Winning a Deal in Private Equity: Do Educational Networks Matter?

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Abstract

Networks can establish business connections and facilitate information flows. But how valuable are they in competitive settings, such as the deal generation of private equity? We find that access to a diverse set of universities is important for fund performance. In addition, educational ties between acquiring partner and target firm management are frequent (around 15%) and increase the odds of winning a deal (by 79%). When competing with other funds, exclusivity rather than the school's ranking matters. Educational ties also allow mitigating prevailing home bias. Yet, the pure existence of network-based relationships does not automatically lead to better deal performance.

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1 Introduction

Investors commit capital to private equity funds in order to gain access to valuable investment opportunities that they may not be able to address through other channels. As a result, one important value-add of the fund managers, which also requires a significant amount of their time, is to uncover and secure these opportunities. But from where do the managers source their investments? Existing research names personal and professional networks a powerful source of deal flow (Fenn et al. (1997), Teten and Farmer (2010), and Gompers et al. (2016a)). Furthermore, it highlights the importance of proprietary and self-generated deals as a major performance driver (compared to the use of agents). However, are networks a differentiating factor for funds to identify and win deals when competing with one another? If so, what kind of features make them so valuable and under which conditions do they perform best? Finally, do transactions that are originated through a network generate superior returns?

To address these questions empirically, we investigate whether pre-existing ties between the management teams of a fund and the acquisition target influence the transaction likelihood as well as subsequent investment performance. In detail, we analyze if a fund's success ratio to win a deal increases in case a partner and the target firm CEO share the same university background. As Engelberg et al. (2012) and Rousseau and Stroup (2015) point out, the expected effect of prior (interpersonal) relationships is not obvious as they can likewise provide access to private information and blind a decision maker. However, in an opaque and increasingly competitive market such as private equity (PE), their relevance may simply come from investment identification. In particular, we focus on the buyout sector where funds compete for a small number of potential deals. While the number of companies to be acquired by each fund is relatively low, the capital commitment per transaction is large. Thus, the investor also faces significant transaction risk related to each investment. Social ties represent one way for the fund managers to simultaneously facilitate the investment identification and to mitigate such risks.

In this paper, we apply a counterfactual approach in which funds with a similar investment profile compete for an acquisition. As we are able to observe which fund ultimately succeeds, we can derive the characteristics that drive this outcome. While fund managers and CEOs have very different career paths, we expect a substantial intersection from academic affiliations as both represent relatively elite groups. Similar ties proof valuable in public markets where mutual funds use them for their investment choice and generate higher performance with such holdings (Cohen et al. (2008)). In addition, the benefits of a common educational background as a means to establish connections and facilitate information flows is widely documented in the financial literature. This includes, for example, evidence on security analysts, CEOs, and bankers who all benefit from networks related to their previous educational attainments (e.g., Cohen et al. (2010), Butler and Gurun (2012), Engelberg et al. (2012)). Finally, as educational ties are formed many years before the actual investment takes place and their potential information relevance becomes apparent to the manager, they do not suffer from reverse causality.

To measure the network effect, we need a common platform that spans across industry boundaries and is substantial in size for relationship generation. Our novel data set comprises the investment activity of more than 2,000 buyout funds, which are mostly headquartered in the U.S. and Western Europe, as well as the education and professional history of more than 4,500 individual partners that manage these funds. A rare feature is the allocation of partners at the fund rather than investment firm (General Partner) level. Management teams in private equity comprise a small number of experienced professionals who are highly incentivized by own financial commitments and their compensation arrangements. Observing the allocation directly at the fund level reduces noise related to larger organizations that manage multiple lines and sequences in parallel. Besides the partner profiles, we obtain biographies on more than 4,500 CEOs. Each of them is heading one of the portfolio companies at the point of time that it is acquired by one of the buyout funds in our data sample. For our analysis, we focus on traditional buyout and growth transactions and exclude add-on as well as venture deals due to their different dynamics. Target firms are mature companies and represent public or private enterprises that span over various industry sectors and geographic regions. In addition, we only include investments up to 2010 to allow for sufficient time to measure subsequent performance. This leaves us with a final sample of 3,051 investments comprising 2,606 companies and 2,599 individual CEOs. These are carried out by 3,584 partners from 1,233 individual funds and 681 unique general partners. For each of the involved individuals, our database lists their educational achievements as well as a textual biography.

We contribute to the network literature on several dimensions: First, we show that access to a greater number of universities is related to better fund performance. A more diversified educational background of managers gives the fund access to a wider alumni network. Hochberg et al. (2007) and Brown et al. (2012) show that the economic value of a network increases with its size (for syndications and CEOs). Through attending different universities, the partners are able to (passively) accumulate networks from which they may benefit in their work as investors. We empirically explore that it pays off for the investment firm to hire professionals from schools with large alumni networks or to diversify as our results reveal a positive and significant relationship to fund performance that seems primarily driven by degrees from high-ranked schools. This suggests managers are indeed receiving benefits, i.e. higher returns, from a broader institutional diversity even though deal sourcing may not be the only value attached to this exposure.

Second, we determine the role educational networks play for the deal generation success of buyout funds. We find the existence of a tie to be frequent (15% of transactions) and significantly improving the odds to win a deal (by 79%). More importantly, we document that a higher degree of exclusivity (i.e., lower competition among funds with educational ties) increases the odds up to tenfold. Thus, it is not necessarily the largest and widest network and the one which produces the highest number of CEOs that is of value for the fund. Instead, the evidence suggests the value of a network in competitive settings is greatly elevated by the exclusivity of its ties. In addition, we show that proximity to the acquired firm matters, which we measure as the geographic distance between the closest fund office and the company's headquarter. The closer a fund is located to its target top management, the higher the odds to win a deal. In this context, we interpret proximity as a local network. Our results provide funds characterized by few local offices but a national reach with good news as it seems possible to overrule the existence of a local network in case educational ties are in place. The findings also remain robust controlling for previous experience of the partners in professional service firms and banks, where other networks are likely to arise, and for various restrictions on deal and fund characteristics (e.g., sub-setting on U.S. and European deals). Evaluating differences between the various investment categories buyout funds use, we document stronger evidence for management buyouts/ins, whereas, for example, the effect on going private transactions is limited. For the former the personal benefit and interest of the management team is stronger as they have an own interest into the success of the transaction, where they typically co-invest alongside the investor. Thus, it seems the value of a tie is also conditional on the circumstances to which it is applied as well as on the potential benefits for either involved party.

Finally, we investigate the direct relevance of networks for investors by evaluating whether transactions with a pre-existing educational tie generate higher returns. However, we do not find evidence that the deal sourcing channel is a systematic driver for individual investment performance in either direction. Pre-existing networks may help to win a deal but do not necessarily lead to transactions with superior performance, measured by either IRR or TVPI multiple. Instead, we confirm the relevance of market timing, namely the length of the holding period and the prevailing market return during the former, which may be related to skill or luck of the manager. Both factors show a strong impact. It seems that while the funds may use educational ties for investment generation, subsequent returns are still primarily driven by market timing and value-enhancing measures the funds implement during the lifetime of the investment.

Our findings complement the established literature on management networks by addressing the importance of exclusivity. In addition to a wide range of authors that analyze the importance of networks in financial transactions (e.g., Cai and Sevilir (2012), Renneboog and Zhao (2014), Ishii and Xuan (2014)), we introduce the degree of network exclusivity as a decisive factor in benefiting from educational ties. We show that large or very prestigious networks may lose their appeal in case everyone has access to them. As deal sourcing is an important part of the buyout business model, fund managers devote large amounts of their time and energy to it. Yet, we know very little how these efforts relate to subsequent performance. In our paper, we investigate how transactions are generated through networks and how they perform subsequently. This complements recent studies on the attribution of deal-level returns (e.g., Acharya et al. (2013), Puche and Braun (2015), Braun et al. (2016)). By analyzing in detail how buyouts funds are using their local and educational networks to succeed in transactions we link our results to a comprehensive survey by Gompers et al. (2016a) on the investment behavior of general partners. In our study, we are able to provide empirical evidence supporting the stated importance of networks from the survey by showing their relevance as an identification means in the deal sourcing of buyout funds.

We differentiate our work from existing studies in the field of venture capital as deal sourcing networks of buyout funds are of a different kind (e.g., Sunesson (2009), Bengtsson and Hsu (2015)). While educational ties in venture capital proxy for similarity between the actors, for buyout investors they may serve more as an identification and access purpose to potential target firms. In addition, in the case of start-up companies, the founding entrepreneurs actively reach out to funds, whereas in the case of buyout funds it is typically the fund partner that approaches potential target firms. We also focus on the initial relationship building process through social ties compared to the repeated business relationships modeled through economic ties (e.g., Sorensen and Stuart (2001, 2008), Hochberg et al. (2007, 2010, 2015)). Lastly, compared to venture capital and other asset classes, networks in the buyout model require access to very senior managers of often large but privately held companies (e.g., compared to young entrepreneurs in venture capital or public companies for mutual and hedge funds).

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 details the data source, sample generation, and counterfactual approach. Empirical results and robustness tests are presented in Section 4. Section 5 concludes.

2 Related literature

2.1 Deal sourcing in the buyout industry

The private equity industry has become an important asset class over the last decades managing more than $2.4 trillion in assets under management, with around two-thirds related to buyout and growth activity.[1] Buyout funds are typically set up as a limited liability partnership with a fixed lifetime of 10-12 years. The investor capital is managed by a management company called a general partner (GP) that receives both an annual fixed and performance fee to do so (Phalippou (2007)). The general partner can raise and manage more than one fund at a time but usually assigns one or more partners to a specific fund.[2] The partners are then responsible for the fund's deal sourcing activities as well as the management of the investments. The final investment decision is typically made by a GP-wide investment committee (Bengtsson and Hsu (2015)). The selection of the individual portfolio company is key as specific firms may provide interesting opportunities to unfold one or multiple value creation pillars in order to generate a (superior) return for the investors. These comprise, for example, a revision of the capital structure (leveraging), resolution of an undervaluation (multiple expansion), as well as operational and governance improvements (Achleitner et al. (2010)). Thus, superior access to investments is deemed a key capability of a successful private equity fund.

Differences in the deal sourcing approach are considered an important performance driver. Fenn et al. (1997) outline that investors are intensively competing with their agents (such as investment banks and deal brokers) to identify potential targets. They

[1] *Source:* Preqin, Private Equity Spotlight, September 2016 (data as of 31st December 2015).
[2] These key employees are referred to as buyout fund partners in the following.

note that deals from the former tend to be less attractive due to additional fees and bid-up prices by competing investors during lengthy and expansive auction processes. In a related study, Teten and Farmer (2010) conclude that funds with substantial scale in deal origination as well as a focus outside the most competitive markets tend to be top-quartile performers. The authors report that personal and professional relationships provide almost half of the internal deal flow, followed by word-of-mouth and cold calls. More recently, Gompers et al. (2016a) survey a broad sample of general partners and name proprietary deals, where the fund acts as an exclusive buyer, an important determinant of value creation. Even though almost half of closed deals are considered "proprietary in some way", exact deal sources remain vague. Around a third are denoted as "proactively self-generated", whereas around 5-10% originate from each the management's and the investor's executive network. The remaining balance is again related to agents, such as investment banks and deal brokers, and other private equity firms (presumably resulting in secondaries and co-investments). All three studies agree that executives the fund managers know from prior (or failed) acquisitions remain valuable. However, despite the frequent notion of the importance of active deal sourcing for the funds and the role of the investor's networks across different studies, empirical evidence on the origins of the initial relationships and contacts remains relatively sparse.

