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# Ever-higher hanging Fruit: Analysing the Evolution of Private Equity Returns and Market Competition.

## A post-2000 analysis of US private equity returns.

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## ABSTRACT

This paper investigates the evolution of private equity (PE) returns to investors and how they are affected by permanently increasing competition. It uses net multiples on investment as the dependent variable and raised capital and dry powder as proxies for competition, as independent variables. It considers sample data consisting of 1998 PE funds based in the U.S. with vintages years ranging from 2000 to 2022 and employs cross-sectional OLS regressions to obtain the effect of an array of variables on returns. The paper concludes that raised capital has a negative and statistically significant effect on returns, and that buyout funds' returns are not more vulnerable to accumulated capital than funds following other strategies. These results shed light on the recent past of the PE and can be useful for prospective investors.



**Keywords:** private equity, returns, fundraising, competition, net returns.

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# CHAPTER 1 Introduction

Private equity (PE) markets have reached an all-time high volume of deals worth just under one trillion US dollars in 2021, and over 13.1 trillion dollars in assets under management worldwide in 2022. With investors making abnormal returns and high fees for PE firms, who manage the funds, it is unclear whether the asset class can continue to ouperform public markets in the future. Threats to the persistence of high returns come from different angles, but perhaps the most important one is competition in the industry, with rapid growth of 20% per annum since 2018, which could crowd out abnormal profits. The business model itself, which has been criticized due to its ambiguous added value, can also threaten the profits for investors, if funds cannot add enough value to their portfolio companies to produce profits after fees. After 2021, when the world economy came to a halt, high interest became a reality again which has increased the costs of debt. Higher yields on bonds raised costs for PE firms, who fund their acquisitions through the use of risky debt, and lowered valuations for investments that need to be sold at the end of a fund's life. These conditions have slumped the industry and left a backlog of firms which will eventually be sold when more favourable conditions arise. However, the golden days for private equity may be over even if interest rates go back to near zero, as competition in the market increases, and profitable investments become hard to find for a funds that raise growing amounts of capital each year. For this reason, we will analyse the effect of competition on the returns of PE investments in the last two decades and discern effects that can help us understand the evolution of the industry and produce insights for the future.

Previous academic papers have researched similar topics. Notably, Kaplan and Schoar (2005) conducted a comprehensive analysis of PE performance, shedding light on factors influencing returns and the persistence of outperformance compared to public equity markets due to focus on sectors with higher returns. Moreover, Gompers and Lerner (2000) discussed the effects of increased influxes of capital on the competition and investment strategies within the industry. Almost two decades after that, Brown and Kaplan (2019) discuss the relationship between fundraising and valuations, comparing it with public market multiples. Furthermore, Harris et al. (2013) investigated the effects of increased competition on PE returns, underscoring the challenges posed by overcrowded markets and its implications for investors. Finally, Ilmanen (2020) delves into the effect of excess capital on valuations, and how this is closing the gap of valuations with public companies. These articles collectively contribute to the current understanding PE competition and will be expanded on with this research, building on these findings, with a focus on more recent years.

The motivation for this paper comes from the increasingly important role that private equity firms play in financial markets and the high criticism of the industry, as well as the recent peak in deal

flow in recent years. If this asset class is going to play a continued important role in providing investors with returns on their capital, it is essential to get a better idea of the drivers of returns at an industry level. On top of providing a better insight on which markets can provide higher returns to investors, the findings of this paper can also shed some light on the ability of private equity markets in providing the necessary capital to help start, expand, and increase efficiency across sectors. This paper, aims to build on previous literature by taking a wholistic approach to analysing returns in PE, shedding light on industry-wide trends, which can be useful for investors and fund managers. Specifically, this paper aims to find **the effect of increased concentration of capital and competition in private equity markets on returns on capital,** possibly uncovering other drivers of returns in the process, at a sector and strategic level.

The data used to carry out this research will be taken from Prequin, using a sample including PE funds with vintage years in from 2000-2022. The dataset includes a wide array of variables, ranging from size and PE firm to various performance indicators, target performances, number of funds from the same fund managers, as well as geographical, industrial and deal size focus. Our analysis will use about 2000 datapoints, all focused on the U.S. market will provide us with a good quasi-random sample to understand the developments of the market for private equity in the largest PE regional market. We will observe performance through net multiples due to lack of private market equivalent data but will control for macroeconomic condition by including base interest rates in our analysis. Furthermore, by only looking at U.S. firms, we can increase the internal validity of this research, as investment opportunities can be assumed to be similar for competitors with the same fund sizes. By using the specific to general approach in our regression, with capital raised and dry powder as the dependent variables, we can interpret the effect of market saturation and the evolution of the industry. Additionally, we can find relevant correlations with market segments, private equity experience of the manager and scope of the fund with the returns provided by the fund. In this way, we can answer our research question without overlooking other relevant insights.

With this research, I expect to find out that increased competition in the form of higher market saturation, has eroded the returns for investors in private equity, as “low hanging fruit” is harder to find and competition leads to higher efficiency, and consequently lower margins. I also expect to see the effect of a refinement the industry altogether boosting returns as well high dependence on low interest rates in recent years, which can temporarily counter the effect of increased competition on returns. If this were true, the assumption could be made that the market for private equity investments will continue to grow until the expected return is equal to that of public markets, which would lower the average return for investors. This could be insightful for investors committing their capital for long periods of up to ten years, as their capital could be better invested elsewhere. Finally, I think that the effect of competition

within sectors will vary greatly as new trends in tech and medical technologies relieve pressure from more established sectors, allowing for higher returns.

# CHAPTER 2 Theoretical Framework

## 2.1 Previous Literature

### 2.1.1 Private equity

The private equity industry finds its origins in the mid 1900's post-war environment but became truly relevant in the 1980's thanks to the intensive use of high yield or junk bonds that facilitated high leverage deals and boosted leverage buyouts (LBOs) for the first time in history. This period was pivotal, setting the foundational structures and strategies that propelled private equity into becoming a major component of the global financial system (Gompers & Lerner, 2000). The core business of PE was that of purchasing firms, and selling it later in time at a profit. In present times, PE funds have several strategies to create value for investors, ranging from venture capital for small fast growing firms, to distressed capital funds that target distressed mature companies. However, the main strategy followed by funds, and the one that has made PE famous is the buyout fund, which consists of buying mature firms with good cash-flow and increase its valuation, relying heavily on debt to purchase the target firms. This increase in valuation could be driven by operational improvements, better governance, financial restructuring or a change in market conditions that happen during the investment period.

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With levels of capital streaming into the industry increasing and deal size surging, the industry started moving towards the spotlight, exemplified by the then largest buyout in history of RJR Nabisco. However, the industry was far from what it is today, being far less insitutionalized and familiar to investors. After its expansion in the 1980s, it would go through two other main cycles, in the 1990's with the popularization of venture capital funds, and in the 2000's riding on the wave of the dot com bubble, and seeing the formalization of the industry we now know. This shift marked the beginning of a more structured and professional industry. Scholars like Gompers and Lerner (2000) have noted that regulatory changes and financial innovations during this period facilitated the rapid expansion of the industry, enabling private equity to become a significant force in global finance. This era underscored a shift in focus towards maximizing company value through better management and strategic realignment, which remains a cornerstone of private equity strategy today (Ljungqvist 2024).

At inception, investment opportunities in private equity were presented in the form of close ended publicly traded funds, but in recent times, almost all PE funds are organized under limited partnerships. This legal structure provides a close-ended investment vehicle with a set time horizon,

typically of 10 years, with extensions being commonly used. In this structure, limited partners (LPs) commit to provide a set amount of capital to the fund, as well as to pay the general partners (GPs) through a fee system (Kaplan & Stromberg, 2009). LPs typically commit almost all of the capital in a fund, but GPs are usually required to post 1% of the fund as well. GPs are mostly private equity firms, who manage often multiple funds and take care ofoperational matters. They typically consist of small teams of highly specialized bankers or investment professionals, who can bring operational improvements to companies (Kaplan & Stromberg, 2009). Funds start investing in their "vintage year" once the capital fromt LPs is commited, and PE firms tend to have funds with vintrage years a coupe of years apart.

LPs are investors, antd they commit their capital to funds but have no influence on daily activities, being described by Mauboussin & Callahan (2020) as passive investors. Even though in the early stages of the industry, individuals accounted for a large part of the committed funds, LPs are primarily institutional investors, who can buy fund "tickets", the minimum investment, which are often priced at millions. Commited capital has been growing yearly at at rate of 10% from 2003 to 2019, even including the slowdownd that followed the financial crisis of 2008 (Time Partners). Studies such as the ones by Gompers and word (2000) have noted how changes in regulation, particularly those that enabled more extensive and more global fundraising capabilities, directly contributed to an expansion of the scale at which private equity firms could operate. Their research underscored how these regulatory changes, along with financial market innovations, provided new opportunities for PE firms to leverage extensive networks of institutional investors and tap into significant sources of capital.

Another distinctive characteristic of private equity investments is their illiquidity. Given that investors' capital is locked in for the duration of the fund, typically ten years, these investments are inherently riskier than more liquid assets. Consequently, investors demand higher returns to compensate for this illiquidity, known as the illiquidity premium. Research, such as that conducted by Kaplan and Schoar (2005), indicates that private equity has historically provided returns that compensate for this higher risk and illiquidity, although the magnitude of these returns can vary greatly depending on prevailing market conditions and the managerial prowess of the GPs. Only financial intitutions that can tolerate the long horizon of such investments, such as pension funds or insurance conpanies can lock in capital for such periods, which is therefore compensated (Gompers & Lerner, 1989).

