Classification of the university and endowment size (Tables 11 and 12).

The dependent variable in the regressions is the annual number of hirings/firings of external managers, which I model with a Poisson regression[19]. As a further specification (similar to Yermack (1996)[20]), I estimate a least squares model in which the dependent variable is equal to the net annual change in number of managers for each endowment (appointments minus terminations). In separate regressions, I also replace the Peer Hiring/Firing Dummy with the average number of managers hired/fired by peers during the previous period.

Table 7 shows that endowments are more likely to hire and fire managers if their peers hired or fired many managers recently. A higher average number of past hirings and firings by peers has a positive effect on the number of manager hiring and firing events by an endowment during the following year. Moreover, the number of manager hiring and firing events also rises when peer endowments are hiring or firing more managers on average than the whole sample of institutions. For the hiring result in Column 1, the "Peer Hiring Dummy" is highly significant and indicates that if peers have hired more managers than the whole sample during the previous year, the number of new manager hirings by the endowment will be higher by 39% (at the mean of the other independent variables). Similarly, the main explanatory variable in Column 3, "Hiring Average by Peers", shows that an endowment whose peers hired one more manager on average the previous year, will increase manager hirings by 7% next year. The regression results for the firing decisions have similar interpretations. The peer effect in hirings and firings of investment managers also emerges from the OLS model of the net annual change in number of managers employed. Past net additions in manager numbers of peers have a positive and significant effect on endowment manager net additions next year.

[19]Examples of studies that have used Poisson regressions to model count variables include Lerner (1995), Hermalin and Weisbach (1988) and Yermack (1996), who study the determinants of the number of new board members and the number of director appointments or departures in companies.

[20]Yermack (1996) studies the effect of company performance on the director appointments and departures (Poisson) and changes in board size (OLS).

These results show that endowments follow their peers in manager hiring and firing decisions, and are more likely to hire or fire investment managers if their peers have recently done so.

4.3 Response time to appointments and terminations

In this last section of the peer effects analysis, I examine the time that endowments take to respond after peer hiring or firing decisions of specific managers. For every manager that is hired or fired by two or more endowments in the sample, I calculate the time (number of years) that elapses between each pair of endowments hiring/firing this manager. Then, I use the characteristic distances of the endowments/universities in every pair (at the year that the second endowment hires or fires the common manager) to explain the time lag of the events. The characteristic distances calculation is similar to that of Section 4.1.

I use a time-to-event survival analysis to model the regression. More specifically, a fully-parametric "accelerated failure time" model with a log-logistic distribution can exhibit a non-monotonic hazard function which increases at early times and decreases at later times. This allows me to take into account that earlier responses to other endowments' manager appointments and terminations might be more informative than later ones. Since I only have annual data available, I approximate each response time at the middle point of the time interval (between 0 and 1 year, adding 0.5 years to the time variable). For example, if the hiring response time between two endowments is 2 years, I estimate this as 2.5 years.

Table 8 shows the results. In the hiring regression, the average response time for a pair of endowments is 2.5 years. The regression coefficients generally have a positive sign, which means that the more similar endowments are in their institutional characteristics, the shorter they take to respond to manager hiring and firing of other institutions. For example, if the "geographical distance" between the endowments is increased by one unit, the manager hiring response period is extended by 16%. The remaining regression coefficients have similar interpretations, and these effects seem quite stronger in hiring decisions than in firing decisions. This result is also robust to a simple Poisson model (Table 13).

This result shows that endowments are more likely to respond faster to specific manager appointments or terminations of endowments in their peer groups.

5 Conclusion

This paper uses unique long-term data on university endowments to examine the role of peer effects in decisions of external investment manager appointments and terminations. I show that endowments with similar characteristics are more likely to appoint the same external managers, that endowments follow their peers in the frequency of external manager hiring and firing, and respond faster to the specific appointment and termination decisions of endowments in their peer groups. The results support the existence of peer effects in university endowments' decisions about external investment managers.

The analysis can also be extended to examine appealing manager characteristics for different categories of endowments, especially the well-resourced institutions. For example, Yale University "pays particularly close attention to start-up and early-stage firms run by seasoned principals, believing that investment talent and entrepreneurial drive outweigh the risks of backing an unproven firm". Moreover, the paper could also assess the endowments' ability to select superior managers and address the benefits or costs in following peers by examining whether this tendency produces greater average returns for endowments or not.

Overall, this study sheds light on the external manager selection procedure of institutional investors with a long investment horizon. The analysis suggests that institutional investor herding effects are prevalent not only in decisions about their financial assets, but also in decisions about the investment managers of their portfolios.

