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Syndicate effects of venture capital backed start-ups in Europe and the United States

To what extent is the difference in performance of venture capital backed start-ups between Europe and the United States due to syndicate effects?

Abstract

This thesis investigates whether syndicate venture capital backed start-ups perform better than non-syndicate venture capital backed start-ups in Europe and in the U.S. With a total sample of 384 start-ups we find that syndicate venture capital backed start-ups have a lower underpricing in comparison with non-syndicate venture capital backed start-ups. We also find evidence that syndicate venture capital backed start-ups have a higher innovation level in comparison with non-syndicate venture capital backed start-ups. Furthermore, we find that the long-term public performance of syndicate venture capital backed start-ups in Europe is higher than the long-term public performance of non-syndicate venture capital backed start-ups in Europe. In this paper we provide evidence that syndicate venture capital backed start-ups have a significant positive influence on the long-term operating performance. There is a better long-term operating performance in the U.S. in comparison with Europe and this is due to syndication effects.

Keywords: Venture Capital, Syndicate, Initial Public Offerings, Performance.
JEL Classification: G24, G32, M13.

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1. Introduction

Venture capital (VC) firms can have an impact on the economy of a country by stimulating innovation and growth (Bernstein, Giroud, & Townsend, 2016). In the first quarter of 2016, VCs raised $13 billion, which is the most since the dot-com bubble in 2000 (Winkler, 2016). VCs serve as the intermediary between the investors and the entrepreneurs (Brander, Amit & Antweiler, 2002). VCs review and invest in young companies (Gompers, 1995). We define these young companies as start-ups. To make successful investments, VCs often combine forces with other VCs if they invest in a start-up (Lerner, 1994a). In this case they can have the advantages of synergies. A better relationship with other VCs, so a better networked VC, has a positive effect on the performance of VCs in the United States (Hochberg, Ljungqvist, & Lu, 2007). If at least two VCs combine forces to provide funding for a start-up, the funding is defined as a syndicate deal (Brander et al., 2002; Hochberg et al., 2007; Tian, 2012). We define a start-up that is backed by two or more VCs as a syndicate VC-backed start-up and a start-up that is backed by solely one VC during the whole funding as a non-syndicate VC-backed start-up. Syndication among VC firms can result in a better overall performance for the portfolio start-ups (Tian, 2012). Manigart, Lockett, Mueleman, Wright, Landström, Bruining, Desbrières and Hommel (2006) investigate the syndication motives of VCs in Europe. Manigart et al. (2006) find that the reasons for syndication among VCs in Europe differ from the reasons in the U.S. They show that, according to the statistics of the European Venture Capital Association (2002), 28.7% of all the deals in 2001 are syndicate in Europe. Manigart et al. (2006) do not investigate if syndication in Europe has a positive effect on the performance of either the VC or the start-up.

Besides syndication, the performance of the start-ups on the public market is important for the VC firms (Lerner, 1994b). The bulk of the profits of the VC firms is depended on an IPO of the start-up (Lerner, 1994b). There are many earlier empirical papers on the performance of start-ups on the public market for the short-term and the long-term (Lerner, 1994b; Hamao, Packer & Ritter, 2000; Wang, Wang & Lu, 2003; Da Silva Rosa, Velayuthen & Walter, 2003; Bessler & Seim, 2012).

Tian (2012) investigates if the performance of VC-backed start-ups is depended on syndication. However, Tian (2012) does not provide evidence on the differences of the performance of syndicate VC-backed start-ups in Europe and the United States. Chahine, Arthurs, Filatotchev and Hoskisson (2012) investigate the differences of public performance of syndicate VC-backed start-ups in the U.S. and the United Kingdom. Chahine et al. (2012) find that a more diverse VC syndicates is associated with higher underpricing and lower aftermarket performance. They find that this is more persistent in the U.S. than in the U.K. This is contradictory with Tian (2012). Tian (2012) finds that VC syndication results in a lower underpricing and higher aftermarket performance.

There is more academic interest in VCs operating in Europe over the last years (Anderloni & Tanda, 2012). Kelly (2009) finds that European VCs underperform U.S. VCs. Also, other empirical papers investigate the differences of the performance of VCs active in Europe and the U.S. (Jeng &

Wells, 2000; Hege, Palomino & Schwienbacher, 2003; Schwienbacher, 2005). Hege et al. (2003) finds that syndication is a more important factor for the U.S. than in Europe. In their dataset 50% of the VCs in Europe are syndicated deals whereas, 80% of the VCs in the U.S. are syndicated deals. Hege et al. (2003) focus on the type of exit and the internal rate of return rather than on the return on the public market or the post-IPO operational measures. Hege et al. (2003) find that VCs have a better performance in the U.S. than in Europe. We will explore whether there is a difference in the performance of VC-backed start-ups in Europe and the U.S. due to syndication effects.

Therefore, the research question investigated in this paper is:

"To what extent is the difference in performance of VC-backed start-ups in Europe and the U.S. due to syndication effects?"

We have a total sample of 348 VC-backed start-ups (U.S. and Europe combined). The short-term performance of VC-backed start-ups will be measured by the first trading day of the VC-backed start-up, in accordance with Barry Muscarella, Peavy and Vetsuypens (1990), Megginson and Weiss (1991), and Lerner (1994b). We will use the initial return measure to investigate the short-term performance of the VC-backed start-ups (Ritter, 1984; Megginson & Weiss, 1991; Loughran & Ritter, 2004). Furthermore, we will also investigate the long-term performance of the VC-backed start-ups with the buy and hold abnormal returns and the cumulative abnormal returns in accordance with Ritter (1991), Espenlaub, Garrett and Mun (1999) [1], da Silva Rosa et al. (2003), Chahine and Fiatotchev (2008), and Bessler and Seim (2012). We will also test for robustness with the long-term performance of the VC-backed start-ups with the operating measures EBITDA/Revenue and EBITDA/Assets (Tian, 2012). We will also measure the difference in innovation levels for VC-backed start-ups with the innovation measures RDRT and RDAT[2] (Gompers, 1995). The syndication of start-ups will be measured by the number of VCs that provide the funding for the start-up. We will investigate if the performance on the public market of syndicate VC-backed start-ups is better than non-syndicate VC backed start-ups. We will measure this with the ordinary least squared method (OLS) by including either the short-term, the long-term performance or post-IPO operating performance measures as the dependent variables and a syndication dummy as the independent variable (amongst other independent variables), in accordance with Tian (2012). Furthermore, we will use a dummy as the independent variable for the geographic location of the VC and the start-up (either Europe or the U.S.). We will eventually investigate if there are any differences for the performance of the VC-backed start-ups between Europe and the United States in the period of 1997 until 2015. We will also investigate the

[1] Espenlaub et al. (1999) only uses the CAR methodology.
[2] RDRT stands for research and development expenditures divided by revenue. RDAT stands for research and development expenditures divided by assets.

differences for the performance of the VC-backed start-ups between Europe and the U.S. with the Wilcoxon rank sum-test (for difference in medians) and the t-test (for difference in means).

The major findings in this paper are that syndicate VC-backed start-ups have a lower underpricing effect compared to non-syndicate VC-backed start-ups. We also find evidence that syndicate VC-backed start-ups have a higher innovation level in comparison with non-syndicate VC-backed start-ups. Furthermore, we find that the long-term public performance of syndicate VC-backed start-ups in Europe is higher than the long-term public performance of non-syndicate VC-backed start-ups in Europe. In this paper we provide evidence that syndicate VC-backed start-ups have a significant positive influence on the long-term operating performance. There is a better long-term operating performance in the U.S. in comparison with Europe and this is due to syndication effects. We also find that more VCs in a syndicated deal does not necessarily lead to a better operating performance of the start-up. The results of this paper show that it is beneficial for an investor or a VC to hold a long-term share of a syndicate VC-backed start-up in Europe that does an initial public offering.

The remainder of this paper is structured as follows. Section 2 provides a theoretical background of VCs and summarizes prior literature. Subsection 2.7 formulates the hypotheses based on prior literature. Section 3 discusses the numerous databases used in this paper. Section 4 outlines the methodology for measuring the short-term and the long-term performance of VC-backed start-ups. Section 5 highlights the regressions and discusses the results of the paper. Section 6 concludes by directly answering the research question and the hypotheses.

2. Literature

2.1 Definitions of VC

Venture capital firms invest in young private companies, we define these as start-ups. VCs take an active role in monitoring and helping the portfolio start-up by focusing on the internal growth. The goal of a VC is to make a certain return through an exit of the start-up. VCs can exit through a sale of the portfolio start-up to another investor or to a larger company, or through an initial public offering (IPO) (Metrick & Yasuda, 2011). With an IPO the VC sells its stake in the portfolio start-up in the open market (Metrick & Yasuda, 2011). Often VCs only sell a part of their stake in the start-up. Exits may also be unsuccessful due to bankruptcy of the start-ups. Knill (2009) states that 50% of the VC profits come from only 7% of the investments. Around 33% of venture capital investments result in losses and 15% of the start-ups go bankrupt (Knill, 2009).

Venture capitalists raise their financing in a VC fund. The vintage year of a VC fund is the first year of raising funding (Hochberg et al., 2007). A VC fund is structured as a limited partnership, where there are general partners and limited partners. The general partners are the venture capitalists that decide in which start-ups to invest the funds. The limited partners only provide financing, thus, have limited rights. (Metrick & Yasuda, 2011). The limited partners consist of pension funds, financial firms, insurance companies, university endowments, and individuals (Sahlman, 1990). Limited partners provide a small percentage of the total funding, but expect a return between 25% and 30% (Zider, 1998). A fund typically has a lifetime of around 10 years (Hochberg et al., 2007; Korteweg & Nagel, 2016). The average time to exit a start-up is 4.2 years (Das, Jo, & Kim, 2011). After exit, VCs invest in a new start-up and the whole process starts again.

2.2 Difference Business Angels and VC

VCs are often compared with angel investors. In a certain way they are similar, both invest in private companies and after a certain amount of time they sell their stake. However, angel investors only invest their own money and do not need the investments of limited partners. Furthermore, angel investors tend to do smaller investments than VCs (Denis, 2004). But the capital flow of angel investors and VCs is quite similar (Metrick & Yasuda, 2011). VCs often put a board member on the portfolio company, to track the company and give proper advice. Especially, if it is a younger company and it has a problem finding the right talent the VC can use its network and provide the right people for the company (Metrick & Yasuda, 2011). Angel investors are more likely to invest in the "*Seed*" stage of the start-up (Fenn, Liang & Prowse, 1997). The different stages of start-up development will be discussed in subsection *2.3*. Furthermore, the investments by angel investors are also seen as very risky (Werth & Boeert, 2013). Data on angel investors is difficult to obtain (Denis, 2004). Wong (2002) made an extensive survey of start-ups and constructed a final sample of 143 start-ups between 1994 and 2001. Wong (2002) found that angel investors can play an important role in networking if the start-up needs additional funding with VCs. This is in accordance with the research by Werth and Boeert (2013). They found that start-ups in which better connected angel investors invested, are more likely to receive subsequent funding by venture capitalists. Better connected businesses more often exit successfully. Thus, according to Denis (2004) angel investors can be seen as complementary to VCs and are not to be seen as a direct competitor of the VCs.

2.3 Different stages of VC

In general there are four stages of investments when a venture capital firm invests in a start-up (Brander, Amit & Antweiler, 2002; PWC Venture Capital Money Tree Report, 2017; KPMG Venture Pulse, 2017). These different stages are related to different periods within the start-up development. Brander et al. (2002) found that the median time that a start-up receives its first funding is within three to four years after the founding of the start-up.

The first stage can be defined as the "*Seed*" stage. This is typically the stage where there is only an idea and it can be the case that the start-up is not founded yet. The venture capital firm in this case can help with founding the company. The "*Seed*" stage is also the riskiest stage for a venture capital firm to invest in. In accordance with Bygrave (1987), Gompers (1995), and Brander et al. (2002) start-ups receive less financing in the "*Seed*'' stage of the start-up. Brander et al. (2002) found that only 1% of the start-ups received funding the first year of their existence.

The second stage can be defined as the "*Early* Stage" or *"Start-up investment"* stage. In the second stage the start-up is already founded but it is before the first sales of the start-up (Brander et al., 2002). The start-up is likely not older than one year and uses the money for product development, prototype testing and test marketing (Sahlman, 1990).

The third stage can be defined as the "early growth phase" or *Expansion Stage.* The third stage is the stage in which the start-up already made its first sales but the sales are not enough to finance on-going operations. (Brander et al., 2002). The start-up has high growth and the risk to outside investors is reduced (Sahlman, 1990).

The fourth stage can be defined as "follow-on" or "mezzanine" or *Later Stage* (Brander et al., 2002; PWC Venture Capital Money Tree Report, 2017). This is the stage where the start-up is likely to do an exit, through an IPO or a M&A deal, and is already profitable. Late stage investments are not likely to involve in a high return as there are already previous investments made by earlier investors. However, it is likely that these companies will exit and the investment will have a positive influence on the reputation of the VC (Lerner, 1994b; Sorenson et al., 2001). There is a benefit for the VCs who will invite other VCs for the last stage investing namely, they hope that the syndication partner will offer them opportunities in later rounds of their own deals (Lerner, 1994b).

Figures 1 and *2* give an overview of the investments (in millions USD) of venture capital firms retrieved from the PWC Venture Capital Money Tree Report (2017) and KPMG Venture Pulse Report

(2017). *Figure 1* shows the median deal size in millions USD of VCs in the U.S. per different stage and per quarter. *Figure 2* shows the global median deal size in millions USD per stage and per year.
In accordance with the empirical literature, *Figures 1* and *2* show that the investments in the "*Seed*" stage are much lower than the investments in the other stages.

