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Heterogeneity as a Performance Driver: An Empirical Analysis of Syndicated Buyouts in the Nordics

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ABSTRACT

This study examines the impact of heterogeneity among private equity syndicate members on the investment performance. It draws on a unique and hand-collected set of data on 125 syndicated buyouts in the Nordics exited between 1998 and 2021. We find that the effect of heterogeneity on deal-level returns is not one-sided. We show that syndicates with a higher share of buyers different from financial sponsors (i.e., more heterogeneous ones) tend to perform worse, while syndicates without any direct prior ties among their members (i.e., more heterogeneous ones) tend to perform better. We conclude that there is no generic effect of heterogeneity among syndicate members on return metrics in buyout deals. Hence, it is crucial to break down heterogeneity into several well-defined dimensions and analyze their effect separately.

Keywords: *Private Equity, Buyouts, Syndication, Heterogeneity, Performance Measurement*

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List of Abbreviations

EV	Enterprise Value
GP	General Partner
IPO	Initial Public Offering
IRR	Internal Rate of Return
LP	Limited Partner
MOIC	Multiple of Invested Capital
OLS	Ordinary Least Squares
P2P	Public-to-Private
PE	Private Equity
PME	Public Market Equivalent
UK	United Kingdom
US	United States
VC	Venture Capital
VIF	Variance Inflation Factor

1 Introduction

2021 was a year of records for the private equity industry. The global buyout market has recovered at a tremendous pace after a strong temporary drop amid the Covid-19 pandemic and hit a total deal value of more than US$1.1 trillion in 2021 – the highest one ever seen. The total buyout volume increased by nearly 40% from the previous record level of US$800 billion in 2006, just before the global financial crisis (MacArthur et al., 2022). With mounting dry powder, a limited number of target companies, record-high valuations, and thus an increasingly competitive bidder environment, it appears more and more important for private equity firms to form syndicates (in the following also referred to as "clubs" or "consortia") with other buyers to enable the financing of even larger transactions. Although the share of club deals in the United States declined from about 40% to 20% between 2004 and 2018, recent developments may pave the way for a resurgence of syndicated buyout deals (Dowd, 2021). Indeed, strikingly many large club deals took place in 2021. One example is one of the largest-ever leveraged buyouts of Medline for US$34 billion by Blackstone, Carlyle, and Hellman & Friedman.

In fact, there is also evidence in the academic literature that syndicated investments tend to outperform standalone investments (Brander et al., 2002; Guo et al., 2011). Potential return drivers of syndicated private equity deals include gaining access to a larger pool of prospective deals (Wilson, 1968), obtaining a qualified second opinion on the investment opportunity (Lerner, 1994), and accessing complementary management skills of syndication partners (Brander et al., 2002). Although it is well established that the diversity of a group composed of multiple institutions largely determines the group's performance (Powell et al., 1996), the impact of heterogeneity among consortium members on investment returns has only received limited attention in the academic literature.

Against this background, we aim to shed light on how heterogeneity among syndicate members affects the performance metrics of syndicated buyout deals. To analyze this effect, we draw on a unique and hand-collected set of data on 125 syndicated buyouts in the Nordics exited between 1998 and 2021, and run an Ordinary Least Squares regression. Compared to most research on syndication, we do not consider venture capital deals but solely focus on buyouts, i.e., for-control acquisitions in which majority stakes of more mature companies are acquired. Our definition of syndicated buyout deals includes one private equity buyer (general partner) and at least one other buyer, which can be another private equity firm but, for example, also a strategic buyer, pension fund, sovereign wealth fund, insurance company, and family office.

Given the predominant confidentiality about deal-level returns in the private equity industry, only very few studies with proprietary datasets have actual performance data for individual investments to study return drivers. To overcome this data availability issue, we follow Nikoskelainen & Wright (2007), Acharya et al. (2013), and Valkama et al. (2013) and calculate commonly used performance metrics – the multiple of invested capital and internal rate of return – for the deals in our sample based on the target's enterprise value at entry and exit. While we collected the enterprise values from commercial databases and public deal announcements, we could also gather actual (equity-based) performance data for 36 deals in our dataset (29%) from press articles and exclusively shared information from three general partners. We find a correlation of 0.94 and 0.88 between the enterprise- and equity-value-based multiple of invested capital and internal rate of return for these deals, proving the validity of our performance proxy.

In comparison to Chahine et al. (2012), who aggregate different characteristics of syndicate members into only one variable to measure the effect of heterogeneity on the investment performance, we believe that the comprehensive heterogeneity term must be broken down into several dimensions to observe potentially diverging effects. We construct indicators for heterogeneity for which we analyze the effect on the investment performance across three different dimensions: resource endowment, reputation, and prior ties. First, resource endowment refers to a firm's key characteristics, strategy, and capabilities. We study heterogeneity in the dimension of resource endowment by analyzing the differences among syndicate members in terms of investor type (e.g., financial vs. strategic buyer), country of headquarters, and company size. Second, we define reputation as the experience, trustworthiness, and competence of syndicate partners. Since we have different buyer types in our sample, we use the differences in the firms' ages of a syndicate to measure heterogeneity in terms of reputation. Last, prior ties refer to an existing history of repeated interactions among the syndicate members. We construct two variables to observe whether a syndicate member syndicated with another buyer in the consortium in the past (direct ties) and the overall average ratio of syndicated deals for the consortium members (indirect ties). The existence of prior ties implies a familiarity between syndicate members and thus less heterogeneity. It should be noted that the selection of these dimensions was motivated by a framework on the stability and success of strategic alliances by Jiang et al. (2008). Moreover, by decomposing heterogeneity into these three dimensions, we believe to cover not only important areas of return drivers but also the three dimensions of heterogeneity – variety, separation, and disparity – outlined by Harrison & Klein (2007).

In fact, we do not find a one-sided effect of heterogeneity on the investment performance across our three heterogeneity dimensions. Even within the three dimensions, we observe diverging effects on the returns of buyout deals, demonstrating the importance of granularly decomposing the concept of heterogeneity. Nevertheless, we find that individual components of heterogeneity among consortium members can have an important impact on a syndicate's realized return. Namely, we find evidence that syndicates with higher shares of buyers different from financial sponsors (i.e., more heterogeneous ones) tend to perform worse, while syndicates without any direct prior ties among their members (i.e., more heterogeneous ones) tend to perform better. Against our expectations, heterogeneity in terms of geography, size, and age does not affect the investment performance.

We contribute to the existing literature by showing that the examination of heterogeneity among syndicate members in buyout deals requires a thorough decomposition of the heterogeneity construct into several well-defined dimensions to allow for the identification of potentially offsetting effects. Furthermore, we show that individual effects of heterogeneity can be an important performance driver in syndicated buyouts. Hence, our findings might be of interest to private equity firms by directing the focus on the criteria they should look for when choosing their syndicate partners. By studying the relationship between heterogeneity and investment performance, we simultaneously contribute to the limited number of studies on deal-level returns in private equity.

The remainder of this study is structured as follows. Section 2 outlines the relevant literature for our research topic. In Section 3 we develop our hypotheses. While Section 4 describes the data collection process, our sample as well as all variables entailed in our proposed regression model, Section 5 presents and discusses the regression results. Section 6 concludes.

2 Related Literature

Research on the relationship between heterogeneity in private equity (PE) syndicates and investment performance is very limited. In this section, we present an overview of the key papers focusing on this relationship. We also outline how our study differentiates itself from the existing literature and what it contributes.

First, Gompers et al. (2016b) analyze the impact of heterogeneity on the investment performance in the venture capital (VC) industry. They analyze how diversity of venture capitalists on an individual level, i.e., education, ethnicity, gender, and previous employer, affects the formation of a syndicate. They conclude that venture capitalists generally tend to partner with others who are very similar in terms of ethnicity and gender. Furthermore, they find that the investment performance is positively affected by similarities in ability-related traits (e.g., education at a leading school) but negatively affected by similarities in traits independent of ability (e.g., ethnicity and gender). In contrast to Gompers et al. (2016b), our study investigates the relationship between heterogeneity and investment performance on an organizational (and not individual) level.

On the organizational level, Cumming & Dai (2010) find that heterogeneity in terms of geographic distance between VC firms' headquarters has a negative relationship with success, which they define as the likelihood of a successful exit (initial public offering (IPO) or trade sale). This is in line with the findings of Chemmanur et al. (2010), who also find a negative relationship between distance and successful exits. Geographical distance is an important determinant of heterogeneity, as it may indicate different languages, time zones, cultures, and legislations among syndicate members. Compared to these papers, our study investigates not only the distances but several other heterogeneity determinants, such as investor type, size, age, and prior ties. Closest to our approach is Chahine et al. (2012), who study the impact of heterogeneity in a VC syndicate on the investment performance (post-IPO). They use the affiliation, age, and origin of each syndicate member as determinants to form a single overall indicator for heterogeneity. The authors count the number of different realizations in each determinant (e.g., three different origins would result in an origin measure of three) and then simply add up all realizations across the three determinants to determine the heterogeneity in a syndicate. They find a significant negative relationship between performance and heterogeneity on a syndicate level. However, the study by Chahine et al. (2012) does not outline how the three individual heterogeneity determinants affect the investment performance. In contrast, our study allows the

observation of individual, potentially diverging, effects of heterogeneity determinants on the investment performance.

Although Du (2016) does not explicitly study the impact of heterogeneity on return metrics but on the VC syndicate formation process, we believe that this paper is relevant for our study, as it also analyzes the individual effects of several heterogeneity determinants. However, Du (2016) solely focuses the discussion on heterogeneity in terms of experience – measured as the number of transactions in the past five years – and only controls for important other heterogeneity determinants, such as investor type, geographical distance, and prior ties. The paper finds that, on average, VC firms tend to partner with firms that have similar experience levels. On the other hand, VC firms may benefit from partnering with firms that are different from themselves in the long term. The author argues that co-investing with similar partners has the advantage of relatively lower transaction costs but the downside of potentially limited learning opportunities.

Outside the PE industry, there is no consensus on the effect of heterogeneity on organizational performance in strategic alliances. On the one hand, Powell et al. (1996), for instance, find that the number of partners in an alliance has a positive effect on performance due to more diverse learning backgrounds. However, Zhang (2014) states that this relationship only holds if the partners have had relations with each other in the past. On the other hand, Goerzen & Beamish (2005) conclude that a higher degree of heterogeneity among partners can have a negative effect on performance due to higher coordination costs. In line with this study, Gulati (1995) finds that a higher degree of heterogeneity can lead to a lower level of trust among the partners. To cope with these counteracting effects of heterogeneity on performance, a non-linear relationship between heterogeneity and performance is suggested by Sampson (2007).

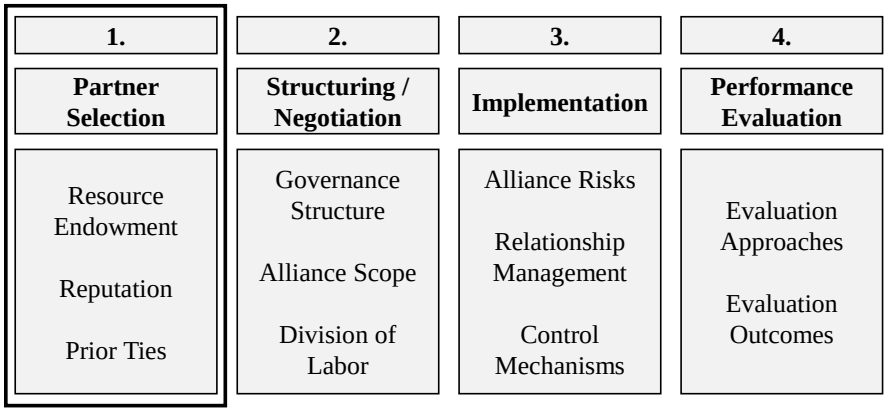
After studying the existing literature, we understand that heterogeneity among partners has an important impact on the syndicate formation and success. However, we also realize that the direction of this impact is neither obvious nor well understood. For example, a higher degree of heterogeneity among partners may have a negative effect on performance by causing coordination problems but simultaneously may have a positive effect on performance through a higher level of complementary resources and learning opportunities. Therefore, by decomposing heterogeneity into several dimensions, we aim to contribute to the understanding of how individual heterogeneity determinants affect the investment performance of syndicated deals – a question that has never been addressed in the existing literature on buyouts so far.

3 Hypotheses Development

Our study aims to examine the relationship between heterogeneity among PE syndicate members and the investment performance. We use a framework by Jiang et al. (2008) on the stability and success of strategic alliances to motivate our selection of different heterogeneity determinants.[1] The framework is presented in Figure 1.

Figure 1: The four stages of strategic alliances

The figure below shows the framework by Jiang et al. (2008) outlining the four stages of strategic alliances. The framework presents the evolutionary dynamics of strategic alliances and shows drivers that are critical for the stability and the success of an alliance. We focus on the first stage: partner selection. In the partner selection stage, firms follow their preferences to choose partners with specific resource profiles, goals, incentives, and strategies. In our analysis, we do not consider the other three stages. The structuring and negotiation stage includes, for instance, decisions on appropriate governance structures, incentives and scope alignment, as well as the coordination of labor and other collaborative activities. The third stage – implementation – focuses on carrying out initially proposed agreements and processes. Thereby, the focus is on controlling alliance risks as well as managing the relationships among the alliance partners. The final stage covers the performance evolution of the strategic alliance. In this stage, partners consider their costs and payoffs resulting from the alliance and decide whether to maintain the collaborative relationship or not.



In our analysis, we solely focus on heterogeneity in the partner selection stage of the framework for three reasons. First, there is limited and restricted accessibility of data in the PE industry outside the partner selection stage. Second, the partner selection for a strategic alliance is critical for the stability and survival of the alliance (Beamish & Inkpen, 1995; Dussauge & Garrette, 1995; Jiang et al., 2008). Third, partner selection appears to be the stage in which firms have the highest influence on the heterogeneity in the consortium by choosing similar or different syndicate partners. Therefore, in our analysis, we identify measures of heterogeneity in the partner selection pillar across the dimensions of resource endowment, reputation, and prior ties. Resource endowment refers to the key characteristics, strategies, and capabilities of

[1] In line with Lerner (1994) and Wright & Lockett (2003), we also consider PE syndicates as a form of a strategic alliance. We base our analysis on a framework provided by Jiang et al. (2008), since, to the best of our knowledge, there is no such framework for the PE industry.

the syndicate members. Reputation is considered as their experience, trustworthiness, and competence. Last, prior ties refer to the history of repeated interactions among the syndicate partners. We ensure that we cover a sufficiently broad spectrum of heterogeneity for our analysis since we can match the three dimensions of the partner selection pillar with the three different heterogeneity categories – variety, separation, and disparity – outlined by Harrison & Klein (2007). Please refer to Appendix 1 for a more detailed description of the matching.

In the following subsections, we develop our hypotheses. We form six different hypotheses across the dimensions of resource endowment, reputation, and prior ties. This allows us to observe potentially diverging effects across and even within the dimensions of heterogeneity. Table 1 at the end of the section presents an overview of our hypotheses.

3.1 Resource Endowment

Resource endowment is one of the driving determinants of the relationship between heterogeneity and performance (Cobeña et al., 2017). Yet, resource endowment is probably the vaguest and hardest dimension to define of all three, as one can take many different aspects into account. We consider resource endowment as a mix of tangible and intangible aspects associated with a firm's key characteristics, strategies, and capabilities.[2] Similar to the related literature, we focus on the following three areas to measure heterogeneity: investor type, distance between headquarters, and size.[3] We believe that the combination of these three areas helps to sufficiently cover the broad dimension of resource endowment.

Investor type

Besides PE firms, other investor types in a syndicate can be strategic buyers, pension funds, sovereign wealth funds, insurance companies, or family offices. As our analysis is primarily based on PE, we consider a syndicate homogenous if it only consists of general partners (GPs). The inclusion of other types increases heterogeneity as they have different incentives and motivations. For instance, a strategic buyer might enjoy synergies with the target and thus might appear less performance-driven for the investment itself compared to a PE sponsor (Guo et al., 2011). A strategic buyer might also not be able to provide financial capital but operational experience in a specific industry (Roosenboom & van den Bosch, 2012). On the other hand, a pension fund might primarily provide financial capital but only limited operational support.

[2] This is in line with Collis (1994).
[3] Investor type is used by Roosenboom & van den Bosch (2012) and Du (2016). Distance is used by Sorenson & Stuart (2001), Cumming & Dai (2010), Chemmanur et al. (2010) and Du (2016). Size is used by Roosenboom & van den Bosch (2012).

Thus, a PE buyer is the only type that offers all three characteristics: return driven, access to financial capital, and operational experience. Based on this, we derive our first hypothesis:

H1.1: The lower the share of buyers different from financial sponsors among the syndicate members (i.e., less heterogeneity), the better the investment performance.

Geography

In our study, large distances between syndicate members' headquarters indicate a heterogeneous syndicate. Existing literature provides evidence that there is a negative relationship between the distance of headquarters and investment performance.[4] Intuitively, larger distances could for instance indicate differences in languages, legislations, cultures, or time zones. All four of the mentioned aspects might lead to frictions among syndicate members, and thus negatively affect the effectiveness of communication and collaboration.[5] This in turn might limit the syndicate members' ability to support the target company. Therefore, we construct our second hypothesis:

H1.2: The lower the geographical distances among syndicate members (i.e., less heterogeneity), the better the investment performance.

Size

As the final area of resource endowment, we measure heterogeneity in terms of size. The idea is that larger firms have different cultures, hierarchies, and governance structures, compared to smaller ones.[6] Hence, variations in size might require more effort to coordinate different partners and their beliefs. Furthermore, large differences in size can cause inequalities of power. Thus, managers of smaller firms might feel disadvantaged, increasing the potential of conflicts in the syndicate. Therefore, we believe that similarity in size contributes to better investment performance.[7] If syndicates consist of different buyer types, commonly employed size measures in the PE industry, such as assets under management or number of deals, are not suitable. However, independent of the buyer type, larger companies tend to acquire larger ones and thus have a higher average historical deal size.[8] This brings us to our third and final hypothesis for the dimension resource endowment:

[4] Cumming & Dai (2010) and Chemmanur et al. (2010) provide evidence for this relationship.
[5] A relevant study for this is Humphery-Jenner & Suchard (2013).
[6] This was studied by Rothkegel et al. (2006).
[7] Hagedoorn & Narula (1996) and Alvarez & Barney (2001) present different issues of alliances between firms of different sizes.
[8] We look at the average of historical deal sizes of firms to overcome the effect of occasionally small or large deals.

H1.3: The more similar the average historical deal size among syndicate members (i.e., less heterogeneity), the better the investment performance.

3.2 Reputation

Jiang et al. (2008) define reputation as the trustworthiness, competence, and experience of syndicate partners. In the following, we mainly mean the latter part – experience – when we refer to reputation. First, firms with a good reputation are reluctant to pair up with firms of lower status to avoid being associated with them. Second, differences in reputation might cause higher agency costs in syndicates.[9] The reason is that a firm with a good reputation is likely to incur high agency costs to monitor the member with a worse reputation to overcome the problem of asymmetric information in syndicates. Therefore, firms tend to syndicate with firms of similar reputations to mitigate these costs.

Age

We use a firm's age as an indicator of reputation. Intuitively, older firms have satisfied their customers for a longer time (i.e., survivorship of PE and other firms) and thus tend to have a better reputation in the market.[10] It can be argued that a lower variety in age among the syndicate members leads to a lower degree of information asymmetries among the firms. Based on the above, we derive our hypothesis for reputation:

H2.1: The more similar the age among syndicate members (i.e., less heterogeneity), the better the investment performance.

3.3 Prior Ties

Finally, we consider prior ties, i.e., repeated direct interactions between syndicate members or indirect interactions through third parties. If firms paired up previously, the setup is considered homogenous, as they might know each other well (directly or indirectly), potentially creating an environment with a high level of resource similarity. If it is their first partnership, the setup is considered heterogeneous, since they must align on the ways of working and build trust.