### 2.1.2 Private Equity Returns

Following the foundational aspects of the PE industry, it is crucial to understand how private equity returns are generated. Returns primarily come from capital appreciation achieved by enhancing the operational and financial health of portfolio companies strategically. PE funds target undervalued or

underperforming companies, aiming to increase their value through leaner management, and then exit these investments at a higher market price, usually within a 4 to 7-year timeframe (Axelson et al 2013). These returns are typically realized through strategic redirection, operational improvements, and financial restructuring. The initial acquisition in this process is often significantly funded through debt, leveraging the investment, which can substantially amplify returns on equity if the turnaround strategies are successful (Kaplan & Stein, 1993). Mispricing in financing has also been discussed to drive returns of buyout funds in certain windows of time. Exploiting these mismpricing through the issuance of "junk", or non-investment-grade bonds, amplifies PE's returns on equity, as debt is one of the main costs (Kaplan & Stromberg, 2009).

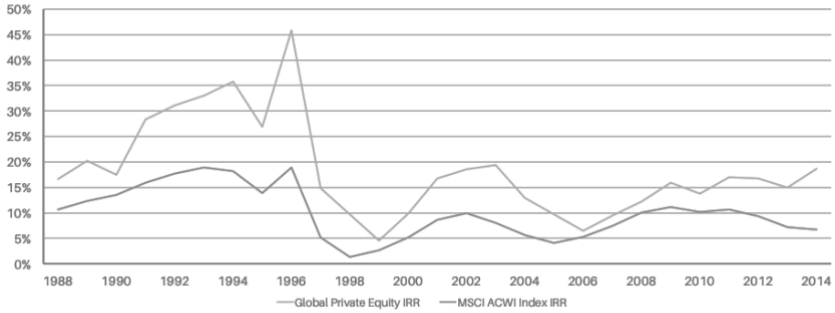
Buyout funds' reliance on large quantities of high yield debt can not be understated, as it introduces a high level of risk. If the company underperforms, the debt can become unsustainable, leading to large losses and even liquidation of assets. Axelson et al. (2013) highlighted a negative correlation between fund performance and deal leverage, indicating that excessive borrowing does not invariably contribute positively to PE returns. This relationship underscores the delicate balance PE firms must navigate in leveraging their investments to optimize returns without overextending its risk. Regulation on admissible debt levels for private equity firms has complicated PE firms' desire to lever companies as much as possible in recent decades, but decreasing bond yields have countered this effect, as found in Ilmanen's paper (2020).

Specialization within private equity is a discussed driver of returns. Cressy, Munari, and Malipiero (2007) emphasize that firms specializing in specific sectors can leverage their deep industry knowledge to improve value creation, highlighting the benefits of in-depth expertise over a generalized investment approach. Furthermore, the strategic use of financing windows—specific periods when favourable financing terms are available—can also substantially impact returns by reducing costs and enhancing equity returns upon exit (Cressy, Munari, & Malipiero, 2007). A similar study by Gruener & Marburguer (2022) further researched the effects of specialization on fund returns. The results indicate that PE firms that specialize on a few industries generate higher returns, but that geographical specialization in specific region does not. These positive returns can originate from better specific managerial and operational knowledge, but also through better connections in the industry, superior knowledge on pricing of illiquid assets. However, firms PE firms' ability to consistently generate abnormal returns is disputed, with studies arguing mean reversion for funds launched after very successful funds by the same firm (Rossi, 2019).

Some research has also pointed to macroeconomic factors affecting the performance of private equity funds. Sommer (2012) finds that funds that are started in periods of economic downturn can capitalize on lower valuations for target companies, improving returns. This paper also finds that investments in PE are highest in times of economic prosperity, which negatively affects returns. This

factor cannot be fully controlled by PE firms, as most launch funds on a periodic basis of 2 to 5 years, and can not always time to enter after economic downturn (Ljungqvist 2024). Other studies focus on the effect of synergies leading to operational imporvements and higher exit valuations. Banga (2019) delves into the possible added return of buy and build strategies, which consist of buying a "platform" company to which other acquisitions can be incorporated to not only benefit from operational imporvements, but also capitalize on the synnergies that arise. This strategy is employed mostly by growth funds.

Figure 1: Internal rate of return of global private equity and MSCI index from 1988 to 2014.




*Source: Burgiss Private iQ, as of September 30, 2018. Global Private Equity includes buyout, venture, growth, and generalist private equity funds. Contemporaneous IRRs of the MSCI ACWI are derived via Direct Alphas as per Gredil, Griffiths, and Stucke (2014).*

Historically, buyout fund returns have outperformed public markets, with research finding a 3.5% value wheighed alpha on public market equivalents (Harris, 2013). This same study finds a 20% outperformance over equities over the life of an average fund. Studies researching the nature of these positive abnormal returns found that they might partly be caused due to a higher risk that comes with the investment, dson top of a illiquidity premium. In fact, Brown & Kaplan (2019) finds betas of target companies to be between 1 and 1.3, with the average being 1.2, which could explain the alpha genreated by buyout funds, as the market goes up on average. Furthermore, investment in smaller companies can also lead to robust returns. As Brown (2019) discusses, smaller companies often offer greater growth potential and operational flexibility than larger, publicly traded companies, providing ripe opportunities for private equity firms to implement aggressive growth strategies and realize substantial returns.

The historical context of PE returns also reflects the cyclical nature of this industry, heavily influenced by broader economic conditions and market liquidity. The initial successes in the 1980s, as documented by Kaplan and Stein (1993), attracted significant capital inflows into the market, leading to intense competition for deals. This influx of capital, in turn, resulted in many transactions in the late 1980s being overpriced and excessively leveraged with high-risk debt. Such conditions often precipitated market corrections, with many of these highly leveraged deals failing in subsequent years.

### 2.1.3 Measuring Returns

The reporting of returns in private equity is not a straighforward matter, unlike in public markets, as pricing information is scarce. GPs are largely responsible for pricing their fund's portfolio, and thanks to loose guideline, as well as the low liquidity of their assets, they can somewhat manipulate unrealised returns. Actual returns can only be calculated when a fund is liquidated, or when assets suddenly become liquid. Factors such as the timing of the exit, prevailing economic conditions, and market sentiment at the time of exit all play crucial roles in the final return realized. For instance, returns on deals made at the peak of economic cycles may appear unfavorably skewed when these investments are liquidated during downturns. The World Economic Forum has noted the variability in fund performance, stating that a winning fund is as likely to be followed by a loser, which highlights the unpredictability and subjectivity in PE returns (Lerner, Andrews, and Sheth 2022).

Artificial smoothing of returns is another critical aspect to consider. Unlike public market investments that frequently mark assets to market values, private equity investments are typically revalued less often, sometimes only several times throughout the life of the investment. This practice can lead to artificially smooth return profiles, potentially misleading investors about the true risk and performance of their investments. However, as Ilmanen (2020) points out, institutional investors often appreciate this smoothing as it aligns with their long-term investment horizons and risk management strategies, providing a more stable foundation for strategic asset allocation.

The timing of returns is a significant lever under the control of general partners (GPs) in private equity. GPs can optimize returns through strategic decisions on the timing of exits and repricing of assets, aiming to exit their investments during favourable market conditions or when sector-specific circumstances are most advantageous. While can enhance unrealised returns, it can also introduce biases in performance reporting, particularly if exits are strategically timed to coincide with fundraising efforts to attract new investors (Kaplan & Stromberg, 2009). Furthermore, studies found that LPs perceive a lower risk for their stake in the fund, as assets are not continuously priced, and the pricing is up to interpretation of the GPs. This leads to biases, where GPs reprice their portfolios often when they appreciate but do this less when it can confirm a poor performance (Harris, 2013).

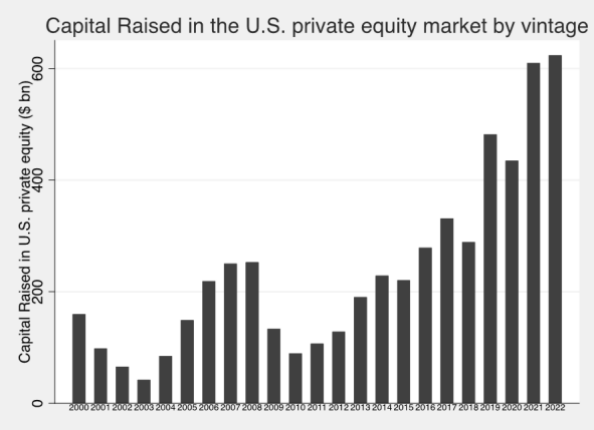
In private equity, returns are typically recorded by two principal metrics: multiples and internal rates of return (IRR). Multiples, such as cash-on-cash returns or total value to paid in capital (TVPI), offer investors a straightforward, easily understandable comparison between the initial investment and its exit value, serving as a snapshot of the value creation achieved during the investment period. These are preferred for their simplicity and transparency. On the other hand, IRR accounts for the time value of money, providing an annualized effective compounded return rate. However, the sensitivity of IRR to the timing of cash flows, combined with its dependence on reinvestment rate assumptions. This can

present an overly optimistic view especially if significant returns are realized later in the investment period. The tendency to reprice portfolio companies more frequently when they appreciate, but not when they decrease in value is also mitigated by using multiples on investment, such as TVPI and distributed to paid in capital (DPI) as they look at the return on investment net of fees. Kaplan and Schoar (2005) suggest, while both IRR and multiples correlate strongly with the public market equivalent (PME), multiples often provide greater explanatory power, offering a robust indicator of fund performance relative to public markets.

