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A Comparison of Venture Capital Performance In Europe And The U.S.

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Abstract

We analyze the performance of venture capital funds in Europe and the United States. We compare the historical backgrounds of both markets and their legislative framework. The most recent research by Oehler et al 2007 showed returns in the European venture capital market that lagged behind those of its overseas counterpart. We provide empirical evidence that the gap in performance between both markets has been closed, using both the internal rate of return and direct alpha provided by the Preqin database. The evidence for the effect of legislation on fund performance seems inconclusive due to ambiguous results. Furthermore, we show that the assets under management of a venture capital fund has a positive impact on its performance.

Contents

1. Introduction

Over the last 75 years, venture capital has seen a lot of changes. Before the second World War, venture capital (VC) was primarily the domain of wealthy families. In 1946, the American Research and Development Corporation was founded. Since then, VC has become increasingly popular with venture backed acquisitions reaching an all-time high in January 2021 (VC funding record .2021). VC is a subset of private equity where venture capitalists provide capital to startups to expand their business. The VC market has gone through a large expansion, experiencing double digit growth from 2014-2019 (Trend in VC market, 2020). Venture backed fundraising surged to 126.9 billion USD in the first quarter of 2021 and is expected to remain robust globally in the second quarter (KPMG, 2021). However, the question that immediately seems to arise is whether the performance of the funds in this growing market is doing as good.

More precisely, this research examines the difference in performance between VC funds in the U.S. and in Europe. This comparison was previously drawn by Hege et al. in 2003 who compared the relatively new market of venture financing in Europe with the more mature one in the U.S. They concluded that the significantly better performance of the U.S. could be attributed to their capacity to screen projects better than in Europe due to their more mature market. Oehler et al. seems to confirm this view in 2007 but argues it is due to Europe's complicated patent system and its lack of retention of highly qualified employees.

Now, 14 years later, the European VC market seems to have matured with the Venture Pulse report by KPMG reporting the fifth straight quarter of increases in European VC investments as a testament to the growing maturity of the European startup ecosystem (KPMG, 2021). Therefore, one starts to wonder whether the European VC market is still lagging behind the one in the U.S. in terms of performance. This paper searches for the answer to question:

"How does the U.S. venture capital market compare to its European Counterpart?"

I try to answer this question by examining the differences in internal rate of return (IRR) between U.S. and European VC funds, correcting for core-industry and scale. The reason for studying these regions is to see whether Europe has finally caught up to the U.S in terms of performance, after years of development in maturity and business environment. Through this, we aim to get a more thorough understanding of these VC markets and discuss possible explanations for this gap based on differences in legal and fiscal landscape. We define the European VC market as all venture capital funds located in Europe, meaning they thus have to adhere to the overarching legislation of the EU.

The remainder of this paper is structured as follows. In the next section I will present the theoretical framework behind both VC markets, the relevant literature and a brief discussion of the hypotheses of the sub-questions. Section 3 will describe the dataset and afterwards we will discuss the methodology. Afterwards, we will look at the results and give an interpretation of them in my discussion. Finally, we will conclude with a discussion of the limitations and provide recommendations for further research.

2. Theoretical Framework

2.1 Venture capital Funds

Venture capital funds can be defined as pooled investment funds that manage the money of investors looking to invest in startups or small to medium sized enterprises with high growth potential. VC funds can be distinguished based on their strategy which is based on their focus on a certain stage of funding. For instance, VC funds focusing on early stage funding invest in earlier investment rounds such as the seed rounds or Series A. Late stage funds focus on investing later in the cycle in a Series B or Series C. These funding rounds will be clarified later in this section.

A venture capital fund is structured as follows. The firm organizes a limited partnership to hold the investments. Within this structure, there is an important distinction between two parties. The first one is the limited partner (LP). These are often institutions or high net-worth individuals contributing capital to the fund. In essence, they are the investor. The other party is the general partner (GP). They are responsible for all management decisions of the partnership and it is their responsibility to act for the benefit of the LP. The compensation structure consists of an annual management fee of 1 to 2 percent plus a carried interest of up to 20% of the partnership profits called a “carry” (Gompers & Lerner, 1999).

A characteristic feature of VC is its high uncertainty and high rate of failure (Schmitt, Rosing, Zhang, & Leatherbee, 2018). And as one would expect, with this uncertainty comes the possibility of high returns (Hellmann & Puri, 2000). VC funds differ from mutual funds or hedge funds in the sense that they focus on a very specific type of early-stage investment. Furthermore, VC funds are seldom silent partners and often take a more active role in their investment by holding seats in the board and providing guidance to the startup. It is even common practice to give an equal number of seats to the founders and to outside investors (Brealey, Myers, Allen, & Mohanty, 2012).

VC is a risky business as 80% of startups fail (Feinleib, 2012). However, some companies make it far enough to receive external funding. Usually funding is structured as follows. First the company receives funding from the founders, friends, family or other supporters. This is called pre-seed funding. Then comes seed funding, also known as angel investing. Although this is the first official equity funding stage and is usually funded by another business venture or enterprise, the startup usually does not have a proven track record yet. Normally, series A investors purchase around 10 to 30% of the equity which is intended to capitalize the company for 6 months to 2 years (Inc.com, 2012). After Series A comes Series B funding. This round appears similar to round A but focuses more on taking the business past the development stage. Furthermore, this round often attracts new VC funds that specialize in later-stage investing. A series C funding round most often occurs in businesses that are already quite successful but need capital for new projects such as expanding into new markets or developing new projects. The most well-known success-stories in the VC world are startups such as Uber, Airbnb or Stripe. These can be classified as unicorns, which are companies valued at $1 billion or more. Due to the growing popularity of strategies such as the get big fast strategy, startups founded between 2012 and 2015 were growing in valuation twice as fast as companies founded between 2000 and 2013 (Vigrass, 2016). This caused the number of unicorns to climb from just 39 in 2013 to more than 700 as of June 2021 (Fan, 2016); (CB Insights, 2021).

2.2 Origins of Venture capital

In order to completely understand the world of venture capital, we briefly discuss its history. Before the second World War, VC consisted mostly of sporadic investments and acquisitions by wealthy families such as the Rockefellers or the Pierpont Morgans (Bridge, 2014). Only after World War II, the first private equity investments could be distinguished with the founding of the American Research and Development Corporation (ARDC) in 1946. ARDC was founded to encourage private sector investments in businesses run by soldiers who were returning from the war. ARDC had its first major success story in VC when their 1957 investment of $ 70.000 in Digital Equipment Corporation (DEC) was valued at $ 35.5 million after its initial public offering (IPO) in 1968 (Earls, 2004).

In 1958, the Small Business Investment Act was passed which allowed the U.S. Small Business Administration to license small private companies in order to close the gap between the capital markets and small businesses in the U.S. The primary thought behind this act was to foster technological innovations to compete with the Soviet-Union. In the decade hereafter, the common form of private equity funds as we know them began to emerge.

2.3 History of the U.S. VC market

In the 1980's, public successes such as ARDC's investment into DEC had led to a major proliferation of VC firms. This number grew from a couple at the start of the 1980's to more than 650 firms by the end of the decade (New York Times, 1989). Due to this increased competition, along with the collapse of the market for IPOs - caused by the stock market crash of 1987 - caused the VC industry to be hampered with worsening returns. After this downfall, foreign funds predominantly from Asia stepped in and were investing in U.S. startups at unprecedented rates. In response, U.S. companies began to sell off their in-house VC units and shifted their focus on investing in more mature companies. These were less risky and provided the investors with quicker and often bigger returns. These investments happened often in the form of a leveraged buyout (LBO), where a company is acquired primarily using borrowed money (New York Times, 1989). This market was already booming but soared even more near the turn of the decade.