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Figures and Tables

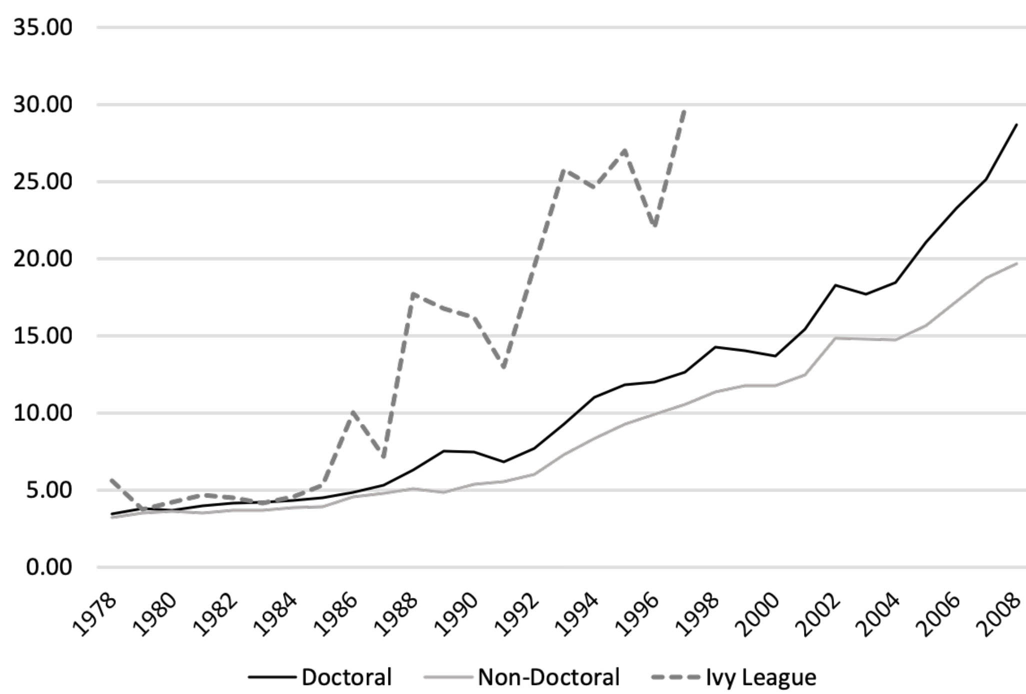

Figure 1: Average number of managers employed by university endowments for 1978-2008