Figure 1: *PWC US Median deal sizes by stage in millions USD*

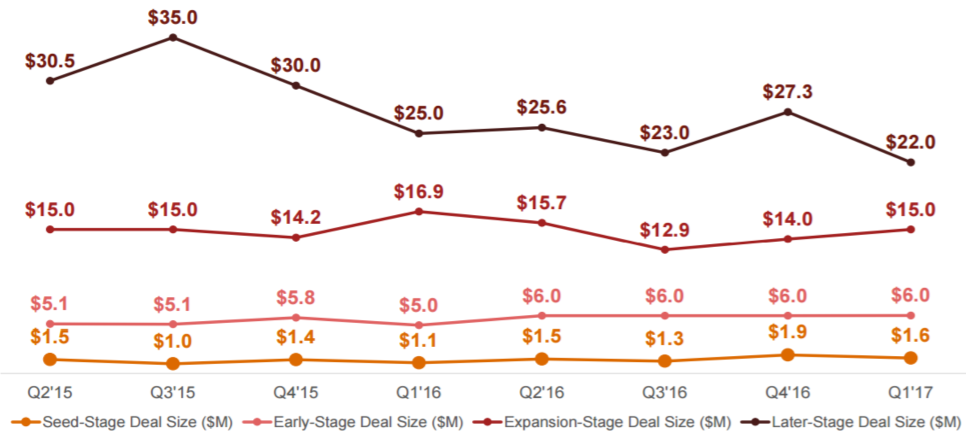
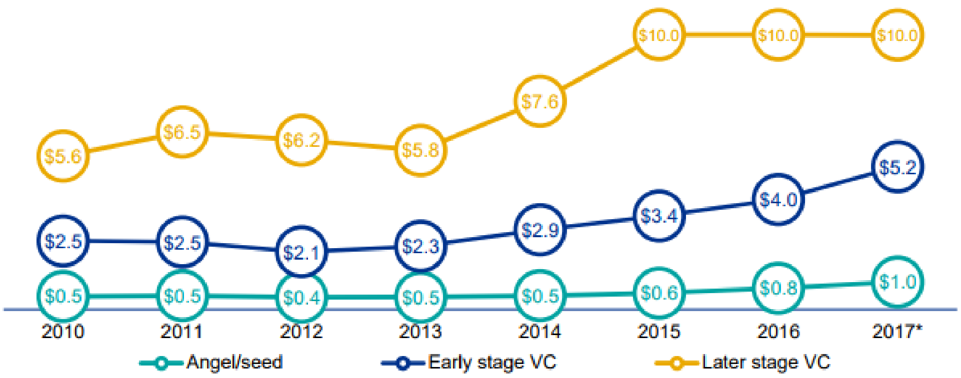


Figure 2: *KPMG Global median deal size by stage in millions USD*



2.4 VCs and IPO performance

There is earlier empirical research on IPO performance of VC-backed start-ups. *Table 1* gives an overview of the main results of earlier empirical results regarding IPO performance of VC-backed IPOs and non-VC backed IPOs. However, there is less research regarding IPO performance of syndicate VC-backed start-ups (Tian, 2012).

It is interesting that there are differences in the existing literature regarding the initial returns of the VC-backed start-ups and the non-VC-backed IPOs. Some papers appear to have found a higher initial return on the first trading day or a higher underpricing for non-VC-backed IPOs (Wang, Wang & Lu, 2003; Chahine & Filatotchev, 2008). Whereas, others have found a larger initial return on the first trading day, higher underpricing, for VC-backed IPOs. The initial results for the VC-backed IPOs on the first trading day differ between 0.74 % and 42.97% (Bessler & Seim, 2012; Krishan, Maulis & Sigh, 2011). There appears to be a certain trend over the last few years that the most recent VC-backed IPOs have lower initial returns, a lower underpricing (Bessler & Seim, 2012; Anderloni & Tanda, 2015).

Barry et al. (1990) conclude that IPOs with higher quality VCs are less underpriced. This is in accordance with the grandstanding hypothesis of Gompers (1996). The grandstanding hypothesis of Gompers (1993) and Gompers (1996) state that a young VC is willing to occur costs for a greater underpricing in order to establish a reputation and successfully raise capital for new funds.
Tian (2012) finds that syndicated VC-backed start-ups have a higher underpricing than individual VC-backed start-ups. Tian (2012) states that the difference disappears if the internet bubble from 1999-2000 is excluded. Tian (2012) finds with a 2SLS regression, IPO underpricing as the dependent variable and a syndication dummy as the independent variable (amongst others), a negative coefficient for the syndication dummy. This means that syndicate VC-backed start-ups experience on average a lower underpricing than non-syndicate VC-backed startups.

In *Table 1* VC-backed startups in the U.S. appear to have a higher initial return, higher underpricing, in comparison with the VC-backed start-ups in Europe. Krishan et al. (2011) even find a mean return of 42.97% for their VC-backed IPO sample. It should be noted that they look at the first-day raw stock return instead of the underpricing measure.

Table 1: IPO performance of VC-backed start-ups

Table 1 gives an overview of earlier empirical research for IPO performance of VC-backed start-ups in the short-term. The papers are aligned in a chronical order. The trading days differ per paper but mostly they consist of the initial return on the first trading day (measured with the offer price). The Geography is the word location that the authors have investigated. If authors have only investigated a certain country, we include in parentheses the world location. AS stands for Asia, OC stands for Oceana and EU for Europe. The sample size consists of solely the VC-backed start-ups IPOs. The significance for the difference of the initial returns is mostly tested with a t-test (mean) or a Wilcoxon rank-sum test (median). Significance levels are defined with *, **, *** respectively, 10%, 5% or 1% significance levels.

Paper	Period	Trading days	Geography	Sample size	Initial return VC-backed start-ups	Initial return non-VC-backed start-ups
Barry et al. (1990)	1978-1987	(0,1)	US	433	8.43%	7.47%
Megginson & Weiss (1991)	1983-1987	(0,1)	US	320	7.1%*	11.9%*
Lerner (1994b)	1978-1992	(0,1)	US	136	15.40%[3]	n.a.
Jain & Kini (1995)	1977-1988	(0,1)	US	136	3.77%**	0.00%**
Espenlaub et al. (1999)	1992-1995	(0,6)	UK (EU)	135	9.54%[4]	9.35%
Hamao, Packer & Ritter (2000)	1989-1995	(0,1)	JP (AS)	210	19.2%***	12.70%
Bradley & Jordan (2002)	1990-1999	(0,1)	US	1463	30.37%***	16.62%***
Wang, Wang & Lu (2002)	1987-1999	(0,1)	SP (AS)	64	20.7%*[5]	n.a.
Da Silva Rosa et al. (2003)	1991-1999	(0,1)	AU (OC)	38	33.07%	24.49%***
Wang, Wang & Lu (2003)	1987-2001	(0,1)	SP (AS)	82	13.3%***	27.6%***
Lee & Wahal (2004)	1980-2000	(0,1)	US	2208	26.82%*	19.36%*
Chahine & Filatotchev (2008)	1996-2002	(0,2)	FR (EU)	122	2.00%***[6]	5.80%***
Krishan, Maulis and Sigh (2011)	1993-2004	(0,1)	US	822	42.97%***[7]	17.83%
Tian (2012)	1980-2005	(0,1)	US	1998	15.00%***[8]	10.45%***[9]
Bessler & Seim (2012)	1996-2010	(0,1)	EU	384	0.74%***	n.a.
Anderloni & Tanda (2015)	1997-2007	(0,1)	EU	114	6.80%***	10.59%***

Table 2 gives an overview of the main results of earlier empirical results regarding long-term performance of VC-backed IPOs and non-VC backed IPOs. It is quite interesting that some empirical studies find negative long-term performance for VC-backed IPOs (Lerner, 1994; Hamao et al., 2000). The investigated number of trading days also differ among earlier studies. It is interesting that Chahine

[3] Initial return of VC backed start-up on first trading day funded by a VC with an age below or equal to the median age.
[4] Based on the six-day return; the offer price and the closing price of the six-day return.
[5] Hot-issue periods excluded.
[6] Based on the closing price of the second day of trading.
[7] The first-day raw stock return.
[8] Syndicate VC-backed IPO.
[9] Non-syndicate VC-backed IPO instead of non-VC backed IPO.

and Filatotchev (2008) find a high mean abnormal return of 32.5% for a one-year holding period. Whereas, Bessler and Seim (2012) found a mean abnormal return of 9.08% for also a one-year holding period. Obviously, the country where the IPOs are issued is of importance as Bessler and Seim (2012) focus on whole Europe and Chahine and Filatotchev (2008) only focus on France.

There does not seem to be a certain trend over the last years regarding the long-term performance for VC-backed IPOs. However, it is possible that the long-term returns for VC-backed IPOs have slightly dropped the last few years. As, Chahine and Filatotchev (2008) and Bessler and Seim (2012) investigate overlapping periods. The two periods overlap for six years (1996-2002), it appears that the last couple of years (from 2002 until 2010) the long-term returns for VC-backed IPOs have slightly dropped. Tian (2012) finds on average a higher abnormal return for syndicate VC-backed firms in comparison with non-syndicate VC-backed firms.

Table 2: Long-term performance of VC-backed start-ups

Table 2 gives an overview of earlier empirical research for IPO performance of VC-backed start-ups in the long-term. The papers are aligned in a chronical order. The methods differ per paper but mostly they consist of the 1-year, 2-year or 3-year BHAR or CAR methods. We assume 252 trading days per year. The Geography is the word location that the authors have investigated. If authors have only investigated a certain country, we include in parentheses the world location. AS stands for Asia, OC stands for Oceana and EU for Europe. The sample size consists of solely the VC-backed start-ups IPOs. The significance for the initial returns is mostly tested with a t-test (mean) or a Wilcoxon signed-rank test (median). Significance levels are defined with *, **, *** respectively, 10%, 5% or 1% significance levels.

Paper	Period	Trading days	Geography	Sample size	Return VC-backed start-ups	Return non-VC-backed start-ups
Lerner (1994b)	1978-1992	(0,59)	US	136	-4.6%***	6.1%
Brav & Gompers (1997)	1972-1992	(0,1260)	US	934	46.4%[10]	22.50%
Hamao et al. (2000)	1989-1995	(0,756)	JP (AS)	355	-38.90%	-28.20%
Espenlaub et al. (1999)	1992-1995	(0,504)	UK (EU)	135	0.14%[11]	-3.11%
Da Silva Rosa et al. (2003)	1991-1999	(0,454)	AU (OC)	38	31.47%[12]	2.23%
Wang et al. (2003)	1987-2001	(0,176)	SP (AS)	82	10.5%*	0.04%*
Chahine & Filatotchev (2008)	1996-2002	(0,252)	FR (EU)	122	32.5%***[13]	10.30%
Krishnan et al. 2006)	1993-2004	(0,756)	US	822	0.85%***[14]	-0.90%
Tian (2012)	1980-2005	(0,756)	World	2141	2.11%***[15]	1.34%[16]
Bessler & Seim (2012)	1996-2010	(0,250)	EU	365	9.08%*	2.55%

[10] Equally weighted buy-and hold returns on average. Returns are calculated by compounding daily returns up to the end of the month of the IPO and from then on compounding monthly returns for 59 months.
[11] Measured as the cumulative average abnormal return.
[12] The 24-month equal weighted cumulative buy-and hold abnormal return.
[13] Results are based on the Buy and Hold abnormal returns.
[14] Return is measured over the 36 months after the issue month.
[15] Syndicate VC-backed firms
[16] Non-syndicate VC-backed firms

There are other studies that also investigated IPO performance of VC-backed start-ups for instance: Gompers (1996). Gompers (1996) investigates the importance of the reputation of VCs. He investigates this by developing the grandstanding hypothesis. Younger VCs take a portfolio company public earlier in comparison with older VCs. If a VC has more IPOs he has a better reputation and therefore can more successfully raise capital for new funds. Gompers (1996) finds that the IPOs backed by younger VCs experienced more underpricing in comparison with the older VCs. As the younger VCs are willing to incur costs to take the company public earlier, what results in more underpricing for VC-backed start-ups by younger VCs. Furthermore, the period that young VCs have been on the board of directors at the IPO is shorter and younger VCs also hold smaller equity stakes. Gompers (1996) investigates this for two samples. Firstly, he investigates 433 VC backed IPOs in the period 1977 until 1987 and secondly, he investigates all the IPOs that were done by 62 VCs between August 1, 1983 and July 31, 1993. For the age of the VC, Gompers (1996), investigates the Lexis/Nexis's COMPNY Database. He classifies all the VCs that are younger than six years at the IPO date, as young VCs and the VCs that are older than six years at the IPO date, as old VCs. Interesting is that the Venture Economic Funds database shows that older VCs raise new funds every two to four years in comparison with young VCs who raise new funds only every five or six years. The data of Gompers (1996) also shows that the young VCs have a lower follow-on fund in comparison with the older VCs, respectively, 77.5 million dollars and 120.4 million dollars. He concludes that young VCs have a new fund raising sooner after an IPO in comparison with older VCs. It seems that the reputation of the VCs is important to determine success for the VC. In this paper we use VC control variables similar to the reputation measures Gompers (1996) used.

2.5 VC industries

The different industries where VCs invest in and where there are VC-backed IPOs do not differ a lot amongst earlier empirical research. Barry et al. (1990) found in their dataset that the 2-digit SIC code 73, the business services sector, has the most VC-backed IPOs with 21.8%. Jain and Kini (1995) find that the computers and data processing services sector has the most VC-backed IPOs with 17.64%[17]. Lee and Wahal (2004) find that the 2-digit SIC code 28[18] has the most VC-backed IPOs with a percentage of 58.0%. The second largest VC-backed IPOs according to Lee and Wahal (2004) were in the 2-digit SIC code 35[19] with 53.5%. Giot and Schwienbacher (2007) find that the computer industry is the largest with VC-backed IPOs with 29.7%. Giot and Schwienbacher (2007) only find that 6.5% of the VC-backed IPOs were done in the biotech sector. Anderloni and Tanda (2015) find that most of the VC-backed IPOs are done in the IT related sector with a percentage of 61.40% and that 38.60% of

[17] SIC code 737
[18] For Chemicals and allied products sector see Appendix B
[19] For IIndustrial and Commercial Machinery and Computer Equipment see Appendix B

the VC-backed IPOs are done in the pharmaceutical or biotech sector. Lerner (1994b) was one of the first to investigate VC-backed IPOs solely done in the biotech sector.

Thus, according to earlier empirical research most of the VC-backed IPOs are done in the Computer services- or a related- sector but there is a possible trend towards VC-backed IPOs in the biotech sector. In this paper we will also show which industries have the most VC-backed IPOs.