### 2.1.4 Competition in Private Equity

The PE industry has undergone remarkable growth, characterized by a substantial increase in both the number of funds and the amount of capital committed, as illustrated in figures 2 and 3. This influx of capital has led to heightened competition within the industry, impacting investment strategies and the overall market dynamics (Gompers & Lerner, 2000). The evolving landscape is further influenced by sector-specific shifts, particularly towards high-growth areas such as technology and healthcare, see figure 5 in the appendix, reflecting broader economic trends and a strategic pivot towards sectors with higher returns (Kaplan & Schoar, 2005).

Figure 2: capital raised by vintage in the U.S. private equity market.

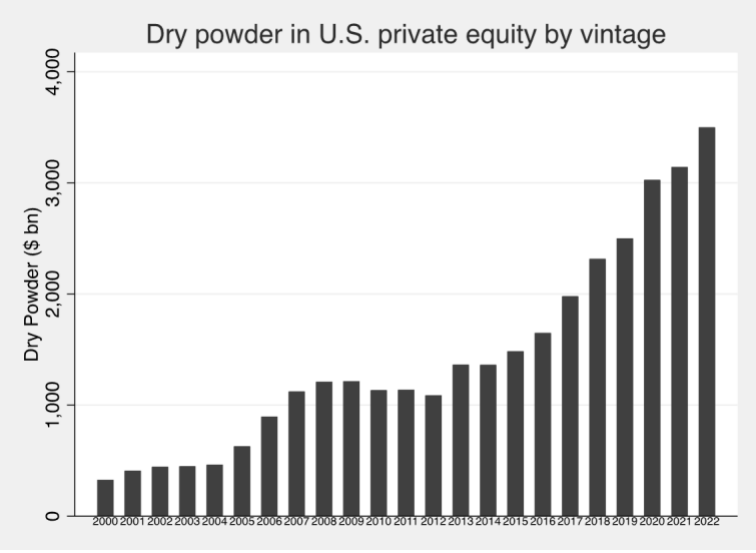



The relationship between committed funds and private equity performance has become a critical area of study. Brown and Harris (2020) note that the cyclical nature of PE commitments, influenced by economic and market cycles, significantly affects fundraising activities and investment valuations. Kaplan and Schoar (2005) and Gompers and Lerner (2000) find that increased commited capital to PE drives competition for deals up, and leads to the dilution of returns. Furthermore, Brown and Kaplan (2019) discuss the inverse relationship

between public market equivalents (PMEs) and fundraising, suggesting that as more funds enter the market during periods of high valuation, fundraising efficiency tends to decrease. This dynamic indicates that the timing of fund commitments is crucial, yet only the commitment of funds can be controlled, not the timing of the investment itself as contributions to funds span over the first years of the fund. This makes it hard for LPs to time the market, which can be attempted in public markets.

Recent trends in the industry have significantly altered the nature of competition among private equity firms. There is a growing emphasis on sophisticated investment strategies that include operational improvements and industry consolidations, often leveraging sector-specific expertise to drive substantial value creation (Kaplan & Stromberg, 2009). Additionally, the significant accumulation of dry powder — capital committed to PE funds but not yet deployed — highlights the challenges of finding adequate investment opportunities that meet return thresholds in a competitive market. This scenario often leads to intensified competition and potentially overinflated asset prices, affecting overall investment quality. As can be seen in figure 6 in the appendix, valuations for portfolio companies vary in time and within sectors, also in part due to competition.

Figure 3: dry powder in the U.S. private equity market from 2000 to 2022.




The increasing levels of dry powder, as seen in figure 3, have also impacted valuation multiples, rise as more capital chases a limited number of high-quality deals. Ilmanen (2020) discusses how this excess capital leads to increased valuations, narrowing the gap between public and private market valuations. Moreover, Bauga (2019) notes that high levels of

undeployed capital can lead to inflated asset prices, ultimately impacting the returns achievable from these investments. Gompers & Lerner (2000) argue a similar point, stating that high liquidity in a fund increases the pressure to invest, deteriorating deal quality. This can also be true for the industry as a whole, and an issue excaerbated by the low yield environment of the past decades, which increases liquidity at an industry level.This trend necessitates a disciplined investment approach to ensure that capital deployment aligns with strategic investment opportunities without compromising quality.

The private equity sector is characterized by its dynamic nature, influenced by an array of factors including capital inflows, evolving investment focus, and competitive dynamics. As the industry matures, these elements collectively shape the competitive landscape, requiring PE firms to continually adapt to maintain their edge in achieving high returns. The academic insights from Demaria (2013) highlight how capital inflows, particularly from institutional investors, reshape the competitive dynamics and affect investment strategies within the industry. Firms that develop niches or specialize in particular sectors can mitigate some of the adverse effects of increased competition by leveraging their deeper market knowledge to execute more effective investment strategies (Cressy, Munari, & Malipiero, 2007).

### *2.2 Expectations and Hypothesis*

Even though the mentioned studies have already discussed some reltations concerning PE returns and campotetition, there are none that have focused only on the effects of competion in the private equity market in the U.S. in recent decades. Harris (2014) carried out similar research, however, the timespan of the data used, starting at 1984, reflects a past state of the industry. Furthermore, this paper will focus only on PE returns, controlling for relevant variables, but not including public equities. In this paper, we expect to find that increased reaised capital by the PE industry diminishes returns for investors, net of fees and that the effect of competition in the industry exists to different degrees, as buyout funds attract more capital. This in turn, means that the effect of excess capital in the buyout stratewgy has a larger negative effect on net returns than for other strategies, such as growth, fund of funds and co-investment funds. These expectations can be summarized with the following two hypothesis.

Hypothesis 1: Increased competition in the U.S. private equity industry, measured as an increase in yearly commited capital negatively affects PE net returns on invested capital.

Hypothesis 2: The effect of competition, measured by dry powder available on the vintage year of a fund is negative on net returns, is negative and more significant for buyout funds than other strategies.

# CHAPTER 3 Data

For the research carried out in this paper, the main dataset is sample cross-sectional fund-level data from the alternative investments-specialized database Prequin. The used dataset consists of nearly 2000 individual funds, containing a large array of variables at the fund level from the year 2000 to the present. Prequin is the largest and arguably most reputable source of data for private equity and is trusted and used by most professionals in the industry. The data sample it provides, can be used for research, but the main use is for investors and industry insiders who want to have insights on the market or any certain fund. The reputational effect of being included in such a platform are high. The collection method for their data is varied, and a lot is inputted by funds directly. Data also comes from LP's reports, and they can request further data under the freedom of information act. They have strict guidelines for the submission of fund-level data, which is revised and cross-checked to ensure the highest possible accuracy of the data. Most of the funds included in the sample are based in North America, with a primary focus on the U.S. This is not an issue, as it is unsurprising, giving the development of the U.S. private equity market in respect to other geographies, and is appropriate to this analysis as we will focus on the North American region.

More data was also taken from the Prequin dataset to carry out this analysis, specifically median valuations in private equity, dry powder in the aggregate and in specific strategies, capital raised and number of funds. This time series data is collected for the years 2000-2022 and is again obtained by Prequin through direct submission and validation by their internal team. All values were retrieved for the private equity industry, for funds registered in North America. This englobes all the funds that operate with a focus in the U.S. that are also locals, as even though many are registered in the U.S. Virgin Islands these fall under North America. This focus solely on local U.S. funds both for the industry level data and the fund level data also ensures that our results are not biased against funds who operate in the U.S. but are not locals and might therefore have access to fewer deals or worse opportunities.

The final source of data that will be used in this research is time series data for the U.S. federal funds effective rate and the CCC U.S. high yield option adjusted spread provided by the Federal Reserve Bank of Saint Luis. These two time series datasets are important to control for the effect of the rising cost of debt, which is private equity's main instrument in creating returns. This data is available for the period 2000-2022 and is presented on a yearly frequency, taking the average for the entire year's values.

Separating the cost of borrowing will be pivotal to this analysis, as it can separate the costs of borrowing for private equity, which relies on junk bonds to finance their purchases, from the federal funds rate, since the year 2000 indicates the state of the U.S. economy. This will allow to discern the effect of increasing rates on private equity from that of increased cost of low rated debt, which can indicate low confidence in private equity individually, and not necessarily a weak U.S. economy.

The data used however has some limitations that while not necessarily deteriorating to the quality of this analysis, must be kept into account. Firstly, is the fact that while the data is crosschecked and verified, submissions are voluntary, and therefore there might be a bias towards better performing funds being more available, and in turn better multiples and returns being present in this sample than in the population of the total private equity market. This can bias some of the estimators positively as their coefficients would have to capture this "abnormal" positive performance respect to the market, if there is one. This however is a limitation that can be contained, as private equity firms that submit information once are likely to submit information on posterior funds, which on average should regress to the mean performance of the industry. Another limitation is the span of the data that is the span of the study, as even though there is fund level data from 1985 up to the present, albeit in smaller quantities, we can only examine the period starting in 2000 up to 2022. This is due to the span of the junk bond spreads and the valuation medians, committed capital amounts and dry powder levels only being available since 2000. Furthermore, we exclude funds with vintages after 2022 as we can presume that those funds have not had sufficient time to carry out their investments and price them properly, a limitation recognized by L'Her et al (2016).

Finally, a last limitation we have with our data is that because we aggregate funds in vintage years, we need to match the aggregation level for variables such as committed capital, valuation multiples, federal fund rates and spreads. This can remove some of the accuracy from this analysis, but it is simply not possible to use a lower aggregation, such as monthly as this frequency is not available for all datasets.

