University of Cambridge
Judge Business School

Essays in Asset Management:
Long Horizon Investing

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November 18, 2019

This dissertation is submitted for the degree of Doctor of Philosophy

Declaration

This thesis is the result of my own work and includes nothing which is the outcome of work done in collaboration except as declared below and specified in the text.

Chapter 2 "Network Connections in Private Equity Investments of University Endowments" is a sole-authored paper. Chapter 1 "Peer Effects in Investment Manager Selection: Evidence from University Endowments" and Chapter 3 "Are University Endowments Really Long-Term Investors?" are co-authored with my supervisors Dr David Chambers and Prof Elroy Dimson. I was responsible for half of the work in each of these papers.

The thesis is not substantially the same as any that I have submitted, or, is being concurrently submitted for a degree or diploma or other qualification at the University of Cambridge or any other University or similar institution. This dissertation does not exceed the 80,000 word limit set by the Cambridge Judge Business School Degree Committee.

Charikleia Kaffe

Murray Edwards College

November 2019

To my beloved parents

Acknowledgements

I am greatly thankful to my supervisors, Dr David Chambers and Prof Elroy Dimson, for the guidance, encouragement and opportunities to get involved with the academic community they have provided me throughout my time as their student.

I would also like to thank the Finance Faculty at the Judge Business School, and especially Dr Oğuzhan Karakaş, Dr Paul Kattuman, Prof Bart Lambrecht, Prof Raghavendra Rau and Dr Pedro Saffi for their helpful comments on my work and insights about academia. Special thanks is also due to the PhD Programme Administrator Ms Joanna Blakeman for her invaluable administrative and pastoral support throughout the PhD and to Prof Jennifer Howard-Grenville and Prof Stefan Scholtes for their helpful academic advice and guidance as PhD Programme Directors. I also thank Prof George Constantinides for hosting me for a term as a visiting student at the University of Chicago, Booth School of Business. For helpful feedback on my work and stimulating discussions, many thanks goes to fellow PhD colleagues Thilo Kind and Vaska Atta-Darkua.

For providing me with access to data, I thank Ken Redd at NACUBO, John Griswold and Larry Tavares at the Commonfund, Stefano Cirillo at Preqin and Nick Shaw at the Cambridge University Endowment Fund.

I am deeply grateful to the Cambridge Judge Business School (CJBS), the Cambridge Trust George and Marie Vergottis Foundation, the Economic and Social Research Council (ESRC), Murray Edwards College and the Foundation for Education and European Culture for financial and research support throughout my PhD.

Last but not least, my deep and sincere gratitude goes to my beloved family for their continuous and unparalleled love, help and support. This journey would have not been possible without them.

Essays in Asset Management: Long Horizon Investing

Charikleia Kaffe

Abstract

This dissertation consists of three related essays that contribute to the literature on the behavior of institutional investors and particularly endowments - distinctive because of their long horizon.

The vast majority of endowments delegate the management of their assets to external managers. My first essay provides evidence that decisions taken by endowments about their external investment manager appointments (and terminations) are influenced by the behavior of their peers. This analysis exploits a novel hand-collected dataset on U.S. university endowments and their external investment manager appointments across all the main asset classes for each year over 1978-2008. The study documents that endowments are more likely to appoint the same external manager if their peers do so, are more active in hiring and firing managers when their peers are more active and respond faster to hiring and firing decisions by their peers in respect of a given external manager.

The second essay examines the network connections between endowments and Private Equity (PE) managers. Buyout (BO) and Venture Capital (VC) investment networks are examined separately. Using data from 1988 to 2008, I identify the characteristics of the centrally located endowments and managers in the network. While VC networks were more developed than their BO counterparts at the beginning of the sample period, both networks grew denser over time in terms of number of players and connections. The identity of their key institutions (central endowments and managers) stayed the same throughout the period examined. Centrally located managers have better investment returns and win new endowment mandates in subsequent periods. Personal connections between individuals working at endowments and BO firms also play an important role in

manager selection by endowments.

The third essay examines the long-term evolution of the investment strategy of U.S. university endowments, using a unique long-term dataset on characteristics and asset allocations from 1900 to 2016 of twelve important endowments. The analysis documents their early adoption of equity investing in the 1930s and their more recent shift into alternative assets from the 1980s. The essay then considers whether endowments famed for their long horizon exploit this advantage to invest countercyclically during periods of market turbulence. I find that endowments do exhibit countercyclical behaviour, decreasing their allocation to risky assets during the run-up to a crisis and increasing it after the onset of a crisis.

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Introduction

This dissertation consists of three related essays in asset management and long-horizon investing, focusing on the investments of university endowments in the United States. Endowments are distinctive among investors in having long-term investment objectives, consistent with preserving intergenerational equity (Tobin (1974)). The investment styles of endowments have gained increased attention in recent years for their favorable returns and use of alternative assets. The "U.S. Endowment Model", also called the "Yale Model" as it was developed by David Swensen at Yale University, has three main distinctive features: a bias towards equities and equity-like assets, a strong preference for delegating to and selecting idiosyncratic active managers, and a large allocation to alternative assets, including buyouts (BO), venture capital (VC) and hedge funds (Swensen (2009)). This investment style has been copied by many university endowments and other institutional investors since it first appeared.

During the past few decades, plan sponsors have shifted towards a delegated portfolio management model (Blake et al. (2013)). Asset owners choose to have a large portion of their assets managed externally and to award mandates in both public and private markets to specialist investment management firms. The selection of external managers is an important strategic decision for asset owners as it determines their relative performance to their peers. This practice creates a complex network of connections between external managers (who each oversee a portion of the portfolio of an asset owner), and asset owners employing the same investment managers. Such a network allows for interactions between institutions.

My dissertation focuses on a particular class of asset owner, namely endowment funds. I exploit an extensive hand-collected data set on U.S. university endowments to study the factors influencing their external investment manager selection and the evolution of their investment strategy over the long run. The essays contribute to the literature along several dimensions. First, I examine the determinants of external manager selection in public and private markets, including the importance of peer effects. My second essay studies the importance of professional and personal network connections in asset management, with a focus on private markets. The third essay examines the asset allocation strategies of the most important university endowments since the beginning of the 20th century and whether they behave countercyclically around times of financial crises, consistent with their long horizon.

The dissertation is structured as follows:

The first essay provides evidence that the behavior of peer institutions plays a role in decisions by asset owners about external investment manager appointments and terminations. Prior literature has focused on peer effects and herding in security or asset class selection of individual and institutional investors, as well as in strategic corporate decisions. This study is the first to address peer effects when asset owners choose which external investment managers to delegate their portfolio to. This analysis exploits a hand-collected dataset on external investment manager appointments by U.S. university endowments across all the main asset classes, spanning over 30 years (1978-2008). The essay studies the determinants of the commonalities in external manager selection among institutions, the influence of peers in the frequency of manager appointments and terminations, and the determinants of how fast institutions respond to hiring and firing decisions of other institutions.

My main findings are that the more similar endowments are in terms of institutional characteristics (such as Carnegie Classification, geographic location and asset size), the more similar manager appointments they tend to make. Endowments are more likely to hire and fire managers if their peers hired or fired managers with higher frequency in the past. 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. The study shows 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. Overall, the results provide evidence that peer effects play a significant role in the selection of external investment managers by asset owners such as university endowments.

The second essay studies the importance of network connections in asset management by focusing on private investments. I undertake network analysis to examine how endowments and PE managers - Buyouts (BO) and Venture capital (VC) - gain access to each other through their institutional and personal connections. An analysis of delegated portfolio management in a social network context is important because it highlights a crucial yet under-researched topic, namely the ability of institutions to exploit their firm- and individual-level connections in making investment decisions. Network connections are created when endowments give PE managers a portion of their assets to manage. My analysis confirms the shift of endowment portfolios towards PE investments in recent years, both in terms of portfolio asset allocation and increasing number of investment managers used.

There are several important findings in this study. First, endowment centrality relates positively to measures of size, especially for VC networks, while manager centrality relates negatively to measures of asset size and the managers' age, suggesting that the smaller and younger managers are getting hired by the most well-connected endowments. Second, with regards to the network structures, VC networks were more developed than their BO counterparts at the beginning of the sample, both in terms of players and the connections between them. Whilst both networks have grown denser over time, the identity of their key institutions (central endowments and managers) has stayed the same throughout the period examined. In particular, large endowments, supporting old universities with many students tend to stay in a central network location for a prolonged period. Third, network positioning appears important for PE managers. A high manager centrality is related to better investment performance and more subsequent hirings by other university endowments. These results suggest that external PE managers can exploit their position to expand their client base and grow their assets. Fourth, professional and educational connections of individuals working in investment management matter for manager selection in private markets. Endowments are more likely to allocate funds to PE managers if their employees/partners are alumni of the school the endowment supports, or if they have worked in the investment management function of that endowment in the past.

The third essay examines the investment strategy evolution of U.S. university endowments and their investing behavior around the most important financial crises since the beginning of the 20th century. The study uses a unique long-term dataset on endowment characteristics and allocations from 1900 to 2016 of twelve important U.S. university endowments. The evolution of their investment strategy exhibits two major shifts in asset allocation: from bonds to stocks in the 1930s and from stocks to alternative assets in the 1980s. Moreover, the Ivy League schools (and notably, Harvard, Yale, and Princeton) led the way in these asset allocation moves in both eras. I explore the rationale behind these major shifts in investment strategy.

In this essay, I also consider whether these supposedly long-horizon investors behave as such by analyzing their asset allocation responses before and after financial crises. More specifically, I examine their behavior at the time of the six "worst" crises in the U.S. since 1900 as defined by Reinhart and Rogoff (2009): 1906-1907, 1929, 1937, 1973-74, 2000 and 2008. In each episode, I compute the active change in the allocation to "risky assets", defined as equities and alternative assets. I decompose the total change in risky asset allocations into a passive change (due to the overall market movement) and an active change (due to rebalancing decisions taken by the endowment). Typically, during the run-up to a crisis, these endowments actively decrease their risky asset allocation; while after the onset of the crisis, they actively increase the allocation as asset prices fall. This evidence suggests that endowments tend to invest countercyclically, in accordance with their long-term horizon.

The final chapter of the dissertation concludes with some implications of my research to date and suggestions for further research.

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1. Peer Effects in Investment Manager Selection: Evidence from University Endowments

Abstract

This paper provides evidence that the behavior of peer institutions plays a role in decisions by asset owners about external investment manager appointments and terminations. The analysis exploits a novel hand-collected dataset on U.S. university endowments and their external investment manager appointments across all the main asset classes over 30 years. The findings document that endowments are more likely to appoint the same external manager if their peers do so, are more active in hiring and firing managers when their peers are more active and respond faster to hiring and firing decisions by their peers in respect of a given external manager. This study is the first to address peer effects when asset owners choose which external investment managers to delegate their portfolio to.

Keywords: Delegated investment management, manager selection, peer effects, herding, university endowments

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 to which external investment managers to delegate their portfolio. Such an analysis is enabled through a novel hand-collected dataset on university endowment manager appointments spanning over 30 years.

University endowments are entities that manage non-profit 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), 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 the sample in 2008 adopt the external management approach (at least for part of their investment 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 effectively compete against each other on investment performance (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)) for most of the period that

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

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

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) Do 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 find that the more similar endowments are (especially in terms of Carnegie Classification, location and market value), the more likely they are to hire the same managers.[2] Second, I find that endowments are more likely to hire and fire managers if their peers hired or fired managers with higher frequency in the past. 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 their 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 result suggests that endowments track more closely the specific manager hiring and firing behavior of endowments similar to them. Overall, the results provide evidence that peer effects play a significant role in the selection of external investment managers by university endowments.

The rest of the paper is organized 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. Section 5 concludes.

[2]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/.

2 Related Literature

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

There is an extensive literature on institutional and individual investors exploring 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) develop a model showing 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 behavior and skill in mutual funds, while other papers examine herding behavior 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)) or bonds (Cai et al. (2019))). This literature considers herding in the selection of stocks and other securities, while this study addresses herding by asset owners in the selection of external investment managers.

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 trader behavior and returns, and that traders central to the network earn higher returns and trade earlier than peripheral ones. 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. 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) concludes 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.[3] The aforementioned studies measure network connections in an indirect way (for example, through shared attributes such as educational background), since 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 of a firm voluntarily providing 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 and the determinants of commonalities in these choices.

With regards to manager selection and termination decisions in the institutional investor space, Goyal and Wahal (2008) examine plan sponsors and show that the performance of fired managers is no different from the performance of newly hired ones. Therefore the expertise of plan sponsors in

[3] Other related papers falling 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 organization, and Kaustia and Knüpfer (2012) who show that investors are more likely to enter the stock market after their neighbors have enjoyed above average portfolio returns.

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. Lastly, 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, there have been a number of studies of university endowments - the focus of this paper. 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 (2013), Chambers and Dimson (2015), 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 it important to explore their investment manager decisions.[4] Lerner et al. (2008), who investigate the factors behind 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, as examined by Lerner et al. (2007). More recent literature, however, finds that endowments' superior performance is driven mostly from their access to top-performing venture capital partnerships, and disappears after 2000 (Sensoy et al. (2014)). Sensoy et al. (2014) attribute this erosion of endowments' advantages to a maturation of the private equity industry. Moreover, endowments seem to directly benefit from having experts in alternative investments serving on university boards (Binfare et al. (2018)). The literature has also shown that endowments operate in a highly competitive environment and 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 external manager selection is an important strategic decision for asset

[4]Other papers studying endowment risk-taking, spending rules and payouts are Brown et al. (2010), Brown et al. (2014), and Dimmock (2012).

owners such as pension funds and endowments, and make it reasonable to expect that peer effects play a critical role.

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 1977-2008. The main data source of endowment managers are the annual NACUBO reports.[5] After 2008, these reports no longer disclosed this manager information. From this panel data set, I am able to infer all manager hiring and firing events each year from changes in the annual 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

The endowment managers data is hand-collected from a series of annual reports by NACUBO. Since 1970, NACUBO has distributed yearly surveys to university endowments asking questions regarding their investment practices. From 1977-2008, endowments listed their external 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 analyzed in the past.

Table 1 shows the variables included in the NACUBO reports under the "Investment Managers" section each year. External investment manager names are reported from 1977, and asset class breakdown from 1978 onwards. For a smaller part of the sample, the asset class mandates are further refined with the manager's allocation to mandates in the US or internationally from 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"

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

represents mandates such as large cap or small cap 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. Lastly, for 1995-2005, the "% of pool" represents the percentage of the investment portfolio delegated to each manager.

Despite participating in the NACUBO surveys, not all university endowments report their external investment managers in the "Investment Managers" section. Table A.1 in the Appendix reports the yearly percentage of institutions reporting their managers. I identify a university as not reporting managers if it reports its annual market value in the NACUBO report, but declines to respond to the "Investment Managers" section of the report. Universities managing their assets internally (for all or part of their mandates) tend to also indicate this in the "Investment Managers" section. Through the sample period, the proportion of universities reporting every year ranges from 81% to 98%. There also seems to be no selection bias in terms of size of those endowments that disclose their managers.

The asset class categories and mandates are sometimes reported differently throughout the sample. Therefore, to keep the sample consistent through time and make sure 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 A.2 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 asset classes minimizes these reporting biases. Last, I take into account 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). In these cases, I identify the hirings and firings using only the manager names from the consecutive reports.[7]

The NACUBO data also contains yearly cross-sectional characteristics of the endowment port-

[7] For example, let us consider an endowment that changes its mandate reporting from Balanced to Stock/Bonds. If Manager A was employed by the endowment for a Balanced mandate in 1998 and is still employed by it in 1999 under a Stock and Bond mandate, then I identify no hiring/firing decision.

folios such as market values, asset allocation and nominal returns.[8] 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 survey has a very high annual rate of compliance by endowments (Goetzmann and Oster (2012)). However, very large elite institutions such as the Ivy League Schools stopped reporting their managers in the "Investment Management" section of the NACUBO reports in 1998.

IPEDS

I source data on the characteristics of the universities which own endowments from IPEDS.[9] The data includes university-specific variables such as the name of the university, Zip Code, state, Carnegie Classification, 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 failing to provide information are barred from accessing federal funding (Brown et al. (2012)).

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 which consider it to be their peer and the overlap of these two lists.[10] This data provides a helpful indication of peer relationships or aspirations of peer classifications among U.S. universities, as reported by the universities themselves.

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

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

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

Investment Manager Datasets

For part of my analysis, I match the managers to the Informa PSN Enterprise database on institutional managers, which is free from survivorship bias. 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.[11] This dataset is primarily used by plan sponsors and consultants to track the performance of external investment managers and by these managers themselves to compare their performance to their peers (Heisler et al. (2007)). For each manager, 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. 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 styles) and match this performance to the corresponding endowment manager.[12] I also source other manager characteristics such as the fund location (state and Zip Code), the date 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 datasets, such as the Broadridge Marketplace and the Nelson's Directory of Investment 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 which starts at 110 and rises to 722 in number. The average endowment in 2008 was managing around US$300 million, but the underlying dispersion in endowment size is large. For example, in 2008 Harvard was managing US$36 billion while Georgia Perimeter College was managing only around US$600,000. 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

[11] See Busse et al. (2010) for more details on the data.

[12] I create the composites because the variation in the performance of the products of the same manager for the same mandate is low.

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". 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)).

Figure 1 classifies institutions into "Ivy League" schools, "Doctoral" Carnegie classification schools, and the remaining "Non-Doctoral" 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 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).[13] Table 3 shows that endowments, on average, manage less than 10% of their AUM internally and hence delegate 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 late 1970s and early 1980s, 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 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 upward trend 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 analyzed next to the number of investment firms employed to manage these asset classes.

I examine whether endowments have any tendency to select "local" external managers. This result relates to a large literature 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

[13]The size classifications of the endowments and the relevant Figure A.1 can be found in the Appendix.

investment within the U.S. market, whereby U.S. investment managers exhibit a strong preference for equities of local firms.[14] Table 4 summarizes the average distance of the endowment from the headquarters of the equity managers it selects (Endowment Manager Average Distance) compared to average distances of all available managers they could have selected (Benchmark Managers Average Distance). Table 4 shows that, on average, endowments choose managers they are geographically closer to, and that the differences in average distances are statistically significant. 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. There exist several potential reasons why geographic closeness to the selected managers might matter for endowments. An explanation could be that endowments' information set about the availability and skill of potential managers is better locally, due to better access to local information, a raised sense of trust or a better ability of the endowment to assess local managers. Another reason could be that endowments, being institutions with a social purpose, might face political (or student) pressure to invest locally. This might be particularly true for endowments of public institutions (similar to Hochberg and Rauh (2013) that examine public pension funds). In unreported results, I split the sample into private and public institutions. I find that after 2000 (where I have a large number of public universities reporting compared to the beginning of the period), home bias effects of the same level are prevalent in both public and private institutions. This result gives support to the information/trust channel for the home bias effect.

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 (every second year is reported 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 11 or more 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.

[14] Other papers on home bias: Portes and Rey (2005) show that investors not only over-invest in their home equity market but they also invest most heavily in markets 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 the sample. Endowments learn about the hiring and firing decisions of their peers through the NACUBO reports, the financial press and personal connections, and can be influenced by their choices.[15] 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 given year if, conditional on the university reporting managers in the Investment Managers section of the NACUBO report the same 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 each 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 driving the commonality in managers selected by any pair 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:

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

[15] Participating institutions in the NACUBO survey receive complimentary access to full reports and receive access to institutionally specific confidential data.

Similar measures of commonality have been used in the finance literature to calculate common ownership of stocks and overlapping holdings by mutual funds (see Antón and Polk (2014) and Pool et al. (2015)).

Table 5 reports summary statistics of the number of common managers and the proportion of manager commonality in endowment pairs. The average number of common managers across all pairs has gone up over time and has a very high dispersion (ranges from 0 to 20 managers in some endowment pairs). The average number of common managers for equity and fixed income in 2008 is high at 0.37, considering that this average is calculated from all possible pairs of endowments. The proportion 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. The average proportion of portfolio commonality is around 0.05 for the reasons explained above, but ranges from 0 to 0.75 for some endowment pairs.

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 their relative 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, which specifies the internal point latitude and longitude for all Zip Code tabulation areas in the United States.[16] 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 both 0 Carnegie Classification (both are Doctoral institutions) and about 173 miles apart (great-circle distance).

The regression specification is the following:

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

$$Proportion\,of\,Manager\,Commonality_{i,j} = a + \beta_1 * MV\,Dist_{i,j} + \beta_2 * Age\,Dist_{i,j} + \\ + \beta_3 * Geographic\,Dist_{i,j} + \beta_4 * Status\,Dist_{i,j} + \varepsilon_{i,j} \quad (2)$$

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 are the common managers they tend to employ for their portfolios. For example, 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 100 managers (holding everything else constant). The characteristics which have stayed important as determinants of manager commonality over time are the geographic location, the market value of the endowment, as well as the Carnegie Classification ("Status").

One might argue that the commonality in managers could be driven by a specific asset class in endowments' portfolios, and more particularly by the illiquid investments that might be more resistant to being switched than the liquid ones. To alleviate this concern, in Table A.3, I break down the manager commonality result in liquid asset classes (equity and fixed income), and illiquid asset classes (alternative assets such as private equity and hedge funds). The commonality in manager appointments seems prevalent both in liquid as well as illiquid asset classes. To reinforce my result, I also substitute the numerical values of the market value and age distances with their difference in percentile rankings of the variables, in a way similar to Antón and Polk (2014).[17] Table A.4 of the Appendix shows that the baseline results of the regression seem to hold even under this reasonable scaling of the explanatory variables.

Overall, the regression analysis shows that commonality in manager appointments by endowments is associated with similarities in their institutional characteristics.

[17] Along the same lines, Antón and Polk (2014) measure stock similarities through differences in stocks' percentile rankings on particular firm 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 each 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 resembling 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, endowment and time fixed effects. The specification I use is the following:

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

The data from the Chronicle of Higher Education is used to identify peer institutions, as it contains the names of peer universities for every university, as reported by the institutions themselves. Other peer-matching techniques in the literature that rely on a variety of observable institutional characteristics might be insufficient for our purposes. Correctly identifying the network is crucial, especially for educational institutions such as endowments, that do not only have financial but also social and other goals (such as reputation, social responsibility, support for education, etc.). Therefore, I consider the network derived from the Chronicle of Higher Education to be the most accurate, "capture-all" representation of the peer relationships.

The dependent variable in the regressions is the annual number of hirings/firings of external managers, which I can model with a Poisson regression.[19] Therefore, the regression assumes that the

[18] Kaustia and Rantala (2015) study the influence of peers in stock split decisions, and use a dummy explanatory variable 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.

[19] The regression model takes the following form: if x is a vector of independent variables, then Y can be modeled as $log(E(Y/x)) = \alpha + \beta' x$. I perform a chi-squared goodness of fit test on the manager hiring and firing data, and I cannot reject the hypothesis that the data follows a poisson distribution (p-value of the test statistic approaches 1).

dependent variable has a Poisson distribution, and that the logarithm of its expected value can be modeled by a linear combination of unknown parameters.[20] In separate regressions, I also replace the Peer Hiring/Firing Dummy with the average number of managers hired/fired by peers during the previous year. Control variables include the change in endowment market value and its age, as well as investment return during the previous year.

The one-year lag in the decision to hire/fire managers takes care of the influence of contemporaneous common shocks to endowments. I also include control variables related to the decision of the endowment to hire or fire, such as the change in the market value of the endowment as well as its past financial performance. Therefore, the coefficient of the peer hiring/firing variable identifies a peer effect on the propensity to hire/fire, under the assumption that other motives for hiring/fire are controlled for. Year and endowment fixed effects included in the regressions also take into account all common time-varying shocks affecting the perceived desirability of a hiring/firing, as well as unobserved endowment-specific characteristics.

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 10% (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 hire one more manager than average one year will increase manager hirings by around 2% the next year. The regression results for the firing decisions have similar interpretations.[21]

[20]Examples of studies using 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.

[21]The asset classes examined are both liquid (equity and bonds) and illiquid (private equity and hedge funds). I appreciate that peer effects could be of different importance among these classes due to the characteristics of their respective assets. While following peers in liquid asset classes could be straightforward, to do so following other endowments in illiquid asset classes might not always be feasible because of barriers to replication (constrains in investment in these PE funds). However, such a possibility would bias my results against finding a peer effect in these asset classes. Moreover, endowment decision clustering around firing decisions could appear as PE or VC funds reach

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 endowments take to respond after peer hiring or firing decisions of specific managers. For every manager 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 every pair of endowments/universities in the year the second endowment in a pair 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. When survival data are right-censored, two of the most frequently used regression models are the relative risk model (Cox (1972)) and the accelerated failure time (AFT) model (e.g., Kalbfleisch and Prentice (2002)). Survival-type analyses have originated in the field of biostatistics but have been used in various settings in the finance literature to model issues like bank failure or IPO survival (Lane et al. (1986), Hensler et al. (1997), Evrensel (2008)). The AFT model is appealing in my setting because it is analogous to the classical linear regression approach, directly linking the expected time to event (hiring/firing) to covariates. The regression specification is the following:

$$T_i = X_i^T \beta + \epsilon_i \tag{4}$$

where T is the log-transformed time to event (hiring/firing), X is the covariates vector, β is the vector of the regression parameters and ϵ_i is idd. 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

maturity and do not get re-invested into by all endowments. Although this might be true in some cases, endowments could also exit a PE investment through a secondary market transaction, which would also create a firing event in my dataset. Therefore, clustering due to fund liquidations would be mitigated.

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 less time they take to respond to manager hiring and firing of other institutions. For example, if the "geographical distance" between the endowments decreases by one standard deviation, the manager hiring response time drops by 16%. The remaining regression coefficients have similar interpretations, and these effects are stronger in hiring decisions than in firing decisions. This result is consistent with endowments following closely the decisions of their peers in order to find attractive managers, but behaving more idiosyncratically when firing managers after having worked with them in the past.

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

5 Conclusion

This paper uses unique long-term data on university endowments to examine the role of peer effects in their decisions about 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 manager hiring and firing decisions of endowments in their peer groups. The results support the existence of peer effects in university endowments' decisions about external investment managers.