[9] This is in line with Chung et al. (2000), Lerner et al. (2007) and Casamatta & Haritchabalet (2007).
[10] Relevant studies include Datta et al. (1999), Meuleman et al. (2009), and Sharifzadeh & Walz (2012) and Du (2016). Another potential indicator for reputation is the number of deals in the target's industry. Yet, we decided for age to avoid overweighting the reputation of PE firms, whose core business is acquiring companies as opposed to strategic buyers, who are involved in a much lower number of transactions.

Direct Ties

We argue that direct prior ties have a positive influence on future relationship stability and success.[11] This means that a homogenous syndicate, i.e., one that has had direct prior ties among the members, performs better than a heterogeneous one, i.e., with no prior ties. The idea is that if two firms syndicated together in the past and decide to pair up again, then one can assume the syndicate members have worked well together, set up good communication channels, and built trust (Gulati, 1998). Such a syndicate fulfills critical prerequisites for successful future collaboration, e.g., trust and a good understanding of one another. Hence, our hypothesis is:

H3.1: Direct prior ties among syndicate members in historical deals (i.e., less heterogeneity) have a positive influence on the investment performance.

Club deals

Similarly, if syndicate members previously collaborated a lot with other investors, the respective club deal can be viewed as more homogeneous and vice versa. These indirect prior ties provide information and legitimacy to other syndicate members, thus reducing information asymmetries and increasing trust between one another.[12] Hence, we derive our last hypothesis:

H3.2: The more extensive prior ties to other collaboration partners in historical deals (i.e., less heterogeneity), the better the investment performance.

Table 1: Overview of hypotheses

The table presents the hypotheses in the dimensions of resource endowment, reputation, and prior ties.

Dimension	Variable	#	Hypothesis
Resource Endowment	Investor type	1.1	The lower the share of buyers different from financial sponsors among the syndicate members (i.e., less heterogeneity), the better the investment performance.
	Distance	1.2	The lower the geographical distances among syndicate members (i.e., less heterogeneity), the better the investment performance.
	Size	1.3	The more similar the average historical deal size among syndicate members (i.e., less heterogeneity), the better the investment performance.
Reputation	Age	2.1	The more similar the age among syndicate members (i.e., less heterogeneity), the better the investment performance.
Prior Ties	Direct ties	3.1	Direct prior ties among syndicate members in historical deals (i.e., less heterogeneity) have a positive influence on the investment performance.
	Club deals	3.2	The more extensive prior ties to other collaboration partners in historical deals (i.e., less heterogeneity), the better the investment performance.

[11] This is supported by Kim & Inkpen (2005), Richards & Yang (2007), and Jiang et al. (2008).

[12] Relevant studies are Walker et al. (1997), Gulati (1998) and Sorenson & Stuart (2001). We later define the corresponding variable as the average ratio of syndicated to total deals for all syndicate members. Although it may be seen as an indicator for experience, we argue that by considering a ratio instead of an absolute number, the variable reflects the likelihood of engaging in club deals.

4 Data and Methodology

This section provides an overview of the data sample and the research design to test the hypotheses outlined in the previous section. First, we explain the data collection and sample derivation process in Section 4.1. Second, our sample of syndicated buyout deals in the Nordics is shown in Section 4.2, which is followed by a description of all variables (Section 4.3) entailed in our proposed regression model (Section 4.4).

4.1 Data Collection

Given the confidentiality of post-transaction data in the PE industry, the existing research with a focus on deal-level returns remains limited. Unlike, for example, Valkama et al. (2013) and Braun et al. (2017), we do not have access to proprietary datasets from buyout funds or fund-of-fund managers to obtain detailed transaction-level cash flows (including dividends paid and additional equity injections) for return calculations. Instead, we use the commercial databases *S&P Capital IQ* and *Mergermarket* to derive not only our sample of syndicated PE deals but also the respective returns. While *S&P Capital IQ* is considered the most comprehensive database of global buyout transactions (Strömberg, 2008; Bernstein et al., 2017), *Mergermarket* often contains more background information on transactions. However, both databases only report the entry and exit for each deal separately. Therefore, it is required to manually match the entry and exit for each deal to construct our sample. Moreover, we must collect the enterprise value (EV) of the target firm at entry and exit dates to calculate returns (see Section 4.3.1).

We retrieved investment data from both *S&P Capital IQ* and *Mergermarket* for all PE entries and exits with target companies headquartered in the Nordics, i.e., Sweden, Denmark, Norway, Finland, and Iceland, for the total time span both databases cover until 20 February 2022. The initial sample includes all entries in which the deal type is specified as "Leveraged Buyout", "Management Buyout" or "Going Private" and all exits in which the seller is specified as "Private Equity / Venture Capital" on *S&P Capital IQ*. In a similar fashion, all entries and exits are included in which the buyer and seller are classified as "Private Equity" on *Mergermarket*. As shown in Table 2, the sample originally includes a total number of 7,411 and 5,475 combined entries and exits on *S&P Capital IQ* and *Mergermarket*, respectively. In a first step, the two separate data lists of the two databases were reduced by all deals with only one buyer or seller, as we focus only on syndicated deals (Filter 1). As a next step, all remaining deals that appear twice due to the aggregation of the entries and exits were sorted out. Moreover, we excluded syndicates in which the target company's management is the only co-investor, all

syndicate members are associated with different investment vehicles from the same GP, or no GP is included. As the focus of our study is on buyout deals, we also sorted out VC investments, minority stake acquisitions, and asset deals (Filter 2).

Table 2: Sample derivation

The table below shows the sample construction process. The initial sample covers all PE entries and exits in the Nordics over the total timespan of the databases S&P Capital IQ and Mergermarket until 20 February 2022. After the elimination of deals out of our scope, all remaining 125 entries and 125 exits were matched, resulting in a total of 125 completed deals (i.e., each entry was matched with its corresponding exit).

		S&P Capital IQ	Mergermarket
Private equity entries with Nordic targets		3,659	3,406
Private equity exits with Nordic targets		3,752	2,069
Total deals		**7,411**	**5,475**
Excluding deals with only one buyer or seller	**Filter 1**	-5,557	-3,922
Remaining deals after Filter 1		**1,854**	**1,553**
Excluding double counts through aggregation of entry and exit deal lists		-213	-197
Excluding deals with no GP in the syndicate		-318	-306
Excluding venture capital funding rounds		-571	-319
Excluding deals in which minority stakes (<50%) were acquired	**Filter 2**	-24	-47
Excluding buyouts with management as only co-investor		-2	-32
Excluding deals where all syndicate members are different funds from same GP		-37	-14
Excluding asset deals (acquisition of properties)		-55	0
Remaining deals after Filter 2		**634**	**638**
			Aggregation
Remaining deals after Filter 2			**1,272**
Excluding double counts through aggregation of deals lists from both databases			-406
Excluding investments that are not exited yet	**Filter 3**		-103
Excluding deals for which entry and/or exit have no disclosed enterprise value			-513
Remaining deals after Filter 3			**250**
Matching entries and exits of the remaining deals			**125**

Thereafter, the two reduced deal lists from the two databases were merged. After eliminating all deals listed twice through the aggregation of the lists, the remaining entries and exits for all target companies were matched. All investments that were not exited by 20 February 2022 were eliminated from the sample. Finally, for all remaining matched deals, we checked the availability of the entry and exit EVs, which are both needed for our calculations of the investment performance. Besides the use of *S&P Capital IQ* and *Mergermarket* to collect EVs, we reviewed the available deal announcements from the buyer, seller, or transaction advisors as well as news articles for all remaining entries and exits. All matched deals for which no EV for entry and/or exit could be found were sorted out (Filter 3). This leaves us with a total number of 125 entries and 125 exits, resulting in a total sample size of 125 matched syndicated buyout deals in the Nordics.[13]

[13] When we consider other studies on deal-level returns in PE, such as Groh & Gottschalg (2011), Valkama et al. (2013) and Acharya et al. (2013), we realize that sample sizes are generally not large. They analyze the return drivers of 133 buyout deals in the United States (US) between 1984 and 2004, 321 buyout deals in the United Kingdom between 1995 and 2004, and 395 buyouts deals in Western Europe between 1991 and 2007, respectively. It should be noted that our sample size is automatically limited due to our focus on syndicated deals and on the much smaller PE market in the Nordics.

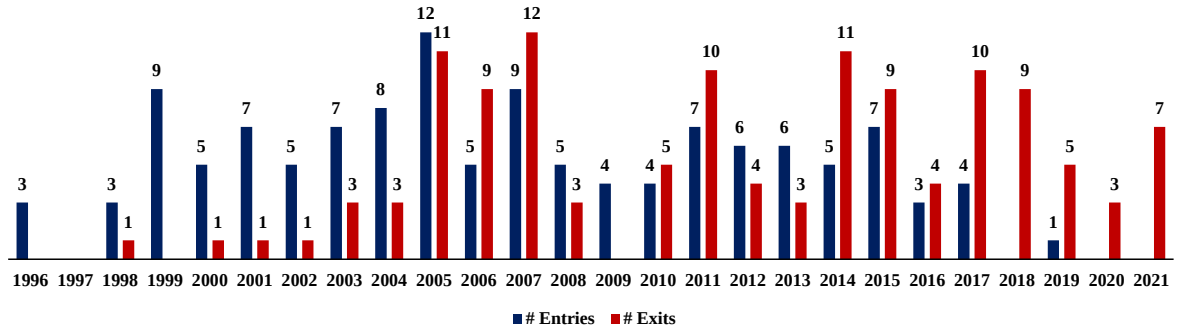
Compared to other studies which use proprietary transaction data from selective fund-of-fund managers or buyout funds, we expect our sample derived from commercial databases to be less biased towards specific buyers. However, it might be more biased towards more successful deals, as EVs of successful deals are more likely to be reported.

4.2 Sample Description

Our final sample of 125 realized syndicated buyout deals with targets headquartered in the Nordics is very diverse from multiple perspectives. First, in terms of timing, the earliest realized buyout deal in our sample was entered in March 1996 while the last one was entered in December 2019. Considering the distribution of the entry dates in Figure 2, the majority of the deals were entered before the global financial crisis. The pattern of the strong pre-crisis resurgence of buyout syndicates with a subsequent decline is consistent with the existing literature (Officer et al., 2010). On the other hand, the earliest exit in our sample was realized in July 1998 and the latest one in November 2021.[14] The average holding period in our sample amounts to five years and is in line with the existing literature (Kaplan & Strömberg, 2009).

Figure 2: Distribution of entries and exits over the sample period

The figure below illustrates how the 125 entries and 125 exits are distributed over the sample period. The deals are clustered into the respective years in which they are closed (based on S&P Capital IQ).



Second, in terms of valuation, the entry EVs of the target companies range from €8 million to €10,200 million, while the average (median) is €581 million (€202 million). At the exit, the EVs range from €5 million to €14,209 million with an average (median) of €1,273 million (€454 million) (see Table 3). This implies that the average (median) EV increased by 2.19 (2.25) times during the ownership of the syndicate.

Last, it is interesting to note that the average (median) number of syndicate members in our sample is 2.48 (2.00), while the maximum number of buyers in a deal is six.

[14] 15 investments were exited through an IPO, while the other 110 investments were either sold to strategic buyers or other financial investors.

Table 3: Descriptive statistics for main deal characteristics

The table below contains descriptive statistics on the main deal characteristics (n = 125). Whenever available, the EVs for entry and exit are extracted from the deal announcements and converted from the stated currency into € at the respective historical exchange rate. Otherwise, the EVs are taken from S&P Capital IQ or Mergermarket (average if available on both databases).

	Mean	Std Dev	Min	25th	Median	75th	Max
Holding period (years)	5.02	2.54	0.87	3.11	4.71	6.48	15.94
Entry EV (€ million)	581	1,166	8	73	202	661	10,200
Exit EV (€ million)	1,273	2,281	5	190	454	1,332	14,209
# Syndicate members	2.48	0.83	2.00	2.00	2.00	3.00	6.00

Our sample of 125 transactions includes 110 distinct target companies, indicating that some companies are targets of different syndicates at multiple times in our sample. As shown in Table 4, twelve target companies account for two deals in our sample, while one company is the target of four different syndicates. The headquarters of 44 (40%) targets are in Sweden. 28 (25%), 23 (21%), 14 (13%), and 1 (1%) targets are headquartered in Denmark, Norway, Finland, and Iceland, respectively. Based on the targets' *S&P Capital IQ* classification, 29 (26%) companies operate in the Industrials industry, which is followed by 18 (16%) and 14 (13%) companies that operate in the industries of Consumer Discretionary and Health Care, respectively.

Table 4: Overview of target companies in the sample

The upper table on the left-hand side shows a company is the target of a syndicate in our sample, while the lower table indicates the geographical distribution of target companies based on their headquarters according to S&P Capital IQ and Mergermarket. The table on the right-hand side shows the distribution by industry of all targets based on their S&P Capital IQ classification.

Number of deals per target in sample	#	%
1 Deal	97	88%
2 Deals	12	11%
3 Deals	0	0%
4 Deals	1	1%
Total number of targets	**110**	**100%**

Headquarters of targets in sample	#	%
Sweden	44	40%
Denmark	28	25%
Norway	23	21%
Finland	14	13%
Iceland	1	1%
Total number of targets	**110**	**100%**

Industries of targets in sample	#	%
Industrials	29	26%
Consumer Discretionary	18	16%
Health Care	14	13%
Information Technology	13	12%
Communication Services	11	10%
Materials	9	8%
Consumer Staples	6	5%
Energy	3	3%
Utilities	3	3%
Financials	2	2%
Real Estate	2	2%
Total number of targets	**110**	**100%**

Furthermore, our sample of 125 transactions includes a total number of 173 distinct buyers. As shown in Table 5, 120 buyers are part of only one syndicate in our sample. The remaining 53 buyers are members of at least two syndicates in our sample. EQT, 3i Group, and Ratos are the three most active buyers and are involved in 14, 10, and 10 deals, respectively. Moreover, in 28 transactions at least one buyer was already an existing shareholder in the target company prior to the deal and reinvested as part of the syndicate.

Table 5: Overview of buyers in the sample

The upper table on the left-hand side shows the number of deals per buyer in the sample, while the lower table indicates the classification of the buyer (based on S&P Capital IQ and websites of buyers). The table on the right-hand side shows the geographical distribution of the buyers based on their headquarters according to S&P Capital IQ and Mergermarket

Number of deals per buyer in sample	#	%
1 Deal	120	69%
2 Deals	26	15%
3 Deals	12	7%
4 Deals	5	3%
5 Deals	2	1%
> 5 Deals	8	5%
Total number of buyers	**173**	**100%**

Classification of buyers in sample	#	%
GP	108	62%
Other financial investor	35	20%
Strategist	30	17%
Total number of buyers	**173**	**100%**

Headquarters of buyers in sample	#	%
Sweden	38	22%
Norway	22	13%
Denmark	20	12%
Finland	12	7%
United States	34	20%
United Kingdom	26	15%
Germany	4	2%
Switzerland	4	2%
China	4	2%
France	3	2%
Netherlands	1	1%
Ireland	1	1%
Canada	1	1%
Singapore	1	1%
Indonesia	1	1%
Australia	1	1%
Total number of buyers	**173**	**100%**

We classified the 173 buyers as "General Partner" (GP), "Other financial investor" or "Strategist" based on information available on *S&P Capital IQ* and the websites of the buyers. Generally, GPs manage PE funds to which Limited Partners (LPs) – principally institutional investors – commit a certain amount of capital. "GPs" in our sample can be both independent (e.g., Blackstone) and affiliated with large financial institutions, such as an investment bank (e.g., Goldman Sachs Private Equity). We define "Other financial investors" as all financial buyers that are not GPs. Our sample mainly includes pension funds (e.g., Sixth AP Fund), sovereign wealth funds (e.g., GIC), insurance companies (e.g., Allianz), and family offices (e.g., Kirkbi), which are usually LPs and co-invest with GPs on the deal level, but sometimes also conduct buyouts independently. Last, we define a "Strategist" as a strategic buyer who is often operating in a similar industry as the target company and follows a buy-and-hold strategy. Examples from our sample include Ericsson, IBM, and Vattenfall. We classified 108, 35, and 30 buyers as "GPs", "Other financial investor", and "Strategist", respectively. While, per definition, every syndicate in our sample includes at least one GP, only 66 syndicates include GPs as the only type of buyer. At least one "Other financial investor" or "Strategist" is involved in 36 and 27 transactions, respectively.

Considering the geographical distribution of the buyers in our sample, we find that 92 (53%) are headquartered in the Nordics, highlighting the tendency of the investors to invest locally. However, a large number of 34 (20%) and 26 (15%) investors are US- and UK-based,

respectively. This is not surprising given the high amount of buyout funds headquartered in these countries (i.e., making cross-border investments).

An extensive transaction list covering all 125 deals in our sample – including target country and industry, all syndicate members, the entities from which the target was bought and to which the target was sold, the entry and exit closing dates, and the EV for entry and exit – can be found in Appendix 2. Similarly, a list of all 173 buyers in our sample – including country of headquarters, founding year, and buyer type classification – can be found in Appendix 3. See Appendix 4 for more statistics on the buyers with the highest deal activity covered in our sample.

4.3 Variable Description

This subsection provides an overview of the dependent, independent, and control variables entailed in our regression model. While the dependent variables measure the investment performance, the independent variables reflect the heterogeneity among the buyers in the syndicate and are derived from the hypotheses in Section 3. A summary of all variables, the exact calculation method applied and the source of data for the construction of the variables can be found in Appendix 5. Furthermore, Section 4.3.4 contains the descriptive statistics for all the variables. It should be noted that for all GPs in our sample the variables are calculated on a firm level and are not based on specific funds they manage. As GPs have an indefinite lifespan as opposed to funds with a limited life of around ten years, only firm-level (and not fund-level) calculations allow the construction of reasonable heterogeneity variables that are suitable for both GPs and other financial investors / strategic buyers. However, regardless of the comparison with other types of buyers, Hochberg et al. (2007) find that the key characteristics of GPs, such as experience and network, are more accurately captured when looking at the firm level, which reflects the total number of funds raised.

4.3.1 Dependent Variables

Similar to the fund level, performance on the deal level is typically measured in both academic literature and practice by the multiple of invested capital (MOIC) and internal rate of return (IRR) metrics (see, e.g. Gompers et al., 2016a; Braun et al., 2017; Harris et al., 2020).[15] On a deal level, MOIC is a performance measure that divides the total cash inflows by the total cash

[15] Some studies on the drivers of deal-level returns additionally use measures of the public market equivalent (PME) to overcome some limitations of the MOIC and IRR metrics (see, e.g., Acharya et al., 2013; Braun et al., 2017). The PME is a return measure which is adjusted for the performance of public markets during the holding period (see, e.g., Kaplan & Schoar, 2005). However, MOIC and IRR remain the standard return measures in practice.

outflows associated with a particular investment and thus compares the amount of equity investors take out from an investment compared to their equity contribution. In contrast, the IRR additionally takes the timing of these cash flows into account and equates their present value to zero. As both measures complement each other, we consider them in tandem to obtain a comprehensive picture of the deal-level return.

Given the predominant confidentiality about returns in the PE industry, investors usually neither report MOIC and IRR nor deal-level cash flows to calculate the metrics. As we have no access to proprietary data but aim to ensure a sufficiently large sample size, we use EVs at entry and exit from commercial databases (*S&P Capital IQ* and *Mergermarket*) and public deal announcements as input to our MOIC and IRR calculations and thereby approximate the actual (equity-based) investment performance for a given deal. Putting all together, our first dependent variable *MOIC* is calculated by dividing the total EV at the exit of an investment by the total EV at entry. Whenever a portfolio company was exited by the sale of multiple business units at different times, we added the EV of all these units at their respective exit date to compute the total exit EV. For all 125 deals in our sample, we checked for multiple exits by analyzing the corporate timeline of the target companies on *S&P Capital IQ* and searching for public announcements about partial exits during the holding period. The same method was used to identify potential add-on acquisitions, for which the cash outflows can be considered as additional entries. However, we could not find any with disclosed EVs. Therefore, we must assume for our whole sample that no add-on acquisitions were conducted. Since this understates the EV at entry, we expect our variable to be biased upward. Similarly, we compute our second dependent variable *IRR* by equating the EV at the entry to the sum of discounted EVs related to all exited units at their exit date and then solve for the discount rate.[16]

Although many studies use only equity-based returns, Nikoskelainen & Wright (2007), Acharya et al. (2013), and Valkama et al. (2013) also use EV MOIC and IRR measures.[17] The

[16] Whenever available, the EVs for entry and exit are extracted from the deal announcements and converted from the stated currency into € at the respective historical exchange rate. Otherwise, the EVs are taken from *S&P Capital IQ* or *Mergermarket* (average if available on both databases). For all IPO exits, we define the EV at exit as the market value of the company at the beginning of the first day of trading plus the net debt of the company at this time (based on *S&P Capital IQ*). Despite continued ownership after the IPO date, we assume that the syndicate members fully exit the firm at the time of the IPO. Furthermore, it should be noted that for all existing shareholders who reinvested and became part of the syndicate, the calculated investment performance refers to the period since the reinvestment and not to the entire holding period.