## Variables

### Dependent Variable

The Dependent variable at the centre of this analysis is the *netmultiple*, as provided directly by Prequin for each fund. This variable represents the realised or expected value for investors, depending on the extent to which the fund is liquidated. It is based on the DPI and RVPI values of each fund, which are net of fees. It therefore represents the multiple of value created for every dollar invested by a LP. For this research, we use *netmultiple* as a proxy for true fund performance.

*netmultiple:* can be obtained by adding the DPI and RVPI both in percentage form and dividing the addition by a factor of 100. This variable represents the received or expected to receive dollar value for each dollar invested into the fund by LPs.

Independent Variables

*raisedbillions:* raised capital to private equity markets in the U.S. on a given calendar year, in billions.
*drypowder:* dry powder (funds available to invest) in the U.S. private equity market, measured in billions at the end of each year.

Control Variables

To control for differences in funds' performance that might arise from
*vintage*: variable contains a numerical value, referring to the year of the vintage of that specific fund. This vintage year will later be used to merge the datasets and add industry level or macroeconomic data.
*strategy:* string variable that describes the strategy followed by the GP, having four possible values: "Buyout" "Co-investment" "Growth" or "Fund of Funds".
*primaryregion:* this variable specifies the region of focus for each investment fund. For this analysis we only use fund that focus on North America.
*fundsize:* this numerical value denotes the final closing value of capital commitments to the fund in millions of dollars.
*fundnumbero:* this numerical variable denotes weather the fund is the first fund set up by a particular private equity firm. A value of 1 indicates the fund being the first fund launched by that firm.
*fundnumbers:* this numerical variable indicates the position of a fund in a series of funds from the same private equity firm. A value of 1 indicates the fund being the first fund of a given series of funds.
*mainindustry:* string variable that includes one of eight core industries that the fund specializes on.
*medevebitda:* this numerical value is the median ev/ebitda multiple for private equity transactions in the U.S. for a given year.
*medevrevenue*: median value of ev/revenue paid for private equity transactions in the U.S. for a given year.
*fedrate:* federal funds rate for U.S. treasuries, average value for a entire year.
*spread:* spread between the U.S. federal fund rate and junk rated bond yields, average yearly value.
*venturepowder:* powder (funds available to invest) in the U.S. private equity, venture capital, measured in billions at the end of each year.
*buyoutpowder:* powder (funds available to invest) in the U.S. private equity, buyouts, measured in billions at the end of each year.

*growthpowder:* powder (funds available to invest) in the U.S. private equity, growth, measured in billions at the end of each year.
*coinvestmentpowder:* powder (funds available to invest) in the U.S. private equity, co-investment, measured in billions at the end of each year.
*fundoffundspowder:* powder (funds available to invest) in the U.S. private equity, venture investment, measured in billions at the end of each year.

# CHAPTER 4 Method

## *4.1 Method Explanation*

To answer the questions central to this paper, we will make use of OLS regression on the cross-sectional data to obtain the coefficients of the estimators for the relevant independent and control variables. A specific to general approach will be used, including all potentially relevant estimators, and ending up selecting only those that respect OLS assumptions and economic theory. The reduction of the more extensive model will be carried out by looking at the collinearity and added explanatory power. This will finally yield a simplified and correct regression from which to evaluate the possible drivers of PE fund performance.

## *4.2 Descriptive statistics*

Firstly, we will look at the descriptive statistics from the dataset as well as the distribution of relevant variables of funds from our dataset. As can be seen from the table below, complete data was used, yielding the same number of observations for all variables.

Table 1: descriptive statistics for the dependent, independent, and control variables.

| Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| netmultiple | 1,998 | 1.8441 | 1.0504 | 0 | 26.81 |
| raisedbill~s | 1,998 | 257.7060 | 155.367 | 42.24 | 623.86 |
| fundnumbero | 1,998 | 6.9505 | 10.4797 | 1 | 108 |
| fundsize | 1,998 | 1068 | 2126.11 | 0.5 | 24713.8 |
| medevebitda | 1,998 | 9.2269 | 1.6132 | 4.8 | 12.7 |
| fedrate | 1,998 | 1.8159 | 1.8944 | 0.0787 | 6.23743 |
| spread | 1,998 | 10.7232 | 4.1749 | 5.8685 | 20.9978 |
| L1_spread | 1,998 | 10.5467 | 4.0179 | 5.8685 | 20.9978 |
| L2_spread | 1,998 | 11.0065 | 4.0755 | 5.8685 | 20.9978 |

| | | | | | |
|---|---|---|---|---|---|
| L3_spread | 1,998 | 11.3919 | 4.5145 | 5.8685 | 20.9978 |
| diversifiedi | 1,998 | 0.6291 | 0.4832 | 0 | 1 |
| buyoutpowder | 1,998 | 494.5843 | 229.3762 | 147.4 | 948 |
| coinvestme~r | 1,998 | 11.8984 | 12.8401 | 0.9 | 48.1 |
| fundoffund~r | 1,998 | 119.4719 | 58.2341 | 36.8 | 274.8 |
| growthpowder | 1,998 | 107.1672 | 91.4195 | 10.7 | 339.6 |

Table 1 shows the mean, standard deviation and ranges for our considered variables, presenting some noteworthy remarks. The performance of funds is highly variable, ranging from a total loss of the initial investment to over a 26-fold return. The variables for funds raised and drypowder also show an extensive range, having increased by a factor of ten and almost fifty respectively from the early 2000's to 2022. Dry powder in buyout funds is by far the largest, but excess liquidity in co investment funds has increased the most. The number of funds per firm with a mean of 7 indicates that on average private equity firms launch several funds, with the top players mounting close to 100 individual funds. The average fund series with 3 to 4 funds suggests that even market know how dissipates over time, with maximum values much lower than overall funds per firm. Fund size shows a large range and standard deviation, which is logic given the diversity of our dataset. The median yearly valuation metrics show a relative stability, with a low standard deviation, but a considerable range. The same is true for the federal funds rate and the spread with junk rated bonds, which shows the extent to which economic conditions have changed in our chosen period.

Table 2: distribution of PE funds in dataset by industry

| **mainindustry** | **Freq.** | **Percent** | **Cum.** |
|---|---|---|---|
| Business Services | 49 | 2.45 | 2.45 |
| Consumer Discretionary | 105 | 5.26 | 7.71 |
| Diversified | 1,257 | 62.91 | 70.62 |
| Energy & Utilities | 48 | 2.40 | 73.02 |
| Financial & Insurance Services | 42 | 2.10 | 75.13 |
| Healthcare | 127 | 6.36 | 81.48 |
| Industrials | 111 | 5.56 | 87.04 |
| Information Technology | 203 | 10.16 | 97.20 |
| Raw Materials & Natural Resources | 6 | 0.30 | 97.50 |
| Real Estate | 6 | 0.30 | 97.80 |
| Telecoms & Media | 44 | 2.20 | 100.00 |
| **Total** | 1,998 | 100 | |

Table 2 displays the distribution of main industries of focus for investment at a fund level. Most funds are diversified, meaning that they focus on several industries. After diversified, the most common main industries of focus are information technology, healthcare, consumer discretionary, and industrials, with other sectors trailing behind in frequency. These sectors have undergone a lot of growth in the past decades, and perhaps for this reason are the more frequent ones on which firms focus. Furthermore, the choice to specialize in one main industry leads to increased specialization but could also prove to be negative for diversification purposes.

### *4.3 Variable Construction*

The metric used as a proxy for fund performance is the net multiple. It represents the received or expected to receive return as a multiple for the investment made by LPs. This variable is chosen as it ignores fee structures, making findings more generalisable, as fees can vary in several ways across funds, and are excluded from this analysis. This proxy for performance is the most appropriate for this analysis, as compared with IRRs, as it ignores timings, which are less determinant to LPs, due to higher patience and expectations of illiquid, long-term investments. The net multiple variables can be calculated using the following formula:

Equation 1:

$$netmultiple = \frac{DPI(\%) + RVPI(\%)}{100}$$

Regarding independent variables, three lags were created for the *fedrate* and *spread* variables. This will help discern the effect of these variables in the years following the launch of the funds. The lagged variables are constructed following:

Equation 2:

$$LT\_fedrate(vintage) = fedrate(vintage + T)$$

Equation 3:

$$LT\_spread(vintage) = spread(vintage + T)$$

Furthermore, a binary variable for industry will be created in the process or refining our model, indicating if the fund had a single industry focus, or a diversified approach across multiple industries. This variable takes value 1 when the *mainindustry* variable is “Diversified”, else it takes value 0. Dummy variables were also constructed to be able to capture the effects of dry powder across different private equity strategies. These variables were constructed by taking the dry powder for a given strategy and multiplying it by a dummy variable that take value 1 for a given strategy. It therefore retrieves the dry powder level for the fund’s strategy for the vintage year of the fund. For instance, the variable that retrieves dry powder for buyout funds is structured in the following way:

Equation 4:

$$gen\ buyout\ = (strategy\ ==\ \text{"Buyout"})$$

$$gen\ drypowder\_buyout = buyout * buyoutpowder$$

### *4.3 Model Building*

Following a specific to general approach to develop the most appropriate model for this regression, the first model included all possible predictors that could add power to the regression. This led to the following extensive model:

Equation 5:

$$\begin{aligned} netmultiple = {} & \beta_1 raisedbillions + \beta_3 fundnumbero + \beta_4 fundnumbers + \beta_5 fundsize \\ & + \beta_6 medevebitda + \beta_7\, medevrevenue + \beta_8 spread + \beta_9\, L1\_spread \\ & + \beta_{10} L2\_spread + \beta_{11} L3\_spread + \beta_{12} fedrate + \beta_{13}\, L1\_fedrate \\ & + \beta_{14} L2\_fedrate + \beta_{15} L3\_fedrate + \beta_{16} industry\ dummy + \varepsilon \end{aligned}$$

The first step to simplify this model is to determine the appropriate number of lags that optimizes this model. To do this, we compare all the possible combinations of regressions with different numbers of lags for both *fedrate* and *spread*, taking the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) into account for our decision. These information criteria don't give an absolute value for the quality of the model, but minimizing this value is optimal, as it indicates that the model loses the least information, accounting for the added complexity of adding additional variables. The model with 3 lags of spread and 0 lags of *fedrate* provides the lowest value for both AIC and BIC and will therefore be the one adopted.