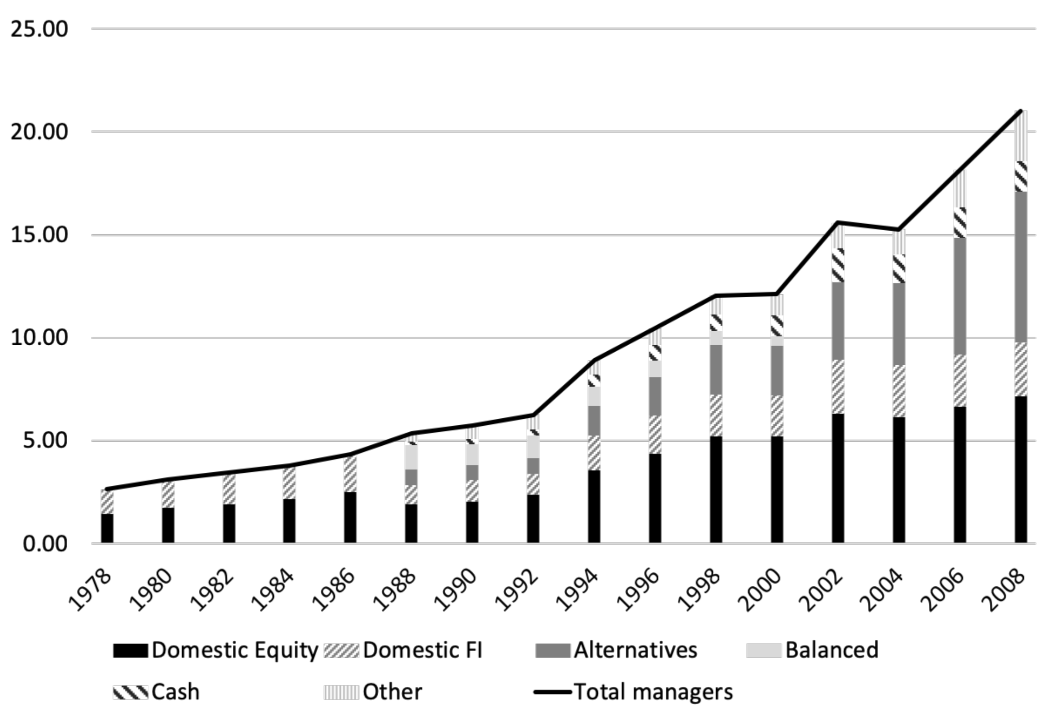

Figure 2: Average number of managers employed by asset class

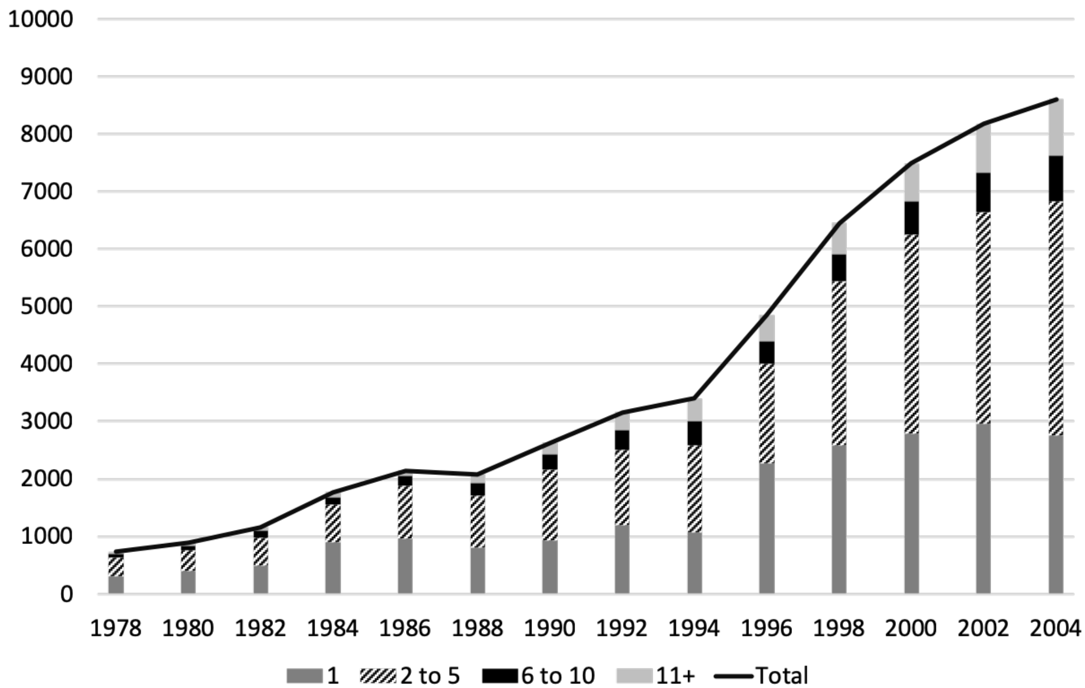

Figure 3: Number of managers hired by multiple endowments (5-year rolling windows)

Table 1: External Investment Manager Variables reported by NACUBO

This table reports the variables included in the Investment Managers sections of the NACUBO reports. "Geography" represents the location of the portfolio investments and can be U.S. (Domestic), International or Foreign, "Type" represents categories such as large or small for public equities, hedge funds or private equity for alternative investments, and "Style" represents asset categories such as growth or value for equities, short or long-term for fixed income, etc. Last, the "percentage of pool" represents the percentage of the portfolio that is delegated to each manager.

Year	Manager Name	Asset Class	Type	Style	Geography	% of pool
1977	Yes	-	-	-	-	-
1978-1987	Yes	Yes	-	-	-	-
1988-1994	Yes	Yes	-	-	Yes	-
1995-2001	Yes	Yes			Yes	Yes
2002-2005	Yes	Yes	Yes	Yes	Yes	Yes
2006-2008	Yes	Yes	Yes	Yes	Yes	-

Table 2: University Endowment Summary Statistics

This table reports summary statistics for all university endowments in the sample, for the period 1978-2008. The summary statistics reported are the number of universities included in the dataset each year, the market value (MV) of the average endowment in the sample, the average age, the percentage of the universities that belong to the Doctoral Carnegie Classification, and the average full-time equivalent (FTE) students.

Year	Number of Universities	MV Average ($000s)	Age Average	% Doctoral Class.	FTE students Average
1978	110	66,810			
1980	142	76,887			
1985	258	100,844	129	31%	8,805
1990	343	153,958	126	21%	4,517
1995	436	218,334	124	17%	5,532
2000	509	264,575	122	28%	8,548
2005	702	250,053	119	23%	7,448
2008	722	292,180	118	21%	9,245

Table 3: Asset Allocation of University Endowments

This table reports the average asset allocation percentages that are delegated to external managers, as well as the average percentage of the endowment investment portfolios that are managed internally. More specifically, each column depicts the sum of the percentages delegated to every manager of each asset class, averaged throughout endowments. The percentages are reported for all years they are available in NACUBO (1995-2005).