However, the LBO market was riddled with hostile takeovers and excessive use of leverage, with the RJR Nabisco deal being a characteristic example, having a debt to equity ratio of 23 to 1 by the end of March 1990 (New York Times, 1990). Furthermore, this boom was primarily fueled by financing through high-yield debt, also known as junk bonds. Most of these bonds were underwritten by Drexel Burnham Lambert (Brewer & Jackson, 2000). When Drexel eventually had its downfall, this market collapsed. Alongside this collapse, companies found techniques to protect themselves against hostile takeovers such as a shareholder's rights plan, also known as a poison pill. This is a defensive tactic which consists of a plan that gives shareholders the right to buy more shares at a discount if one shareholder buys a certain percentage of the company. This essentially allowed other shareholders to dilute the bidders interest until it had lost its value (Mäntysaari, 2010). To add to this, the Financial Institutions Reform, Recovery and Enforcement Act of 1989 was enacted, which prohibited investment of savings and loans in bonds rated below investment grade (BBB). All these factors marked the end of the first private equity boom.

This downturn in the private equity market was short lived, lasting from 1990 to 1992, before the industry began to improve. Due to the malicious practices of private equity in the 1980's, the industry needed to earn back their legitimacy and respectability. It did so by focusing more on long term company development and proposing attractive deals instead of the hostile takeovers that had characterized PE in the previous decade. The use of leverage also declined with LBOs becoming relatively scarce during the start of the 1990's (Kaplan & Stromberg, 2009). In the meantime, the VC industry started to pick up speed once again. Venture capital had become overlooked in the '80s due to low returns compared to the LBOs, causing growth of the industry to remain limited until 1995.

In the second half of the decade, the VC market began its boom especially with technology companies from Silicon Valley benefiting from the public interest in the state-of-the-art phenomenon of the Internet among other computer technology. A few important drivers for this development can be identified. The Federal Reserve had been lowering interest rates which increased the availability of capital (New York Times, 1996). Furthermore, the Taxpayer Relief Act of 1997 lowered the top marginal capital gains tax in the U.S., making people more willing to make speculative investments. These developments combined with the passing of the Telecommunications Act of 1996 - which goal was to let anyone enter any communications business - caused the Tech industry to boom. Between 1995 and 2000, $ 108.2 billion was invested in Internet-related startups, which would later be referred to as the Dot-com Bubble (Chang, 2004).

Yahoo! was a prime example of this period, being founded in 1994, having its IPO just 2 years later and being valued more than $ 125 billion at its peak in the beginning of 2000 (Solomon, 2016). In this period, the Nasdaq Composite stock market index rose 400%, reaching a price-earnings ratio of 200. These rapidly increasing stock prices along with the general notion that companies would soon become profitable, caused investors to overlook traditional warning signs such as these unreasonably high price-earnings ratios. Even high-ranking individuals such as then-Chair of the Federal Reserve, Alan Greenspan, justified the exorbitant stock valuations by stating that it was caused by underestimated output growth, and that large-scale productivity gains were just a few years away (Teeter & Sandberg, 2017).

Around the turn of the century, the VC market was characterized by hefty returns and excessive spending on things like Super Bowl ads and so-called Dotcom parties. However, a few important events caused the bubble to burst. At the start of 2000, Alan Greenspan announced a hike in interest rates which sparked a discussion whether tech ventures would be hurt by this. After news hit that Japan had once again entered a recession, a large global selloff was triggered. Additionally, more and more news articles began to emerge, questioning the viability of the large number of unprofitable listed companies which made shareholders question their investments. By 2002, more than $ 5 trillion in market value had been wiped out and the bubble had burst (Goodnight & Green, 2010). After the Dot-com Bubble burst, many VC funds had to write off large proportions of their investment portfolios, causing a lot of them to end up under water, meaning fund values were below investment values. Because of this, the investors in these funds wanted to reduce their exposure, causing them to unload commitments in the secondary market with heavy losses. By mid-2003, the VC industry had shrunk to approximately half of its size.

Around that time, accounting scandals such as Enron and WorldCom among others, had caused the enactment of the Sarbanes-Oxley act in 2002. This law set requirements for all U.S. companies (primarily public ones) and was designed to increase corporate responsibility and tighten accounting regulation. These requirements brought higher costs with them, due to bureaucratic compliance (Coates & John, 2007). Because of these compliance costs, it became less attractive for venture capital funds to bring their companies public which dramatically reduced the number of IPOs from 269 in 1999 to just six in 2008 (Sarbanes & Oxley, 2002). Next to that, the Federal Reserve had lowered interest rates, reducing cost of debt, increasing the ability to finance large acquisitions. Because of this, the LBO had its resurgence, with the transaction volume reaching $ 500 billion by the latter part of 2005 and the beginning of 2006 (Acharya, Franks, & Servaes, 2007). However, the VC funds (which were responsible for a lot of the transaction volume during the dotcom bubble raised only 25.1 billion (Taub, 2007). However, when the subprime mortgage crisis hit at the end of 2007, capital became much less available causing the number of deals to plummet to a six-year low in the first quarter of 2009 (Rizzi, 2009). VC backed investments have been on the rise ever since with them hitting $ 69 billion in the first quarter of 2021 (KPMG, 2021).

2.4 History of the European VC market

The European Venture capital market developed much later than the one in the U.S. The European PE market was effectively formalized in 1983 with the formation of the EVCA, which was later rebranded as Invest Europe in 2015 (Lavine, 2015). Realized returns of venture investments in Europe had long been below the required return, which was often given as the reason for the underdevelopment of this industry (Hege, Palomino, &

Schwienbacher, 2009). Another possible reason for this underdevelopment is the lack of potential exit strategies through IPOs in European countries as described by Black and Gilson (Black & Gilson, 1998). It was not until the late 90s that VC investment took off, reaching $ 12 billion in 1999 (Hege et al., 2009). This growth was initially driven by the boom in high tech industries during the Dotcom Bubble.

After the introduction of the Euro, the single currency environment created more integrated European debt and equity markets, which helped foster a significant private equity market for the first time. However, following the decline in asset prices during 2000 and 2001 after the bursting of the bubble, activity in the European Private equity market declined significantly. When the stock prices readjusted in 2004, investors moved towards less risky investments which increased the popularity of buyouts in more mature industries, and decreased popularity of VC for a few years (European Central Bank, 2005). After this decrease in popularity, VC investments swung back and forth for a few years, decreasing after the financial crisis of 2008 and climbing back to $ 16 billion in 2015 (KPMG, 2017).

Following the 2008 financial crisis, the European Union sought to implement legislation to regulate the investment industry at a European level. In order to accomplish this, the Alternative Investment Fund Managers Directive was passed mid-2011. Its goal was to bring transparency and security to the way these funds are managed and operated in order to bring stability to the European financial system. The AIFMD was often criticized, with studies showing that the majority of fund managers thought the new regulation would reduce the competitiveness of the EU's investment industry and have an overall negative impact (UK Government, 2013). The AIFMD did increase investor protection and transparency. This however, came at a cost due to the compliance costs that came with the directive, hitting especially smaller funds hard (Kokkila, 2016). Despite tightened regulation, the European VC market kept a steady growth with European VC investment hitting $ 49 billion in 2020 (KPMG, 2021).

2.5 Hypotheses

Using the relevant literature as a foundation, I have developed the following hypotheses for my sub-questions.

Hypothesis 1: *the U.S. VC market does not outperform the European VC market in terms of IRR*

Papers such as the one by Hege et al from 2003 - who prove that the European VC market underperforms relative to the one in the U.S. - give reason to believe that the European VC market still has not fully caught up to the one overseas. Furthermore, the reasons to explain this phenomenon presented in the paper by Oehler et al. such as lower employee retention and a more inefficient patent system have not been through significant changes in the last 10 years (Oehler et al., 2007). However, these papers are far from recent and with sources such as the report presented by KPMG, proclaiming the maturity of this market, it seems plausible that the European VC market has closed the gap to its overseas counterpart.

Hypothesis 2: *there exists a negative correlation between fund size and IRR*

The literature on this issue is divided. Some find a positive relation whereas some find negative ones. In their 2009 paper on fund size and performance, Chan et al demonstrated that fund size detracts from performance. They explained this deterioration in performance through the higher market impact costs facing large managers. Furthermore, they also showed that managers expecting to face higher market impact costs may construct their portfolio differently as to reduce expected market impact. Therefore, they form different portfolios than otherwise would have been formed, thus incurring an opportunity cost of avoiding market impact cost. However, we can also find academic work contradicting the findings by Chan et al. For instance, in 2005 Ammann and Moerth found a positive relation between fund size and performance in hedge funds, which they explained by the higher total expense ratio of small funds.