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

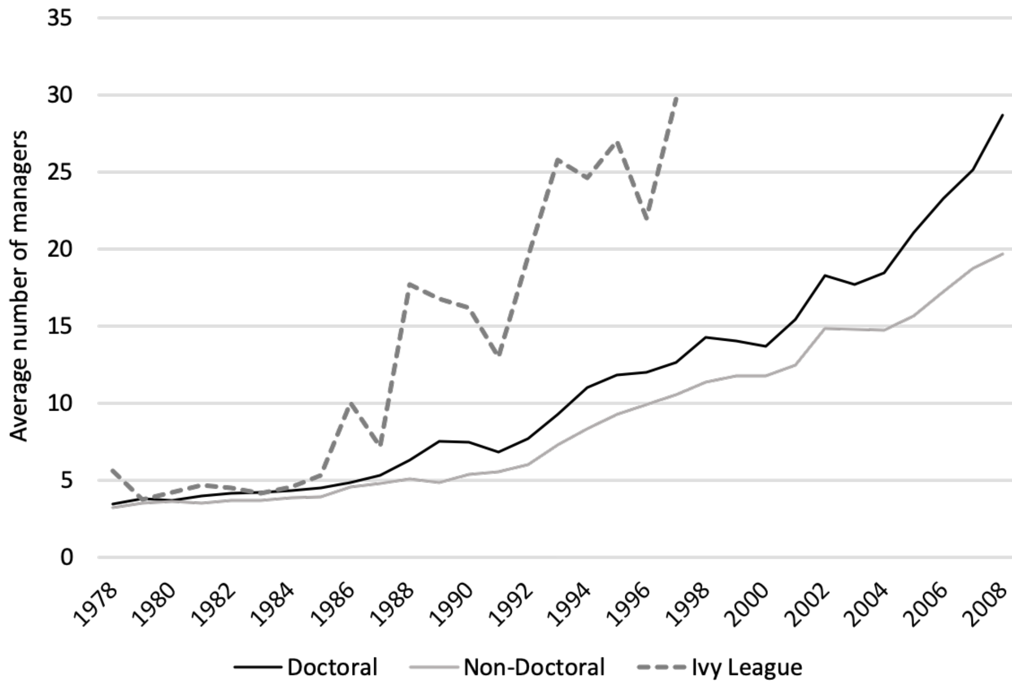

Figure 1: Average number of managers employed by university endowments for 1978-2008

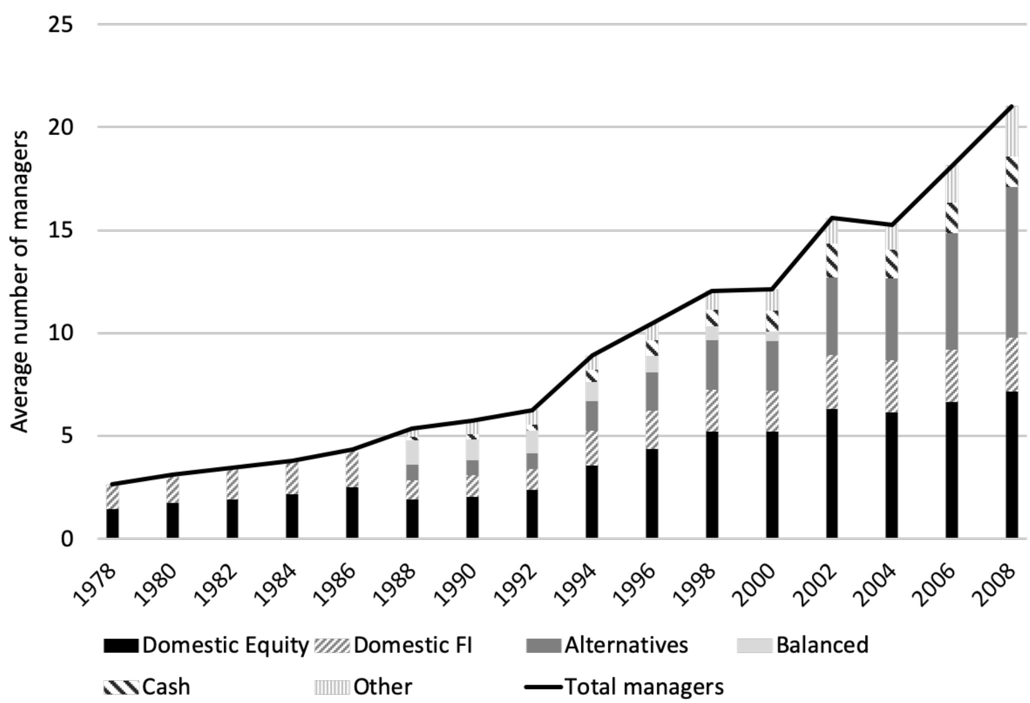

Figure 2: Average number of managers employed by asset class

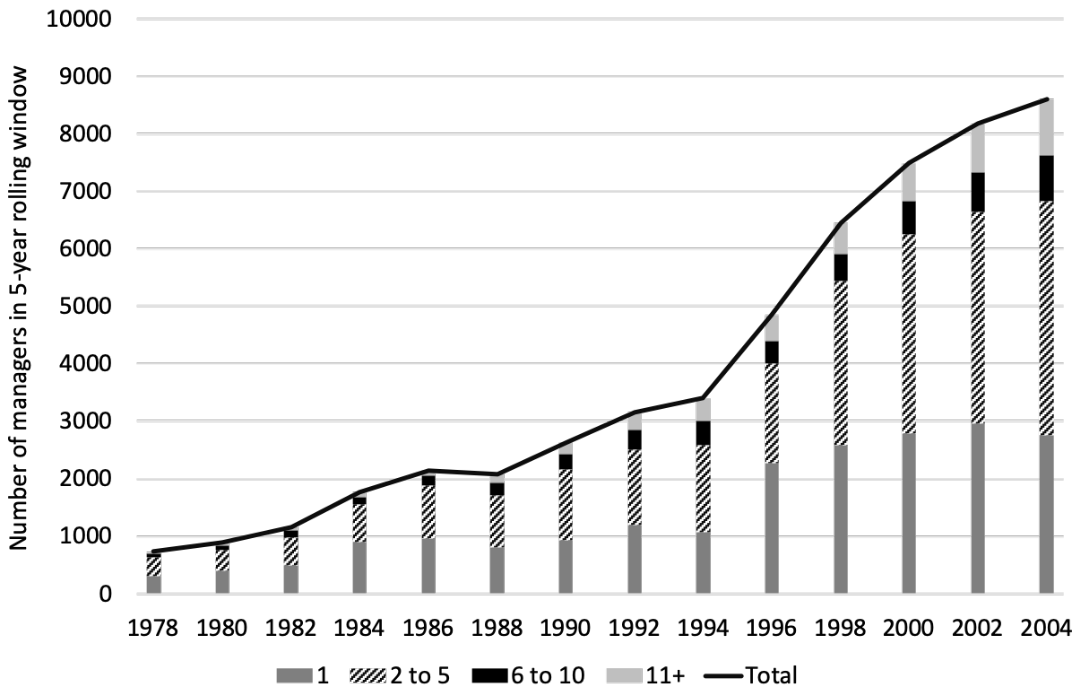

Figure 3: Number of managers hired by multiple endowments (5-year rolling windows)

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" reveals whether the external manager mandate is U.S. (Domestic), International or Foreign. "Type" represents categories such as large cap or small cap for public equities, hedge funds or private equity for alternative investments. "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 endowment fund 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 (measured in thousand dollars), the average age (measured in years), the percentage of the universities that belong to the Doctoral Carnegie Classification (offer PhD degrees), 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 percentage delegated by endowments to external managers in the four main asset classes, as well as the average percentage managed internally. Equity and Fixed Income include both domestic and international mandates, and alternative assets inlcude private equity (buyouts and venture capital) and hedge funds. 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 that they employ (Endw. Man. Avg. Distance) and the equity managers in their benchmark (Bench. Man. Avg. Distance), as well as the differences of the distances and their significance for every year through 1992-2008. The geographic location distances are calculated through the haversine formula which determines the great-circle distance between two points on a sphere given their longitudes and latitudes. T-statistics and p-values of the test that the average distance of the managers employed by the endowment is different than the average distance of the managers in its benchmark are reported in the last two columns.

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

Table 5: Commonality Variables Summary Statistics

This table reports summary statistics for manager commonality 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
Proportion of manager 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 proportion of manager commonality measure (number of common managers per pair of endowments scaled by the total number of unique managers employed by the pair) on the differences in characteristics of the endowments and their respective universities. The results are reported at three points in time, namely 1984, 1997 and 2008. The market value and total assets of the endowment are measured in billions, the age is measured in years and is scaled by a factor of 100, and the distance is measured in miles and is scaled by a factor of 100,000. The Status Distance represents a variable of the Carnegie Classification (degree levels that universities offer) difference between each endowment pair. The yearly regressions include endowment fixed effects. Standard errors are reported in the parentheses.

	Dependent variable:		
	Scaled Number of Common Managers		
	1984	1997	2008
	(1)	(2)	(3)
Market Value Distance	-0.005	-0.004^{***}	-0.002^{***}
	(0.004)	(0.001)	(0.0003)
Age Distance	0.0004	0.002^{*}	-0.003^{***}
	(0.002)	(0.001)	(0.0004)
Geographic Distance	-0.036^{***}	-0.033^{***}	-0.003^{**}
	(0.007)	(0.004)	(0.001)
Status Distance	-0.0003	-0.001^{***}	-0.001^{***}
	(0.001)	(0.0003)	(0.0001)
Constant	0.005	0.009	0.003
	(0.042)	(0.055)	(0.039)
Endw FE?	Yes	Yes	Yes
Observations	3,729	20,194	80,402
R^2	0.051	0.194	0.144
Adjusted R^2	0.021	0.183	0.138
Residual Std. Error	0.042	0.055	0.039
F Statistic	1.687^{***}	17.986^{***}	25.252^{***}
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 the hiring and firing peer effects for peer institutions as reported by the institutions themselves (Chronicle of Higher Education data). Columns 1-4 estimate Poisson regressions of the count variable (number of hirings and firings). Columns 1 and 2 regress the number of hirings/firings on a Dummy that is 1 if peers hired/fired more than all the endowments in the previours period and 0 otherwise. Columns 3 and 4 regress the number of hirings/firings on the previous year's average of hirings/firings by peer institutions. The Market Value is measured in thousand dollars, Age in years, and lag(Return) is the previous year's return. The regressions are for years 1984-2008, include year and endowment fixed effects, and standard errors are clustered by time.

	Dependent variable:			
	Numb. Hired	Numb. Fired	Numb. Hired	Numb. Fired
	(1)	(2)	(3)	(4)
Peer Hiring D	0.1055^{***}			
	(0.0245)			
Peer Firing D		0.0571^{**}		
		(0.0253)		
Peer Hiring Average			0.0118^{***}	
			(0.0043)	
Peer Firing Average				0.0332^{***}
				(0.0071)
Change in Market Value	-0.0614^{***}	0.0019	-0.0618^{***}	0.0003
	(0.0093)	(0.0054)	(0.0093)	(0.0053)
log(Age)	0.6642	1.1744^{**}	0.6605	1.1372^{**}
	(0.4440)	(0.5574)	(0.4443)	(0.5565)
lag(Return)	-0.0051^{***}	-0.0044^{*}	-0.0048^{**}	-0.0045^{*}
	(0.0020)	(0.0024)	(0.0020)	(0.0024)
Constant	-3.3505^{*}	-5.9862^{**}	-3.3359^{*}	-5.7948^{**}
	(1.9759)	(2.4810)	(1.9772)	(2.4772)
Year FE?	Yes	Yes	Yes	Yes
Endw FE?	Yes	Yes	Yes	Yes
Observations	5,117	5,117	5,117	5,117
Log Likelihood	−11,643.1800	−10,235.4600	−11,648.7900	−10,227.2600
Akaike Inf. Crit.	24,320.3500	21,504.9200	24,331.5800	21,488.5200

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 measured in years and is scaled by a factor of 100 and the distance is measured in miles and is scaled by a factor of 1,000. The estimation period for the regressions is 1979-2008, and the specifications include year fixed effects (for the year that the second endowment hires or fires the common manager). Standard errors are clustered by time.

	Dependent variable:	
	Years Elapsed Hirings	Years Elapsed Firings
	(1)	(2)
Market Value Distance	0.017***	0.0003
	(0.002)	(0.004)
Age Distance	0.013**	0.018**
	(0.006)	(0.009)
Geographic Distance	0.152***	0.074
	(0.034)	(0.048)
Total Assets Distance	0.00003***	0.00004***
	(0.00000)	(0.00000)
Status Distance	0.006***	−0.017***
	(0.002)	(0.003)
Constant	0.904***	6.199***
	(0.006)	(0.014)
Year FE?	Yes	Yes
Observations	138,904	71,304
Log Likelihood	−323,010	−164,690
χ^2	447***	4,099***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix

A. Data Classifications

Investment Manager Reporting

Most universities that participate in the NACUBO study report their external investment managers in the "Investment Managers" section of the NACUBO report. I can identify a university as choosing not to report its investment managers when I can find market values reported in the same report, but I do not find the university in the "Investment Managers" section of the same report.

Table A.1 calculates the percentage of universities (from the ones that report in NACUBO), that also report in the "Investment Managers" section. Throughout the sample, the majority of the universities per year report in this section (the total reporting percentage every year ranges from 81% to 98%). This observation is consistent throughout the years of my sample as well as the different market value categories. The only category with relatively low percentage reporting was the one with the highest market value (more than $1 bil) during the early 2000s for three years.

Asset Class Transformations

I classify each asset class under a broader category according to Table A.2.

Market Value Categories

I source endowment market values from NACUBO - universities participating in the annual surveys contribute the size of their endowment assets. This 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).

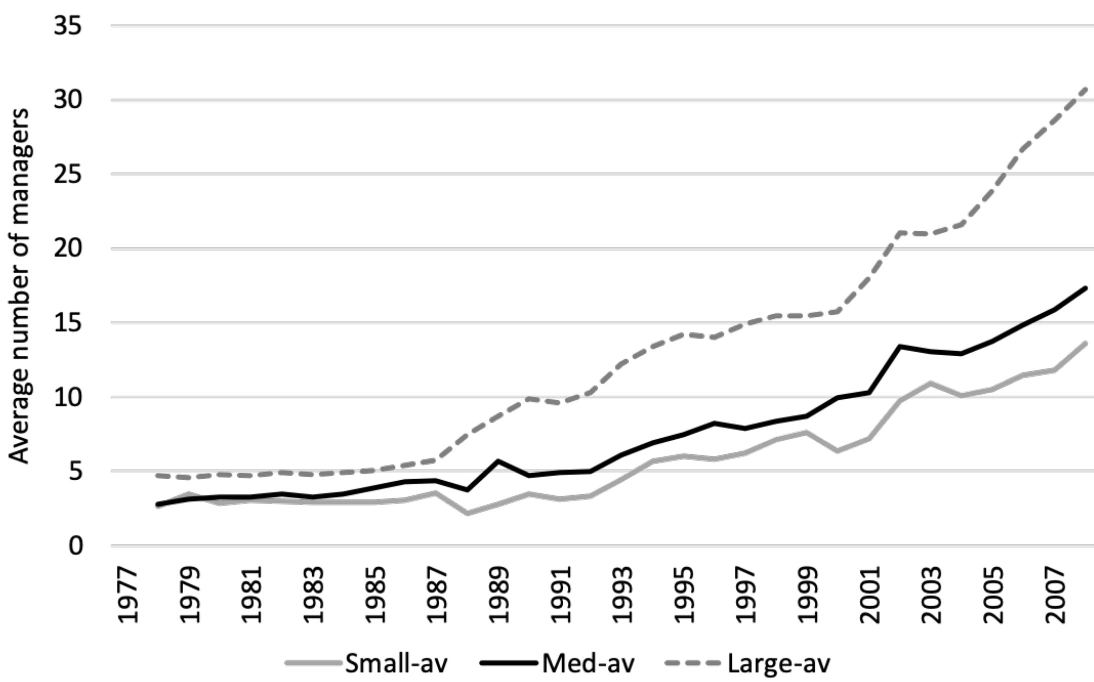

Figure A.1: Average number of managers employed by endowment size

Table A.1: Percentage of endowments that report in the NACUBO Investment Managers Section

This table calculates the percentage of endowments that report investment managers in the Investment Managers section of the NACUBO reports. I identify an endowment as reporting in general in the NACUBO report if it reports its market value. I identify an endowment as not reporting in the Investment Managers section if it reports its market value but not its external managers.

Year	Fraction Reporting	>1 bil ($)	500 m - 1 bil ($)	100 m - 500 m ($)	<100 m ($)
1988	0.85	0.80	1.00	0.93	0.82
1993	0.92	0.69	0.79	0.95	0.93
1994	0.95	0.88	1.00	0.95	0.95
1995	0.95	0.82	0.90	0.98	0.95
1996	0.90	0.75	0.93	0.90	0.91
1997	0.93	0.88	0.89	0.94	0.93
1998	0.94	0.87	0.93	0.95	0.93
1999	0.81	0.62	0.81	0.83	0.83
2000	0.89	0.55	0.87	0.94	0.91
2001	0.95	0.66	0.96	0.96	0.98
2002	0.96	0.85	0.93	0.97	0.98
2003	0.96	0.82	0.94	0.97	0.97
2004	0.96	0.83	0.96	0.96	0.98
2005	0.97	0.82	0.98	0.97	0.99
2006	0.97	0.82	0.98	0.97	1.00
2007	0.98	0.91	0.98	0.98	1.00
2008	0.96	0.84	0.92	0.97	0.98

Table A.2: Asset Class Transformations

This table reports the asset allocation re-classifications of the data, to ease the 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

Table A.3: Determinants of Manager Commonality - Asset Class Breakdown

This table reports results from a regression of the manager commonality measure on differences in characteristics of the endowments/universities. The proportion of manager commonality measure is defined as the number of common managers per pair of endowments scaled by the total number of unique managers employed by the pair. 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. The regressions include endowment fixed effects.

	Dependent variable:				
	Proportion of Manager Commonality				
	1984-EqFI	1997-EqFI	2008-EqFI	1997-AltRE	2008-AltRE
	(1)	(2)	(3)	(4)	(5)
Market Value Distance	-0.001	-0.003^{***}	-0.001^{***}	-0.008^{***}	-0.002^{***}
	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)
Age Distance	-0.001	0.004^{***}	-0.002^{***}	-0.008^{***}	0.001
	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)
Geographic Distance	-0.039^{***}	-0.019^{***}	0.010^{***}	-0.008	-0.006^{**}
	(0.007)	(0.005)	(0.002)	(0.017)	(0.003)
Status Distance	-0.001	-0.002^{***}	-0.000^{***}	-0.003^{***}	-0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Constant	0.012^{***}	0.037^{***}	0.028^{***}	0.070^{***}	0.027^{***}
	(0.001)	(0.001)	(0.000)	(0.003)	(0.001)
Endw FE?	Yes	Yes	Yes	Yes	Yes
Observations	7,497	35,503	146,596	10,009	100,117
Adjusted R^2	0.0048	0.0043	0.0010	0.0121	0.0022
Residual Std. Error	0.041	0.066	0.055	0.119	0.065
F Statistic	9.98^{***}	39.70^{***}	38.34^{***}	31.64^{***}	57.42^{***}

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

Table A.4: Determinants of Manager Commonality - Ranks

This table reports robustness checks for the regression of the manager commonality measure on differences in characteristics of the endowments/universities. The proportion of manager commonality measure is defined as the number of common managers per pair of endowments scaled by the total number of unique managers employed by the pair. The results are reported at three points in time, namely 1984, 1997 and 1997. The dependent variable is the manager commonality measure and the independent variables are the differences in characteristics of the endowments and universities. The dependent variables are the absolute values of the differences in endowment characteristics such as market value (measured in $US billions - percentile rank), age (measured in years - percentile rank), geographic distance (measured in miles). The Status Distance is the Carnegie Classification (types of degrees the university offers) distance between the pair. The regressions include endowment fixed effects and standard errors are reported in the parentheses.

	Dependent variable:		
	Proportion of Manager Commonality		
	1984	1997	2008
	(1)	(2)	(3)
Market Value Distance (Ranks)	-0.0121^{***}	-0.0161^{***}	-0.0200^{***}
	(0.0022)	(0.0014)	(0.0005)
Age Distance (Ranks)	-0.0063^{**}	-0.0022	0.0010^{**}
	(0.0029)	(0.0018)	(0.0005)
Geographic Distance	-0.4325^{***}	-0.1209^{**}	-0.0831^{***}
	(0.1009)	(0.0573)	(0.0216)
Status Distance	0.0000	-0.0000^{***}	-0.0051
	(0.0000)	(0.0000)	(0.0211)
Constant	0.0067	0.0071	0.0175
	(0.0407)	(0.0550)	(0.0213)
Endw FE?	Yes	Yes	Yes
Observations	7,497	37,939	170,219
R^2	0.0415	0.1852	0.1303
Adjusted R^2	0.0260	0.1794	0.1273
Residual Std. Error	0.0407	0.0550	0.0422
F Statistic	2.6821^{***}	31.9582^{***}	44.5718^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

2. Network Connections in Private Equity Investments of University Endowments

Abstract

In a social network setting, this paper examines how endowments and Private Equity (PE) managers gain access to each other through their institutional and personal connections. Buyout (BO) and Venture Capital (VC) investment networks are examined separately. Using data from 1988 to 2008, I identify the characteristics of the centrally located endowments and managers in the network. While VC networks were more developed at the beginning of the sample than their BO counterparts in terms of number of players and connections between them, both networks have grown denser over time. However, the identity of their key institutions (central endowments and managers) has stayed the same throughout the period examined. Centrally located managers have better investment returns and win new endowment mandates in subsequent periods. Personal connections between individuals working at endowments and PE firms also play an important role in manager selection by endowments.

Keywords: Endowments, Networks, Private Equity, Buyouts, Venture Capital

1 Introduction

University endowments are a class of institutional investors with a very long-term investment horizon. In the recent past, endowments have shifted their investment portfolios away from "traditional" investments in public equities and bonds, in favor of "alternative" assets such as private equity (PE) and hedge funds. This investment style, called the "US endowment model" or "Yale model" (as David Swensen developed it at Yale University) has been copied by many university endowments and other institutional investors since the 1980s.

The rising importance of PE investments for endowments can be attributed to several factors. Such investments allow endowments to exploit their long-term horizon and flexible spending needs to harvest the illiquidity premia of private assets, or to identify and gain access to outperforming managers given that private equity markets are less efficient than public markets (Swensen (2009)). PE investments could be particularly crucial for endowments, which are large institutions with an excellent reputation and alumni networks, as their connections could provide them with easier access to top-performing managers than other types of investors (Lerner et al. (2008)).

During the past few decades, endowments and other plan sponsors have shifted towards a "decentralized" norm in delegated portfolio management.[1] Plan sponsors such as endowments allocate mandates (including PE) to various external investment management firms. This creates a complex network of connections between managers who each oversee a portion of the investment portfolio of an endowment, and between endowments employing the same investment managers. Such a network allows the potential for interactions between institutions.

My paper brings evidence of the importance of networks in asset management. Exploiting a unique database that contains a long time-series and cross-section, I examine the connectedness between university endowments and PE firms. I split investments into Buyout (BO) and Venture Capital (VC) networks and examine them separately to see whether BO or VC networks behave differently. This might be the case as VC is generally viewed as being dominated by the top-performing firms and because of previous research on VC networks (see Hochberg et al. (2007) and Hochberg et al. (2010)). Therefore, I hypothesize that VC firms are not going to connect with BO firms either directly or indirectly via an endowment. I explore the structure of relationships in the

[1] Blake et al. (2013) investigate the shift towards decentralized investment management for pension funds.

endowment-manager network and its evolution over time, and the determinants of central network positioning for endowments and PE firms. I also hypothesize that central location of PE firms (which represents exposure to centrally-located endowments), benefits their investment returns and asset growth in terms of winning new endowment mandates. Last, I investigate social networks of individuals working in investment management (endowment trustees and PE portfolio managers) and examine whether personal connections mapped through education or common past employment play a role in PE investment selection by endowments.

Previous work has shown that endowments, especially those of the Ivy League educational institutions, possess superior investment selection ability, especially in PE. According to Lerner et al. (2008), top endowments might have superior ability to select and access managers, as higher endowment returns accompanied the shift towards alternative investments. However, the literature has not been able to pinpoint the channel through which endowments make successful investments, although qualitative evidence has suggested that they benefit from the superior choices of their investment committees (Lerner et al. (2008)). Regarding their manager selection for private investments, Yale states in their 2018 endowment report that:

> Yale's venture capital program, one of the first of its kind, is regarded as among the best in the institutional investment community; the University is frequently cited as a role model by other investors. [...] The University's venture capital portfolio contains an unparalleled set of manager relationships, significant market knowledge, and an extensive network.

My paper uses network analysis and graph theory to study the external PE manager appointments of university endowments over the course of 20 years, 1988-2008.[2] One prior study of managers and plan sponsors in public equities has suggested that central positioning in a network helps managers receive information about their competitors, which leads to better investment performance (Rossi et al. (2018)). My paper uses U.S. data on endowments and their external PE managers to explore a similar question. This research question is of particular interest as PE investments, due to their nature of being executed in private markets, are less easily replicated and more likely to arise through network connections between firms or individuals than investments in public markets.

[2]The dataset stops in 2008 due to the ceasing of manager reporting after this date. Please refer to Section 3 of the paper for further details.

I identify network connections for endowments and their investment managers in the data in three different ways. First, each endowment connects with an external PE (BO or VC) manager whenever it gives them a portion of their assets to manage. Second, each PE firm manages only a portion of an endowment's overall assets, with sometimes many other firms managing the rest of the portfolio. I therefore map a network between PE managers which each oversee a portion of the same endowment. For example, if a BO Manager A manages a portion of the portfolio for an endowment client who has also hired Manager B, this creates a manager-to-manager connection between Managers A and B. Third, I connect endowments which hire the same PE manager for their respective funds. For example, if a BO firm manages a portion of endowments 1 and 2, this creates a connection between endowments 1 and 2. These measures of network connectedness help illustrate different aspects of the importance of each individual in the network.

My data allows several findings. First, I confirm the already established shift of endowment portfolios towards PE investments, both in terms of portfolio asset allocation and number of investment managers used for PE. I then identify a network of connections for each endowment and manager. I find that endowment centrality relates positively to the market value of the endowment, age and size of the student body of the university, especially for VC networks. Manager centrality relates negatively to measures of asset size of PE managers as well as the manager's age. This suggests that the smaller and younger managers are getting hired by the most well-connected endowments. With regards to the network structure, VC networks were more developed than their BO counterparts at the beginning of the sample (more players and more connections). However, both networks have grown denser over time and their key institutions (central endowments and managers) have stayed the same throughout the period examined. In particular, large endowments, supporting old universities with many students tend to stay in a central network location for a prolonged time.

Second, a central network position of PE managers is related to better investment performance and more subsequent hirings by other university endowments. These results suggest that managers can exploit their position to expand their client base and grow their assets.

Third, professional and educational connections of individuals working in investment management matter for manager selection in private markets. Endowments are more likely to allocate funds to PE managers if their employees/partners went to the same school the endowment supports, or if they have worked in the investment management function of the endowment in the past. This result is consistent with endowments exploiting their superior alumni networks and their top profile to gain access to private investments. This finding expands Binfare et al. (2018), who conclude that expertise in alternatives and larger professional networks are associated with higher allocations to alternatives and better investment results. My paper looks at specific investments in private markets, and how connections between individuals affects their selection.

The paper proceeds as follows. Section 2 discusses the relevant literature of networks, university endowments and PE firms. Section 3 describes the data sources and matching procedure. Section 4 describes the network identification, computes various network measures and examines their evolution. Section 5 investigates endowment and manager centrality measures, their persistence and their influence over subsequent PE manager hirings. Section 6 maps network connections between individuals and examines their role in PE manager selection, and Section 7 concludes.

2 Related Literature

This study contributes to the literature on social networks, delegated portfolio management, private equity investing, and endowments.

The prior literature conjectures that information diffusion through social networks affects investor trading behavior, returns, and corporate governance. There are various channels through social network connections could manifest. These channels can relate to information exchange and reduction of asymmetric information, enhanced sense of trust for specific individuals and companies, as well as lack of attention that leads to limited choice sets.

A number of studies present empirical evidence that social networks play an important role in explaining investors' trading decisions and portfolio returns. Studying information diffusion, Pareek (2009) presents evidence of information linkages between funds with large positions in the same stocks, while Rossi et al. (2018) suggest that network centrality of external equity managers of UK pension plans is positively related to risk-adjusted performance and growth in assets under management.[3] Buraschi and Porchia (2012) find that central firms, with the ability to transfer a distress state to other firms' fundamentals, have higher expected stock returns, while Ozsoylev et al. (2014) add that central investors in terms of information signals trade earlier than peripheral

[3] Other papers on information transfers in the financial markets are Bursztyn et al. (2014) and Garmaise and Moskowitz (2003).

investors. Hong et al. (2004) suggest that measures of sociability relate to increased stock market participation, and Kaustia and Knüpfer (2012) show that investors are more likely to enter the stock market after their neighbors have enjoyed above average portfolio returns. In bond markets, Li and Schürhoff (2019) find that dealers in the over-the-counter municipal market form trading networks with other dealers to mitigate search frictions. Network effects are also industry-wide. Ahern (2013) examines networks of intersectoral trades and finds that stocks in central industries, on average, earn higher returns than stocks in more peripheral industries.