A second literature stream focuses directly on the acquisition targets and infers transaction and firm characteristics that appeal to private equity firms (e.g., Lehn and Poulsen (1989), Opler and Titman (1993), and Weir et al. (2005)). While these studies relate primarily to the target itself, they also highlight the evolving nature of the buyout industry. At its beginnings, leveraged buyouts dominated the industry in which the investor takes a public company private to restructure it. Since then the market has advanced and spread into a variety of different deal types. According to data from Kaplan and Strömberg (2009), the industry concentrates more and more on private companies, both in the form of independent firms and divisions of larger corporations. It now covers more industries and geographies, especially transactions that originate in Western Europe have gained a significant share of the overall activity. As the industry grows mature and becomes more international, an increasing number of funds compete for the same investments. Metrick and Yasuda (2011) name the level of competition among funds the main factor influencing performance, followed by financing conditions. In addition, competition for investment targets also originates from strategic acquirers that constantly monitor the market. This has different implications for the funds which affect their deal sourcing efforts. Some authors report a recent decline in performance persistence (see Sensoy and Kaplan (2015) for a review on the topic) indicating that it becomes more challenging to exclusively spot promising investments and acquire them at favorable terms. Other studies document a countercyclical relationship of capital and deal flow to fund performance (e.g., Phalippou (2007), Ljungqvist et al. (2009)). This likely drives funds to broaden deal sources and increasingly tap upon their own networks to close deals early on. Finally, in a recent study of mergers and acquisitions, Ishii and Xuan (2014) call for an extension of the traditional target centered view by the acquirer-target relationship. In their study, the authors record that social ties influence decision making as well as the subsequent performance of mergers between corporate firms.

2.2 The role of educational networks

There is a growing literature in finance on networks including their importance for investment decisions (see Allen and Babus (2009) for an overview).[3] In particular, social ties that are established between the members of top management teams across different organizations or interest groups, and the ones based on a shared educational background prove valuable across a variety of research areas. These linkages range from companies that receive better credit terms from banks (Engelberg et al. (2012)), over the CEO and her compensation level (Butler and Gurun (2012), Brown et al. (2012), and Engelberg

[3]On a more general note, social networks, according to Granovetter (2005), serve three purposes: flow and quality of information, source of reward and punishment, and "trust" that others will do the "right" thing. Kuhnen (2009) adds that they can help to overcome asymmetric information, moral hazard, and costly search. In addition, they can facilitate monitoring but may be subject to favourism.

et al. (2013)) and her board relations (Nguyen (2012) and Fracassi and Tate (2012)), to sell-side security analysts in order to initiate relationships with the senior management of the firms they track (Cohen et al. (2010)).

As a tie itself cannot prove the existence of direct interactions, Ishii and Xuan (2014) argue that the concept of a "social tie" or "social connection" also captures other dimensions such as homophily.[4] They highlight that educational ties may not only be established by the attendance of the same institution and potential interactions in extra-curricular activities but as well by the commonalities among the group of people attracted to this institution. Further, Cohen and Malloy (2010) note that "alumni networks turn out to be an especially effective kind of social network. [...] because people often self-select into undergraduate and graduate programs [...] which generates both a higher level of interaction and longer-lived relationships." They conclude that this allows amassing information about other graduates as well as common acquaintances. Finally, research in the economic and sociological literature stresses the value of weak ties between individuals, i.e., acquaintances (Granovetter (1973, 1983)). These tend to be of most importance for leadership positions (Wegener (1991), Brown et al. (2012)). Through attending different universities investment managers are able to (passively) accumulate large networks which may pay off well in their work as investors.[5]

To be of relevance for the investment fund's deal origination, a tie need to be established between the management teams of the acquiring party and its investment target. This means that not only the fund managers need to be active network participants but the target management should be open to such approaches. However, there should be little doubt about the connectedness of CEOs as they are typically the owner of powerful networks themselves (e.g., Gottesman and Morey (2006a), Kirchmaier and Stathopoulos (2008)). Brown et al. (2012) report that there is economic value to network size for the

[4]Borrowing their definition, homophily relates to "affinity for those who share similar backgrounds."

[5]Klein et al. (2004) examine advice, friendship, and adversarial networks and find that individuals who are highly educated became high in advice and friendship centrality. In addition, evidence from the strategic management literature shows the importance of the first relationship and the ongoing influence of initial networks (Milanov and Shepererd (2013)).

CEO, measured by the number of social ties, in the form of higher compensation levels. Liu (2014) relate CEO connectedness with their turnover probability in a similar fashion. In addition, outsiders, such as security analysts, frequently use educational ties to gain direct access to senior corporate management (Cohen et al. (2010)).

In the public takeover market, Cai and Sevilir (2012) and Renneboog and Zhao (2014) document that board relationships between the involved firms influence transaction likelihood and performance likewise. Ishii and Xuan (2014) extend the evidence to social ties between the companies. Focusing on investment firms, Cohen et al. (2008) find mutual fund managers to invest heavily in firms to which they are connected via corporate board members and to perform significantly better with these holdings. Similarly, for venture capital investors, Gompers and Xuan (2009) shows that a public company benefits from a common venture capitalists investor that they share with a private target firm, and Sunesson (2009) reports an increased likelihood of matching a venture capitalist with an entrepreneur as well as with another venture capitalist when sharing the academic background.[6] Jääskeläinen and Maula (2014) differentiate between direct and indirect ties, and mention the latter to promote the identification of investment opportunities, whereas the former ease the investor's quality assessment. Further evidence on the importance of shared characteristics comes from Bengtsson and Hsu (2015) and Gompers et al. (2016b). While the former find that co-ethnicity increases the likelihood for venture capital investments, the latter investigate how ethnic, educational, and career background influence syndication. Another focus is often given to MBA degrees that are frequently observed in top management teams. In educational studies, the wide network of alumni and organizations such a degree opens up, is regularly described as a pure side-benefit (Baruch and Peiperl (2000)). However, their value can incorporate much more, for example, the formation and reproduction of transnational ties (Hall (2011)). In the venture capital literature, the MBA degree is used as a proxy for business and management education (e.g.,

[6] Besides social ties, the venture capital literature documents the value of economic ties (prior co-investments) as well as the role of spatial distance with regards to syndication networks. For details we refer to Sorensen and Stuart (2001, 2008), Hochberg et al. (2007, 2010, 2015), and Chen et al. (2010).

Dimov and Shepherd (2005), Patzelt et al. (2009), Zarutskie (2010), Cai et al. (2013)), while in the area of mutual funds and corporate managers it is investigated with regards to superior skills and management performance (e.g., Gottesman and Morey (2006a,b)).

Evidence on the existence and the value of relationships in the buyout space is more scarce. Stuart and Yim (2010) show that board networks influence the likelihood of becoming a target company in a going-private transaction. Wu (2011) focuses on syndication networks for leveraged buyout investments and highlights the role of MBA networks for co-investments. Siming (2014) investigates connections based on past employment between the fund management and financial advisers. He concludes that such relationships provide access to profitable business opportunities. Besides the networking aspect, some studies emphasize manager characteristics to be of general importance. With regard to value creation, Acharya et al. (2013) document that an operational and financial background of the deal partner matters depending on the nature of the transaction (organic/inorganic). Degeorge et al. (2016) use data on educational background and career paths to show the benefits of complementary skill sets between buyer and seller during secondary buyouts. Finally, Lopez-de Silanes et al. (2015) investigate team dynamics and the scalability of the organization concluding that more homogeneous management backgrounds (consulting, finance, other) lead to smaller diseconomies of scale.

The relevance of networks for the deal sourcing efforts of buyout funds has, to the best of our knowledge, not been investigated so far. In addition, there are some important differences between buyout funds and other asset classes that limit the transferability of earlier findings between them. First, while educational ties in venture capital proxy for similarity between the actors, for buyout investors they may serve more as an identification and access purpose to potential target firms. Compared to venture investments, buyout transactions are dominated by the fund(s) and typically lead to a majority takeover. Second, deal sourcing networks for buyout purposes are of a different kind as they have to connect the investment professional with very senior managers, i.e., the CEO, compared to (typically) young entrepreneurs. In venture investments, the founder of a company is key as the business model is still in an early development stage. Thus, the venture capital-linked literature on networks interprets educational networks to a larger extent as a quality signal as a start-up heavily depends on its entrepreneurs. Third, the start-up entrepreneur has to actively reach out in order to convince an investor (Sørensen (2007) subsequently refer to the matching as "two-sided"). In a buyout context, the fund typically acquires a company with a proven business model and prevailing financing. This makes the success of the investment less dependent on the existing management team or the provision of additional capital. Lastly, in a notable number of cases the management team is even replaced as part of a company reorganization after the investment is completed (e.g., Gompers et al. (2016a)). This weakens the motivation for the existing management team to play an active role in the initial relationship building. In these cases, the network likely serves the partners more as a platform to identify targets in the first place and to establish initial relations. Overall, we expect educational networks to help the fund managers in their deal sourcing efforts.

3 Data and methodology

3.1 Sample selection strategy

The data is sourced from PitchBook, a U.S. database for global M&A, Private Equity and Venture Capital transactions.[7] We split the following discussion of the data set into three components: funds, partners, and deals (including CEOs).

First, we obtain information on buyout funds on a global basis spanning vintage years from 1978 to 2010.[8] For this period 3,837 funds from 1,723 General Partners are listed,

[7] PitchBook (www.pitchbook.com) obtains data from filings, press releases, and websites. Research teams collect, verify, and integrate the information and survey companies, advisers, investors, and lenders to cross-validate collected data. In a recent strudy, Brown et al. (2015) compare commercial private equity data sets of PitchBook, Preqin, Cambridge Associates, and Burgiss. They conclude that for North America all provide similar performance signals while outside coverage varies substantially. Harris et al. (2016) find the performance data of Burgiss and Pitchbook qualitatively and quantitatively similar.

[8] A buyout defines a transaction where a fund acquires a significant amount of equity in a business, whereas vintage indicates the year that a fund held its final close and/or began making investments. We

whereby 55% of funds reside in the U.S., followed by 26% from Europe, and another 9% from Asia. Table 1 breaks down information on the funds split by vintage year. The average fund manages USD 540 million in capital (median: 197) and is the 3.9th fund of the general partner (median: 2.0). On roughly a third of funds performance information as an internal rate of return (IRR) and/or money multiple (TVPI) is available as a last reported figure.[9] The average fund provides investors with an IRR of 12.5% (median: 11.7%) and a total value of 1.6 times the paid-in capital (TVPI, median: 1.5).