Finally, the paper by the Jenner 2012 provided a more nuanced perspective on the subject. In his research in which he researches 1222 U.S. funds, Jenner describes that large PE funds have several advantages compared to small ones. Such as better connections with other financial institutions and international diversification. However, the performance of large funds is worse than those of small funds, especially in investments in small companies. For this, they provide 4 reasons. Large PE funds can generate economies of scale by reducing staff per invested dollar. This could cause them to spread staff too thinly for small investments and thus destroy value by reducing the attention that professionals give each company. Furthermore, large PE funds' advantages lie mainly in using their connections with large institutions in order to obtain better financing terms. This favors large companies due to the benefit of finance related connections increasing with the amount of financing needed. Next to that, small funds might have a first mover advantage when investing in small companies due to the capital and location constraints being faced by them, causing these funds to find the best investments in the set of small companies before large funds can do so. Lastly, large funds are likely to invest in small companies when they have excess cash. This might induce agency conflicts which destroys value. Jenner finds empirical evidence that large funds earn lower returns on average, especially when investing in small companies. After considering the research mentioned above, we derive that the paper by Jenner 2012 has the largest sample size and the most comprehensive explanation for a negative relation between fund size and performance. Therefore, we hypothesize that there exists a negative relation between fund size and IRR in both markets.

3. Data

In this section we will first discuss the validity of the database I used to conduct the empirical part of my research. Then I will discuss possible biases that arise such as survivorship, self-selection and backfill bias. Afterwards, we will take a look at some descriptive statistics of our dataset and lastly, we will discuss the methodology I used to clean my data.

3.1 Database

To conduct the empirical part of my research, I used the Preqin database. Preqin offered the most comprehensive dataset at my disposal and is often used in recent academic research on fund performance (Buchner, Mohamed, & Schwienbacher, 2017). Furthermore, other databases such as Zephyr only contained mergers and acquisitions deals themselves, whereas we are only interested in the performance of VC funds themselves. Preqin collects their data through a number of sources such as FOIA requests[1], public filings or industry-recognized news sources. Furthermore, they also maintain relationships with fund managers who provide them with data voluntarily (Preqin, 2019).

3.2 Biases

According to the European legislation concerning Private equity funds described in the AIFMD (Alternative Investment Fund Managers Directive), funds with assets under

[1] Freedom of Information Act requests can be made in order to gain access to data held by national or local governments

management of more than € 500M (or € 100M unleveraged) are required to make annual reports available to investors and the authorities of the relevant member state (KPMG, 2015). Thus, VC funds operating below this threshold are not required to report this data which makes our dataset prone to a form of selection bias called self-selection bias. This bias arises when the observations of interest select themselves into a sample (Heckman, 1990). The reliance of a dataset on voluntary reporting (due to a lack of reporting requirements for small funds) might incentivize funds with a good performance to use databases such as Preqin as a marketing instrument in order to advertise themselves (Harris, Jenkinson, & Stucke, 2012). On the other hand, underperforming funds might choose to refrain from reporting in these databases, thus leaving us with a sample of predominantly well-performing funds. However, Preqin aims to use multiple sources to verify their data with an average of four sources reporting data for each fund. This enables them to cross-validate voluntary data contributions (such as ones from general partners) with other sources, thus decreasing the problem of selection bias, due to the fact that the dataset is not comprised only of voluntary contributions (Preqin, 2017).

Another bias that we have to take into account is the Backfill Bias. This bias describes the problem that fund managers only start reporting returns after these turn favorable, in order to use them as a marketing instrument. When they start reporting these returns, they do not have an incentive to retroactively fill possibly negative historical returns back into the set, because it decreases average performance (Bongaerts & Charlier, 2009). However, in our set this issue does not arise because all IRR observations are calculated from the year of inception of the fund. Thus, funds cannot choose to leave out previous unfavorable returns in order to boost apparent fund performance. They can, however, stop reporting returns once they start to decline.

Lastly, a bias that frequently arises when using commercial data is Survivorship Bias. This bias arises when a dataset is used that does not include observations of failed or bankrupt funds. Our dataset includes funds with different types of statuses. A fund can be closed, meaning that they have finished fundraising but are still deploying capital. A fund can be liquidated, meaning they have returned all capital to investors and are no longer active. Or a fund can still be in the fund-raising phase at their first or second close. This means that our dataset does not leave out failed or bankrupt funds and also includes liquidated funds that are no longer active which mitigates some of the survivorship bias.

3.3 The dataset

To conduct this research, we split our dataset in observations before 2007 and the entire dataset with observations ranging from 1996 to 2020. Below, we see the descriptive statistics for our dataset until 2007. Some descriptive statistics are not available due to there being only 1 or sometimes even zero observations. We see that there are substantially more observations of U.S. funds than European funds. Furthermore, a lot of the funds in our dataset are active in either healthcare or information technology. Our dataset is comparable to Hege et al in the sense that our data also contains funds located in the EU and U.S. next to the fact that they also use the MSCI index to discount returns. However, our dataset also differs in some ways from the one used by Hege et al. For instance, they use the Nasdaq to discount U.S. returns instead of the S&P 500 used by this research. Furthermore, our sample size for European funds is a lot larger in our research considering they only have 146 companies in their final sample.

Before 2007

Table 1	Nr. Of			IRR						Alpha				
Category	**U.S. Funds**	**EU Funds**		**Mean**	**σ**	**Median**	**Skewness**	**Kurtosis**		**Mean**	**σ**	**Median**	**Skewness**	**Kurtosis**
Consumer Discretionary (1)	5	0		6.426	14.192	3.38	0.414	1.911		n/a	n/a	n/a	n/a	n/a
Consumer Discretionary, Energy & Utilities (2)	7	1		0.558	19.317	-1.275	0.0279	1.512		n/a	n/a	n/a	n/a	n/a
Diversified (3)	156	16		10.585	40.488	3.08	3.145	18.286		2.307	7.619	1.135	1.786	5.486
Energy & Utilities (4)	10	1		-12.098	25.233	-3.430	-1.324	3.319		n/a	n/a	n/a	n/a	n/a
Financial & Insurance (5)	4	1		1.708	17.064	6.620	-0.785	2.188		n/a	n/a	n/a	n/a	n/a
Healthcare (6)	146	13		3.385	18.804	3.470	4.590	40.336		-0.480	4.664	-2.782	0.742	2.087
Healthcare IT (7)	86	8		11.828	50.487	3.16	7.083	60.5402		-0.431	5.002	-1.851	0.479	1.5
Industrials (8)	2	0		-0.05	9.687	-0.05	0	1		n/a	n/a	n/a	n/a	n/a

IT (9)	172	20		15.868	42.333	3.655	2.692	12.942		2.069	5.224	3.636	-0.238	1.524
IT, Telecoms & Media (10)	79	5		17.358	68.316	2.39	5.294	36.027		-1.449	3.050	-0.452	-1.269	3.601
Telecoms & Media (12)	34	1		12.872	78.969	-1.8	4.525	23.886		0.019	5.476	0.01	0	1