[17] Valkama et al. (2013) outline that the analysis of returns based on EVs is notable, as buyouts are often financed by different types of securities. For example, equity providers may also invest in other instruments in the form of strip financing (Jensen, 1986), which makes them more interested in the return related to all types of capital they have invested and not just equity.

performance approximations based on EV MOICs and IRRs only coincide with the equity-based measures if transactions are fully financed by equity at time of the entry and targets have no outstanding net debt at time of the exit (i.e., the leverage effect is not reflected). Furthermore, our return measures do not capture other potential changes in the capital structure, such as dividends paid and additional equity injections during the holding period.[18]

To test the suitability of our EV-based performance metrics as a proxy for actual returns, we screened all public deal announcements and related press articles for the reported (equity-based) MOIC and IRR. We could collect data for 18 out of 125 investments. Moreover, we reached out to all 45 still-active GPs headquartered in the Nordics in our sample to obtain the reported MOIC and IRR for their respective buyouts in our dataset. As expected, only a few GPs disclosed the returns to us due to strict data confidentiality. Namely, EQT Partners AB, Priveq Advisory AB, and Axcel Management A/S provided us with performance data for eleven, four, and three of their investments included in our sample, respectively. In total, we therefore collected the reported MOIC and IRR for 36 out of 125 buyouts (29%) and find a very high correlation between our EV-based performance proxies and the equity-based reported performance (see Appendix 6 for details). More precisely, the Pearson correlation coefficient between the EV MOIC and reported MOIC amounts to 0.94 (significant at the 1% level). The correlation coefficient between the EV IRR and reported IRR is only slightly lower and amounts to 0.88 (significant at the 1% level).[19] Given this high correlation, we believe we found a suitable proxy for the actual investment performance by using an EV-based MOIC and IRR measure. In addition, our assumption that no add-on acquisitions were conducted by the portfolio companies in our sample does not appear to have a big effect on our applied performance measures.

4.3.2 Independent Variables

Based on our three identified dimensions in which we measure heterogeneity, we form independent variables to test our hypotheses from Section 3.

[18] Therefore, exited buyouts may provide a significant return on the invested equity without any increase in the EV during the holding period. For example, Achleitner et al. (2010), who analyze 206 buyout transactions in Europe closed between 1991 and 2005, find that one-third of the PE sponsors' returns can be attributed to the use of leverage (ignored by EV-based measures). Furthermore, Valkama et al. (2013), who measure both the (index-adjusted) equity and EV IRR for 321 buyouts in the UK between 1995 and 2004, find a correlation of 0.64 between both performance metrics, showing that the variation between the two measures can be significant.

[19] Since we also consider deals after the global financial crisis as opposed to Valkama et al. (2013), we believe that our higher correlation coefficient can be explained by the reportedly lower use of leverage in buyouts since the global financial crisis (Bernstein et al., 2019). Regulatory and cultural differences between the Nordics and the UK may be another factor that explain different leverage levels and contribute to a higher correlation coefficient.

Resource endowment

First, to analyze the effect of different buyer types within a syndicate on the investment performance, we construct the variable *HYBRID* (see *Hypothesis 1.1*). It measures the ratio of non-GPs in a syndicate to all members of a syndicate, i.e., the ratio of "Other financial investors" and "Strategists" to all syndicate members. While the variable takes values in the interval [0,1),[20] observations with a higher realization of the variable can be considered more heterogeneous. As mentioned before, the type classifications of all 173 buyers in our sample are based on publicly available information on *S&P Capital IQ* and the websites of the buyers.

Second, the variable *DIST* measures the natural logarithm of the average pairwise distance (in kilometers) between all syndicate members based on the countries in which they are headquartered (see *Hypothesis 1.2*). Hence, observations with a higher realization of the variable can be considered more heterogeneous. We determined the countries in which the target companies in our sample are headquartered by using *S&P Capital IQ* and *Mergermarket*. In accordance with the related literature, we then obtained bilateral country distances for all countries covered in our dataset from *CEPII* (Mayer & Zignago, 2011).[21]

Third, we set up the variable *SIZE* to measure the relative variability of the size between all syndicate members. More precisely, for each deal in our sample, we calculated the coefficient of variation (defined as standard deviation divided by average) for all average deal values (in € million) of the syndicate members before the respective deal (see *Hypothesis 1.3*). Therefore, higher realizations of the variable imply a higher degree of heterogeneity in terms of size. Compared to other measures of heterogeneity, such as Blau's index or Shannon's measure of entropy, the coefficient of variation can measure heterogeneity more appropriately for continuous numeric values, such as size or age (Harrison et al., 1988). First, for all 173 distinct buyers in our sample, we retrieved a list of all their globally entered investments from *S&P Capital IQ* (excluding deals classified as "Private Placements"). Then, we used these deal lists to calculate the average deal value for all syndicate members before the respective buyout (observation) in our sample. Finally, we used all average deal values of the syndicate members to compute the

[20] Given our definition that a buyout syndicate must consist of at least one GP, the variable *HYBRID* can never take the value 1 (which would mean that there is a buyout deal in our sample without a GP).
[21] The *CEPII* database is accessed via http://www.cepii.fr/CEPII/fr/bdd_modele/presentation.asp?id=6. The distance between two countries is calculated based on bilateral distances (in kilometers) between the biggest cities of those two countries. If two observations are from the same country, the database uses the country's area in square kilometers to calculate its internal distance. Thus, no bilateral country distance in the dataset is zero.

coefficient of variation for each observation. It should be noted that the average deal value of the buyers depends on the entry date of our sampled deals and changes over time.

Reputation

The variable *AGE* captures the relative variability of the age between all syndicate members. For each deal in our sample, we calculated the coefficient of variation based on the age (defined as the number of years since founding) of all syndicate members before the respective deal (see *Hypothesis 2.1*). Thus, higher realizations of the variable imply a higher degree of heterogeneity in terms of reputation. To determine the age of each syndicate member at the time a deal is entered, we collected the founding year of all 173 buyers in our sample from *S&P Capital IQ* and the websites of the buyers.

Prior ties

The variable *TIES* is a dummy that captures whether at least two syndicate members of a buyout deal in our sample previously formed another consortium to invest in a different target company (see *Hypothesis 3.1*). If collaboration took place before, the variable takes the value of 1 and 0 otherwise. If none of the buyers interacted before (*TIES* = 0), the newly formed syndicate can be considered heterogeneous. We used individual deal lists for all 173 buyers from *S&P Capital IQ* to check for pairwise previous collaboration of all syndicate members.

Finally, the variable *CLUB* measures the average ratio of syndicated to total deals for all syndicate members before the respective deal in our sample (see *Hypothesis 3.2*). Therefore, lower realizations of the variable, i.e., less overall syndication in the past, imply that the syndicated deal is on average a more heterogeneous one. Again, the calculations are based on the deal lists of all 173 buyers from *S&P Capital IQ*.

4.3.3 Control Variables

In accordance with the existing literature and the properties of our dataset, we control for certain deal-specific variables as well as time, industry, and country fixed effects in our analysis.

Deal-specific variables

First, the variable *EV* controls for the deal size using the natural logarithm of the entry-level EV (in € million) of the buyout target, as it can influence the absolute performance and relative importance of various value drivers (see, e.g., Achleitner et al., 2010). Second, we use the control variable *MEMBER* to indicate the absolute number of syndicate members for the buyouts in our sample. As the number of consortium members has an impact on the possible extent of

several benefits of syndication, such as expertise sharing (see, e.g., Lerner, 1994), its effect on the investment performance must be studied. Since any additional syndicate member might lead to an increasingly strong rise in coordination costs and thus marginally decreasing returns (see, e.g., Goerzen & Beamish, 2005), we also control for the squared number of syndicate members (*MEMBER_SQ*). Moreover, *HOLDING* controls for the effect of the holding period (years from entry until exit date) on the return measures (see, e.g., Acharya et al., 2013). Finally, the variable *EXIT* is a dummy to capture if an investment is exited through an IPO, in which case it takes the value of 1, or a sale, for which *EXIT* equals 0 (see, e.g., Valkama et al., 2013).

Time fixed effects

Similar to Cumming & Dai (2010) and Acharya et al. (2013), we also consider time fixed effects by assigning the deals in our sample based on their entry date to the following four time periods: 1996-2001 (dot-com-bubble), 2002-2007 (pre-financial crisis), 2008-2012 (financial crisis) and 2013-2019 (post-financial crisis). We use dummy variables to capture time fixed effects.

Industry fixed effects

Furthermore, we consider industry fixed effects by assigning the target companies in our sample to eleven different industries based on their *S&P Capital IQ* classification. However, as our sample includes a low number of observations in some industries, we focus on the three dominant industries with the most observations in our sample to construct industry dummy variables. Namely, we use dummies for the industries "Industrials", "Consumer Discretionary" and "Health Care", which in total cover 69 – and thus more than half – of our 125 observations.

Country fixed effects

We also control for country fixed effects and include dummy variables to indicate if target companies are headquartered in Sweden, Denmark, Norway, Finland, and Iceland. Since only a few deals are located in Finland (15) and Iceland (1), we summarize these two geographies in one dummy variable.

4.3.4 Descriptive Statistics

Table 6 shows the descriptive statistics for all dependent and independent variables based on our sample of 125 transactions in the Nordics exited between 1998 and 2021. The average (median) *MOIC* and *IRR* (based on EVs) are 2.93x (2.00x) and 31.4% (17.7%), respectively.[22]

Table 6: Descriptive statistics for variables in regression

The table contains the descriptive statistics for all our dependent and independent variables (n = 125). Since we log-transformed the variable DIST, we additionally report the respective untransformed value below. Similarly, we also show the average deal size (in € million) and average age (in years) among all syndicate members to ease the interpretation of our variables SIZE and AGE (coefficients of variation).

Variables	**Mean**	**Std Dev**	**Min**	**25th**	**Median**	**75th**	**Max**
MOIC	2.93x	2.69x	0.10x	1.51x	2.00x	3.14x	17.94x
IRR	31.4%	64.4%	-61.3%	8.8%	17.7%	33.1%	620.1%
HYBRID	0.23	0.26	0.00	0.00	0.00	0.50	0.75
DIST	6.77	1.35	4.36	5.53	6.62	8.27	9.69
SIZE	0.94	0.49	0.00	0.52	0.99	1.41	1.73
AGE	0.64	0.39	0.00	0.35	0.64	0.89	1.69
TIES	0.25	0.43	0.00	0.00	0.00	0.00	1.00
CLUB	0.37	0.23	0.00	0.15	0.34	0.56	1.00

Other	**Mean**	**Std Dev**	**Min**	**25th**	**Median**	**75th**	**Max**
DIST : Average pairwise distance (km)	2,033	2,718	78	252	749	3,908	16,123
SIZE : Average deal size (€ million)	276	321	0	59	153	365	1,698
AGE : Average age (years)	26.34	24.54	1.74	10.78	16.79	36.00	144.34

The minimum and maximum *MOIC* (*IRR*) of 0.10x (-61.3%) and 17.94x (620.1%), respectively, indicate the high dispersion of returns in our dataset. In particular, we find a larger number of positive extreme values for our return metrics (see Appendix 7) – a widely recognized issue in the academic literature. For example, our dataset includes eleven and seven deals with a *MOIC* of >7x and *IRR* of >100%, respectively. An overview of the ten deals with the highest *MOIC* and *IRR* in our sample can be found in Appendix 8. However, our sample also includes eleven deals with a negative IRR but no total write-off, as in many other studies. See Appendix 9 for descriptive statistics on *IRR* and *MOIC* by subsamples that classify investments by geography (Panel A), industry (Panel B), number of syndicate members (Panel C), entry periods (Panel D), and exit route (Panel E).

When we consider the independent variables, Table 6 shows that the mean (median) realization of the variable *HYBRID* is 0.23 (0.00), implying that the ratio of GPs to the total

[22] Only to a limited extent, these results can be compared with the ones of Valkama et al. (2013), who also report EV-based (but index-adjusted) IRRs. The reason is that 121 out of 321 UK buyouts in their sample are total write-offs with an IRR of minus 100%, leading to a total average (median) IRR of only 4.9% (3.9%). Other studies on deal-level returns that employ equity-based return measures report relatively higher values, which appears natural since our measures ignore the leverage effect. Namely, Achleitner et al. (2010) find an average (median) MOIC and IRR of 3.5x (2.8x) and 42.8% (33.0%), respectively. Similarly, Acharya et al. (2013) report an average (median) MOIC and IRR of 4.4x (3.0x) and 56.1% (43.2%), respectively. Despite limited comparability to our sample, these somewhat high numbers indicate that our return measures are not overly biased towards successful deals.

number of syndicate members is on average 77% and that more than half of the syndicates in our sample consist of only GPs. The maximum share of non-GPs amounts to 75%. Furthermore, the mean (median) of the variable *DIST* before log-transformation indicates that the average pairwise distance among all syndicate members is 2,033 (749) kilometers. We also find that the mean (median) share of Nordic buyers in a syndicate is 56.8% (50.0%). While the minimum average distance of 78 kilometers refers to syndicates with only Danish buyers (internal country distance), the maximum average distance of 16,123 kilometers belongs to a consortium with an Australian and Canadian buyer. For the variable *SIZE*, we see that the ratio between the standard deviation and the mean of the syndicate members' average deal sizes (in € million) is on average 0.94. We also show that the mean (median) of syndicate members' average deal sizes before closing of the transaction amounts to €276 (€153) million. Please note that our minimum average deal size is €0 because no syndicate member has any existing prior deals with disclosed deal values on *S&P Capital IQ*. With a comparably lower average of 0.64, the variable *AGE* indicates that the ages of the syndicate members are relatively less spread out than their average deal sizes. Our sample also includes deals in which all buyers have the same year of founding (*AGE* = 0). The mean (median) of the syndicate members' average age prior to closing of the transaction amounts to 26.34 (16.79) years. Furthermore, the mean of 0.25 for the *TIES* dummy implies that one quarter of our 125 sample deals (31 deals) include consortium members that already syndicated before. The average (median) for *CLUB* is 0.37 (0.34), meaning that the average ratio of syndicated to total deals of all syndicate members is 36.8% (34.0%).

Last, we consider the pairwise correlations between our different variables. Most interestingly, we see that the Pearson correlation coefficient of 0.39 between our dependent variables *MOIC* and *IRR* is only moderately positive, highlighting the importance to study both return measures in tandem (see correlation matrix in Appendix 10). We also verify there is no strong correlation between our independent variables, making us confident that our proxies capture different aspects of heterogeneity.

4.4 Research Design

In line with the existing research on deal-level returns (see, e.g., Valkama et al., 2013; Achleitner & Figge, 2014; Lopez-de-Silanes et al., 2015) and the properties of our data, we use an ordinary least squares (OLS) regression model with robust standard errors to test our hypotheses from Section 3. Furthermore, we need to find a suitable estimation method that takes into ac-

count the right-skewed distribution of our dependent variables *MOIC* and *IRR*. Although positive outliers are a well-recognized issue in the PE literature, existing studies do not employ a consistent methodology to thoroughly account for them. Jones & Rhodes-Kropf (2003) and Cochrane (2005) suggest that the return metrics of PE investments can be best represented by a lognormal distribution. Therefore, many studies use a logarithmic transformation of returns as dependent variables in their analyses instead of the returns themselves (see, e.g., Aigner et al., 2008; Cumming & Walz, 2010; Achleitner & Figge, 2014). Other measures include winsorizing and trimming the data as well as running quintile regressions (see, e.g., Valkama et al., 2013; Braun et al., 2017).

We follow Lossen (2007) and Aigner et al. (2008) and employ a Box-Cox test in order to examine whether logarithmic transformations of *MOIC* and *IRR* better fit the data than the linear specification of the return metrics. Since these tests favor a log-transformation,[23] we log-transform our dependent variables and set up the following regression model to test our hypotheses, while Y_i can be both $\ln(MOIC_i)$ and $\ln(1 + IRR_i)$:

$$Y_i = \alpha + \beta_1 HYBRID_i + \beta_2 DIST_i + \beta_3 SIZE_i + \beta_4 AGE_i + \beta_5 TIES_i + \beta_6 CLUB_i + \varepsilon_i \quad (1)$$

Additionally, we trim our dataset by the top and bottom 1% in terms of *MOIC*, implying a cut out of two extreme values on each side. Hence, 121 observations in our sample remain for our analysis.[24] As a final remark, we show in Appendix 11 that multicollinearity does not appear to be an issue for our analysis.

[23] In the Box-Cox test, we find estimated parameters for the dependent variables *MOIC* and *IRR* of $\lambda = 0.04$ and $\lambda = 0.00$, respectively. λ equal to 0 implies that a logarithmic transformation of the dependent variables is favorable, while λ equal to 1 is equivalent to the linear functional form of the dependent variables. Thus, we find strong support for a log-transformation of both *MOIC* and *IRR*. For details on the Box-Cox test see Box & Cox (1964).
[24] We also control for *EV*, *MEMBER*, *MEMBER_SQ*, *HOLDING* and *EXIT*, as well as time, industry, and country fixed effects (see Section 4.3.3). For presentation purposes, control variables are not included in Equation (1).

5 Empirical Results

Initially, we discuss our results in Section 5.1, before we briefly touch upon the robustness of our results in Section 5.2. The regression output can be found in Table 7.

Table 7: Heterogeneity's effect on investment performance

We analyze the relationship between heterogeneity among syndicate members and deal-level investment performance with a geographical focus on the Nordics. The table below shows the regression output for our OLS regression with robust standard errors. We account for extreme returns by trimming the top and bottom 1% of our sample in terms of MOIC and log-transforming our dependent variables. In Model (1) and (2), we use the variable HYBRID to measure the share of non-GP buyers in the syndicate. In Model (3) and (4), we break this variable into the two variables FIN_INV and STRAT, which measure the ratio of "Other financial investors" and "Strategists" among the syndicate members, respectively. We control for time, industry, and country fixed effects. For a detailed discussion of the variables, please refer to Section 4.3. Robustness tests are presented in Appendix 12. *The robust standard errors for each variable are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.*

Variables	**(1)** **ln(*MOIC*)**	**(2)** **ln(1+*IRR*)**	**(3)** **ln(*MOIC*)**	**(4)** **ln(1+*IRR*)**
HYBRID	-0.410*	-0.163*		
	(0.242)	(0.095)		
FIN_INV			0.119	-0.145
			(0.284)	(0.173)
STRAT			-0.935***	-0.181*
			(0.284)	(0.098)
DIST	0.013	0.005	0.043	0.006
	(0.056)	(0.019)	(0.057)	(0.021)
SIZE	-0.001	-0.032	0.018	-0.031
	(0.123)	(0.037)	(0.117)	(0.036)
AGE	0.104	0.000	0.195	0.003
	(0.194)	(0.049)	(0.195)	(0.050)
TIES	-0.314**	-0.100*	-0.298*	-0.099*
	(0.158)	(0.053)	(0.156)	(0.055)
CLUB	0.490*	0.113	0.476*	0.113
	(0.284)	(0.097)	(0.278)	(0.098)
EV	-0.173***	-0.054***	-0.169***	-0.054**
	(0.060)	(0.020)	(0.058)	(0.021)
MEMBER	-0.075	0.308	-0.106	0.307
	(0.447)	(0.239)	(0.445)	(0.245)
MEMBER_SQ	0.035	-0.041	0.034	-0.041
	(0.062)	(0.033)	(0.062)	(0.034)
HOLDING	-0.008	-0.043***	-0.012	-0.043***
	(0.039)	(0.011)	(0.038)	(0.012)
EXIT	0.413**	0.169**	0.412**	0.169**
	(0.188)	(0.070)	(0.178)	(0.070)
Constant	1.564**	0.344	1.346*	0.337
	(0.750)	(0.287)	(0.739)	(0.269)
Observations	121	121	121	121
Time fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.069	0.285	0.119	0.279

5.1 Discussion

In this section, we present and discuss the results obtained from the estimation model described in Section 4.4. At a first glance, as shown in Table 7, we do not observe one generic effect of

heterogeneity among syndicate members on the investment return. Yet, we find a negative effect of the share of buyers different from financial sponsors and a positive effect of direct prior ties on investment returns. In the following section, we first discuss the significant results, before we quickly summarize effects that we expected but could not find evidence for.