2.6 VC syndications and networks

Syndicates can be seen as co-investments between VCs. Syndication is defined as a form of inter-firm alliance in which two or more VC firms invest in a start-up and share a joint pay-off (Lerner, 1994a). The lead investor in the syndicated investment can be seen as the investor who started investing as the first investor (Brander et al., 2002). The lead investor can also be seen as the investor who invests the largest amount in the portfolio start-up (Hochberg et al., 2007; Das, Jo & Kim, 2011). There are two possible definitions of VC syndicates. One definition states that syndicates between VCs arise when two or more VCs invest in a start-up within the same funding round. The other definition states that two or more VCs are part of a syndicate when they have invested in a start-up no matter what the exact funding round is (Brander, Amit & Antweiler, 2002; Hochberg et al., 2007; Tian, 2012). VC syndicates are a subset of a network. The reason for this is because the VCs that participate in the same syndicated deal are in the same VC network. However, VC firms that are in the same network do not necessarily co-invest in the same syndicated deal (Tian, 2012). Hochberg et al. (2007) has a similar definition of VC syndicates namely networks exist of both current syndicate partners of the VC and past syndicate partners of the VC.

In earlier empirical research there are several reasons why VCs are involved in a syndicate. According to Manigart and Wright (2013) there are three reasons why a VC firm participates in a syndicate. Namely, risk sharing, risk reduction and access to future deal flow. Risk sharing is on the VC firms portfolio level. VC syndicates tend to have a more diversified portfolio. As, some VCs only have access to certain deals it is useful to syndicate with other VCs to ensure that they have more access to other deals and thereby creating a more diversified portfolio. Risk reduction is on the start-up level. It can be risky for certain VCs to solely invest in a certain start-up and if they combine forces with other VCs the riskiness decreases. With respect to access to future deal flows syndicated VCs benefit from an earlier syndicate and therefore have access to a wider VC network. Therefore, it is more likely that they will have access to future deal flows.

Hochberg et al. (2007) state that syndication with other VCs is very important for three similar reasons. Firstly, VCs invite other VCs to invest so that in the future they will return the favour. Secondly, by checking the willingness of other VCs to invest in the same company the VC can pool correlated signals and can therefore make a better selection of investments in the case of uncertainty.

As the other VCs are not willing to invest in the company if the company is not that promising. Thirdly, every VC has a specific sector or a certain local specification. By combining forces with other VCs, they can more easily have diversifications in their portfolio companies regarding sectors and locations. Furthermore, if a VC has better relationships with other VCs they can improve securing their fundraising for future portfolio companies.

According to Tian (2012) the main reason that a VC involves a syndicate is if a VC already has a lot of exposure to a certain industry and wants to co-invest with other VCs to be less dependent on that industry. According to Bygrave (1987) the main reason that a VC involves a syndicate is if there is a certain scarcity for promising start-ups. By co-investing, all of the VCs are still able to benefit from the scarcity. Brander et al. (2002) give a different reason namely that VCs want to have a second opinion on a doubtful start-up and therefore look for other VCs who are willing to co-invest, the *selection hypothesis*. If the other VCs are willing to invest the doubts of the lead investor are gone, as the other VCs will only invest if the start-up is promising.

The reasons why VCs syndicate also differ per geographic region. According to Manigart et al. (2002) the motives in Europe to syndicate among VC firms differ from the motives in North America. In Europe the motives to syndicate mostly consist of the financial benefits (desire to share risk and to increase portfolio diversification). Other motives as the desire to build strong and trustworthy networks or to increase deal flow are considered less important for Europe VC syndications. The VCs in North America mostly syndicate to exchange firm specific resources or deal flow considerations. Manigart et al. (2002) also find that younger VCs syndicate more than older VCs in Europe. The younger VCs in Europe clearly understand that syndication is a way to improve the reputation of the VC. In this paper we will investigate if the age of the VC is an important factor for the performance of the start-up on the public market and for the post-IPO operating performance.

Previous literature has investigated several other reasons regarding the benefits of syndication: window dressing (Lakonishok, Shleifer, Thaler & Vishny, 1994; Lerner, 1994a), deal flow generation (Lockett & Wright, 2001), value adding (Brander et al., 2002; Das, Jo & Kim; 2011), improved selection (Cumming, 2006a; Lerner, 1994a), portfolio diversification (Cumming, 2006b; Kaiser & Lauterbach; 2007) and certification (Chahine et al., 2007). Muelleman et al. (2009) focus on the costs of syndication namely agency costs. Brander et al. (2002) found that VC firms with syndicated investments tend to have higher returns in comparison with standalone investments.

Diversification for VC firms in general is also often discussed in previous literature (Norton & Tenenbaum, 1993; Milanov, Dimov & Shepherd, 2006; Knill, 2009; Cressy, Malipiero and & Munari, 2012). Clercq, Sapienza and Zaheer (2008) investigated if the involvement of individual VC firms is dominated by the syndicated group. They found out that individual VC firms first pay particular attention to the characteristics and incentives of the other syndicated group members before they calibrate their own behaviour. According to Clercq et al. (2008) a possible result of the above-mentioned theory is that the start-ups receive less service.

2.7 Hypotheses

There has been earlier empirical research on VC-backed start-ups that did an IPO but not often in combination with syndicated deals. We will investigate if syndicated deals of VC-backed start-ups will benefit on long-term (higher returns), short-term performance (lower underpricing) on the public market for our period in Europe and the US. In compliance with the papers of Hochberg et al. (2007), Kelly (2009), Lerner (1994b), Lee and Wahal (2004), Brav and Gompers (1997), Barry et al. (1990), Mueleman et al. (2009) and Tian (2012) the following hypotheses are made:

2.7.*1 Value-added and Screening hypothesis*

A VC has more contacts with top-tier investment banks and therefore may be able to trigger higher quality analysts to follow the firm. Hereby lowering potential asymmetric information between the firm and investors. Besides that, institutional investors are the primary source of capital for venture capital. Therefore, institutions may be more likely to buy shares in the start-ups that are taken public by VCs with whom they have invested. Because there is more information available and higher possibility of institutional shareholding VC-backed start-ups are less sensitive to investor sentiment.
Thus, if a start-up has more than one VC on board it is likely that the long-term performance on the public market will be greater in comparison with a start-up that only has one VC on board. If, there are more VCs investing in a start-up it is more likely that the start-up will experience a lower underpricing. As, the offer price of the start-up will represent a better estimation of the intrinsic value of the start-up.

Furthermore, if there are more VCs looking at a certain start-up in the screening process it is likely that they will find more reasons to not invest in comparison with the case that there is only one VC looking at a certain start-up. Thus, if there is an investment done by two or more VCs in a start-up it is more likely that the start-up is promising. As, more VCs have viewed the start-up and could not find reasons to not invest. Therefore, it is expected that a start-up will perform better on the public markets if investments are made by two or more VCs. We expect that this will have a positive outcome for the post IPO performance and the IPO performance (lower underpricing on the first trading day) of the VC-backed start-ups.

$H_{1.1}$: The underpricing effect of syndicate VC-backed start-ups on the public market is lower than the underpricing effect of non-syndicate VC-backed start-ups.

$H_{1.2}$: The long-term performance of syndicate VC-backed start-ups on the public market is higher than the long-term performance of non-syndicate VC-backed start-ups.

2.7.2 Selection and Cost hypothesis

An alternative hypothesis produces the opposite empirical implications. The selection hypothesis states that VCs want to have a second opinion on certain doubtful start-ups to know for certain that the start-up is promising enough. Whereas, the more promising start-ups do not need a second opinion of another VC. The VCs will therefore not look for co-investment opportunities with other VCs. As, they want to solely invest in the more promising start-ups. In accordance with this hypothesis it is expected that a start-up with a standalone investment by a VC has a higher performance on the public market than a start-up with a syndicated investment by two or more VCs.

In a syndicated deal the co-investors are likely to follow the lead investor and rely on the lead investor's monitoring capabilities. The lead investor is the investor who likely has the biggest share of equity. Therefore, the lead investor acts as an agent for the co-investors of the syndicated deal. If the co-investors want to observe the actions of the lead investor it can be perceived as costly and time consuming. Furthermore, a decision is taken by consensus, meaning that the lead investor must discuss with the co-investors before acting and thereby it will result in more time-consuming decision making and higher transaction costs. In the case that there are more co-investors the equity share per investor is likely to be lower. This will likely result in free-riding costs, as there is a lower incentive to monitor the start-up properly. Thus, there are certain costs involved with syndicated deals. Therefore, it is expected that the performance of syndicate VC-backed start-ups will result in a lower performance on the public market and possibly a higher underpricing.

$H_{2.1}$: The underpricing effect of non-syndicate VC-backed start-ups on the public market is lower than the underpricing effect of syndicate VC-backed start-ups.

$H_{2.2}$: The long-term performance of non-syndicate VC-backed start-ups on the public market is higher than the long-term performance of syndicate VC-backed start-ups.

2.7.3 Innovation hypothesis

When VCs combine forces and invest in a start-up the individual risk of each VC is smaller. Therefore, VC syndicates can invest in more research and development expenditures intensively and riskier start-ups. If a start-up invests more in research and development expenditures, it nurtures the innovation of the start-up. Thus, syndicate VC-backed start-ups are likely to have higher a higher level of innovation in comparison with non-syndicate VC-backed start-ups. The innovation level is measured as the total investments done for research and development (divided by the sales and the assets), in accordance with Gompers (1995), and the number of patents that are issued by the start-ups (Tian, 2012). We will investigate if syndicate VC-backed start-ups have a higher level of innovation. It is likely, that this will have a positive outcome for the performance of the syndicate VC-backed start-up on the public market in the long-run and the short-run (lower underpricing).

H_3: Syndicate VC-backed start-ups have a higher level of innovation in comparison with non-syndicate VC-backed start-ups

2.7.4 Geographic public market hypothesis

In the U.S. there are more syndications among VCs in comparison with Europe (Hege et al., 2003). We expect that therefore the public performance and the operational performance of the start-ups in the U.S. will be more positive in comparison with the start-ups in Europe. This will result in a lower underpricing in the U.S. in comparison with Europe and a higher long-term performance on the public market in the U.S. in comparison with Europe.

$H_{4.1}$: The underpricing effect of syndicate VC-backed start-ups is lower in the U.S. in comparison with Europe.

$H_{4.2}$: The long-term performance syndicate VC-backed start-ups on the public market in the U.S. is higher than the long-term performance of the syndicate VC-backed start-ups in Europe.

2.7.5 Geographic operating performance hypothesis

Besides, investigating the performance of syndicate VC-backed start-ups on the public market we also investigate the long-term operating performance for robustness. We expect that syndicate VC-backed start-ups have a better long-term operating performance, in accordance with Tian (2012). Furthermore, because syndication is more active in the U.S. we expect that the long-term operating performance in the U.S. will be higher than the long-term operating performance in Europe. The operating performance will be measured with the EBITDA (earnings before interest, tax, depreciation and amortization divided by the revenue) (ROS) and the Return On Assets (RAT).

H_5: The long-term operating performance of syndicate VC-backed start-ups is higher in the U.S. in comparison with Europe.

3. Data

3.1 Databases

The data for this paper is acquired from the Zephyr database, Orbis database, Thomson One database, Crunchbase database, Datastream database, Bloomberg Terminal and Compustat Database. We investigate the period ranging from 1997 until 2015.

3.1.1 Zephyr Database

The Zephyr database is distributed by Bureau van Dijk and contains data of venture capital deals worldwide. We collect all venture capital deals in Europe and the U.S. from 1997 until 2015. We use a Boolean search consisting of: deals between 01-01-1997 and 31-12-2015, EU (VCs and start-ups) and US (VCs and start-ups) solely completed deals, start-up is listed and financing costs of either development capital or venture capital financing. We get a dataset consisting of a total of 587 VC deals in Europe and 1166 VC deals in the U.S. We only look at completed deals. Furthermore, we require that:

1. The (equity) deal value is reported[20];
2. The Target name is reported (the start-up);
3. The Acquirer name(s) is (are) reported (the VC firm)[21] (necessary for matching with Thomson One database);
4. The Acquirer is either from Europe or the US[22];
5. The country code(s) of the Acquirer(s) is (are) reported;
6. The primary SIC code of the Target is reported;
7. The IPO date is reported (necessary for calculating the *Age* of the start-up);
8. The ISIN Number is reported (necessary for matching with Datastream database and converting to CUSIP to match with Compustat);
9. The BVD ID Number is reported (necessary for matching with Orbis database);
10. The Deal Financing consists of either:
    a. Development capital[23];
    b. Venture capital.

Although we use a Boolean search with financing based on solely Development capital or Venture Capital, Zephyr still reports other financing deals. The Zephyr database reports Venture Capital as deal

[20] Zephyr also reports estimated deal values. We also include these estimated deal values in our database as often the exact deal values are not known. We exclude 77 EU start-ups and 42 US start-ups whereby the deal value is not reported
[21] Zephyr often includes investors if they are unknown we exclude these in our database
[22] Zephyr reports a deal if one of the VC's is either from the US or from the EU. We exclude all start-ups that are financed by foreign VC's
[23] Development capital are early stage venture capital investments, according to Zephyr.

financing if it contains an element of Venture Capital activity of the acquirer's side of the deal. Furthermore, Development Capital can consist of investments by VC firms or Private Equity firms. We exclude deals that are financed by either (solely) angel investors, (solely) convertible loan notes, new bank facilities or PIPE (private investments in public equity) (Espenlaub et al., 1999; Hochberg et al., 2007). Zephyr reports a start-up even if some of the VCs are non-EU (EU dataset) and non-US (US dataset). We exclude all start-ups that are financed by foreign VCs (non-EU and non-US). We exclude these foreign VC-backed start-ups because we want to make a comparison between the VC-backed start-ups in Europe and the VC-backed start-ups in the US. If there is an overlapping of VCs that operate in Europe and in the U.S., the comparison will not be optimal. Zephyr reports some deals as Private Equity, often Private Equity firms work together with their own VC fund with other VC firms and therefore we do not exclude these deals in our dataset. However, with a non-syndicated deal and the deal is labelled as Private Equity we do exclude it. We exclude exits of companies as sometimes Zephyr also sees these as a venture capital investment[24]. We exclude all start-ups from the financial and insurance sectors recognized by Standard Industrial Classification (SIC) codes 6000 to 6999 (Bessler & Seim, 2012; Tian, 2012).