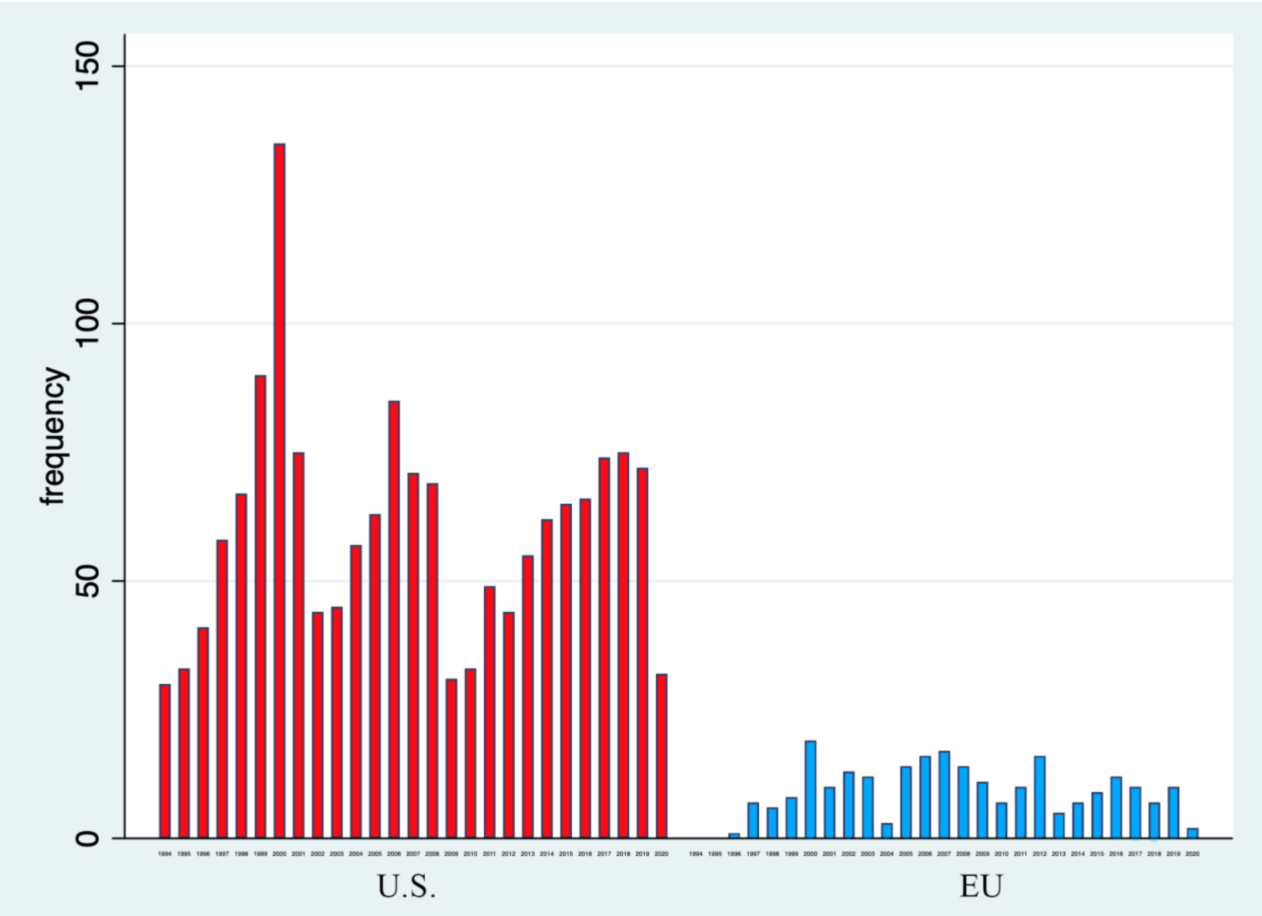
After 2007

Table 2	IRR Observations			IRR						Alpha				
Category	**U.S. Funds**	**EU Funds**		**Mean**	**σ**	**Median**	**Skewness**	**Kurtosis**		**Mean**	**σ**	**Median**	**Skewness**	**Kurtosis**
Business Services (1)	8	0		4.35	11.416	1.29	0.901	2.959		n/a	n/a	n/a	n/a	n/a
Consumer Discretionary (2)	22	2		15.324	24.489	12.315	0.909	4.254		-2.984	6.023	-4.141	0.340	1.5
Diversified (6)	253	43		11.412	32.970	6.395	3.467	24.324		-2.109	16.146	-2.859	0.693	7.924
Energy & Utilities (7)	23	3		-5.388	24.593	-2.505	-0.286	4.459		n/a	n/a	n/a	n/a	n/a
Financial & Insurance (8)	4	1		1.708	17.064	6.620	-0.785	2.188		n/a	n/a	n/a	n/a	n/a
Finance & Healthcare (9)	1	0		n/a	n/a	n/a	n/a	n/a		n/a	n/a	n/a	n/a	n/a
Healthcare (10)	258	30		11.649	31.233	6.850	6.758	76.937		18.329	50.252	6.919	3.889	21.122
Healthcare IT (11)	114	12		13.281	44.157	5	7.778	75.741		-2.089	9.066	-4.448	1.180	3.303
Industrials (12)	6	0		-5.462	20.218	-0.05	-0.388	1.542		n/a	n/a	n/a	n/a	n/a
IT (13)	381	46		16.759	31.275	12	2.864	19.72098		2.545	13.508	4.347	-0.530	4.005

IT, Telecoms & Media (14)	93	7		16.678	62.902	5.38	5.707	42.209		1.359	6.840	-0.452	1.420	4.761
Real Estate (16)	8	0		4.35	11.416	1.29	0.901	2.959		n/a	n/a	n/a	n/a	n/a
Telecoms & Media (17)	22	2		15.324	24.489	12.315	0.909	4.254		-2.984	6.023	-4.141	0.340	1.5

3.4 Cleaning the data

Before we can perform our analysis, we first need to clean our data. Preqin does not show the Net IRR for funds in the first 3 years of their fund cycle but displays an n/m or n/a. We need to change these values to dots in order for STATA to interpret them as missing values. Furthermore, some numerical variables are stored as strings which we need to encode into integers. Then we generate 4 new variables with binary values stating whether a Fund is located in an EU country (1), if the fund started before 2007, if a US fund started before Sarbanes-Oxley and lastly if a European Fund started after the AIFMD. In some cases, a fund starts before the introduction of certain legislation and continues after its implementation. In



our dataset, we only have 1 observation of the IRR over the entire lifetime of the fund combined with the fact that we do not have information when the fund ended. Therefore, it is important to note we cannot know for certain if a fund incepted right before new legislation, made the majority of its returns afterwards.

Then, we rename our variables of interest and drop the ones we do not need. Lastly, we need to remove observations from our dataset, before the EU was formed. Since the EU has been existed for a long time and countries have come and gone ever since, we define the formation of the European Union by the signing of the Maastricht Treaty, which was signed in November 1993. Thus, we drop all observations before 1994.

4. Methodology

In order to arrive at an answer to the research questions, we use the variables provided by the Preqin database as a proxy for the explanatory relationships we want to investigate. In this section, we will discuss the variables of interest and their possible shortcomings. Afterwards we will go through the statistical measures used to test our hypotheses, the validity of the dataset and how we arrived at our model.

4.1 Variables

To examine performance, we use both the Internal Rate of Return (IRR) and Alpha as a proxy. The IRR is often used in private equity research as a measure of profitability of investments and is also used by three quarters of the CFOs to evaluate capital projects (Kelleher & MacCormack, 2004). This widespread adaptation serves as an advantage due to the large presence of observations with the IRR in our dataset. In essence, the IRR is the discount rate that makes the net present value equal to zero. Mathematically, this translates into: $\sum_{t=1}^{T} \frac{C_t}{(1+IRR)^t} - C_0$where Ct is the net cash inflow during period t, C0 is the total initial cost and t is the number of periods. Despite its frequent academic and professional use, the IRR is also prone to distortions caused by reinvestments. For instance, if the true reinvestment rate is lower than the calculated IRR, this measure will overestimate the annual equivalent return for a project (Kelleher & MacCormack, 2004). In our dataset the IRR is defined as the net internal rate of return earned by a limited partner from inception of the fund to date after fees and carry. This IRR is based upon the realized cashflows and the valuation of remaining interests and partnerships, after fees and carry. Furthermore, the IRR is an absolute measure of return that does not consider the average sentiment of the market.

Therefore, we also utilize another measure that is available in our dataset, the direct Alpha. Alpha is often used in finance to judge an investment's ability to beat the market. In the single-index model, developed by William Sharpe in 1963, the alpha coefficient is the intercept of the security characteristic line: $SCL: R_{i,t} - R_f = \alpha + \beta_i (R_m - R_f) + \varepsilon_{i,t}$. This model assumes that there is only 1 macroeconomic factor that causes systematic risk affecting all stock returns which can be represented by the rate of return on a market index.