Equation 6:

$$\begin{aligned} netmultiple = {} & \beta_1 raisedbillions + \beta_2 drypowder\ \beta_3 fundnumbero + \beta_4 fundnumbers \\ & + \beta_5 fundsize + \beta_6 medevebitda + \beta_7\, medevrevenue + \beta_8 spread \\ & + \beta_9\, L1\_spread + \beta_{10} L2\_spread + \beta_{11} L3\_spread + \beta_{12} fedrate \\ & + \beta_{13} industry\ dummy + \varepsilon \end{aligned}$$

Table 3: Indicators for fit of the regression drawn from equation 6.

| | |
|---|---|
| **Number of obs.** | 1,998 |
| **F(22, 1975)** | 10.22 |
| **Prob > F** | 0.0000 |
| **R-squared** | 0.1022 |
| **Adj R-squared** | 0.0922 |
| **Root MSE** | 1.0008 |

Table 4: Results of regression of net multiple on raised billions, dry powder and control variables, including dummy variables for main industry.

| **netmultiple** | **Coefficient** | **Std. err.** | **t** | **P>t** | **[95% conf.** | **interval]** |
|---|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| raisedbillions | -0.0017 | 0.0006 | -2.62 | 0.009 | -0.0029 | -0.001 |
| drypowder | -0.0002 | 0.0001 | -1.65 | 0.099 | -0.0004 | 0.0000 |
| fundnumbero | -0.0023 | 0.0024 | -0.97 | 0.334 | -0.0071 | 0.0024 |
| fundnumbers | 0.0090 | 0.0101 | 0.90 | 0.371 | -0.0108 | 0.0289 |
| fundsize | -0.0000 | 0.0000 | -2.10 | 0.035 | -0.0000 | 0.0000 |
| medevebitda | 0.0265 | 0.0269 | 0.98 | 0.326 | -0.0264 | 0.0794 |
| medevrevenue | -0.0288 | 0.1651 | -0.17 | 0.862 | -0.3525 | 0.2949 |
| spread | -0.0165 | 0.0078 | -2.13 | 0.033 | -0.0318 | -0.0013 |
| L1_spread | -0.0297 | 0.0089 | -3.34 | 0.001 | -0.0471 | -0.0122 |
| L2_spread | -0.0097 | 0.0114 | -0.85 | 0.395 | -0.0321 | 0.0127 |
| L3_spread | -0.0320 | 0.0073 | -4.39 | 0.000 | -0.0463 | -0.0177 |
| fedrate | -0.1084 | 0.0195 | -5.57 | 0.000 | -0.1465 | -0.0702 |
| industry_dummy1 | 0.4807 | 0.4357 | 1.10 | 0.270 | -0.3737 | 1.3351 |
| industry_dummy2 | 0.4649 | 0.4224 | 1.10 | 0.271 | -0.3634 | 1.2932 |
| industry_dummy3 | 0.6109 | 0.4111 | 1.49 | 0.137 | -0.1953 | 1.4172 |
| industry_dummy4 | 0.1348 | 0.4353 | 0.31 | 0.757 | -0.7188 | 0.9884 |
| industry_dummy5 | 0.3023 | 0.4388 | 0.69 | 0.491 | -0.5582 | 1.1627 |
| industry_dummy6 | 0.6082 | 0.4204 | 1.45 | 0.148 | -0.2163 | 1.4326 |
| industry_dummy7 | 0.5320 | 0.4221 | 1.26 | 0.208 | -0.2958 | 1.3598 |
| industry_dummy8 | 0.7979 | 0.4175 | 1.91 | 0.056 | -0.0209 | 1.6166 |
| industry_dummy9 | 0 | (omitted) | | | | |
| industry_dummy10 | 0.4646 | 0.5824 | 0.80 | 0.425 | -0.6775 | 1.607 |
| industry_dummy11 | 0.5378 | 0.4373 | 1.23 | 0.219 | -0.3198 | 1.395 |
| _cons | 2.9320 | 0.5161 | 5.68 | 0.000 | 1.9199 | 3.944 |

After running the regression for this model, as can be seen in (table above), some predictors that are central to this research show a low statistical significance, perhaps due to collinearity with similar variables. The most extreme example is the median valuation ratios, which are both statistically insignificant, as well as the fund number in the series and the overall fund number, for which the same issue exists. Furthermore, one of our two main independent variables, *drypowder* is only significant at a 90% significance level, which could be connected to a correlation with *raisedbillions*. However, due to this variable being central to the question at hand, it can not be dropped altogether. To simplify the model and reduce redundant variables, we will take out *medianevrevenue* and *fundnumbers*. This choice is motivated by the importance of EBITDA valuation multiples in later stage private equity. As opposed to venture capital, where revenue multiples can be more useful for non-profit generating companies, EBITDA multiples provide a better valuation proxy for the targets of later stage funds. As for dropping

*fundnumbers*, it allows us to analyse the long-term effect of GP's experience in the industry as a predictor of fund performance.

Finally, given the low significance of the dummy variables for the industry of focus for a given fund, we will modify the variable by generating a binary variable which equals 1 when the fund is diversified across industries, and 0 otherwise. This will shadow some industry specific insights but bring clarity to the importance of having a diversified industry approach. The resulting model is:

Equation 7:

$$netmultiple = \beta_1 raisedbillions + \beta_2 drypowder + \beta_3 fundnumbero + \beta_4 fundsize + \beta_5 medevebitda + \beta_6 fedrate + \beta_7 spread + \beta_8 L1spread + \beta_9 L2spread + \beta_{10} L3spread + \beta_{11} fedrate + \beta_{12} diversifiedi + \varepsilon$$

Table 5: Multicollinearity test for aggregated drypowder model and model with drypowder by strategy.

| **Variable** | **VIF** | **Variable** | **VIF** |
|---|---|---|---|
| drypowder | 16.40 | drypowderbuyout | 9.41 |
| raisedbillions | 14.21 | raisedbillions | 7.82 |
| medevebitda | 3.67 | drypowdergrowth | 7.19 |
| L2_spread | 2.81 | drypowderfundoffunds | 4.72 |
| fedrate | 2.52 | medevebitda | 3.66 |
| L1_spread | 2.49 | L2_spread | 2.61 |
| L3_spread | 2.10 | L1_spread | 2.47 |
| spread | 2.03 | spread | 2.04 |
| fundnumbero | 1.08 | L3_spread | 2.03 |
| diversifiedi | 1.06 | fedrate | 1.65 |
| fundsize | 1.04 | fundnumbero | 1.32 |
| | | fundsize | 1.14 |
| | | diversifiedi | 1.13 |
| Mean VIF | 4.49 | Mean VIF | 3.63 |

Looking at the Variance Inflation Factor (VIF) test on carried out on the resulting model in the left side of table 5, we can observe unusually high values for *drypowder* and *raisedcapital*. This is unsurprising, considering the low significance observed in previously in the extensive model. However, VIF values larger than 15 indicate very high multicollinearity, which might also exist due to the presence of another variable. Dividing the drypowder variable in four dummy variables for dry powder in each fund strategy can help target the effect of excess liquidity more precisely. The right side of table 5 shows a steep reduction in VIF values, under 10, which is commonly deemed acceptable. However, there remains some multicollinearity between drypowder across strategies, valuation multiples, raised capital,

available liquidity and spreads, which is however understandable and can be tolerated. This finally yields the following model.

Equation 8:

$$netmultiple = \beta_1 raisedbillions + \beta_3 fundnumbero + \beta_4 fundsize + \beta_5 medevebitda + \beta_6 fedrate + \beta_7 spread + \beta_8 L1spread + \beta_9 L2spread + \beta_{10} L3spread + \beta_{11} diversifiedi + \beta_{12} buyoutpowder + \beta_{13} coinvestmentpowder + \beta_{14} fundoffundspowder + \beta_{15} growthpowder + \varepsilon$$

# CHAPTER 5 Results & Discussion

## 5.1 Interpretation

To understand the results from our statistical analysis, it is important to have a good understanding of how to interpret the results in the first place. Having used an OLS regression with several linear predictors, we obtain coefficients, which indicate the magnitude and sign of our effects. This implies that an increase by one unit in the independent variables leads to a change in the magnitude of the coefficient on our dependent variable, net multiple. For dummy variables, the coefficient is the change on the dependent variable when the dummy variable takes value 1. Furthermore, this section will look at the statistical significance of each predictor, denoted by the P-values. Values close to 0 indicate statistical significance, and are of great importance, as statistically insignificant coefficients require further explanations to be considered as valid predictors.

The statistical significance of the whole regression is also important and, values for F-tests are presented, which tests the statistical significance of the model. Again, values near 0 indicate high significance. Finally, R squared values and adjusted R squared are also presented, which indicate how much of the variability in the dependent variable is explained by the model. A value of 1 indicates that the model has perfect explanatory power. The adjusted R squared value considers how much variability is accounted for by the model, while putting a negative weight on the use of excessive regressors.