Studying trust and personal connections in corporate boards and governance, Cohen et al. (2008) find that mutual fund managers place larger individual stock bets and generate significantly better performance if their managers are connected with their board members. Kuhnen (2009) finds that directors tend to hire advisory firms they have worked with in the past, while Nguyen (2012) finds that a CEO well-connected with the board of directors is less easily fired after bad performance and is more likely to find a good job later. Bouwman (2011) examines how network effects of directors serving in multiple companies with different governance practices, cause these practices to eventually converge, and Gaspar and Massa (2011) 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 organization. My study follows a different approach to all the foregoing in seeking to identify network connections arriving from the selection of external PE managers by university endowments, in a delegated investment management setting.

Social networks have also gained increased attention in recent studies in economics. There exists expanding literature exploring contagion and cascades especially in the banking sector, and relating institutional networks to issues such as liquidity, defaults and foreign debt holdings (Elliott et al. (2014); Cabrales et al. (2017); Kobayashi and Takaguchi (2018)). Acemoglu et al. (2015) discusses the relationship between the interbank network density and financial stability, and finds that density can enhance financial stability when shocks are small, but can lead to the propagation of large shocks and a more fragile financial system. Moreover, Brunetti et al. (2019) study the interconnectedness of the bank network before and after the financial crisis. These studies suggest that the density and structure of institutional networks are essential for the stability of the banking market.

In the alternative investments space, Hochberg et al. (2007) look at networks of venture capital firms through syndicated investments and find that better-networked firms experience significantly better performance (IPO exits). Moreover, Hochberg et al. (2010) show that incumbent venture capital firms use their networks to restrict the entry of new firms, thereby strengthening their bargaining power over entrepreneurs. In a setting similar to this paper's, Bhagwat (2013) finds that two given VC firms are three times more likely to syndicate an investment if their managers overlapped at an educational institution, and their subsequent investments are associated with better investment outcomes. The prior literature has also studied the evolution of the PE investment space and has discovered patterns pointing to a maturing of the industry. PE returns have changed since the 1990s (see Robinson and Sensoy (2013); Harris et al. (2014)). Venture capital performance has declined substantially, both in absolute terms and relative to public markets, while buyout performance has been less affected. Moreover, despite the fact that PE performance has been highly cyclical (periods of high fundraising have been followed by periods of low performance), Brown et al. (2019) show that investor timing strategies in terms of their capital commitments do not produce substantial gains.

My paper also relates to the literature of delegated investment management as it explores the outsourcing of endowment funds to PE firms. Delegating the investment management of funds has long been established as a feature of plan sponsor behavior (Blake et al. (2013); Rossi et al. (2018)). A similar concept, subadvising funds, is also common in the mutual funds industry (see Debaere and Evans (2014); Chuprinin et al. (2015)). However, studying the delegated investment management of plan sponsors has been difficult due to the lack of data about the investments of these institutions. For this reason, the previous literature has focused on UK funds. My paper uses a hand-collected dataset of PE firms that manage funds for university endowments, which allows me to gain insights about delegated investment management of institutions with long horizons in private markets.

Last, this paper relates closely to the literature on investment strategies of university endowments. David Swensen (2009), the head of the Yale University endowment and a very successful investor in PE, has argued that endowments are better equipped to assess and evaluate investments with severe asymmetric information, such as alternative investments. It is often argued that early movers in the PE industry are at an advantage, with the Yale and Harvard University endowments often cited as examples (see Sensoy et al. (2014) and Swensen (2009)). The Yale endowment explicitly follows a policy of reinvesting in partnerships to maximize its access to future funds (Lerner and Leamon (2004)). Da Rin and Phalippou (2017) suggest that more experienced investors may have learnt over time how to perform more effective due diligence, while Lerner et al. (2007) find that endowments substantially outperform other types of investors on their investments in funds raised between 1991 and 1998, especially in PE partnerships, due to improved access and experience in in-vesting. Binfare et al. (2018) suggest that endowments' expertise in alternatives and their extensive professional networks are associated with higher allocations to alternatives and better investment results. On the other hand, Sensoy et al. (2014) find that the investment advantage of university endowments and their superior returns disappear after 2000 mainly due to the maturation of the PE industry. After 2000, endowments' investing behavior into VC is similarly successful than that of other institutions (Cavagnaro et al. (2019)). Studying the 1991-2011 period, Barber and Wang (2013) conclude that university endowments on average do not exhibit any ability to beat high-level benchmarks through selection or timing skills and that "elite" institutions benefit from higher re-turns on alternative assets. The authors do not, however, develop specific measures of networks or expertise. This paper identifies networks through the selection by endowments of PE firms, and uses theses connections to study the manager selection process of institutions in private markets.

3 Data

My novel data set exploits data on PE (BO and VC) managers for U.S. university endowments from 1988-2008. The data is hand-collected from the "Investment Managers" section of the annual NACUBO reports.[4] For each university endowment, I source the names of the investment management firms employed every year to manage mandates, as well as the types of mandates (BO or VC) and sub-mandates used (for example, Distressed Securities or Multi-Strategy). For example, Endowment A in 2000, employs PE Firm X to manage "Private Equity, Distressed Securities". The data starts in 1988 as endowments did not report any investments in PE before this date, and the last year available in the dataset is 2008 as NACUBO's practice of reporting endowment managers (for all asset mandates, including PE) stopped altogether that year.

I source data on the characteristics of the universities which own endowments from IPEDS.[5]

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

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

The data includes university-specific variables such as the name of the university, Zip Code, state, Carnegie Classification, 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.[6]

Despite participating in the NACUBO surveys, not all university endowments report their external investment managers in the "Investment Managers" section. Table A.2 in the Appendix reports the yearly percentage of institutions reporting their managers. I identify a university as not reporting managers if it reports its annual market value in the NACUBO report, but declines to respond to the "Investment Managers" section of the report. Universities managing their assets internally (for all or part of their mandates) tend to also indicate this in the "Investment Managers" section. Through the sample period, the proportion of universities reporting every year ranges from 81% to 98%. There also seems to be no selection bias in terms of size of those endowments that disclose their managers.[7]

Tables 1 to 3 report summary statistics for the university endowments in my sample. The cross section of institutions is large, and ranges from around 260 institutions in the beginning of the sample to 722 universities at the end of the sample. About 30% of the universities belong to the "Doctoral" Carnegie classification (they offer PhD degrees). Table 2 shows that the proportion of the endowments' portfolios allocated to alternative assets has increased substantially over time, especially for the largest funds, at the expense of equity and bond investments. The average number of external managers selected for endowment portfolio mandates has more than tripled over the time period, which depicts the adoption of the delegated investment management practice. The number of PE managers has risen the most over my sample period, a trend which matches the increase of PE allocations in endowment portfolios.

The BO and VC manager data from NACUBO have undergone classification changes during the years of reporting. While the "Venture Capital" mandate has been reported consistently as such during the years available, the classification of Buyouts has changed from LBOs to PE. A detailed report of the different classifications of PE investments for each year can be found in Table A.1.

[6] Providing information through IPEDS is mandatory for all U.S. post-secondary institutions, and institutions failing to provide information are barred from accessing federal funding (Brown et al. (2012)).

[7] I am considering ways to expand the time-series component of the data. A possible route could be to gain access to data on General Partners (GPs) and Limited Partners (LPs), and identify university endowments as some of their LPs (for example, through Cambridge Associates). Expanding the time horizon of the study would also help examine whether the global financial crisis changed the PE investing behavior of endowments. Acquiring a dataset of LP investments resembling that of Cavagnaro et al. (2019) would be beneficial.

To identify cross-sectional and time-series characteristics of the PE firms hired by university endowments, I source data from Thomson Reuters and Preqin, available since 1988. I source characteristics of firms such as their location, age, and the funds they raised over the sample period from Thomson Reuters. I obtain data on PE performance from Preqin. Preqin's dataset provides fund-level measures of performance such as IRRs and multiples, as well as the assets under management of the PE firms.[8] The data provide an accurate match of more than 72% of the PE manager appointments in the NACUBO reports over 1988-2008. As seen in Table 4, the number of firms matched to Thomson Reuters ranges from 148 in the beginning of the period to 362 at the end of the period. Table 4 also presents some of the PE manager characteristics such as the year they were founded, and indicators of their size such as the average number of companies they invest in, their equity per company, as well as the firms' latest fund sizes.

Additionally, to identify university trustees, I match Boardex North America data from 1988-2008 to the university endowments in the sample. I define the trustees of the endowments as individuals whose role titles are related to the endowment's investment management function (e.g. Trustee, CIO or CFO/Treasurer).[9] I source the trustees' education as well as their past employment and achievements through Boardex. About 75% of the universities in the sample can be matched to Boardex. The number of universities reporting individuals in the investment management functions of the endowment is 138 (23%) and the number of distinct individuals between 1988 and 2008 is 225. The average appointment duration for a trustee of an endowment is 6.5 years, but this number varies considerably. Individuals stay in position between a few months and 33 years. This variable is both left and right-censored since some trustee appointments start before 1988 and finish after 2008. Finally, the universities reporting trustees through Boardex are almost double in asset size ($800k) and in full-time students (7k), and more tilted towards the "Doctoral" Carnegie Classification category than the universities which do not report through Boardex.

[8]Most endowments in my sample do not report the exact fund they invest in, but rather the PE firm name. Therefore, I create performance composites for each PE firm using all its available funds at a given point in time. One concern might be that some PE firms have multiple funds with varying performance across them. In order to mitigate this concern, I observe that the average number of funds that each PE firm has running in any given period is around six, with the majority (60%) of PE firms having between one and four funds.

[9]Lerner et al. (2008) use a similar approach in identifying endowment staff as anyone whose title includes words such as "investment," "endowment," or "asset," or whose titles otherwise indicate direct involvement in endowment management.

I match the Boardex data with the BO firms to identify their portfolio managers. Boardex does not include "Venture Capital" in their firm sectors. Therefore I only use BO firms for this part of the analysis. I can match 60% of the names of BO firms hired by university endowments with Boardex data. I source the characteristics of their portfolio managers such as their past education and achievements, which I use to examine their social network connections with the universities that employ them. Boardex also includes associations between companies based on common past employment of their employees, which I also use to connect endowments and BO firms.

4 Network of Endowments, Buyout and Venture Capital Managers

For each endowment, a Board of Trustees specifies investment objectives, spending policies, and gives responsibilities to the investment office which can choose to manage the funds itself (internally) or to delegate management to external asset management firms. In the outsourcing regime, the investment committee may delegate substantial discretion to a full-time staff including a Chief Investment Officer (CIO) and a range of investment professionals (Binfare et al. (2018)). All endowments that report in the "Investment Management" section of the NACUBO surveys in 2008 adopt the external management approach (at least for part of their portfolio) and delegate mandates to investment managers expecting them to deliver a certain level of performance.

Moreover, alternative asset strategies and investments into PE firms have become increasingly crucial for endowments in the recent past. Table 3 examines the asset allocation of the university endowments' portfolios to investments such as PE. Endowments have gradually increased their average asset allocation as well as the average number of managers they employ. The rest of the paper focuses on endowments' PE investments and analyses their specific manager appointments.

4.1 Network Identification and Connections

The extensive network of endowments and the firms they hire can be represented through a bipartite network. I work with two types of agents: endowments and PE firms. The natural representation of the overall (affiliation) network of this kind is a graph with two types of nodes (endowments and PE firms) and edges connecting endowments with the PE firms they employ. In this bipartite graph, nodes fall in two distinct sets and edges only make connections between the two sets. Figure 1 is a simplified example of such a graph for the year 2008 for five endowments and their respective BO firms, where common BO firm appointments connect endowments. The endowments in Figure 1 are Pomona College, Michigan State University, Albion College, University of Portland and University of Illinois. In 2008, Pomona College and Michigan State University hired four common managers for their BO investments, namely Bain Capital, Madison Dearborn, Cerberus Capital Management and Blackstone. University of Portland and University of Illinois did not have any common managers with the aforementioned universities, but shared Adams Street Partners for their PE investments. Albion College only invested with Common Fund, which also was one of Michigan State University's managers.

I also project the network onto each of its two separate sets of vertices (endowments and managers) to understand the relative prominence of nodes (institutions) in each projection of the network. Figures 2 and 3 illustrate these projections for BO managers and endowments accordingly for 2008. When endowments are the units of analysis, the nodes represent endowments and edges represent shared managers. When PE managers are the units of analysis, the nodes represent managers and edges represent shared endowment appointments. Figure 2 connects two BO firms, Drum Capital Management and Alta Equity Partners. In 2008, these two BO firms were co-managing parts of endowments' portfolios with Common Fund. Figure 3 connects two universities, Yeshiva University and Chapman University. Each of these universities is connected with other universities employing the same BO managers, and they both have at least one common managers with Howard University and the University of Iowa and Foundation. A similar network of affiliations could be created for VC manager appointments of endowments.

I use all connections between endowments and PE firms each year to construct a time series. Having illustrated a simple representation of the network connections in Figures 1 to 3, Figure 4 makes use of the full set of connections in the data to examine the evolution of the network over two decades. Figure 4 plots the network connections illustrated in Figure 1 at years 1988, 1998, and 2008. The grey squares represent university endowments, and the black circles represent PE firms. The BO panel represents the network of endowments with BO firms, and the VC panel represents the network of endowments and VC firms. The network of connections between endowments and their managers has become significantly denser over time for both BO and VC investments. The density of the network connections partly comes from the fact that, over time, a lot more endowments and PE firms have entered the network, creating connections between them. As previously mentioned, PE investments have become a popular investment for university endowments in recent years. However, another aspect of density comes from the fact that endowments over time become more connected (either directly or indirectly) with PE managers. In order to make sure that the increased density of the network does not come from a mechanical effect of having more players in the network, I normalize the centrality measures to take into account the entry of more players and examine their time series in a more formal setting in Table 6. Moreover, the VC network was denser than its BO counterpart in the beginning of the sample as depicted in Panels A for 1988, but the BO network has expanded to a great extent over time. As evident in Figure 4, while endowments did not appoint as many BO managers at the beginning of the sample as in VC, the BO network seems to have caught up to the VC counterpart by the end of the sample.

4.2 Network Centrality Measures

Network analysis aims to describe the structure of relationships among a set of actors (in my case, institutions such as endowments and PE firms). An institution's importance in the network is measured by the "centrality" of its position, representing its involvement in relationships with others.

There are different ways to measure centrality, and each focuses on different dimensions of a network. I consider three different measures, namely degree centrality, eigenvector centrality and betweenness.

A. Degree Centrality

Degree centrality measures connectedness by counting the number of direct links each entity has to others. This measure can reveal the level of activity in the network, as well as the most important (active) institutions. For a specific institution (node) in the network, degree centrality is the path through which information flows (Rossi et al. (2018)). The degree centrality of a node i at time t, DE_{it}, is defined as

$$DE_{it} = \frac{d_{it}}{N_t - 1} \tag{1}$$

where d_{it} is the number of connected neighbors for the node i at time $t$and N_t is the total number of nodes in the network at time t. By definition, degree centrality depends on the size of the network, as more extensive networks have a higher number of connected actors. In my setting, the network of endowments and managers has evolved over time both in size and in composition. To compare degree centralities over time, I normalize them by the number of nodes in the network (maximum number of ties possible).

B. Closeness - Eigenvector centrality

While degree counts the number of relationships an actor has, closeness takes into account their "quality". Measures of closeness focus on the proximity of an actor to other actors in the network. An actor with high closeness centrality has the shortest paths to other actors which allows them to receive and distribute information quicker than others.

A particularly useful measure of closeness is "eigenvector centrality". The eigenvector is a weighted degree centrality in which each connection of a given node is weighted by the respective centrality score of that connection. Let A be the adjacency matrix of the network graph, λ be the largest eigenvalue of A and x be the corresponding eigenvector ($Ax = \lambda x$). Then, the i_{th} component of the eigenvector x gives the eigenvector centrality score of the i_{th} node in the network. The eigenvector centrality of the i_{th} node is proportional to the sum of centralities of i's neighbors (j) and is defined as

$$x = \frac{1}{\lambda}Ax \;\rightarrow\; x_i = \frac{1}{\lambda}\sum_{j=1}^{N} A_{i,j}x_j \tag{2}$$

Therefore, an endowment or manager with a high eigenvector score is likely to be at the center of a cluster of key actors that themselves have high eigenvector scores. This actor can communicate directly with those key entities compared with an actor with a low eigenvector score on the periphery of the network.

C. Betweenness

Betweenness centrality captures how important a node is in connecting other nodes, so it identifies entities with the ability to control information flow throughout the network (gatekeeper entities). Betweenness measures the number of shortest paths connecting different nodes passing through each node. The betweenness of node i at time t, BE_{it}, is defined as

$$BE_{it} = \frac{\sum_{k \neq j; i \neq k; i \neq j} \frac{P_i(k,j)}{P(k,j)}}{(N_t - 1)(N_t - 2)/2} \tag{3}$$

where $P_j(k,j)$ is the number of shortest paths between k and j that pass through i, and $P(k,j)$ is the number of shortest paths between k and j.

A higher value of betweenness suggests a more central network positioning (more paths). For example, a node with high betweenness has many paths running through it, allowing it to transfer information to the rest of the network. However, even if a node has very few paths running through it, it might still play an important role if it is positioned between different network clusters.

Each of these measures capture a different aspect of the network and help understand its different dimensions. Degree centrality depends on having many connections, while eigenvector centrality weighs these connections with respect to how isolated they are. For eigenvector centrality, a central node should be one connected to other powerful nodes. Betweenness centrality calculates how many pairs of individuals would have to go through one node in order to reach one another in the minimum number of stops. Therefore, it monitors the ability of a node to control information in the network.

Table 5 reports the distribution of the network centrality measures (degree, betweenness, eigenvector centrality) for endowments and PE firms for 2008. Panels A and B report summary statistics for BO networks, and Panels C and D for VC networks. Over time, there is a discernible rise in the average centrality measures of both endowments and managers. Most notably, in the beginning of the period, managers in the VC network appear more connected than their BO counterparts. However, BO manager connections have risen considerably, more than those of VC managers (Panels B and D). This is accordance with Figure 4 and corresponds to the rise of the popularity in BO investments by endowments. The average betweenness centrality varies considerably over time as more players (nodes) being present in the network means that there is a larger number of paths connecting any pairs of nodes.[10] However, across time, there exist players that are very central (high maximum centralities) and ones that are very peripheral and disconnected from the rest of the network (zero centralities).

[10] Note that betweenness measures the number of shortest paths that connect two nodes that pass through a specific node

4.3 Network Evolution

Figure 4 suggested that the network of endowments and their managers has become substantially denser over time. To formally examine the network's evolution, I study the time-series of its average centrality measures. I examine a snapshot of the BO and VC network each year, and standardize each centrality measure by subtracting its time-series average and dividing by its standard deviation over the full sample. The standardized centrality measure for every year is constructed as follows, and has mean zero and unit variance (similar to Rossi et al. (2018)):

$$S\,Net\,Cent_t = \frac{Net\,Cent_t - mean(Net\,Cent_t)}{stdev(Net\,Cent_t)} \tag{4}$$

I calculate the time-series averages for the one-mode representations of the networks (for endowments and managers). Table 6 presents the time series of the average normalized centrality measures for endowments and managers from 1988 to 2008. The similar upward trend of the standardized centrality measures (degree, betweenness, eigenvector centrality) suggests that centrality measures for endowments and managers have increased over time, and share common components. Rossi et al. (2018) find a similar pattern for UK equities.

5 Network Positioning and Effects

This section investigates the positioning of institutions (PE firms and endowments) in the network, and identifies the key players and their persistence. It also examines whether the network positioning of BO and VC firms relates to the probability of getting new mandates from endowments in the future, as well as their investment performance.

5.1 Determinants of Centrality Measures

Centrality measures for endowments and managers depict how important each institution is in the network of associations. Tables 7 and 8 examine the relationship between endowments' and managers' characteristics and centrality measures in a panel setting. I normalize each of the network centrality measures for endowment or manager j by scaling it by the cross-sectional average (NET_{jt}/NET_t), in order to account for time series trends in the overall network structure.

Table 7 presents the results for endowments. Panel A examines the centrality of endowments in BO networks, while Panel B in VC networks. Regressions (2)-(4) present results for three network centrality measures of interest, namely degree, betweenness and eigenvector centrality, while Regression (1) for an equally-weighted average of all the normalized centrality measures. Panel B suggests that older endowments with higher market values and more Full-Time Equivalent (FTE) students tend to be critical in the network of connections for the VC network. However, there is no consistent endowment characteristic that determines the importance of endowments in the BO network, as depicted in Panel A.

Table 8 performs the same analysis for BO and VC managers and the regressions have similar coefficient interpretations. Panel A examines the centrality of BO managers, while Panel B that of VC managers. Centrality measures for managers in both BO and VC networks relate negatively to measures of the manager's age, while the manager's size also seems to be important for the VC networks. This suggests that the smaller and younger managers tend to get picked by the most well-connected endowments. This result supports the popular belief that some endowments (and especially the large, prestigious ones) have the capacity to invest in a variety of funds and oftentimes pick idiosyncratic, young managers with which they form investment relationships from an early stage. This effect is stronger for the VC managers (Panel B).

5.2 Persistence of Centrality Measures

I track the evolution of the individual centrality measures for endowments and managers over time. Following Brown and Goetzmann (1995) and Goetzmann and Ibbotson (2010), I use a nonparametric methodology based upon contingency tables. I identify an endowment/manager as "central" in any year if its centrality measure is above the median centrality measure of all endowments/-managers reported that year, and as "peripheral" otherwise. I use 5-year intervals and only include the endowments/managers existing in all periods examined. In robustness tests, I also use periods ranging from 1-5 years.

Table 9 measures the number of institutions whose rank has stayed consistent over time (above or below median) or not, focusing on the centrality measure "Degree". Central-Central (CC) for 1992 is the count of the "central" players in 1992 which were also "central" in 1997. The odds ratio (Column 6) is the number of repeat central/peripheral players to the number of those which switch

$((CC * PP)/(CP * PC))$. The working hypothesis is that if centralities in the initial period cannot predict centralities in the next periods, then the odds ratio would be 1. The distribution of the log odds ratio (L) is approximated as normal with $L \sim N(log(OR), \sigma^2)$, and the standard error of the natural log of the odds ratio is approximated as $\sigma_{log(odds\, ratio)} = \sqrt{\frac{1}{C,C} + \frac{1}{C,P} + \frac{1}{P,C} + \frac{1}{P,P}}$ (see Brown and Goetzmann (1995)).[11]

The table shows that "central" or "peripheral" players in terms of degree centrality ranking per year continue having similar rankings compared to other institutions in the future. The odds ratios are above 1 in all cases and are statistically significant (the lowest bound of the confidence interval is greater than 1), especially in the latest periods of the sample, where the number of observations is also increased. This result generally holds for both endowments and managers, in BO and VC networks alike. Therefore, the network's structure tends to persist, meaning that the "key" and "non-key" institutions tend to stay the same over time.

5.3 Manager Network Centrality and New Mandates

In this section, I explore whether a PE firm's centrality in the previous year affects the number of new mandates the firm wins in the future. I hypothesize that more centrally located firms would get hired by more LPs the next period (a higher past network centrality measure would positively relate to the number of new mandates from other university endowments the next period). This hypothesis is consistent with well-connected managers in the network (employed by well-connected endowments) getting more opportunities to win further mandates through the network information flow than their not-so-well-connected counterparts. The centrality measures help take into account not only the number of connections a PE firm has with endowments, but also the quality of these connections.

In the regression outlined in Table 10, I examine the probability of a manager winning a new mandate by an endowment the next year through a logit regression. I focus on the influence of the manager's past network centrality measures on this probability. The regression results show that a high network centrality is associated with a greater probability that the manager wins an extra mandate by a different endowment next year. For example, increasing Degree Centrality by one

[11] To test the hypothesis that the population odds ratio equals one, the two-sided p-value is $2P(Z < - \mid L \mid / \sigma_{log(odds\, ratio)})$, where P denotes a probability and Z denotes a standard normal random variable.

standard deviation holding all other variables constant, increases the probability of a BO manager being hired by an additional endowment next year by almost 2.5 times (Panel A). This result is evident for all centrality measures (degree, eigenvector centrality and betweenness) and controlling for manager characteristics such as size and performance, time and manager fixed effects. In the Appendix, I check the robustness of this result to using a Poisson regression for the number of new mandates a manager gets next year (Table A.3), as well as to using a different manager performance measure than the IRR, namely the Value Multiple (Table A.4). The results remain qualitatively unchanged.

Overall, the results show that a more "connected" PE manager is more likely to gain further mandates by endowments in the future.

5.4 Network Centrality and Manager Investment Performance

This section addresses how the PE managers' location in the network is associated with their investment performance. I hypothesize the presence of a positive relationship between network centrality and investment performance in a delegated investment management setting in private markets. Rossi et al. (2018) confirm this relationship for public markets of UK equities.

I use the Internal Rate of Return (IRR) as a measure of manager performance, and present results from panel regressions using centrality as a covariate, while controlling for manager characteristics. Table 11 uses the centrality measures degree (Regressions (1)-(2)), eigenvector centrality (Regressions (3)-(4)) and betweenness (Regressions (5)-(6)), and shows results with and without the interaction term Network Centrality*Assets Under Management (AUM) of the PE manager.

Table 11 shows that there is a strong positive association of centrality with manager performance both for BO and for VC managers. The coefficients on the network measures are economically and statistically significant. In Panel A, one standard deviation increase in degree network centrality is associated with an increase in the expected BO manager return of approximately 3.4% per year. The corresponding results are stronger for VC firms both in terms of economic and statistical significance. Moreover, I find a significant negative interaction term of centrality and VC firm size in Panel B Regressions (1) and (3). This result confirms that the performance of small VC managers is more sensitive to network centrality than that of large managers. There is no such effect for BO firms. A possible explanation for this effect could relate to the nature of investing of VC firms, which includes small amounts of money and uses syndication (Lindsey (2008)). These characteristics could emphasize the importance of being well-connected in a network, especially for small players.

Overall, a more central network position places a manager in an advantageous position to receive and process information, as discussed in Rossi et al. (2018). More connected managers gain further mandates from university endowments and have better investment performance, consistent with these managers improving their ability to exploit investment opportunities through their network connections. A more central network position would make it easier for a firm to observe its competitors' actions, gather information about their successful strategies, and become more visible to endowments, which would relate to future mandates.

6 Individual Network Connections

In this section, I examine whether network connections between individuals play a role in the selection of PE firms by university endowments. PE investments take place in private markets, thus exploring the influence of personal connections on finding and accessing such investment opportunities is of particular interest. These personal connections could either cause concern about possible conflicts of interest in the selection of PE firms by endowments, or provide the means for efficient information transfer about alpha-generating PE managers which might benefit the endowment and, as a result, the university it supports. I connect firms with endowments using data on individuals working on the investment management side of endowments and PE firms. I also connect firms with endowments using data on the education of the individuals managing the PE funds (i.e. whether they are alumni of the university the endowment supports).

I hypothesize that it is more likely for endowments to allocate mandates to PE firms whose managers have a personal connection to the university or the endowment trustees, either through past employment at the same fund, common education or by being alumni of the university.