Table 1 about here: Buyout fund sample by vintage year

Second, the PitchBook database lists management teams for more than half of the funds (2,173). A rare feature is the allocation of the individuals at the fund rather than the investment firm (General Partner) level. This information is sourced from regulatory filings, fundraising information, investor websites and surveys, and complemented with the person's role and position within the firm.[10] We follow this classification with a few exceptions, where the partner carries an obvious non-managing position title (e.g., Analyst, Associate), and refer to them collectively as partners of the fund.[11] Our data also includes partners who have historically been involved in the fund even though the individual has left the investment firm in the meantime. The average management team in our sample consists of 3.1 partners (median: 2.0) comprising more than 4,500 individuals who work on average in 1.4 funds (median: 1.0).[12] For 92% (2,005) of funds, information on biography and educational background of the individuals as well as for almost all partners their investment office location is available.

limit the sample period up to the vintage year 2010 as we subsequently conduct a performance analysis that would not make sense for funds that are still in an early stage of their lifetime.

[9] The internal rate of return (IRR) is the rate at which the net present value of all cash flows equals zero. Total value to paid-In (TVPI), also called investment or money multiple, represents the money returned to investors plus the unrealized investments relative to the capital contributed to the partnership. In the database, 1,193 funds report an IRR and 1,353 funds a TVPI multiple (with an overlap of 1,040). Figures are displayed "as-is" from investor reports, who predominantly report them net of fee.

[10] E.g., appearance as lead partner in transactions or as a board member for portfolio companies.

[11] Their actual job titles comprise a variety of titles, e.g., Founding Partner, Managing Partner, Partner, Managing Director, Senior Partner, Investment Director, Director, Operating Partner, Managing Principal, Principal, General Partner (list not exhaustive).

[12] Zarutskie (2010) reports an average management team size of 2.2 for first-time venture funds.

Third, the buyout funds from our sample are involved in approximately 34,000 transactions spanning 25,800 companies.[13] The majority of transactions are classified as either buyout or growth/expansion (around 85%) which will be the focus of our analysis. We exclude venture capital transactions (around 10% of the initial data sample) due to the specific characteristics of these deals. Target firms are mature companies with an average age of 35 years at time of deal (median: 26 years). Around a third of transactions is classified as add-on acquisitions. These typically support a prior acquisition, often in a buy-and-build strategy, and will be excluded from our analysis as they follow their own dynamics and determinants (e.g., the management of the acquiring portfolio company is actively involved).[14] Over 80% of the transactions carry the name of the CEO at the time of the deal and PitchBook is able to provide biography and educational background for more than 9,000 individuals. After filtering for buyout and growth transactions and excluding add-on transactions, around 4,500 CEOs remain.

3.2 Biographies of partners and CEOs

The personal information on each individual in the database comprises the name, a textual biography, and a list of educational achievements. The latter split into the name of the degree institution, the degree type, the degree field, and the degree year. A majority of managers graduated from well-known institutions and most are represented with more than one academic degree. Table 2 presents the most frequently observed institutions for both partners and the target company CEOs involved in one of the buyout transactions introduced in Subsection 3.1. On average, the partners obtained 1.8 degrees, slightly more than the average of 1.6 for their corporate counterparts. In unreported analyses we confirm that for both groups around half of the degrees are undergraduate degrees. Thus, the partners are more likely to have post-undergraduate degrees and an MBA, which is

[13] Some companies are involved in multiple deals over time and within one transaction more than one fund may invest at the same time.

[14] Morkoetter and Wetzer (2015) show that add-on transactions differ particularly in terms of enterprise value, return on assets, and leverage.

the second most common degree type, compared to their corporate counterparts. Cohen et al. (2008) report similar findings for investment managers in the mutual fund industry. There is also a much higher concentration on a selected number of schools among them. The 25 and 100 most frequent degree institutions for partners make up 52% and 73% of degrees while only 24% and 48% for CEOs, respectively. It is noteworthy that the concentration on high-ranking schools is even larger for MBA degrees among the partners. Especially, Harvard enjoys an apparent presence by heading both lists with the highest number of graduates. This finding is consistent with earlier studies on senior managers in the investment industry (e.g., Cohen et al. (2008, 2010), Sunesson (2009), Zarutskie (2010)). We want to stress this point as our analysis on educational ties requires the partner and CEO to graduate from the same institutions. We argue the more overlap in graduates we have, the more likely an investment will be the case.

Table 2 about here: Degree institutions of partners and CEOs

Taking a closer look at the partners and institutional diversity at the fund level we observe the following. A fund has its managers on average educated at 4.2 different academic institutions (median: 3.0). The average exposure to different MBA institutions is much lower at 1.3 business schools (median: 1.0) despite a high share of MBA graduates among the partners. Around half of the managers obtained an MBA degree (mean and median) and a third graduated from an Ivy League school (mean: 36%, median: 25%). Harvard (mean: 19%), the University of Pennsylvania (mean: 9%), and Stanford (mean: 6%) represent the most frequent institutions.

The value of the educational attainment for deal sourcing may also depend on the partner's previous professional experience. To account for this, we examine the (relationship-oriented) work history of the partners with regard to professional service firms and banks. Specifically, we parse experience in management/strategy consulting, with a major accounting firm, and with an (investment) bank.[15] We observe around a third of funds

[15]Consulting includes McKinsey & Co, BCG, Bain & Co, Oliver Wyman, Roland Berger, Booz/Strategy&, and L.E.K., whereas accounting comprises PwC, Deloitte, KPMG, EY, and Arthur

have partners with prior banking experience, a tenth with consulting experience, and a fourteenth with a major accounting firm (team mean 30%, 10%, and 7%, respectively).

3.3 Investment sample

Before describing the counterfactual approach in the next subsection, we filter the data set for available values on key variables. In Subsection 3.1, we derived an initial sample of 4,500 CEOs for whom education is available. These are involved in a buyout or growth transactions, exclusive of any add-on investments. The deals are carried out by buyout funds up to vintage year 2010 for which the biography and education of at least one partner is available in the database.[16] In addition, we only include the transactions where a fund invests for the first time in order to determine the initial contact point.[17] This leaves a baseline of 4,635 individual investments into 3,898 companies.

First, as our data set only covers funds up to vintage year 2010 we cannot fully model the competitive situation in the years after and, thus, exclude investments from subsequent years.[18] Second, we exclude the few transactions where either the deal date or location or industry of the target firm is missing. Third, we only include funds for which size and sequence number as well as the office location of at least one partner is known. Finally, we restrict the sample to investments that take place within the five year period following the vintage year of the fund. The last criterion is enforced for consistency with the counterfactual approach (see description below). This leaves us with a final sample of 3,051 transactions comprising 2,606 companies and 2,599 individual CEOs. They are carried out by 3,584 partners from 1,233 individual funds and 681 unique general partners. Around 2/3 of the funds are U.S. based and around a quarter are first

Anderson. Banking is based on a list of 50 global banks compiled by "The Banker" as well as major investment banks such as Lehman Brothers, Bear Stearns, Lazard, Rothschild (list not exhaustive).

[16]We enforce the criterion through the availability of the name of the degree institution. This excludes some individuals for whom only information on the type, field, or year of the degree is listed.

[17]This excludes, for example, situations where a fund raised its stake in the company.

[18]For example, when a fund invests in 2012 it is likely that also funds with vintage year 2011 compete for it. However, these are excluded from the sample due to the required time lag on performance. In this respect, our estimates can be considered as conservative.

timers. Table 3 presents a break-down of the investments by geography, industry, type, and year. Around two-thirds of transactions are in North American based companies with almost all remaining being European-focused. The funds invest in all kinds of geographic distance. Further, the industry split exhibits a high concentration on business and consumer services, followed by the information technology and healthcare sector. In terms of transaction type, we observe that the minority of investments represent a traditional delisting of a public company. Further, around 12% of them are classified as management buyout/in and 13% as secondary buyout. Investment years range from the 1980s up to 2010 yet most of our deals took place in the post-2000 period.

Table 3 about here: Characteristics of investment sample

In a final step, we add performance information for the investments in the form of a deal IRR and TVPI multiple. We source this data from PitchBook, Preqin, and one anonymous investor. This approach yields 535 deal-level IRRs (mean: 29%, median: 20%) and 624 TVPI multiples (mean: 3.0x, median: 2.4x).[19] As we are not able to obtain this information for the complete data set, the discussion on empirical results will outline how we account for a possible introduction of selection bias into our results.

3.4 Counterfactual approach

Under perfect information we would be able to identify all funds that evaluated a target firm and subsequently joined the bidding (if existing). As our data sample does not provide us with such information, the counterfactual approach serves as an alternative. It allows us to identify funds with a suitable profile that could have invested in the target firm as well and that act as competitors to the winning fund. This approach follows closely the literature on social, board, and syndication ties (e.g., Gompers and Xuan (2009), Sunesson (2009), Stuart and Yim (2010), Siming (2014), Bengtsson and

[19]The variables are winsorized at the 1% tail.

Hsu (2015), Gompers et al. (2016b)).[20] To assess the value of educational networks, we determine whether ties between the management teams of the fund and the target firm give the fund an edge over other potential bidders during this deal generation process.

We create our set of counterfactual investments similar to Bengtsson and Hsu (2015) and set out the following three criteria: (i) the fund is at the point of time the deal takes place in its investment period, which we define as the 5-year period following the vintage year[21], (ii) the fund makes at least one other investment in the same geographic region, and (iii) at least one other investment in the same industry sector.[22] The criteria are deliberately defined broadly as we include various controls in the following analysis to account for differences between the funds.[23] This procedure leaves us with a set of around 750,000 counterfactual bidders and an average competition ratio of 247 from other funds (median: 243). While this number appears high, it is important to understand what exactly it measures. It represent all the funds that in principle could have identified the same target firm and invested as well. However, it is not saying that every fund has actually evaluated the company and/or competed in a bidding process.[24] The goal is to explain the access the winning fund has to the target via the use of a network measure. To further mitigate potential concerns about the high counterfactual investment ratio we present a variety on robustness checks on model specification, including several fixed

[20]Gompers and Xuan (2009) investigates the likelihood of becoming the acquisition target of a public company, while Sunesson (2009) uses a cross-section from 2002 to investigate the matching behavior between venture capitals with entrepreneurs as well as with other venture capitalists. Stuart and Yim (2010) relate board interlocks with the probability of going private transaction. Siming (2014) simulates the mandates of financial advisers by private equity firms. Bengtsson and Hsu (2015) analyze ethnic matching between entrepreneurial founders and venture capital partners in the U.S., and Gompers et al. (2016b) the syndication likelihood among venture capital partners.

[21]Private equity funds usually have a lifetime of 10-12 years and invest in the first couple of years after initiation. Degeorge et al. (2016), for example, discuss investment periods for buyout deals and define a "bought late" dummy in their analysis with a cut-off when the fund is older than 2.5 years.

[22]The definitions follow the classification in the database and allow for a wide range of competition as we expect the educational ties to bridge across borders (e.g., country). Geographic region splits into Africa, Americas, Asia, and Europe. Industry sector differentiates between Business Products and Services (B2B), Consumer Products and Services (B2C), Energy, Financial Services, Healthcare, Information Technology, and Materials and Resources. We refer to Table 3 for related statistics.