Throughout the analysis, we continue to refer to Model (1) and (2) of our regression output in Table 7. Model (3) and (4) are only used to examine the effect of the variable *HYBRID* in more detail. Although the two dependent variables *MOIC* and *IRR* differ substantially from each other, we find very consistent results across the two models and thus can generalize our discussions when we study the effect of heterogeneity on the investment performance. The consistency of our results implies that they are robust to changes in the return metrics.

Before we test our hypotheses in the next step, we observe insightful results for the deal-specific control variables. The transaction size (*EV*) appears to negatively affect both *MOIC* and *IRR*. While the number of syndicate members does not have a statistically significant effect on the investment return, the holding period (*HOLDING*) has a negative effect on the *IRR*. Last, deals in which portfolio companies are exited via IPO (*EXIT = 1*) seem to outperform ones exited via sale (*EXIT = 0*).

Investor type *(HYBRID)*

We expected that hybrid syndicates consisting of different buyer types (i.e., more heterogeneity) yield a lower investment performance (see *Hypothesis 1.1*). In fact, we find a negative effect, which is statistically significant at the 10% level, for the variable *HYBRID* on both *MOIC* and *IRR* (see Model (1) and (2) in Table 7). This implies that a higher share of non-GPs among the syndicate members appears to negatively affect the return metrics. To analyze this effect more thoroughly, we break the *HYBRID* variable into the two variables *FIN_INV* and *STRAT*, which measure the share of "Other financial investors" and "Strategists" among the syndicate members, respectively, and re-run our regressions. The outputs for Model (3) and (4) show that the effect of *HYBRID* is mainly driven by *STRAT*, i.e., the share of strategic buyers in the syndicate. The effect of *STRAT* on the investment performance is negative for *MOIC* and *IRR* and statistically significant at the 1% and 10% level, respectively.[25]

[25] In addition, we find that of the 27 deals where at least one strategic buyer was part of the consortium, in 14 cases this buyer was already an existing shareholder but reinvested and then became part of the consortium. To check that the effect of the *STRAT* variable is not skewed by a possible impact of reinvestments on deal performance, we run another regression by including a dummy that indicates if at least one existing shareholder reinvested (28 deals). However, we find that the negative effect for *STRAT* remains statistically significant at the same levels and reinvestments do not appear to have an impact on the investment performance.

As outlined by Guo et al. (2011), strategic buyers often possess more comprehensive industry-specific and operational knowledge than GPs but, among other things, less expertise in value creation or the structuring of transactions. Despite the resulting high potential of resource pooling, which may facilitate a high growth of the target company, we believe that the negative effect of syndication between GPs and corporate acquires on return metrics is due to potentially misaligned incentives. While financial sponsors generally acquire companies to make return on a subsequent sale, strategic buyers primarily seek the realization of synergies after the post-acquisition integration of the target. However, conflicts might arise if both buyer types with different interests syndicate and make joint decisions for the future of the target company. For example, corporate buyers might be interested to allocate a substantial part of the target company's budget to research and development to use insights for their own operations and benefit from synergies. On the other hand, financial investors might be reluctant to agree to such large cash outflows in order to avoid deteriorating returns, potentially creating tensions between the two buyer types. These misaligned incentives may make collaboration and fast decision-making in hybrid syndicates more difficult, affecting the value creation and eventually return generation.

To assess the extent to which the incentives of the different types of buyers are misaligned, a thorough study of the shareholder agreement for the syndicated deal can be helpful. It contains not only the goals of the partnership but also important rights and provisions for the various parties. This corresponds to the second pillar of the strategic alliance framework by Jiang et al. (2008), "Structuring / Negotiation", which provides the foundation for whether incentives and scopes are aligned among the buyers.

Direct ties *(TIES)*

We expected that direct prior ties among syndicate members in historical deals (i.e., less heterogeneity) have a positive influence on the investment performance (see *Hypothesis 3.1*). We find a statistically significant effect. However, against our initial beliefs, we find evidence that direct prior ties among syndicate members have a negative effect on the investment performance (see Model (1) and (2) in Table 7). The effect is statistically significant at the 5% and 10% level in Model (1) and Model (2), respectively.

There is no consensus on the relationship between direct prior ties and performance in existing research. For our hypothesis development, we followed the findings by Kim & Inkpen (2005), Richards & Yang (2007), and Jiang et al. (2008), who all argue that direct prior ties have a positive influence on success, meaning that a homogenous syndicate, i.e., one that has

had direct prior ties among the partners, performs better than a heterogeneous one, i.e., no prior ties. However, there are also reasons why this effect might work in the opposite direction. Both Beamish & Inkpen (1995) and Kim & Inkpen (2005) argue from a heterogeneity perspective. More specifically, they suggest that repeated syndication can lead to redundant information gathering and thus can increase resource similarity among partners. This in turn limits the ability to complement each other's capabilities and can ultimately lead to the implementation of standard solutions, which might not be applicable on a generic basis, instead of implementing more creative solutions. Another intuitive way to explain this negative relationship of direct prior ties with performance can simply be the fact that performance on a deal level in PE is not persistent (Braun et al. 2017). The idea is that syndicate members will only partner up again if their past collaboration has been a success. Now, considering the last deal was a success, the likelihood that the members partner up again appears high. Nevertheless, according to Braun et al. (2017), success in the past does not give any indication about the return of future deals. Hence, if the following deals are not of similar success, one will observe a negative relationship between direct prior ties and investment performance (similar to the concept of mean reversion). To validate our argument related to the mean reversion of returns in repeated syndications, one would need to analyze the returns of all historical deals for which pairwise collaboration of the club deal members occurred. However, due to the limited availability of return data in the PE industry, we were not able to control for this effect and leave the question open for future research.

Interestingly, indirect prior ties have the opposite effect on the investment performance. This relationship is covered in the section below.

Club deals *(CLUB)*

We expected that more extensive prior ties to other collaboration partners in historical deals (i.e., less heterogeneity) lead to better investment performance (see *Hypothesis 3.2*). In line with our expectations, we find that a higher density of prior ties to other collaboration partners has a positive influence on the investment performance (see Model (1) and (2) in Table 7). Yet, while we find a statistically significant effect (10% level) in Model (1), the effect in Model (2) is not statistically significant. This inconsistency requires careful conclusions about this effect.

As a quick remark, if syndicate members collaborated a lot with other buyers in prior deals, we consider the respective syndicate as rather homogenous. On the other hand, less collaboration makes a club deal scenario more heterogeneous. Walker et al. (1997), Gulati (1998), and Sorenson & Stuart (2001) suggest a positive relationship between *CLUB* and performance.

Prior ties to any other investors increase the likelihood of indirect collaboration with the partners of the syndicate. Consider the following example: Both firm A and firm B partnered with firm C in the past. Hence, firm A and firm B have an indirect prior tie through firm C. This indirect prior tie can provide information and legitimacy from firm A to firm B and vice versa, reducing the potential of conflicts and increasing trust between one another. We observe that *TIES* and *CLUB* have opposite effects on return metrics.[26] Hence, the overall effect of the prior ties dimension is inconsistent throughout the two different indicators.

Against our expectations, we could not find any evidence for the effects associated with the remaining variables *DIST*, *SIZE*, and *AGE*. In the following, we briefly discuss these results.

Distance *(DIST)*

We expected that lower geographical distances among syndicate members (i.e., less heterogeneity) lead to a better investment performance (see *Hypothesis 1.2*). Against our expectations, we do not find an effect of heterogeneity in terms of distance between syndicate members' headquarters. The coefficient for the variable *DIST* is consistently positive but insignificant in both regressions (see Model (1) and (2) in Table 7).

The reason we do not find a significant effect for *DIST* could be that there are offsetting components of heterogeneity working in different directions, i.e., with a simultaneous positive and negative influence on the investment performance. For instance, on the one hand, one can argue that larger distances may come along with different languages, legislations, cultures, and time zones (Fritsch & Schilder, 2008). This can increase frictions and conflicts and thus can negatively impact the way syndicate members communicate with each other (Humphery-Jenner & Suchard, 2013), potentially limiting the support for the target company. On the other hand, the investment performance of a club deal might benefit from heterogeneity in terms of distance due to a broader and more international network, which particularly helps if the target company aims to expand its operations in new geographic areas (Chetty & Holm, 2000).

We believe that our variable *DIST* must be broken down into several components to understand the effect of geographical differences on return metrics. In the following, we suggest some measures by considering an example in which a US and Nordic investor jointly acquire a company located in the Nordics. First, one could measure the (positive) effect of partnering with a US investor by observing if there has been a disproportionately large business activity increase of the portfolio company in the US market after completion of the syndicated deal.

[26] Running the regression with only *TIES*, instead of *TIES* and *CLUB*, yields similar results as in Model (1) and (2).

Second, it may be insightful to observe if the US buyer has dedicated teams located in Europe, or even in the Nordics. This may undermine differences in languages, legislations, cultures, and time zones. However, it should also be taken into account that some employees of the deal team can be located in different geographies to properly reflect the aforementioned differences among the buyers.

Size *(SIZE)*

We expected that more similar syndicates in terms of average historical deal size (i.e., less heterogeneity), have a better investment performance compared to relatively less similar ones (see *Hypothesis 1.3*). Against our expectations, we do not find a significant effect (see Model (1) and (2) in Table 7).

In line with Lerner (1994) and Lockett & Wright (2001), we argue that firms prefer to choose partners of similar sizes and financial resources for syndication. Firms of different sizes have different cultures, hierarchy organizations, and governance structures (Rothkegel et al., 2006). Hence, it would require much more effort to coordinate heterogeneous partners and their beliefs. Differences in size can also cause inequalities of power, making managers of smaller firms feel disadvantaged and thus increasing the potential for conflicts in the syndicate (Alvarez & Barney, 2001). However, we do not find any evidence that syndicates with similarly large buyers outperform ones with buyers of different sizes.

Reputation *(AGE)*

We expected that similarities in terms of age (i.e., equal reputation) among syndicate members (i.e., less heterogeneity) lead to a better investment performance (see *Hypothesis 2.1*). However, we do not find a significant effect (see Model (1) and (2) in Table 7).

There is evidence that firms tend to partner with firms with a similar reputation. Chung et al. (2000), Casamatta & Haritchabalet (2007), and Lerner et al. (2007) argue that syndicates consisting of buyers with different reputations have higher agency costs. This is because the partner with the higher reputation is encouraged to monitor partners with a worse reputation. However, we do not find any empirical support that syndicates with members of a similar reputation outperform ones with members of different reputations.

While we considered age on the firm level, we believe that it is more appropriate to examine the deal experience (e.g., number of years or deals) of all responsible managers in the deal teams of the syndicate members. For instance, consider a recently established PE firm, which was founded by partners who gained longstanding experience at top-performing funds.

In terms of age (or number of deals) this firm will have a worse reputation compared to others whose partners might be less experienced. However, it is difficult to capture reputation on an individual level, since this type of information is usually not publicly available.

5.2 Robustness Tests

To check the robustness of our results, we have to ensure that the sample reflects a reasonable share of the population. First, we believe that our sample might somewhat overweight small transactions, as shown in Appendix 7. Therefore, we exclude transactions with an entry EV of €25 million or less from our sample for our first robustness test. This reduces our sample by six observations. Then, we run the same regression as outlined in Equation (1), but with the reduced sample. Second, we account for the fact that our sample includes transactions with a holding period of less than 18 months (i.e., "quick flips"). In line with Siming (2010), we argue that operating enhancing measures play only a minor role in quick flips. Thus, it is questionable whether heterogeneity between syndicate members can affect the investment performance in such a short holding period, while the observations still might affect our results. Therefore, we exclude the five transactions with a holding period of less than 18 months. Again, we run the same regressions as outlined in Equation (1), but with the reduced sample.

The negative effect of *STRAT* and the positive effect of *TIES* on *MOIC* and *IRR* remain robust if small deals and quick flips, respectively, are excluded from the sample. The effect of *CLUB* on *MOIC* and *IRR*, however, does not appear to be robust. Please refer to Appendix 12 for a detailed overview of the results of our robustness checks.

6 Conclusion

This study examined the impact of heterogeneity among PE syndicate members on the investment performance. It draws on a unique and hand-collected set of data on 125 syndicated buyouts in the Nordics exited between 1998 and 2021. We find that the effect of heterogeneity on deal-level returns is not one-sided. We show that syndicates with higher shares of buyers different from financial sponsors (i.e., more heterogeneous ones) tend to perform worse, while syndicates without any direct prior ties among their members (i.e., more heterogeneous ones) tend to perform better. In our study, heterogeneity in terms of geography, size, and age does not affect the investment performance. We conclude that there is no generic effect of heterogeneity among syndicate members on return metrics in buyout deals.

Therefore, in contrast to Chahine et al. (2012), we suggest decomposing the heterogeneity construct as granularly as possible with well-defined dimensions to get a comprehensive view on separate effects of heterogeneity on the investment performance. Only by identifying the individual aspects of heterogeneity, one can provide insights to PE firms on what the key focus should be when selecting their partners. For instance, our study indicates that PE buyers must closely align goals with strategic buyers, as differing incentives in a syndicate might negatively affect the investment performance. Moreover, the results indicate that the decision to syndicate again with the same partners after successful deals may be too hasty. Although our study focuses on the area of PE, we believe that our findings can be applied not only to the related areas of VC and growth capital but also to strategic alliances in general.

Furthermore, we believe that through the utilization of the strategic alliance framework by Jiang et al. (2008), we covered a sufficient spectrum of heterogeneity dimensions in our analysis. However, we only investigated one of the framework's four pillars: partner selection. Given limited and restricted data availability, one of our study's main shortcomings is that we could not retrieve data on heterogeneity measures across the other three pillars of the framework, i.e., structuring/negotiation, implementation, and performance evaluation. For example, investment performance might be affected by heterogeneity in the governance structure (e.g., board composition), the division of labor (e.g., how responsibilities are split among syndicate members), or control mechanisms in place (e.g., monitoring, directing, and evaluating progress). Yet, information across the other pillars of the framework is generally not publicly available.

A second limitation of our analysis is that, compared to other studies on deal-level returns, we did not have access to proprietary return data exclusively provided by GPs or fund-

of-fund managers. Instead, our sample relies on data from commercial databases and public deal announcements. This comes along with two drawbacks. On the one hand, our used commercial databases usually neither include reported MOIC and IRR metrics nor timed cash flow data for the calculation of the investment performance for PE investments. Despite the proven validity of our performance proxies based on EVs, we neglect effects of the capital structure on the performance metrics, leading to a potential underestimation of our return data. On the other hand, as investors might be less willing to publish bad performance indications, our sample might contain relatively successful transactions – a commonly observed selection bias in the PE literature.

We suggest the following for future research to contribute to the understanding of the relationship between the heterogeneity among syndicate members and the investment performance of buyouts and to overcome the limitations of our study. First, we believe that tailored surveys and interviews with syndicate members can help to gather rather qualitative information, which can be used to establish new important heterogeneity measures with potential impacts on the investment performance. On the one hand, such surveys and interviews could address a pre-deal perspective – as we do – and examine, for example, potential discrepancies in different value creation strategies (operational, financial, and governance) commonly employed by the syndicate members. On the other hand, surveys or interviews could even help to analyze heterogeneity from a post-deal perspective with a focus on the collaboration among all syndicate members in a specific deal, allowing to cover the other pillars of the framework by Jiang et al. (2008). Second, in accordance with Brown et al. (2020), we suggest future research on deal-level returns to make use of newly available and comprehensive performance data on over 45,000 portfolio company investments by PE funds from *Burgiss*, a data provider to LPs. As *Burgiss* sources data from hundreds of LPs of various sizes from around the world, the platform allows the construction of larger and more unbiased sample sizes. Moreover, the emergence of new commercial data analytics platforms, such as *DealEdge*, which also provide comprehensive (but anonymized) coverage of deal-level returns, may also allow for more in-depth research.

References

Acharya, V. V., Gottschalg, O. F., Hahn, M., & Kehoe, C. (2013). Corporate governance and value creation: Evidence from private equity. *The Review of Financial Studies*, *26*(2), 368-402.

Achleitner, A. K., Braun, R., Engel, N., Figge, C., & Tappeiner, F. (2010). Value creation drivers in private equity buyouts: Empirical evidence from Europe. *The Journal of Private Equity*, *13*(2), 17-27.

Achleitner, A. K., & Figge, C. (2014). Private equity lemons? Evidence on value creation in secondary buyouts. *European Financial Management*, *20*(2), 406-433.

Aigner, P., Albrecht, S., Beyschlag, G., Friederich, T. I. M., Kalepky, M., & Zagst, R. (2008). What drives PE? Analyses of success factors for private equity funds. *The Journal of Private Equity*, *11*(4), 63-85.

Alvarez, S. A., & Barney, J. B. (2001). How entrepreneurial firms can benefit from alliances with large partners. *Academy of Management Perspectives*, *15*(1), 139-148.

Beamish, P. W., & Inkpen, A. C. (1995). Keeping international joint ventures stable and profitable. *Long Range Planning*, *28*(3), 2-36.

Bernstein, S., Lerner, J., & Mezzanotti, F. (2019). Private equity and financial fragility during the crisis. *The Review of Financial Studies*, 32(4), 1309-1373.

Bernstein, S., Lerner, J., Sorensen, M., & Strömberg, P. (2017). Private equity and industry performance. *Management Science*, 63(4), 1198-1213.

Box, G. E., & Cox, D. R. (1964). An analysis of transformations. *Journal of the Royal Statistical Society: Series B (Methodological)*, *26*(2), 211-243.

Brander, J. A., Amit, R., & Antweiler, W. (2002). Venture-capital syndication: Improved venture selection vs. the value-added hypothesis. *Journal of Economics & Management Strategy*, *11*(3), 423-452.

Braun, R., Jenkinson, T., & Stoff, I. (2017). How persistent is private equity performance? Evidence from deal-level data. *Journal of Financial Economics*, *123*(2), 273-291.

Brown, G. W., Harris, R. S., Hu, W., Jenkinson, T., Kaplan, S. N., & Robinson, D. T. (2020). Private equity portfolio companies: A first look at Burgiss holdings data. *Working Paper.*

Casamatta, C., & Haritchabalet, C. (2007). Experience, screening and syndication in venture capital investments. *Journal of Financial Intermediation*, *16*(3), 368-398.

Chahine, S., Arthurs, J. D., Filatotchev, I., & Hoskisson, R. E. (2012). The effects of venture capital syndicate diversity on earnings management and performance of IPOs in the US and UK: An institutional perspective. *Journal of Corporate Finance*, *18*(1), 179-192.

Chemmanur, T. J., Hull, T., & Krishnan, K. (2010). Do local and international venture capitalists play well together? A study of international venture capital investments. *Working Paper*.

Chetty, S., & Holm, D. B. (2000). Internationalisation of small to medium-sized manufacturing firms: a network approach. *International Business Review*, *9*(1), 77-93.

Chung, S., Singh, H., & Lee, K. (2000). Complementarity, status similarity and social capital as drivers of alliance formation. *Strategic Management Journal*, *21*(1), 1-22.

Cochrane, J. H. (2005). The risk and return of venture capital. *Journal of Financial Economics*, *75*(1), 3-52.