## 5.2 Correlations

Firstly, we will look at the correlations for our variables to understand how they are connected. We can do this by looking at the correlogram for the variables in the refined model.

Table 6: Correlogram of dependent, independent and control variables from equation 8.

| | **netmul~e** | **raised~s** | **fundnu~o** | **fundsize** | **medeve~a** | **fedrate** | **spread** | **L1_spr~d** | **L2_spr~d** | **L3_spr~d** | **diversifiedi** | **buyout** | **coinvest** | **fundof** | **growth** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| netmultiple | 1,000 | | | | | | | | | | | | | | |
| raisedbillions | -0,225 | 1,000 | | | | | | | | | | | | | |
| fundnumbero | -0,038 | 0,134 | 1,000 | | | | | | | | | | | | |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| fundsize | -0,077 | 0,166 | 0,131 | 1,000 | | | | | | | | | | | |
| medevebitda | -0,136 | 0,791 | 0,148 | 0,137 | 1,000 | | | | | | | | | | |
| fedrate | -0,055 | -0,145 | -0,111 | -0,007 | -0,093 | 1,000 | | | | | | | | | |
| spread | 0,026 | -0,276 | -0,034 | -0,068 | -0,483 | -0,029 | 1,000 | | | | | | | | |
| L1_spread | 0,020 | -0,364 | -0,046 | -0,080 | -0,394 | -0,234 | 0,413 | 1,000 | | | | | | | |
| L2_spread | 0,010 | -0,387 | -0,018 | -0,045 | -0,349 | -0,208 | -0,125 | 0,499 | 1,000 | | | | | | |
| L3_spread | 0,005 | -0,334 | -0,041 | -0,040 | -0,270 | -0,045 | -0,262 | -0,098 | 0,495 | 1,000 | | | | | |
| diversifiedi | 0,044 | -0,137 | 0,139 | 0,009 | -0,123 | 0,117 | 0,045 | 0,053 | 0,029 | 0,040 | 1,000 | | | | |
| buyoutpowder | -0,171 | 0,898 | 0,160 | 0,153 | 0,733 | -0,374 | -0,252 | -0,328 | -0,319 | -0,342 | -0,152 | 1,000 | | | |
| coinvestmepowder | -0,238 | 0,924 | 0,144 | 0,155 | 0,665 | -0,327 | -0,201 | -0,172 | -0,146 | -0,261 | -0,159 | 0,902 | 1,000 | | |
| fundoffundspowder | -0,183 | 0,812 | 0,123 | 0,122 | 0,643 | -0,417 | -0,237 | -0,180 | -0,302 | -0,331 | -0,132 | 0,852 | 0,862 | 1,000 | |
| growthpowder | -0,199 | 0,924 | 0,158 | 0,158 | 0,719 | -0,407 | -0,244 | -0,211 | -0,165 | -0,255 | -0,167 | 0,947 | 0,974 | 0,836 | 1,000 |

Starting by looking at the variables with the highest correlations, we can see that there is a high correlation between *raisedbillions* and the different *drypowders*, which already was mentioned in the multicollinearity assessment in the methods section. However, as stated previously, due to the centrality of those variables for this research, we will accept this high correlation, as the findings from both variables are central to different hypothesis. Furthermore, both variables have a high correlation with the median valuation variable, which is unsurprising given that higher availability of funds can drive up valuation for target firms due to a decreased price of liquidity.

Another correlation that is noteworthy is the one of the spreads, which represents the yield of junk bonds, with its lags. There is high correlation between successive lags, of relatively large magnitude and positive sign for all lags. However, this correlation is negative and smaller for non-adjacent lags, meaning that the spread tends to reverse after two years year, albeit in smaller magnitudes. Finally, looking at the federal funds rate, it has negative correlations with spreads, including lags, dry powder, raised capital, which can be explained as high rates are employed in times of crisis, which coincided with low investment. However, a surprising observation is seeing that it is correlated with diversification of industries for funds. In times of economic downturn, funds seem to rely on diversification to hedge macroeconomic risks.

### 5.3 Regression Results

The results of the OLS regression for the simplified model yields the following coefficients, which will be discussed in this section.

Table 7: Measures of fit for the regression in equation 8.

| | |
|---|---|
| **Number of obs** | 1,998 |

| | |
|---|---|
| **F(10, 1988)** | 16.33 |
| **Prob > F** | 0.0000 |
| **R-squared** | 0.1034 |
| **Adj R-squared** | 0.0970 |
| **Root MSE** | 0.9982 |

Firstly, we look at the statistical fit of our final model. The results from table 7 show that the F-test value of almost zero indicate that the aggregate model has statistical power at a high significance level. The R-squared, with a value of 0.1034, as well as the adjusted R squared, tell us that the model explains around 10 percent of the variation in net multiple returns. This number is important, as it shows that the model can explain some of the changes in net multiple returns, but is incomplete, as much of the other change cannot be explained by the model. However, as we are focused on the effect of increased competition measured through raised capital and dry powder in the market, we do not necessarily need to capture the entire effects driving fund performance to answer our questions.

Table 8: regression results for models with only independent variables, gradually adding variables.

| **netmultiple** | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| **raisedbillions** | -0.0010** | -0.0001 | -0.0014* | -0.0142** |
| | (0.0004) | (0.0060) | (0.0007) | (0.0007) |
| **buyoutpowder** | -0.0003 | -0.0001 | -0.0011*** | -0.0021** |
| | (0.004) | (0.0004) | (0.0004) | (0.0005) |
| **coinvestmentpowder** | -0.0790*** | -0.0691*** | -0.0549*** | -0.0542*** |
| | (0.0103) | (0.0139) | (0.0151) | (0.0151) |
| **fundoffundspowder** | 0.0024*** | 0.0012 | 0.0003 | 0.0002 |
| | (0.0009) | (0.0012) | (0.0013) | (0.0013) |
| **growthpowder** | 0.0096*** | 0.0068*** | 0.0086*** | 0.0088*** |
| | (0.0017) | (0.0025) | (0.0026) | (0.0026) |
| **fundnumbero** | | -0.0014 | -0.0016 | -0.0021 |
| | | (0.0022) | (0.0022) | (0.0022) |
| **fundsize** | | -0.0001* | -0.00001* | -0.0000* |
| | | (0.0001) | (0.0001) | (0.0000) |
| **medevebitda** | | -0.0111 | -0.0270 | -0.0232 |
| | | (0.0286) | (0.0287) | (0.0287) |
| **fedrate** | | -0.0419* | -0.0676*** | -0.0688*** |
| | | (0.0228) | (0.0231) | (0.0232) |
| **spread** | | -0.0019 | -0.0148* | -0.0150* |
| | | (0.0064) | (0.0084) | (0.0084) |
| **L1_spread** | | | -0.0270*** | -0.0277*** |
| | | | (0.0094) | (0.0094) |
| **L2_spread** | | | -0.0086 | -0.0091 |
| | | | (0.0114) | (0.0113) |
| **L3_spread** | | | -0.0339*** | -0.0342*** |

| | | | | |
|---|---|---|---|---|
| | | | (0.0073) | (0.0073) |
| **diversifiedi** | | | | 0.0650 |
| | | | | (0.0479) |
| **_cons** | 1.8859*** | 2.0967*** | 3.713*** | 3.698*** |
| | (0.0881) | (0.2345) | (0.4063) | (0.4064) |
| **Observations** | 1,998 | 1,998 | 1,998 | 1,998 |
| **F** | 37.05 | 19.36 | 17.43 | 0.0000 |
| **Ajusted R-squared** | 0.0828 | 0.0842 | 0.0966 | 0.0970 |
| **Root MSE** | 1.006 | 1.005 | 0.998 | 0.9982 |

*Notes: This table shows the regression coefficients, robust standard errors in parentheses. Meaning of stars: (***) p<0.01, (**) p<0.05, (*) p<0.10*

Looking at table 8, we can interpret the coefficients for our regressions. Looking at model 1, the effect of raised billions is statistically significant but small. The effect for dry powder is significant for all strategies except buyoupowder, and has relatively large effect, with differing signs. Now focus on the coefficients of the explanatory variables in model 4. Looking at the variables central to our hypothesis, we see that *raisedbillions* has a negative coefficient and is statistically significant at a 5% level. The coefficient means that with every increase in capital raised of a billion dollars for a given year, funds with that vintage year are expected to have a lower net multiple by 0.00124, all else equal. This result is central to answering our first hypothesis, as more capital raised for a vintage year effectively raises competition for a limited amount of targets, increasing the cost of investments and lowering profits, which translates to returns for LP's.

Interpreting the value for the strategy-specific-drypowder, we encounter a mixed coefficients depending on the strategy. For buyout funds, increased dry powder leads to a 0.01 decrease in net multiple per billion dollars. This coefficient is statistically significant and aligns with previous literature. For co investment funds, the effect is larger, also negative and highly statistically significant, which might also be due to less availability for co-investment opportunities, as majority ownership is increasingly more realistic with larger capital reserves. For funds of funds, the coefficient is positive, relatively small, but positive. This result is astounding but can perhaps be explained by the repackaging of funds by other funds, which can produce returns as demand for those funds still underdeveloped relative to the possible supply of funds to be repackaged. Finally, growth powder is statistically significant, and has a positive effect on net multiple by a coefficient of 0.008. This does not align with findings from previous literature but could be explained by the success in growth companies in tech and biotech in recent decades, which can be debated. To answer our second hypothesis, we run a test of linear combinations of regressors, which will test for the effect of buyout powder to be more largely negative than that of drypowder in fund of funds strategies, growth and co-investment.