[23]Outlining the difficulty to define criteria for generating a control group, Stuart and Yim (2010) even use an unrestricted comparison sample based on all public firms.

[24]Fenn et al. (1997) note that some investment banks actively distribute their offering memorandums to up to 100 potential investors.

effects settings, and confirm our main results for both a random draw and propensity score matching (see Subsection 4.4). Finally, when assessing the competition level over time, we note an increase in the number of potential investors per deal. This is consistent with the growth of the buyout industry and indicates that deal sourcing has likely become more competitive for the funds over the years. Yet, a comparable increase in the number of competing funds that also have an educational tie cannot be detected. Thus, if the hypothesis that educational ties increase the likelihood of winning an investment is true than its importance should also increase with more competition.

If educational ties are indeed an important driver for deal generation, we should observe this case more frequently than expected. Table 4 shows a cross-tabulation of actual versus counterfactual investments with educational ties (Panel A) and MBA ties solely (Panel B). Out of the 3,051 investments in our final sample, 453 have an educational tie, whereas 130 have a tie based on an MBA degree. From these descriptive statistics we can see that the share of ties is two times as high for the actual investments (14.9%) compared to the counterfactual sample (7.4%). Similarly, when we perform the analysis based on common MBA degrees the resulting ratio for ties is more than 1.5 as high for actual investments (4.3% compared to 2.4%). This gives a first indication that educational networks may play a role for buyout funds when they source their investments.

Table 4 about here: Investment generation and educational ties

4 Empirical results

4.1 Does school diversity pay off?

Our empirical analysis starts with an investigation whether access to a greater number of universities is related to better fund performance. We expect that a more diversified educational background of the partners, measured as the fund's school diversity, gives access to a wider range of networks. This opens up more (exclusive) investment opportunities to the team, which in turn benefits the fund's overall performance. We use ordinary least squares (OLS) to estimate the impact of school diversity on fund performance based on the following cross-sectional specification

$$\begin{aligned} Performance_i &= \alpha + \beta\, Schools_i + \delta\, Experience_i + \\ &\quad \gamma\, Fund_i + \lambda\, Vintage_i + \varepsilon_i \ , \end{aligned} \tag{1}$$

where each observation represents one fund. As dependent variable, we employ the IRR and the TVPI multiple as the most commonly used performance measures in private equity. The key variable of interest is the university count, $Schools_i$. The vector $Experience_i$ measures the partner's exposure to consulting, accounting, and banking prior to joining the fund as a fraction of the management team. Another vector, $Fund_i$, includes attributes on size and sequence as well as indicators for first time and U.S. based funds. As common in the private equity literature, we add vintage year fixed effects to account for performance differences related to the fund's inception period. Table 5 shows our results. It lists coefficient estimates and standard errors clustered on investor level for academic degrees overall in Panel A and for the subset of MBA degrees in Panel B.

Table 5 about here: School diversity and fund performance

In a first step, we count the number of unique universities represented in the management team of each fund.[25] All schools are included from which at least one of the partners obtained an academic degree yet each individual institution counts only once per fund. This approach implicitly incorporates the concept of weak ties by being comprehensive through the coverage of all institutions and by not diluting the measure through overweighting individual schools (Granovetter (1973, 1983)). We document that funds with a higher institutional diversity show a positive and significant influence on the fund's

[25] We use a logarithmic transformation to better account for the long tail of the distribution.

performance (Panel A of Table 5). An increase of 25% in the academic exposure, or approximately one additional school given a mean of 4.2 institutions per fund in the database, raises the expected annualized return by 0.2% or around 1.4% of initial capital base.[26] For an average fund with \$540 million in capital this translates into \$7.6 million additional distributions. Therefore, an additional fund partner who has a different academic background diverging from the existing partners is able to add an economically meaningful value to the fund and its investor base. When we restrict the school measure to the subset of business schools, which are known for their strong and geographically dispersed alumni networks, and reestimate Equation (1), we obtain similar results for the MBA degrees (Panel B of Table 5). This set-up does not yet control for the magnitude and quality of the university network as each institution is equally weighted (e.g., Harvard as the university with the highest share of fund partner and CEO affiliation is counted the same way as any other university).

Therefore, in a second step, we split our sample into different subsets based on the school's position in academic rankings (see columns (2) and (4)). We use the Times Higher Education Ranking of 2010 and the Financial Times MBA Ranking of 2010.[27] We argue that a university's position in the rankings is positively correlated with the magnitude and quality of its network. We interpret magnitude and quality in this context not with regard to the education offered but by the number of alumni in CEO and fund partner positions (see Table 2). Our results suggest that the prior evidence is primarily driven by degrees from high-ranked schools. It appears that managers are indeed receiving benefits, i.e., higher returns for their investors, from a broader exposure with significant benefits coming from top schools. This finding indicates that fund teams should strive to diversify in particular among the Top-10 schools. However, some additional remarks need to be made. First, this may be the result of either access to particular strong alumni networks or be rooted in the diversity among students. Second, this effect may

[26] Multiplying the regression coefficients of 0.022 and 0.142 with $log(1.25)$, respectively.

[27] A discussion of alternative rankings is included in the robustness checks (see Subsection 4.4).

not only arise from access to additional networks as weaker evidence for MBA degrees indicates. One may argue that the top schools simply provide superior education or better upfront candidate selection. Yet, in unreported regressions, we repeat the analysis using the share of top schools in the fund team's overall educational profile. We cannot find a significant relationship between the education obtained from a top-ranked school and fund performance. Lastly, the lower ranked schools may well complement the higher ranked schools yet their total effect is not strong enough to significantly drive performance on the fund level. We will follow up with this hypothesis in the next subsection when dealing with the relevance of educational ties for the sourcing of individual investments.

Our control variables on fund size and sequence number are not significant which is in line with previous performance studies that report a mostly insignificant relationship (e.g., Kaplan and Schoar (2005)).[28] In addition, we do not find the U.S.-based and first time fund indicator variables to influence performance. The U.S. dummy variable is motivated by our global data set and a potentially different role of educational networks in the United States. On the other hand, first time funds may use different approaches as they still need to prove themselves in the market. Yet, both do not seem to matter a lot for ultimate investment performance. Finally, the relative share of fund partners with previous experience in the consulting, accounting, and banking industry, does not exert influence either. Teams with a stronger focus on these sectors could have built alternative networks over time or developed other approaches based on their specific experience. Controlling for these alternative networks supports our evidence on education.

While this initial analysis provides a first idea about the value networks play for the fund management, it cannot fully distinguish its origin. It may well be that other characteristics such as a more effective team work through the more diverse educational background contributes to the effect. In addition, the exposure becomes only relevant if the same school is able to produce senior managers on the corporate side as well. As we

[28]In particular, we follow the main literature and include fund size as a control variable. We can also confirm that fund size stays insignificant if we drop our school measure. In addition, we do not include the team size as an additional control variable as it is highly correlated to fund size.

have seen in the descriptive statistics, the range of schools CEOs graduate from is much broader than for the fund partners. Thus, the next section directly addresses educational ties individually on the deal level and their effect on the deal generation of a fund.

4.2 Can networks help to win a deal?

Our next analysis determines the role educational ties play for the deal sourcing success. Let index j refer to the deals in the investment sample and index i to the buyout funds that compete for each transaction. We define a multivariate logistic regression model with a binary response variable $Y_{i,j}$, which is set to one if fund i wins deal j (actual investment) and to zero otherwise (counterfactual investment), and probability π_{ij}. The odds are then defined as the ratio of probability π_{ij} to its complement $1 - \pi_{ij}$, and the logit transformation gives the expected log of the odds as

$$\begin{aligned} ln\left(\frac{\pi_{i,j}}{1-\pi_{i,j}}\right) &= \alpha + \beta\, Educational\ Tie_{i,j} + \\ &\quad \psi\, Distance_{i,j} + \delta\, Experience_i + \\ &\quad \gamma\, Fund_i + \lambda\, FE_j(Year,\ Region,\ Industry)\,. \end{aligned} \tag{2}$$

The key variable is the $Educational\,Tie_{i,j}$ between the partners of fund i and the CEO of target firm j. In addition, the model includes control variables for the geographic distance between the target firm's headquarter and the closest fund office as well as the partners' professional experience and the fund's main attributes. As fixed effects we use investment year, geographic region, and industry sector.[29] Panel A of Table 6 reports our results. We find that funds with an educational tie to the target company CEO increase their odds to win the deal by 79% compared to other funds active in the market at the same time (Column (1)).[30] This is in line with the univariate evidence and represents an economic significant effect. Educational ties with an overlap in either degree type or time

[29]Refer to Table 9 for the full model and alternative specifications of fixed effects.

[30]Exponentiating the regression coefficient of 0.583 results in an odds ratio of 1.79.

as well as MBA ties are also highly significant. In particular, the ties with an overlapping graduation period result in a high increase in the odds (both educational and MBA ties) which confirms earlier evidence from mutual funds (Cohen et al. (2008)).

Table 6 about here: Educational ties and the odds to win a deal

A. The exclusivity of educational ties

Our findings show that not only ties from high-ranked schools matter (though they are highly significant) but the relatively more rare ties from lower-ranked schools exert influence on the success rate whenever they exist (Panel A of Table 6). For example, when we split the ties into several ranking classes, the increase in the odds ranges from 30% for top-10 schools to above 300% for non-top 100 schools (Column (5)). This finding may be driven by a lower level of competing funds that have access to the same network. To further investigate the differences between the university ranking groups, we standardize the $Educational\,Tie_{i,j}$ variable by its degree of exclusivity among the competing funds. Specifically, we divide the indicator variables by the number of counterfactual bidders that have an educational tie as well to arrive at the following scaled version of educational ties

$$Scaled\,Educational\,Tie_{i,j} = \frac{Educational\,Tie_{i,j}}{\sum_{i=1}^{n} Educational\,Tie_{i,j}}\,. \tag{3}$$

This effectively transforms the binary variables into a probability (values bound between zero and one). We reestimate Equation (2) and present results in Panel B of Table 6. It follows that the funds ultimately winning the deal have higher odds of doing so when their tie is more unique (up to ten times). For example, the adjusted measure for transactions where the winning fund has a tie from a top-10 school has an average of only 1.8%, while non-top 100 schools have an average of 26.5% (the overall sample mean is 10.3%). The resulting regression output remains stable with one notable difference: the top-10 ranking group becomes insignificant indicating that the edge a tie provides to the fund diminishes if this is not anymore a differentiating factor to competing funds. This uncovers another benefit of networks. It is not necessarily only the largest and widest network and the one which produces the highest number of CEOs which is of value for the partners. Yet, the ones which provide exclusivity seem to drive the results most. Recalling that the CEOs graduated from many more different universities than the fund partners themselves attended, less represented schools appear to be important for the deal generation.