We combine all the funding rounds of the company as the Zephyr database often does not give the exact number round for every corresponding funding (e.g. seed stage, later stage, early stage). We use the definition that if one funding round is categorized as a non-syndicate, but other funding rounds are categorized as a syndicated deal, then the VC deal in total is categorized as a syndicated deal (Brander et al., 2002; Hochberg et al., 2007; Tian, 2012). The Zephyr database does not provide a definition for the Lead VC and therefore we look at the average of all the VCs instead of solely the Lead VC. [25] The total number of participants in a VC deal are given by the Zephyr database and we cross-check it with the deal comments. We identify a start-up as syndicated if at least two VCs have invested in the start-up. Investments by the start-up owners in combination with one VC are not seen as a syndicated deal, as the company owners do not bring synergies similar to that of a VC. In our dataset, some start-ups are taken over by other companies after they went public. When a start-up is acquired by another company after the start-up went public, the Ticker code and the ISIN code of the start-up changes. The Ticker and the ISIN code change to the digit codes of the acquirer. Therefore, we doublecheck the reported Tickers and the ISIN codes with the corresponding Target name (start-up name). Our final dataset consists of 153 start-ups in Europe and 194 start-ups in the U.S.. We exclude targets that were incorporated before 1990.[26] Our dataset consists of 356 VC firms in Europe and 598 VC firms in the U.S.

[24] Selling stakes of the start-up to other companies (rather than doing an IPO).
[25] We match the VCs with the start-ups and we take the average of all the VC variables provided by Thomson One and Crunchbase.
[26] Often these firms cannot be classified anymore as a start-up. They were already relative big when they got their first investment.

3.1.2 Orbis Database

With the retrieved BVD ID numbers we match the syndicated and non-syndicated deals with the Orbis database to gather information of the start-up. The Orbis database is also distributed by Bureau van Dijk. The information we gather for the start-ups are the following:

1. Date of incorporation (date of birth of the start-up)[27];
2. Research and developments costs (in EUR thousands);
3. Number of issued patents;
4. EBITDA (in EUR thousands);
5. Total revenue (in EUR thousands);
6. Number of employees of the start-up;
7. Total revenue (in EUR thousands)

The Orbis database only provides data 7 years prior to 2017. Furthermore, the variable total revenue results in no observations for the U.S. and Europe. We need the pre-IPO and the post-IPO variables of our start-ups for the short-term performance and the long-term performance, respectively. The Compustat database provides historical values for the European and the U.S. dataset. We match the identifiers of our start-ups with the Compustat database (see subsection 3.1.7.)

In some cases, the date of incorporation is higher than the IPO date (Orbis often sees a name change as the incorporation date). In this case we get the correct incorporation date according to Bloomberg data. We exclude start-ups that were incorporated before 1990. The date of incorporation is used to determine the age of the start-ups when going public. The age of start-ups, as measured in months, is determined as follows:

$$Age_{Startup} = Date_{IPO} - Date_{incoroporation}$$

The information for the VC firms we gather from the Orbis database is not useful for our research. The Orbis database only provides information that is given by balance sheets and profit and loss statements. For our VC dataset we require different information, such as number of deals provided by the VC and number of companies invested in by the VC. Therefore, we use the Thomson One database and Crunchbase for our VC dataset.

3.1.3 Thomson One Database

The Thomson One database is more accurate than the Orbis database for information on the VC firms. The identifiers retrieved from Orbis and Zephyr do not match with the Thomson One database.

[27] Orbis often only gives the year as incorporation date. To calculate the age, we need the exact date thus for every year we use the first value which is the 1st of January.

Therefore, we use the names of the VCs to match with the information retrieved from the Thomson One database[28]. In Thomson One we search for all the VC investors in VC deals for the period between 1995 and 2015 in the US and in Europe. We retrieve the following information from the Thomson One database:

1. Date of incorporation (date of birth of the VC);
2. Name of VC firm (if there is a name change we correct it);
3. Assets under management (in EUR);
4. Amount of Equity invested (in EUR);
5. Number of funds raised;
6. Number of companies invested in;
7. Number of deals done by the VC.

We match our VC firms with the start-ups and take the average of all the VC firms that participated in the funding for the start-up. $Age_{VC} = Date - Date_{incoroporation}$

We calculate the age of the VC by taking the difference of the date *12-31-2015* and the incorporation date of the VC. The age is measured in months.

3.1.4 Crunchbase Database

The Thomson One database is our primary database for retrieving information on the VC firms. If the VC firms retrieved from the Zephyr database are not a match with the Thomson One database, we doublecheck with the Crunchbase database. The Crunchbase database is more accurate than the Orbis database for information on the VC firms[29]. Crunchbase is an online database where millions of data points are collected of start-ups, private companies and investors. We gather the following information of the Crunchbase database:

1. Date of incorporation (date of birth of the VC firm to double check)[30];
2. Total number of companies invested in by the VC;
3. Total number of deals done by the VC;
4. Total amount of funds raised[31]

[28] See subsection 4.1. for more information on the matching principle.
[29] We look everything up manually to gather information on the VC firm.
[30] In the case of the European Database there are also banks that operate as Venture Capital firms with a certain fund in this case we use the first investment date known by the fund as the incorporation date (rather than the incorporation date of the whole bank). We also retrieve information about the deal size of the Venture Capital firm of the website of the VC firm.
[31] We assume that the total amount of funds raised is approximately the same as the assets under management.

3.1.5 Thomson Reuters Datastream database

Thomson Reuters Datastream database is a timeseries database. We use the Datastream database to match the ISIN numbers of the start-ups with the exact prices on the public market. We also look at the long-term return, therefore, we take the long-term prices of our VC-backed start-ups. From the Thomson Reuters Database we retrieve the following:

1. Unadjusted closing price at first trading day;
2. Unadjusted long term closing prices.

We use the unadjusted closing- and unadjusted opening- price and not the adjusted prices. The definition that Datastream uses for the default adjusted prices differ per country (Datastream, 2017). Furthermore, the adjusted prices are corrected for subsequent capital actions and the adjusted prices are padded (Datastream, 2017). Padding means that in the case the public market is closed on bank holidays the prices are repeated from the last trading date until a new trading day or date occurs. If a working day is not a trading day there will still be a price. For these reasons we use the unadjusted prices of Datastream.

In some cases the IPO date is in late 2015 or even later resulting that the 1-year, 2-year and 3-years return is not in the dataset yet. This is because we use the deal values between 1997 and 2015 for the start-ups and not the IPO dates. We do not exclude these start-ups in our dataset. The offer price is not recorded in the Thomson Reuters Datastream database. Therefore, we use the offer price provided by the Bloomberg Terminal.

3.1.6 Bloomberg Terminal

The Bloomberg Terminal brings together real-time data on every market, unparalleled news and research, powerful analytics, communications tools and world-class execution capabilities — in one fully integrated solution (Bloomberg L.P., 2017). We use the Bloomberg Terminal to look up the following:

1. Offer prices (matched with ISIN codes)[32];
2. Acquired start-ups (check if the start-ups are taken over or not)[33].

We match the ISIN codes retrieved from Zephyr to match with the offer prices provided by Bloomberg. If the ISIN codes are no match we doublecheck with the Ticker codes retrieved from

[32] Datastream reports the prices in the local currency therefore we also look up the offer prices in the local currency in Bloomberg. For our descriptive statistics we convert our offer prices to Euro's based on the currency rate at the IPO date.

[33] If a start-up is acquired by another firm and that firm goes public Zephyr reports the start-up as an IPO. Therefore, we double check this with Bloomberg. Already public start-ups that are acquired by another firm get the ISIN code and ticker of the acquirer

Zephyr. In some cases we cannot obtain the offer prices as there are unknown. We do not exclude these start-ups in our dataset[34].

3.1.7 Compustat databases

The *Compustat North America* database contains annual and quarterly data of listed American and Canadian companies. The *Compustat Global* database contains annual and quarterly data of listed companies (excluding American and Canadian companies). The Orbis database can only provide fundamental data 7 years prior to 2017. Therefore, we use the data obtained from the *Compustat* database to fill in missing values. For our US dataset we have a lot of missing fundamental values for our start-ups that we retrieved from the Orbis Database. We compare the variables obtained from Orbis with the variables of *Compustat Global* and we include missing variables. We look up the fundamentals for the years. We retrieve the following from the *Compustat* database:

1. Total Revenue (EUR in thousands)[35];
2. Research & Development costs (EUR in thousands);
3. EBITDA (EUR in thousands);
4. Employees;
5. Assets (EUR in thousands).

We obtain the fundamentals for the years 1996 until 2016.

3.1.8 CRSP database

We use the CRSP database to retrieve the benchmark. We use the following benchmarks:

1. CRSP equally weighted index returns (from 01-01-1995 until 31-12-2016)
2. CRSP value weighted index returns (from 01-01-1995 until 31-12-2016)

The CRSP database provides the CRSP index which is a combination of the following indices NYSE/AMEX/NASDAQ/ARCA. The 2017 CRSP index returns are not obtainable from the CRSP database. We replace the missing values with the value zero.

[34] The data provided by Datastream results in zero missing values and therefore we can still use these for the long-term observation

[35] Compustat North America only reports values in USD. We convert all the values in EUR with the appropriate conversion rate. Compustat Global reports values in the currency of the start-ups country. We also convert all these values in EUR with the appropriate conversion rate.

3.2 Descriptive Statistics

3.2.1 Targets

Table 3 shows the descriptive statistics of the Europe target dataset. Panel A is the descriptive statistics table for the VC-backed start-ups in Europe, including the syndicate and the non-syndicated VC-backed start-ups. The pre-IPO variables are the average variables before the IPO of the start-up. The post-IPO variables are the average variables after the IPO of the start-up. For our initial return (IR) regressions we use the pre-IPO variables, 1-year prior to the IPO. For the CAR and BHAR regressions we use the post-IPO variables and we match the X-year CAR and the BHAR with the start-up variables X year(s) after to the IPO. Wherein X stands for 1, 2 or 3 years. It is interesting that the *mean* of the age of the start-ups at the IPO is slightly under 10 years (107 months). The *mean* of the patents of the VC-backed start-ups is slightly over 13. However, the median is only 3 thus apparently there are some VC-backed start-ups that issue a lot of patents (and are treated as outliers with the median). It is also interesting that the *standard deviation* for assets and revenues is very high in comparison with the other *standard deviations*. The average offer price for Europe dataset is slightly above €8,--. The offer prices are often given in other currencies and are converted in Euros. Therefore, the minimum offer price is also quite low (0.0163 Euro). The number of observations differ per variable as not all the data is provided by the databases that we use for our research. Furthermore, it is interesting that all the post-IPO variables seem to be higher in comparison with the pre-IPO variables. We have the lowest number of observations for the *Employees* variable and the *R&D* variable.

Panel B is the descriptive statistics table for the syndicated VC-backed start-ups in Europe. Worth noting is that the *maximum* of all the Pre-IPO and Post-IPO variables are the same as the *maximum* of the Pre-IPO and Post-IPO variables of the total sample. Thus, the non-syndicated deals have a lower *maximum* for the Pre-IPO and Post-IPO variables. Furthermore, it is interesting that the *mean* of the issued patents for the Europe syndicated deals is higher than the *mean* of the issued patents for all Europe deals. This means that syndicated VC-backed start-ups apparently issue more patents. Apparently, there are on average approximately four investors that participate in the funding of a start-up in Europe. The mean of the deal value for the syndicate VC-backed start-ups is around 19 million Euros. Whereas, the total sample has an average deal value of around 15 million Euros.

Panel C is the descriptive statistics table for the non-syndicated VC-backed start-ups in Europe. It is interesting that indeed the *maximum* for the Pre- and Post- variables are lower in comparison with the *maximum* for the Pre- and Post- variables of the syndicated deals. It is also interesting that the *mean* of the age of the start-ups in the non-syndicated deals is lower in comparison with the *mean* of the age of all the syndicate deals. Apparently, non-syndicate VC-backed start-ups have an IPO earlier. Furthermore, it is also interesting that the *mean* of the deals for the non-syndicated deals is lower than the *mean* of the syndicated deals.

Table 3: Descriptive Statistics Europe dataset

The sample includes in total 153 startups from which 114 syndicated VC-backed start-ups and 39 non-syndicated VC-backed startups. The Investors is the number of VC firms that participated in the total funding of the start-up. The Deal Value is the total funding of the start-up and is given in Euros (thousands). The Age at IPO is the age of the start-up at the time it went public (in months). The Pre- variables are the variables 1-year prior to the IPO date. The Post- variables are the averages of the 1-year, 2-year and 3-year after the IPO date. The EBITDA are the Earnings before Interest and Depreciation and Amortization, given in Euros (thousands). The Employees is the number of persons that were working at the start-up. The Patents are the total number of patents that the start-up has issued until 2015. The R&D Expenditures are the Research and Developments costs given in Euros (thousands). The Revenues are the total revenues given in Euros (thousands). The Assets are the total amount of assets given in Euros (thousands). The Offer Price is given in Euros.

Variables	**N**	**Mean**	**SD**	**Min**	**Max**	**Median**
Panel A: All Europe VC-backed start-ups						
Deal Value	153	15,399	36,196	14.16	300,000	5,000
Investors	153	3.373	2.518	1	12	3
Age at IPO	153	107.1	58.26	11	321	99
Patents	153	13.90	28.24	0	199	3
Offer Price	125	8.202	7.765	0.0163	40	6.800
Pre-Revenue	128	43,617	261,863	0	2.396e+06	1,890
Pre-R&D	98	3,196	4,000	0	25,330	1,586
Pre-Assets	140	40,525	209,264	0	2.228e+06	8,419
Pre-Employees	92	329.5	1,890	1	16,987	32.50
Pre-EBITDA	137	1,123	42,529	-105,310	472,500	-1,034
Post-Revenue	114	71,228	382,001	0	3.299e+06	4,458
Post-R&D	83	8,015	10,601	0	57,584	4,110
Post-Assets	123	90,833	307,869	327.6	2.327e+06	21,308
Post-Employees	92	393.0	1,726	0	12,404	62.67
Post-EBITDA	121	1,364	54,407	-79,846	541,133	-3,243
Panel B: Syndicate Europe VC-backed start-ups						
Deal Value	114	19,539	41,004	264.4	300,000	9,151
Investors	114	4.184	2.433	2	12	3
Age at IPO	114	114.4	60.93	17	321	102
Patents	114	15.56	26.61	0	138	4
Offer Price	98	8.297	6.259	0.114	32	7.495
Pre-Revenue	104	51,052	289,885	0	2.396e+06	2,915
Pre-R&D	80	3,704	4,211	0	25,330	2,527
Pre-Assets	108	49,577	237,422	0	2.228e+06	10,477
Pre-Employees	74	386.9	2,102	1	16,987	39.50
Pre-EBITDA	107	1,603	48,116	-105,310	472,500	-1,286
Post-Revenue	89	84,873	430,908	0	3.299e+06	4,859
Post-R&D	67	9,293	11,299	0	57,584	5,655
Post-Assets	94	110,900	349,684	982.7	2.327e+06	23,920
Post-Employees	72	471.7	1,942	7	12,404	73.17
Post-EBITDA	92	2,301	62,311	-79,846	541,133	-3,918
Panel C: Non-Syndicate Europe VC-backed start-ups						
Deal Value	39	3,296	6,259	14.16	36,254	1,700
Investors	39	1	0	1	1	1
Age at IPO	39	85.69	43.63	11	172	84
Patents	39	9.026	32.44	0	199	0
Offer Price	27	7.858	11.88	0.0163	40	2
Pre-Revenue	24	11,399	31,306	0	129,228	891.0
Pre-R&D	18	934.8	1,506	0	4,534	173.0
Pre-Assets	32	9,975	23,265	20.87	127,894	3,506
Pre-Employees	18	93.61	279.2	1	1,204	20.50
Pre-EBITDA	30	-585.6	3,994	-7,290	14,785	-418.4
Post-Revenue	25	22,651	55,511	0	261,914	3,655
Post-R&D	16	2,665	3,842	0	15,802	1,425
Post-Assets	29	25,790	33,314	327.6	124,142	13,676
Post-Employees	20	109.6	275.4	0	1,265	39.50
Post-EBITDA	29	-1,608	7,467	-22,581	20,303	-1,173

Table 4 shows the frequency distribution of the SIC Codes for our Europe dataset. It is interesting that the sectors *Engineering, Business Services*, *Medical*, *Electronics* and *Chemicals* are the five largest sectors for both the syndicate VC-backed start-ups and the non-syndicate VC-backed start-ups. Furthermore, it is interesting that there are many sectors where only two start-ups are operating in. Apparently, the industries for start-ups both syndicated and non-syndicated VC-backed is quite diverse in Europe.