However, in our dataset Alpha is defined a bit differently. Preqin calculates the direct Alpha by discounting the fund cash flows by the relevant public market index value. For the U.S. funds we use the S&P 500 Direct Alpha and for the European funds we use the MSCI Europe Standard Direct Alpha. One might argue for the use of a different public market equivalent (PME) that is more relevant to private equity such as the Russel 2000 which tracks small-cap stocks in the U.S. or the MSCI Europe Small Cap ETF which does the same for Europe. Preqin does provide the Russell 2000 direct Alpha, however it does not provide a European equivalent. Therefore, we choose to use the S&P 500 and the MSCI Europe Standard as PME, since they both monitor the large cap stock markets and provide us with the sentiment of the general economy.

A disadvantage of using this measure is the lack of observations with this data in our set. This might be explained by the additional requirement to specify the cash flows instead of only the IRR, causing an extra hurdle for CFOs to provide this information. To make our research as comprehensive as possible, we will test our hypotheses using both the IRR sample and the Direct Alpha sample and compare the results.

We also include fund size, year of inception, fund strategy and core industry as control variables that might also affect the fund's performance. Fund size is defined as assets under management in millions of U.S. dollar. Preqin calculates this through the sum of the dry powder and the value of unrealized portfolio investments. Dry powder is calculated by the fund's latest close size minus the capital called amount. The unrealized value is calculated by the RVPI percentage multiplied with the called capital. RVPI stands for the residual value paid in which is a valuation that represents the amount at which an asset can be acquired or sold. It is important to note that there exists a lag of 6 months for the latest quarter end data to become available on the Preqin database.

Fund strategy is defined by the fund's focus on the stage at which they invest. This can either be early stage, early stage: seed, early stage: start-up, expansion/late stage or venture general in which case they do not focus on a certain stage. Our industry variable defines where the focus of the fund lies with regard to a certain area.

4.2 Analysis

In order to perform our analysis, we start off with specifying our model. We run various regressions and compare the different values of the Akaike's Information Criterion (AIC) and choose the model with the lowest value (Akaike, 1998). These AIC values for different models can be found in appendix A.

4.2.1 Validation of previous research

Firstly, we will examine the same time period as the research conducted by Oehler et al in 2007, in order to discover if our results align. To do this, we regress using only the observations before 2007. After examining the AIC, we found the following specification of the model to be most effective:

$$Regression\ 1: IRR = \beta_0 + \beta_1 FundSize + \beta_2 IsEU + \beta_3 Year + e_i$$

To ensure that our ordinary least squares (OLS) regression provides us with the best linear unbiased estimates (BLUE), we need to verify the assumptions stated in the classical linear regression model (Brooks, 2019). When verifying these assumptions, we find that there exists heteroskedasticity in our dataset which forces us to use robust standard errors. Considering we also have missing observations in our dataset, we want to know whether these are Missing Completely at Random (MCAR), meaning that missingness of observations does not depend on explanatory variables in our dataset. We test for this using Little's test of MCAR after which we reject the null hypothesis of missingness being completely at random, meaning estimates might be biased (Li, 2013).

To make our research as complete as possible, we regress once again using the same methodology as with the IRR, but instead use Alpha as a performance metric instead of the IRR and find the following model to be most effective:

$$Regression\ 2: Alpha = \beta_0 + \beta_1 FundSize + \beta_2 Strategy + \beta_3 IsEU + \beta_4 Year + e_i$$

4.2.2 Modelling with all observations

After verification of the findings by Oehler et al, we estimate several new regressions using all observations in our dataset. Once again, we specify our model by picking the one that yields the lowest AIC. For the IRR-model, the following specification was most effective:

$$Regression\ 3: IRR = \beta_0 + \beta_1 FundSize + \beta_2 Industry + \beta_3 Strategy + \beta_4 IsEU + \beta_5 Year + e_i$$

Afterwards, we used the same methodology to estimate the model using Alpha as performance metric which gave us the following specification:

$$Regression\ 4: Alpha = \beta_0 + \beta_1 FundSize + \beta_2 Industry + \beta_3 Strategy + e_i$$

4.2.3 Two-sample t-test

Lastly, we perform two-sample t-tests in order to discover whether there exist significant differences in a split of our sample. We compare the performance of all U.S. funds before the passing of the Sarbanes-Oxley act in mid 2002, to the ones after the act. Afterwards we compare all European funds before the passing of the AIFMD in 2011, with those after the passing of this directive. We use both the IRR and the Alpha as performance metrics in order to be as comprehensive as possible. We consider a p-value below 0.05 significant.

5. Results

In this section we will discuss the results of the analysis performed in section 4. In Table 3, we can see the results of the four different regressions and the corresponding significance. Firstly, we will discuss the results of the verification of the findings by Oehler et al. using only the observations before 2007. Then we will discuss the findings of our analysis using all observations. Lastly, we will discuss the findings from our two-sample t-tests.

When examining the results from our regression on the data before 2007, we see some contradicting results. If we use the IRR as a performance metric, European VC fund returns were actually higher than those in the U.S, thus contradicting the findings by Oehler who found that European funds significantly underperform compared to the ones in the U.S. When looking at regression 2 however, we actually see a negative coefficient of the IsEU variable meaning that returns were lower in Europe before 2007 at 1% significance. This result is in line with the findings of Oehler. An important note to make right away is to consider the small number of observations of Alpha for EU funds before 2007 in our dataset. Thus, we need to take the validity of the results from regression 2 with a grain of salt.

When we examine the results for regression 3 and 4 using all observations including the ones after 2007, we can see that both coefficients for the IsEU variable are non-significant. Therefore, we cannot reject the null hypothesis of no difference in fund performance between the EU and the U.S. In other words, the European VC market has finally caught up to its overseas counterpart.

With regards to the fund size and performance, we observe a positive relation between the size of a Fund and its performance in both of the regressions using all observations[2]. Thus, we reject the null hypothesis of no relation between these two variables at 1%. These findings are inconsistent with the hypothesis proposed in section 2.5 based on the findings of Fama and French.

<u>Table 3</u>	**Regression 1 (<2007)** IRR	**Regression 2 (<2007)** Alpha	**Regression 3** IRR	**Regression 4** Alpha
FundSize	0.018***	0.0014	0.006***	0.009***
IsEU	10.78***	-7.7820***	-0.434	-6.032
Industry: • **Consumer Discretionary** • **Consumer Discretionary, Energy & Utilities** • **Diversified** • **Energy & Utilities** • **Financial & Insurance, Healthcare** • **Healthcare** • **Healthcare IT** • **Industrials** • **IT** • **IT, Telecoms & Media** • **Raw Materials & Natural Resources** • **Telecoms & Media**	n/a	n/a	4.997 23.032*** -4.887 2.976 -5.992 10.607*** 1.469 12.073*** 3.989 -10.408 3.823 5.744 -2.88 1.862	-5.18051 1.40285 18.1260*** 4.2445 1.5114 4.005 4.4809 8.4638*** 3.7165
Strategy: • **Early Stage: Seed** • **Early Stage: Start-up** • **Expansion/Late Stage**	n/a n/a n/a n/a	-6.581*** -0.086 12.393** -1.690	-4.674 -.0154 -1.008 -3.833	4.0678 -1.1874 -.8189 -5.1552

[2] Note: we also ran these regressions with a quadratic term for FundSize. These findings were non-significant and therefore omitted from the research

• **Venture (General)**				
Year • **1997**	-3.2034***	n/a	.31006	n/a
• **1998**	-12.5472***	n/a	-14.0545***	n/a
• **1999**	-12.3084***	n/a	-11.5493***	n/a
• **2000**	-15.0429***	-6.6006***	-13.9060***	n/a
• **2001**	-11.6207***	-3.0580	-10.7223***	n/a
• **2002**	-11.4078***	-3.9586***	-13.6991***	n/a
• **2003**	-8.5709***	-4.9900***	-10.7439***	n/a
• **2004**	-13.1076**	-6.8605***	-15.6725**	n/a
• **2005**	-7.0568***	-2.1812	-6.4787**	n/a
• **2006**	-13.1401***	-5.2484**	-12.4297***	n/a
• **2007**	n/a	n/a	-5.6508*	n/a
• **2008**	n/a	n/a	-6.6964**	n/a
• **2009**	n/a	n/a	-7.0219**	n/a
• **2010**	n/a	n/a	0.4231	n/a
• **2011**	n/a	n/a	-0.00004	n/a
• **2012**	n/a	n/a	1.0217	n/a
• **2013**	n/a	n/a	-0.4894	n/a
• **2014**	n/a	n/a	11.9256	n/a
• **2015**	n/a	n/a	0.3407	n/a
• **2016**	n/a	n/a	1.8267	n/a
• **2017**	n/a	n/a	3.5997	n/a

• **2018**	n/a	n/a	3.0021	n/a
• **2019**	n/a	n/a	n/a	n/a
• **2020**	n/a	n/a	n/a	n/a
*/**/*** *Represent significance at 10%*, 5% *& 1% respectively*				

In our two-sample t-tests, we make the following observations. When looking at the performance before and after the institution of Sarbanes-Oxley, we see that the performance was lower after the passing of the legislation at 10% significance, when using IRR as the relevant performance metric. When using Alpha however, we do not have any significant findings. Thus, our findings with regard to the effect of Sarbanes-Oxley are somewhat inconclusive and therefore we cannot reject the null hypothesis of no significant difference.