Year	Equity	Fixed Income	Alternative Assets	Cash	Internally Managed
1995	47.3%	24,5%	0.0%	3.1%	9.4%
1996	49.5%	19.8%	0.0%	2.6%	6.5%
1997	58.3%	21.0%	0.0%	2.4%	6.7%
1998	56.0%	21.3%	0.0%	2.3%	5.8%
1999	56.5%	21.4%	0.0%	2.2%	4.9%
2000	55.5%	20.2%	0.0%	2.8%	5.3%
2001	55.1%	21.9%	0.0%	3.0%	4.3%
2002	56.9%	26.8%	7.4%	5.4%	3.1%
2003	57.0%	25.6%	8.6%	5.4%	2.5%
2004	59.9%	22.0%	9.6%	5.2%	5.9%
2005	58.1%	21.4%	11.7%	4.7%	5.1%

Table 4: Local bias in Manager Selection by University Endowments

This table tests for local bias in endowment manager selection. The columns report the average distance of endowments (in miles) from the equity managers in their benchmark and the equity managers they employ, as well as the difference of the distances and its significance for every year through 1992-2008.

Year	Benchmark Avg Distance	Employed Avg Distance	Difference (miles)	t-statistic	p-value
1992	1,578	1,315	262	1.82	0.04
1993	1,542	1,213	328	2.73	0.00
1994	1,549	1,263	286	2.66	0.00
1995	1,556	1,214	342	3.65	0.00
1996	1,551	1,120	431	5.17	0.00
1997	1,566	1,173	392	4.74	0.00
1998	1,574	1,232	342	4.28	0.00
1999	1,580	1,257	323	3.96	0.00
2000	1,640	1,451	188	2.45	0.01
2001	1,633	1,486	147	2.14	0.02
2002	1,619	1,487	132	2.10	0.02
2003	1,603	1,491	113	2.01	0.02
2004	1,620	1,490	131	2.35	0.01
2005	1,620	1,483	137	2.58	0.00
2006	1,645	1,488	157	3.18	0.00
2007	1,647	1,524	122	2.40	0.01
2008	1,665	1,578	87	1.64	0.05

Table 5: Commonality Variables Summary Statistics

This table reports the commonality variables summary statistics for 1984, 1997 and 2008. It lists the number of common managers between pairs of endowments as well as the percentage of their manager commonality. The manager commonality is measured as the number of common managers between each pair of endowments scaled by the sum of unique managers employed by the pair. Eq-FI are the equity and fixed income managers, Alt-RE are the alternative assets and real estate managers.

Variable	Statistic	1984 Eq-FI	1997 Eq-FI	1997 Alt-RE	2008 Eq-FI	2008 Alt-RE
Number of common managers	Mean	0.04	0.31	0.09	0.37	0.19
	Std. Dev.	0.22	0.55	0.31	0.69	0.58
	Min	0.00	0.00	0.00	0.00	0.00
	Max	3.00	5.00	7.00	9.00	20.00
% of Portfolio Commonality	Mean	0.01	0.03	0.02	0.02	0.02
	Std. Dev.	0.04	0.07	0.08	0.05	0.05
	Min	0.00	0.00	0.00	0.00	0.00
	Max	0.50	0.67	0.67	0.75	0.67

Table 6: Determinants of Manager Commonality Between Endowments
This table reports results from a regression of the manager commonality measure (number of common managers per pair of endowments scaled by the total number of unique managers employed by the pair) on differences in characteristics of the endowments and corresponding universities. The results are reported at three points in time, namely 1984, 1997 and 2008. The market value is measured in billions, the age is scaled by a factor of 100 and the distance in miles is scaled by a factor of 100,000. The Status Distance represents a variable of the Carnegie Classification distance between the pair.

	Dependent variable:		
	Scaled Number of Common Managers		
	1984	1997	2008
	(1)	(2)	(3)
Market Value Distance	−0.0010	−0.0034***	−0.0020***
	(0.0016)	(0.0003)	(0.0001)
Age Distance	−0.0008	0.0003	−0.0016***
	(0.0011)	(0.0007)	(0.0003)
Geographic Distance	−0.3925***	−0.1425***	−0.0632***
	(0.0661)	(0.0447)	(0.0157)
Status Distance	−0.0005	−0.0022***	−0.0012***
	(0.0004)	(0.0002)	(0.0001)
Constant	0.0117***	0.0387***	0.0303***
	(0.0010)	(0.0007)	(0.0003)
Observations	7,497	38,217	152,060
R^2	0.0053	0.0065	0.0047
Adjusted R^2	0.0048	0.0064	0.0046
Residual Std. Error	0.0411	0.0586	0.0454
F Statistic	9.9851***	62.7097***	178.2104***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 7: Peer Effects in the Frequency of Hiring and Firing of External Managers
This table reports peer effects in the frequency of hiring and firing external managers where peers are identified by the Chronicle of Higher Education. Columns 1-4 estimate Poisson regressions of the number of hirings and firings (count variable). Columns 1 and 2 regress the number of hirings/firings on a Dummy that takes the value of 1 if peers hired/fired more than all the endowments in the sample during the previous period and 0 otherwise. Columns 3 and 4 regress the number of hirings/firings on the previous year's average hirings/firings by peer institutions. Column 5 estimates a least squares model in which the dependent variable is equal to the net annual change in number of managers for each endowment (manager hirings minus firings) and the explanatory variable is the average net change of peers managers in the previous period. The regressions are for years 1984-2008 and include year fixed effects.