Cobeña, M., Gallego, Á., & Casanueva, C. (2017). Heterogeneity, diversity and complementarity in alliance portfolios. *European Management Journal*, *35*(4), 464-476.

Collis, D. J. (1994). Research note: how valuable are organizational capabilities?. *Strategic Management Journal*, *15*(S1), 143-152.

Cumming, D., & Dai, N. (2010). Local bias in venture capital investments. *Journal of Empirical Finance*, *17*(3), 362-380.

Cumming, D., & Walz, U. (2010). Private equity returns and disclosure around the world. *Journal of International Business Studies*, *41*(4), 727-754.

Datta, S., Iskandar-Datta, M., & Patel, A. (1999). Bank monitoring and the pricing of corporate public debt. *Journal of Financial Economics*, *51*(3), 435-449.

Du, Q. (2016). Birds of a feather or celebrating differences? The formation and impacts of venture capital syndication. *Journal of Empirical Finance*, *39*, 1-14.

Dussauge, P., & Garrette, B. (1995). Determinants of success in international strategic alliances: Evidence from the global aerospace industry. *Journal of International Business Studies*, *26*(3), 505-530.

Fritsch, M., & Schilder, D. (2008). Does venture capital investment really require spatial proximity? An empirical investigation. *Environment and Planning A*, *40*(9), 2114-2131.

Dowd, K. (2021). The Biggest Firms In Private Equity Are Clubbing Up Once Again. *Forbes*. Retrieved April 24, 2022, from https://www.forbes.com/sites/kevindowd/2021/05/09/the-biggest-firms-in-private-equity-are-clubbing-up-once-again/?sh=3cd696712f25.

Goerzen, A., & Beamish, P. W. (2005). The effect of alliance network diversity on multinational enterprise performance. *Strategic Management Journal*, *26*(4), 333-354.

Gompers, P.A., Kaplan, S. N., & Mukharlyamov, V. (2016a). What do private equity firms say they do?. *Journal of Financial Economics*, *121*(3), 449-476.

Gompers, P. A., Mukharlyamov, V., & Xuan, Y. (2016b). The cost of friendship. *Journal of Financial Economics*, *119*(3), 626-644.

Groh, A. P., & Gottschalg, O. (2011). The effect of leverage on the cost of capital of US buyouts. *Journal of Banking & Finance*, *35*(8), 2099-2110.

Gulati, R. (1995). Social structure and alliance formation patterns: A longitudinal analysis. *Administrative Science Quarterly*, 619-652.

Gulati, R. (1998). Alliances and networks. *Strategic Management Journal*, *19*(4), 293-317.

Guo, S., Hotchkiss, E. S., & Song, W. (2011). Do buyouts (still) create value?. *The Journal of Finance*, *66*(2), 479-517.

Hagedoorn, J., & Narula, R. (1996). Choosing organizational modes of strategic technology partnering: international and sectoral differences. *Journal of International Business Studies*, *27*(2), 265-284.

Harris, R. S., Jenkinson, T., Kaplan, S. N., & Stucke, R. (2020). Has persistence persisted in private equity? Evidence from buyout and venture capital funds. *National Bureau of Economic Research.*

Harrison, D. A., & Klein, K. J. (2007). What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of Management Review*, *32*(4), 1199-1228.

Harrison, D. A., Price, K. H., & Bell, M. P. (1998). Beyond relational demography: Time and the effects of surface-and deep-level diversity on work group cohesion. *Academy of Management Journal*, 41(1), 96-107.

Hochberg, Y. V., Ljungqvist, A., & Lu, Y. (2007). Whom you know matters: Venture capital networks and investment performance. *The Journal of Finance*, *62*(1), 251-301.

Humphery-Jenner, M., & Suchard, J. A. (2013). Foreign VCs and venture success: Evidence from China. *Journal of Corporate Finance*, *21*, 16-35.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review*, *76*(2), 323-329.

Jiang, X., Li, Y., & Gao, S. (2008). The stability of strategic alliances: Characteristics, factors and stages. *Journal of International Management*, *14*(2), 173-189.

Jones, C. M., & Rhodes-Kropf, M. (2003). The price of diversifiable risk in venture capital and private equity. *Working Paper*, Columbia University.

Kaplan, S. N., & Schoar, A. (2005). Private equity performance: Returns, persistence, and capital flows. *The Journal of Finance*, *60*(4), 1791-1823.

Kaplan, S. N., & Strömberg, P. (2009). Leveraged buyouts and private equity. *Journal of Economic Perspectives*, 23(1), 121-46.

Kim, C. S., & Inkpen, A. C. (2005). Cross-border R&D alliances, absorptive capacity and technology learning. *Journal of International Management, 11*(3), 313-329.

Lerner, J. (1994). The syndication of venture capital investments. *Financial Management*, 16-27.

Lerner, J., Cestone, G., & White, L. J. (2007). The Design of Syndicates in Venture Capital. *Social Science Research Network Scholarly Paper*, (967310).

Lockett, A., & Wright, M. (2001). The syndication of venture capital investments. *Omega, 29*(5), 375-390.

Lopez-de-Silanes, F., Phalippou, L., & Gottschalg, O. (2015). Giants at the gate: Investment returns and diseconomies of scale in private equity. *Journal of Financial and Quantitative Analysis*, *50*(3), 377-411.

Lossen, U. (2007). *Performance of private equity funds: does diversification matter?* (pp. 95-133). DUV.

MacArthur, H., Burack, R., De Vusser, C., & Yang, K. (2022). The Private Equity Market in 2021: The Allure of Growth. *Bain & Company*. Retrieved April 24, 2022, from https://www.bain.com/insights/topics/global-private-equity-report/.

Mayer, T., & Zignago, S. (2011). Notes on CEPII's distances measures: The GeoDist database.

Meuleman, M., Wright, M., Manigart, S., & Lockett, A. (2009). Private equity syndication: Agency costs, reputation and collaboration. *Journal of Business Finance & Accounting*, *36*(5-6), 616-644.

Nikoskelainen, E., & Wright, M. (2007). The impact of corporate governance mechanisms on value increase in leveraged buyouts. *Journal of Corporate Finance*, *13*(4), 511-537.

Officer, M. S., Ozbas, O., & Sensoy, B. A. (2010). Club deals in leveraged buyouts. *Journal of Financial Economics, 98*(2), 214-240.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative Science Quarterly*, 116-145.

Richards, M., & Yang, Y. (2007). Determinants of foreign ownership in international R&D joint ventures: Transaction costs and national culture. *Journal of International Management*, *13*(2), 110-130.

Roosenboom, P., & Van Den Bosch, B. W. (2012). Syndicate Partner Selection: who Syndicates with Whom?. In *The Oxford Handbook of Private Equity* (p. 199). Oxford University Press.

Rothkegel, S., Erakovic, L., Shepherd, D., & Shepherd, D. (2006). Strategic alliances between SMEs and large firms: An exploration of the dynamic process. *Management Revue*, 50-71.

Sampson, R. C. (2007). R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation. *Academy of Management Journal*, *50*(2), 364-386.

Sharifzadeh, A., & Walz, U. (2012). Syndication of VC Investments, Governance, and Contract Design. In *The Oxford Handbook of Venture Capital*.

Siming, L. (2010). Private equity firms as market makers. *The Journal of Private Equity*, *14*(1), 8-16.

Sorenson, O., & Stuart, T. E. (2001). Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology*, *106*(6), 1546-1588.

Strömberg, P. (2008). The new demography of private equity. *The Global Impact of Private Equity Report*, *1*, 3-26.

Valkama, P., Maula, M., Nikoskelainen, E., & Wright, M. (2013). Drivers of holding period firm-level returns in private equity-backed buyouts. *Journal of Banking & Finance*, *37*(7), 2378-2391.

Walker, G., Kogut, B., & Shan, W. (1997). Social capital, structural holes and the formation of an industry network. *Organization Science*, *8*(2), 109-125.

Wilson, R. (1968). The theory of syndicates. *Econometrica: Journal of the Econometric Society*, 119-132.

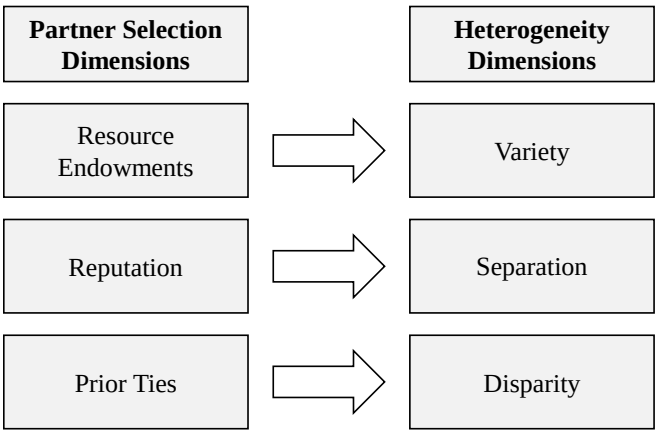
Wright, M., & Lockett, A. (2003). The structure and management of alliances: syndication in the venture capital industry. *Journal of Management Studies*, *40*(8), 2073-2102.

Zhang, P. (2014). Understanding diversification strategy in venture capital market. *Entrepreneurship Research Journal*, *4*(3), 277-296.

Appendix

Appendix 1: Matching of partner selection dimensions with heterogeneity dimensions

The figure shows the matching of the dimensions of the Partner Selection stage from the framework by Jiang et al. (2008) with the heterogeneity dimensions outlined by Harrison & Klein (2007). According to Harrison & Klein (2007), the dimensions of heterogeneity have neither been fully understood nor clearly defined yet. With their study, Harrison & Klein (2007) aim to narrow this gap by creating a framework where they divide heterogeneity into three distinctive types variety, separation, and disparity. This framework is supposed to facilitate conceptualization and research design within the field of heterogeneity by breaking heterogeneity down into three dimensions. We ensure that we cover a sufficiently broad spectrum of heterogeneity for our analysis since we can match the three dimensions of the partner selection pillar from the framework by Jiang et al. (2008) with the three heterogeneity dimensions from Harrison & Klein (2007). First, "Variety" refers to differences in the kind or category of alliance members. For example, this can include knowledge or experience. "Variety" can be matched with "Resource Endowment". Second, "Separation" is considered a horizontal distance, which reflects for example differences in position or opinion of alliance members. "Separation" can be matched with "Reputation". Last, "Disparity" in strategic alliances refers to differences in the concentration of valued social assets or resources. "Separation" can be matched with "Prior Ties". The arrows indicate which dimension of the partner selection framework is matched to which dimension of heterogeneity.



Appendix 2: List of transactions in the sample

The table below shows all 125 deals in our sample including target country and industry, all syndicate members, the entities from which the target was bought and to which the target was sold, the entry and exit closing dates, the holding period in years, and the EV for entry and exit in € million. Please note that the abbreviation P2P refers to Public-to-Private deals.

#	Target	Country	Industry	Consortium	Bought from	Sold to	Entry date	Exit date	Holding	Entry EV	Exit EV
1	Aalborg Industries A/S	Denmark	Industrials	Altor Equity; Maj Invest Equity	Axcel Management; FIH Partners	Alfa Laval Corporate	9/27/2005	5/12/2011	5.62	161	549
2	Ahlsell AB	Sweden	Industrials	Cinven; Goldman Sachs Private Equity	Nordic Capital	CVC	9/11/2005	5/9/2012	6.66	1,200	1,800
3	Aibel AS	Norway	Industrials	Herkules Capital; Ferd Capital	Newgate Private Equity; 3i Group; CCMP Capital	Ratos; Sjatte AP-fonden; Ferd Capital	7/31/2007	4/11/2013	5.70	670	1,160
4	Aibel AS & Vetco Gray, Inc	Norway	Industrials	Newgate Private Equity; 3i Group; CCMP Capital Advisors	ABB	Herkules Capital; Ferd Capital	7/12/2004	7/31/2007	3.05	786	2,170
5	A-Katsastus Oy	Finland	Consumer Discretionary	MB Funds; Finnish Industry Investment; Varma Mutual Pension Insurance; LocalTapiola	Finnish government	Bridgepoint	4/30/2003	11/17/2005	2.55	59	400
6	Aleris Holding AB	Sweden	Health Care	EQT; ISS Group	ISS Group	Patricia Industries	2/1/2005	8/9/2010	5.52	202	495
7	Alimak Group AB	Sweden	Industrials	3i Group; Ratos	Karolin Invest	Triton	4/1/2001	1/17/2007	5.80	50	240
8	Ålö AB	Sweden	Industrials	3i Group; Balticgruppen	Balticgruppen	Altor Equity; Fort Knox FÖRvaring	10/18/2002	7/8/2011	8.73	115	240
9	Ålö AB	Sweden	Industrials	Altor Equity; Fort Knox FÖRvaring	3i Group; Balticgruppen	JOST Werke	7/8/2011	1/31/2020	8.57	246	250
10	Ambea AB	Sweden	Health Care	3i Group; Intermediate Capital	Priveq	KKR; Triton	4/22/2005	3/31/2010	4.94	207	850
11	Ambea AB	Sweden	Health Care	KKR; Triton	3i Group; Intermediate Capital	IPO / CVC; Ilmarinen Pension Insurance; Varma Mutual Pension Insurance; LocalTapiola	3/31/2010	8/10/2018	8.37	850	2,633
12	AniCura TC AB	Sweden	Health Care	Nordic Capital; Fidelio Capital	Fidelio; Stiftelsen Djursjukhus i Stor-Stockholm	Mars Petcare	6/18/2014	11/27/2018	4.45	220	2,000
13	Anticimex AB	Sweden	Industrials	EQT; Volito; Sjätte AP-fonden; AMF Fonder; Cubera Private Equity	EQT	Alecta Pensionsforsakring; EQT; AMF Fonder; GIC; Melker Schörling; Interogo	12/31/2017	11/16/2021	3.88	2,300	5,931
14	Arcus ASA	Norway	Consumer Staples	Ratos; HOFF Norske Potetindustrier	Sucra; HOFF Norske Potetindustrier	IPO	9/30/2005	11/30/2016	11.18	103	398
15	Assemblin VS AB	Sweden	Industrials	Segulah Advisor; Priveq	NCC	Triton	2/8/2002	6/22/2006	4.37	47	83
16	Attendo AB	Sweden	Health Care	Bridgepoint Advisers; Melker Schörling	P2P	IK Investment; Intermediate Capital; Varma Mutual Pension Insurance	3/11/2005	1/23/2007	1.87	254	493
17	Attendo AB	Sweden	Health Care	IK Investment; Intermediate Capital; Varma Mutual Pension Insurance	Bridgepoint Advisers; Melker Schörling	IPO	1/23/2007	11/29/2015	8.85	493	1,475
18	AutoStore AS	Norway	Industrials	Thomas H. Lee Partners; EQT	EQT	IPO	12/31/2019	10/20/2021	1.81	1,616	14,209
19	Biovitrum AB	Sweden	Health Care	Nordic Capital; MPM Capital; Nextgear Invest	Pharmacia	Patricia Industries; Priveq; Fjärde AP-fonden	9/28/2001	3/18/2004	2.47	230	22
20	Biovitrum AB	Sweden	Health Care	Patricia Industries; Priveq; Fjärde AP-fonden	Nordic Capital; MPM Capital; Nextgear Invest	Swedish Orphan Biovitrum	3/18/2004	1/14/2010	5.83	22	397
21	BTJ Nordic AB	Sweden	Consumer Discretionary	Litorina; Ratos	KF Media; Svensk Biblioteksforening	Per Samuelson (chairman of the board)	6/12/2003	5/31/2013	9.98	48	5
22	Byggfakta Scandinavia AB	Sweden	Communication Services	Duke Street; MB Funds; Segulah Advisor	TR Organisation	Construction Market Data Group	3/31/1996	7/10/1998	2.28	8	28
23	C More Entertainment AB	Sweden	Communication Services	Baker Capital; Nordic Capital; Strax	Vivendi	Kanal 5 Holding	10/31/2003	3/8/2005	1.35	70	249
24	Cederroth AB	Sweden	Consumer Staples	CapMan; Litorina	Alberto Culver	Orkla	7/31/2008	8/31/2015	7.09	159	215
25	Com Hem AB	Sweden	Communication Services	Providence; Carlyle	EQT	BC Partners	1/26/2006	9/21/2011	5.65	1,056	1,821
26	Controlled Polymers A/S	Denmark	Materials	Chrispa; Blue Equity Management	Founder	Americhem	8/31/2015	8/31/2020	5.01	10	27
27	CPS Color Group Oy	Finland	Materials	IK Investment; MB Funds; Swisslog Holding	Tikkurila	Nordic Capital	10/10/2000	6/17/2008	7.69	290	100
28	Cramo AB	Sweden	Industrials	IK Investment; Intermediate Capital	Securum	Geveke	3/30/1996	5/30/2000	4.17	202	431
29	Crayon Group Holding ASA	Norway	Information Technology	Kommunal Landspensjonskasse; Norvestor Equity	P2P	IPO	1/26/2012	11/8/2017	5.79	105	183
30	Crem International AB	Sweden	Industrials	SEB Venture Capital; Priveq	Accent Equity; Olaso family; Georg Moller (private investor)	Welbilt	11/6/2012	4/19/2018	5.45	87	179
31	Cybercity A/S	Denmark	Information Technology	Advent International; Verdane; Lehman Brothers Private Equity; Nordic Venture Partners; Merrill Lynch Private Equity	Founder	Telenor	3/24/2000	7/5/2005	5.28	67	186
32	Dahl International AB	Sweden	Consumer Discretionary	EQT; Ratos	P2P	Compagnie de Saint-Gobain	11/1/1999	5/12/2004	4.53	425	686
33	Dako A/S	Denmark	Health Care	Intermediate Capital; EQT	Novo Nordisk	Agilent Technologies Europe	5/31/2007	6/21/2012	5.06	973	1,688
34	Dalum Papir A/S	Denmark	Materials	AS Dansk Erhvervsinvestering; LD Pensions; Invest Miljø	Stora Enso	ArjoWiggins Le Bourray	2/28/1999	9/3/2007	8.52	40	64
35	Damcos A/S	Denmark	Information Technology	3i Group; Danfoss	Danfoss	Emerson Electric	10/21/2004	1/10/2007	2.22	51	162
36	Dynal Biotech ASA	Norway	Materials	Nordic Capital; Ratos	Dyno Nobel; Dynea; A.L. Industrier	Life Technologies	10/16/2001	4/1/2005	3.46	177	324
37	Eltel Networks Oy	Finland	Industrials	CapMan; Fenno Management	Fortum Oyj	IK Investment	6/29/2001	2/2/2005	3.60	33	190
38	Enermet Group Oy	Finland	Industrials	IK Investment; MB Funds; Fortum Oyj	Fortum Oyj	Bayard Group	8/27/1999	7/14/2006	6.88	102	90
39	Eniro Norge AS	Norway	Communication Services	TPG Capital; Lightyear Capital	Telenor	Eniro Group	11/16/2001	12/5/2005	4.05	680	1,130
40	Envac AB	Sweden	Industrials	3i Group; Ratos	Atle Industri	Stena Adactum	3/27/2001	5/19/2005	4.15	28	62