Table 4: Europe frequency distribution by SIC Code

The sample includes 153 start-ups in total from which 114 syndicated VC-backed start-ups (Y) and 39 non-syndicated VC-backed startups (N). The *SIC* Code is the 2-digit code and the industry description is matched with the 2-digit SIC Code. The percentages are in bracelets and they are given per column. The *SIC* Codes listed are all those that have at least two observations in total. The *SIC* codes that have less observations are combined in *Other*.

SIC	**Industry Description**	**N**	**Y**	**Total**
10	Metal Mining	0	2	2
		(0.00)	*(1.75)*	*(1.31)*
13	Oil and Gas Extraction	1	1	2
		(2.56)	*(0.88)*	*(1.31)*
28	Chemicals and Allied Products	4	6	10
		(10.26)	*(5.26)*	*(6.54)*
30	Rubber and Miscellaneous Plastic Products	0	2	2
		(0.00)	*(1.75)*	*(1.31)*
34	Fabricated Metal Products	1	1	2
		(2.56)	*(0.88)*	*(1.31)*
35	Industrial and Commercial Machinery and Computer Equipment	2	3	5
		(5.13)	*(2.63)*	*(3.27)*
36	Electronic & Other Electrical Equipment & Components	3	11	14
		(7.69)	*(9.65)*	*(9.15)*
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	4	6	10
		(10.26)	*(5.26)*	*(6.54)*
39	Miscellaneous Manufacturing Industries	1	1	2
		(2.56)	*(0.88)*	*(1.31)*
48	Communications	0	2	2
		(0.00)	*(1.75)*	*(1.31)*
49	Electric, Gas and Sanitary Services	1	1	2
		(2.56)	*(0.88)*	*(1.31)*
50	Wholesale Trade - Durable Goods	0	2	2
		(0.00)	*(1.75)*	*(1.31)*
56	Apparel and Accessory Stores	0	2	2
		(0.00)	*(1.75)*	*(1.31)*
57	Home Furniture, Furnishings and Equipment Stores	1	1	2
		(2.56)	*(0.88)*	*(1.31)*
73	Business Services	9	18	27
		(23.08)	*(15.79)*	*(17.65)*
80	Health Services	1	1	2
		(2.56)	*(0.88)*	*(1.31)*
87	Engineering, Accounting, Research, and Management Services	6	48	54
		(15.38)	*(42.11)*	*(35.29)*
89	Services, Not Elsewhere Classified	1	1	2
		(2.56)	*(0.88)*	*(1.31)*
-	Other	4	5	9
		(10.24)	*(4.40)*	*(5.85)*
	Total	39	114	153
		(100.00)	*(100.00)*	*(100.00)*

Table 5 shows the descriptive statistics for the accounting measures for our Europe dataset. It is quite interesting that the mean and the median of the *Pre-ROS* variable is higher (less negative) for the syndicate VC-backed start-ups in comparison with the non-syndicate VC-backed start-ups. However, the mean and the median of the *Post-ROS* variable appears to be higher for the non-syndicate VC-backed start-ups. This is due to data availability. For the syndicate VC-backed start-ups we have less matched data for the positive Post-EBITDA variables. The mean of the *Pre-ROA* variable appears to be higher for the syndicate VC-backed start-ups in comparison with the non-syndicate VC-backed start-ups. However, the mean and the median of the *Post-ROA* variable seems to be lower for the syndicate VC-backed start-ups in comparison with the non-syndicate VC-backed start-ups. The mean of the *Pre-RDRT* variable appears to be higher for the non-syndicate VC-backed start-ups. However, the mean of the *Post-RDRT* variable seems to be higher for the syndicate VC-backed start-ups.

Table 5: Descriptive Statistics Europe dataset Accounting Measures

The sample includes in total 153 startups from which 114 syndicated VC-backed start-ups and 39 non-syndicated VC-backed startups. As, shown in Table 3 we have some missing values for the fundamental variables. Therefore, not all the accounting measures are available. All Pre- variables are the variables one year prior to the IPO. All Post- variables are the averages of the 1 year, 2 years and the 3 years after the IPO. ROS stands for EBITDA divided by Revenues. ROA stands for EBITDA divided by Assets. RDRT stands for Research and Development Expenditures divided by Revenues. RDAT stands for Research and Development Expenditures divided by Revenues.

Variables	**N**	**Mean**	**SD**	**Min**	**Max**	**Median**
Panel A: All Europe VC-backed start-ups						
Pre-ROS	101	-13.94	51.60	-320.6	0.655	-0.220
Pre-ROA	136	-1.008	7.149	-83.22	0.524	-0.202
Pre-RDRT	63	9.451	44.02	0	333.7	0.215
Pre-RDAT	96	0.667	3.191	0	31.15	0.177
Post-ROS	102	-101.2	520.5	-4,039	0.363	-0.650
Post-ROA	114	-0.290	0.405	-2.011	0.249	-0.169
Post-RDRT	66	119.6	539.3	0.005	3,568	0.935
Post-RDAT	75	0.257	0.224	0.006	1.000	0.233
Panel B: Syndicate Europe VC-backed start-ups						
Pre-ROS	80	-10.01	43.91	-320.6	0.655	-0.200
Pre-ROA	106	-0.314	0.447	-1.833	0.524	-0.200
Pre-RDRT	55	8.946	45.54	0	333.7	0.247
Pre-RDAT	79	0.316	0.348	0	1.876	0.220
Post-ROS	79	-110.9	583.5	-4,039	0.363	-0.693
Post-ROA	89	-0.294	0.410	-2.011	0.249	-0.173
Post-RDRT	55	125.4	586.8	0.005	3,568	0.920
Post-RDAT	63	0.267	0.234	0.006	1.000	0.233
Panel C: Non-Syndicate Europe VC-backed start-ups						
Pre-ROS	21	-28.88	73.50	-291.9	0.454	-0.302
Pre-ROA	30	-3.458	15.14	-83.22	0.392	-0.248
Pre-RDRT	8	12.92	33.95	0	96.81	0.178
Pre-RDAT	17	2.297	7.512	0	31.15	0.0539
Post-ROS	23	-67.81	186.8	-685.4	0.307	-0.317
Post-ROA	25	-0.274	0.396	-1.094	0.205	-0.103
Post-RDRT	11	90.66	173.8	0.012	479.6	1.696
Post-RDAT	12	0.206	0.161	0.015	0.510	0.196

Table 6 shows the descriptive statistics of the U.S. target dataset. Panel A shows the descriptive statistics for the VC-backed start-ups in the U.S., including the syndicate and the non-syndicated VC-backed start-ups. The pre-IPO variables are the variables 1-year before the IPO of the start-up. The post-IPO variables are the average variables of the 1-year, 2-year and 3-year variables, after the IPO of the start-up. For our initial return (IR) regressions we use the pre-IPO variables, 1 year prior the IPO. For the CAR and BHAR regressions we use the post-IPO variables and we match the X-year CAR and the BHAR with the start-up variables X year(s) after to the IPO. Wherein X stands for 1, 2 or 3 years. It is interesting that the *mean* of the age of all the start-ups at the IPO date in the U.S. is slightly below the age of the start-ups at the IPO date in Europe. However, the *median* of the age of all the start-ups at the IPO date in the U.S. is slightly above the age of the start-ups at the IPO date in Europe. The *mean* of the patents of the VC-backed start-ups is slightly over 34, thus a lot of VC-backed start-ups issue more than one patent. This appears to be a big difference with the average issued patents in Europe. The number of observations differ per variable as not all the data is provided by the databases that we use for our research. Furthermore, it is interesting that all the means of the post-IPO variables appear to be higher than the means of the pre-IPO variables, expect for the post-EBITDA variable.

Panel B shows the descriptive statistics for the syndicated VC-backed start-ups in the U.S. Worth noting is that the *maximum* of the Pre- and Post- variables are the same as the *maximum* of all the Pre- and Post- variables of the total sample (Panel A)[36]. Furthermore, it is interesting that the *mean* of the issued patents for the U.S. syndicated VC-backed start-ups is higher than the *mean* of the issued patents for the total sample. This means that syndicated VC-backed start-ups in the U.S. apparently issue more patents than non-syndicate VC-backed start-ups. Apparently, there are on average approximately five investors that participate in the funding of a start-up in the U.S. Furthermore, it is interesting that all the post-IPO variables appear to be higher in comparison with the pre-IPO variables.

Panel C shows the descriptive statistics for the non-syndicated VC-backed start-ups in the U.S. It is interesting that almost all the *maximum* for the Pre- and Post- variables are lower in comparison with the *maximum* Pre- and Post- variables of the syndicated deals. It is also interesting that the *mean* of the age of the start-ups in the non-syndicated deals is lower in comparison with the *mean* of the age of all the Europe deals. The *mean* of the number of employees is even higher than the *mean* of the syndicate VC-backed start-ups in Europe. Furthermore, it is also interesting that the *mean* of the deal value for the non-syndicated deals is lower than the *mean* of the syndicated deal value.

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[36] Except for the *Employees* variable.

Table 6: Descriptive Statistics US dataset

The sample includes in total 194 startups from which 163 syndicated VC-backed start-ups and 31 non-syndicated VC-backed startups. The Investors is the number of VC firms that participated in the total funding of the start-up. The Deal Value is the total funding of the start-up and is given in Euros (thousands). The Age at IPO is the age of the start-up at the time it went public (in months). The Pre- variables are the variables 1-year prior to the IPO date. The Post- variables are the averages of the 1-year, 2-year and 3-year after the IPO date. The EBITDA are the Earnings before Interest and Depreciation and Amortization, given in Euros (thousands). The Employees is the number of persons that were working at the start-up. The Patents are the total number of patents that the start-up has issued until 2015. The R&D Expenditures are the Research and Developments costs given in Euros (thousands). The Revenues are the total revenues given in Euros (thousands). The Assets are the total amount of assets given in Euros (thousands). The Offer Price is given in Euros.

Variables	**N**	**Mean**	**SD**	**Min**	**Max**	**Median**
Panel A: All US VC-backed start-ups						
Deal Value	194	54,144	88,412	452.4	899,148	35,949
Investors	194	5.237	3.268	1	16	5
Age at IPO	194	102.2	50.02	2	290	100
Patents	194	34.84	71.14	0	664	11
Offer Price	191	10.54	5.210	0.00740	34.52	10.28
Pre-Revenue	173	66,257	112,872	0	699,453	37,139
Pre-R&D	163	13,501	16,329	0	118,993	8,955
Pre-Assets	175	101,046	267,495	87.99	2.745e+06	37,643
Pre-Employees	97	454.4	692.0	4	4,460	288
Pre-EBITDA	173	-3,670	35,954	-158,507	202,536	-6,884
Post-Revenue	162	188,548	390,021	0	2.633e+06	82,032
Post-R&D	154	40,247	55,353	0	380,529	22,738
Post-Assets	162	420,474	1.164e+06	290.2	1.201e+07	141,624
Post-Employees	161	811.0	1,237	6.500	7,600	427.3
Post-EBITDA	162	-7,939	131,365	-319,931	1.259e+06	-16,939
Panel B: Syndicate US VC-backed start-ups						
Deal Value	163	60,604	94,362	452.6	899,148	42,669
Investors	163	6.043	2.938	2	16	6
Age at IPO	163	103.9	50.30	5	290	100
Patents	163	37.68	75.88	0	664	13
Offer Price	163	10.56	5.199	0.0894	34.52	10.17
Pre-Revenue	146	64,800	111,985	0	699,453	36,149
Pre-R&D	139	14,124	16,536	0	118,993	9,850
Pre-Assets	148	102,426	281,693	87.99	2.745e+06	36,966
Pre-Employees	79	391.3	444.3	14	2,625	290
Pre-EBITDA	146	-5,258	35,390	-158,507	202,536	-8,200
Post-Revenue	134	197,948	421,940	0	2.633e+06	81,248
Post-R&D	128	42,367	57,101	0	380,529	24,182
Post-Assets	134	447,589	1.269e+06	579.4	1.201e+07	141,624
Post-Employees	133	759.4	1,135	6.500	7,600	406.3
Post-EBITDA	134	-8,145	143,513	-319,931	1.259e+06	-18,690
Panel C: Non-Syndicate US VC-backed start-ups						
Deal Value	31	20,173	28,034	452.4	112,224	10,281
Investors	31	1	0	1	1	1
Age at IPO	31	93.16	48.29	2	205	95
Patents	31	19.87	34.54	0	148	7
Offer Price	28	10.43	5.367	0.00740	24.18	11.20
Pre-Revenue	27	74,138	119,441	0	599,502	48,798
Pre-R&D	24	9,895	14,882	0	59,170	4,433
Pre-Assets	27	93,481	173,635	966.0	862,527	39,060
Pre-Employees	18	731.1	1,303	4	4,460	282.5
Pre-EBITDA	27	4,913	38,424	-50,951	169,648	3,626
Post-Revenue	28	143,560	165,988	0	597,700	98,651
Post-R&D	26	29,808	45,295	0	188,461	13,374
Post-Assets	28	290,707	366,497	290.2	1.227e+06	153,501
Post-Employees	28	1,056	1,640	7	6,817	479.5
Post-EBITDA	28	-6,951	38,018	-88,168	59,058	-6,782

Table 7 shows the frequency distribution of the SIC Codes for our U.S. dataset. It is interesting that the sectors *Chemicals*, *Business Services* and *Engineering* are the three largest sectors for the non-syndicate VC-backed start-ups. Whereas, the sectors *Chemicals, Electronic, Medical, Business Services* and *Engineering* are the largest for our syndicate VC-backed start-ups. Apparently, there are differences between the sectors of the Europe non-syndicate VC-backed start-ups and the US non-syndicate VC-backed start-ups. Furthermore, the industries for the start-ups both syndicated and non-syndicated VC-backed is less diverse in the U.S. in comparison with Europe. There are less sectors where all the start-ups are operating in. The group *Other* are combined SIC Codes from which only one start-up is operating in a certain sector.