	Dependent variable:				
	Numb. Hired	Numb. Fired	Numb. Hired	Numb. Fired	Net Change
	Poisson	*Poisson*	*Poisson*	*Poisson*	*OLS*
	(1)	(2)	(3)	(4)	(5)
Peer Hiring Dummy	0.3436***				
	(0.0178)				
Peer Firing Dummy		0.2172***			
		(0.0204)			
Hiring Average by Peers			0.0657***		
			(0.0032)		
Firing Average by Peers				0.0804***	
				(0.0055)	
Net Change Average					0.0806**
					(0.0336)
Change in Market Value	−0.0358***	−0.0002	−0.0375***	−0.0062	−0.0440
	(0.0086)	(0.0053)	(0.0086)	(0.0051)	(0.0303)
log(Age)	0.2752***	0.2903***	0.2821***	0.2901***	0.2145
	(0.0229)	(0.0269)	(0.0228)	(0.0267)	(0.1492)
lag(Return)	0.0111***	0.0089***	0.0125***	0.0081***	0.0182
	(0.0017)	(0.0020)	(0.0017)	(0.0020)	(0.0115)
Constant	−1.4775***	−1.8507***	−1.3915***	−1.7983***	−0.7291
	(0.1513)	(0.1797)	(0.1509)	(0.1789)	(0.8530)
Year FE?	Yes	Yes	Yes	Yes	Yes
Observations	5,117	5,117	5,117	5,117	5,035
R^2					0.0334
Adjusted R^2					0.0282
Log Likelihood	−14,777.3900	−12,583.0700	−14,784.9400	−12,547.9000	
Akaike Inf. Crit.	29,610.7800	25,222.1300	29,625.8900	25,151.7900	
Residual Std. Error					4.1999
F Statistic					6.4058***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: Determinants of the Response Time of Endowments in Hiring and Firing External Managers
This table reports the results of a survival analysis of the number of years that elapse between two endowments hiring the same manager. The specification is an Accelerated Failure Time model, following the log-logistic distribution. The market value and total assets are measured in billions, the age is scaled by a factor of 100 and the distance in miles is scaled by a factor of 10,000. The estimation period for the regressions is 1979-2008.

	Dependent variable:	
	Years Elapsed Hirings	Years Elapsed Firings
	(1)	(2)
Market Value Distance	0.017***	−0.001
	(0.002)	(0.004)
Age Distance	0.013**	0.012
	(0.006)	(0.009)
Geographic Distance	0.152***	0.119**
	(0.034)	(0.049)
Total Assets Distance	0.00003***	0.0001***
	(0.00000)	(0.00000)
Status Distance	0.006***	−0.001
	(0.002)	(0.003)
Constant	0.904***	0.888***
	(0.006)	(0.008)
Observations	138,904	71,304
Log Likelihood	−323,010.500	−166,497.800
χ^2	447.224***	484.928***
Note:		*p<0.1; **p<0.05; ***p<0.01

Appendix

I. Data Classifications

Asset Class Transformations

I classify each asset class under a broader category according to Table 9.

Market Value Categories

I also source endowment market values from NACUBO - universities participating in the annual surveys contribute the size of their endowment assets. This also enables me to use the Market Values section of the endowment study as an indication of which endowments choose to report their managers. I assume that endowments that report market values but do not appear in the Investment Managers section of the report do not disclose their managers.

I classify the universities into size categories: small, medium and large. These categories are dynamically adjusted every decade according to the classifications provided by the NACUBO report of the corresponding year. I end up with the following classifications after combining the NACUBO categories:

"Small" classification: $<$ 10 million (1977-1986), $<$10 million and 10-25 million (1987-1996), $<$25 million (1997-2006), $<$25 and 25-50 million (2007-2008).

"Medium" classification: 10-50 million (1977-1986), 25-50 and 50-100 million (1987-1996), 25-100 and 100-400 million (1997-2006), 50-100 and 100-500 million (2007-2008).

"Large" classification: $>$50 million (1977-1986), 100-200 and $>$200 million (1987-1996), $>$400 million (1997-2006), 500 million - 1 billion and $>$1 billion (2007-2008).

Table 9: Asset Class Transformations
This table reports the asset allocation re-classifications/matching of the data. Since asset classes are reported differently throughout the sample, I re-classify each asset class into a broader asset category to keep the sample uniform and be able to identify hirings and firings accurately.