Table 9: results of test on difference between buyoutpowder and dry powder in other strategies.

| | Coefficient | Std. err. | t | P>\|t |
|---|---|---|---|---|
| buyoutpowder-fundoffundpowder | -0.0013 | 0.0016 | -0.82 | 0.410 |
| buyoutpowder-growthpowder | -0.0098 | 0.0029 | -3.37 | 0.001 |
| buyoutpowder-coinvestmentpowder | 0.0531 | 0.0149 | 3.57 | 0.000 |

Table 9 provides the results on testing weather buyout drypowder has the largest negative effect on net multiples compared to other strategies. The negative signs in the coefficient columns for funds of funds and growth indicate that buyout drypowder is more deteriorating than pent up liquidity in the other strategies. However, for funds of funds, the result is not statistically significant, as the P-value is large. Furthermore, co-investment drypowder has a statistically significant larger negative effect than in buyouts. For these reasons, we must reject our second hypothesis, as we cannot say with statistical confidence that buyout drypowder has a larger negative effect on PE returns than dry powder for funds with other strategies.

### 5.4 Control Variables

In table 8, considering the control variables, the number of numbers a GP launches has a negative, but not statistically significant effect. This is in line with previous research, which argued that GP's experience does not translate to increased returns to investors. Fund size also has a negative effect, which is statistically more significant, but of small magnitude. Again, this is unsurprising, and argued in previous literature, suggesting that managers with shining performances tend to raise larger funds, but not don't necessarily excel in generating returns at scale. This can also include the effects of more capital being attracted to the industry, as more capital seeks funds to invest in, biasing *fundnumbero* with the effect of our dependent variables.

The effect of *medevebitda* negative but not statistically significant. This might be due to the valuation multiples being highly connected with macro variables such as federal funds rate or spread, which captures the explanatory power instead. Indeed, fedrate has a large negative effect on returns, with a coefficient of 0.6. This can be explained as higher rates follow economic distress in an economy, which might hinder profitability. The *spread* variable and its lags all have negative coefficients, which is to be expected as private equity relies greatly on debt to generate returns for investors. What is noteworthy is that the magnitude of the effect steadily increases through the lags, except for the second lag, having the largest negative coefficient in the third lag. This indicates that as the fund matures, and

possibly engages in the most intense acquisition period, the importance of the availability of affordable debt increases. Out of the four variables, the first and third lag have high statistical significance. Spread is less statistically significant, and the second lag has very low statistical significance. Finally, the diversification variable has a positive and large effect, albeit not highly statistically significant.

## 5.5 Robustness check

### 5.5.1 Omitted Variable Bias

Even though the model for the regression was set up thoughtfully, and considering all possible relevant control variables that can isolate the effect of raised capital and dry powder, omitted variable bias (OVB) needs to be considered. Omitting a relevant variable could bias all the estimators, undermining the effects found by our regression. Economic thought is the only certain way to rule out OVB, and there is no reason to think that our model suffers from it. Nonetheless, we can run the Ramsey test, which can indicate whether there is presence of OVB. In this test, the null hypothesis is that the model has no omitted variables.

Table 10: Results of Ramsey test for omitted variables on the model of equation 8.

| | |
|---|---|
| **F(3, 1980)** | 0.86 |
| **Prob > F** | 0.4590 |

A P-value of 0.46 indicates that there is not statistically significant evidence of OBV, and that therefore, until an omitted variable is found, the current model is correct. If an omitted variable were to be found, we cannot assume that our results still hold. Multicollinearity concerns can be assuaged by looking at the VIF testing in the previous section.

### 5.5.2 Heteroskedasticity

Further, we can check for heteroskedastic errors, as this would bias all regressors and require the use of robust errors. We test using the White test, which reveals that there is not statistically significant heteroskedasticity in our final model. Having obtained the simplified model, and having ensured its appropriateness, we can now proceed to interpret its findings.

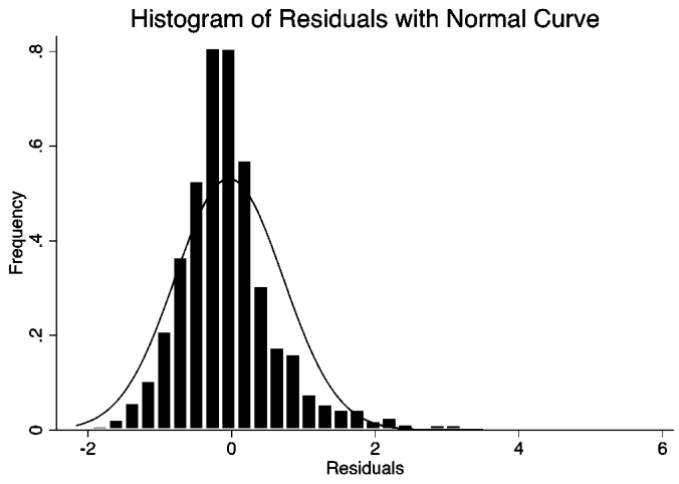
Table 11: White test results for model 4 from table 8

| Source | chi2 | df | p |
|---|---|---|---|
| Heteroskedasticity | 40.67 | 63 | 0.9870 |
| Skewness | 11.59 | 14 | 0.6395 |
| Kurtosis | 1.08 | 1 | 0.2990 |
| Total | 53.34 | 78 | 0.9853 |

### 5.5.3 Normality of residuals

Another important check to do is to make sure that the residuals are normally distributed. This is a required assumption of OLS, and a non-normal distribution would void our OLS regression's validity. To check for this, we can look at the histogram of residuals in figure 4 below, which clearly indicates a normal distribution, with small tails, and is centred around 0. Perhaps, the only limitation is that the mean is slightly in the negative area, meaning that our model could be slightly biased towards larger net multiple. However, given that there is not an abnormal distribution of residuals, there is no reason to believe the assumption of OLS is broken. We can therefore proceed with the discussion of results.

Figure 4: Histogram of residuals of regression from model 4 in table 8.




### 5.6 Discussion

This paper aimed at finding the effect of increased competition in PE markets in the shape of higher levels of fundraising and drypowder accumulating in the industry; after carrying out our cross-sectional OLS regressions and having obtained robust results, we can proceed to the discussion in relation to previous studies and the set hypothesis.

Our first hypothesis set the expectation that increased capital, measured by higher levels of raised capital would negatively affect PE returns, measured by net multiples. As mentioned in section 5.4, the coefficient of raisedbillions in model 4 of table 8 is largely negative, and statistically significant

at a 5% level. This result implies that as raised capital increases throughout the year, as it has for almost every year in the sample, returns for investors decrease. This finding is in line with previous literature, and confirms the results of Harris (2014), Kaplan and Schoar (2005) and Gompers and Lerner (2000), indicating a persistence in higher competition, caused by increases in fundraising, leading to a deterioration in returns to investors. It is also in line with the findings of Brown and Kaplan (2019), which pointed out a inverse relationship between PMEs and fundraising. Aggregating the findings from both papers can enrich the literature on PE competition, as it could demonstrate that competition within PE has a larger effect than competition in public equity markets, which can be a instrumental finding to investors. However, limiting ourselves to the findings of this paper, we can conclude that our first hypothesis was correct, as the results confirm our initial suggestion.

The second hypothesis proposed in this paper expected the effect of dry powder for buyout funds to be more largely negative than for other strategies. Once again, the results from table 8 indicate that excess dry powder for buyout funds has a negative effect on net multiples e of -0.0021 per additional billion dollars in drypowder. The coefficients for the dry powder in growth and funds of funds strategies are positive, but not statistically significant for funds of funds. For co-investment funds however is more negative than the one for buyout funds at -0.054, and statistically significant. This would prove our hypothesis to be false, and in table 9 we run a test to see if the difference between regressors is significant. Here again we see that the difference between buyout powder and co-investment powder is positive and statistically significant at a 99% level. Furthermore, the difference is negative, but statistically insignificant for funds of funds powder. This is evidence to reject our hypothesis, as there co investments powder has a larger negative effect on net multiples than buyout dry powder, and the larger effect in buyout than in funds of funds is not even significant. This indicates that even though buyout funds see the most absolute amounts of dry powder accumulating, the deteriorating effect on returns is not the largest for this strategy. This can be due to the relative amounts, respective deal flow, or other metrics being smaller, or due to other strategies being more sensible because of their business model. Co investment funds for example buy small stakes in companies, and perhaps, this limits how large the industry can get while sustaining high returns, as stakes in demanded companies become to expensive to allow for profits. This finding is crucial, as it shows that higher absolute competition in the form of dry powder does not imply the worst effect on returns in a specific strategy. These findings build on previous research, and perhaps can be tied to increased specialization leading to higher returns even when competition increases, following the ideas presented by Cressy, Munari, and Malipiero (2007).

Further relevant findings from our research relate to the federal rate in the vintage year of the fund, which has the largest negative, and statistically significant effect on net multiples out of all the variables. This result indicates that funds that start investing in a high-rate environment are worst performers, which is a valuable insight for investors who might be interested in PE opportunities in

present times, with high rates in the context of the last decades. The lags of the spread of high yield bonds, used to finance PE acquisitions, also have a negative effect, statistically significant to different extents depending on which lag of the spread. This insight is valuables, but not easy to implement for investors, as the future of bond markets is hard to predict. These findings stand in line with previous ideas by Kaplan and Stromberg (2009) and Ilmanen (2020), who touch on the role of cost of borrowing for PE funds, and the possibility to exploit mispricing in the price of debt to have access to unique investment opportunities.