There are several channels through which this hypothesis might work. First, allocating mandates to connected managers could be due to the endowment trustees' trust in the managers of the PE fund and to more accurate information acquisition about their investment qualities, as a result of lower information asymmetry. Second, endowment trustees might have limited attention during the search for a manager, allocating funds to an existing PE firm they are acquainted with instead of expanding the search to the whole universe of available managers. Third, conflicts of interest may arise if endowments allocate mandates to managers with whom they have a personal relationship, irrespectively of their investment performance and practices.

6.1 Networks of Individuals

6.1.1 Boardex Network Associations

The Boardex North America dataset includes pre-created Company and Organizational Networks as well as Individual Networks. Any two organizations are connected through the common appointment of an individual at both institutions in the same period. I use the Company and Organizational Networks to draw connections of university endowments with the PE firms they hire, by matching the institutions in Boardex to the endowments and PE firms in the data. The Boardex networks include the names of individuals who connect two institutions, the institutions and their types (for example, universities or BO firms), the role of the individual at each of the institutions (for example, trustee or board member) and the start and end dates of the appointment. For example, an individual named "S Banks" was appointed as Chairman of the Board of ABRY Partners LLC and was also a Trustee of Case Western Reserve University between 2002-2003. In the data, these appointments create a connection between ABRY Partners and Case Western Reserve University. I use these connections after the start of the common appointment. In the example above, ABRY Partners LLC and Case Western University are connected after 2002.

Using the Boardex data on network associations, I find 140 such unique endowment-manager associations for the years 1988-2008 (I only use overlaps starting before 2008, which is the last year of my endowment sample). To match more connections spanning past appointments, I also connect the endowments and PE firms manually. In this part of the analysis, I focus on BO firms, as Boardex does not include a "Venture Capital" sector in their company classifications.

6.1.2 Manual Matching of Individual Networks

I identify trustees of university endowments in the data by sourcing individuals with a job description related to the investment management section from Boardex. I also identify investment managers of PE funds in the same way. I then identify connections between the individuals in the investment management function of the endowments and the portfolio managers of PE funds. BoardEx includes comprehensive biographical data on individuals in business, ranging from top executives and board directors to mid-level managers. Moreover, Boardex includes a variety of information regarding each person's profile (name, age, education), employment history, awards and affiliations with nonprofit organizations. As already discussed, the percentage of universities reporting individuals in the investment management functions of the endowment through Boardex is around 25%.[12]

I use the "Individual Profiles - Education and Employment" sections of the Boardex data to identify the managers of the PE firms and track their education and achievements. Using the Education data, I can identify investment professionals working at PE funds who are alumni of the universities reported in my data (for example, obtained an undergraduate or graduate degree by the university). In my empirical analysis, I use separate dummy variables to indicate the type of connection of the PE firm to the endowment. I create a dummy variable (Employment Connection) to indicate that the investment manager of the PE firm has also worked as a trustee in the endowment in the past and another dummy variable (Education Connection) to indicate that the investment manager has obtained a degree from the university that the endowment is supporting.

6.2 Determinants of PE Manager Selection by Endowments

In this section, I study the determinants of a PE firm's success at being hired by an endowment, focusing on personal connections. More specifically, I explore how much more likely it is for an endowment to hire a PE firm to manage its portfolio if its trustees have a current or past connection to the managers of the firm.

For my empirical analysis, I use a methodology similar to that of Kuhnen (2009). For each year endowments make a hiring decision of a manager, the set of potential candidates for allocating PE mandates includes all PE firms active in the market. I identify the PE managers an endowment could choose from as the universe of the PE funds included in Boardex. I restrict the firms to the ones reporting their portfolio managers to rule out cases where not identifying an individual connection is due to lack of data. I also exclude managers currently employed by the endowment, as well as those which have a minimum investment larger than the endowment's size (on the assumption that

[12]Guidestar also has detailed information on non-profit organizations, including the individuals associated with these organizations.

the endowment would not be able to invest due to shortage of funds). Lastly, I also require that the managers in the manager-endowment pairs can be matched to their institutional characteristics through Thomson Reuters. Subsampling the data according to the criteria above results in 119 endowments choosing from 461 managers for their portfolios over 1988-2008. These PE firms are in the Thomson Reuters dataset, and also report their managers through Boardex.

As in Kuhnen (2009), I model the process of selecting a PE manager using the random utility model of McFadden (1973). Kuhnen (2009) suggests this model is the most appropriate estimation procedure in settings where only the best alternative amongst many is chosen. For an endowment i, the utility from choosing an investment manager j is $y_{ij} = \beta' x_{ij} + \epsilon_{ij}$, where x_{ij} is a vector of characteristics of the PE manager and ϵ_{ij} are unobservable factors which affect utility. If PE manager j is the choice for endowment i maximizing the endowment's utility, McFadden (1973) shows that the probability that a candidate PE manager j is chosen is the following[13]:

$$Prob(y_i = j|x_i) = \frac{e^{\beta' x_{ij}}}{\sum_{h=0}^{J} e^{\beta' x_{ih}}} \tag{5}$$

I use a panel data set containing all possible pairs of endowment-manager relationships at the time of hiring, according to the constraints mentioned above. In binary logistic regressions, the dependent variable y takes the value 1 or 0 for each endowment-manager pair if the endowment hired the manager or not, accordingly. The explanatory variable is also binary and takes the value 1 if the endowment has an individual connection to the manager, and 0 if not. For every year in my sample, I label an endowment as "actively hiring" if the endowment is adding a new PE manager to its yearly list of managers. I am not able to identify endowments that considered hiring PE managers in a particular year but in the end did not. Thus, the results presented will indicate what characteristics of PE firms endowments look for when deciding to allocate mandates, conditional on them actively hiring a new PE firm. As potential determinants of the choice of PE firms, I include PE firm characteristics that relate to reputation, such as AUM or age.

Estimating the conditional logit model in equation (5) shows that connection measures are

[13] McFadden (1973) assumes independently distributed ϵ_{ij} with Weibull distribution $F(\epsilon_{ij}) = exp(-e^{-\epsilon_{ij}})$.

significant and positive predictors of which PE manager is selected, controlling for observable characteristics of candidate firms. The estimation results in Table 12 suggest that employment and education connections of individuals working in PE firms play a role in their selection by university endowments. If the managers of the PE firm are connected to the endowment trustees or are alumni of the university, they are more likely to be hired by the endowment. The economic magnitude of the coefficients is also significant. For example, if an endowment is considering hiring a PE firm, it is 10 times more likely to hire a PE firm that employs someone who has graduated from the university the endowment supports. Similarly, an employment connection of the PE firm with the endowment in the past makes it 14 times more likely for the firm to be selected.

I also test whether the magnitude of the assets of either the endowment or the PE manager affects the measures of connectedness. I hypothesize that, for example, larger funds might be less likely to hire based on connections, potentially due to better governance mechanisms to avoid conflicts of interest. On the other hand, a larger university might have a more connected and loyal alumni base that might magnify the connectedness effect. In the regressions, I interact measures of connectedness and the assets of the PE firms or the endowments (Assets Under Management and Market Values, respectively). However, I find no differential effect in support of either of the aforementioned hypotheses.

Overall, the results show that personal connections of individuals working in investment management play a role in the selection of PE firms by university endowments.

6.3 Network Channels

In this analysis, I examine the networks of institutions as well as individuals working on these institutions (for the BO firms). These two types of connections are used to examine different questions relating to PE manager appointment by endowments. For the institutional network, I examine whether a manager that is well-connected with endowments and other managers is more likely to gain further investment from other endowments as well as better investment performance. For the network of individuals, I focus on the specific manager appointments by endowments, and examine whether acquaintance of their respective managers makes it more likely to invest together in the future.

To try to disentangle the potential channels for the information and network effects to flow, I examine the correlation of an endowment's centrality with the average centrality across all managers that it invests in. For the BO network, I find no evidence of a relationship between an endowment's centrality and the average centrality of its managers. However, for the VC network, there exists a correlation of around 10% and is statistically significant.

This evidence is consistent with the hypothesis that the BO networks are mainly influenced by the personal connections of the endowment and firm managers, while the influence of institutional networks is larger for endowments and VC firms.

7 Conclusion

University endowments provide an excellent laboratory to study how social networks affect choices made by an asset owner in private markets. These endowments have a long term investment horizon and often have the institutional flexibility to pursue fairly unrestricted investment opportunities. Using a novel hand-collected data set of endowments beginning in 1988, I study their PE firm appointments. Endowments' adoption of decentralized investment management, employing multiple investment firms to manage their portfolios, gives rise to a network of connections between them and PE managers.

In a social network setting, this study considers how endowments and PE managers gain access to each other through their network connections, and whether critical network positioning of institutions plays a role in endowments' selection of investments. A network analysis takes into account both the number and the quality of connections through which information can flow. I separate PE investments in BO and VC and study them separately. In the beginning of the period examined, the network structure of endowments and VC firms was much more developed than its BO counterpart in terms of number of players and connections between them. However, both networks have grown denser over time and the identity of their key institutions has stayed the same. Central network positioning of PE managers is positively associated with the number of new mandates they gain from other university endowments in subsequent periods, as well as their investment performance. Moving from firm-level to individual-level networks, I consider connections of endowment trustees and PE portfolio managers. I find that if an individual was employed by an endowment in the past or is an alumnus of the university the endowment supports, the likelihood of her firm getting hired by the endowment rises significantly.

Overall, an analysis of delegated portfolio management in a social network context is important as it can determine a crucial yet under-explored source of investment opportunities, namely the ability of institutions to exploit their firm- and individual-level connections. My paper provides evidence that these connections are particularly important for investments in the private space.

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Figures and Tables

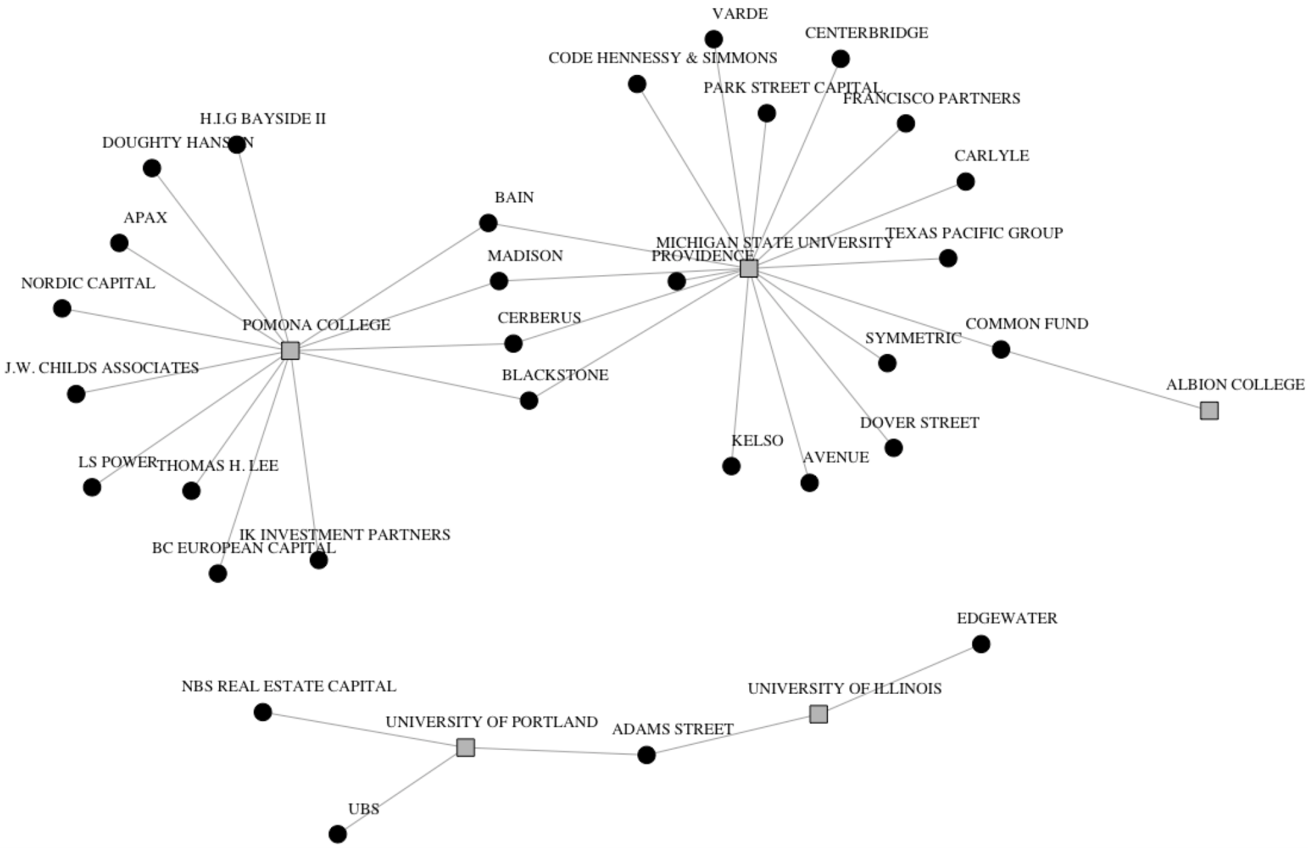


Figure 1: Bipartite network for five endowments and their BO investment managers in 2008 The grey squares represent university endowments, and the black circles represent BO firms. The name of the university endowment or BO manager is provided above its respective node.

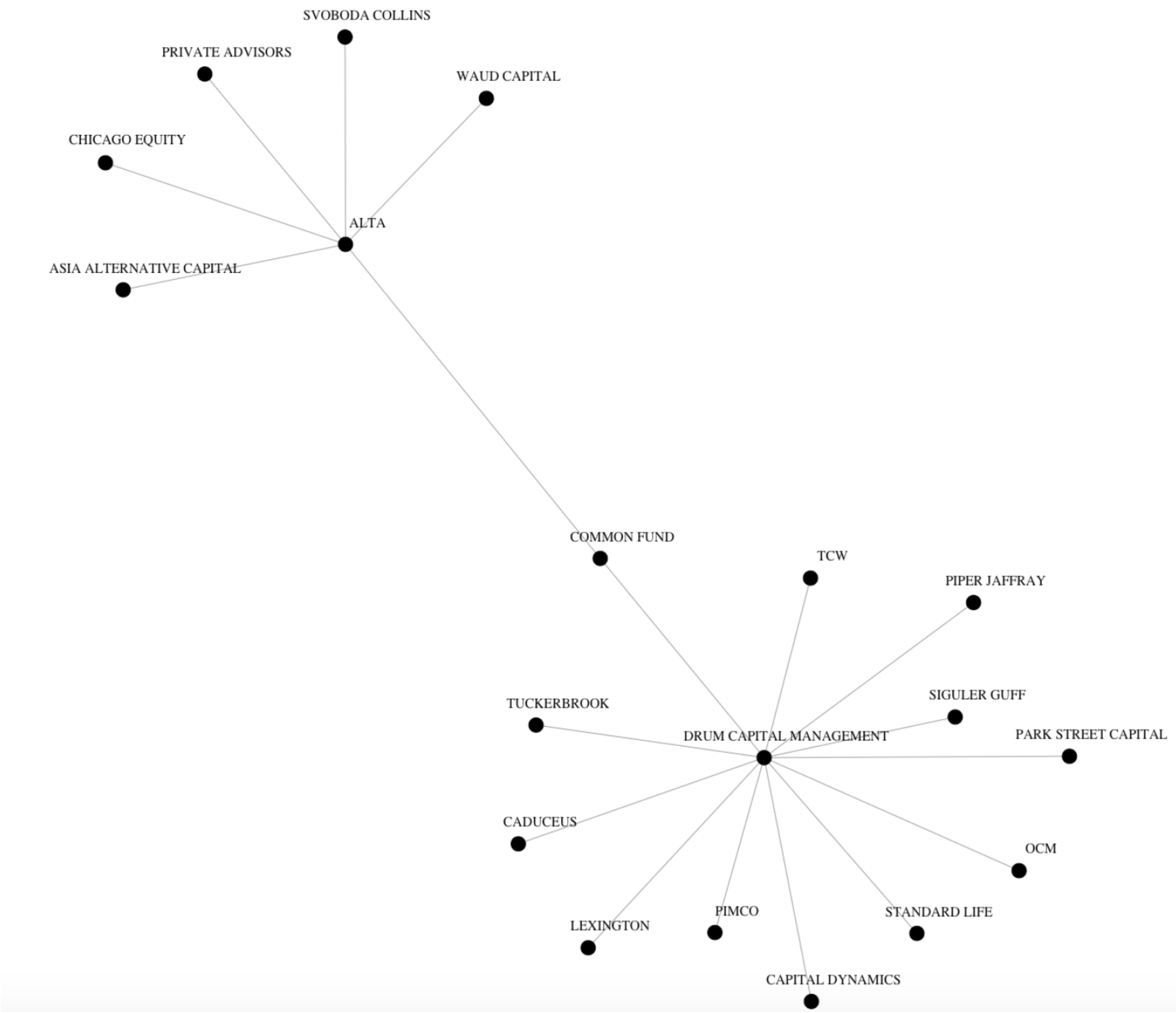


Figure 2: PE Investment Managers: One-mode projections of the two-mode affiliation network This figure plots a network example of two BO firms (Drum Capital Management and Alta Advisors) connected through same university endowment appointments in 2008. The name of the BO manager is provided above its respective node.

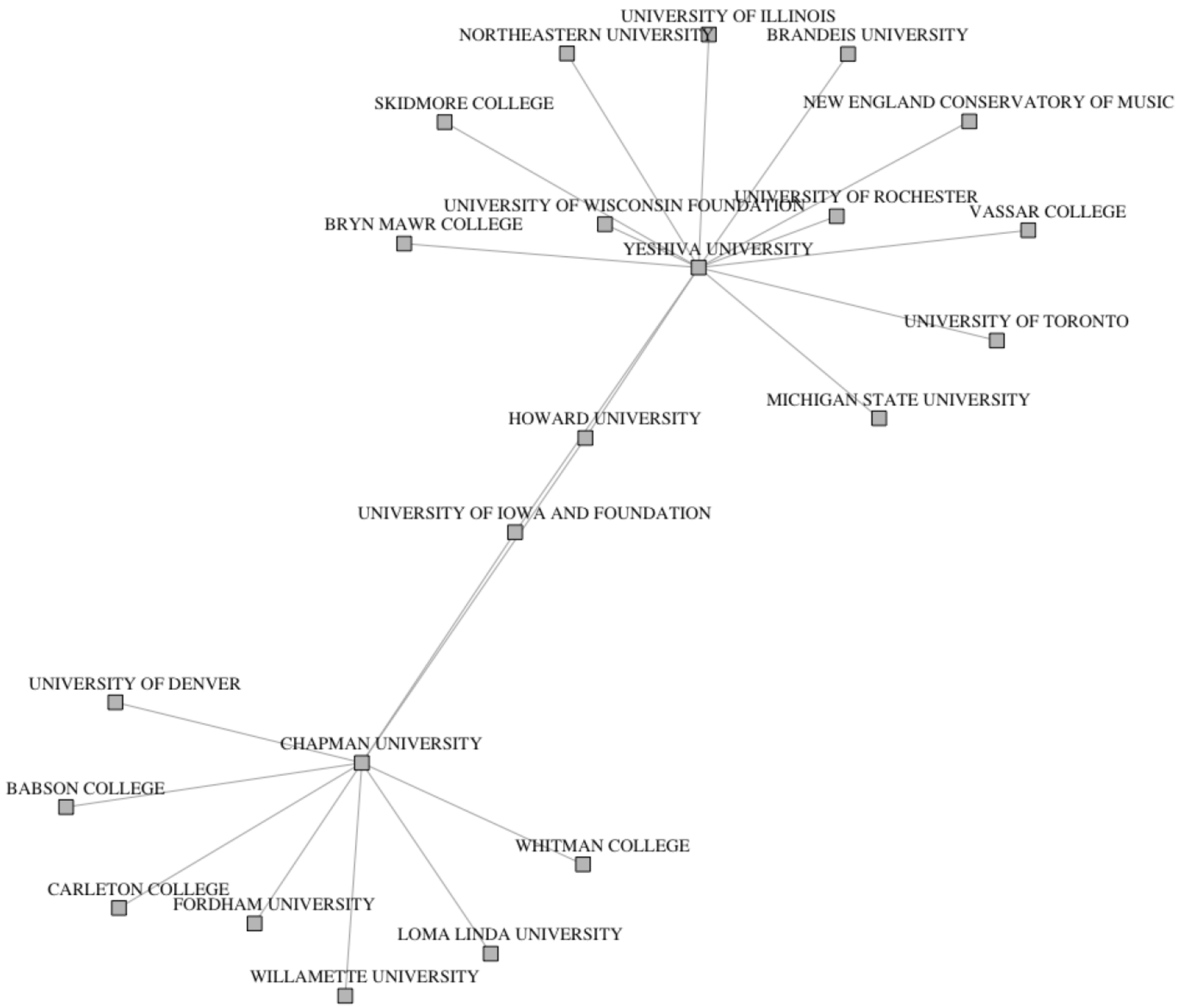
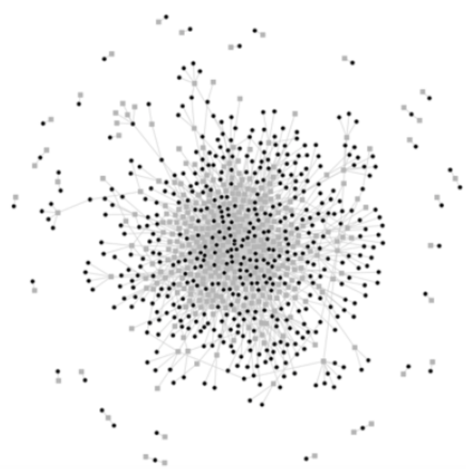


Figure 3: Endowments: One-mode projections of the two-mode affiliation network
This figure plots a network example of two endowments (Chapman University and Yeshiva University) connected through same BO investment manager appointments in 2008. The name of the university endowment is provided above its respective node.

BO Panel A: 1988

BO Panel B: 1998



BO Panel C: 2008

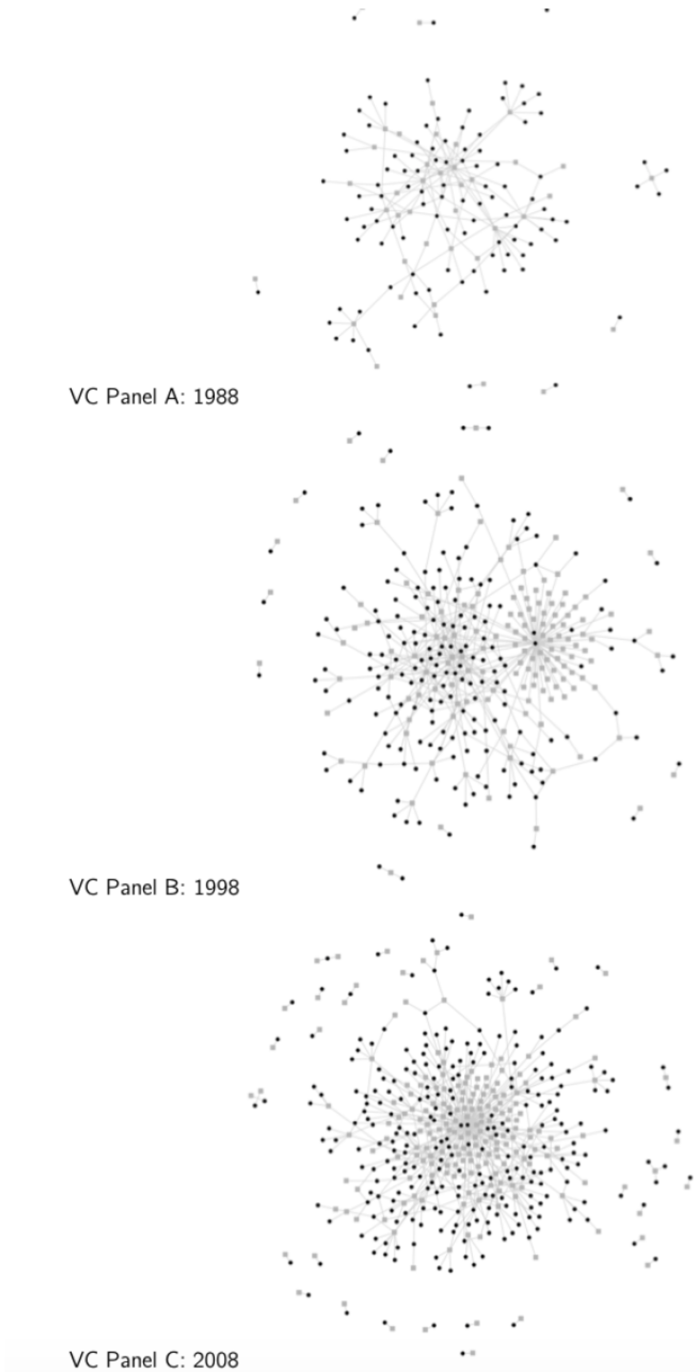


Figure 4: Evolution of network connections of university endowments with BO and VC managers
This figure plots the evolution of the network connections between university endowments and BO and VC managers from 1988 to 2008. The grey squares represent university endowments, and the black circles represent BO or VC firms.

Table 1: University endowment summary statistics

This table reports summary statistics for all university endowments in the sample, for the period 1985-2008. The summary statistics reported are the number of universities included in the dataset each year, the market value (MV in thousands US dollars) of the average endowment in the sample, the average age (in years), the percentage of the universities that belong to the Doctoral Carnegie Classification (offer PhD degrees), and the average full-time equivalent (FTE) students.

Year	Number of Universities	MV Average ($000s)	Age Average	% Doctoral Class.	FTE students Average
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 2: Asset allocation of university endwoments

This table presents the portfolio allocation of the university endowments in the sample, for years 1989 and 2008. Alternative assets are hedge funds and PE investments (BO and VC). Equity and Bonds include both domestic as well as international mandates. Endowments are split with respect to their market values in years 1989 and 2008. I calculate both dollar-weighted and equal-weighted averages of endowment asset allocations.

Total Endowment Size	Equity	Bonds	Alternative Assets	Real Estate	Other	Cash
1989						
Over $1 billion	49.7	16.4	4.6	4.7	0.6	7.0
From $501 million to 1 billion	49.0	31.9	5.1	2.5	0.4	7.7
From $100 million to 500 million	52.9	27.9	1.3	2.1	0.4	12.4
Under $101 million	46.8	32.3	0.6	2.2	0.2	13.0
Dollar-weighted average	46.6	24.0	3.2	2.8	0.4	8.7
Equal-weighted average	48.6	30.8	1.1	2.3	0.2	12.5
2008						
Over $1 billion	37.9	9.9	25.3	5.8	0.0	0.9
From $501 million to 1 billion	40.3	11.1	26.5	5.6	0.0	1.1
From $100 million to 500 million	48.5	14.5	18.0	4.4	0.0	1.8
Under $101 million	53.3	19.8	9.7	3.4	0.0	3.4
Dollar-weighted average	34.8	9.7	23.5	5.1	0.0	0.5
Equal-weighted average	49.5	16.7	14.9	4.1	0.0	2.5

Table 3: Endowment fund summary statistics

This table calculates the average number of managers employed by university endowments for their total portfolio mandates, their Buyout (BO) and Venture Capital (VC) investments. Manager figures are averaged accross university endowments, irrespectively of whether the universities allocate parts of their portfolio to BO or VC.