B. Educational versus local networks

We interpret proximity to a target firm's headquarter, and thus the company's top management, as a component of local networks. Fund partners may use their regional business and social relationships (e.g., country clubs) to sweet-talk a CEO and win the transaction. We calculate geographical proximity as

$$Distance_{i,j} \quad = \quad min\,(\,Haversine\,(\,Headquarter_j,\ Office_{i,k}\,)\,)\,, \tag{4}$$

which calculates the minimum geographical distance (in km) between the headquarter of the target company involved in deal j and the investment offices (index k) where at least one of the partners of fund i is located.[31] We find the distance to be strongly negative (see Column (2) in Table 7). The closer the investment office of a fund is to the target firm's headquarter, the greater are the odds to actually win a deal. This is bad news for funds operating out of major financial centers, such as Chicago and New York in the U.S., in case they have to compete against funds located closer to a target firm's headquarter. Yet, the finding is in line with earlier research that report a home bias in the investment industry. For example, in the venture capital market, Sorensen and Stuart (2001, 2008) show that the likelihood of an investment decreases with a wider geographic distance.

However, we are interested whether the presence of educational networks can support the partners despite the geographic distance. The literature provides evidence on the existence of such distant ties (Chen et al. (2010)). Thus, we interact the educational

[31]Distance is expressed in log kilometers in the regressions and calculated according to the Haversine method assuming a spherical earth and ignoring ellipsoidal effects (radius of the earth 6,378,137 meter).

tie with geographic distance. We find that the presence of a tie seems to significantly mitigate the negative effect of not being located nearby. The magnitude of the interaction is around a fifth of the negative control for geographic distance. Thus, it seems that fund managers can use their educational networks to mitigate the lack of a local network. In an alternative setting (Column (3)), we look at transatlantic investments to find that results are primarily driven by U.S. funds investing overseas, rather than the opposite direction. This complements evidence from Jääskeläinen and Maula (2014) who find that network ties to foreign venture markets facilitate exits.

Table 7 about here: Value drivers of educational ties

C. Additional value drivers of educational ties

Lastly, we identify a set of features and conditions that drive the value of educational ties. Results for selected variables are depicted in Table 7. First, we evaluate the strength of a tie by investigating the incremental value of a redundant tie. Contrary to evidence on CEOs (Engelberg et al. (2013)), we observe that the existence of additional ties fosters the connection and increase the likelihood for the fund even more to be successful in the deal generation (see Column (1)). Second, with regards to fund level controls, we see a strong significance on the main effects of fund size and first time funds (included in Table 9), yet not on their interactions with the educational tie. Similarly, we do not find effects for the U.S. fund and the sequence indicator. The negative interaction effect on fund size may indicate that large funds established alternative networks which allows them to substitute for alumni networks. Third, experience variables for the management team, such as consulting, accounting or banking, do not drive our results (shown in Table 9). This may be interpreted in such a way that prior work experience of fund partners does not give a fund access to networks acquired in these histories providing value for the deal sourcing activity (e.g., Siming (2014) reports that past employment at a financial adviser is beneficial for future mandates). Fourth, we differentiate among frequent deal categories. We find stronger evidence for the benefit of existing ties for management buyouts/ins (MBO/MBI), whereas the effect on going private transactions is limited. These results seem intuitive given a higher personal relevance for the management team in the former, whereas the latter is more transparent given the listing of the company. The interaction with secondary transactions is positive. In a secondary buyout, one fund sells its portfolio company to another fund. In case the CEO of the portfolio company and a partner of the acquiring fund share the same alma mater, the deal likelihood increases. This may indicate that the fund manager and/or CEO reaches out to its network partner in order to facilitate the transaction. Interestingly, it appears that the CEO has an active role in selection its new owner, whereas normally the fund would be expected to be in the driving seat. Fifth, we include fund performance as an explanatory variable in two specifications. While this information is not available upfront when the deal decision is made it allows us to give an indication whether funds tend to win deals by over-paying (and subsequently have low return measures). However, neither the variable nor the interaction term are significant for IRR and TVPI multiple.

4.3 Are ties driving performance?

In a last step, we investigate the relevance of our results for investors by evaluating whether investments sourced via an (educational) network perform better. Three potential outcomes exist, namely investments sourced from networks lead to higher, lower, or equal returns. First, one may argue that transactions from a network lead to higher quality investments as they offer exclusivity and, thus, represent more attractive opportunities. Second, one may argue that a partner is inclined to buy a company she would normally not buy or, at least, not for the agreed price. The rationale is that the existing relationship to the CEO blinds, or even worse, generates willingness to grant the former fellow student a favor. However, there exists a major argument against such a conflict of interest as partners are highly incentivized via carried interest structures. Finally, one may argue that the investments sourced from the partners' network should not necessarily have an impact on the deal-level performance as other value-adding pillars matter much more. These comprise, for example, a revision of the capital structure (leveraging), resolution of an undervaluation (multiple expansion), as well as operational and governance improvements (Achleitner et al. (2010)). Only a multiple expansion would be impacted via a low entry valuation (as result of a close network relationship). However, still the exit valuation would matter independent on the entry valuation and the relationship in place. Operational and financial improvements take place only following the acquisition and are independent of the network relationship at the point of deal. Or in other words, while one may have a very good network in place, it does not help to generate post-acquisition value if there is not sufficient value creation throughout the holding period.

Univariate evidence suggests that the performance of deals with and without ties is not statistically different (average IRR of 18.9 versus 19.7%, TVPI of 3.03x versus 2.98x). As we are only able to retrieve performance data on a subset of the investment sample, we start by verifying that our main results hold for this sample as well. While both sub-samples have slightly higher ratios of educational ties (18.9 and 19.1%), running the same regressions as in Table 9 we confirm similar findings. In addition, we use a Heckman selection model to account for potential selection bias in the upcoming performance regressions. The outcome selection equation contains the same set of independent variables, except for the educational tie, and, in addition, fixed effects for deal year, geographic region, and industry of the target company. To estimate, the effect of educational ties for deal-level performance, our baseline model writes

$$\begin{aligned} Performance_j \;&=\; \alpha + \beta\, Educational\ Tie_j + \delta\, Experience_j + \\ &\quad\; \gamma\, Fund_j + \xi\, Investment_j + \lambda\, Year_j + \varepsilon_j\ . \end{aligned} \tag{5}$$

Results are presented in Table 8, in Panel A for the baseline model and in Panel B for interactions with deal types. The dependent variable $Performance_j$ is the deal-level IRR and TVPI multiple. Control variables are similar to the previous regressions with the additions of two investment related variables, namely the holding period and the prevailing market return, and fixed effects on the investment year. The former measures time between entry and exit and the latter is a total index return during the former.[32] As noted in the introduction, prior evidence from the venture capital market is mixed and the expected value on returns is not obvious. It could be driven by improved information or blindness. Our findings do not show a significant effect for the educational ties. Only the interaction for MBO/MBIs shows some evidence in combination with the ties. Controlling for the length of the holding period and the market return during the former shows negative and positive evidence, respectively. Due to the time sensitivity of investments, the negative (positive) impact of holding period (market return) is not surprising as private equity exits are highly driven by the overall economic environment. This complements recent investigations on the drivers of deal level performance (e.g., Achleitner et al. (2010), Acharya et al. (2013), and Braun et al. (2016)).

Table 8 about here: Educational ties and investment performance

4.4 Robustness checks

We employ three additional robustness checks on methodology and data sample.

First, one could argue that our counterfactual approach results are biased by the applied selection procedure. Thus, we use different sets of fixed effect and model specifications to confirm their robustness. We choose a similar selection procedure as presented by Bengtsson and Hsu (2015) given the similarity of the research question (the authors focus on ethnic matches). Table 9 presents our results. It also shows the full list of coefficients on our control variables that are (partially) omitted in the earlier sections. It splits models between the full sample (Columns (1) to (4)) and a one-for-one random draw to counter the chance that results are driven by a high counterfactual ratio (Columns (5)

[32] For North American deals, we use the MSCI North America, for European deals the MSCI Europe, and for the remaining investments the MSCI World (all retrieved from Thomson Reuters in USD).

to (8)). The latter is tested by Bengtsson and Hsu (2015) for the very same reasons.[33] The first specification in each block follows the same logistic regression formula of deal generation success on educational ties from the main empirical results (see Equation (2)). The second model estimates an OLS model instead but leaves everything else constant. Finally, the remaining two specifications change the fixed effects to the company and the investor level, respectively. For the OLS models we use two-way cluster-robust standard errors on investor and company level. The logistic regressions cluster standard errors on the investor level. The coefficients on educational ties (Panel A) as well as MBA ties (Panel B) are highly significant across all specifications. We observe that in all settings the impact of educational ties remains significantly positive with regards to winning the deal. In addition, the random draw supports our results.

Table 9 about here: Robustness checks on model specification

Second, one may argue that our results are driven by some overrepresented components and features of our data sample and do not apply in general. In order to mitigate these concerns, we present the coefficients of the educational ties and MBA ties for various sub-samples in Table 10. We split the sample based on deal characteristics (geography, distance) and fund attributes (vintage, size, performance). Each row in the table reports the coefficients and standard errors from two separate regressions, one for the educational ties and one for the MBA ties compared to other types of academic degrees. Our results seem not to be driven by the sample selection as the influence of ties remain intact. In particular, we show that the effect persists when analyzing the competition among funds considering only investments that took place in Europe and North America, respectively. In particular, the significance remains for various clusters of geographic distance. We look at both local sourcing (below 100 km) and overseas investing (above 1,000 and 5,000 km).

[33] The creation of random simulation groups is also employed in Renneboog and Zhao (2014). In addition, we implemented a propensity score matching approach (which, for example, is used in Siming (2014)), based on the set of control variables and nearest neighbor, and obtain similar results for academic and MBA degrees.

With regards to fund attributes, we investigate the pre-2001 and post-2000 periods. In recent years performance persistence is reduced due to a maturing industry as well as the movement of individuals and knowledge between the investors (Braun et al. (2016)). The results also do not seem to be driven by U.S. funds or first time funds as both sub-samples confirm the earlier findings from the interaction effects. Lastly, we split the fund sample between large and small funds as well as high and low performers (in terms of IRR and TVPI) to increase confidence into the general interpretation of our results. Interestingly, the main conclusions can also be derived using MBA degrees only.

Table 10 about here: Robustness checks on data subsets

Third, we show that our findings are not influenced by the choice on university ranking definitions. We use the Academic Ranking of World Universities (ARWU) from the Center for World-Class Universities at Shanghai Jiao Tong University instead of the Times Higher Education (THE) World University Rankings and the U.S. News and World Report for Business Schools instead of the Financial Times (FT) full-time global MBA programs. For the fund level regressions we find similar results. The broader set of schools shows higher coefficients on the second block (Top 11-30) but low ranked schools are again close to zero. The results on business schools are almost identical. For the deal level regressions, results are largely consistent for both the scaled and unscaled variables. Only the top 10 variable is weakly significant with all other ranking classes again highly significant and with increasing coefficients.

5 Concluding remarks

We build upon the literature on the relevance of social ties using a novel data set based on the profiles of private equity fund managers and their investment targets. Our analysis reveals that educational networks indeed matter for the investment choice of buyout investors. During their competitive sourcing process, the existence of such ties eases identification and access to potential acquisition targets. This confirms earlier notions in the literature that personal and professional networks are an important channel for investors to identify target firms. It also stresses the general importance of social ties to overcome organizational boundaries and, especially, confirms the role of weak ties ("acquaintances") for senior managers documented in the sociological literature.