#	Target	Country	Industry	Consortium	Bought from	Sold to	Entry date	Exit date	Holding	Entry EV	Exit EV
41	EVRY ASA	Norway	Information Technology	Apax; Folketrygdfondet; Polygon Global	Posten Norge; Folketrygdfondet; Telenor	TietoEVRY	3/16/2015	12/5/2019	4.73	845	1,962
42	EWOS AS	Norway	Consumer Staples	Bain Capital; Altor Equity	Cermaq	Cargill	10/31/2013	10/8/2015	1.94	825	1,350
43	Falck A/S	Denmark	Health Care	Nordic Capital; ATP Private Equity	P2P	PFA Holding; Kirkbi; Lundbeckfond Invest	6/29/2005	7/4/2011	6.02	603	1,461
44	Fertin Pharma A/S	Denmark	Health Care	EQT; Bagger-Sørensen	Bagger-Sørensen	PMI Global Services	1/1/2017	9/15/2021	4.71	376	690
45	Gambro AB	Sweden	Health Care	Patricia Industries; EQT	P2P	Baxter International	5/31/2006	9/6/2013	7.27	3,773	5,490
46	Gant Sweden AB	Sweden	Consumer Discretionary	3i Group; L Catterton Management	PVH	IPO	7/1/2003	4/5/2006	2.76	82	450
47	Get AS	Norway	Communication Services	Partners Group; Newgate Private Equity	Liberty Global	Goldman Sachs Private Equity; Quadrangle Capital	1/19/2006	12/31/2007	1.95	445	745
48	Get AS	Norway	Communication Services	Goldman Sachs Private Equity; Quadrangle Capital	Newgate Private Equity	TDC	12/31/2007	10/20/2014	6.81	726	1,670
49	Global Refund AB	Sweden	Information Technology	Apax; Fexco	Avis Budget Group	Barclays Private Equity	8/24/1999	8/7/2007	7.96	150	360
50	Hemnet Group AB	Sweden	Communication Services	General Atlantic; Sprints Capital Management	Swedbank Fastighetsbyran	IPO	1/9/2017	4/8/2021	4.25	211	2,235
51	HusCompagniet A/S	Denmark	Consumer Discretionary	FSN Capital; Kirkbi	Axcel Management	EQT	5/31/2011	8/31/2015	4.25	134	268
52	Huurre Group Oy	Finland	Industrials	Bridgepoint Advisers; LocalTapiola; Foinco Invest	Merita Bank	Kaupthing	3/25/1998	3/4/2003	4.95	35	145
53	Icopal A/S	Denmark	Industrials	Axcel Management; Kirkbi; Carlisle	P2P	Investcorp	5/5/2000	7/26/2007	7.23	671	861
54	Inspecta Group Oy	Finland	Industrials	3i Group; Intermediate Capital	MB Funds	ACTA Holding	8/21/2007	6/9/2015	7.81	243	202
55	ISS A/S	Denmark	Industrials	EQT; Goldman Sachs Private Equity	Franklin Resources	IPO	5/9/2005	3/13/2014	8.85	4,030	6,950
56	Jamo A/S	Denmark	Consumer Discretionary	BancBoston Capital; FSN Capital	Preben Jacobsen (private investor); Julius Mortensen (private investor)	Klipsch Group	8/15/2001	2/15/2005	3.51	78	14
57	Jøtul As	Norway	Consumer Discretionary	Accent Equity; Whitecliff; Selvaag Invest; Havfonn	P2P	Accent Equity; Ratos	6/24/2004	7/20/2006	2.07	58	44
58	KappAhl AB	Sweden	Consumer Discretionary	Nordic Capital; Accent Equity	Kooperativa Forbundet ekonomisk forening	IPO	10/28/2004	2/23/2006	1.32	214	596
59	Kemira Chemicals Oy	Finland	Materials	Montagu; MB Funds; Tianguis; Silverfleet Capital	Nokia; UPM-Kymmene	Kemira	12/31/1996	2/7/2005	8.11	189	345
60	KMD A/S	Denmark	Information Technology	EQT; ATP Private Equity	Kommunernes Landsforening	Advent International; Sampension	3/9/2009	12/20/2012	3.79	269	661
61	KMD A/S	Denmark	Information Technology	Advent International; Sampension	EQT; ATP Private Equity	NEC Corporation	12/20/2012	2/21/2019	6.18	661	1,129
62	Kongsberg Automotive ASA	Norway	Consumer Discretionary	BancBoston Capital; IK Investment; FSN Capital	P2P	FSN Capital	2/15/1999	7/6/2001	2.39	73	151
63	KP Komponenter A/S	Denmark	Industrials	Capidea Management; Industri Udvikling	Industri Udvikling; Founders	Segulah Advisor	11/29/2007	5/15/2014	6.46	53	67
64	Labeyrie Fine Foods PLC	Iceland	Consumer Staples	LBO France; Lur Berri	Kaupthing Singer & Friedlander; Kjalar Invest; Lur Berri; Alta Food	PAI Partners	1/30/2012	7/22/2014	2.48	334	567
65	LEAF AB	Sweden	Consumer Staples	Nordic Capital; CVC	Corbion	Cloetta	3/1/2005	12/16/2011	6.80	850	755
66	Lindorff Group AB	Sweden	Industrials	Sponsor Capital; Altor Equity	Gjensidige Forsikring	Patricia Industries; Altor Equity	1/15/2004	7/16/2008	4.50	163	1,160
67	Lindorff Group AB	Sweden	Industrials	Patricia Industries; Altor Equity	Sponsor Capital; Altor Equity	Nordic Capital	7/16/2008	10/21/2014	6.27	1,160	2,100
68	MacGregor Group AB	Sweden	Industrials	IK Investment; Gambro	Gambro	Cargotec	9/11/1998	3/4/2005	6.48	172	184
69	Maritii Oy	Finland	Consumer Discretionary	CapMan; Fenno Management	Rautakirja	Leo Longlife	5/1/1998	10/9/2006	8.45	40	61
70	Max Matthiessen AB	Sweden	Financials	Altor Equity; Bure Equity	Swedish National Debt Office	Willis Towers Watson	8/24/2009	10/8/2014	5.13	47	197
71	Mediplast AB	Sweden	Health Care	Priveq; RoosGruppen; Procurator	Procurator	Addtech Life Science	7/29/2010	7/1/2015	4.93	28	51
72	Navico Holding AS	Norway	Information Technology	Altor Equity; Goldman Sachs Private Equity	Kongsberg Maritime	Brunswick	10/31/2005	10/4/2021	15.94	75	880
73	Neas Energy A/S	Denmark	Utilities	ATP Private Equity; VIA Equity	NEAS Holding	Centrica	6/1/2015	10/5/2016	1.35	112	215
74	Nebula Top Oy	Finland	Information Technology	Ratos; Rite Ventures	Rite Ventures	Telia	4/2/2013	7/3/2017	4.25	83	165
75	Netcompany Group A/S	Denmark	Information Technology	FSN Capital; Danica Pension	Founders	IPO	2/1/2016	6/7/2018	2.35	268	1,618
76	Nets A/S	Denmark	Information Technology	Advent International; Hellman & Friedman; GIC; Fisher Lynch Capital; StepStone Group; Bain Capital	186 primarily Denmark- and Norway-based banks	Nexi	7/9/2014	6/30/2021	6.98	1,945	8,050
77	NeuroNova AB	Sweden	Health Care	HealthCap; Patricia Industries; SLS Venture	Founders	Newron Pharmaceuticals	9/10/2003	12/17/2012	9.28	12	15
78	Nordic Cinema Group AB	Sweden	Communication Services	Bonnier; Ratos	Ratos	Bridgepoint Advisers	5/2/2013	7/31/2015	2.25	363	501
79	Nordic Cinema Group AB	Sweden	Communication Services	Bonnier; Bridgepoint Advisers	Bonnier; Ratos	AMC Entertainment	7/31/2015	3/28/2017	1.66	501	893
80	Nordic Nest AB	Sweden	Consumer Discretionary	Nordstjernan; COE Investments; Stella Capital	Verdane	BHG Group	12/4/2015	12/31/2020	5.08	19	168
81	Nordic Paper Holding AB	Sweden	Materials	Orlando Management; Petek	NorgesInvestor; Petek; Richard Heiberg Invest; JSR Invest; Hartvig Wennberg	Shanying International	11/20/2014	10/24/2017	2.93	298	250
82	Nordic Shelter Solutions-Group Oy	Finland	Industrials	Veidekke; Helmet Capital	Veidekke	Accent Equity	3/25/2002	5/7/2008	6.12	25	23
83	Nordic Waterproofing AB	Sweden	Industrials	Axcel Management; Kirkbi	Trelleborg Engineered Systems	IPO	1/31/2011	6/10/2016	5.36	70	220
84	Norse Cutting & Abandonement AS	Norway	Energy	EV Private Equity; Cubera Private Equity	Founders	Oceaneering International	7/10/2008	3/31/2011	2.72	14	43
85	Nycomed A/S	Denmark	Health Care	Blackstone; AlpInvest; aPriori Capital	Nordic Capital	HarbourVest; aPriori Capital; Coller International; Nordic Capital; Avista Capital	11/29/2002	5/9/2005	2.44	1,145	1,800

#	Target	Country	Industry	Consortium	Bought from	Sold to	Entry date	Exit date	Holding	Entry EV	Exit EV
86	Nycomed A/S	Denmark	Health Care	HarbourVest; aPriori Capital; Coller International; Nordic Capital; Avista Capital	CSFB; Blackstone; AlpInvest	Takeda	5/9/2005	9/30/2011	6.40	1,800	9,600
87	Oglaend Industrier AS	Norway	Industrials	Segulah Advisor; Futurum Utvikling	Founders; Gunnstein Austigard (private investor); Roald Hoff (private investor)	Hilti Corporation	12/4/2013	8/23/2017	3.72	90	211
88	Opera Software AS	Norway	Information Technology	Qihoo 360 Technology; Beijing Kunlun Tech; Golden Brick Capital Management	Otello	IPO	11/4/2016	7/27/2018	1.73	520	1,220
89	Paroc Group Oy	Finland	Materials	IK Investment; Partek; Kone Corporation	Kone Corporation	Accent Equity; BG Capital Group; Argan Capital	8/31/1999	2/12/2003	3.45	141	197
90	Paroc Group Oy	Finland	Materials	Accent Equity; BG Capital Group; Argan Capital	IK Investment; Partek; Kone Corporation	Arcapita	2/12/2003	8/31/2006	3.55	197	620
91	Petainer AB	Sweden	Materials	Alpina Capital; Next Wave	Rexam	KKR	11/11/2009	5/3/2016	6.48	18	140
92	Phadia AB	Sweden	Health Care	Silverfleet Capital; Triton	Pfizer	Cinven	4/23/2004	1/31/2007	2.78	465	1,285
93	Phonero AS	Norway	Communication Services	Norvestor Equity; Kistefos	Kistefos	Telia	11/9/2015	4/10/2017	1.42	143	253
94	Raufoss Naeringspark ANS	Norway	Real Estate	H.I.G. Capital; Ness, Risan & Partners	Storebrand Livsforsikring; NLI Eiendomsinvest; Storebrand Optimer Raufoss	Skattum Eiendom; SKB Eiendom; Olsen Eiendom	2/24/2016	1/15/2019	2.89	136	204
95	RenoNorden AS	Norway	Industrials	Accent Equity; CapVest; PineBridge Investments	Norvestor Equity	IPO	9/27/2011	12/15/2014	3.22	162	239
96	Saxo Bank A/S	Denmark	Financials	General Atlantic; TPG Capital; PT Sinar Mas Group	Espirito Santo Financial Group; General Atlantic; Banco Espírito Santo	Sampo; Geely Financials Denmark	12/14/2011	9/14/2018	6.76	1,298	1,332
97	Scandic Hotels AB	Sweden	Consumer Discretionary	Accent Equity; EQT	Hilton Worldwide	IPO	4/26/2007	12/2/2015	8.61	833	957
98	Scandlines ApS	Denmark	Industrials	3i Group; Allianz Capital; Deutsche Seereederei Rostock	Deutsche Bahn; Danish Ministry of Transport and Energy	First State Investments; Hermes Investment Management	8/31/2007	6/21/2018	10.81	1,560	2,562
99	Serena Properties AB	Sweden	Real Estate	Ratos; Redito	Varma Mutual Pension Insurance	Fastighets AB Balder	11/20/2015	9/30/2017	1.86	192	206
100	STARK Group ApS	Denmark	Consumer Discretionary	CVC; abrdn Capital	Codan; LD Pensions; ATP Private Equity	Ferguson	5/15/2003	9/25/2006	3.37	801	1,879
101	SteelSeries ApS	Denmark	Consumer Discretionary	L Catterton Management; ClearVue	WP Holding	Axcel Management	9/30/2012	9/30/2019	7.00	58	268
102	Stiga AB	Sweden	Consumer Discretionary	Vencap; UBS Capital	Monark	AAC Capital	1/1/2000	11/27/2003	3.91	97	555
103	StormGeo AS	Norway	Industrials	DNV; EQT	TV 2; Reiten & Co	Alfa Laval Corporate	4/11/2014	6/1/2021	7.15	301	364
104	Stream AS	Norway	Energy	Converto Capital Management; HitecVision; Camar Invest	Aker	MRC Global	11/19/2009	1/6/2014	4.13	74	190
105	Suomen Terveystalo Työterveys Oy	Finland	Health Care	MB Funds; Ilmarinen Pension Insurance	Finnish government	Terveystalo Healthcare	2/11/2000	8/31/2007	7.56	10	128
106	Superfos Industries A/S	Denmark	Materials	IK Investment; Ratos	Ashland	RPC Group	11/30/1999	2/18/2011	11.23	363	240
107	TDC A/S	Denmark	Communication Services	Apax; Blackstone; KKR; Permira; Providence	P2P	IPO	1/20/2006	11/25/2010	4.85	10,200	12,843
108	TDC Song AS	Sweden	Communication Services	Providence; Vattenfall; Stena Adactum	Stena Adactum	TDC	2/15/1999	10/29/2004	5.71	66	544
109	Teleca AU-System AB	Sweden	Information Technology	Permira; IBM; Ericsson; Nordea Fonder	Ericsson; Telia	Teleca	4/7/1999	2/19/2002	2.87	125	135
110	TitanX Engine Cooling AB	Sweden	Industrials	EQT; Fouriertransform	Valeo	Tata AutoComp Systems	5/30/2008	1/2/2017	8.60	49	68
111	Unifeeder A/S	Denmark	Industrials	Nordic Capital; Danica Pension	Montagu	DP World	12/31/2013	12/6/2018	4.93	400	659
112	Vaasan Oy	Finland	Consumer Staples	CapVest; PineBridge Investments	EQT	Lion Capital	3/3/2004	7/31/2007	3.41	252	425
113	Värmevärden AB	Sweden	Utilities	Macquarie Private Equity; Capstone Infrastructure	Fortum Varme	J.P. Morgan Asset Management	3/31/2011	2/21/2017	5.90	200	454
114	Vattenfall Lämpö Oy	Finland	Utilities	Ilmarinen Pension Insurance; TIAA; Goldman Sachs Private Equity; 3i Group	Vattenfall	Allianz Capital; Macquarie Private Equity; The State Pension Fund of Finland	1/11/2012	2/28/2018	6.14	1,540	3,971
115	Verisure Midholding AB	Sweden	Consumer Discretionary	EQT; Melker Schörling; Investment AB Latour	P2P	Hellman & Friedman; Bain Capital	2/28/2008	9/15/2011	3.55	1,046	2,334
116	Verisure Midholding AB	Sweden	Consumer Discretionary	Hellman & Friedman; Bain Capital	EQT; Melker Schörling; Investment AB Latour	Hellman & Friedman	9/15/2011	10/21/2015	4.10	2,334	5,263
117	Vest-Wood A/S	Denmark	Industrials	Polaris Private Equity; Axcel Management; Akina	P2P	JELD-WEN	4/24/2002	1/31/2006	3.78	323	621
118	Visma AS	Norway	Information Technology	Intermediate Capital; Hg Capital	Cevian Capital	Hg Capital; Montagu; KKR; Intermediate Capital	7/12/2006	9/27/2010	4.21	523	1,408
119	Visma AS	Norway	Information Technology	Hg Capital; Montagu; KKR; Intermediate Capital	Intermediate Capital; Hg Capital	Cinven; KKR	9/27/2010	8/21/2014	3.90	1,408	2,524
120	Visma AS	Norway	Information Technology	Cinven; KKR	Hg Capital; Montagu; KKR	Hg Capital; Cinven; Montagu; Intermediate Capital; GIC	8/21/2014	9/30/2017	3.11	2,524	4,700
121	Visma AS	Norway	Information Technology	Hg Capital; Cinven; Montagu; Intermediate Capital; GIC	Cinven; KKR	Hg Capital; Canada Pension Plan Investment Board	9/30/2017	5/31/2019	1.67	4,700	6,500
122	Vizada SAS	Norway	Communication Services	Hutton Collins; Apax; Altamir Amboise	Telenor	Astrium	9/6/2007	12/19/2011	4.29	315	673
123	Welltec A/S	Denmark	Energy	Riverside; Barings	Founder	Summit Partners	7/6/2005	7/30/2007	2.07	70	548
124	WhiteAway A/S	Denmark	Consumer Discretionary	Verdane; eEquity; Retail Online Holding	eEquity	Anders Povlsen (private investor)	8/31/2013	7/14/2014	0.87	30	165
125	XXL ASA	Norway	Consumer Discretionary	EQT; Dolphin Management	Orkla; Insitusjonen Fritt Ord	IPO	6/2/2010	10/3/2014	4.34	388	1,249

Appendix 3: List of buyers in sample

The table below shows all 173 buyers in our sample including the country of their headquarters (S&P Capital IQ and Mergermarket), their founding year (S&P Capital IQ and website of buyers), and a classification of the buyer, i.e., "GP", "Other financial investor" or "Strategist" (S&P Capital IQ and website of buyers).

#	Name	Country	Founding year	Type of buyer
1	3i Group	United Kingdom	1945	GP
2	abrdn Capital	United Kingdom	1998	GP
3	Accent Equity	Sweden	1994	GP
4	Advent International	United States	1984	GP
5	Akina	Switzerland	1998	GP
6	Allianz Capital	Germany	1998	Other financial investor
7	Alpina Capital	United Kingdom	2004	GP
8	AlpInvest	Netherlands	2000	GP
9	Altamir Amboise	France	1995	Other financial investor
10	Altor Equity	Sweden	2003	GP
11	AMF Fonder	Sweden	1973	Other financial investor
12	Apax	United Kingdom	1981	GP
13	aPriori Capital	United States	1985	GP
14	Argan Capital	United Kingdom	1995	GP
15	AS Dansk Erhvervsinvestering	Denmark	1983	GP
16	ATP Private Equity	Denmark	2001	Other financial investor
17	Avista Capital	United States	2005	GP
18	Axcel Management	Denmark	1994	GP
19	Bagger-Sørensen	Denmark	1915	Other financial investor
20	Bain Capital	United States	1984	GP
21	Baker Capital	United States	1995	GP
22	Balticgruppen	Sweden	1987	Strategist
23	BancBoston Capital	United States	1959	GP
24	Barings	United States	1940	GP
25	Beijing Kunlun Tech	China	2008	Strategist
26	BG Capital Group	United States	1996	GP
27	Blackstone	United States	1985	GP
28	Blue Equity Management	Denmark	2013	GP
29	Bonnier	Sweden	1804	Strategist
30	Bridgepoint Advisers	United Kingdom	1984	GP
31	Bure Equity	Sweden	1992	GP
32	Camar Invest	Norway	1994	Other financial investor
33	Capidea Management	Denmark	2006	GP
34	CapMan	Finland	1989	GP
35	Capstone Infrastructure	Canada	2004	Strategist
36	CapVest	United Kingdom	1999	GP
37	Carlisle	United States	1917	Strategist
38	Carlyle	United States	1987	GP
39	CCMP Capital Advisors	United States	1984	GP
40	Chrispa	Denmark	1999	Other financial investor
41	Cinven	United Kingdom	1977	GP
42	ClearVue	China	2012	GP
43	COE Investments	Sweden	2015	Other financial investor
44	Coller International	United Kingdom	1990	Other financial investor
45	Converto Capital Management	Norway	2009	Other financial investor
46	Cubera Private Equity	Norway	2006	GP
47	CVC	United Kingdom	1981	GP
48	Danfoss	Denmark	1933	Strategist
49	Danica Pension	Denmark	1842	Other financial investor
50	Deutsche Seereederei Rostock	Germany	1952	Strategist
51	DNV	Norway	2013	Strategist
52	Dolphin Management	Norway	2000	Other financial investor
53	Duke Street	United Kingdom	1988	GP
54	eEquity	Sweden	2010	GP
55	EQT	Sweden	1994	GP
56	Ericsson	Sweden	1876	Strategist
57	EV Private Equity	Norway	2002	GP