Year	Total Number of Managers (av)	Number of BO Managers (av)	Number of VC Managers (av)	% Allocation in PE	max	% Allocation in VC	max
1988	7.0	0.09	0.74	0.20	10.80	0.70	18.30
1990	7.3	0.10	0.60	0.17	7.90	0.59	11.90
1992	7.7	0.09	0.57	0.14	9.40	0.53	13.40
1994	11.1	0.14	0.80	0.18	9.60	0.63	12.60
1996	12.4	0.19	0.98	0.24	8.50	0.82	14.60
1998	14.4	0.47	1.03	0.48	12.10	0.84	12.60
2000	14.4	0.56	1.05	0.93	21.90	2.36	33.60
2002	17.8	1.04	1.22	1.30	22.70	1.18	21.00
2004	17.9	1.12	1.07	1.57	21.00	1.03	20.00
2006	21.0	1.79	1.23	2.27	26.20	1.02	20.00
2008	24.1	2.60	1.18	3.48	26.00	1.06	17.90

Table 4: Private equity manager summary statistics

This table reports summary statistics for all Private Equity (PE) managers associated with the university endowments in the sample, for the period 1988-2008. All figures are expressed in US dollars, and are averaged across the investment managers in the sample.

Year	No. of Firms	Avg Equity Per Company	No. of Comp.	No. of Deals	Sum of Eq. Invest.	Founded Year	Latest Fund Size
1988	148	9,186,431	11.5	13.5	51,230,399	1979	708,073,891
1990	141	2,473,012	10.1	13.2	18,344,399	1979	733,713,180
1992	150	5,431,579	10.5	14.1	31,834,308	1981	781,659,767
1994	173	3,237,870	9.4	12.1	24,728,501	1982	718,696,904
1996	227	5,551,971	11.7	14.9	50,120,803	1984	691,984,188
1998	288	6,838,666	11.7	13.8	60,765,168	1985	668,655,525
2000	375	10,573,126	17.5	20.7	150,008,948	1987	638,657,946
2002	336	9,620,506	8.1	9.0	58,857,273	1988	652,289,378
2004	332	9,682,711	10.0	11.4	83,487,762	1989	743,623,680
2006	361	10,862,546	10.8	12.5	116,177,139	1989	673,891,956
2008	362	16,570,062	11.1	13.0	124,163,671	1990	646,860,292

Table 5: Summary statistics and network centrality measures

This table presents the distribution of the centrality measures for endowments and managers. In these networks, endowments are connected through common manager appointments, and managers are connected through common endowment appointments. Panels A and B report summary statistics for Buyout (BO) networks, and Panels C and D for Venture Capital (VC) networks. Statistics are reported in years 1988, 1993, 1998, 2003 and 2008.

Panel A: University Endowments (BO)

	Measure	Mean	Std. Dev	Min	Max
2008	Degree	96.8	78.6	0.0	225.0
	Betweenness	106.5	205.9	0.0	1535.1
	Eig. Centrality	0.4	0.3	0.0	1.0
2003	Degree	53.0	47.6	0.0	120.0
	Betweenness	74.2	176.2	0.0	1120.6
	Eig. Centrality	0.4	0.4	0.0	1.0
1998	Degree	14.6	13.0	0.0	40.0
	Betweenness	33.5	105.0	0.0	823.2
	Eig. Centrality	0.4	0.5	0.0	1.0
1993	Degree	1.6	2.0	0.0	8.0
	Betweenness	1.2	5.0	0.0	26.0
	Eig. Centrality	0.2	0.3	0.0	1.0
1988	Degree	2.2	2.1	0.0	6.0
	Betweenness	0.8	2.1	0.0	7.0
	Eig. Centrality	0.6	0.2	0.2	1.0

Panel B: BO Managers

	Measure	Mean	Std. Dev	Min	Max
2008	Degree	20.0	24.8	0.0	240.0
	Betweenness	308.8	1624.4	0.0	31921.0
	Eig. Centrality	0.1	0.1	0.0	1.0
2003	Degree	9.9	12.0	0.0	94.0
	Betweenness	146.5	581.5	0.0	6979.2
	Eig. Centrality	0.1	0.1	0.0	1.0
1998	Degree	6.7	7.4	0.0	50.0
	Betweenness	48.9	194.5	0.0	1677.5
	Eig. Centrality	0.2	0.2	0.0	1.0
1993	Degree	2.1	2.5	0.0	8.0
	Betweenness	0.4	2.2	0.0	12.0
	Eig. Centrality	0.2	0.4	0.0	1.0
1988	Degree	4.4	3.4	0.0	10.0
	Betweenness	1.3	3.4	0.0	13.0
	Eig. Centrality	0.5	0.3	0.0	1.0

Panel C: University Endowments (VC)					
	Measure	Mean	Std. Dev.	Min	Max
2008	Degree	71.0	56.6	0.0	129.0
	Betweenness	41.9	98.2	0.0	571.2
	Eig. Centrality	0.6	0.5	0.0	1.0
2003	Degree	71.4	56.3	0.0	135.0
	Betweenness	43.1	122.2	0.0	819.9
	Eig. Centrality	0.5	0.4	0.0	1.0
1998	Degree	47.2	37.3	0.0	103.0
	Betweenness	47.5	138.8	0.0	1011.5
	Eig. Centrality	0.4	0.4	0.0	1.0
1993	Degree	19.1	17.1	0.0	54.0
	Betweenness	27.1	65.1	0.0	383.0
	Eig. Centrality	0.3	0.3	0.0	1.0
1988	Degree	5.5	5.2	0.0	21.0
	Betweenness	16.0	28.2	0.0	137.2
	Eig. Centrality	0.2	0.2	0.0	1.0

Panel D: VC Managers					
	Measure	Mean	Std. Dev	Min	Max
2008	Degree	8.7	11.8	0.0	134.0
	Betweenness	158.7	1186.8	0.0	19003.5
	Eig. Centrality	0.1	0.2	0.0	1.0
2003	Degree	10.3	14.5	0.0	124.0
	Betweenness	119.5	744.1	0.0	11365.2
	Eig. Centrality	0.1	0.2	0.0	1.0
1998	Degree	11.6	14.2	0.0	70.0
	Betweenness	121.7	394.8	0.0	3264.4
	Eig. Centrality	0.1	0.2	0.0	1.0
1993	Degree	8.9	8.6	0.0	53.0
	Betweenness	76.6	243.7	0.0	1667.2
	Eig. Centrality	0.1	0.2	0.0	1.0
1988	Degree	8.6	7.5	0.0	39.0
	Betweenness	62.2	172.6	0.0	990.5
	Eig. Centrality	0.2	0.2	0.0	1.0

Table 6: Time series of the average normalized centrality measures for managers and endowments

This table presents the standardized centrality measures (Degree, Betweenness, Eigenvector Centrality) for the one-mode network of endowments (E) and managers (M), from 1988-2008. The standardized measures are calculated according to Equation (4). Each year I subtract from each centrality measure its time series average and divide it by the standard deviation over the full sample. Panel A presents the results for the Buyout (BO) network and Panel B presents the results for the Venture Capital (VC) network.

Panel A: BO Network

Year	Deg. E	Bet. E	Eig. E	Deg. M	Bet. M.	Eig. M
1988	-0.89	-0.41	0.43	-0.46	-0.18	2.14
1990	-0.90	-0.41	-0.40	-0.63	-0.18	0.51
1992	-0.91	-0.42	-0.56	-0.56	-0.18	1.56
1994	-0.88	-0.41	-0.25	-0.53	-0.18	0.64
1996	-0.87	-0.37	-0.28	-0.51	-0.17	0.71
1998	-0.68	-0.23	0.00	-0.32	-0.14	0.26
2000	-0.52	-0.30	0.24	-0.39	-0.15	0.16
2002	-0.04	-0.14	0.24	-0.21	-0.05	0.01
2004	0.01	0.10	0.13	-0.11	0.04	-0.03
2006	0.17	0.11	-0.05	0.14	0.03	-0.17
2008	0.66	0.19	-0.07	0.46	0.12	-0.29

Panel B: VC Network

Year	Deg. E	Bet. E	Eig. E	Deg. M	Bet. M.	Eig. M
1988	-0.95	-0.21	-0.64	-0.12	-0.07	0.17
1990	-0.92	-0.12	-0.46	-0.28	-0.08	0.24
1992	-0.82	-0.15	-0.29	-0.20	-0.09	0.43
1994	-0.51	-0.08	-0.18	-0.05	-0.05	-0.01
1996	-0.25	-0.03	-0.06	-0.02	-0.05	0.12
1998	-0.11	0.08	-0.10	0.12	0.01	-0.04
2000	-0.02	-0.01	0.22	-0.17	0.00	0.01
2002	0.25	-0.03	0.06	0.11	0.00	-0.11
2004	0.24	0.12	0.04	-0.03	0.02	-0.13
2006	0.47	0.05	0.19	0.04	0.07	-0.09
2008	0.37	0.03	0.23	-0.11	0.06	-0.16

Table 7: Endowment centrality measures and endowment characteristics

This table shows the relationships between endowments' centrality measures (average centrality (Column 1), Degree, Betweenness and Closeness (Columns 2-4)) with endowment characteristics such as Market Value, Carnegie Classification (Status), and Full-Time Equivalent (FTE) Students. The Market Value of the Endowment is measured in million US dollars and the FTE students are scaled by a factor of 1,000. The panel regressions are from 1988-2008 and include endowment and year fixed effects. Standard errors are in the parentheses and are clustered by time. Panel A shows results for endowments in Buyout (BO) networks, and Panel B shows results for endowments in Venture Capital (VC) networks.

PANEL A: BO Managers

	Dependent variable:			
	Average Centrality	Degree	Betweenness	Closeness
	(1)	(2)	(3)	(4)
Market Value	0.04***	0.01***	0.15***	0.0002***
	(0.01)	(0.002)	(0.02)	(0.00)
Status	2.30	−2.77	9.16	0.04***
	(1.49)	(1.92)	(5.96)	(0.00)
FTE Students	−0.13	1.04	−0.50	−0.01**
	(0.74)	(0.50)	(2.99)	(0.00)
Endw FE?	Yes	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes	Yes
Observations	1,683	1,683	1,683	1,683
R^2	0.03	0.01	0.03	0.02
Adjusted R^2	−0.25	−0.28	−0.25	−0.26
F Statistic	15.39***	3.10**	15.37***	9.44***
Note:				*p<0.1; **p<0.05; ***p<0.01

PANEL B: VC Managers

	Dependent variable:			
	Average Centrality	Degree	Betweenness	Closeness
	(1)	(2)	(3)	(4)
Market Value	0.02***	0.01*	0.07**	0.0001**
	(0.005)	(0.002)	(0.02)	(0.00)
Status	3.48	−2.24	13.92	0.01
	(2.15)	(1.12)	(8.62)	(0.00)
FTE Students	2.96***	0.98	11.82***	0.01*
	(0.51)	(0.43)	(2.05)	(0.01)
Endw FE?	Yes	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes	Yes
Observations	2,067	2,067	2,067	2,067
R^2	0.05	0.01	0.05	0.01
Adjusted R^2	−0.14	−0.19	−0.14	−0.19
F Statistic	28.49***	3.46**	28.48***	3.43**
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 8: Manager centrality measures and manager characteristics

This table shows the relationships between the average centrality measure of a manager in the network (Column 1) as well as the each of the centrality measures (Columns 2-4) with the characteristics of the manager such as the number of companies that the General Partner is invested in, its AUM, year founded, etc. All figures are in US dollars. The panel regressions are from 1988-2008, include year and manager fixed effects. Standard errors are reported in the parentheses and are clustered by time. Panel A shows results for managers in Buyout (BO) networks, and Panel B shows results in Venture Capital (VC) networks.

PANEL A: BO Managers

	Dependent variable:			
	Average Centrality	Degree	Betweenness	Eig. Cent.
	(1)	(2)	(3)	(4)
Numb. Companies Invested	−0.08	−0.002	−0.30	−0.0003
	(0.25)	(0.02)	(1.01)	(0.00)
Sum Equity Invested	0.01	0.001	0.03	−0.0000
	(0.02)	(0.00)	(0.07)	(0.00)
Firm numb. Deals	0.12	0.01	0.50	−0.0000
	(0.19)	(0.02)	(0.78)	(0.00)
Firm AUM	0.26*	0.01	1.06*	0.0002
	(0.14)	(0.01)	(0.59)	(0.00)
Firm Age	−2.30***	−0.18**	−9.20***	−0.002***
	(0.06)	(0.08)	(2.51)	(0.00)
Man. FE?	Yes	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes	Yes
Observations	1,301	1,301	1,301	1,301
R^2	0.01	0.01	0.01	0.02
Adjusted R^2	−0.35	−0.35	−0.35	−0.34
F Statistic (df = 5; 954)	1.86*	1.49	1.86*	3.22***

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

PANEL A: VC Managers

	Dependent variable:			
	Average Centrality	Degree	Betweenness	Eig. Cent.
	(1)	(2)	(3)	(4)
Numb. Companies Invested	−0.04	0.01	−0.17	0.0003
	(0.07)	(0.01)	(0.26)	(0.00)
Sum Equity Invested	−0.003	−0.0003	−0.01	0.0000
	(0.004)	(0.00)	(0.02)	(0.00)
Firm numb. Deals	0.10*	0.01	0.41*	−0.0001
	(0.06)	(0.01)	(0.24)	(0.00)
Firm AUM	−0.07	−0.02**	−0.28	−0.0003**
	(0.04)	(0.01)	(0.17)	(0.00)
Firm Age	−1.49**	−0.10*	−5.98**	−0.0000
	(0.49)	(0.04)	(1.97)	(0.00)
Man. FE?	Yes	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes	Yes
Observations	1,887	1,887	1,887	1,887
R^2	0.01	0.01	0.01	0.01
Adjusted R^2	−0.21	−0.22	−0.21	−0.22
F Statistic (df = 5; 1535)	3.66***	3.23***	3.67***	2.05*

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

Table 9: Degree persistence for managers and endowments

This table reports contingency tables for the ranking of centrality measures for endowments and managers. I examine Buyout (BO) and Venture Capital (VC) networks separately. I identify an endowment as central in a year if its centrality measure is above the median centrality measure of all endowments reported that year, and as peripheral otherwise. The same method is used to identify central and peripheral players for BO and VC managers. The tables are compiled using 5-year intervals and only include the endowments or managers that exist in both periods examined. For example, CentralCentral (CC) for 1992 is the count of central players in 1992 that were also central players in 1997. The odds ratio is the number of repeat central or peripheral players to the number of those that switch categories over the interval examined. For brevity, data points in 4 years are reported. Column 6 reports the Odds Ratio, column 7 is the log(Odds Ratio), column 8 reports the standard error of the log(Odds Ratio), and column 9 reports the lower bound of the confindence interval (Odds Ratio different than 1). Panel A presents results for BO networks and Panel B for VC networks.

PANEL A: BO

BO Managers								
Year		Central (t+5)	Peripheral (t+5)	Sum	Odds R. (OR)	log(OR)	SE	CI Lower
1992	Central (t)	2	1	3	8.0	2.1	1.7	0.3
	Peripheral (t)	1	4	5				
		3	5					
1996	Central (t)	4	1	5	11.0	2.4	1.3	0.9
	Peripheral (t)	1	11	12				
		5	12					
2000	Central (t)	22	1	23	101.2	4.6	1.1	10.9
	Peripheral (t)	5	23	28				
		27	24					
2002	Central (t)	38	7	45	7.6	2.0	0.5	2.9
	Peripheral (t)	22	31	53				
		60	38					

University Endowments in BO Networks								
Year		Central (t+5)	Peripheral (t+5)	Sum	Odds R. (OR)	log(OR)	SE	CI Lower
1992	Central (t)	1	1	2	2.5	0.9	1.6	0.1
	Peripheral (t)	2	5	7				
		3	6					
1996	Central (t)	4	3	7	8.0	2.1	1.3	0.6
	Peripheral (t)	1	6	7				
		5	9					
2000	Central (t)	6	1	7	5.8	1.8	1.1	0.7
	Peripheral (t)	28	27	55				
		34	28					
2002	Central (t)	18	1	19	13.5	2.6	1.0	1.7
	Peripheral (t)	52	39	91				
		70	40					

PANEL B: VC

Panel 1: VC Managers								
Year		Central (t+5)	Peripheral (t+5)	Sum	Odds R. (OR)	log(OR)	SE	CI Lower
1992	Central (t)	13	6	19	2.6	1.0	0.7	0.7
	Peripheral (t)	9	11	20				
		22	17					
1996	Central (t)	24	1	25	22.3	3.1	1.1	2.6
	Peripheral (t)	14	13	27				
		38	14					
2000	Central (t)	39	9	48	19.5	3.0	0.5	7.2
	Peripheral (t)	10	45	55				
		49	54					
2002	Central (t)	55	5	60	47.7	3.9	0.6	15.7
	Peripheral (t)	12	52	64				
		67	57					

Panel 2: University Endowments in VC Networks								
Year		Central (t+5)	Peripheral (t+5)	Sum	Odds R. (OR)	log(OR)	SE	CI Lower
1992	Central (t)	3	16	19	1.5	0.4	1.0	0.2
	Peripheral (t)	2	16	18				
		5	32					
1996	Central (t)	1	4	5	1.6	0.5	1.2	0.2
	Peripheral (t)	7	45	52				
		8	49					
2000	Central (t)	8	2	10	24.7	3.2	0.8	4.7
	Peripheral (t)	12	74	86				
		20	76					
2002	Central (t)	14	1	15	113.3	4.7	1.1	13.6
	Peripheral (t)	11	89	100				
		25	90					

Table 10: Centrality measures and the probability of winning a new mandate

This table reports the (logit) regression of a dummy variable that is equal to 1 if the manager wins a new mandate by an endowment in year t, regressed on the centrality of the manager during the previous year t-1. Column 1 reports results with respect to the network measure Degree centrality, Column 2 reports results for Eigenvector Centrality, and Column 3 for Betweenness centrality. IRR is the internal rate of return of the PE firm, AUM are its assets under management in US$mil, and Age is the number of years since the inception of its first fund. All regressions include year and manager fixed effects, span the time period 1989-2008 and standard errors are clustered by time. Panel A presents results for Buyout (BO) networks, and Panel B for Venture Capital (VC) networks.

PANEL A: BO Managers

	Dependent variable:		
	Probability of winning extra mandate		
	(1)	(2)	(3)
Lag Degree	0.884***		
	(0.239)		
Lag Eigenvector Cent		0.597***	
		(0.190)	
Lag Betweenness			0.502***
			(0.128)
Lag IRR	0.020*	0.019	0.018
	(0.012)	(0.012)	(0.012)
Lag Firm AUM	0.038	0.045	0.029
	(0.091)	(0.091)	(0.091)
Lag Firm Age	−0.015	−0.012	−0.011
	(0.021)	(0.021)	(0.021)
Constant	2.321	−37.006	−19.108
	(15,208)	(15,208)	(10,754)
Year FE?	Yes	Yes	Yes
Manager FE?	Yes	Yes	Yes
Observations	502	501	490
Log Likelihood	−186.752	−188.924	−184.550
Akaike Inf. Crit.	639.505	641.848	623.101
Note:	*p<0.1; **p<0.05; ***p<0.01		

PANEL B: VC Managers

	Dependent variable:		
	Probability of winning extra mandate		
	(1)	(2)	(3)
Lag Degree	1.004***		
	(0.248)		
Lag Eigenvector Cent		0.852***	
		(0.202)	
Lag Betweenness			0.326***
			(0.112)
Lag IRR	−0.003	−0.003	−0.005
	(0.007)	(0.007)	(0.007)
Lag Firm AUM	0.023	0.025	0.027
	(0.082)	(0.080)	(0.083)
Lag Firm Age	−0.076	−0.080	−0.089
	(0.084)	(0.082)	(0.082)
Constant	20.734	20.865	22.010
	(10,754)	(10,754)	(10,754)
Year FE?	Yes	Yes	Yes
Manager FE?	Yes	Yes	Yes
Observations	623	623	623
Log Likelihood	−210.304	−209.764	−215.006
Akaike Inf. Crit.	698.608	697.528	708.013
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 11: Network centrality and performance

This table reports results for panel regressions of the PE manager's performance on the manager's centrality measures (degree, eigenvector centrality, betweenness). Degree is presented in columns 1-2, Eigenvector Centrality is presented in columns 3-4 and Betweenness in columns 5-6. The panel regressions use as control variables the assets under management (in million US dollars) and the age of the PE firm (in years). Standard errors are reported in the parentheses and are clustered by time. The time period is 1989-2008, the regressions include year and manager fixed effects and standard errors are clustered by time. Panel A presents results for Buyout (BO) networks, and Panel B for Venture Capital (VC) networks.

PANEL A: BO Managers

	Dependent variable:					
	BO Performance (IRR)					
	(1)	(2)	(3)	(4)	(5)	(6)
Degree	3.383*	3.441**				
	(1.704)	(1.224)				
Eigenvector Cent			2.720*	2.348*		
			(1.376)	(1.166)		
Betweenness					1.230	1.515*
					(0.722)	(0.967)
AUM	−0.189	−0.167	−0.010	−0.169	−0.086	−0.120
	(0.284)	(0.123)	(0.254)	(0.124)	(0.161)	(0.120)
Age	0.497***	0.476***	0.491***	0.485***	0.497***	0.478***
	(0.122)	(0.120)	(0.121)	(0.121)	(0.122)	(0.121)
Degree*AUM	0.010					
	(0.217)					
Eig. Cent.*AUM			−0.131			
			(0.181)			
Between.*AUM					−0.063	
					(0.159)	
Constant	3.270	3.220	4.020	4.560	5.402*	5.520*
	(3.470)	(3.386)	(3.322)	(3.228)	(3.068)	(3.048)
Manager FE?	Yes	Yes	Yes	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	233	233	233	233	233	233
R^2	0.082	0.082	0.078	0.076	0.077	0.076
Adjusted R^2	0.066	0.070	0.062	0.064	0.061	0.064
F Statistic	5.102***	6.832***	4.817***	6.261***	4.743***	6.294***

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

PANEL B: VC Managers

	Dependent variable:					
	VC Performance (IRR)					
	(1)	(2)	(3)	(4)	(5)	(6)
Degree	11.752***	7.820***				
	(3.322)	(2.392)				
Eigenvector Cent			10.256***	6.526***		
			(2.751)	(1.850)		
Betweenness					2.913	2.025
					(2.152)	(1.344)
AUM	0.333	−0.227	0.299	−0.232	−0.078	−0.150
	(0.394)	(0.280)	(0.366)	(0.280)	(0.304)	(0.283)
Age	0.154	0.179	0.156	0.172	0.164	0.182
	(0.220)	(0.221)	(0.219)	(0.220)	(0.226)	(0.224)
Degree*AUM	−0.707**					
	(0.350)					
Eig. Cent.*AUM			−0.673**			
			(0.293)			
Between.*AUM					−0.207	
					(0.280)	
Constant	10.650*	12.978**	11.859**	14.576***	19.315***	19.128***
	(5.628)	(5.491)	(5.419)	(5.310)	(5.184)	(5.180)
Manager FE?	Yes	Yes	Yes	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	381	381	381	381	381	381
R^2	0.042	0.031	0.049	0.036	0.010	0.008
Adjusted R^2	0.032	0.024	0.039	0.028	−0.001	0.0004
F Statistic	4.104***	4.083***	4.829***	4.630***	0.924	1.052
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 12: Connections and Other Predictors of PE Manager Selection by University Endowments

This table presents a conditional logit model of PE manager selection by university endowments. Each endowment hiring a PE manager at time t can choose among all PE managers existing at time t-1. The dependent variable is a dummy variable equal to 1 for the endowment-manager pairs with a hiring event at time t. Employment Connection is a dummy variable equal to 1 if a trustee of the university and a member of the managing team of the PE firm have worked together in the past, and 0 otherwise. Education Connection is a dummy variable equal to 1 if the managing team of the PE fund includes alumni of the university. Lag Manager AUM is the PE manager assets under management the previous year, Lag Manager Age is the age of the PE firm (in years), and Lag Endw MV is the market value (in US$ mil) of the endowment that makes the hiring. The rest of the variables are interaction terms. The regression contains hiring decisions for years 1988-2008 and includes year and manager fixed effects.

	Dependent variable:				
	Dummy = 1 if Endowment Hired the PE Manager				
	(1)	(2)	(3)	(4)	(5)
Employment Connection	2.760***		2.593***		2.356***
	(0.142)		(0.164)		(0.102)
Education Connection		2.473***		2.379***	2.285***
		(0.198)		(0.188)	(0.148)
Lag Manager AUM	−0.028***	−0.024***	−0.012***	−0.011***	−0.012***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Lag Manager Age	0.011***	0.010***	−0.003	−0.003	0.003
	(0.001)	(0.001)	(0.028)	(0.027)	(0.008)
Lag Endw. MV			0.001***	0.001**	0.001**
			(0.000)	(0.000)	(0.001)
Empl. Conn * Lag Man. AUM			−0.008		−0.008
			(0.009)		(0.032)
Empl. Conn * Lag Endw. MV			−0.001		0.003
			(0.013)		(0.021)
Educ. Conn * Lag Man. AUM				0.009	−0.008
				(0.012)	(0.022)
Educ. Con * Lag Endw. MV				−0.003	0.003
				(0.014)	(0.032)
Manager FE?	Yes	Yes	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes	Yes	Yes
Observations	63,283	63,283	63,283	63,283	63,283
Max. Possible R^2	0.101	0.101	0.096	0.096	0.096
Log Likelihood	−420.145	−399.312	−408.115	−396.359	−510.690
Note:	*p<0.1; **p<0.05; ***p<0.01				

Appendix

A. Data

A1. Asset Classifications

NACUBO's asset classifications for PE mandates have changed over time. While the VC asset classification has remained constant throughout the sample, the BO asset classification has gone through various name changes. Table A.1 illustrates these.

Table A.1: Asset Classification Changes for PE Investments

This table presents the time series of NACUBO's asset classifications for reporting external PE investment managers (BO and VC).

Year	Category Name
1984-1993	Venture Capital and Leveraged Buyouts
1994-1997	Venture Capital and Buyouts
1998-1999	Venture Capital and Non-Venture Private Equity (Buyouts)
2000-2001	Venture Capital and Private Equity (Buyouts)
2002-2008	Venture Capital and Private Equity

A2. Investment Manager Reporting

Most universities that participate in the NACUBO study report their external investment managers in the "Investment Managers" section of the NACUBO report. I can identify a university as choosing not to report its investment managers when I can find market values reported in the same report, but I do not find the university in the "Investment Managers" section of the same report.

Table A.2 calculates the percentage of universities reporting in NACUBO, that also report in the "Investment Managers" section. Throughout the sample, the majority of the universities per year report in this section (the total reporting percentage every year ranges from 81% to 98%). This observation is consistent throughout the years of my sample as well as the different market value categories. The only category with relatively low percentage reporting was the one with the highest market value (more than 1 US$ bil) during the early 2000s.

Table A.2: Percentage of endowments that report in the NACUBO Investment Managers Section

This table calculates the percentage of endowments that report investment managers in the Investment Managers section of the NACUBO reports. I identify an endowment as reporting in general in the NACUBO report if it reports its market value. I identify an endowment as not reporting in the Investment Managers section if it reports its market value but not its external managers.