Asset Class	Transformation
Absolute Return	Alternative Assets
Alternative Assets	Alternative Assets
Arbitrage	Alternative Assets
Balanced	Balanced
Buyouts	Alternative Assets
Cash	Cash and Other Investments
Cash and Other Investments	Cash and Other Investments
Commodities	Alternative Assets
Distressed Obligations	Alternative Assets
Distressed Securities	Alternative Assets
Equity	Equity
Equity Real Estate	Real Estate
Event Arbitrage	Alternative Assets
Faculty Mortgages	Cash and Other Investments
Fixed Income	Fixed Income
Fixed Income High-Yield	Fixed Income
Foreign Equity	Equity
Foreign Fixed Income	Fixed Income
Hedge Funds	Alternative Assets
Leveraged Buyouts	Alternative Assets
Managed Futures	Alternative Assets
Non-Venture Private Equity	Alternative Assets
Oil & Gas	Alternative Assets
Other	Other
Private Equity	Alternative Assets
Real Estate	Real Estate
Real Estate - Equity	Real Estate
Real Estate - Mortgage	Real Estate
Short-Term	Cash and Other Investments
Timber	Alternative Assets
Various	
Venture Capital	Alternative Assets

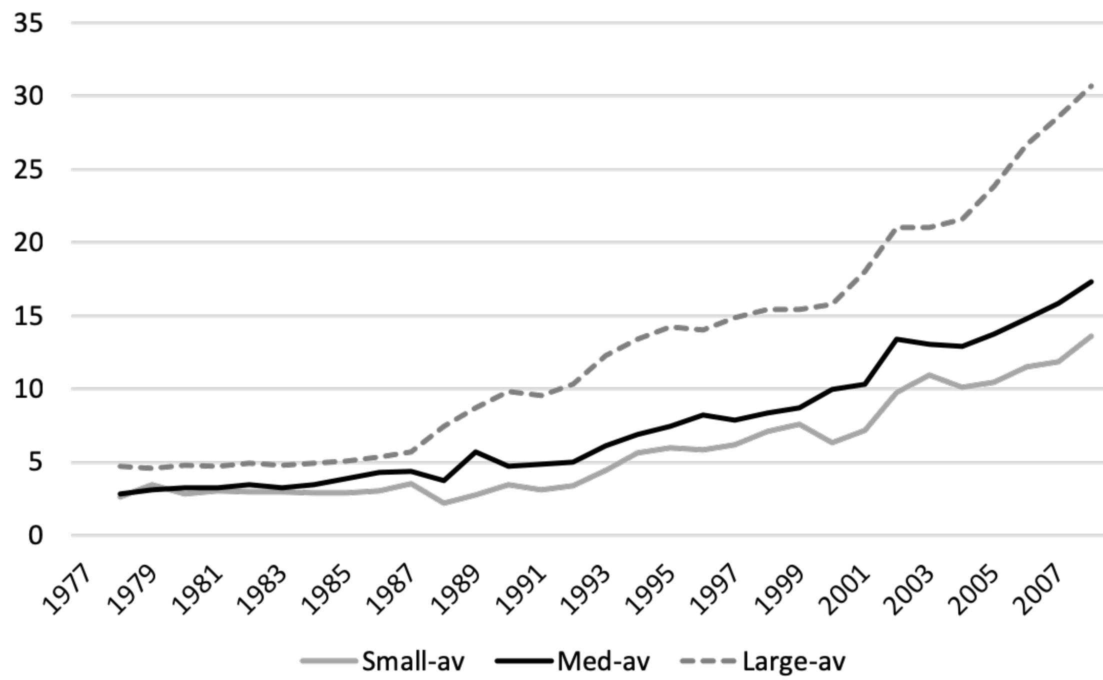

Figure 4: Average number of managers employed by endowment size

II. Robustness Checks

In this section, I check the robustness of the manager commonality result (Table 6) by transforming the control variables, and the robustness of the peers hiring and firing result (Table 7) with respect to the identification of peer institutions and the choice of regression specification.

With respect to the manager commonality baseline result, I scale the independent variables of market value and university age. Similar to Antón and Polk (2014), I calculate the absolute value of the difference in characteristic percentile ranking across the endowments in the pair. The negative coefficients of the characteristics in Table 10 show that the main result continues to hold.

The baseline regression of the peers hiring and firing result identifies peers with respect to the Chronicle of Higher Education data (which institutions each university considers to be their peers). In Tables 11 (hiring decisions) and 12 (firing decisions) I identify peers with respect to "status" (Carnegie Classification of the university) and size of the endowment - characteristics that determine the commonality of manager appointments in endowment pairs. In this specification, the peer groups are updated every year so that the peer classifications stay constant for every endowment hiring or firing observation (calculated in the current and previous year). Broadly, the results hold under

Table 10: Determinants of Manager Commonality - Ranks
This table reports robustness checks for the regression of the manager commonality measure (number of common managers per pair of endowments scaled by the total number of unique managers employed by the pair) on differences in characteristics of the endowments/universities. The results are reported at three points in time, namely 1984, 1997 and 1997. The market value and age distances are the absolute values of the differences in characteristic percentile rankings across the endowments in the pair. The age of the universities is scaled by a factor of 100 and the distance in miles is scaled by a factor of 100,000. The Status Distance represents a variable of the Carnegie Classification distance between the pair.