Table 7 Frequency distribution by SIC Code

The sample includes 194 start-ups in total from which 163 syndicated VC-backed start-ups (Y) and 31 non-syndicated VC-backed startups (N). The SIC Code is the 2-digit code and the industry description is matched with the 2-digit SIC Code. The percentages are in bracelets and they are given per column. The SIC Codes listed are all those that have at least two observations in total.

SIC	**Industry Description**	**N**	**Y**	**Total**
28	Chemicals and Allied Products	3	12	15
		(9.68)	*(7.36)*	*(7.73)*
35	Industrial and Commercial Machinery and Computer Equipment	0	2	2
		(0.00)	*(1.23)*	*(1.03)*
36	Electronic & Other Electrical Equipment & Components	2	8	10
		(6.45)	*(4.91)*	*(5.15)*
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	1	18	19
		(3.23)	*(11.04)*	*(9.79)*
49	Electric, Gas and Sanitary Services	0	2	2
		(0.00)	*(1.23)*	*(1.03)*
59	Miscellaneous Retail	2	0	2
		(6.45)	*(0.00)*	*(1.03)*
73	Business Services	11	65	76
		(35.48)	*(39.88)*	*(39.18)*
80	Health Services	1	2	3
		(3.23)	*(1.23)*	*(1.55)*
87	Engineering, Accounting, Research, and Management Services	7	48	55
		(22.58)	*(29.45)*	*(28.35)*
-	Other	4	6	10
		(12.92)	*(3.66)*	*(5.20)*
	Total	31	163	194
		(100.00)	*(100.00)*	*(100.00)*

Table 8 shows the descriptive statistics for the accounting measures for the U.S. dataset. It is quite interesting that the mean and the median of the *Pre-ROS* variable is lower (more negative) for the syndicate VC-backed start-ups in comparison with the non-syndicate VC-backed start-ups. However, the mean of the *Post-ROS* variable appears to be higher (less negative) for the syndicate VC-backed start-ups. The mean and the median of the *Pre-ROA* variable appears to be lower for the syndicate VC-backed start-ups in comparison with the non-syndicate VC-backed start-ups. However, the mean of the *Post-ROA* variable seems to be higher (less negative) for the syndicate VC-backed start-ups in comparison with the non-syndicate VC-backed start-ups. The median of the *Pre-RDRT* variable appears to be higher for the syndicate VC-backed start-ups. This also seems to be the case for the median of the *Post-RDRT* variable.

Table 8: Descriptive Statistics U.S. dataset Accounting Measures

The sample includes in total 194 startups from which 163 syndicated VC-backed start-ups and 31 non-syndicated VC-backed startups. As shown in Table 6 we have some missing values for the fundamental variables. Therefore, not all the accounting measures are available. All Pre- variables are the variables one year prior to the IPO. All Post- variables are the averages of the 1 year, 2 years and the 3 years after the IPO. ROS stands for EBITDA divided by Revenues. ROA stands for EBITDA divided by Assets. RDRT stands for Research and Development Expenditures divided by Revenues. RDAT stands for Research and Development Expenditures divided by Revenues.

Variables	**N**	**Mean**	**SD**	**Min**	**Max**	**Median**
Panel A: All U.S. VC-backed start-ups						
Pre-ROS	143	-5.733	28.95	-321.9	0.601	-0.127
Pre-ROA	173	-0.579	1.748	-17.27	0.612	-0.210
Pre-RDRT	133	4.369	23.24	0	256.7	0.222
Pre-RDAT	163	0.536	1.209	0	10.75	0.275
Post-ROS	144	-42.25	289.0	-3,305	0.525	-0.159
Post-ROA	162	-0.945	8.528	-108.5	0.286	-0.140
Post-RDRT	137	30.72	214.9	0	2,398	0.237
Post-RDAT	154	0.245	0.288	0	2.606	0.187
Panel B: Syndicate U.S. VC-backed start-ups						
Pre-ROS	120	-6.184	31.19	-321.9	0.601	-0.163
Pre-ROA	146	-0.607	1.834	-17.27	0.612	-0.225
Pre-RDRT	113	4.824	25.11	0	256.7	0.231
Pre-RDAT	139	0.567	1.293	0	10.75	0.284
Post-ROS	119	-21.24	101.0	-735.0	0.525	-0.163
Post-ROA	134	-0.282	0.713	-7.457	0.286	-0.152
Post-RDRT	113	15.08	75.07	0	496.5	0.245
Post-RDAT	128	0.261	0.306	0	2.606	0.192
Panel C: Non-Syndicate U.S. VC-backed start-ups						
Pre-ROS	23	-3.379	11.97	-57.30	0.315	0.074
Pre-ROA	27	-0.427	1.193	-5.773	0.500	0.026
Pre-RDRT	20	1.799	5.145	0	23.040	0.161
Pre-RDAT	24	0.359	0.477	0	2.321	0.206
Post-ROS	25	-142.2	659.3	-3,305	0.338	-0.056
Post-ROA	28	-4.122	20.46	-108.5	0.244	-0.046
Post-RDRT	24	104.3	488.7	0	2,398	0.219
Post-RDAT	26	0.169	0.159	0	0.586	0.120

3.2.2 VCs

Table 9 shows the descriptive statistics of the Europe VC dataset. Panel A shows the descriptive statistics for all the matched VCs in Europe, including the syndicated and the non-syndicated matched VCs. It is interesting that the *mean* of the age of the average of the VCs in Europe is slightly above 250 months. This means that the average matched VC in our dataset is around 22 years old. It is also notable that the *standard deviation* for the assets under management and the Total Known Equity is very high in comparison with the other *standard deviations*. The number of observations differ per variable as not all the data is provided by the databases that we use for our research. Panel B is the descriptive statistics table for the syndicated VCs in Europe. Worth noting is that the *maximum* of all the variables is the same as in Panel A. It is interesting that the *mean* of the age of the Europe syndicated matched VCs is higher than the *mean* of the matched VCs in Panel A.

Panel C is the descriptive statistics table for the non-syndicated VCs in Europe. It is interesting that the *maximum* for all the variables are lower in comparison with the *maximum* for all the variables of the syndicated deals. It is also interesting that the *mean* of the age of the non-syndicated VCs in the is lower in comparison with the *mean* of the age of all the VCs in Europe.

Table 9: Descriptive Statistics Europe VC dataset

The sample includes the average variables of all the VC firms matched with the startup. In total we have 139 average VC firm observations from which 107 average syndicated VC firms and 32 average non-syndicated VC firms. The Assets Under Management is the average assets under management given in € (millions). The Total Investments in Companies is the average number of companies a VC has invested in. The Total number of Funds managed is the average number of funds managed by the VC firm. The Total Number of Deals is the average number of deals that a VC firm participated in. The Age of VC is the average age of the VC firms at 31-12-2015 (in months). The Total Known Equity is the average amount of known equity that a VC firm has in € (millions).

Variables	**N**	**Mean**	**SD**	**Min**	**Max**	**Median**
Panel A: All combined VC firms						
Assets Under Management	120	1,460	3,751	4.180	32,106	496.6
Total Investments in Companies	139	111.2	171.4	2	1,454	67
Total number of Funds Managed	137	11.64	11.85	1	76	8
Total number of Deals	139	180.0	305.4	2	2,517	91
Age of VC	137	256.7	130.1	47	851	221
Total Known Equity	129	379.5	1,166	0.120	8,084	75.94
Panel B: Syndicate combined VC firms						
Assets Under Management	100	1,671	4,076	4.180	32,106	511.5
Total Investments in Companies	107	128.3	187.5	4	1,454	77.67
Total number of Funds Managed	106	12.83	11.95	1	76	9.667
Total number of Deals	107	210.4	337.6	6	2,517	118
Age of VC	106	258.7	121.0	71	851	239
Total Known Equity	101	465.4	1,305	0.980	8,084	79.20
Panel C: Non-syndicate combined VC firms						
Assets Under Management	20	404.3	366.1	9.150	1,104	350.2
Total Investments in Companies	32	53.94	78.04	2	414	32.50
Total number of Funds Managed	31	7.548	10.73	1	52	3
Total number of Deals	32	78.38	108.0	2	521	36.50
Age of VC	31	249.8	159.6	47	623	203
Total Known Equity	28	69.68	88.95	0.120	343.4	37.56

Table 10 shows the descriptive statistics of the U.S. VC dataset. Panel A shows the descriptive statistics for all the matched VCs in the U.S., including the syndicated and the non-syndicated matched VCs. It is interesting that the mean of the age of the average of the VCs in the U.S. is slightly above 300 months. This means that the average matched VC in our dataset is around 25 years old. It is also notable that the standard deviation for the assets under management and the Total Known Equity is very high in comparison with the other standard deviations. The number of observations differ per variable as not all the data is provided by the databases that we use for our research.

Panel B is the descriptive statistics table for the syndicated VCs in the U.S. Worth noting is that the *maximum* of all the variables is not the same as in Panel A. It is interesting that the *mean* of the age of the Europe syndicated matched VCs is higher than the mean of the matched VCs in Panel A. Panel C is the descriptive statistics table for the non-syndicated VCs in Europe. It is interesting that the maximum for the Total Known Equity and the Total Investments in Companies are higher than the maximum of these variables in Panel B. It is also interesting that the mean of the age of the non-syndicated VCs in the is lower in comparison with the mean of the age of all the VCs in Europe.

Table 10: Descriptive Statistics US VC dataset

The sample includes the average variables of all the VC firms matched with the startup. In total we have 193[37] average VC firm observations from which 163 average syndicated VC firms and 30 average non-syndicated VC firms. The Assets Under Management is the average assets under management given in € (millions). The Total Investments in Companies is the average number of companies a VC has invested in. The Total number of Funds managed is the average number of funds managed by the VC firm. The Total Number of Deals is the average number of deals that a VC firm participated in. The Age of VC is the average age of the VC firms at 31-12-2015 (in months). The Total Known Equity is the average amount of known equity that a VC firm has in € (millions).

Variables	**N**	**Mean**	**SD**	**Min**	**Max**	**Median**
Panel A: All combined VC firms						
Assets Under Management	182	3,810	7,321	9.209	62,964	1,390
Total Investments in Companies	193	173.2	163.8	1	1,249	135.6
Total number of Funds Managed	192	11.22	9.506	1	83	9.125
Total number of Deals	193	444.5	474.2	1	3,803	333.8
Age of VC	192	303.5	96.74	35	647	291.1
Total Known Equity	186	1,348	4,176	0.650	51,973	511.0
Panel B: Syndicate combined VC firms						
Assets Under Management	161	3,636	6,800	9.209	62,964	1,413
Total Investments in Companies	163	180.7	131.5	3	595	160.1
Total number of Funds Managed	163	11.39	7.652	1	51	10.17
Total number of Deals	163	464.1	363.7	3	1,552	369.6
Age of VC	163	305.9	87.79	101	647	299
Total Known Equity	162	1,071	1,839	4.250	17,632	584.9
Panel C: Non-syndicate combined VC firms						
Assets Under Management	21	5,139	10,632	39.72	43,851	851.8
Total Investments in Companies	30	132.1	281.1	1	1,249	29
Total number of Funds Managed	29	10.24	16.63	1	83	4
Total number of Deals	30	338.1	857.9	1	3,803	46.50
Age of VC	29	289.9	137.9	35	563	275
Total Known Equity	25	3,097	10,396	0.650	51,973	188.4

[37] For one start-up we do not find any information about the VCs that have participated in the funding

4. Methodology

4.1 Matching

Firstly, we have different matching principles for our start-up dataset. We have the following identifiers provided by our primary database, Zephyr:

1. Target names;
2. BVD ID identifiers;
3. ISIN codes;
4. Tickers;
5. SIC codes.

We match the different funding rounds/deal values of a start-up with each other based on the Target names (start-up names) provided by Zephyr. We match the different funding rounds because Zephyr does not always provide information on the round of funding (early stage, late stage e.g.). Furthermore, we follow the definition for syndicate deals provided by Brander et al. (2002), Hochberg et al. (2007) and Tian (2012). Afterwards we match the BVD ID identifiers with every start-up name. The BVD ID code is a unique code for every company that is provided by Bureau van Dijk. The BVD ID code is a 10-digit code combined with a 2-digit country code.

After combining all the funding rounds/deal values for every start-up we have the total funding/deal value that a start-up has received before the IPO. We then categorize the start-ups as a syndicate VC-backed start-up or as a non-syndicate VC-backed start-up. Thus, we combine the VCs with the start-ups. As stated in the introduction, in the case that only one VC provides the funding for the start-up during the whole funding period the start-up is categorized as a *non-syndicate VC-backed start-up*. If there are two or more than two VCs that provide funding during the whole funding period for the start-up we categorize the start-up as a *syndicate VC-backed start-up*.

To gather information about the start-up we match the BVD ID identifiers of the start-ups provided by the Zephyr Database with the Orbis database. The Orbis database has relevant fundamental information about the start-ups.[38] With the Orbis database it is possible to upload a specified list of BVD ID codes.