Then we do the same for the AIFMD regulation in Europe. When using IRR, we find the mean performance to be significantly higher after the passing of the legislation. When using Alpha as a performance measure, we find the exact opposite but at 10%. However, it does have to be noted that the sample size for European funds when using Alpha was only 21 observations. Still, our evidence is inconclusive and therefore we cannot reject the null of no significant difference.

Table 4	**IRR**			**Alpha**		
	Interpretation	p-value	Test statistic	Interpretation	p-value	Test statistic
Sarbanes-Oxley	µ1>µ0*	0.098	-1.295	NSF	0.189	0.883
AIFMD	µ0>µ1***	0.004	2.694	µ1>µ0*	0.060	-1.626

The results describe which sample mean is significantly larger, where µ1is the sample before the relevant legislation, and µ0is after. To clarify:

- *If* µ0>µ1*performance is higher after the legislation*
- *If* µ1>µ0 *performance is lower after the legislation*

//*** Represent significance at 10%*, 5% *& 1% respectively*

NSF stands for No Significant Findings

6. Discussion

In this section we present a discussion of our findings. We will go over the interpretation of our results, possible future research and some shortcomings we encountered

6.1 Interpretation of results

Based on the results of regression 1 and 2 using data before 2007, it is difficult to draw a conclusion, considering we have contradicting findings and thus inconclusive evidence. The findings of regression 1 using the IRR as performance measure, provide a stark contrast to the findings by Oehler et al and Hege et al. We actually find that the returns of European VC funds are higher than those in the U.S. Contrary to regression 1, regression 2 using the Alpha does find the same relation as Oehler et al and Hege et al, and shows that VC returns are lower in Europe. Hege discounts the IRR with a relevant public market equivalent to arrive at an excess return measure similar to Alpha. This could explain why the results of regression 1 using the IRR do not confirm previous findings, whereas using the excess return does confirm previous findings.

One could argue that considering that Alpha uses the return in excess of a public market equivalent, this contradiction could have been caused by extraordinarily high returns in the European PME causing the alpha to become lower than those of U.S. funds. When examining the returns of both PME's over the period 1996 until 2007, we see that the European PME has a compounded annual growth rate (CAGR) of 11.41% and that the U.S. PME has a CAGR of 9.11%. Despite the existence of year-on-year effects caused by the compounding of returns, it is unlikely that this small spread could have caused such a drastic difference in results. It is important to note however that there were only a small number of observations of alpha available in our dataset for European funds, thus making the results of our second regression somewhat unreliable.

Based on our results of regression 3 and 4 we can conclude that when using all observations, we did not find a significant difference in returns between VC funds in Europe and the U.S. This indicates that the previously shown gap in performance between both markets has now been closed. This finding is consistent with the hypothesis posed in section 2.5, stating that the U.S. VC market does not outperform its European counterpart anymore. To clarify this finding, we mention several possible explanations. As mentioned previously, in the last 20 years, several important financial laws have been passed. Sarbanes-Oxley being the most important one for the U.S. and the Alternative Investment Managers Directive being the most important one for Europe. Sarbanes-Oxley has often been criticized for damaging U.S. capital markets due to its restrictive regulation and increased compliance costs (Sarbanes & Oxley, 2002). It also reduced the attractiveness of the exit through IPO, with IPOs plummeting in the years after the passing of the legislation. Considering this was one of the most lucrative ways to exit a VC investment, it would seem probable that this law had a negative impact on fund performance.

However, tightened regulation also increases transparency and protection of investors. Huang & Zhang showed in 2012 that expanded disclosure prompts outsiders' interference in the diversion of corporate resources, thereby creating shareholder value and reducing agency costs. This reduction in agency costs actually improves efficiency which should increase returns. Thus, there are multiple perspectives on the impact of these regulations. Our results are not conclusive enough to explain our findings using the institution of these legislations. Further research on the impact of both regulations on both VC markets is needed to draw conclusions

Now we will discuss the results related to our second hypothesis. Our findings show that the fund size has a small but positive significant impact on the performance, thus we reject the null hypothesis of no significant impact. These findings contradict the ones by Chan et al who found a negative impact between fund size and fund performance. Our findings are more in line with those by Ammann et al who demonstrated a positive relation between fund size and performance, caused by the lower total expense ratio of large funds (Ammann & Moerth, 2005). Legislation such as Sarbanes-Oxley and the AIFMD might also strengthen economies of scale in the investment industry. As stated in section 2.4, both legislations have brought extra compliance costs with them (Kokkila, 2016). Due to these compliance costs hitting small firms relatively harder, economies of scale can arise thus benefiting larger firms. Since our results comparing returns before and after legislation are inconclusive, it is difficult to provide an empirically substantiated claim that both legislations increased economies of scale in the investment industry. This might be an interesting topic for future research to examine.

6.2 Shortcomings

When conducting this research, we ran into a number of limitations with the first one being the dataset. The lack of reporting requirements for small funds causes relevant databases in the Private equity industry to be largely reliant on voluntary reporting. This causes a number of biases who are extensively discussed in section 3.2. It was difficult to find a comprehensive database to conduct my research from the ones at my disposal. Preqin provided the best data, even though it still had some flaws. Due to the voluntary nature of their data gathering, quite some observations had missing values for a number of the variables of interest. This significantly reduced my dataset caused by the necessary omission of missing observations. An important side note that has to be made with regard to this missing data is the lack of the missingness completely at random (MCAR). In short, MCAR means that the missingness of observations is not related to other variables. We performed Little's test to verify this and found that the data was not MCAR (Li, 2013). Possible explanations for this observation might be that other factors might have affected this missingness. For instance, firms underperforming the market might want to report their IRR to Preqin, but not the Alpha considering it might have a negative impact on the public image of said firm. In order to deal with a lack of MCAR without omitting observations, one can impute the observations using Random Forest. This method is popular in biomedical research but still not without its limitations. If the dataset is highly skewed or if non-linearity is present, imputation using Random Forest should be used with care (Hong & Lynn, 2020). Considering the non-normal distribution of errors in our dataset, this method would have only yielded limited results.

Another issue with our dataset was the overrepresentation of certain funds. For instance, 87% of the funds in our dataset where U.S., causing European funds to be underrepresented in our sample. Furthermore, some sectors were much more prevalent in our dataset such as IT and Healthcare comprising more than half of our dataset.

The lack of a more complete dataset also manifested itself in other areas. The Preqin database only provided performance metrics related to the IRR. Despite its frequent use in finance and academics, the internal rate of return has some large shortcomings which we discussed in section 4.1. The fact that this metric can be easily distorted or adjusted is reason for us to examine the results of this research with a healthy amount of skepticism.

Preqin did also provide observations with the Alpha, which functioned as a better metric than the regular IRR. However, a lot of observations for the Alpha of funds in our dataset were missing, causing the sample size to be decreased significantly. A possible explanation for this might be the required additional information of cash flows that have to be specified in order to calculate this metric, causing an additional hurdle for fund managers to overcome.