Year	% reporting (total)	>1 bil ($)	500 m - 1 bil ($)	100 m - 500 m ($)	<100 m ($)
1988	0.85	0.80	1.00	0.93	0.82
1993	0.92	0.69	0.79	0.95	0.93
1994	0.95	0.88	1.00	0.95	0.95
1995	0.95	0.82	0.90	0.98	0.95
1996	0.90	0.75	0.93	0.90	0.91
1997	0.93	0.88	0.89	0.94	0.93
1998	0.94	0.87	0.93	0.95	0.93
1999	0.81	0.62	0.81	0.83	0.83
2000	0.89	0.55	0.87	0.94	0.91
2001	0.95	0.66	0.96	0.96	0.98
2002	0.96	0.85	0.93	0.97	0.98
2003	0.96	0.82	0.94	0.97	0.97
2004	0.96	0.83	0.96	0.96	0.98
2005	0.97	0.82	0.98	0.97	0.99
2006	0.97	0.82	0.98	0.97	1.00
2007	0.98	0.91	0.98	0.98	1.00
2008	0.96	0.84	0.92	0.97	0.98

B. Robustness

B1. New Mandates - Regression Specification

Table A.3 checks the robustness of the result in Table 10 using a Poisson regression specification. In Table A.3, I regress the number of new mandates each BO (Panel A) or VC firm (Panel B) gets on the past network centrality of the firm. The regression controls for manager characteristics relating to reputation such as the firm's size and age, as well as year and manager fixed effects. Table A.3 shows that for the baseline estimation (an equally-weighted average of centrality measures), a higher lagged centrality measure for the manager leads to a higher number of new mandates won the next period[14]. The result holds for all measures of centrality examined in Section 4 (degree,

[14] Poisson regressions are often used in studies to model count variables and contingency tables. For example, Lerner (1995), Hermalin and Weisbach (1988) and Yermack (1996) study the determinants of the number of new

betweenness and eigenvector centrality). Panel A shows that increasing Degree Centrality by one standard deviation holding all other variables constant, increases the probability of a BO manager being hired by an additional endowment next year by almost 2.2 times (Panel A). The rest of the coefficients have similar interpretations. Overall, the result in Table 10 holds for a different regression specification that takes into account the number of new mandates gained by the endowment.

B2. Manager Performance - Value Multiple Measure

I examine the robustness of the regression specification in Table 10 to the choice of performance measure for BO and VC firms. In Table A.4, I control for performance using the Value Multiple measure instead of the IRR, and the regression results remain unchanged.[15] There still exists a positive and significant association of the lagged network centrality measure with the probability of the firm winning a new endowment mandate the next period.

board members and the number of director appointments or departures in companies.

[15] According to Preqin, this multiple is defined as the ratio between the total value that the LP has derived from its interest in the partnership (i.e. distributed cash and securities plus the value of the LP's remaining interest in the partnership) and its total cash investment in the partnership. It is a measure of 'profit' or 'loss' for the LP.

Table A.3: Centrality measures and the number of new mandates - Regression Specification

This table reports the (Poisson) regression of the number of new mandates each manager gains at year t, regressed on the centrality of the manager during the previous year t-1. Column 1 reports results with respect to the network measure Degree centrality, Column 2 reports results for Eigenvector Centrality, and Column 3 for Betweenness centrality. IRR is the internal rate of return of the PE firm, AUM are its assets under management in $mil, and Age is the number of years since the inception of its first fund. All regressions include year and manager fixed effects, span the time period 1989-2008 and standard errors are clustered by time. Panel A presents results for Buyout (BO) networks, and Panel B for Venture Capital (VC) networks.

PANEL A: BO Managers

	Dependent variable:		
	Number of New Mandates Won		
	(1)	(2)	(3)
Lag Degree	0.809***		
	(0.115)		
Lag Eigenvector Cent		0.685***	
		(0.091)	
Lag Betweenness			0.318***
			(0.042)
Lag IRR	0.009	0.009	0.003
	(0.007)	(0.007)	(0.007)
Lag Firm AUM	−0.009	0.027	0.020
	(0.047)	(0.050)	(0.050)
Lag Firm Age	−0.013	−0.015*	−0.012
	(0.009)	(0.009)	(0.009)
Constant	−18.642	−38.307	−19.802
	(9,426)	(13,331)	(9,426)
Year FE?	Yes	Yes	Yes
Manager FE?	Yes	Yes	Yes
Observations	502	501	490
Log Likelihood	−405.735	−398.342	−394.740
Akaike Inf. Crit.	1,075.469	1,060.683	1,043.479
Note:	*p<0.1; **p<0.05; ***p<0.01		

PANEL B: VC Managers

	Dependent variable:		
	Number of New Mandates Won		
	(1)	(2)	(3)
Lag Degree	0.721***		
	(0.126)		
Lag Eigenvector Cent		0.561***	
		(0.099)	
Lag Betweenness			0.244***
			(0.054)
Lag IRR	0.005	0.005	0.004
	(0.004)	(0.004)	(0.004)
Lag Firm AUM	0.016	0.022	0.027
	(0.038)	(0.039)	(0.039)
Lag Firm Age	−0.040	−0.039	−0.043
	(0.037)	(0.039)	(0.038)
Constant	−0.045	0.217	0.962
	(1.229)	(1.236)	(1.216)
Year FE?	Yes	Yes	Yes
Manager FE?	Yes	Yes	Yes
Observations	623	623	623
Log Likelihood	−367.678	−368.580	−374.580
Akaike Inf. Crit.	1,011.356	1,015.160	1,027.161
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A.4: Centrality measures and the number of new mandates - Performance measure

This table reports the (Poisson) regression of the number of new mandates each manager gains at year t, regressed on the centrality of the manager during the previous year t-1. Column 1 reports results with respect to the network measure Degree centrality, Column 2 reports results for Eigenvector Centrality, and Column 3 for Betweenness centrality. Value Multiple is the value multiple return measure of the PE firm, AUM are its assets under management in $mil, and Age is the number of years since the inception of its first fund. All regressions include year and manager fixed effects, span the time period 1989-2008 and standard errors are clustered by time. Panel A presents results for Buyout (BO) networks, and Panel B for Venture Capital (VC) networks.

PANEL B: VC

	Dependent variable:		
	Probability of winning extra mandate		
	(1)	(2)	(3)
Lag Degree	1.045***		
	(0.256)		
Lag Eigenvector Cent		0.887***	
		(0.208)	
Lag Betweenness			0.328***
			(0.113)
Lag Value Mult.	0.040	0.043	−0.019
	(0.095)	(0.093)	(0.095)
Lag Firm AUM	0.022	0.024	0.026
	(0.082)	(0.080)	(0.083)
Lag Firm Age	−0.076	−0.080	−0.087
	(0.084)	(0.081)	(0.081)
Constant	20.239	20.435	21.678
	(10,754.010)	(10,754.010)	(10,754.010)
Year FE?	Yes	Yes	Yes
Manager FE?	Yes	Yes	Yes
Observations	623	623	623
Log Likelihood	−210.343	−209.736	−215.310
Akaike Inf. Crit.	698.685	697.472	708.620
Note:	*p<0.1; **p<0.05; ***p<0.01		

PANEL A: BO Managers

	Dependent variable:		
	Number of New Mandates Won		
	(1)	(2)	(3)
Lag Degree	0.809***		
	(0.115)		
Lag Eigenvector Cent		0.685***	
		(0.091)	
Lag Betweenness			0.318***
			(0.042)
Lag IRR	0.009	0.009	0.003
	(0.007)	(0.007)	(0.007)
Lag Firm AUM	−0.009	0.027	0.020
	(0.047)	(0.050)	(0.050)
Lag Firm Age	−0.013	−0.015*	−0.012
	(0.009)	(0.009)	(0.009)
Constant	−18.642	−38.307	−19.802
	(9,426)	(13,331)	(9,426)
Year FE?	Yes	Yes	Yes
Manager FE?	Yes	Yes	Yes
Observations	502	501	490
Log Likelihood	−405.735	−398.342	−394.740
Akaike Inf. Crit.	1,075.469	1,060.683	1,043.479
Note:	*p<0.1; **p<0.05; ***p<0.01		

3. Are University Endowments Really Long-Term Investors?

Abstract

This paper examines the investment strategy evolution of U.S. university endowments as well as their investing behavior around the most important financial crises since the beginning of the 20th century. I use a unique long-term dataset on endowment characteristics and allocations from 1900 to 2016 of twelve important U.S. university endowments. The analysis documents the evolution of their asset allocations, including the early adoption of equity investing in the 1930s and the more recent shift into alternative assets. Endowments also invest countercyclically around crises, decreasing their allocation to risky assets before a crisis onset and increasing them after a crisis onset, in marked contrast to other types of institutional investors.

Keywords: Investments, financial markets, crises, university endowments

1 Introduction

Endowments are investment funds aiming to meet the needs of their beneficiaries over multiple generations and to adhere to the principle of intergenerational equity (Tobin (1974)). Hence, they are distinctive among investors in having the opportunity to focus on long-term investment objectives while not having to worry so much about short-term liquidity needs. The styles and strategies of some university endowments in particular, have provided a template many subsequent institutional and individual investors have followed in recent years. While scholars have previously examined the history of insurance companies and investment trusts, very little long-run analysis has been undertaken of such long-horizon investors as university endowments, notwithstanding the fact that many are long-lived.

This study exploits a new long-run data set of endowment investments to examine two questions. Firstly, I analyze how the investment strategy of U.S. university endowments has evolved since the beginning of the 20th century. In particular, I document the major shifts in their asset allocation over this time. Secondly, I examine whether these funds do, indeed behave as long-term investors by examining their investment behavior around the time of major financial crises. Recent studies have found that such institutional investors as pension funds and mutual funds behave procyclically during crises – that is, buying assets when prices are high and selling them when they are low (Manconi et al. (2012), Papaioannou et al. (2013), Duijm and Steins Bisschop (2018)). According to Jones (2017), a considerable segment of institutional investors had incentives to "bubble ride" during crises due to such factors as benchmarking, peer group herding pressure and short-term performance evaluation windows. In contrast, one might expect endowments to exploit their long investment horizon and to behave countercyclically – that is, selling assets when prices are high and buying them when they are low.

To address each of these questions, I exploit hand-collected data on the twelve wealthiest U.S. university endowments in the early decades of the 20th century. For each university, I collect data from 1900 to the present on endowment characteristics such as their asset allocations and investment returns. In terms of the evolution of their investment strategy, I document two major shifts in asset allocation consistent with prior studies: the first from bonds to stocks beginning in the 1930s and the second from stocks to alternative assets beginning in the 1980s. Moreover, the Ivy League schools (and notably, Harvard, Yale and Princeton) led the way in these asset allocation moves in both eras. I explore the rationale behind these major shifts in investment strategy.

Next, I analyze the asset allocation responses of endowments before and after the onset of the six "worst" financial crises since 1900 in the U.S. as defined by Reinhart and Rogoff (2009): 1906-1907, 1929, 1937, 1973-74, 2000 and 2008. In each episode, I calculate the active portfolio allocation changes in risky assets (equities and alternative assets). Following Calvet et al. (2009) and Bams et al. (2016), I deconstruct the total changes in risky asset allocations into a passive change (due to the overall market movement) and an active change (due to rebalancing by the endowment). My main finding is that typically during the run-up to a crisis, endowments decrease their active risky allocations; while after the crisis onset, they actively increase these allocations as risky asset prices fall. This evidence suggests that endowments do, indeed tend to invest countercyclically.

The rest of the paper is structured as follows. Section 2 provides the background on university endowment management since the inception of university endowments. Section 3 discusses the relevant literature on financial market crises, institutional investor strategies around times of distress, and endowment investing. Section 4 describes the data, while Section 5 documents the evolution of university endowment investment strategies over the long run. Section 6 analyses their behavior around the most important crises since the beginning of the 20th century. Section 7 concludes.

2 Historical Evolution of Endowment Investing

The so-called "U.S. endowment model", often attributed to Yale University and its chief investment officer (CIO) David Swensen, is an investment approach characterized by diversification, active management, equity orientation and illiquid assets (Swensen (2009)). Chambers and Dimson (2015) claim that the writings of John Maynard Keynes were a considerable influence on David Swensen. More specifically, Chambers and Dimson (2013) and Chambers et al. (2015) document Keynes's revolutionary shift to equities in the early 1920s and evaluate his investment strategies, suggesting that some of the lessons he learned remain relevant to endowments today. Moreover, Keynes had investment insights in switching into equities, as his move preceded the leading U.S. university endowments in the mid-20th century. In retrospect, equities have had a very substantial long-term real return since 1900 and proved to be the best performing investment of the 20th century (Dimson et al. (2002, 2018)).

In recent years, endowments emerged as a class of highly sophisticated institutional investors with considerable amounts of capital and excellent reputation. Their long-term investment profile and their low short-term liquidity needs have helped them take more risks and move into new (for each era) asset classes earlier than other investors. Moreover, nowadays, endowment investment committees are composed of financially literate members led by CIOs with relevant industry experience. In explaining the reasons for their long-term investment success, Yale University, for example, regularly considers opportunities and strategies ignored by other investors and relies heavily on the identification of top-tier managers (Yale Endowment Report, 2017). Yale has used its extensive network to foster partnerships with idiosyncratic, alpha-generating managers, and established its reputation for collaborating with premier firms that might otherwise be reluctant to open to outside capital. U.S. university endowments have evolved to become a distinctive and innovative class of investment institutions.

2.1 Inception Until the 1960s

The style of investment management practiced by endowments has changed dramatically since their inception (Kochard and Rittereiser (2008)). Endowment funds can be traced back to the fifteenth century when donors in England made gifts to universities to support them in perpetuity. Usually, these gifts carried the restriction that the donated capital needed to be preserved, although the income from the endowment could be spent. Donors frequently restricted the use of an endowment for a specific purpose, such as professorships or scholarships. Endowments were intended to be a permanent source of income for institutions that traditionally did not have income.

Up to the end of the 1960s, endowment assets were managed by wealthy trustees of the colleges and were placed under strict rules forbidding delegation of investment decisions and limiting discretion in spending (Kochard and Rittereiser (2008)). Ellis and Vertin (1991) suggest that American colleges and universities did not increase their endowments through investment management as much as other general growth funds. The performance track record of endowments was also not comparable to their current performance records. For example, around 1928 and for nearly a decade, Yale devised a rebalancing plan out of equities and into bonds, which led Yale to miss out on one of the greatest bull markets post-World War II (Ellis and Vertin (1989)).

2.2 Changes in the 1970s

Towards the end of the 1960s, McGeorge Bundy at the Ford Foundation became concerned about the rising costs of higher education and studied ways to make the management of the endowment more productive. In 1969, the Foundation published two studies as "Reports to the Ford Foundation", suggesting changes in the management of the endowments. The reports identified endowments as corporations with one beneficiary and its trustees as representatives of the institution responsible for setting policy on spending and investing. Investing was allowed to be delegated to outside investment advisers, subject to the appropriate monitoring of the trustees. In the Ford Foundation annual report published in 1967, Bundy wrote:

> We believe there may be room for great improvement here. It is far from clear that trustees have reason to be proud of their performance in making money for their colleges. We recognize the risks of unconventional investing, but the true test of performance in the handling of money is the record of achievement, not the opinion of the respectable.

Few institutions had the capacity to manage their endowments pursuing this new recommended investment approach. As a result, the Commonfund was established as an investment company that pools the assets of its members and manages them professionally. The Commonfund remains a leading asset manager for university endowments today, with almost 10% of all U.S. university endowment mandates outsourced to it (by count of mandates). Moreover, in collaboration with NACUBO (National Association of College and University Business Officers), it produces benchmarking reports for U.S. university endowments up to today.[1]

2.3 The 1980s until Recent Years

In recent years, the investment complexity of the world's capital markets has driven the need for professional management of assets and prompted endowment trustees to hire full-time investment professionals as CIOs.[2] Since the 1980s, universities have shifted into allocating a considerable amount of their portfolios to highly sophisticated alternative investments. Each endowment has an investment office deciding on investment policy and which can choose to

[1] NACUBO is an advocacy organization devoted to improving management practices in the higher education industry and compiles yearly reports about the investment practices of university endowments.

[2] For example, Harvard Management Company was founded in 1974 to manage the university's endowment and is made up of more than 13,000 individual funds invested as a single entity, as of 2019 according to their endowment report.

manage the funds itself (internally) or to delegate management to external asset management firms. Outsourcing the investment management of endowment portfolios has become 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 university endowments in the U.S. surveyed in the NACUBO reports have adopted the external management approach for at least part of their portfolio.

The above suggests that endowment management has changed over the past century. Endowments have evolved into a class of sophisticated and professionally managed investors. My prior is that this professionalization of the management of endowments makes them more likely to able to exploit their long-term horizon and behave countercyclically later in the 20th century compared to earlier. I examine this conjecture later in the paper.

3 Related Literature

The research questions of this paper are related to the literature on financial market crises, institutional investor strategies around times of distress, and endowment investing.

The U.S. financial markets have suffered from multiple crises since the beginning of the 20th century, and the literature has looked at their predictors, similarities, and contributing factors. Several academics such as Jordà et al. (2011), Carlson (2015) and Danielsson et al. (2018) take a historic perspective on crises using very long datasets spanning more than a century and study their economic effects, the tools used to predict them and the effectiveness of their deterring mechanisms. Others, such as Bordo et al. (2001) and Almunia et al. (2014) discuss similarities among crises over time, their frequency, severity, and the policies used to remedy them.[3]

Economic historians have also explored the extent to which irrational investor behavior drove bubble episodes preceding market crashes, with particular emphasis on 1929 in the U.S. (Nicholas (2008), De Long and Shleifer (1991), Rappoport and White (1993), Rappoport and White (1994), Shiller (2005)). This literature suggests that the aggregate behavior of (retail) investors was

[3]Other papers related to the literature of the history of economic crises are Eichengreen and Bordo (2003), Shachmurove (2011), and Carlson and Wheelock (2016).

procyclical. Moreover, Cohn et al. (2015) present evidence that a decline in stock prices makes investors more fearful and risk averse, which could lead to an increase in selling that pushes prices further down. This paper specifically considers whether institutional investors as represented by endowments behaved differently both in 1929 and during other crisis episodes, given their ability to invest with a long horizon.

This paper relates to the large literature on institutional investor herding behavior. Previous research has shown that institutional investors such as mutual funds exhibit herding behavior mainly due to their incentive contracts and reputational considerations. Maug and Naik (2011) suggest that since managers are evaluated against one another, they tend to ignore their own information to "go with the flow" and not deviate from their benchmark, while Dasgupta et al. (2011) suggest that reputational concerns might also lead fund managers to imitate past trades. Froot et al. (1992) show that if speculators have short horizons, they may herd on the same information, trying to learn what other informed traders know.[4] All the above studies suggest that managers and investors tend to imitate one another. Although endowment objectives and organizational structures differ from those of other investors, their managers still operate in a competitive environment for investment performance. Therefore, it is interesting to explore whether they also tend to exhibit herding behavior.

This study connects with the literature on institutional investor strategies around times of distress, focusing mainly on the most recent financial crisis (2007-2008). Papaioannou et al. (2013) discuss the procyclical behavior of institutional investors such as pension funds and mutual funds during the crisis, while Duijm and Steins Bisschop (2018) also find evidence of procyclical behavior by Dutch insurance companies during the crisis. Moreover, Manconi et al. (2012) discuss the role of institutional investors such as mutual funds in propagating the crisis when faced with liquidity shocks by selling corporate bonds. Ben-David et al. (2012) show that hedge funds exited the U.S. stock market en masse as the financial crisis evolved, primarily in response to the tightening of funding by investors and lenders. During the 1999-2000 dot-com bubble, young inexperienced managers displayed procyclical behavior by increasing their technology holdings during the run-up and decreasing them during the downturn (Greenwood and Nagel (2009)), while U.S. life insurers contributed to the market crash post-2000 by selling equities in a falling market (Impávido and Tower (2009)). Lastly, Dass et al. (2008) claim that herding behavior related to contractual incentives of mutual funds partially caused the dot-com bubble.

[4] Other papers relevant to the herding and trading literature are Sias (2004), Nofsinger and Sias (1999), Bulow and Klemperer (2002) and Dennis and Strickland (2002).

A competing view suggests that countercyclical behavior and rules to rebalance back to strategic benchmarks around the time of the financial crisis have been favorable for institutions such as Norway's sovereign wealth fund (Dahlquist and Ødegaard (2018)). Perold and Sharpe (1988) also suggest that countercyclical investment (that buys stocks when their prices fall and sells them when they rise) capitalizes on reversals and outperforms a buy-and-hold strategy. Lakonishok et al. (1994) suggest that value strategies produce higher returns because they exploit the suboptimal behavior of the typical investor. Additionally, Chien et al. (2012) find that intermittent rebalancing more than doubles the effect of aggregate shocks on the time variation in risk premia. Lastly, investment into equities by endowments during the 1930s crisis when equity prices were falling (Goetzmann et al. (2010)) and sophisticated trading by hedge funds during the dot-com bubble (reducing exposure to individual stocks before prices collapsed (Brunnermeier and Nagel (2004))), provide notable examples of countercyclical behavior by institutional investors.

In this analysis, I look closely at the investing behavior of endowment funds during the most important crises since the beginning of the 20th century. My hand-collected dataset covers a longer period than previously available for other institutional investors, and includes the actual asset allocations, characteristics and investment returns of endowments. Brown et al. (2010) suggest that asset allocation policy can account for most of the time series variation in endowment portfolio returns, while Ang (2012) and NBIM (2012) claim that rebalanced portfolios have displayed both higher returns and lower risk than a passive portfolio over a long period. Therefore, studying the rebalancing decisions of endowments helps to uncover the trading behavior of large institutional investors with a long investment horizon as well as their performance during crises.

Last, this paper relates to the literature on endowment investing. Lerner et al. (2008) investigate the factors accounting for university investment success and attribute the dramatic growth in endowment size to high investment returns related to the quality of student body and use of alternative assets. They 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. Lerner et al. (2007) find that endowments have exceptional selection abilities for venture capital partnerships. However, Sensoy et al. (2014) find that the investment advantage of university endowments and their superior returns disappear after 2000 mainly due to the maturation of the PE industry. Moreover, Brown et al. (2010) examine the relationship between asset allocation and performance and show that asset allocation is an important determinant of the level and variation in the time series of returns. Furthermore, they find that university endowments as a group do not generate significant risk-adjusted returns. Similarly, Barber and Wang (2013) utilize style attribution models and find no outperformance for the average endowment once hedge fund and private equity indexes are included in their model. Gilbert and Hrdlicka (2015) study the opportunity cost of building a large and risky endowment in terms of forgone internal investment by suggesting a model which explains the large heterogeneity in endowment size and allocation to risky assets. Last, Goetzmann and Oster (2012) examine the role of strategic competition among university endowments on their asset allocation shifts, with a special focus on the recent shift towards alternative investments.

Other influential studies on endowments have focused on risk taking, payouts, and spending rules. Tobin (1974) proposes a spending rule based on the notion of intergenerational equity, while Merton (1993) derives a model for optimizing investment and expenditure policy taking into account the university's objectives and sources of income. Dimmock (2012) tests the relationship between the volatility of non-financial income and endowment portfolios, showing that universities with high background risk have lower portfolio standard deviation and that elite universities hold riskier portfolios. Brown et al. (2014) find that endowments respond to market shocks by reducing their payouts following negative shocks. Last, Brown and Tiu (2013) examine spending rules revisions and find that larger endowments with lower historical portfolio returns and payout levels are more likely to alter their spending formulas.

My study adds to the above literature by describing the evolution of U.S. university endowment asset allocation over more than a century and by analyzing the extent to which they are able to exploit their long horizon by investing countercyclically around the time of financial crises.

4 Data

This paper employs a novel hand-collected dataset covering the investments of twelve U.S. university endowments for the period 1900-2016. The endowments which make up the data set are Brown University, Columbia University, Cornell University, Dartmouth University, Harvard University, Princeton University, University of Pennsylvania (UPenn), Yale University, Massachusetts Institute of Technology (MIT), University of Chicago, Johns Hopkins University (JHU) and Stanford University. All are large private doctoral institutions (i.e., universities offering Ph.D. degrees) and the wealthiest university endowments in existence in the early decades of the 20th century. The data contains individual endowment characteristics including their asset allocation breakdown, endowment market value and investment returns (fiscal years end in June).[5]

Table 1 describes the variables in the dataset, along with their sources. The data up to 1974 is hand-collected from the archives of the universities. The remaining sources include University Treasurer Reports, reports from the National Association of College and University Business Officers (NACUBO) and the Commonfund, the Higher Education General Information Survey (HEGIS), the Integrated Postsecondary Education Data System (IPEDS), and the Voluntary Support for Education (VSE) dataset produced by the Council Aid to Education. The NACUBO/Commonfund data is free of survivorship bias, as most educational institutions (and their endowments) are quite enduring (Barber and Wang (2013)).

Table 2 presents summary statistics for the twelve university endowments in the sample, such as the year of establishment, endowment fund size at selected dates in the sample (1926, 1970, 1985, 2016), and growth rates of endowment assets over the past century in real terms. Ivy League Schools are reported in Panel A and Non-Ivy League Schools in Panel B. Ivy League schools are older than Non-Ivy League schools. All endowments in the sample are quite large and grew at a real annualized rate of about 4%. As of 2016, the largest endowments are Harvard, Yale, and Princeton (H-Y-P), with Harvard reaching a market value of US$35 billion. To the best of my knowledge, this is the most comprehensive long-run dataset covering the investments of the largest U.S. university endowments.

In order to examine endowment investing behavior during financial crises, I source the dates of the most important crises since the beginning of the 20th century using the data from Reinhart and Rogoff (2009). I also cross-check these dates with the data from Robert Shiller's website and confirm that the crisis years coincide with the peaks and falls of the S&P500 index.[6] I identify six

[5]For the early years of the sample and for any year in which endowments did not report their returns, I calculate returns by multiplying the asset allocation weight for each endowment-year with a corresponding asset-class benchmark return. Data on Harvard, Yale and Princeton (H-Y-P) stock holdings until the 1980s indicate that endowments dramatically increased the number of stocks in their portfolio from the mid-1920s onwards. At that time, H-Y-P held around 100 stocks in their portfolios, a number which rose to 300 in the late-1930s. After adopting equity investing around the 1930s, all three endowments held large, diversified portfolios invested in large-cap U.S. stocks (Foo (2013)). I therefore infer that endowments were closet indexers.

To further test the validity of this assumption, I calculate the difference of returns using this methodology with the actual returns of the endowments for the years that they are available. I use the 1974-1983 decade as a sample period because of the likelihood of the similarity with my estimated period. After the 1980s the management of the endowments changed significantly with the introduction of alternative assets. Such a change would make endowment returns to substantially diverge from conventional benchmarks. Taking the absolute values of the differences in returns, my estimation methodology produces returns that are on average 3% different from the actual returns with a standard deviation is 2% (on an average of 10.5% return). Therefore, I conclude that the assumptions for estimating the endowment returns estimation at the beginning of the sample are reasonable.

[6]Robert Shiller's data can be found here: http://www.econ.yale.edu/~shiller/data.htm.

important crises, by the % decline of the S&P500 composite index from peak to trough around the crises dates. The crises I examine are as follows: 1906-1907 (Panic of 1907, -38%), 1929 (Wall Street Crash of 1929, -84%), 1937 (Economic Recession of 1973-74, -45%), 1973 (Stock Market Crash of 1973-74, -25%), 2000 (Dot-Com Bubble of 2000, -43%) and 2008 (Financial Crisis of 2008, -51%).

5 Endowment Investing Over the Long Run

5.1 Asset Allocation Evolution

Endowment investing exhibited two major developments over the past century, the adoption of common stock investing and the more recent shift into alternative assets. In this section, I examine these asset allocation strategy changes, as well as the characteristics of the universities initiating them.

5.1.1 Allocation Strategy Changes

Figure 1 plots the average endowment portfolio allocations to the four main asset classes: fixed income, equity, real estate and alternative investments. Fixed income exposure is approximated as the total allocation to bonds, mortgages and cash, equity allocation contains both common and preferred stock, and alternative investments include private equity (venture capital and buyouts) and hedge funds. The graph displays allocations starting from 1926, the first date with available allocations for all endowments in the sample. While prior research concentrates on the period after 1983, this data covers almost a century of investing.

At the beginning of the 20th century, endowments were unlike modern equity-focused portfolios, allocating most of their portfolios to bonds. Equity was a new asset class and Goetzmann et al. (2010) claim that equity investing during the early 20th century was deemed by investors to be too risky to form a significant proportion of their portfolio. Therefore, the average endowment in the early decades of the last century focused on bonds and allocated less than 10% of its portfolio into equities, a proportion which rose to around 60% from 1960 to 1990. This equity allocation was subsequently diminished during the past two decades, as funds shifted into other risky assets.