	Dependent variable:		
	Scaled Number of Common Managers		
	1984	1997	2008
	(1)	(2)	(3)
Market Value Distance (Ranks)	-0.0102^{***}	-0.0169^{***}	-0.0231^{***}
	(0.0021)	(0.0014)	(0.0005)
Age Distance (Ranks)	-0.0068^{**}	-0.0015	0.0021^{***}
	(0.0028)	(0.0019)	(0.0005)
Geographic Distance	-0.4916^{***}	-0.1250^{**}	-0.1366^{***}
	(0.0990)	(0.0615)	(0.0227)
Status Distance	0.0000	-0.0000^{***}	-0.0004^{***}
	(0.0000)	(0.0000)	(0.0001)
Constant	0.0165^{***}	0.0424^{***}	0.0357^{***}
	(0.0014)	(0.0009)	(0.0004)
Observations	7,497	38,217	152,060
R^2	0.0073	0.0065	0.0145
Adjusted R^2	0.0068	0.0064	0.0145
Residual Std. Error	0.0411	0.0597	0.0449
F Statistic	13.7399^{***}	62.3574^{***}	626.6182^{***}
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

different definitions of peers. However, the identification of peers using the Chronicle of Higher Education data is the preferred model.

Table 11: Peer Effects in the Frequency of Hiring - Alternative Peer Classifications
This table presents robustness checks for the manager hiring decisions of endowments using different definitions of peer institutions. Peers are identified with respect to their size decile in columns 1 and 2, and with respect to their Carnegie Classification (Status) in columns 3 and 4. Columns 1 and 3 regress the number of manager hirings of the endowment on the previous year average of hirings by peer institutions. Columns 2 and 4 regress the number of hirings on a Dummy that takes the value of 1 if peers hired more than all the endowments in the previous period and 0 otherwise. The regressions are for years 1984-2008 and include year fixed effects.

	Dependent variable:			
	Numb. Hired			
	Size	Size	Status	Status
	(1)	(2)	(3)	(4)
Hiring Average by Peers	0.0823***		0.1263***	
	(0.0019)		(0.0063)	
Peer Hiring Dummy		−0.1470***		0.2950***
		(0.0255)		(0.0419)
Change in Market Value	−0.0474***	−0.0402***	−0.0385***	−0.0387***
	(0.0062)	(0.0061)	(0.0087)	(0.0087)
log(Age)	0.2356***	0.3197***	0.2520***	0.3086***
	(0.0121)	(0.0120)	(0.0166)	(0.0164)
lag(Return)	0.0053***	0.0060***	0.0068***	0.0070***
	(0.0010)	(0.0010)	(0.0014)	(0.0014)
Constant	−1.0455***	−1.3420***	−1.0878***	−1.3652***
	(0.0849)	(0.0858)	(0.1186)	(0.1180)
Year FE?	Yes	Yes	Yes	Yes
Observations	15,325	15,325	7,971	7,971
Log Likelihood	−43,942.2700	−44,712.2800	−23,431.7800	−23,603.8100
Akaike Inf. Crit.	87,942.5400	89,482.5600	46,921.5600	47,265.6100
Note:				*p<0.1; **p<0.05; ***p<0.01

I also check the robustness of the results with respect to the specification chosen to model the "count" dependent variable, number of hirings/firings. The Poisson regression assumes that the variance equals the expected value. In order to take into account over-dispersion in the data, I use a quasi-poisson specification (variance is assumed to be a linear function of the mean). The results are reported in Table 13 and show that the baseline result holds under this different estimation.

Table 12: Peer Effects in the Frequency of Firing - Alternative Peer Classifications
This table presents robustness checks for the manager firing decisions of endowments using different definitions of peer institutions. Peers are identified with respect to their size decile in columns 1 and 2, and with respect to their Carnegie Classification (Status) in columns 3 and 4. Columns 1 and 3 regress the number of manager firings of the endowment on the previous year average of firings by peer institutions. Columns 2 and 4 regress the number of firings on a Dummy that takes the value of 1 if peers fired more than all the endowments in the previous period and 0 otherwise. The regressions are for years 1984-2008 and include year fixed effects.