The Orbis database can only look up variables seven years prior to the current year and for our U.S. dataset we have a lot of missing values. We do retrieve the number of patents of the start-ups from the Orbis database. For the other variables we fill in the missing variables retrieved from the Compustat database. We do this to look up the pre-IPO variables and the post-IPO variables. For the U.S. start-ups we convert our *International Security Identification Number* (ISIN) codes to CUSIP codes to match with the Compustat North America database. The ISIN code is also a 10-digit code

[38] See subsection 3.1 Databases *Orbis Database* for more information

combined with a 2-digit country code. The ISIN code is also provided by the Zephyr database. However, the ISIN code is not the same as the BVD ID code. The ISIN codes are unique for every public traded company and it is suitable for many other databases. The CUSIP codes are based on the ISIN codes minus three digits namely the last number of the ISIN code and the 2-digit country codes of the ISIN code. With the Compustat North America database it is possible to upload a specified file of identifiers to specify a search with the needed variables. For our Europe dataset we also look up the pre-IPO and post-IPO variables with the Compustat Global database, but we do not need to convert the ISIN codes into CUSIP codes. The Compustat Global database, in contrast with the Compustat North America database, immediately recognizes the ISIN codes. The pre-IPO variables are the variables of the start-ups in our dataset 1 year prior to the IPO. We match the dates for the data given by Compustat and Orbis with the IPO dates for the pre-IPO variables and the post-IPO variables. The post-IPO variables are the variables for the same year as the dependent variables (e.g. for the 1-year CAR we use the variables 1 year after the IPO).

Unfortunately, the Orbis database or the Compustat database does not provide any information about the offer price of the start-up when it goes to the public market. Therefore, we match with the Bloomberg Terminal to retrieve the offer prices of our start-ups. We match the ISIN identifiers, provided by Zephyr, with the Bloomberg Terminal to retrieve the offer prices of every start-up. To match the ISIN codes with Bloomberg we need to add an extra 2-digit exchange country code and the name "EQUITY". If we do not find a match for the offer price of a start-up based on the ISIN code we match the start-up with the Tickers provided by Zephyr. The Tickers are identifiers only suitable for Bloomberg. Tickers are a 4-digit code combined with the 2-digit exchange country code and the name "EQUITY". The 4-digit code is basically a shortcut of the start-up name.

Furthermore, we also match the ISIN 10-digit code of our start-ups with the Thomson Reuters Datastream database to retrieve the unadjusted opening price and the unadjusted closing price for the start-ups. Unlike, the Bloomberg Terminal the Thomson Reuters Datastream database immediately recognizes the ISIN identifiers without the extra added 2-digit exchange code. The Zephyr database provides 4-digit SIC codes. We convert these in 2-digit SIC codes to get a better overview which start-ups are operating in a certain main industry. We match the 2-digit SIC codes with the industry description provided by the SIC Code database. See *Table 4* and *Table 7* for an overview of the industries description based on the 2-digit SIC codes for our Europe and U.S. dataset, respectively.

Secondly, we match all the VCs that have invested in a start-up with each other. We control for VCs that do a funding more than once in the same start-up. We do the matching based on the name of the VC and the start-up. We match the VC names with the BVD ID identifiers provided by the Zephyr database to lookup variables for the VC with the Orbis Database. As stated earlier, the Orbis Database does not provide information that is useful for our VC dataset.

Therefore, we match the VCs from the Zephyr database with the Thomson One database. Unfortunately, it is not possible to upload specified identifiers to lookup variables for a certain company in the Thomson One database. As stated earlier, we retrieve all the VCs in Europe and the U.S that participated in a VC funding between 1995 and 2015. The BVD ID codes provided by the Zephyr database do not match the Thomson ID codes. We do the matching based on the names of the VCs. Often, the names of the VCs partial match. We correct the dataset for certain name changes of the VCs. Sometimes, there is no match based on the VC names with the Thomson One dataset. Therefore, we also manually lookup the VC names in the Crunchbase database. We combine the VCs that we have looked up in the Crunchbase database with the dataset retrieved from the Thomson One database.

As stated earlier, we combine all the funding rounds of the start-up and therefore we combine all the VCs with each other for every start-up. We then take the average of the variables of the VCs and these averages are then matched with the required start-up.

To match the unadjusted closing prices and the offer prices with each other we include another variable namely *id*. The *id* code represents a number for every start-up name and we match the closing prices and the offer prices with each other based on the *id* code. This matching principle is used for calculating the underpricing of the start-ups.

4.2 Underpricing and long-term performance

First, we discuss the methodology for the short-term performance and the long-term performance of the start-ups. Afterwards we discuss the methodology for the OLS method.

4.2.1 Underpricing

The short-term performance is calculated with the underpricing (UP) formula (Ritter, 1984; Barry et al., 1990; Megginson & Weiss, 1991; Lerner, 1994b; Loughran & Ritter,2004). We define UP as the initial return (IR). The IR for firm *i* is calculated as the percentage change from the offer price $(P_{i,OP})$ to the unadjusted closing price $(P_{i,CP})$ on the first trading day (Ritter 1984; Loughran & Ritter 2004):

$$IR_i = \frac{P_{i,CP} - P_{i,OP}}{P_{i,OP}} \tag{1}$$

4.2.2 Long term performance

For the long-term performance we will use the 1 year, 2 years and 3 years abnormal returns based on our dataset of daily returns. We define a month as 21-trading days. We define a year as twelve 21-trading day intervals (252 days). We will use the cumulative abnormal return (CAR) and the buy-and-hold abnormal return (BHAR) for our paper in accordance with Ritter (1991), Espenlaub et al., (1999)[39], da Silva Rosa et al. (2003), Chahine and Fiatotchev (2008) and Bessler and Seim (2012).

The long-run market performance measures are calculated up to the three years after the IPO, against different market indices using an event-time approach. We use two market model benchmarks

[39] Espenlaub et al. (1999) only uses the CAR methodology

namely the CRSP Equally-weighted and the CRSP Value-weighted in accordance with Ritter (1991)[40]. The CRSP index is a combination of the indices NYSE/AMEX/NASDAQ/ARCA. The CRSP index contains solely a combination of American indices. It is possible that the CRSP index is a better match for our U.S. dataset in comparison with our Europe dataset. We choose for the CRSP index as the benchmark instead of, for example the MSCI world, because historical prices (before 2000) are not available (unlike the CRSP benchmark). We need the daily historical prices to calculate the abnormal returns with the BHAR and with the CAR method. We do check for important historical events in Europe with the (IPO) year fixed effects dummy.

Returns are calculated for two intervals namely the initial return period, the return on the first trading day and the aftermarket period. The initial return period is defined as *month 0*, and the aftermarket period includes the following *36 months*. The event months are defined as successive 21 trading day periods. Thus, returns for the first month consist of the returns on listed days 2–22, the second month of returns consist of the returns on listed days 23–43, and so on. We define a year as a twelve 21-trading day interval (252 trading days), we define two years as a twenty-four 21-trading day interval (504 trading days) and we define three years as a thirty-six 21-trading day interval (756 trading days) (Ritter, 1991).

Cumulative abnormal returns

Cumulative abnormal returns are arithmetic returns (Brooks, 2014**).** The benchmark-adjusted return for stock *i* in event month *t* is defined as:

$$ar_{it} = r_{it} - r_{mt} \tag{2}$$

In the above formula $ar_{it}$is the abnormal return for start-up i in event month *t.* r_{it} is the return of start-up *i* in event month *t* and r_{mt} is the return of benchmark m in the event month t.

The average benchmark-adjusted return on a portfolio of *n* stocks for event month *t* is the equally-weighted arithmetic average of the benchmark-adjusted returns:

$$AR_t = \frac{1}{n}\sum_{i=1}^{n} ar_{it} \tag{3}$$

In the above formula AR_t is the equally weighted arithmetic average of the abnormal returns. *N* is the number of start-ups in our datasets. The part ar_{it} is the abnormal returns for start-up *i* in event month *t.* The cumulative benchmark-adjusted aftermarket performance from event month q to event month *s* is the summation of the average benchmark-adjusted returns:

[40] Ritter (1991) only uses the CRSP-value weighted but we also include the CRSP-equal weighted as a benchmark. Dividends are excluded in the benchmark.

$$CAR_{q,s} = \sum_{t=q}^{s} AR_t \tag{4}$$

Buy and hold abnormal returns

Buy and hold abnormal returns are geometric returns (Brooks, 2014). We use the buy and hold abnormal returns to calculate the abnormal returns on a daily basis:

$$BHAR = \frac{1}{n}\sum_{i=1}^{n}\left[\left(\prod_{t=1}^{T}(1 + R_{i,t})\right) - \left(\prod_{t=1}^{T}(1 + R_{M,t})\right)\right] \tag{5}$$

Where $(1+R_{i,t})$ represents the return of the start-up *i* at time *t* and $(1+R_{M,t})$ is the return on the market index *M* for the same day. The market index *M* is either the CRSP value-weighted or the CRSP equally-weighted. The return of an investment in IPO start-up *i* is compared to an investment in the market index *M* for identical time intervals (*T*), resulting in the performance measure BHAR as the difference between the returns of these two investment alternatives. We begin our analysis on the second day of trading and measure abnormal returns until 756 trading days; 3 years after the IPO. In short, the BHAR performance measure compares the average performance of a buy-and-hold investment in a portfolio consisting of all the start-ups (BHR) to the buy-and-hold investment with the appropriate benchmark (CRSP value-weighted and CRSP equally-weighted).

The difference between the two measures BHAR and CAR is that the CAR immediately calculates the abnormal returns (stock return minus the benchmark return) and then simply sums up the abnormal returns for the appropriate period. Whereas, the BHAR measure first compounds the returns of the start-ups and the benchmark returns, individually, and then measures the abnormal return (takes the difference of the two).

4.3 Mean and median difference tests

First, we will use a standard two-sample mean comparison t-test (Megginson & Weis, 1991) to test if there are any differences in the means of the two subsamples; the syndicated start-ups and the non-syndicated start-ups (and the U.S. and Europe dataset). We also use the Wilcoxon rank-sum test (Lerner, 1994b; Tian, 2012) to test for the equality of medians of the two subsamples; the syndicated start-ups and the non-syndicated start-ups (and the U.S. and Europe dataset). The Wilcoxon rank-sum test is also known as the Mann-Whitney-Wilcoxon test. The Wilcoxon rank-sum test is a nonparametric test. This means that it is also possible to use this test when the sample is not normal distributed. The two-sample mean comparison test is used to test if the means from a variable from two subsamples differs from zero. We group the variables by our variable *syndicate*. We test the null hypothesis that the means of the subsamples are equal: $\mu_x = \mu_y$ (StataCorp., 2013).

$$t = \frac{\bar{x}-\bar{y}}{\left(s_x^2/n_x+s_y^2/n_y\right)^{1/2}} \tag{6}$$

For the Wilcoxon rank-sum test we test the null hypothesis that $X_1 \sim X_2$. Where X_1 and X_2 are two independent random variables. We use the sample sizes n_1 for X_1 and n_2 for X_2 (StataCorp., 2013). The test statistic of Wilcoxon is the sum of the ranks for the observations in the first sample:

$$T = \sum_{i=1}^{n_1} R_{1i} \tag{7}$$

The Mann & Whitney's U statistic is the number of pairs (X_{1i}, X_{2j}) such that $X_{1i} > X_{2j}$ (StataCorp., 2013). These statistics differ only by a constant:

$$U = T - \frac{n_1(n_2+1)}{2} \tag{8}$$

Fisher's principle of randomization provides a method for calculating the distribution of the test statistic. The randomization distribution consists of the $\binom{n}{n_1}$ ways to choose n_1 ranks from the set of all $n = n_1 + n_2$ ranks and assign them to the first sample. It is a straightforward exercise to verify that

$E(T) = \frac{n_1(n+1)}{2}$ (9) and $Var(T) = \frac{n_1 n_2 s^2}{n}$ (10)

Where s is the standard deviation of the combined ranks, r_i for both groups:

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(r_i - \bar{r})^2 \tag{11}$$

This formula for the variance is exact and holds both when there are no ties and when there are ties and we use the averaged ranks (StataCorp., 2013). Using a normal approximation, we calculate

$$z = \frac{T-E(T)}{\sqrt{Var(T)}} \tag{12}$$

When the grouping option is specified, the probability, p is computed as follow:

$$p = \frac{U}{n_1 n_2} \tag{13}$$

4.4 Variables and regressions

We use multiple regressions in this paper to investigate the dependent variables on the independent variables and control variables. The regressions we use in this paper are a combination of the regressions used by Megginson and Weis (1991), Espenlaub et al., (1999), Wang (2002), Hege et al. (2003), Chahine and Fiatotchev (2008), Tian (2012) and Chahine et al. (2012).

The first (base) regression that we test for the *Value-added and Screening/Selection and Cost/Geographic public market* hypotheses is the following:

$$IR = a_0 + a_1 Syndum + \; a_2 USdum + a_2 Log(Deal\,Value) + a_3 Inv + \; a_4 Age + e_i \qquad (14)$$

Where IR is the underpricing effect, the initial return on the first trading day. The dummy variable Syn equals *1* if the start-up is a syndicate VC-backed start-up and equals *0* if the start-up is a non-syndicate VC-backed start-up. The dummy variable US equals *1* if the start-up is from the U.S. and equals *0* if the start-up is from Europe. The independent variable $Log\ (Deal\,Value)$ is the logarithm of the deal value in thousands with a constant. The independent variable Inv represents the number of investors participating in the funding of a start-up. The *Age* variable is the age of the start-up at the time of the IPO.

The second regression we are going to test is equal to the first regression with the added start-up independent variables. We use the operating performance measures ROS (EBITDA/Revenue), ROA (EBITDA/Assets) and we use the innovative measures RDRT (Research and development expenditures/Revenue) and RDAT (Research and development expenditures/Assets)[41]. For the IR regression we use the pre-IPO variables of our start-ups. These are the variables of the start-up one year prior to the IPO.

The third regression we are going to test is equal to the second regression with the added VC reputation control variables, in accordance with Tian (2012) and Nahata (2008).[42] The VC control variables are measured as follows: (i) the total number of funds raised by the VC, (ii) the age of the VC, (iii) the total dollar amount of assets under management of the VC firm, (iv) the total known equity that a VC has invested, (v) and the total number of companies the VC has invested in[43]. The control variable VC_{Age} is the total average matched age of the VC. The control variable VC_{funds} is the total average matched number of funds the VC has raised. The control variable VC_{AUM} is the matched total average assets under management that the VC has. The control variable $VC_{Investments}$ is the total

[41] We test for multicollinearity and find a very high correlation and a high VIF for the RDRT and RDAT with respectively the ROS variable and the ROA variable. Therefore, we exclude the RDRT and the RDAT variable in the initial regression. See subsection 5.1 Multicollinearity for more information.