A final finding that is interesting and is ambiguous with previous literature, is the effect of diversification found in our analysis. Even though Cressy, Munari, & Malipiero (2007) and other papers found that specialization has a positive effect on returns, we analysed the effect of having a diversified array of main operating industries. Even though the coefficient for having a diversified industry approach is not statistically significant, it is positive. This can be seen as a contradiction of the ideas elaborated in Gruener & Marburguer (2022), specifying that being focused on specific industries leads to more positive returns. Our analysis used main industries as the input for this variable, which makes it hard to exactly know the extent of diversification, but the finding is nonetheless noteworthy. The effect found can be caused due to a higher resilience of diversified funds, who can seek profitable opportunities across industries, maximizing the growth on their investments. It also might be caused due to higher resilience to major economic events and crisis, periods which are also included in our sample. To truly understand the effect of diversification on returns in the long term, more exhaustive research needs to be carried out in that subject specifically, but it is a consideration to be had.

The findings derived in this paper contribute and expand on the previous literature on PE returns. We found that the negative effect of capital raised remains statistically significant for our sample of U.S. funds spanning from 2000-20022, increasing the validity of previous studies. We also found the effect of dry powder to not be the most erosive to returns in the buyout fund strategy, which suggests that there can be continued abnormal returns found within that strategy even when competition and buying pressure is at a maximum in that category of funds. Finally, we also drew some insights on the relevance of interest rates and the price of high yield bonds, which are observable to investors, in modelling expected returns. These insights can all contribute to forming an educated strategy to invest in PE understanding recent developments and drivers of returns for this asset class. Furthermore, our found effect of diversification on returns introduces further questions on the role it plays in creating sustained high returns and opens the door to more in depth research on that topic.

# CHAPTER 6 Conclusion

In this thesis we have looked at the effect of increased concentration of capital and competition in private equity markets and its effect on PE returns. Until now, studies considered only a one or two driving factor of returns on private equity, with most research on competition being carried out over a decade ago such as Harris´ (2013). In the meantime, the industry has evolved, in the same way as the degree of competition that it experiences. This study sought to produce an updated and comprehensive overview of the current major effects surrounding competition in PE markets, looking at capital concentration, as well as other possible relevant drivers, such as economic conditions and specialization. We measured returns using net multiples on invested capital and used raised capital and dry powder as proxies for competition and capital accumulation. In doing so, this paper had the goal of identifying: **the effect of increased concentration of capital and competition in private equity markets on returns on capital.**

To answer this question, we sourced cross sectional fund level data from Prequin for almost 2,000 individual funds with vintage years from 2000 to 2022, all based and focused on the U.S. More data on PE fundraising as well as federal rates and bond spreads were merged to ensure sufficient data for meaningful analysis. By taking a specific to general approach, we were able to include our main variables on competition, while also considering any other relevant variables with an effect on PE returns. OLS regressions were the main statistical resource used, on top of robustness tests and economic reasoning to ensure our model was optimal and correct.

Our model revealed that raised capital and accumulated dry powder both have a negative effect on net returns, and that the effect of dry powder in the buyout approach is not as negative as initially thought. It also evidenced that the effect of interest rates and costs of debt put negative pressure on returns. Moreover, it suggests a slight possible positive effect of taking a diversified approach on target industries. It also corroborated previous studies that argue the insignificance of factors such as fund size and previous funds launched by the same PE firm in influencing returns. Therefore, the paper largely extended the findings of previous papers to be true in the more recent period considered by this paper, and at the same time raising some questions on the role of diversification as a predictor of high returns.

The findings in this paper raise some implications for investors, as well as PE firms. Looking at the effect of dry powder between investment strategies, GPs can focus their upcoming funds to the strategies less affected by the accumulation of dry powder, which is currently at historic levels. Managers could shift their focus to strategies that are more resilient to high dry powder levels and be aware that the deterioration in returns could be slower than expected in the buyout sector. Managers should also be aware of possible changing trends in respect to diversification and consider the possibility

of moving away from diversification as a hedging strategy. Implications for investors on the other hand not only include added clarity on which type of fund to invest in, but also provide a clear effect of macroeconomic factors close to the time of investment. As mentioned in the literature review, timing is difficult in PE, but given the high rates in the past years, PE investments might not be optimal at the time, and be more profitable when rates are going back to their near zero usual. Finally, investors can also focus on the value proposition of the fund they want to buy in to and give less importance to less important factors such as fund size and fund number.

To conclude, this thesis did have some limitations, which if improved on, can lead to future insightful research. Firstly, the research approached competition on a quantitative level uniquely, only considering raised capital and capital accumulated as a measure for competition. The measure for competition could be more elaborate, including other measures such as reported competition or data on bidding for target firms by similar funds. Another limitation based on the unavailability of data was the total investment period for each fund. Net multiples, which were used as the performance measure for funds, need to be interpreted in the context of time, as time value of money is a highly relevant factor for investors. This limitation could be solved by obtaining another research level data set and could drastically change the results of this analysis. Finally, a last limitation, which offers great opportunities for research in the future is the role of diversification. In this paper, diversification was used as a binary variable, but using more detailed data on the industry focus of funds and elaborating a more sophisticated method to measure the degree of diversification would expand on the literature on PE and how diversification affects returns. However, given the scope of this thesis, such limitations are to be expected, and do not subtract value from the findings

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# APPENDIX A

Figure 5: Net multiple over vintage year by main industry.

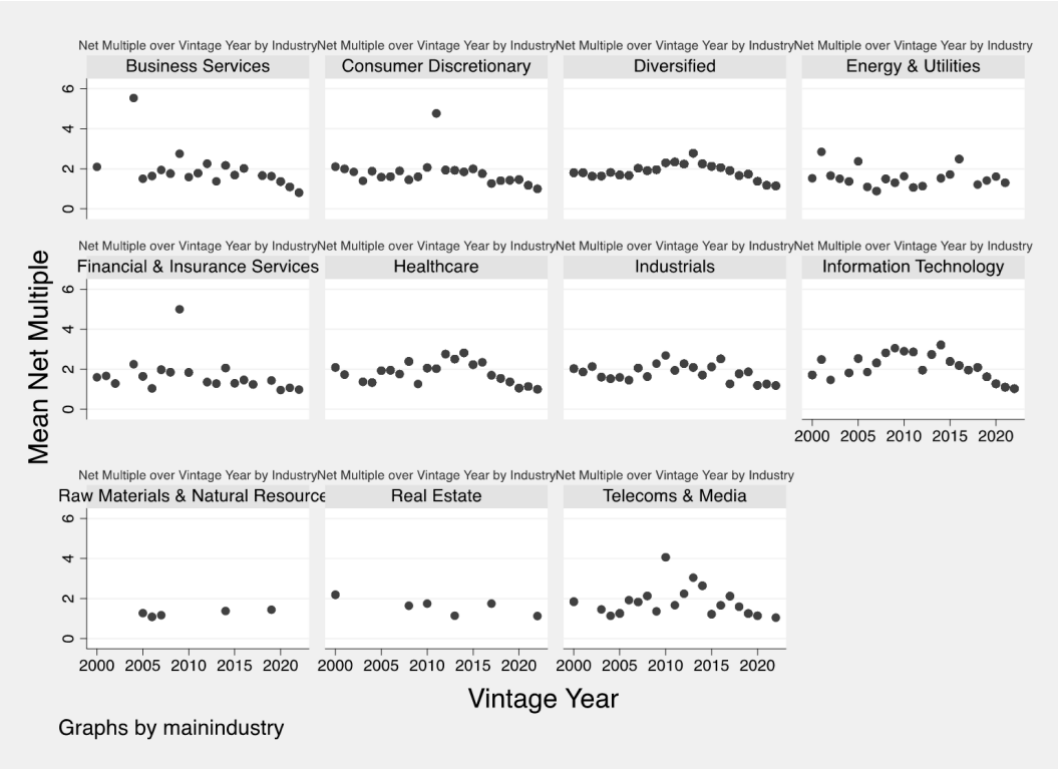


Figure 6: Median EV/EBITDA over vintage years for target companies in U.S. private equity

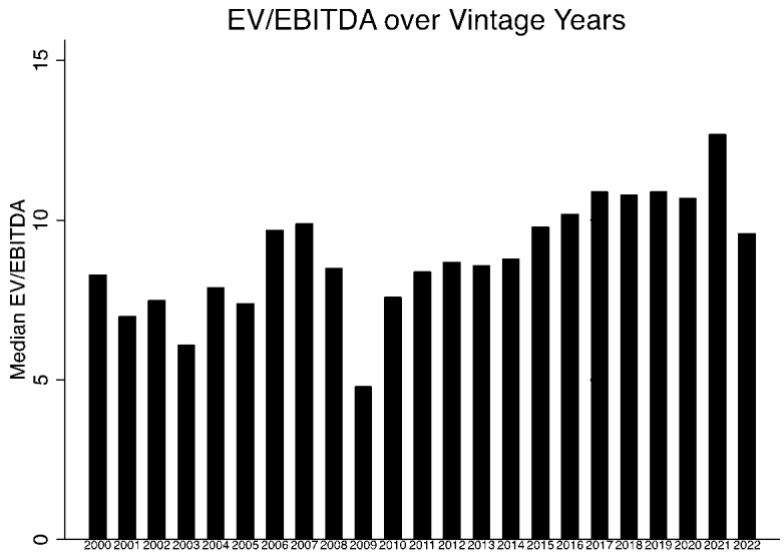

Figure 7: Histogram of fund vintage years in sample.