7. Conclusion

This paper analyzed the performance of Venture capital funds in Europe and the United States. We compared the two historical backgrounds of both markets and legislative framework. We tested performance using both the IRR and the direct Alpha, provided by the Preqin database.

The Venture capital industry has been through a number of ups and downs over the last 70 years since its inception in 1946. The late development of the European VC market has caused the performance of European VC funds to have lagged behind those of their overseas counterpart for quite some time now. In this research, we provide empirical evidence that the gap in performance between both markets has now been closed. The evidence for the effect of legislation on fund performance seems inconclusive due to ambiguous results. This might be partially due to the shortcomings of the Preqin database such as non-MCAR observations, only the availability of IRR as a performance metric and only a small sample of observations with the direct Alpha. We also find a positive relation between fund size and performance, contradicting previous work by Chan et al.

This research focuses only on VC funds in the U.S. and member states of the European Union. Due to the inconclusive nature of the results in this paper, further long-term research is needed to discover whether the institution of the AIFMD played a significant role in the improved performance of European VC funds over the last decade. Furthermore, the impact of these legislations on the existence of economies of scale in the Venture capital market might also be an interesting topic for future research, considering its possible use for advocating larger financial restrictions.

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Appendix

Appendix A. Information Criteria

Results using data before 2007

Model 1

Model	**AIC**	**BIC**	**R2**
• FundSize • Industry • Strategy • Year • IsEU	**1283.353**	**1363.949**	**0.1763**
• Industry • Strategy • Year • IsEU	**8029.163**	**8103.443**	**0.0229**
• FundSize • Industry • Strategy • IsEU	**1276.474**	**1326.071**	**0.1077**
• FundSize • Strategy • Year • IsEU	**1273.736**	**1326.434**	**0.1331**
• FundSize • Year • IsEU	**1264.203**	**1298.301**	**0.1199**

Model 2

Model	**AIC**	**BIC**	**R2**
• FundSize	223.147	241.161	0.6109

• Industry • Strategy • Year • IsEU			
• Industry • Strategy • Year • IsEU	280.472	306.374	0.5756
• FundSize • Industry • Strategy • IsEU	227.037	240.137	0.4952
• FundSize • Strategy • Year • IsEU	220.802	232.265	0.5484
• FundSize • Year • IsEU	238.061	246.249	0.2090

Results using the full dataset

Model 3

Model	**AIC**	**BIC**	**R2**
• FundSize • Industry • Strategy • Year • IsEU	**5313.752**	**5471.375**	**0.1623**
• Industry • Strategy	**13689.4**	**13903.59**	**0.1557**

• Year • IsEU			
• FundSize • Industry • Strategy • IsEU	**5324.128**	**5394.182**	**0.0876**
• FundSize • Strategy • Year • IsEU	**5341.151**	**5459.505**	**0.1325**
• FundSize • Year • IsEU	**5336.712**	**5437.533**	**0.1272**

Model 4

Model	**AIC**	**BIC**	**R2**
• FundSize • Industry • Strategy • Year • IsEU	**2183.94**	**2287.342**	**0.1763**
• Industry • Strategy • Year • IsEU	**2620.879**	**2732.886**	**0.1522**
• FundSize • Industry • Strategy • IsEU	**2180.324**	**2273.386**	**0.1678**
• FundSize	**2208.396**	**2294.779**	**0.1102**

• Strategy • Year • IsEU			
• FundSize • Year • IsEU	**2205.009**	**2277.57**	**0.0925**