	Dependent variable:			
	Numb. Fired			
	Size	Size	Status	Status
	(1)	(2)	(3)	(4)
Firing Average by Peers	0.0292***		0.0547***	
	(0.0032)		(0.0065)	
Peer Firing Dummy		−0.0035		0.1738***
		(0.0123)		(0.0407)
Change in Market Value	−0.0029	−0.0026*	−0.0026	−0.0025
	(0.0018)	(0.0016)	(0.0022)	(0.0021)
log(Age)	0.3193***	0.3260***	0.3107***	0.3215***
	(0.0150)	(0.0150)	(0.0213)	(0.0212)
lag(Return)	0.0022*	0.0023*	0.0022	0.0023
	(0.0013)	(0.0013)	(0.0018)	(0.0018)
Constant	−1.9069***	−1.9127***	−1.8388***	−1.8919***
	(0.1067)	(0.1069)	(0.1514)	(0.1512)
Year FE?	Yes	Yes	Yes	Yes
Observations	14,707	14,707	7,353	7,353
Log Likelihood	−34,199.9500	−34,240.6600	−17,088.1700	−17,110.2800
Akaike Inf. Crit.	68,455.9000	68,537.3200	34,232.3500	34,276.5500
Note:			*p<0.1; **p<0.05; ***p<0.01	

Lastly, I break down the manager commonality result in different asset classes and time periods in my sample in Table 14. The results seem to be consistent both for equity and fixed income mandates, as well as alternative asset and real estate mandates.

Table 13: Response Times - Poisson Specification
This table reports Poisson regression results of the hiring/firing response times. The dependent variable is the number of years that elapse between a pair of endowments hiring/firing the same external investment manager. The independent variables are the differences in characteristics of endowments/universities per pair, at the time that the second endowment hires the manager in common. The market value and total assets are measured in billions, the age is scaled by a factor of 100 and the distance in miles is scaled by a factor of 1,000. The estimation period for the regressions is 1979-2008. Moreover, the regressions include fixed effects for the year that the first endowment of each pair hired the manager that they have in common.

	Dependent variable:	
	Number of Years Elapsed	
	Hirings	Firings
	(1)	(2)
Market Value Distance	0.050***	−0.022***
	(0.001)	(0.003)
Age Distance	−0.039***	0.011**
	(0.003)	(0.005)
Geographic Distance	0.041***	0.032***
	(0.002)	(0.003)
Total Assets Distance	0.013***	0.108***
	(0.001)	(0.002)
Status Distance	0.032***	0.035***
	(0.001)	(0.002)
Constant	2.209***	2.350***
	(0.024)	(0.027)
Year FE?	Yes	Yes
Observations	138,904	71,304
Log Likelihood	−329,634.500	−170,672.100
Akaike Inf. Crit.	659,339.000	341,414.200
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 14: Determinants of Manager Commonality - Asset Class Breakdown

This table reports results from a regression of the manager commonality measure (number of common managers per pair of endowments scaled by the total number of unique managers employed by the pair) on differences in characteristics of the endowments/universities. The results are reported for the equity/fixed income asset classes and for the alternative assets/real estate asset classes separately. The results are reported at three points in time, namely 1984, 1997 and 2008. The dependent variable is the manager commonality measure and the independent variables are the differences in characteristics of the endowments and corresponding universities. The market value and total assets are measured in billions, the age is scaled by a factor of 100 and the distance in miles is scaled by a factor of 100,000. The Status Distance represents a variable of the Carnegie Classification difference between the pair.

	Dependent variable:				
	Scaled Number of Common Managers				
	1984-EqFI	1997-EqFI	2008-EqFI	1997-AltRE	2008-AltRE
	(1)	(2)	(3)	(4)	(5)
Market Value Distance	−0.0010	−0.0030***	−0.0011***	−0.0075***	−0.0023***
	(0.0016)	(0.0003)	(0.0001)	(0.0009)	(0.0002)
Age Distance	−0.0008	0.0044***	−0.0018***	−0.0076***	0.0006
	(0.0011)	(0.0009)	(0.0004)	(0.0029)	(0.0005)
Geographic Distance	−0.0393***	−0.0194***	0.0103***	−0.0077	−0.0064**
	(0.0066)	(0.0052)	(0.0020)	(0.0169)	(0.0029)
Status Distance	−0.0005	−0.0022***	−0.0004***	−0.0030***	−0.0012***
	(0.0004)	(0.0003)	(0.0001)	(0.0009)	(0.0002)
Constant	0.0117***	0.0372***	0.0284***	0.0702***	0.0273***
	(0.0010)	(0.0008)	(0.0003)	(0.0026)	(0.0005)
Observations	7,497	35,503	146,596	10,009	100,117
R^2	0.0053	0.0045	0.0010	0.0125	0.0023
Adjusted R^2	0.0048	0.0043	0.0010	0.0121	0.0022
Residual Std. Error	0.0411	0.0664	0.0551	0.1192	0.0648
F Statistic	9.9851***	39.7006***	38.3418***	31.6382***	57.4184***
Note:					*p<0.1; **p<0.05; ***p<0.01