#	Name	Country	Founding year	Type of buyer
58	Fenno Management	Finland	1997	GP
59	Ferd Capital	Norway	1998	GP
60	Fexco	Ireland	1981	Strategist
61	Fidelio Capital	Sweden	2010	GP
62	Finnish Industry Investment	Finland	1995	Other financial investor
63	Fisher Lynch Capital	United States	2003	GP
64	Fjärde AP-fonden	Sweden	1960	Other financial investor
65	Foinco Invest	Norway	1998	Other financial investor
66	Folketrygdfondet	Norway	1967	Other financial investor
67	Fort Knox FÖRvaring	Sweden	2005	Other financial investor
68	Fortum Oyj	Finland	1998	Strategist
69	Fouriertransform	Sweden	2008	GP
70	FSN Capital	Norway	1999	GP
71	Futurum Utvikling	Norway	2004	Other financial investor
72	Gambro	Sweden	1942	Strategist
73	General Atlantic	United States	1980	GP
74	GIC	Singapore	1983	Other financial investor
75	Golden Brick Capital Management	China	2014	GP
76	Goldman Sachs Private Equity	United States	1996	GP
77	H.I.G. Capital	United States	1993	GP
78	HarbourVest	United States	1982	GP
79	Havfonn	Norway	2003	Other financial investor
80	HealthCap	United States	1996	GP
81	Hellman & Friedman	United States	1984	GP
82	Helmet Capital	Finland	1995	GP
83	Herkules Capital	Norway	2003	GP
84	Hg Capital	United Kingdom	2000	GP
85	HitecVision	Norway	1985	GP
86	HOFF Norske Potetindustrier	Norway	1844	Strategist
87	Hutton Collins	United Kingdom	2002	GP
88	IBM	United States	1911	Strategist
89	IK Investment	United Kingdom	1989	GP
90	Ilmarinen Pension Insurance	Finland	1961	Other financial investor
91	Industri Udvikling	Denmark	1994	GP
92	Intermediate Capital	United Kingdom	1989	GP
93	Invest Miljø	Denmark	1990	GP
94	Investment AB Latour	Sweden	1985	GP
95	ISS Group	Denmark	1901	Strategist
96	Kirkbi	Denmark	1995	Other financial investor
97	Kistefos	Norway	1989	Other financial investor
98	KKR	United States	1976	GP
99	Kommunal Landspensjonskasse	Norway	1949	Other financial investor
100	Kone Corporation	Finland	1908	Strategist
101	L Catterton Management	United States	1989	GP
102	LBO France	France	1998	GP
103	LD Pensions	Denmark	1980	Other financial investor
104	Lehman Brothers Private Equity	United States	1984	GP
105	Lightyear Capital	United States	2000	GP
106	Litorina	Sweden	1998	GP
107	LocalTapiola	Finland	1982	Other financial investor
108	Lur Berri	France	1936	Strategist
109	Macquarie Private Equity	Australia	1994	GP
110	Maj Invest Equity	Denmark	2005	GP
111	MB Funds	Finland	1988	GP
112	Melker Schörling	Sweden	1987	Other financial investor
113	Merrill Lynch Private Equity	United States	1996	GP
114	Montagu	United Kingdom	1968	GP
115	MPM Capital	United States	1996	GP
116	Ness, Risan & Partners	Norway	2000	GP
117	Newgate Private Equity	United Kingdom	2003	GP
118	Next Wave	United Kingdom	2002	GP
119	Nextgear Invest	Sweden	1999	GP

#	Name	Country	Founding year	Type of buyer
120	Nordea Fonder	Sweden	1954	Other financial investor
121	Nordic Capital	Sweden	1989	GP
122	Nordic Venture Partners	Denmark	2000	GP
123	Nordstjernan	Sweden	1890	Other financial investor
124	Norvestor Equity	Norway	1991	GP
125	Orlando Management	Germany	2001	GP
126	Partek	Finland	1899	Strategist
127	Partners Group	Switzerland	1996	GP
128	Patricia Industries	Sweden	1995	GP
129	Permira	United Kingdom	1985	GP
130	Petek	Germany	1986	Strategist
131	PineBridge Investments	United States	1996	GP
132	Polaris Private Equity	Denmark	1998	GP
133	Polygon Global	United Kingdom	2002	Other financial investor
134	Priveq	Sweden	1983	GP
135	Procurator	Sweden	1936	Strategist
136	Providence	United States	1989	GP
137	PT Sinar Mas Group	Indonesia	1962	Strategist
138	Qihoo 360 Technology	China	2005	Strategist
139	Quadrangle Capital	United States	2000	GP
140	Ratos	Sweden	1934	GP
141	Redito	United Kingdom	2014	Strategist
142	Retail Online Holding	Denmark	2011	Strategist
143	Rite Ventures	Sweden	2007	GP
144	Riverside	United States	1988	GP
145	RoosGruppen	Sweden	1898	Strategist
146	Sampension	Denmark	1999	Other financial investor
147	SEB Venture Capital	Sweden	1995	GP
148	Segulah Advisor	Sweden	1994	GP
149	Selvaag Invest	Norway	1984	GP
150	Silverfleet Capital	United Kingdom	1990	GP
151	Sjätte AP-fonden	Sweden	1996	Other financial investor
152	SLS Venture	Sweden	1995	GP
153	Sponsor Capital	Finland	1997	GP
154	Sprints Capital Management	United Kingdom	2015	GP
155	Stella Capital	Sweden	2015	GP
156	Stena Adactum	Sweden	1999	GP
157	StepStone Group	United States	2006	Other financial investor
158	Strax	Sweden	1995	Strategist
159	Swisslog Holding	Switzerland	1900	Strategist
160	Thomas H. Lee Partners	United States	1974	GP
161	TIAA	United States	1918	Other financial investor
162	Tianguis	United Kingdom	1985	GP
163	TPG Capital	United States	1992	GP
164	Triton	Sweden	1997	GP
165	UBS Capital	Switzerland	1993	GP
166	Varma Mutual Pension Insurance	Finland	1998	Other financial investor
167	Vattenfall	Sweden	1909	Strategist
168	Veidekke	Norway	1936	Strategist
169	Vencap	United Kingdom	1987	GP
170	Verdane	Norway	1985	GP
171	VIA Equity	Denmark	2006	GP
172	Volito	Sweden	1991	GP
173	Whitecliff	United Kingdom	1996	Strategist

Appendix 4: Buyers with the highest investment activity

First, the upper table shows the ten buyers involved in the most deals in our sample. Comparing the number of deals in our sample with the total number of syndicated buyouts in the Nordics listed on S&P Capital IQ for these buyers, we can see that our sample covers the majority of transactions. The unrecorded investments are either not exited yet or have no publicly disclosed EV for entry and/or exit. Second, the tables in the center on the left- and right-hand side show the 15 buyers with the highest investment activity in the Nordics and globally out of the 173 buyers in our sample. Similarly, the table at the bottom lists the five most active global buyers by industry (classification as per S&P Capital IQ) out of the 173 buyers in our sample. The orders are created by retrieving all investments (entries) of the 173 buyers until 20 February 2022 from S&P Capital IQ. Deals are only included when they are classified as "Mergers & Acquisitions". Deals classified as "Private Placement" (mainly VC deals) are not considered for better comparison with our sample of only buyout deals.

	Syndicated deals			Total deals	
Ten most active buyers in sample by deal count	**Sample**	**Nordics**	**Global**	**Nordics**	**Global**
EQT	14	18	46	105	256
3i Group	10	18	303	44	738
Ratos	10	11	11	49	53
Nordic Capital	9	22	30	85	116
IK Investment	8	12	33	58	144
Intermediate Capital	8	10	112	13	177
Altor Equity	7	14	16	71	81
MB Funds	6	8	8	26	26
Accent Equity	5	11	11	58	58
Goldman Sachs Private Equity	5	9	187	15	273
Total	**82**	**133**	**757**	**524**	**1,922**

15 most active buyers in the Nordics by deal count	
CapMan	185
EQT	105
Nordic Capital	85
Altor Equity	71
Axcel Management	70
Verdane	68
Industri Udvikling	61
Bure Equity	59
Accent Equity	58
IK Investment	58
Ratos	49
Segulah Advisor	49
Maj Invest Equity	47
Polaris Private Equity	47
3i Group	44

15 most active buyers globally by deal count	
Blackstone	766
3i Group	738
Carlyle	713
KKR	478
CVC	412
Bain Capital	365
Apax	359
Bridgepoint Advisers	356
Advent International	299
Riverside	285
H.I.G. Capital	281
Goldman Sachs Private Equity	273
EQT	256
GIC	248
TPG Capital	209

Five most active buyers globally by deal count in industries	
Industrials	3i Group (236), Carlyle (115), Bridgepoint (91), KKR (80), CVC (76)
Consumer Discretionary	3i Group (148), Blackstone (132), Carlyle (102), CVC (99), Bridgepoint (92)
Health Care	Carlyle (57), 3i Group (53), Riverside (49), Apax (44), Bain Capital (43)
Consumer Staples	CVC (47), 3i Group (43), KKR (30), Bridgepoint (27), Carlyle (23)
Communication Services	Apax (61), Providence (52), 3i Group (51), Carlyle (45), KKR (41)
Materials	3i Group (58), CVC (54), H.I.G. Capital (35), Carlyle (32), Bridgepoint (30)
Information Technology	IBM (179), 3i Group (88), Carlyle (87), Apax (76), Hg Capital (62)
Financials	Blackstone (66), KKR (46), Bain Capital (35), Macquarie (34), Carlyle (33)
Energy	Carlyle (25), KKR (23), EQT (16), 3i Group (15), Blackstone (13)
Utilities	Fortum Oyj (33), Allianz Capital (23), KKR (22), Vattenfall (21), Macquarie (18)
Real Estate	Blackstone (337), Carlyle (167), GIC (86), KKR (76), TIAA (72)

Appendix 5: Variable overview

The table below lists all variables introduced in Section 4.2 and includes a brief description, the calculation method, and the source for the related data to construct the variables.

Variable	Description	Calculation	Source
Dependent variables			
MOIC	Measures the quotient of the enterprise value (EV) at exit and the EV at entry. If business units of portfolio companies are exited separately, the EVs of the business units at their respective exit are added.	$= \frac{\sum_t EV\ at\ exit_t}{EV\ at\ entry}$ $with\ t = Exit\ time\ of\ BUs$ / firm	Mergermarket, S&P Capital IQ, press
IRR	Measures the discount rate that makes the present value of the exit EVs of all business units equal to the entry EV. If business units (BUs) of portfolio companies are exited separately, the IRR formula is non-linear.	$EV\ at\ entry = \sum_t \frac{EV\ at\ exit_t}{(1+r)^t}$ $with\ t = Exit\ time\ of\ BUs$ / firm	Mergermarket, S&P Capital IQ, press
Independent variables			
HYBRID	Measures the ratio of non-GPs to all members of a syndicate (i.e. the ratio of "Other financial investors" and "Strategists" to all syndicate members).	$= 1 - \frac{\#\ GPs\ in\ syndicate}{\#\ Syndicate\ members}$	S&P Capital IQ, websites of buyers
DIST	Measures the natural logarithm of the average pairwise distance between all syndicate members based on the countries they are headquartered in.	$= \ln\left(\frac{\sum All\ pairwise\ distances}{n \times (n-1)/2}\right)$ $with\ n = \#\ Syndicate\ members$	Mergermarket, S&P Capital IQ, CEPII (2011)
SIZE	Measures the relative variability of the average deal size (in € million) between all syndicate members before the respective deal in the sample (coefficient of variation).	$= \frac{Std(Average\ deal\ size)}{Mean(Average\ deal\ size)}$	S&P Capital IQ
AGE	Measures the relative variability of the age (time since founding year) between all syndicate members before the respective deal in the sample (coefficient of variation).	$= \frac{Std(Time\ since\ founding\ year)}{Mean(Time\ since\ founding\ year)}$	S&P Capital IQ, websites of buyers
TIES	Dummy to capture if any of the syndicate members formed a consortium with any other member before the respective deal in the sample.	$1 =$ At least *one buyer pair syndicated before* the deal $0 =$ *No buyer pair syndicated before* the deal	S&P Capital IQ
CLUB	Measures the average ratio of syndicated to total deals for all syndicate members before the respective deal in the sample.	$= \frac{\sum \frac{\#\ Syndicated\ deals}{\#\ Total\ deals}}{\#\ Syndicate\ members}$	S&P Capital IQ
Control variables			
EV	Measures the natural logarithm of the entry enterprise (EV) value for the respective deal in the sample.	$= \ln(EV\ at\ entry)$	Mergermarket, S&P Capital IQ, press
MEMBER	Measures the number of syndicate members for the respective deal in the sample.	$\#\ Syndicate\ members$	Mergermarket, S&P Capital IQ, press
MEMBER_SQ	Measures the squared number of syndicate members for the respective deal in the sample.	$\#\ Syndicate\ members^2$	Mergermarket, S&P Capital IQ, press
HOLDING	Measures the holding period of the respective deal in the sample in years (based on closing dates).	$=\ Exit\ date\ -\ Entry\ date$	Mergermarket, S&P Capital IQ, press
EXIT	Dummy to capture if an investment in the sample is exited through an IPO or a sale (to both financial investors and strategists).	$1 = Invest$ment exited through IPO $0 = Invest$ment exited through sale	Mergermarket, S&P Capital IQ, press
Time fixed effects			
PERIOD_1	Dummy to capture if an investment in the sample occurred in the period from 1996 to 2001.	$1 = Entry$ between 1996 and 2001 $0 = Entry$ in any other year	Mergermarket, S&P Capital IQ,press
PERIOD_2	Dummy to capture if an investment in the sample occurred in the period from 2002 to 2007.	$1 = Entry$ between 2002 and 2007 $0 = Entry$ in any other year	Mergermarket, S&P Capital IQ, press
PERIOD_3	Dummy to capture if an investment in the sample occurred in the period from 2008 to 2012.	$1 = Entry$ between 2008 and 2012 $0 = Entry$ in any other year	Mergermarket, S&P Capital IQ, press
Industry fixed effects			
IND_1	Dummy to capture if the target is active in the industry "Industrials" (as per *S&P Capital IQ*).	$1 = Industrials$ $0 = Any\ other\ industry$	S&P Capital IQ
IND_2	Dummy to capture if the target is active in the industry "Consumer Discretionary" (as per *S&P Capital IQ*).	$1 = Consumer\ Discretionary$ $0 = Any\ other\ industry$	S&P Capital IQ
IND_3	Dummy to capture if the target is active in the industry "Health Care" (as per *S&P Capital IQ*).	$1 = Health\ Care$ $0 = Any\ other\ industry$	S&P Capital IQ
Country fixed effects			
GEO_1	Dummy to capture if the target is headquartered in Sweden.	$1 = Sweden$ $0 = Any\ other\ country$	Mergermarket, S&P Capital IQ
GEO_2	Dummy to capture if the target is headquartered in Denmark.	$1 = Denmark$ $0 = Any\ other\ country$	Mergermarket, S&P Capital IQ
GEO_3	Dummy to capture if the target is headquartered in Norway.	$1 = Norway$ $0 = Any\ other\ country$	Mergermarket, S&P Capital IQ

Appendix 6: Approximated vs. reported investment performance

The table below lists all deals in our sample for which we obtained the reported investment performance. While 18 actual MOICs and IRRs were found in public deal announcements and related press articles, the GPs Axcel Management A/S, EQT Partners AB, and Priveq Advisory AB provided us with actual performance data for another 18 deals. The names of the target companies for these deals are intentionally not reported to avoid potential non-disclosure issues. EVs at entry and exit are reported in € million.

	Enterprise Value (EV)		**Performance proxy**		**Reported performance**		
#	Entry EV	Exit EV	EV MOIC	EV IRR	MOIC	IRR	Source
1	202	495	2.45x	17.7%	3.70x	30.0%	EQT
2	50	240	4.80x	31.0%	4.58x	30.0%	Press
3	115	240	2.09x	8.8%	4.00x	17.2%	Press
4	207	850	4.11x	33.1%	3.50x	28.8%	Press
5	220	2,000	9.09x	64.3%	7.00x	54.9%	Press
6	47	83	1.77x	13.9%	5.60x	49.3%	Priveq
7	254	493	1.94x	42.5%	4.40x	120.7%	Press
8	22	397	17.94x	64.1%	26.80x	80.6%	Priveq
9	87	179	2.06x	14.2%	3.70x	28.0%	Priveq
10	425	686	1.61x	11.1%	3.90x	35.0%	Press
11	973	1,688	1.73x	11.5%	2.30x	17.0%	EQT
12	51	162	3.20x	68.7%	5.20x	150.0%	Press
13	177	324	1.83x	19.1%	2.11x	24.0%	Press
14	28	62	2.21x	21.0%	2.61x	26.0%	Press
15	376	690	1.84x	13.8%	2.50x	22.0%	EQT
16	3,773	5,490	1.45x	6.9%	2.00x	10.0%	EQT
17	82	450	5.46x	84.8%	5.90x	90.0%	Press
18	445	745	1.67x	30.3%	2.20x	50.0%	Press
19	671	861	1.28x	3.5%	2.17x	14.6%	Axcel
20	4,030	6,950	1.72x	6.4%	2.20x	9.0%	EQT
21	269	661	2.46x	26.9%	4.40x	46.0%	EQT
22	334	567	1.70x	23.9%	1.70x	25.0%	Press
23	28	51	1.83x	13.0%	2.10x	16.5%	Priveq
24	83	165	2.00x	17.7%	3.30x	37.0%	Press
25	363	501	1.38x	15.4%	2.20x	42.0%	Press
26	70	220	3.15x	23.8%	3.19x	26.9%	Axcel
27	833	957	1.15x	1.6%	0.90x	-2.0%	EQT
28	192	206	1.08x	4.0%	1.50x	30.0%	Press
29	301	364	1.21x	2.7%	2.20x	12.0%	EQT
30	363	240	0.66x	-3.6%	1.25x	2.0%	Press
31	49	68	1.39x	3.9%	0.90x	-1.0%	EQT
32	200	454	2.27x	14.9%	3.23x	22.0%	Press
33	1,046	2,334	2.23x	25.4%	2.90x	34.0%	EQT
34	323	621	1.93x	18.9%	2.14x	34.7%	Axcel
35	70	548	7.83x	170.8%	9.00x	183.0%	Press
36	388	1,249	3.22x	30.9%	3.50x	30.0%	EQT
Average	476	897	2.94x	26.6%	3.91x	39.6%	
Median	214	494	1.93x	17.7%	3.05x	29.4%	
Std Dev	881	1,420	3.13x	31.9%	4.28x	39.9%	
Min	22	51	0.66x	-3.6%	0.90x	-2.0%	
Max	4,030	6,950	17.94x	170.8%	26.80x	183.0%	

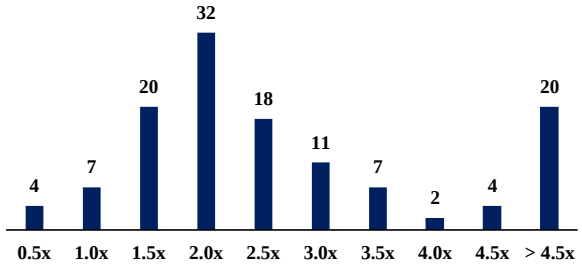
- Pearson correlation coefficient between EV MOIC and actual MOIC (p-value): **0.942** (0.000)
- Pearson correlation coefficient between EV IRR and actual IRR (p-value): **0.882** (0.000)

- Pearson correlation coefficient between EV MOIC and EV IRR (p-value): **0.615** (0.000)
- Pearson correlation coefficient between actual MOIC actual IRR (p-value): **0.466** (0.004)

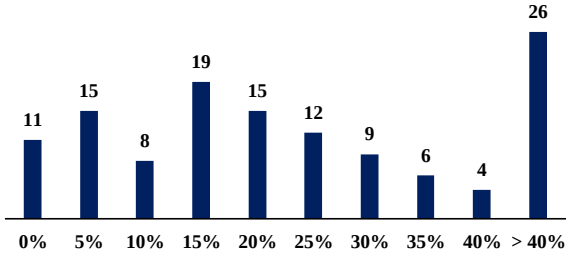
Appendix 7: Distribution of returns, holding period, and enterprise value

The graphs below show the histograms for the MOIC, IRR, holding period (in years) and EV at entry (in € million), respectively. The first bar of each histogram includes all observations in the threshold and below. The graphs are based on all 125 observations in our sample (n = 125).