In addition, we identify a set of features and conditions that drive the value of such linkages. First, the more exclusive the tie is relative to the degree of competition in the market, the higher its value. As academic degrees of senior managers in the private equity industry are concentrated on a small set of schools, the existence of educational ties is an important differentiating factor. In addition, our results show that funds with a broader exposure to different institutions and, thus, access to their networks, perform better. Second, we present a set of value drivers. We show that localness to a target company's headquarter facilitates to win a deal but also observe that educational ties can help to mitigate such a potential home bias and pave the way for long distance investments for the fund. The existence of a redundant tie and the transaction type, e.g., management buyouts/ins, further strengthen the fund's position relative to other bidders. Third, we do not find evidence that investments sourced via networks lead to a superior deal-level performance, which underlines that the value creation process starts after the take-over independent of the access to a specific deal.

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6 Tables

Table 1: Breakdown of buyout funds by vintage year

The table shows for each vintage year summary statistics on the buyout funds available in the PitchBook database (up to 2010). Only closed, fully invested, and liquidated funds are included and a minimum of three funds per year was imposed. *Fund count* reports the total number of funds as well as the number of funds for which an IRR, a TVPI multiple, and at least one partner is available, respectively. *Fund profile* lists the average number of investments and partners tagged to the fund as well as the average and median committed capital. The count of investments includes all types of investments (incl. venture and add-on transactions) and is not restricted to the set of buyout and growth transactions used in the empirical part of the study. The number of fund partners is based on the classification in the database but does not include investment professionals with titles such as "Analyst" or "Associate". *Fund performance* depicts the average and median IRR and TVPI multiple for each vintage year. Performance and capital variables are winsorized at the 1% level. U.S. based funds are classified as such in the database.

	Fund Count				Fund Profile				Fund Performance			
Vintage Year	Total Funds	w/ IRR	w/ TVPI	w/ Partner	Avg. Partner	Avg. Invest.	Avg. Cap.	Med. Cap.	Avg. IRR	Med. IRR	Avg. TVPI	Med. TVPI
	#	#	#	#	#	#	*$m*	*$m*	%	%	*x*	*x*
1978	4	1	1	0		2.0	63	63	5.5	5.5	1.4	1.4
1979	5	1	1	0		3.7	82	50	19.4	19.4	2.5	2.5
1980	7	1	2	0		2.0	57	60	14.2	14.2	2.7	2.7
1981	8	2	2	4	1.5	7.0	69	11	12.8	12.8	2.7	2.7
1982	3	1	1	0		1.0	123	24	39.2	39.2	3.4	3.4
1983	11	2	3	2	5.0	16.2	90	42	9.7	9.7	1.9	1.8
1984	18	4	3	4	1.0	3.2	115	54	27.4	23.5	3.2	3.6
1985	12	4	3	2	1.0	2.0	81	79	8.3	9.4	2.3	2.7
1986	16	5	3	6	1.5	3.9	226	112	36.1	35.7	3.9	4.4
1987	21	13	7	8	1.2	6.7	630	152	17.0	14.1	2.1	2.1
1988	18	6	4	1	1.0	5.6	121	62	25.2	19.0	1.8	1.9
1989	39	13	15	6	2.2	3.7	296	148	22.3	19.8	2.4	2.4
1990	34	8	4	11	1.6	4.9	236	155	4.8	10.3	1.9	2.2
1991	27	13	13	5	1.0	3.7	151	81	28.7	25.0	2.8	3.0
1992	32	10	6	11	1.4	4.8	348	122	15.7	21.7	1.6	1.5
1993	38	17	14	13	1.6	7.0	342	260	21.7	18.8	2.4	2.1
1994	61	22	22	24	1.6	7.8	293	125	20.4	18.2	2.3	2.1
1995	74	26	28	26	2.0	6.3	261	103	14.7	13.3	1.9	1.7
1996	125	40	34	54	1.6	6.7	322	100	9.8	7.3	1.5	1.3
1997	152	46	53	69	1.7	6.7	463	160	7.7	9.1	1.6	1.5
1998	175	71	68	94	2.3	10.8	454	209	6.3	8.8	1.5	1.5
1999	194	66	69	104	2.4	9.8	400	154	12.7	12.6	1.7	1.7
2000	239	81	79	137	2.8	13.1	556	172	14.0	12.2	1.9	1.8
2001	142	53	55	89	3.4	13.2	567	166	20.7	19.2	2.0	1.9
2002	150	46	47	91	2.7	10.8	441	141	16.3	17.6	1.8	1.8
2003	136	44	50	86	3.4	13.1	554	184	21.2	17.8	1.8	1.7
2004	182	48	54	111	2.6	11.4	459	207	12.2	8.2	1.7	1.6
2005	257	87	110	180	3.9	15.0	717	255	8.2	8.2	1.4	1.4
2006	425	121	159	268	3.6	12.8	778	330	8.2	8.5	1.4	1.4
2007	451	129	164	277	3.7	13.7	658	259	10.4	9.9	1.4	1.4
2008	350	95	129	227	3.6	12.0	682	233	10.5	11.6	1.4	1.4
2009	223	60	73	135	3.3	11.6	615	182	14.5	14.0	1.5	1.4
2010	208	57	77	128	3.6	9.9	375	232	9.8	9.8	1.3	1.2
Total	3837	1193	1353	2173	3.1	11.3	540	197	12.5	11.7	1.6	1.5
U.S.	2093	848	918	1296	3.3	13.0	572	202	12.5	12.0	1.6	1.5
Other	1744	345	435	877	2.9	9.0	498	182	12.5	10.4	1.6	1.4

Table 2: Degree institutions of fund partners and CEOs

The table presents the most frequent academic institutions from which fund partners and target company CEOs receive their academic degrees. Individuals can be represented with multiple degrees. MBA degrees are also shown individually. *Fund partners* are working for a buyout fund up to vintage year 2010. *Target firm CEOs* refer to the time of the deal where one of the buyout funds invested in the company for the first time. This includes only buyout and growth transactions and excludes add-on transactions. The table is sorted in a descending order by the number of fund partner degrees. An institution is listed when one of the two groups is represented with at least 50 degrees.

		Fund Partner				Target Firm CEO			
	Academic Institution	N	%	MBA	%	N	%	MBA	%
1	Harvard University	876	12.04	590	28.12	253	3.69	145	12.05
2	University of Pennsylvania	485	6.67	222	10.58	108	1.58	41	3.41
3	Stanford University	314	4.32	163	7.77	100	1.46	36	2.99
4	Columbia University	180	2.47	115	5.48	60	0.88	21	1.75
5	Northwestern University	171	2.35	124	5.91	96	1.40	54	4.49
6	University of Chicago	156	2.14	130	6.20	71	1.04	54	4.49
7	Yale University	121	1.66	15	0.71	38	0.55	4	0.33
8	Dartmouth College	119	1.64	43	2.05	44	0.64	13	1.08
9	University of Virginia	108	1.48	27	1.29	39	0.57	9	0.75
10	Princeton University	99	1.36	1	0.05	21	0.31	0	0.00
11	Cambridge University	97	1.33	1	0.05	35	0.51	0	0.00
12	University of Oxford	96	1.32	1	0.05	37	0.54	1	0.08
13	INSEAD	92	1.26	83	3.96	52	0.76	26	2.16
14	New York University	88	1.21	45	2.14	52	0.76	21	1.75
15	University of Michigan	83	1.14	18	0.86	53	0.77	13	1.08
16	Cornell University	80	1.10	15	0.71	51	0.74	10	0.83
17	ParisTech	79	1.09	5	0.24	54	0.79	10	0.83
18	Duke University	75	1.03	16	0.76	32	0.47	10	0.83
19	University of Texas	73	1.00	16	0.76	84	1.23	24	2.00
20	Georgetown University	72	0.99	9	0.43	30	0.44	3	0.25
21	Massachusetts Institute of Technology	64	0.88	16	0.76	46	0.67	6	0.50
22	Stockholm School of Economics	60	0.82	2	0.10	16	0.23	1	0.08
23	University of Notre Dame	59	0.81	2	0.10	25	0.36	4	0.33
24	University of California, Berkeley	58	0.80	9	0.43	63	0.92	10	0.83
25	University of California, Los Angeles	55	0.76	29	1.38	39	0.57	12	1.00
26	Brown University	53	0.73	0	0.00	25	0.36	0	0.00
27	University of Illinois	53	0.73	2	0.10	48	0.70	4	0.33
28	University of Wisconsin	34	0.47	5	0.24	56	0.82	11	0.91
	Other	3373	46.38	394	18.78	5222	76.23	660	54.86
	Total	7273	100	2098	100	6850	100	1203	100

Table 3: Characteristics of the investment sample

The table presents descriptive statistics on the set of buyout and growth transactions where a buyout fund invests for the first time in the target company. Add-on transactions and investments after 2010 are excluded. Educational background on at least one partner of the investing fund and the CEO must be available for a fund to be considered. Transactions without a date or missing information on the company's location and industry as well as funds with missing location or size are excluded. In addition, only deals where the investment took place within the five year period following the fund's vintage year are considered for comparability with the counterfactual investment sample. *Headquarter region*, *industry sector*, *investment year*, and *transaction type* are based on classifications in the database. *Geographic distance* is the distance between the firm's headquarter and the closest partner of the acquiring fund.

	N	%
Total	3051	
Panel A: Headquarter Region		
North America	2065	67.68
Western Europe	551	18.06
Northern Europe	187	6.13
Eastern/Southern Europe	130	4.26
Other	118	3.87
Panel B: Geographic Distance		
Distance $\leq$ 100 km	730	23.93
Distance 100-500 km	633	20.75
Distance 500-1000 km	458	15.01
Distance 1000-2500 km	709	23.24
Distance $\geq$ 2500 km	521	17.08
Panel C: Primary Industry Sector		
Business Products and Services (B2B)	1000	32.78
Consumer Products and Services (B2C)	730	23.93
Energy	119	3.90
Financial Services	259	8.49
Healthcare	352	11.54
Information Technology	461	15.11
Materials and Resources	130	4.26
Panel D: Transaction Type		
Buyout/LBO	916	30.02
Divestiture/Carveout	269	8.82
Management Buyout/in	363	11.90
Growth/Expansion	578	18.94
Going Private	208	6.82
Recapitalization/Acquisition Financing	320	10.49
Secondary Buyout	397	13.01
Panel E: Investment Year		
1980 - 1994	27	0.88
1995 - 2000	340	11.14
2001 - 2002	201	6.59
2003 - 2004	387	12.68
2005 - 2006	664	21.76
2007 - 2008	777	25.47
2009 - 2010	655	21.47

Table 4: Investment generation and educational ties

The table shows the existence of an educational and MBA tie, respectively. *Actual investments* are the buyout and growth transactions from buyout funds up to vintage year 2010 described in Table 3. *Counterfactual investments* represent potential transactions from buyout funds generated in the simulation analysis that could have invested in the same company as well. To be included for a specific transaction, they are in their investment period at the time of the deal and have invested at least once in the same geographic region and industry sector. We refer to Section 3.3 for more details on the matching procedure. An *educational tie* exists if at least one of the fund partners obtained a degree from the same academic institution as the CEO of the target company at the time of the transaction. An *MBA tie* exists if the partner and the CEO graduated from the same business school.