The real estate weight in U.S. endowment portfolios remained at quite low levels during the whole period. This practice contrasts with that of the wealthiest universities in the United Kingdom, Cambridge and Oxford, which historically devoted a significant amount of their portfolio to real estate. The maximum real estate allocation in the sample is that of Columbia University, as a result of a gift of valuable property in Manhattan in the 1910s.[7]

Finally, alternative assets were introduced to endowment portfolios in 1980 and their popularity rose dramatically thereafter. The strategy involving private equity and hedge funds is commonly known as the "U.S. endowment model" or "Yale model" (Swensen (2009)). The allocation to alternatives grew rapidly and alternatives today have replaced equities as the dominant asset class in the largest university endowment portfolios, which now allocate an average of 50% of their funds to alternatives. This portfolio shift was implemented predominantly at the expense of fixed income and equity investments, as discussed in Brown et al. (2010). Despite the economic turmoil and the recent financial crisis, U.S. university endowments still follow the Yale model and allocate a considerable proportion of their portfolios to alternative assets.

5.1.2 Early Adopters of Changes

Having distinguished these asset allocation trends, I examine the early adopters of these moves. I focus on the allocation changes of equities and alternative investments. I explore the extent of clustering among endowments in the timing of these major asset allocation shifts, and whether this can be explained by endowment characteristics. To do so, I partition universities using multiple criteria such as size, age, geographic region and Ivy-League/Non-Ivy-League university status. I hypothesize that larger institutions might have different investment opportunities and goals than smaller ones. Ivy League schools, which are older institutions, might also have different preferences for asset classes or risk than Non-Ivy League schools. For instance, the younger tech-biased institutions such as Stanford, Chicago, or Cornell might be more innovative than the older Ivy-League schools such as H-Y-P, and move earlier than their peers into new asset classes. Lastly, I hypothesize that geographically close universities might behave in similar ways due to competition effects or the easier diffusion of new ideas due to proximity. I explore some of these hypotheses in Figures 2 to 4, where I report the most distinctive patterns.

Concerning the allocation to equities, small endowments (Figure 2) and Ivy League schools (Figure 3) were more aggressive in switching their allocation towards this new asset class at the beginning of the period compared to the rest. Ivy League schools were also the first to move out of equities in the past two decades. Regarding the allocation to alternative assets, the largest

[7] Today Columbia University is by far the largest landowner in New York City by number of addresses held. The spike in the late 1970s is due to the revaluation of their Rockefeller Center holdings.

and oldest endowments pioneered the move into this asset class starting from the 1980s. More specifically, as already established in the literature and depicted in Figure 4, H-Y-P initiated this move and continued their disproportionately higher allocation to alternative investments. Their allocation to alternatives was also consistently higher than the average Ivy League school. Overall, the above suggests that the older, Ivy League schools initiated both the move into equities and the move into alternative assets.

This obviously invites the question as to whether there is some institutional memory or other characteristic which enables these endowments to repeatedly take the lead.

5.2 Endowment Growth, Returns and Donations

This section examines the returns of the university endowments and the determinants of donations to the endowment. The value of U.S. university endowments has risen dramatically since the beginning of the 20th century, and this evolution can be attributed to both their positive returns as well as the inflow of donations to the universities, which makes examining them an important question. To demonstrate the above claim, Figure 5 replicates a graph included in Yale's 2013 endowment report, titled "Endowment Growth Outpaces Inflation 1950–2013". Figure 5 shows that, even after taking into account inflation and gifts to the endowment, there remains a large portion of Yale's market value that came from superior investment performance, especially after the 1990s. Therefore, the growth in endowments' market value can be disentangled into three components, namely the effect of inflation, gifts to the endowment, and investment performance. Figure 6 performs the same growth attribution for all universities in my sample ranked from highest to lowest assets under management (AUM) in the beginning of the period. The market value of each endowment as of 2016 is depicted over the columns. I find that investment performance has been the most important determinant of endowment AUM growth for larger universities, while gifts have contributed more to the growth of the market value of smaller institutions.

The above suggests that examining endowment returns and inflows of donations is crucial to understanding endowment AUM growth. First, I estimate a long-term risk and return series for all endowments in the dataset since 1927. Table 3 presents the long-term returns for the endowments in terms of arithmetic as well as geometric returns, the standard deviations of their arithmetic returns and Sharpe Ratios. The same statistics for Ivy League, Non-Ivy League schools and relevant benchmarks are also reported. I estimate returns for the periods 1927-

2016 (Panel A) and 1975-2016 (Panel B), as all universities publicly disclosed their endowment returns from 1975. Prior to that date, I estimate endowment returns using their respective asset allocations and benchmark returns for each asset class. The average U.S. university endowment in the sample had a return of 10% (arithmetic return) or 9.2% (geometric return) over 1927-2016. Ivy League endowments fared equally well as Non-Ivy League ones on average and were slightly ahead of a balanced portfolio that constantly allocated 60% in equities (S&P500) and 40% in bonds (AAA corporate bonds Barclays U.S. Investment Grade Index) in terms of their geometric return. Since 1975, these endowments on average returned 12.5% (arithmetic return) and 11.8% (geometric return) and beat the 60/40 benchmark by around 1.5% p.a. This outperformance is consistent with the fact that the management of the endowments has improved over time.

Additionally, I test whether endowment performance positively affects donations. In Table 4, I regress the change in logs of donations to the endowment on lagged endowment returns. I find that high past endowment performance plays a significant role in encouraging subsequent donations to endowment funds (Column 1). However, this effect diminishes after two years (Column 2). This finding is robust to controlling for changes in donor wealth (proxied by state income per capita), changes in endowment size, and university fixed effects. This result suggests that donors are more willing to donate money to university endowments with strong investment management teams achieving higher investment returns. If the university cannot perform as well or better than the donor with the assets, the donor is unlikely to transfer large gifts to it. Their donations play, in this way, an essential role in promoting income to the university in the future. I also examine whether the performance-donation relationship is asymmetric, namely whether donors increase donations to high performers but reduce donations to low performers. In Column 3, I find no such asymmetric response when using a dummy variable to indicate a negative past endowment return. Lastly, the impact of past returns on donations does not change around financial crises. In Column 4, a dummy variable indicating the onset of a financial crisis appears insignificant.

6 Endowment Investment During Financial Crises

6.1 Active Changes in Risky Asset Weight

I explore the risky asset allocation responses of endowments to six of the worst financial crises in U.S. history. I treat equities as the risky asset in endowment portfolios. I calculate the active allocation changes for the following major crises since the beginning of the 20th century: 1906-1907 (Panic of 1907), 1929 (Wall Street Crash of 1929), 1937 (Economic Recession of 1973-74), 1973 (Stock Market Crash of 1973-74), 2000 (Dot-Com Bubble of 2000) and 2008 (Financial Crisis of 2008).

To capture active allocation changes, I use the methodology described in Calvet et al. (2009) and Bams et al. (2016), which decomposes the total change in asset allocation into a passive change (due to market fluctuations) and an active change (due to rebalancing). I estimate the active changes using the equity and bond total return indices data from Dimson et al. (2018).

When the risky asset is equities, the actual change of the risky asset weight can be calculated as:

$$Change\,in\,Risky\,Asset\,Weight \quad = \quad w_{t+1} - w_t \tag{1}$$

I define the passive risky asset return as the return of the equity index: $1+r_{t+1}$. For simplicity, I am assuming that the portfolio is allocated between equities and fixed income, and the fixed income part earns a return of $1 + r_f$. Therefore, the risky asset share in the portfolio could be calculated as follows:

$$w_{p,t+1} \quad = \quad \frac{w_t * (1 + r_{t+1})}{w_t * (1 + r_{t+1}) + (1 - w_t) * (1 + r_{f,t+1})} \tag{2}$$

which is the zero-rebalancing weight in the risky asset. The active change of the endowment risky asset weight due to investment decisions taken by the endowment is then:

$$Active\,Risky\,Asset\,Weight \quad = \quad w_{t+1} - w_{p,t+1} \tag{3}$$

As an indication of allocation changes, Figures 7 and 8 depict cumulative active changes of the equity allocation for the average endowment portfolio before and after each crisis.[8] In both pre-crisis and post-crisis periods, endowments can behave countercyclically (sell before the crisis onset, buy after), procyclically (buy before the crisis onset, sell after), or have no discernible strategy.

Countercyclical behavior post the crisis onset is apparent for almost all episodes since the beginning of the 20th century. Endowments invested in equities in falling markets the year

[8] The y-axis is measured in percentage terms and reported above each column are the p-values of the one-sample t-test of the average active allocation change being statistically different from zero.

directly after the Panic of 1907, during the years after the Wall Street Crash of 1929, the years after the economic recession of 1937-38, and the Dot-Com Bubble of 2000. Moreover, delayed countercyclical behavior by one year was observed for the Stock Market Crash of 1973-74. Countercyclical behavior by endowments before the crisis onset is less pronounced, but it is apparent in the year before the economic recession of 1937-38, the Dot-Com Bubble of 2000, as well as the Financial Crisis of 2008. During these episodes, endowments decreased their exposure to equities in rising markets. Overall, endowments are typically contrarian (Figure 8), and their countercyclical behavior is more prominent during the most recent crises.

In unreported results for years 2000 and 2008, I redefine the risky asset as the sum of public equities and alternative assets.[9] In doing so, I recognize that the latter are typically illiquid in nature and are perhaps less easily traded during crisis periods. My main findings remain qualitatively unchanged when adopting this alternative definition. In the case of illiquid asset changes, part of them could also be driven from the timing of the capital distributions of PE firms. Robinson and Sensoy (2013) show that PE capital distribution takes usually place at the top of the cycle (thus in the run-up) and capital call at the bottom of the cycle. However, the results overall show that the allocation changes around the times of financial crises are due to decisions of endowments to invest or disinvest from risky assets.

6.2 Rebalancing Regressions

I next explore the endowment-level relation between active and passive changes, and employ a similar methodology to the one discussed and implemented in Calvet et al. (2009) and Bams et al. (2016), testing the level of passive changes in the portfolio that is offset by active changes. The specification is as follows:

$$Active\,Change_{t+1} = \gamma_{0,t+1} + \gamma_1 Passive\,Change_{t+1} + \gamma_2 (Pre - Crash/Crash)_t \tag{4}$$

The variable of interest is the $Passive\,Change$ of the risky allocation of the portfolio, and measures how much of the change in equity allocation is explained by passive equity change. A fully passive endowment would be characterized by zero regression coefficients ($\gamma_{0,t+1} = \gamma_1 = 0$). Table 5 summarizes the regressions of the active change in the risky asset weight on its passive change. Regression (1) estimates the above specification and shows that endowments offset the

[9] For this part of the analysis, the alternative assets indexes I use are the Cambridge Associates Private Equity Index and the Hedge Fund Research Fund-Weighted Composite Index.

passive change in their portfolios due to market fluctuations through active rebalancing.

In additional regressions, I include dummy variables which correspond to periods prior to the crisis onset ($Pre - Crash$) and post the crisis onset ($Crash$) in Regressions (4) and (5). The $Pre - Crash$ and $Crash$ Dummies are equal to 1 three years preceding a crisis onset (and 0 otherwise) and equal to 1 three years after a crisis onset (and 0 otherwise), accordingly. I show that while rebalancing is strong over the whole sample period, it is, on average, stronger in $Pre - Crash$ periods. In Regressions (2) and (3), I also split the sample in periods of positive and negative market returns, and find that rebalancing is strong in both sub-samples.

Overall, these results strengthen my conjecture that endowments did indeed behave counter-cyclically as long-term investors since the beginning of the 20th century.

6.3 Allocation Strategies of Mutual Fund Investors Before and After Crises

This section examines whether the investing behavior of university endowments around times of crisis differs from that of other types of investors. The literature has suggested that such investors as mutual funds and pension funds invested procyclically in the most recent financial crisis (Papaioannou et al. (2013)). In this section, I also examine how individual investors behave around crises as proxied by their investment flows into and out of mutual funds.

I use data on U.S. mutual funds downloaded from Morningstar, including fund flows for equity and bond mutual funds. Since the Morningstar data starts in 1989, I can only compare them with those of endowments for the most recent crises, the Dot-Com bubble of 2000 and the Financial Crisis of 2008.

Figure 9 shows that before the onset of both the 2000 and 2008 crises, equity mutual funds experienced high net inflows, possibly due to the high liquidity and low financial market volatility during the pre-crisis period. These inflows declined sharply following the peak of the Dot-Com bubble in 2000 and turned into net outflows following the 2008 crisis. These patterns point to procyclical behavior by investors in mutual funds during the last two crises. A different pattern seems to be prevalent in the case of bond fund flows around crises. In contrast to equity mutual funds, bond funds experienced net inflows after the onset of both crises, while having lower inflows or even outflows before the onset of the crises. This suggests that investors in mutual funds were chasing positive equity returns in the run-up to the crisis by putting money into equity mutual funds and ignoring or even taking money out of less risky bond funds. Similarly, post the crisis onset investors took money out of equity mutual funds in favor of bond mutual funds.

Overall, the results suggest that individual investors in mutual funds exhibited a procyclical behavior around financial crises, in contrast to endowment funds.

7 Conclusion

University endowments are one of the oldest classes of institutional investors, display distinctively long horizons and have pursued an investment approach that many investors subsequently adopted. Therefore, it is particularly interesting to study how they allocated their portfolios over the long-run and the determinants of these decisions, as well as how they invested during the most important financial crises since the beginning of the 20th century.

In the first section of the paper, I document the distinctive trends in endowments' long-term asset allocation such as the early adoption of equity investing and the more recent shift into alternative assets. I highlight that Ivy League schools were the ones initiating the switches into the relatively new asset classes. I also find that on average these endowments performed in line with the typical 60/40 benchmark over the half century up to the early 1970s, but thereafter beat their benchmark. Furthermore, I show that endowment market value growth over the long term was driven by a combination of good investment performance and donations. I also document that past out-performance encourages future donations to endowments.

In the second section of the paper, I examine how these important and supposedly long-term investors behaved around times of crisis. Calculating active risky asset allocation changes, I find that endowments typically exhibited a countercyclical investment pattern, reducing their allocation to risky assets such as equities and alternative assets before the onset of a crisis, and increasing their allocation afterwards. Furthermore, this countercyclical behavior became more pronounced in the two most recent crises, the Dot-Com Bubble and the 2008 Financial Crises. In comparison, investors in mutual funds exhibited strongly procyclical behavior around the two most recent crises.

Overall, this paper uses a novel, hand-collected dataset to help our understanding of the investment strategies of university endowments over the very long run.

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Figures and Tables

Figure 1: Endowment Asset Allocations Over the Long-Run

This figure shows the evolution of the average endowment portfolio weights for four asset classes - bonds, equities, real estate and alternative investments (private equity and hedge funds). "Average" is the average allocation of all endowments, "Min" is the minimum asset allocation and "Max" is the maximum allocation each year.

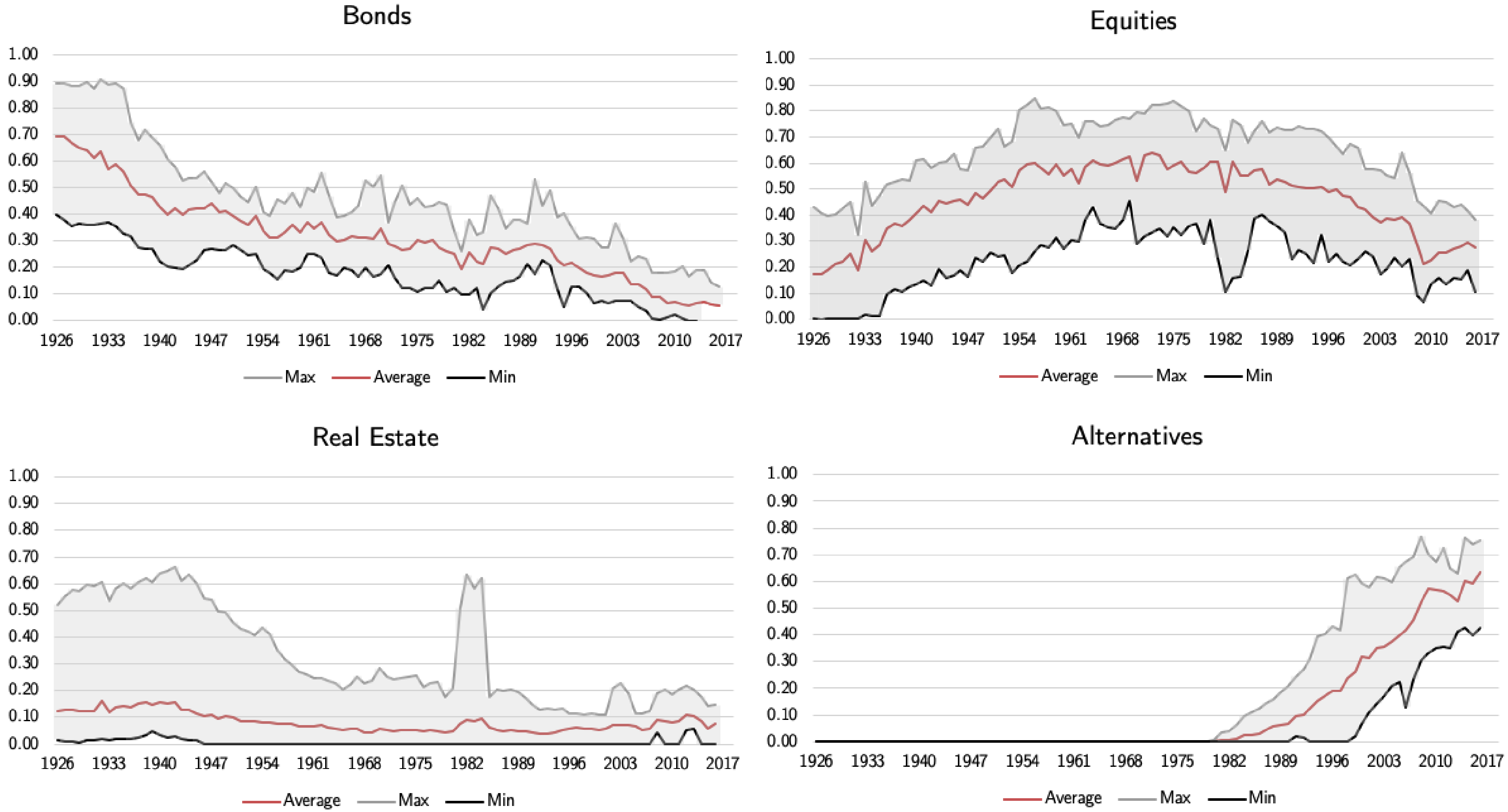

Figure 2: Endowment Equity Allocation Weights (1900 to 2016): Relative Endowment Size

This graph presents average allocations for small vs large university endowments. The y axis is the percentage of the endowment's investment portfolio allocated in equities. The lines depict the equity allocation of large and small universities, while the shaded area depicts the difference between these allocations at any given year. "Large" is the average equity allocation of Harvard, Princeton, Yale, Stanford, while "Small" is the average equity allocation of Brown, Cornell, Dartmouth, Johns Hopkins.

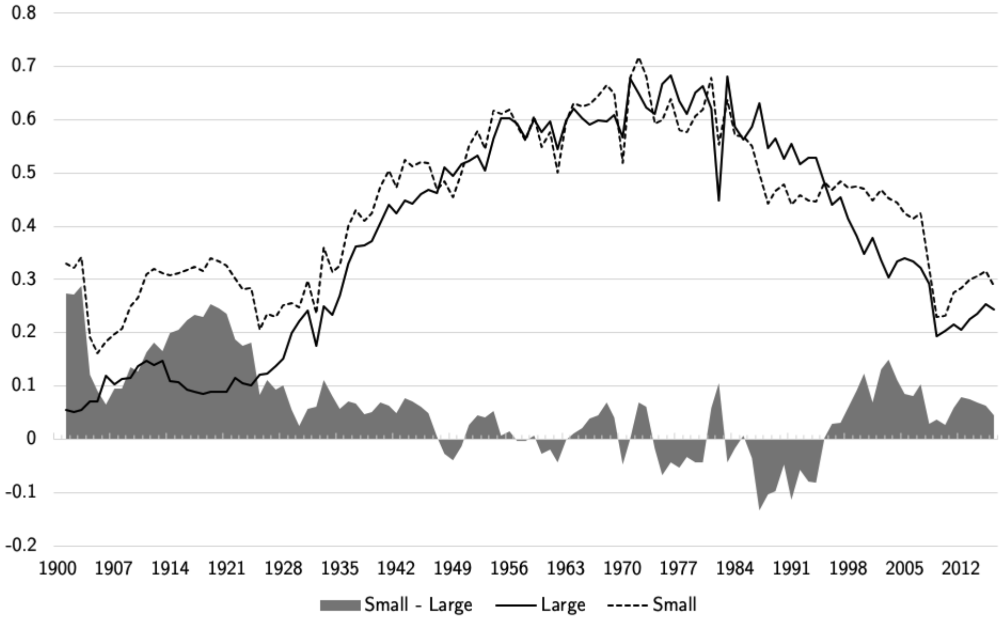

Figure 3: Endowment Equity Allocation Weights (1900 to 2016): Ivy League vs. Non-Ivy League

This graph presents average allocations for Ivy League vs. Non-Ivy League universities. The y axis measures the percentage of the average endowment's investment portfolio allocated in equities. The lines depict the average equity allocation of Ivy League and Non Ivy League universities, while the shaded area depicts the difference between these allocations at any given year. "Ivy League" universities are Harvard, Princeton, Yale, Columbia, University of Pennsylvania, Chicago, Brown, Cornell, Dartmouth, while "Non-Ivy League" universities are Johns Hopkins, MIT, Chicago, Stanford.

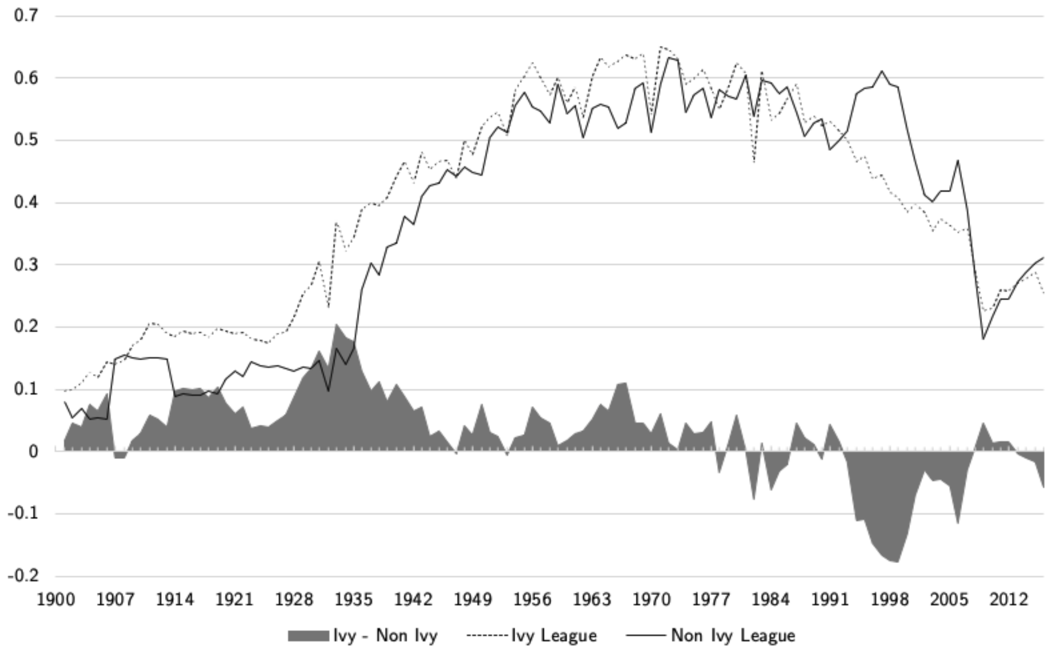

Figure 4: Endowment Alternative Assets Allocation (1980 to 2016): Harvard, Yale, Princeton

This figure presents average endowment allocations in alternative assets (private equity and hedge funds). The y axis measures the percentage of the average endowment's investment portfolio allocated in alternative assets. "HYP" stands for the average allocation of Harvard, Yale and Princeton. Ivy League (ex-HYP) represents the average alternatives allocation of Brown, Columbia, Cornell, Dartmouth and UPenn, and Non Ivy League the average allocation of MIT, Chicago, Johns Hopkins and Stanford.

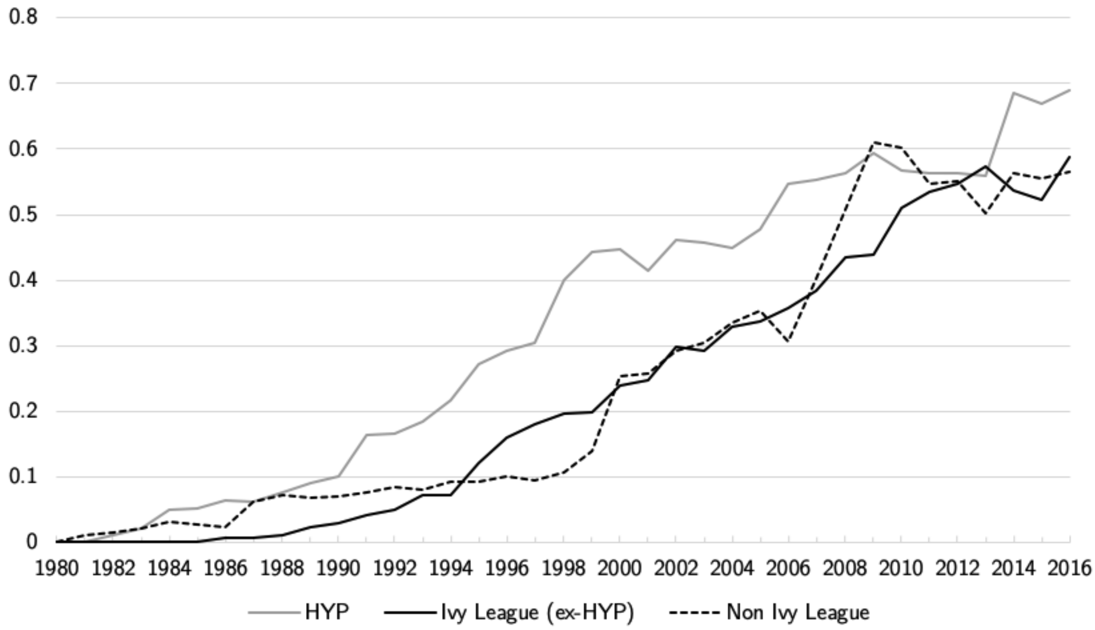

Figure 5: Yale's Endowment Market Value Growth (1950-2016)

This figure shows the growth of the Market Value of Yale's endowment from 1950-2016, replicating a figure that appeared in Yale's 2013 endowment report and expanding the data to 2016. "Endowment Size Inflated" is the endowment's size in 1950 inflated with yearly inflation rates to 2016. "Gifts Inflated" are the gifts to the endowment, also adjusted for inflation to 2016. The Market Values are expressed in $bil.