Appendix B. STATA Code

```
clear

* 1. Import our dataset
                import excel "/Users/casperfeitz/Erasmus University Rotterdam/OneDrive - Erasmus
University Rotterdam/Scriptie/Data/VC Funds US & Eur 1994-2006", sheet("Preqin_Export") firstrow

* 2. Clean and transform our dataset
        * 2.a Rename some variables to make them more comprehensive
                rename NETIRR IRR
                rename AUMUSDMN FundSize
                rename COREINDUSTRIES Industry
                rename STRATEGY Strategy
                rename COUNTRY Location
        3       rename VINTAGEINCEPTIONYEAR Year

        * 2.b Transform data to contain missing datapoints instead of n/a or n/m

                replace IRR = "." if IRR == "n/a"
                replace IRR = "." if IRR == "n/m"

                replace Alpha = "." if Alpha == "n/a"
                replace Alpha = "." if Alpha == "n/m"

                replace NETMULTIPLEX = "." if NETMULTIPLEX == "n/a"
                replace NETMULTIPLEX = "." if NETMULTIPLEX == "n/m"

                replace RVPI = "." if RVPI == "n/a"
                replace RVPI = "." if RVPI == "n/m"

                replace DPI = "." if DPI == "n/a"
                replace DPI = "." if DPI == "n/m"

                replace CALLED = "." if CALLED == "n/a"
                replace CALLED = "." if CALLED == "n/m"

        * 2.c Some variables are stored as string so we need to convert them to a numerical value
                * Net_IRR:
                        destring IRR, gen(IRR_int)
                        drop IRR
                        rename IRR_int IRR

                * Alpha:
                        destring Alpha, gen(Alpha_int)
                        drop Alpha
                        rename Alpha_int Alpha

                * NETMULTIPLEXT:
                        destring NETMULTIPLEX, gen(NETMULTIPLEX_int)
                        drop NETMULTIPLEX
                        rename NETMULTIPLEX_int NETMULTIPLEX

                * RVPI:
                        destring RVPI, gen(RVPI_int)
                        drop RVPI
                        rename RVPI_int RVPI
```

```
		* DPI:
			destring DPI, gen(DPI_int)
			drop DPI
			rename DPI_int DPI
		* CALLED:
			destring CALLED, gen(CALLED_int)
			drop CALLED
			rename CALLED_int CALLED

	* 2.f Our categorical variables need to be encoded as such which we do below
		* Industry:
			encode Industry, gen (Industrycodes)
			drop Industry
			rename Industrycodes Industry

		* Strategy:
			encode Strategy, gen (Strategycodes)
			drop Strategy
			rename Strategycodes Strategy

		* Location:
			encode Location, gen (Locationcodes)
			drop Location
			rename Locationcodes Location


	* 2.g Drop unneeded variables
		drop INDUSTRYVERTICALS ASSETCLASS FUNDID FIRMID NAME FINALCLOSESIZEUSDMN NETMULTIPLEX
RVPI DPI CALLED PREQINQUARTILERANK STATUS FUNDMANAGER GEOGRAPHICFOCUS DATEREPORTED

		* The eu was founded on the first of november 1993. Therefore we drop all observations
before 1994
		drop if Year<1994

	* 2.h Generate a few new binary variable stating:
		* whether a fund is located in the EU (1) or US (0)
			gen int IsEU = 0 if Location == 20
			replace IsEU = 1 if IsEU == .

		* Whether a fund is started before 2007(1) or after(0)
			gen int Before2007 = 1 if Year < 2007
			replace Before2007 = 0 if Before2007 ==.

		* Whether a U.S. fund is started before Sarbanes-Oxley
			gen int BeforeSarbanes = 1 if Year <2003
			replace BeforeSarbanes = 0 if BeforeSarbanes ==.

		* Whether a European fund is started before AIFMD
			gen int BeforeAIFMD = 1 if Year < 2012
			replace BeforeAIFMD = 0 if BeforeAIFMD ==.


*3. Now we do our analysis using both the IRR and Alpha as a performance measure. First we use IRR and
then Alpha and compare the two. We use GETS modelling use the model that minimizes the information
criteria

* Regression 1:
* 3.1 Comparison with previous research. We start off with running the most general regression for
data before 2007. Since that was the publishing year of the most recent research, we want to examine
if we get the same results. We use the model that minimizes Aikake's Information Criterion (AIC).
			reg IRR FundSize i.Year IsEU
		* We test to see if there exists heterogeneity using a Breusch-pagan test
			estat hettest
		* The value of the test statistic is larger than 0.1 meaning we reject the null
hypothesis of homogeneity at 10%. Therefore we have to run the regression once more using robust
standard errors
			reg IRR FundSize IsEU i.Year, robust
		* Now we check if the average value of errors is zero
			predict IRR_res, residuals
		* Test for normality of errors using a Shapiro-Wilk test
			swilk(IRR_res)
		* Errors are not normally distributed. However, considering our sufficiently large
sample size, the violation of the normality assumption is virtually inconsequential meaning we
disregard our finding for the rest of the analysis.
```

```
                        sum(IRR_res)
                * Furthermore we see the mean of the residuals is equal to zero confirming the last
assumption of the CLRM


* Regression 2:
                * Therefore we estimate again with Alpha as the dependent variable and using the model
that minimizes the AIC.
                        reg Alpha FundSize i.Strategy i.Year IsEU
                        estat hettest
                * The value of the test statistic is less than 0.1, meaning we reject the null
hypothesis of homogeneity at 10%. We run the regression again using robust standard errors
                        reg Alpha FundSize i.Strategy IsEU i.Year, robust
                        predict Alpha_res, residuals
                        sum Alpha_res
                * Using Alpha as a performance metric causes the mean of the error term to be almost
equal to zero thus reducing the bias. Furthermore the R-squared of the model using the Alpha is a lot
higher. We can see that our IsEU variable has a significant negative impact (at 1%) on the Alpha, thus
making us able to draw the same conclusion as Oehler et al that fund performance in the EU is
significantly lower.

                * Now we run an MCAR test to check if the observations are missing completely at
random (MCAR) in our variables of interest
                        mcartest Alpha FundSize Industry Strategy IsEU Year if Year<2007, emoutput
nolog
                * We find that the MCAR test is significant at the 1% level meaning our data is not
MCAR. Thus we take this in to account as one of our shortcomings and mention in discussion.
                                drop IRR_res Alpha_res


*----------------------------------------------------------------------------------------------------
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* Now we import the new dataset with all observations

clear

* 1. Import our dataset
                import excel "/Users/casperfeitz/Erasmus University Rotterdam/OneDrive - Erasmus
University Rotterdam/Scriptie/Data/VC Funds US & Eur", sheet("Preqin_Export") firstrow

* 2. Clean and transform our dataset
        * 2.a Rename some variables to make them more comprehensive
                rename NETIRR IRR
                rename AUMUSDMN FundSize
                rename COREINDUSTRIES Industry
                rename STRATEGY Strategy
                rename COUNTRY Location
                rename VINTAGEINCEPTIONYEAR Year

        * 2.b Transform data to contain missing datapoints instead of n/a or n/m

                replace IRR = "." if IRR == "n/a"
                replace IRR = "." if IRR == "n/m"

                replace Alpha = "." if Alpha == "n/a"
                replace Alpha = "." if Alpha == "n/m"

                replace NETMULTIPLEX = "." if NETMULTIPLEX == "n/a"
                replace NETMULTIPLEX = "." if NETMULTIPLEX == "n/m"

                replace RVPI = "." if RVPI == "n/a"
                replace RVPI = "." if RVPI == "n/m"

                replace DPI = "." if DPI == "n/a"
                replace DPI = "." if DPI == "n/m"

                replace CALLED = "." if CALLED == "n/a"
                replace CALLED = "." if CALLED == "n/m"

        * 2.c Some variables are stored as string so we need to convert them to a numerical value
```

```
		* Net_IRR:
			destring IRR, gen(IRR_int)
			drop IRR
			rename IRR_int IRR

		* Alpha:
			destring Alpha, gen(Alpha_int)
			drop Alpha
			rename Alpha_int Alpha

		* NETMULTIPLEXT:
			destring NETMULTIPLEX, gen(NETMULTIPLEX_int)
			drop NETMULTIPLEX
			rename NETMULTIPLEX_int NETMULTIPLEX

		* RVPI:
			destring RVPI, gen(RVPI_int)
			drop RVPI
			rename RVPI_int RVPI
		* DPI:
			destring DPI, gen(DPI_int)
			drop DPI
			rename DPI_int DPI
		* CALLED:
			destring CALLED, gen(CALLED_int)
			drop CALLED
			rename CALLED_int CALLED

	* 2.f Our categorical variables need to be encoded as such which we do below
		* Industry:
			encode Industry, gen (Industrycodes)
			drop Industry
			rename Industrycodes Industry

		* Strategy:
			encode Strategy, gen (Strategycodes)
			drop Strategy
			rename Strategycodes Strategy

		* Location:
			encode Location, gen (Locationcodes)
			drop Location
			rename Locationcodes Location


	* 2.g Drop unneeded variables
		drop INDUSTRYVERTICALS ASSETCLASS FUNDID FIRMID NAME FINALCLOSESIZEUSDMN NETMULTIPLEX
RVPI DPI CALLED PREQINQUARTILERANK STATUS FUNDMANAGER GEOGRAPHICFOCUS DATEREPORTED

		* The eu was founded on the first of november 1993. Therefore we drop all observations
before 1994
		drop if Year<1994

	* 2.h Generate a few new binary variable stating:
		* whether a fund is located in the EU (1) or US (0)
			gen int IsEU = 0 if Location == 23
			replace IsEU = 1 if IsEU == .

		* Whether a fund is started before 2007(1) or after(0)
			gen int Before2007 = 1 if Year < 2007
			replace Before2007 = 0 if Before2007 ==.

		* Whether a U.S. fund is started before Sarbanes-Oxley
			gen int BeforeSarbanes = 1 if Year <2003
			replace BeforeSarbanes = 0 if BeforeSarbanes ==.

		* Whether a European fund is started before AIFMD
			gen int BeforeAIFMD = 1 if Year < 2012
			replace BeforeAIFMD = 0 if BeforeAIFMD ==.

* Regression 3:

* 3.2 Now we compare the findings of our regression using the data before 2007 with a regression using
the complete dataset. Once again we use the model that minimizes the AIC
```

```
* IRR
		reg IRR FundSize i.Industry i.Strategy IsEU i.Year
		* We test for heterogeneity
		estat hettest
		* The test statistic is below 10% meaning we reject the null of homogeneity and run
the regression again using robust errors.
		reg IRR FundSize i.Industry i.Strategy IsEU i.Year, robust
		predict IRR_res, residuals
		sum IRR_res
		* We see that the mean of the errors is close to zero at -6.21e-08. Thus the
assumptions of the CLRM hold. Furthermore we can see that the IsEU coefficient is non significant and
almost zero meaning that whether the fund is located in the EU or not is not explanatory for the
performance.


* Regression 4:

* Alpha
	* Now we perform the same analysis but with the Alpha as performance metric. We use the model
that minimizes the AIC
		reg Alpha FundSize i.Industry i.Strategy IsEU
	* Test for heterogeneity
		estat hettest
		* Test statistic is below 10% meaning we reject the null of homogeneity and run the
regressino again using robust errors
		reg Alpha FundSize i.Industry i.Strategy IsEU, robust
		predict Alpha_res, residuals
		sum Alpha_res
		* We can see that the mean of the errors is close to zero at -8.39e-08. Thus the
assumptions of the CLRM hold. Next to that we can see taht the IsEU coefficient is once again non
significant indicating the lack of a relationship between the Alpha and whether a fund is located in
the EU.



* 4 Comparing returns before and after legislation

	* 4.1 Comparing U.S. returns before and after the passing of Sarbanes-Oxley through a 2 sample
t test by splitting up our sample into observations before the passing of SO and After.
		ttest IRR if IsEU==0, by(BeforeSarbanes)
	* We find no significant difference in IRR before and after Sarbanes-Oxley. We perform the
same analysis but with using the Alpha
		ttest Alpha if IsEU==0, by(BeforeSarbanes)
	* Once again we find no significant difference in returns


	*4.2 Now we do the same but for the European market, using the passing of the AIFMD regulation
comparison.
				ttest IRR if IsEU==1, by(BeforeAIFMD)
	* We find a significant difference in returns before and after the passing of the AIFMD at the
1% significance level. We can interpret the results from the t-test as evidence that returns after the
passing of the AIFMD are larger
		ttest Alpha if IsEU==1, by(BeforeAIFMD)
	* When using Alpha as a performance metric, we do not find a statistically significant
difference in returns. However, it must be noted that our sample size when using Alpha is very small
due to limited observations of Alpha in our European dataset.
```