Panel A: Educational Ties

	Educational Tie		
Investment	No	Yes	Total
Actual	2598	453	3051
	85.2%	14.9%	100%
Counterfactual	694402	55240	749642
	92.6%	7.4%	100%
Total	697000	55693	752693
	92.6%	7.4%	100%

Panel B: MBA Ties

	MBA Tie		
Investment	No	Yes	Total
Actual	2921	130	3051
	95.7%	4.3%	100%
Counterfactual	731316	18326	749642
	97.6%	2.4%	100%
Total	734237	18456	752693
	97.5%	2.5%	100%

Table 5: School diversity and fund performance

The table shows results of cross-sectional regressions of fund performance on school diversity according to Equation (1). The sample includes buyout funds up to the vintage year 2010. The dependent variable is the IRR and the TVPI multiple of the fund, respectively. In Panel A, the *number of schools* is the natural logarithm of a count of all uniquely represented degree institutions from which at least one of the fund partners graduated. In Panel B, only institutions from which at least one *MBA degree* is obtained are included. Subsequently, the count is split based on the school's position in academic rankings (for more details on ranking methodology and robustness refer to Section 4.1). Control variables are the following: The share of fund partners with prior work experience in the *consulting*, *accounting*, and *banking* industry. *Fund size* is the natural logarithm of the fund's committed capital. *Fund sequence* is the natural logarithm on the number of funds the investor has already raised including the current one. *First fund* and *U.S. fund* are indicator variables which equal to one if the fund is the first fund and based in the U.S., respectively. Performance and size variables are winsorized at the 1% level. Each model includes vintage year fixed effects. The table depicts coefficients estimated with Ordinary Least Squares (OLS) and standard errors clustered on investor level (in brackets).

	Dependent variable:			
	IRR		TVPI	
	(1)	(2)	(3)	(4)
Panel A: Academic degrees				
Nbr schools	0.022***		0.142***	
	(0.008)		(0.037)	
Nbr schools (top 10)		0.021**		0.140***
		(0.009)		(0.043)
Nbr schools (top 11-30)		0.016*		0.097**
		(0.010)		(0.046)
Nbr schools (top 31-100)		0.005		0.060
		(0.009)		(0.040)
Nbr schools (non-top 100)		0.001		−0.000
		(0.007)		(0.036)
Consulting	0.034	0.027	0.107	0.060
	(0.025)	(0.025)	(0.099)	(0.098)
Accounting	−0.007	−0.002	0.052	0.062
	(0.030)	(0.030)	(0.133)	(0.135)
Banking	0.006	0.002	0.002	−0.027
	(0.013)	(0.014)	(0.068)	(0.068)
Fund Size	−0.004	−0.005	−0.023	−0.030
	(0.005)	(0.005)	(0.024)	(0.024)
Fund Sequence	−0.005	−0.006	−0.049	−0.058*
	(0.006)	(0.006)	(0.030)	(0.030)
First Fund	0.003	0.003	−0.092	−0.100
	(0.015)	(0.015)	(0.071)	(0.072)
U.S. Fund	0.000	−0.008	−0.034	−0.094
	(0.011)	(0.013)	(0.055)	(0.066)
F.E. Vintage Year	Yes	Yes	Yes	Yes
Observations	847	847	966	966
Adjusted R^2	0.111	0.112	0.165	0.171

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Table 5 – *Continued from previous page*

Panel B: MBA degrees

Nbr MBA schools	0.018**		0.141***	
	(0.009)		(0.039)	
Nbr MBA schools (top 10)		0.016		0.129**
		(0.010)		(0.053)
Nbr MBA schools (top 11-25)		−0.009		0.007
		(0.013)		(0.060)
Nbr MBA schools (top 26-50)		0.001		0.057
		(0.016)		(0.079)
Nbr MBA schools (non-top 50)		0.019**		0.086**
		(0.009)		(0.043)
Controls	Yes	Yes	Yes	Yes
F.E. Vintage Year	Yes	Yes	Yes	Yes
Observations	847	847	966	966
Adjusted R^2	0.109	0.111	0.165	0.166

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

Table 6: Educational ties and the odds of winning a deal

The table shows the results for cross-sectional regressions of a binary investment indicator on the existence of educational ties according to Equation (2). The response variable equals one for actual and zero for counterfactual investments. The latter include for each transaction the buyout funds that are in investment period at the time of deal and that have invested at least once in the same geographic region and industry sector. *Panel A*, presents evidence on *educational ties* where at least one of the fund partners graduated from the same academic institution as the CEO of the target company. *Same type* refers to the academic degree. *Same time* measures a three year window relative to graduation year. The *top school* definitions follow the same ranking from the fund level regressions (Table 5). An *MBA tie* exists if the partner and the CEO graduated from the same business school. A *Non-MBA tie* represents an educational tie that is not based on a shared MBA tie. *Panel B* normalizes educational ties with the number of competing funds that have the same tie. The scaled educational tie variable is calculated according to Equation (3). Each presented model includes vintage fixed effects on the investment's year, geographic region, and industry sector. The table depicts coefficients estimated from a multivariate logit model and standard errors clustered on investor level (in brackets). We refer to Table 9 for the full model including all details on control variables.

	Dependent variable: Investment Indicator						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Binary tie							
Educational tie	0.583***						
	(0.060)						
Educational tie (same type)		0.534***					
		(0.063)					
Educational tie (same time)			1.003***				
			(0.144)				
Educational tie (type, time)				0.958***			
				(0.154)			
Educational tie (top 10)					0.270***		
					(0.081)		
Educational tie (top 11-30)					0.433***		
					(0.114)		
Educational tie (top 31-100)					0.826***		
					(0.116)		
Educational tie (not-top 100)					1.229***		
					(0.106)		
MBA tie						0.539***	
						(0.092)	
Non-MBA tie						0.601***	
						(0.068)	
MBA tie (same time)							1.056***
							(0.232)
Panel B: Degree of exclusivity							
Scaled educational tie	2.340***						
	(0.194)						
Scaled edu. tie (same type)		2.289***					
		(0.228)					
Scaled edu. tie (same time)			3.330***				
			(0.673)				

Continued on next page

Table 6 – *Continued from previous page*

Scaled edu. tie (type, time)				4.024***			
				(0.933)			
Scaled edu. tie (top 10)					−0.006		
					(0.942)		
Scaled edu. tie (top 11-30)					2.232***		
					(0.637)		
Scaled edu. tie (top 31-100)					2.178***		
					(0.431)		
Scaled edu. tie (not-top 100)					2.438***		
					(0.216)		
Scaled MBA tie						2.944***	
						(0.527)	
Scaled Non-MBA tie						2.279***	
						(0.209)	
Scaled MBA tie (same time)							4.356***
							(1.291)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F.E. Deal Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F.E. Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F.E. Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	752,693	752,693	752,693	752,693	752,693	752,693	752,693

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

Table 7: Value drivers of educational ties

The table extends the results for cross-sectional regressions from Table 6 and according to Equation (2). The response variable equals one for actual and zero for counterfactual investments. An *educational tie* exists if at least one fund partners graduated from the same academic institution as the target company CEO. A *redundant tie* indicates at least one additional tie between the fund partners and the CEO exists. *Geographic distance* is measured between the headquarter of the target company and the nearest investment office of a fund partner (log). *U.S fund* indicates that the fund is based in the United States whereas *Europe* and *North America (NA)* deals refer to the target firm headquarter. *Fund size* is the fund's committed capital (log) and first fund is an indicator variable which equals to one if the fund is a first time fund for the investor. *Going Private, secondary buyout, and management buyout/in* are indicator variables which equal to one if the transaction is classified under the respective category in the database and zero otherwise. *IRR* and *TVPI* are performance measures for the funds. Performance and size variables are winsorized at the 1% level. Whenever interaction effects are reported, the specification included the main effect as well. Each presented model includes vintage fixed effects on the investment's year, geographic region, and industry sector. The table depicts coefficients estimated from a multivariate logit model and standard errors clustered on investor level (in brackets). We refer to Table 9 for the baseline model including a list of all control variables.

	Dependent variable: Investment Indicator						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Educational tie	0.437***	0.297***	0.611***	0.941***	0.521***	0.604***	0.613***
	(0.073)	(0.101)	(0.060)	(0.306)	(0.071)	(0.101)	(0.201)
Redundant tie	0.387***						
	(0.099)						
Edu tie ∗ Geo. distance		0.055***					
		(0.017)					
Edu tie ∗ U.S fund / Europe deal			0.575**				
			(0.271)				
Edu tie ∗ no-U.S. fund / NA deal			0.099				
			(0.383)				
Edu tie ∗ Fund size				−0.057			
				(0.042)			
Edu tie ∗ First fund				0.166			
				(0.169)			
Edu tie ∗ MBO/MBI					0.457***		
					(0.172)		
Edu tie ∗ Secondary Buyout					0.306**		
					(0.154)		
Edu tie ∗ Going Private					−0.283		
					(0.232)		
Edu tie ∗ IRR						−0.437	
						(0.572)	
Edu tie ∗ TVPI							−0.049
							(0.115)
Geo. Distance	Yes	−0.262***	No	Yes	Yes	Yes	Yes
		(0.011)					
Main effect	n/a	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F.E. Deal Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F.E. Region	Yes	Yes	No	Yes	Yes	Yes	Yes
F.E. Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	752,693	752,693	752,693	752,693	752,693	432,693	478,822

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

Table 8: Educational ties and subsequent investment performance

The table shows results for cross-sectional regressions of deal performance on educational ties according to Equation (5). The sample includes the subset of investments where performance could be sourced. *Panel A* shows the baseline regression, whereas *Panel B* adds interaction effects for different deal type indicator variables. These comprise management buyouts/ins (MBO/MBI), secondary buyouts, and going private deals. The dependent variable represents the IRR and multiple of the respective investment. An *educational tie* exists if at least one of the fund partners graduated from the same academic institution as the CEO of the target company. *Holding period* describes the investment period for the respective fund whereas *market return* measures the equity market return for the same time frame in the region. We refer to Table 9 for the definition of control variables. The *Heckman model* shows the outcome equation. The selection equation contains the same set of independent variables, except for the educational tie, and, in addition, fixed effects for deal year, geographic region, and industry. The table depicts coefficients estimated with Ordinary Least Squares (OLS) and standard errors clustered on investor level (in brackets).