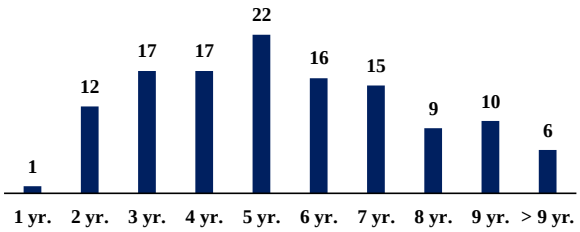
Graph A: MOIC distribution



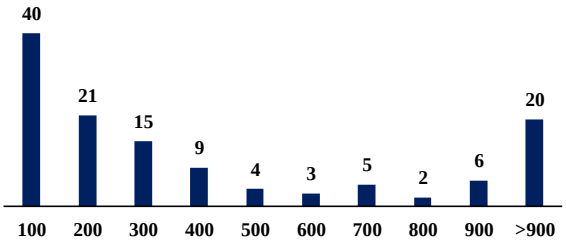
Graph B: IRR distribution



Graph C: Holding period distribution (in years)



Graph D: Entry EV distribution (in € million)



Appendix 8: Ten deals with highest return, holding period, and size

The table below shows the ten deals in our sample with the highest MOIC, IRR, holding period (in years), and EV at entry (in € million). The differences between the MOIC and IRR metrics become clear when comparing the top ten deals by each metric. Only three of the ten best deals by MOIC are among the ten best deals by IRR.

Table A: Ten deals with highest MOIC

Target	Consortium	Entry	Exit	Holding	Entry EV	Exit EV	*MOIC*	*IRR*
Biovitrum AB	Patricia Industries; Priveq; Fjärde AP-fonden	2004	2010	5.83	22	397	17.94x	64.1%
Suomen Terveystalo Työterveys Oy	MB Funds; Ilmarinen Pension Insurance	2000	2007	7.56	10	128	12.52x	39.7%
Navico Holding AS	Altor Equity; Goldman Sachs Private Equity	2005	2021	15.94	75	880	11.74x	16.7%
Hemnet Group AB	General Atlantic; Sprints Capital Management	2017	2021	4.25	211	2,235	10.61x	74.4%
AniCura TC AB	Nordic Capital; Fidelio Capital	2014	2018	4.45	220	2,000	9.09x	64.3%
Nordic Nest AB	Nordstjernan; COE Investments; Stella Capital	2015	2020	5.08	19	168	8.84x	53.6%
AutoStore AS	Thomas H. Lee Partners; EQT	2019	2021	1.81	1,616	14,209	8.79x	233.3%
TDC Song AS	Providence; Vattenfall; Stena Adactum	1999	2004	5.71	66	544	8.29x	44.9%
Petainer AB	Alpina Capital; Next Wave	2009	2016	6.48	18	140	7.91x	37.6%
Welltec A/S	Riverside; Barings	2005	2007	2.07	70	548	7.83x	170.8%

Table B: Ten deals with highest IRR

Target	Consortium	Entry	Exit	Holding	Entry EV	Exit EV	*MOIC*	*IRR*
WhiteAway A/S	Verdane; eEquity; Retail Online Holding	2013	2014	0.87	30	165	5.55x	620.1%
AutoStore AS	Thomas H. Lee Partners; EQT	2019	2021	1.81	1,616	14,209	8.79x	233.3%
Welltec A/S	Riverside; Barings	2005	2007	2.07	70	548	7.83x	170.8%
C More Entertainment AB	Baker Capital; Nordic Capital; Strax	2003	2005	1.35	70	249	3.58x	156.5%
KappAhl AB	Nordic Capital; Accent Equity	2004	2006	1.32	214	596	2.79x	117.2%
Netcompany Group A/S	FSN Capital; Danica Pension	2016	2018	2.35	268	1,618	6.03x	115.0%
A-Katsastus Oy	MB Funds; Finnish Industry Investment; Varma Mutual Pension Insurance; LocalTapiola	2003	2005	2.55	59	400	6.78x	111.6%
Gant Sweden AB	3i Group; L Catterton Management	2003	2006	2.76	82	450	5.46x	84.8%
Hemnet Group AB	General Atlantic; Sprints Capital Management	2017	2021	4.25	211	2,235	10.61x	74.4%
Byggfakta Scandinavia AB	Duke Street; MB Funds; Segulah Advisor	1996	1998	2.28	8	28	3.35x	70.1%

Table C: Ten deals with highest holding period (years)

Target	Consortium	Entry	Exit	Holding	Entry EV	Exit EV	*MOIC*	*IRR*
Navico Holding AS	Altor Equity; Goldman Sachs Private Equity	2005	2021	15.94	75	880	11.74x	16.7%
Superfos Industries A/S	IK Investment; Ratos	1999	2011	11.23	363	240	0.66x	-3.6%
Arcus ASA	Ratos; HOFF Norske Potetindustrier	2005	2016	11.18	103	398	3.85x	12.8%
Scandlines ApS	3i Group; Allianz Capital; Deutsche Seereederei Rostock	2007	2018	10.81	1,560	2,562	1.64x	4.7%
BTJ Nordic AB	Litorina; Ratos	2003	2013	9.98	48	5	0.11x	-20.0%
NeuroNova AB	HealthCap; Patricia Industries; SLS Venture	2003	2012	9.28	12	15	1.26x	2.5%
Attendo AB	IK Investment; Intermediate Capital; Varma Mutual Pension Insurance	2007	2015	8.85	493	1,475	2.99x	13.2%
ISS A/S	EQT; Goldman Sachs Private Equity	2005	2014	8.85	4,030	6,950	1.72x	6.4%
Ålö AB	3i Group; Balticgruppen	2002	2011	8.73	115	240	2.09x	8.8%
Scandic Hotels AB	Accent Equity; EQT	2007	2015	8.61	833	957	1.15x	1.6%

Table D: Ten deals with highest EV (€ million) at entry

Target	Consortium	Entry	Exit	Holding	Entry EV	Exit EV	*MOIC*	*IRR*
TDC A/S	Apax; Blackstone; KKR; Permira; Providence	2006	2010	4.85	10,200	12,843	1.26x	4.9%
Visma AS	Hg Capital; Cinven; Montagu; Intermediate Capital; GIC	2017	2019	1.67	4,700	6,500	1.38x	21.5%
ISS A/S	EQT; Goldman Sachs Private Equity	2005	2014	8.85	4,030	6,950	1.72x	6.4%
Gambro AB	Patricia Industries; EQT	2006	2013	7.27	3,773	5,490	1.45x	6.9%
Visma AS	Cinven; KKR	2014	2017	3.11	2,524	4,700	1.86x	22.1%
Verisure Midholding AB	Hellman & Friedman; Bain Capital	2011	2015	4.10	2,334	5,263	2.25x	21.9%
Anticimex AB	EQT; Volito; Sjätte AP-fonden; AMF Fonder; Cubera Private Equity	2017	2021	3.88	2,300	5,931	2.58x	27.7%
Nets A/S	Advent International; Hellman & Friedman; GIC; Fisher Lynch Capital; StepStone Group; Bain Capital	2014	2021	6.98	1,945	8,050	4.14x	22.6%
Nycomed A/S	HarbourVest; aPriori Capital; Coller International;	2005	2011	6.40	1,800	9,600	5.33x	29.9%
AutoStore AS	Thomas H. Lee Partners; EQT	2019	2021	1.81	1,616	14,209	8.79x	233.3%

Appendix 9: Descriptive statistics for subsamples

The table below presents the average and median MOIC, IRR, EV at entry (in € million), and holding period (in years) based on subsamples of the 125 deals in our dataset. The investments are classified by country of headquarters of the target company (Panel A), industry of the target company (Panel B), number of syndicate members (Panel C), the period of entry (Panel D), and the exit route (Panel E).

		Average				Median			
	# Deals	*MOIC*	*IRR*	*EV*	*HOLDING*	*MOIC*	*IRR*	*EV*	*HOLDING*
Full sample	**125**	**2.93x**	**31.4%**	**581**	**5.02**	**2.00x**	**17.7%**	**202**	**4.71**
Panel A: Geography									
Sweden	51	3.27x	26.6%	432	5.17	2.21x	15.4%	200	5.08
Denmark	30	2.59x	44.7%	952	5.26	1.93x	18.3%	343	5.03
Norway	28	2.65x	30.7%	660	4.26	1.97x	20.5%	352	3.59
Finland	15	3.09x	22.8%	216	5.63	1.82x	16.6%	102	6.12
Iceland	1	1.70x	23.9%	334	2.48	1.70x	23.9%	334	2.48
Panel B: Industry									
Industrials	32	2.45x	22.8%	536	5.77	1.79x	11.8%	167	5.66
Consumer Discretionary	19	3.18x	64.3%	371	4.35	2.30x	27.1%	80	3.73
Health Care	18	4.14x	21.5%	648	5.49	2.44x	16.8%	315	5.29
Information Technology	17	3.06x	29.4%	891	4.85	2.33x	20.5%	394	4.06
Communication Services	13	3.19x	41.8%	1,137	3.58	1.78x	30.3%	363	4.05
Materials	10	2.21x	11.7%	172	6.04	1.70x	9.0%	183	5.74
Consumer Staples	6	1.85x	14.1%	420	5.48	1.66x	14.7%	293	5.10
Energy	3	4.46x	81.9%	53	2.97	2.97x	49.2%	70	2.72
Utilities	3	2.26x	31.5%	617	4.46	2.27x	16.7%	200	5.90
Financials	2	2.60x	16.3%	673	5.94	2.60x	16.3%	673	5.94
Real Estate	2	1.29x	9.5%	164	2.38	1.29x	9.5%	164	2.38
Panel C: Syndicate members									
Two	84	2.90x	27.4%	448	5.16	1.97x	17.2%	204	4.82
Three	29	3.12x	46.4%	366	4.82	2.13x	19.5%	162	4.29
Four	6	2.47x	23.8%	563	4.27	1.81x	11.9%	157	3.39
Five	5	2.67x	21.0%	3,813	4.42	2.58x	21.5%	2,300	4.85
Six	1	4.14x	22.6%	1,945	6.98	4.14x	22.6%	1,945	6.98
Panel D: Entry period									
1996 - 2001	27	2.71x	15.1%	168	5.43	1.82x	11.6%	102	4.95
2002 - 2007	46	3.08x	30.2%	790	5.51	2.11x	16.6%	253	5.29
2008 - 2012	26	2.48x	18.5%	490	5.40	2.15x	16.4%	181	5.41
2013 - 2019	26	3.35x	63.1%	732	3.34	1.96x	24.1%	299	3.02
Panel E: Exit route									
Sale	110	2.82x	28.3%	485	5.02	1.93x	17.7%	199	4.72
IPO	15	3.77x	53.7%	1,286	5.02	2.99x	23.8%	268	4.34

Appendix 10: Correlation matrix

*The table shows the pairwise Pearson correlation coefficients between all our dependent, independent, and deal-specific control variables (n = 125). The asterisk * denotes the significance level of 10%. Most interestingly, we see that the correlation coefficient of 0.39 between our dependent variables MOIC and IRR is only moderately positive, highlighting the importance to study both return measures in tandem. Furthermore, the negative correlation between the dependent variables and EV shows that smaller deals in our sample tend to perform better than larger ones. The correlation between IRR and HOLDING is negative, as observed in previous studies (Nikoskelainen and Wright, 2007; Acharya et al., 2013; Valkama et al., 2013). We verify there is no strong correlation between our independent variables, making us confident that our proxies capture different aspects of heterogeneity. Interestingly, the correlation between HYBRID and DIST is negative, suggesting that "Other financial investors" and "Strategists" tend to co-invest if they are from the same geographic area as the GP. Furthermore, the positive correlation between HYBRID and MEMBER may show that syndicates including different investor types become more likely when the number of consortium members rises. In addition, the positive correlation between the variables DIST and EV was somewhat expected, as our sample includes many US buyout funds that are focused on the large-cap segment and thus tend to team up with buyers from different countries only for large deal sizes. Given the positive correlation between DIST and MEMBER, the geographical heterogeneity appears to be higher for a syndicate with many buyers. Moreover, the negative correlation between SIZE and CLUB (TIES) shows that overall (repeated) syndication tends to be more widespread for syndicate members of similar size. We find the highest (positive) correlation coefficient (0.54) between the variables TIES and CLUB, suggesting that repeated syndication among any pair of the syndicate members tends to happen more often if the syndicate members participate in relatively many club deals. Given the positive correlations between EV and TIES, and EV and MEMBER, we see that larger deals are characterized not only by more repeated interaction between the buyers but also by more buyers in the consortium.*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) *MOIC*	1.00												
(2) *IRR*	0.39*	1.00											
(3) *HYBRID*	-0.02	0.02	1.00										
(4) *DIST*	-0.02	-0.02	-0.16*	1.00									
(5) *SIZE*	0.04	0.01	0.16*	-0.07	1.00								
(6) *AGE*	0.15*	0.09	0.12	-0.02	0.11	1.00							
(7) *TIES*	-0.16*	-0.09	-0.14	0.09	-0.23*	-0.12	1.00						
(8) *CLUB*	-0.08	-0.08	-0.18*	0.14	-0.37*	-0.12	0.54*	1.00					
(9) *EV*	-0.31*	-0.16*	-0.11	0.32*	-0.22*	-0.26*	0.27*	0.27*	1.00				
(10) *MEMBER*	0.00	0.02	0.17*	0.29*	-0.05	-0.03	0.18*	0.02	0.21*	1.00			
(11) *MEMBER_SQ*	0.00	0.01	0.14	0.28*	-0.07	-0.05	0.19*	0.04	0.25*	0.99*	1.00		
(12) *HOLDING*	0.04	-0.36*	-0.06	0.00	0.13	0.04	0.03	0.03	-0.01	-0.06	-0.05	1.00	
(13) *EXIT*	0.12	0.13	0.00	0.06	-0.12	-0.17*	0.13	0.10	0.16*	-0.04	-0.03	0.00	1.00

Appendix 11: Multicollinearity test

In the following table, we present the Variance Inflation Factor (VIF) for our main regressions shown in Table 7. The VIF indicates how much the variation of a variable's coefficient increases as a result of collinearity. Commonly, a VIF greater than 10 indicates a strong presence of multicollinearity. In our analysis, all VIFs except the ones for MEMBER and MEMBER_SQ are below 10. The high values for MEMBER and MEMBER_SQ result logically from the definition and calculation of MEMBER_SQ and thus do not present an issue.

Variables	**(1)** **ln(*MOIC*)**	**(2)** **ln(1+*IRR*)**	**(3)** **ln(*MOIC*)**	**(4)** **ln(1+*IRR*)**
HYBRID	1.420	1.420		
FIN_INV			1.645	1.645
STRAT			1.298	1.298
DIST	1.304	1.304	1.373	1.373
SIZE	1.351	1.351	1.352	1.352
AGE	1.320	1.320	1.362	1.362
TIES	1.653	1.653	1.658	1.658
CLUB	2.044	2.044	2.046	2.046
EV	1.602	1.602	1.606	1.606
MEMBER	55.302	55.302	55.611	55.611
MEMBER_SQ	53.302	53.302	53.708	53.708
HOLDING	1.248	1.248	1.252	1.252
EXIT	1.188	1.188	1.188	1.188

Appendix 12: Robustness tests

*The table below shows the regression output of the robustness test for our OLS regression with robust standard errors. We account for extreme returns by trimming the top and bottom 1% of our sample in terms of MOIC and log-transforming our dependent variables. In Model (5), (6), (9), and (10), we use the variable HYBRID to measure the share of non-GP buyers in the syndicate. In Model (7), (8), (11), and (12), we break this variable down into the two variables FIN_INV and STRAT, which measure the ratio of "Other financial investors" and "Strategists" among the syndicate members, respectively. We control for time, industry, and country fixed effects. For a detailed discussion of the variables, please refer to Section 4.3. We run the robustness tests for all specifications, i.e., for all models including Model (1), (2), (3), and (4) as presented in Table 7. For our first robustness test, we exclude deals with an entry EV smaller than €25 million, resulting in a sample size of 115 observations (minus six observations). The results for the first robustness test are presented in Model (5), (6), (7), and (8). For our second robustness test, we exclude deals with a holding period shorter than 18 months ("quick flips"), resulting in a sample size of 116 observations (minus five observations). The results for the second robustness test are presented in Model (9), (10), (11), and (12) The excluded deals for each specification of the robustness test do not overlap, i.e., the excluded deals in the first robustness test are different from the excluded ones in the second robustness test. The robust standard errors for each variable are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.*

Variables	**(5)** **ln(*MOIC*)**	**(6)** **ln(1+*IRR*)**	**(7)** **ln(*MOIC*)**	**(8)** **ln(1+*IRR*)**	**(9)** **ln(*MOIC*)**	**(10)** **ln(1+*IRR*)**	**(11)** **ln(*MOIC*)**	**(12)** **ln(1+*IRR*)**
HYBRID	-0.483*	-0.175*			-0.388	-0.109		
	(0.245)	(0.102)			(0.246)	(0.072)		
FIN_INV			0.030	-0.138			0.249	0.027
			(0.286)	(0.166)			(0.291)	(0.082)
STRAT			-0.991***	-0.212**			-0.963***	-0.232***
			(0.287)	(0.093)			(0.286)	(0.086)
DIST	0.036	0.007	0.062	0.008	0.011	0.006	0.044	0.014
	(0.054)	(0.019)	(0.055)	(0.021)	(0.056)	(0.016)	(0.056)	(0.016)
SIZE	-0.006	-0.030	0.022	-0.028	-0.006	-0.047	0.008	-0.044
	(0.134)	(0.042)	(0.128)	(0.041)	(0.126)	(0.036)	(0.121)	(0.035)
AGE	-0.004	-0.013	0.095	-0.006	0.096	0.010	0.184	0.029
	(0.186)	(0.053)	(0.191)	(0.055)	(0.204)	(0.047)	(0.203)	(0.049)
TIES	-0.347**	-0.099*	-0.326**	-0.097*	-0.300*	-0.097**	-0.271	-0.091*
	(0.160)	(0.053)	(0.159)	(0.054)	(0.169)	(0.048)	(0.166)	(0.048)
CLUB	0.516*	0.101	0.499*	0.100	0.472	0.092	0.438	0.084
	(0.295)	(0.100)	(0.290)	(0.100)	(0.302)	(0.091)	(0.295)	(0.091)
EV	-0.203***	-0.066**	-0.206***	-0.066**	-0.168***	-0.036**	-0.160***	-0.035**
	(0.063)	(0.027)	(0.060)	(0.027)	(0.061)	(0.016)	(0.059)	(0.015)
MEMBER	0.020	0.359	0.057	0.362	-0.172	0.064	-0.282	0.040
	(0.447)	(0.275)	(0.449)	(0.275)	(0.460)	(0.119)	(0.442)	(0.117)
MEMBER_SQ	0.022	-0.048	0.012	-0.049	0.048	-0.007	0.057	-0.005
	(0.063)	(0.038)	(0.063)	(0.037)	(0.064)	(0.016)	(0.061)	(0.016)
HOLDING	-0.003	-0.039***	-0.004	-0.039***	-0.007	-0.036***	-0.011	-0.036***
	(0.037)	(0.011)	(0.037)	(0.011)	(0.040)	(0.010)	(0.039)	(0.009)
EXIT	0.415**	0.165**	0.412**	0.165**	0.420**	0.173**	0.416**	0.172**
	(0.196)	(0.073)	(0.184)	(0.073)	(0.199)	(0.072)	(0.189)	(0.071)
Constant	1.497*	0.336	1.217	0.315	1.697**	0.526**	1.562*	0.497**
	(0.790)	(0.310)	(0.789)	(0.293)	(0.810)	(0.213)	(0.791)	(0.216)
Observations	115	115	115	115	116	116	116	116
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Small deals	Yes	Yes	Yes	Yes	No	No	No	No
Quick flips	No	No	No	No	Yes	Yes	Yes	Yes
Adjusted R-squared	0.075	0.284	0.121	0.278	0.046	0.227	0.111	0.254