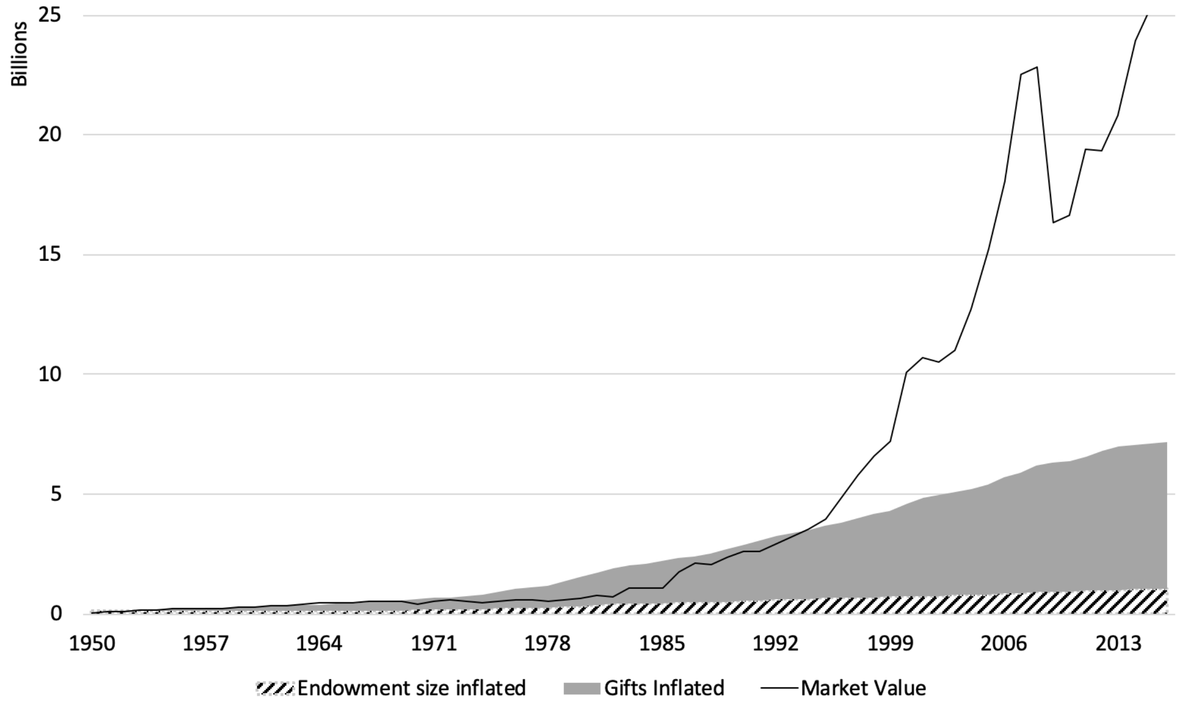

Figure 6: Market Value Growth Attribution of University Endowments (1950-2016)

This figure attributes the Market Value growth of each university endowment from 1950-2016 to the performance of its portfolio and the gifts into the endowment (adjusted for inflation). The y axis calculates the annualized growth rate of the endowments' market value from 1950-2016. "Inflated Size" is the endowment's size in the beginning of the period (1950), inflated with all inflation rates to 2016. "Inflated Gifts" are the gifts into the endowment, also adjusted for inflation. The columns are ordered from left to right with respect to endowment size (highest to lowest) at the beginning of the period examined, namely 1950. The market value of the endowment in $bil as of 2016 is reported over each column.

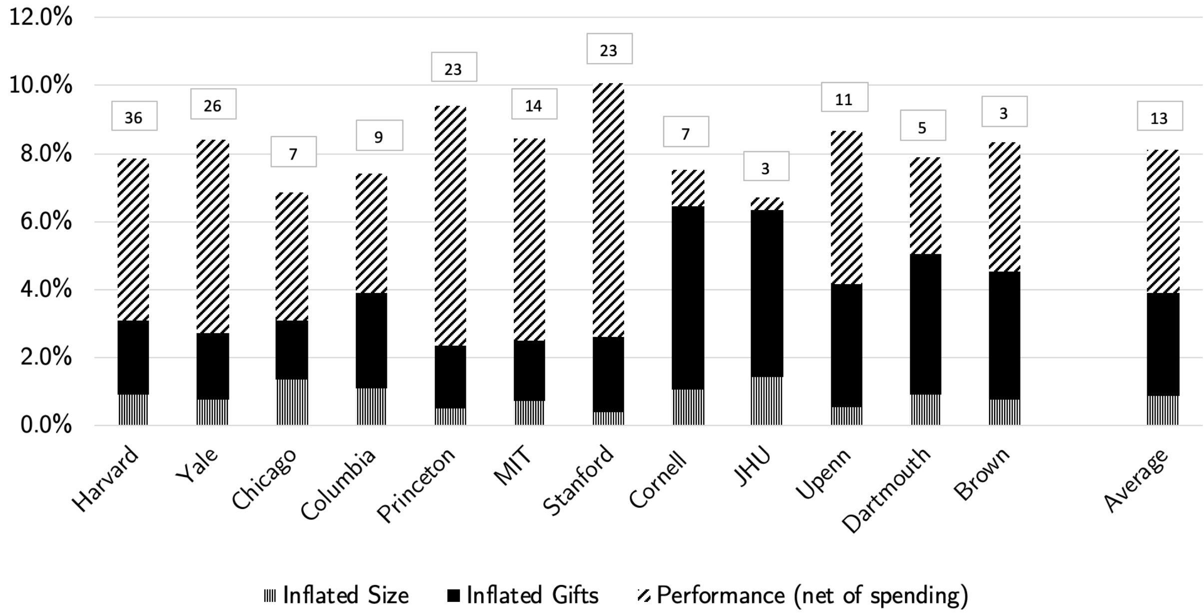

Figure 7: Active changes in the equity allocation of endowments around financial crises

This figure depicts the cumulative active changes in equity allocation of the average endowment portfolio before and after six of the "worst" crises. The y-axis is the active change measured in percentage terms and reported above each column are the p-values of the one-sample t-test of the average active allocation change being statistically different from zero. Time t is the year of the onset of the crisis, t+1 is 12 months after the year of the crisis onset, t+2 is 24 months after the year of the crisis onset, etc. Column t depicts the active equity asset allocation change from t-1 to t, column t+1 depicts the change from t to t+1, column t+2 depicts the change from t to t+2, etc. Using Shiller's monthly data, I note that the 1906, 1929 and 2008 crises had an onset during the second half of the "crisis onset" year. As endowment portfolio characteristics are reported at fiscal years ending June, in order to correctly include the crisis onset in the allocation changes at time t, I use data reported the following year.

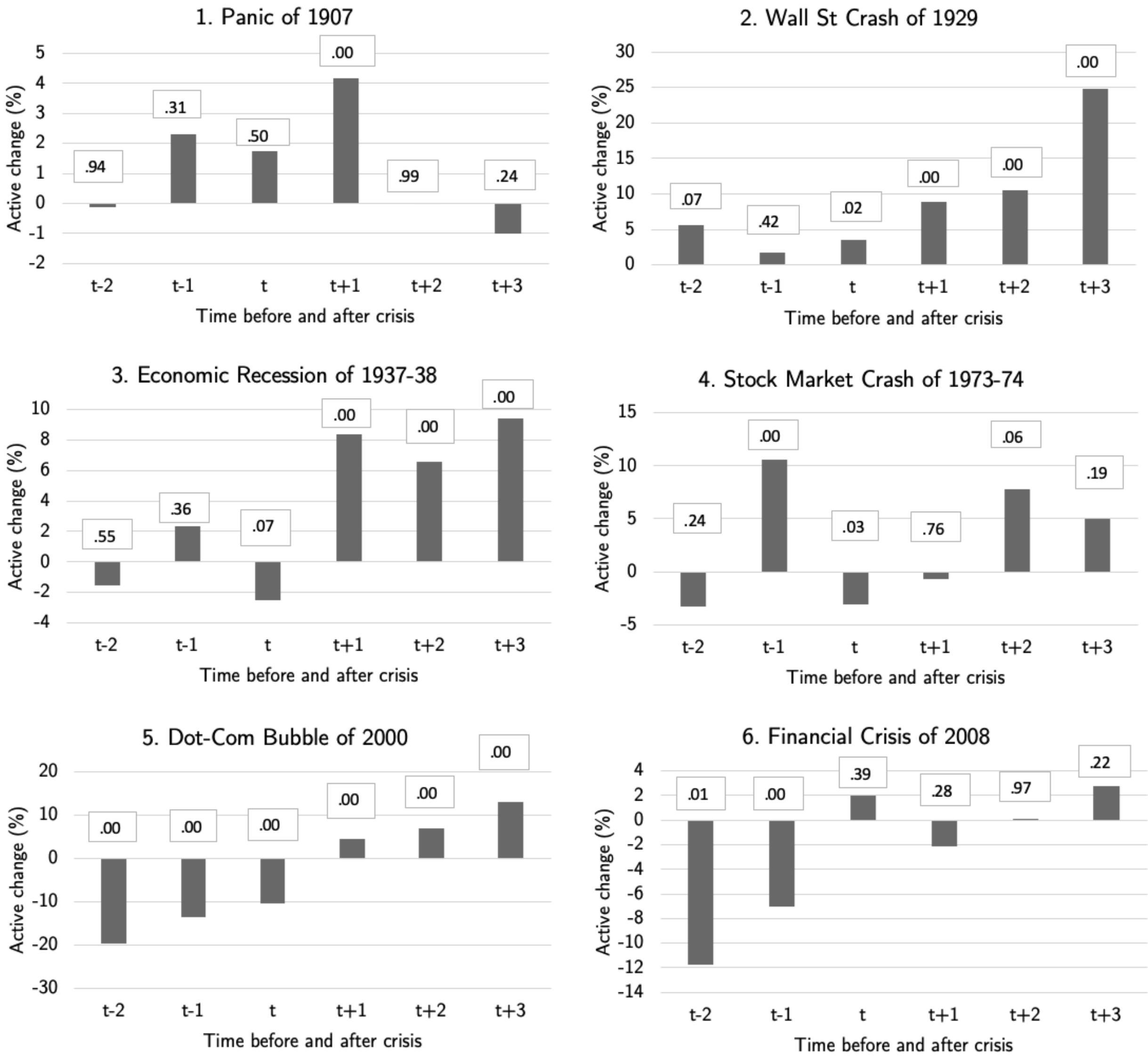

Figure 8: Average of all active changes in the equity allocation of endowments around financial crises

This figure depicts the average of all active changes in the equity allocation of endowments around the six financial crises I examine. The y-axis is measured in percentage terms and reported above each column are the p-values of the one-sample t-test of the average active allocation change being statistically different from zero. Time t is the year of the onset of the crisis, t+1 is 12 months after the year of the crisis, t+2 is 24 months after the year of the crisis, etc. Column t depicts the active equity asset allocation change from t-1 to t, column t+1 depicts the change from t to t+1, column t+2 depicts the change from t to t+2, etc. Using Shiller's monthly data, I note that the 1906, 1929 and 2008 crises had an onset during the second half of the "crisis" year. As endowment portfolio characteristics are reported at fiscal years ending June, in order to correctly include the crisis onset in the allocation changes at time t, I use data reported the following year.

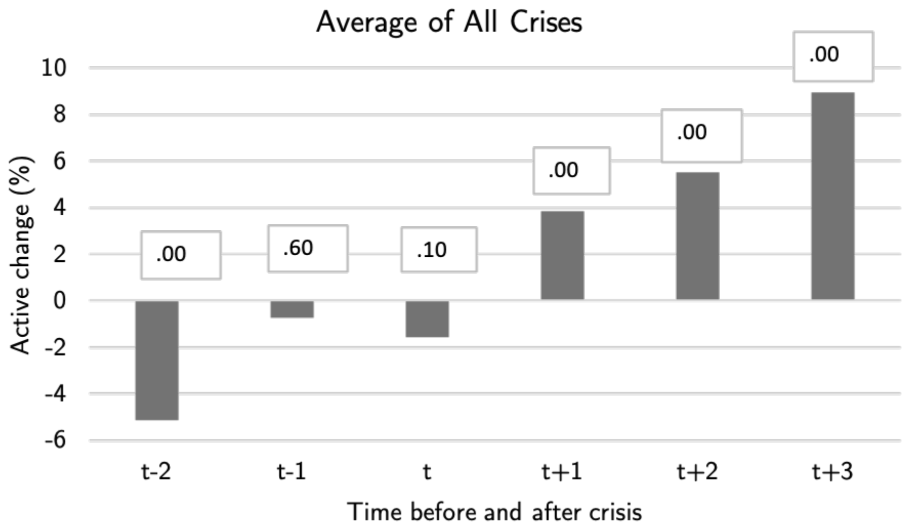

Figure 9: Equity and bond mutual fund yearly *net flows* around financial crises

This figure depicts the yearly net flows of equity and bond mutual funds around the two most recent financial crises, 2000 and 2008. "Equity" figures depict the net flows of equity mutual funds, and "Bonds" figures depict the net flows of bond mutual funds. Time t is the year of the onset of the crisis, t+1 is 12 months after the year of the crisis, t+2 is 24 months after the year of the crisis, etc. Column t depicts the active equity asset allocation change from t-1 to t, column t+1 depicts the change from t to t+1, column t+2 depicts the change from t to t+2, etc. The net flow figures are expressed in $USbil.

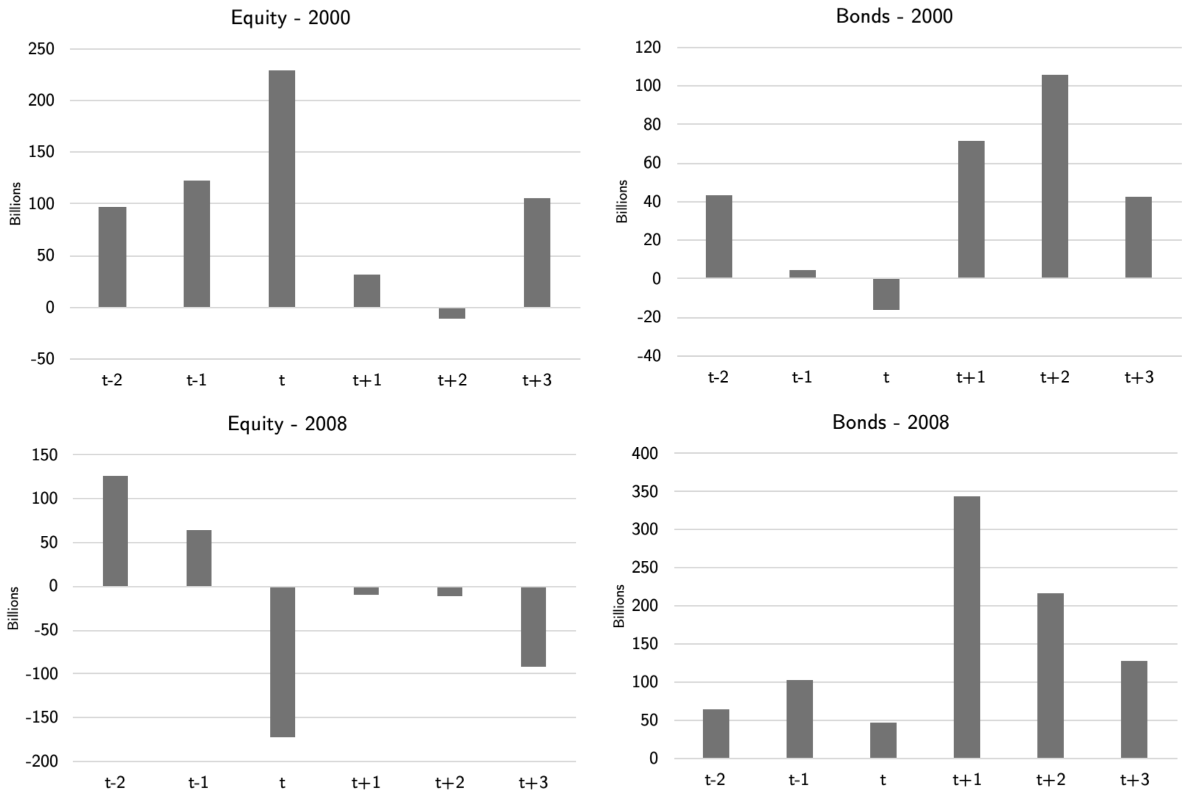

Table 1: Endowment Variable Sources

This table presents the variables included in the dataset along with their year availability and source.

Variable	Source
Asset Allocation	Up to 1974: University Financial Reports 1974-2013: Financial Reports and NACUBO/Commonfund
Allocation and Investments	1900-1956: Book values from Treasurer Reports 1957-2013: MVs from Treasurer reports, NACUBO/Commonfund
Endowment Performance	University financial reports and NACUBO/Commonfund
Endowment Assets	Up to 1974: University Financial Reports 1974-2013: NACUBO/Commonfund
Donations	Up to 1968: JP Jones Annual Survey 1969-2013: Voluntary Support of Education (VSE)
State Income per Capita	FRED (Federal Reserve Bank of St. Louis)
Total Expenditure	1926-1968 and 2011-2013: University Financial Reports 1969-1986: Higher Education General Information Survey (HEGIS) 1987-2010: Integrated Postsecondary Education Data System (IPEDS)

Notes:

1. NACUBO stands for National Association of College and University Business Officers.
2. Please refer to Section 4 for details on the calculation of endowment performance for different time periods.
3. VSE: For more information about the Voluntary Support of Education (VSE) and the Council for Aid to Education, see: http://www.cae.org/content/pro_data_trends.htm

Table 2: Endowment Sample Summary Statistics

The summary statistics reported in this table include the year of establishment of the university each endowment supports, as well as the endowment's size and annualized real growth rate since 1926. The endowment size is reported in million dollars for four selected dates throughout the sample (1926, 1970, 1985, 2016). Ivy League schools are reported in Panel A and Non-Ivy League schools in Panel B.

University	Year of Establishment	Size ($ mil)				Real Gr. Rate
		1926	1970	1985	2016	
Panel A: Ivy League Schools						
Harvard	1636	71	959	2,694	34,541	4.0%
Yale	1701	46	419	1,308	25,408	4.2%
Princeton	1746	16	325	1,519	22,200	5.2%
UPenn	1740	17	131	437	10,715	4.3%
Columbia	1754	56	266	979	9,041	2.8%
Cornell	1865	16	194	518	5,757	3.7%
Dartmouth	1769	9	125	386	4,474	4.1%
Brown	1764	10	86	222	2,963	3.5%
Panel B: Non-Ivy League Schools						
Stanford	1885	29	271	1,083	22,398	4.6%
MIT	1861	17	308	770	13,181	4.6%
Chicago	1890	36	271	640	7,001	3.0%
JHU	1876	24	135	393	3,381	2.6%
Mean		29	291	913	13,421	3.9%
SD		20	233	690	10,287	0.80%

Table 3: Endowment Performance and Risk

This table reports the average endowment arithmetic and geometric returns, the returns of the average Ivy League and non-Ivy League institution in the sample as well as relevant asset-class benchmark returns. Arithmetic Returns (Arith. Ret) are the average arithmetic returns of every calendar year, Geometric Returns (Geom. Ret) are compounded returns over the whole period and Standard Deviations (Std. Dev) are the standard deviations of the yearly arithmetic returns. The 60/40 benchmark is a balanced portfolio (60 percent invested in equities and 40 percent in bonds), rebalanced annually. Panel A presents endowment performance and risk figures for the period 1927-2016, and Panel B for the period 1975-2016.

Panel A: The period 1927-2016

University	Geom. Ret	Arith. Ret	Std. Dev	Sharpe Ratio
Brown	8.7%	9.5%	13.3%	0.43
Columbia	8.8%	9.5%	12.2%	0.46
Cornell	8.4%	9.3%	13.9%	0.39
Dartmouth	9.4%	10.3%	14.7%	0.45
Harvard	9.3%	10.0%	13.0%	0.48
Princeton	10.3%	11.0%	13.2%	0.55
Upenn	8.5%	9.3%	13.3%	0.41
Yale	9.9%	11.0%	15.1%	0.48
MIT	9.3%	10.1%	13.6%	0.47
Chicago	10.0%	10.9%	14.5%	0.48
JHU	8.3%	8.9%	10.7%	0.47
Stanford	9.3%	9.9%	11.3%	0.54
Average Endw.	9.2%	10.0%	13.2%	0.47
Ivy League	9.2%	10.0%	13.6%	0.46
Non-Ivy League	9.2%	9.9%	12.5%	0.49
60/40	9.0%	10.3%	13.6%	0.40
S&P500	9.9%	12.8%	26.2%	0.35

Panel B: The period 1975-2016

University	Geom. Ret	Arith. Ret	Std. Dev	Sharpe Ratio
Brown	10.9%	12.6%	12.7%	0.49
Columbia	11.3%	11.8%	10.1%	0.61
Cornell	10.3%	11.0%	12.7%	0.44
Dartmouth	11.9%	12.7%	11.8%	0.58
Harvard	11.9%	12.6%	12.1%	0.58
Princeton	12.8%	13.6%	12.8%	0.63
Upenn	11.2%	11.6%	11.2%	0.57
Yale	13.4%	14.2%	12.9%	0.67
MIT	12.2%	13.1%	14.4%	0.52
Chicago	12.6%	13.4%	14.6%	0.53
JHU	10.2%	10.7%	11.0%	0.50
Stanford	12.4%	13.1%	12.0%	0.63
Average Endw.	11.8%	12.5%	12.4%	0.56
Ivy League	11.7%	12.5%	12.0%	0.57
Non-Ivy League	11.8%	12.6%	13.0%	0.54
60/40	10.1%	10.8%	12.4%	0.45
S&P500	10.4%	11.7%	17.5%	0.38

Table 4: The impact of past endowment returns on subsequent donations

This table reports results of the log changes in donations to the endowment at time t regressed on lagged endowment returns (time t-1, t-2 and t-3). I include controls such as the change in the size of the endowment and the log change in income per capita of the state each university belongs to (as a proxy for the donors' wealth), from time t-1 to t. In column 3, Negative Ret t-1 is a dummy variable that takes the value 1 if the past return of the endowment was negative, and 0 otherwise. In column 4, Crash t-1 is a dummy variable indicating the onset of a financial crisis the previous period, and Return t-1*Crash t-1 is the interaction variable of the past return and the Crash t-1 variable. The regressions include endowment Fixed Effects and the standard errors are corrected to allow for a fully general structure with heteroskedasticity and serial correlation. The regression covers the period 1927-2016.

	Dependent variable:			
	Change in log donations			
	(1)	(2)	(3)	(4)
Return_{t-1}	0.3756***	0.4085***	0.2462**	0.4107***
	(0.0911)	(0.0924)	(0.1171)	(0.0977)
Return_{t-2}		0.2093**		
		(0.0919)		
Return_{t-3}		0.0051		
		(0.0953)		
Crash_{t-1}				0.0519
				(0.0427)
Change log $\text{Size}_{t-1,t}$	0.2737***	0.2768***	0.2808***	0.2766***
	(0.0897)	(0.0901)	(0.0903)	(0.0898)
Change log Income per $\text{Capita}_{t-1,t}$	0.3125**	0.3225**	0.2882*	0.2986*
	(0.1582)	(0.1610)	(0.1594)	(0.1587)
Negative Ret_{t-1}			−0.0733*	
			(0.0404)	
$\text{Return}_{t-1} * Crash_{t-1}$				−0.2735
				(0.2689)
Constant	−0.0110			−0.0179
	(0.0179)			(0.0188)
Endw. FE	Yes	Yes	Yes	Yes
Observations	973	973	973	973
R^2	0.0307	0.0362	0.0342	0.0323
Adjusted R^2	0.0277	0.0201	0.0191	0.0273
F Statistic	10.2461***	7.1856***	8.4772***	6.4579***
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 5: The effect of passive on active allocation changes

This table reports the pooled regressions of the active change on the passive change of equity, in levels. Year t regressions include endowments that allocate their portfolios in risky assets both at the end of year t minus 1 and at the end of year t.

	Dependent variable:				
	Active Change				
	All	*Pos Mkt.*	*Neg Mkt.*	*Pre-Crash*	*Crash*
	(1)	(2)	(3)	(4)	(5)
Passive Change	−0.327**	−0.535***	−0.102	−0.262*	−0.538***
	(0.139)	(0.186)	(0.258)	(0.140)	(0.143)
log(Size)	0.022***	0.030***	−0.014		
	(0.005)	(0.005)	(0.011)		
Crash Dummy				−0.047***	
				(0.015)	
Pre-Crash Dummy					−0.096***
					(0.016)
Constant	−0.570***	−0.723***	0.207	−0.083***	−0.072***
	(0.099)	(0.107)	(0.248)	(0.006)	(0.006)
Endw. FE	Yes	Yes	Yes	Yes	Yes
Observations	1,063	799	252	1,063	1,063
R^2	0.026	0.050	0.007	0.013	0.038
Adjusted R^2	0.024	0.048	−0.001	0.011	0.036
Residual Std. Error	0.186	0.185	0.187	0.187	0.185
F Statistic	14.210***	20.970***	0.847	6.934***	21.073***
Note:					*p<0.1; **p<0.05; ***p<0.01

Conclusion

This dissertation examines the investment choices of university endowments in the United States. The essays shed light on the external manager selection of asset owners both in public and private markets, their strategies over the long-run and their response to financial crises since the beginning of the 20th century.

The three essays make important contributions to the literature on institutional investor behavior. My first main finding is that peer effects among asset owners play a role in decisions about their selection of external investment managers. Endowments with similar characteristics, especially in terms of Carnegie Classification, geographic location and market value, are more likely to appoint the same external investment managers. Endowments also follow their peers in the frequency of external manager hiring and firing and respond faster to the specific manager hiring and firing decisions of endowments in their peer groups. Taken together these results suggest 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.

My second essay examines how social networks affect external manager choices by an asset owner such as an endowment in private markets. The analysis considers how U.S. university endowments and PE (both BO and VC) managers gain access to each other through their network connections. It also examines whether critical network positioning of institutions (endowments and PE managers) plays a role in manager selection. VC networks were more developed than their BO counterparts at the beginning of the sample, but both networks grew denser over time. The identity of centrally located institutions has stayed the same throughout the sample. Central positioning of PE managers in the network is positively associated with the number of new mandates they gain from other university endowments in subsequent periods, as well as their investment performance. Moving the focus from firm-level to individual-level networks, I find that if an individual was employed by an endowment in the past or is an alumnus of the university which the endowment supports, the likelihood of her PE firm getting hired by the endowment rises significantly.

My third essay exploits data on the most important U.S. university endowments and shows that these endowments were early movers into the new asset classes of the day - equities from the 1930s and alternative assets from the 1980s. Ivy League schools led both these shifts. In terms of investment performance, these endowments were in line with the typical 60/40 benchmark up to the early 1970s, but thereafter beat their benchmark. Their market value growth over the long term is driven by a combination of high investment performance and donations. I also find that their past performance is positively related with future donations. Around times of financial crises, endowments typically exhibit a countercyclical investment pattern. They reduce their allocation to risky assets such as equities and alternative assets before the onset of a crisis, and increase their allocation afterwards, an effect which is more prominent in the two most recent crises: the Dot-Com Bubble and the 2008 Global Financial Crisis. In comparison, investors in mutual funds exhibit strongly procyclical behavior around these crises. The results suggest that endowments indeed exploit their long horizon advantage in making asset allocation decisions.

Overall, this dissertation uses an extensive, hand-collected data set on university endowments to contribute to our knowledge on institutional investor behavior. I establish new findings on manager selection by asset owners in both public and private markets - particularly, the importance of peer effects, and both professional and personal networks - and on the countercyclical asset allocation strategy pursued by long-horizon investors such as endowments.

There are several directions in which I intend to take my future research. The recent introduction of ESG sections in the NACUBO data could help determine what influences the adoption of such mandates by endowments and how it affects their investments, contributing to the expanding literature of responsible investing. My long-run dataset could also be used to examine the effects of changes in tax policy on charitable giving in the U.S. over a long period, as well as the contribution of financial success to academic excellence (such as top faculty, awards, and university rankings).