	Dependent variable: Deal IRR				*Dependent variable: Deal TVPI*			
	OLS	*OLS*	*OLS*	*Heckman*	*OLS*	*OLS*	*OLS*	*Heckman*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Baseline model								
Educational tie	0.018	0.001	0.040	−0.013	0.087	0.108	0.190	0.009
	(0.052)	(0.051)	(0.046)	(0.064)	(0.269)	(0.270)	(0.269)	(0.302)
Geo. Distance		−0.007	−0.012	−0.014		−0.003	−0.013	−0.012
		(0.011)	(0.010)	(0.011)		(0.058)	(0.056)	(0.050)
Consulting		−0.119	−0.026	−0.039		0.229	0.357	0.004
		(0.165)	(0.143)	(0.139)		(0.752)	(0.714)	(0.601)
Accounting		-0.327^{**}	-0.449^{***}	-0.499^{***}		−0.325	−0.557	−1.394
		(0.162)	(0.162)	(0.183)		(0.657)	(0.657)	(0.855)
Banking		−0.020	−0.035	−0.108		−0.173	−0.242	−0.460
		(0.098)	(0.097)	(0.095)		(0.464)	(0.472)	(0.427)
Fund Size		−0.021	0.004	−0.057		-0.415^{***}	-0.336^{***}	-0.840^{***}
		(0.023)	(0.020)	(0.053)		(0.119)	(0.114)	(0.243)
Fund Seq.		0.065^{**}	0.015	0.036		0.078	−0.048	0.037
		(0.032)	(0.037)	(0.036)		(0.161)	(0.177)	(0.170)
First Fund		0.210^{*}	0.188	0.238^{**}		−0.463	−0.551	−0.213
		(0.118)	(0.118)	(0.109)		(0.473)	(0.462)	(0.470)
U.S. Fund		−0.007	0.006	0.030		0.445	0.493^{*}	0.924^{**}
		(0.047)	(0.049)	(0.077)		(0.294)	(0.293)	(0.369)
Holding Period			-0.082^{***}	-0.069^{***}			-0.224^{***}	-0.162^{***}
			(0.013)	(0.009)			(0.045)	(0.043)
Market Return			2.265^{***}	2.237^{***}			4.160^{**}	4.567^{***}
			(0.501)	(0.339)			(1.755)	(1.514)
Deal Year	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Observations	535	535	535	535	624	624	624	624
Adjusted R^2	0.128	0.127	0.292	0.201	0.052	0.069	0.113	0.078
Inverse Mills Ratio				−0.091				-1.510^{**}
Panel B: Deal type interactions								
Educational tie		−0.035	−0.007	−0.083		−0.215	−0.136	−0.328
		(0.059)	(0.055)	(0.081)		(0.308)	(0.309)	(0.372)
* MBO/MBI		0.268^{*}	0.301^{**}	0.386^{*}		2.054	1.976	2.157^{**}
		(0.153)	(0.127)	(0.231)		(1.809)	(1.803)	(1.035)
* Secondary		0.087	0.132	0.183		0.697	0.730	0.850
		(0.176)	(0.154)	(0.156)		(0.674)	(0.654)	(0.721)
* Going Private		−0.054	−0.054	−0.007		−0.219	−0.210	−0.368
		(0.142)	(0.106)	(0.208)		(0.606)	(0.591)	(0.933)
MBO/MBI		−0.023	−0.048	−0.089		-0.847^{**}	-0.932^{**}	-0.706^{*}
		(0.094)	(0.088)	(0.095)		(0.388)	(0.397)	(0.398)
Secondary Buyout		−0.118	−0.070	−0.113		-1.238^{***}	-1.110^{***}	-1.115^{***}
		(0.088)	(0.071)	(0.070)		(0.354)	(0.331)	(0.321)
Going Private		−0.007	0.024	0.008		−0.285	−0.210	−0.173
		(0.094)	(0.094)	(0.083)		(0.444)	(0.442)	(0.378)
Control variables		Yes	Yes	No		Yes	Yes	No
Deal Year		Yes	Yes	No		Yes	Yes	No
Observations		535	535	535		624	624	624
Adjusted R^2		0.123	0.288	0.200		0.088	0.129	0.093

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

Table 9: Robustness checks on model specification

The table shows different variations of the regression setting on educational ties from Table 6. The dependent variable is an indicator which equals one for actual investments and zero for counterfactual investments. The latter include for each transaction the buyout funds which have been in investment period at the time of deal and which have invested at least once in the same geographic region and industry sector. Models 1 to 4 show results based on the full sample as presented before, while Models 5 to 8 use a one-for-one random draw on the counterfactual pairs. An *educational tie* exists if at least one of the partners graduated from the same university as the CEO of the target company. An *MBA tie* exists if both obtained an MBA degree from the same business school. A *Non-MBA tie* represents an educational tie that is not based on a shared MBA tie. *Geographic distance* is measured between the headquarter of the target company and the nearest investment office, where a partner is based and transformed to its logarithmic base. *Consulting*, *Accounting*, and *Banking* measure the share of partners with prior work experience in the respective industry. *Fund size* is the natural logarithm of the fund's committed capital and the *sequence number* is the natural logarithm on the number of funds the respective investor has already raised including the current one. *First fund* and *U.S. fund* are indicator variables which equal to one if the fund is the first fund for the investor and if the fund is based in the U.S., respectively. The table shows coefficient estimates and standard errors (in brackets). Models 1 and 5 show results from a multivariate logistic regression according to Equation (2) with the remaining models using Ordinary Least Squares (OLS) regressions with varying sets of fixed effects. Standard errors in the logistic model are clustered on the investor level, the OLS models use two-way cluster-robust standard errors for investors and companies.

	Dependent variable: Investment Indicator							
	Full Sample				Random draw			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Logit	*OLS*	*OLS*	*OLS*	*Logit*	*OLS*	*OLS*	*OLS*
Panel A: Academic degrees								
Educational tie	0.583***	0.003***	0.005***	0.003***	0.677***	0.142***	0.267***	0.147***
	(0.060)	(0.0004)	(0.001)	(0.0004)	(0.096)	(0.017)	(0.047)	(0.021)
Geo. Distance	−0.252***	−0.002***	−0.002***	−0.002***	−0.331***	−0.068***	−0.123***	−0.064***
	(0.011)	(0.0001)	(0.0001)	(0.0001)	(0.021)	(0.003)	(0.006)	(0.004)
Consulting	0.163*	0.001**	0.001**	0.001	0.124	0.028	0.054	0.023
	(0.089)	(0.0004)	(0.0004)	(0.001)	(0.129)	(0.029)	(0.060)	(0.055)
Accounting	−0.079	−0.0004	−0.001	−0.002	−0.315	−0.066	−0.118	−0.141
	(0.150)	(0.001)	(0.001)	(0.001)	(0.201)	(0.044)	(0.085)	(0.102)
Banking	−0.007	−0.0001	−0.0001	−0.0001	−0.049	−0.011	−0.024	−0.046
	(0.067)	(0.0003)	(0.0003)	(0.001)	(0.095)	(0.021)	(0.044)	(0.046)
Fund Size	0.070***	0.0003***	0.0003***	0.001***	0.130***	0.029***	0.051***	0.067***
	(0.022)	(0.0001)	(0.0001)	(0.0002)	(0.027)	(0.006)	(0.012)	(0.013)
Fund Seq.	−0.103**	−0.0005**	−0.001***	0.003***	−0.106**	−0.023**	−0.042*	0.167***
	(0.041)	(0.0002)	(0.0002)	(0.001)	(0.049)	(0.011)	(0.023)	(0.039)
First Fund	−0.205***	−0.001***	−0.001***	0.0004	−0.358***	−0.079***	−0.120***	−0.00003
	(0.065)	(0.0003)	(0.0003)	(0.001)	(0.092)	(0.021)	(0.044)	(0.037)
U.S. Fund	−0.089	−0.001***	−0.001***	−0.001	−0.053	−0.011	−0.008	−0.088*
	(0.057)	(0.0002)	(0.0002)	(0.001)	(0.084)	(0.019)	(0.038)	(0.052)
F.E. Deal Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F.E. Region	Yes	Yes	n/a	Yes	Yes	Yes	n/a	Yes
F.E. Industry Sector	Yes	Yes	n/a	Yes	Yes	Yes	n/a	Yes
F.E. Company	No	No	Yes	No	No	No	Yes	No
F.E. Investor	No	No	No	Yes	No	No	No	Yes
Observations	752,693	752,693	752,693	752,693	6,102	6,102	6,102	6,102
R^2	0.066	0.005	0.007	0.009	0.151	0.109	0.197	0.255
Panel B: MBA versus other degrees								
MBA tie	0.539***	0.003***	0.004***	0.003***	0.606***	0.135***	0.325***	0.143***
	(0.092)	(0.001)	(0.001)	(0.001)	(0.146)	(0.027)	(0.089)	(0.033)
Non-MBA tie	0.601***	0.004***	0.005***	0.004***	0.723***	0.154***	0.277***	0.154***
	(0.068)	(0.001)	(0.001)	(0.001)	(0.116)	(0.021)	(0.052)	(0.024)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	752,693	752,693	752,693	752,693	6,102	6,102	6,102	6,102
R^2	0.066	0.005	0.007	0.009	0.130	0.094	0.178	0.239

Note: R^2 for *Logit* model reports Nagelkerke's measure. *p<0.1; **p<0.05; ***p<0.01

Table 10: Robustness checks on data subsets

The table shows the results for cross-sectional regressions of a binary investment indicator on the existence of educational ties according to Equation (2) for various subsets of the deal data set. Each cell represents a separate regression under the same formula as Specification (1) in Table 9. The dependent variable is an indicator which equals one for actual and zero for counterfactual investments. The latter include for each transaction the buyout funds which have been in investment period at the time of deal and which have invested at least once in the same geographic region and industry sector. The left column includes all academic degrees, while the right column only includes MBA degrees. An *educational tie* exists if at least one of the partners graduated from the same academic institution as the CEO of the target company. An *MBA tie* exists if both graduated from the same business school. Controls and fixed effects are used as in the original specifications (Tables 6 and 9). The table depicts coefficients estimated from a multivariate logit model and standard errors clustered on investors (in brackets).

	Dependent variable: Investment Indicator	
	Educational tie	MBA tie
Baseline model	0.583***	0.539***
	(0.060)	(0.092)
Deal characteristics		
Deals in North America	0.428***	0.477***
	(0.072)	(0.099)
Deals in Europe	0.872***	0.754***
	(0.111)	(0.256)
Distance <100 km	0.488***	0.500***
	(0.091)	(0.189)
Distance >100 km	0.553***	0.530***
	(0.071)	(0.103)
Distance >1000 km	0.593***	0.456***
	(0.071)	(0.124)
Distance >5000 km	0.874***	0.927**
	(0.288)	(0.441)
Fund characteristics		
Post-2000 vintage	0.612***	0.556***
	(0.068)	(0.106)
Pre-2001 vintage	0.473***	0.488**
	(0.122)	(0.194)
U.S. based	0.444***	0.518***
	(0.071)	(0.099)
Non-U.S. based	0.782***	0.458*
	(0.109)	(0.257)
First timer	0.737***	0.845***
	(0.143)	(0.228)
Non-first timer	0.562***	0.484***
	(0.064)	(0.100)
Large fund†	0.581***	0.538***
	(0.065)	(0.099)
Small fund†	0.606***	0.519**
	(0.149)	(0.264)
High IRR†	0.509***	0.395***
	(0.097)	(0.150)
Low IRR†	0.582***	0.613***
	(0.090)	(0.151)
High TVPI†	0.536***	0.402***
	(0.091)	(0.136)
Low TVPI†	0.519***	0.680***
	(0.110)	(0.167)

† *Above/below median value based on all buyout funds where the respective metric is available.*

*p<0.1; **p<0.05; ***p<0.01