[42] Although we use slightly different variables, the main variables are the same (age, total dollar amount invested and total dollar amount raised).

[43] We exclude the variable number of investments made by the VC because of multicollinearity. For a further explanation see subsection 5.1

average matched number of companies the VC has invested in. The control variable VC_{Equity} is the total average matched amount of known equity the VC has invested.

The fourth regression is equal to the third regression with the industry dummy fixed effects for the industry wherein the start-up is operating. Furthermore, we also use the IPO year dummy fixed effects. These are fixed effects for the year that the start-up did the IPO.

We repeat the fourth regression with the *1 year*, *2 year* and the *3 year* BHAR and CAR. However, there are some differences namely, the dependent variable is then either the CAR or the BHAR of the VC-backed start-ups. Furthermore, we use the post-IPO start-up variables for the CAR and the BHAR regressions. We match the X-year CAR and the X-year BHAR with the start-up variables X year(s) after to the IPO. Wherein X stands for 1, 2 or 3 years. We will only do the regressions with the CRSP value weighted as the benchmark, in accordance with Chahine et al. (2012).

$$BHAR = a_0 + a_1 Syndum + \ a_2 USdum + a_2 Log(Deal\ Value) + a_3 Investors + \ a_4 Age + a_5 ROS + a_6 ROA + a_7 VC\ Controls + a_8 Industrydum + + e_i \quad (15)$$

We also test the regression for the *Geographic operating performance* hypothesis. The regressions are as follows:

$$PostROS = a_0 + a_1 Syndum + \ a_2 USdum + a_2 Investors + a_3 Patents + \ a_4 Age + a_5 PostROA + a_6 PostRDRT + a_7 VC\ controls + a_8 Industrydum + a_9 IPOyeardum + e_i \quad (16)$$

$$PostROA = a_0 + a_1 Syndum + \ a_2 USdum + a_2 Investors + a_3 Patents + \ a_4 Age \ + a_5 PostROS + a_6 PostRDAT + a_7 VC\ controls + a_8 Industrydum + a_9 IPOyeardum + e_i \quad (17)$$

The dependent variables are *ROS* (EBITDA/Revenue) and *ROA* (EBITDA/Assets). The first regression, model (1), is the average of the post-IPO start-up variables. Whereas model (2), (3) and (4) represent the 1-year, 2-year and 3-year post-IPO start-up variables, respectively. The independent variables are the syndication dummy (*Syndum*), U.S. dummy (*USdum*), number of VC investors involved in the financing (*Investors*), number of patents issued by the company (*Patents*), *ROA* (EBITDA/Assets), *RDRT* (Research and development expenditures/Revenue) and *RDAT* (Research and development expenditures/Assets)[44]. The control variables are the *VC controls*, *Industrydum* (fixed effect dummy for the industries based on 2-digit SIC code) and *IPOyear* fixed dummy.

[44] Because of multicollinearity issues we exclude the RDRT as an independent variable if the ROS is also an independent variable. For the same reason we also exclude the RDAT as an independent variable if the ROA is also an independent variable.

We also do a regression for the *Innovation* hypothesis. The regressions are as follow:

$$PostRDRT = a_0 + a_1 Syndum + a_2 USdum + a_2 Investors + a_3 PostROS + a_4 PostROA + a_5 VC\ controls + a_6 Industrydum + a_7 IPOyeardum + e_i \quad (18)$$

$$PostRDAT = a_0 + a_1 Syndum + a_2 USdum + a_2 Investors + a_3 PostROS + a_4 PostROA + a_5 VC\ controls + a_6 Industrydum + a_7 IPOyeardum + e_i \quad (19)$$

$$Patents = a_0 + a_1 Syndum + a_2 USdum + a_2 Investors + a_3 PostROS + a_4 PostROA + a_5 VC\ controls + a_6 Industrydum + a_7 IPOyeardum + e_i \quad (20)$$

The dependent variables are *RDRT* (research and development expenditures/Revenue), *RDAT* (research and development expenditures/Assets) and *Patents* (number of issued patents by the start-up until 2015). The *RDRT* variable and the *RDAT* variable, regression (4) and (5), are the averages of the 1-year, 2-year and 3-year post IPO *RDRT* and *RDAT* variables, respectively. The independent variables, *ROS* and *ROA* are also the averages of the 1-year, 2-year and 3-year post-IPO *ROS* and *ROA* variables, respectively.

5. Results

In our U.S. dataset we have twenty-five missing values for our BHAR and CAR 1-year valuations. These values are missing because these start-ups had their IPO in late 2016. We have the unadjusted closing prices until 30-06-2017 obtained from Datastream. We do not exclude these start-ups because we do have the offer prices for these start-ups and can use it for the underpricing regression.

In our U.S. dataset we have three missing values for the underpricing valuation. The databases do not provide the offer prices for these start-ups. We do not exclude these start-ups in our dataset because we do have the BHAR and CAR valuations for these three start-ups and can use it for the long-term performance regression.

In our Europe dataset we have twenty-eight missing values for our BHAR and CAR 1-year valuations. These values are missing because these start-ups had their IPO in late 2016. We have the unadjusted closing prices until 30-06-2017 obtained from Datastream. Therefore, the 1-year BHAR and CAR cannot be calculated. We do not exclude these start-ups because we do have the offer prices for these two start-ups and can use it for the underpricing regression.

In our Europe dataset we have 28 missing values for the underpricing valuation. The databases do not provide the offer prices for these start-ups. We do not exclude these start-ups in our dataset because we do have the BHAR and CAR valuations for these 28 start-ups and can use it for the long-term performance regression.

5.1 Summary Statistics

Table 11 shows the summary of the statistics for our Europe dataset. Panel A shows the initial returns measured with the underpricing formula. We find that the means of the syndicate VC-backed start-ups and the means of the non-syndicate VC-backed start-ups are significant different at a 10% significance level. The mean initial return of the non-syndicate VC-backed start-ups is higher than the mean initial return of the syndicate VC-backed startups. This is in accordance with a part of the *Value-added and Screening* hypothesis (for the underpricing effect). Apparently, the underpricing is more persistent with non-syndicate start-ups. Panel B shows the cumulative abnormal returns with the CRSP equally weighted as the benchmark. We do not find any significance difference in the means or the medians of the non-syndicate and the syndicate VC-backed startups. Panel C shows the cumulative abnormal returns with the CRSP value weighted as the benchmark. We do not find any significance difference in the means or the medians of the non-syndicate and the syndicate VC-backed startups. Panel D shows the buy and hold abnormal returns with the CRSP equally weighted as the benchmark. We do not find any significance difference in the means of the non-syndicate and the syndicate VC-backed startups. However, we do find a significance difference in the medians for the 2-year period with our buy and hold abnormal returns. The syndicate VC-backed start-ups have a higher buy and hold abnormal return, for a 2-year period, than the non-syndicate VC-backed start-ups. This provides a part of the answer for the *Value-added and Screening* hypothesis for the long-term. The syndicate VC-backed start-ups have a higher performance on the public market in comparison with the non-syndicate VC-backed start-ups. Panel E shows the buy and hold abnormal returns with the CRSP value weighted as the benchmark. We do not find any significance difference in the means or the medians of the non-syndicate and the syndicate VC-backed startups.

Table 11: Summary Statistics Europe dataset

The sample includes in total 151 observations from which 112 syndicated VC-backed start-ups and 39 non-syndicated VC-backed startups. The *trading days* is the number of days that is investigated. *Df* is the degrees of freedom (number of observations minus 2). The means of the returns are given for all the trading days of the *Syndicate* and *Non-syndicate observations.* The *t-test* is the t-statistic for the difference in means. The *Wilcoxon Z* score is the score for the Wilcoxon rank-sum test which test for the difference in the medians. Panel A shows the initial returns for Europe. Panel B shows the cumulative abnormal returns with the CRSP equally weighted as the benchmark. Panel C shows the cumulative abnormal returns with the CRSP value weighted as the benchmark. Panel D shows the buy and hold abnormal returns with the CRSP equally weighted as the benchmark. Panel E shows the buy and hold abnormal returns with the CRSP value weighted as the benchmark. The asterisk; *, **, *** show if there is significance at the, respectively, 10%, 5% or 1% level.

Trading days	**Df**	**Syndicate**	**Non-syndicate**	**t-test**	**Wilcoxon Z**
Panel A: Europe IR					
(0,1)	123	0.028	0.334	1.799*	-1.125
Panel B: Europe CAR EW					
(2,252)	128	0.126	-0.015	-0.670	-0.860
(2,504)	114	0.049	-0.276	-1.303	-1.545
(2,756)	97	-0.134	0.086	0.491	-0.604
Panel C: Europe CAR VW					
(2,252)	128	0.125	0.014	-0.528	-0.669
(2,504)	114	0.071	-0.211	-1.130	-1.337
(2,756)	97	-0.016	0.291	0.692	-0.016
Panel D: Europe BHAR EW					
(2,252)	128	0.238	-0.160	-1.369	-1.216
(2,504)	114	0.228	-0.401	-1.463	-1.822*
(2,756)	97	-0.187	-0.110	0.254	-0.437
Panel E: Europe BHAR VW					
(2,252)	128	0.239	-0.137	-1.272	-0.893
(2,504)	114	0.244	-0.342	-1.356	-1.576
(2,756)	97	-0.085	0.094	0.595	0.318

Table 12 shows the summary of the statistics for our U.S. dataset. Panel A shows the initial returns measured with the underpricing formula. We find that the means of the syndicate VC-backed start-ups and the means of the non-syndicate VC-backed start-ups are significant different at a 5% significance level. The underpricing of the non-syndicate VC-backed start-ups is higher than the underpricing of the syndicate VC-backed startups. This is also in accordance with the *Value-added and Screening* hypothesis (for the underpricing effect). Apparently, the underpricing is more persistent with non-syndicate start-ups. Panel B shows the cumulative abnormal returns with the CRSP equally weighted as the benchmark. We find significance differences in the means of the non-syndicate and the

syndicate VC-backed startups for the 2-year period and the 3-year period. We do not find a significance for the difference in the medians for the cumulative abnormal returns with the CRSP equally weighted as the benchmark.

Panel C shows the cumulative abnormal returns with the CRSP value weighted as the benchmark. We find significance differences in the means of the non-syndicate and the syndicate VC-backed startups for the 2-year period and the 3-year period. The non-syndicate VC-backed start-ups apparently have a higher CAR return in comparison with the syndicate VC-backed start-ups. This provides a part of the answer for the *Selection and Cost* hypothesis. If we evaluate the data more closely we find that this is the case due to two non-syndicate start-ups that have gained a huge increase in the stock price (up to 900% in one year). However, it can be quite common for start-ups they have a huge increase in the stock price and therefore we do not exclude this outlier.

Table 12: Summary Statistics U.S. dataset

The sample includes in total 189 observations from which 160 syndicated VC-backed start-ups and 31 non-syndicated VC-backed startups. The trading days is the number of days that is investigated. *Df* is the degrees of freedom (number of observations minus 2). The means of the returns are given for all the trading days of the *Syndicate* and *Non-syndicate* observations. The *t-test* is the t-statistic for the difference in means. The *Wilcoxon Z* score is the score for the Wilcoxon rank-sum test which tests for the difference in the medians. Panel A shows the initial returns (*IR)* measured with the underpricing formula. Panel B shows the cumulative abnormal returns with the CRSP equally weighted as the benchmark. Panel C shows the cumulative abnormal returns with the CRSP value weighted as the benchmark. Panel D shows the buy and hold abnormal returns with the CRSP equally weighted as the benchmark. Panel E shows the buy and hold abnormal returns with the CRSP value weighted as the benchmark. The asterisk; *, **, *** show if there is significance at the, respectively, 10%, 5% or 1% level.

Trading days	**Df**	**Syndicate**	**Non-syndicate**	**t-test**	**Wilcoxon Z**
Panel A: US IR					
(0,1)	189	0.273	3.794	2.426**	1.551
Panel B: US CAR EW					
(2,252)	179	0.039	0.119	0.541	-0.674
(2,504)	160	0.146	25.629	2.220**	1.045
(2,756)	127	0.264	30.888	2.158**	-0.634
Panel C: US CAR VW					
(2,252)	179	0.032	0.115	0.567	-0.55
(2,504)	160	0.163	25.665	2.222**	1.267
(2,756)	127	0.316	30.978	2.160**	-0.357
Panel D: US BHAR EW					
(2,252)	179	-0.016	-0.025	-0.078	-0.663
(2,504)	160	-0.045	31.118	2.210**	0.700
(2,756)	127	0.104	13.144	2.095**	-0.701
Panel E: US BHAR VW					
(2,252)	179	-0.022	-0.029	-0.058	-0.651
(2,504)	160	-0.036	31.150	2.212**	1.019
(2,756)	127	0.144	13.235	2.102**	-0.351

Panel D shows the buy and hold abnormal returns with the CRSP equally weighted as the benchmark. We find significance difference in the means of the non-syndicate and the syndicate VC-backed startups for the 1-month period, 2-year period and the 3-year period. However, we do not find a significance for the difference in the medians. The non-syndicate VC-backed start-ups have a higher buy and hold return, for the 2-year period and the 3-year period. This also provides a part of an answer for the *Selection and Cost* hypothesis.

Table 13 shows the descriptive statistics for the performance on the public market of the syndicate VC-backed start-ups from the U.S. in comparison with the syndicate VC backed start-ups from Europe. We find that there is a significance difference in the means and the medians for the initial return (the underpricing effect). Furthermore, we also find that the 3-year cumulative abnormal return with the equally weighted CRSP as benchmark is significant different in the means and the medians for U.S. and for Europe. Furthermore, we also find that the BHAR EW and the BHAR VW is significant different in the means of the returns. With the results of *Table 13* we can already answer a part of the *Geographic public market* hypothesis. Namely, the results provide evidence that the 3-year cumulative abnormal return is higher in the U.S. in comparison with Europe. Thus, apparently the long-term performance in the U.S. is higher in Europe for the syndicate start-ups. We do not find evidence that the underpricing effect in the U.S. is lower in comparison with Europe. The underpricing effect seems to be higher in the U.S. than in Europe (Panel A). However, we still need answers if the apparently higher performance of syndicate VC-backed start-ups on the public market is due to syndication effects or that other variables play a role. We also need to provide evidence why the underpricing effect is apparently higher in the U.S. than in Europe. To answer these questions, we test the earlier described regressions.

Table 13: Summary Statistics Syndicate U.S. and Europe dataset

The sample includes in total 261 observations from which 163 U.S. syndicated VC-backed start-ups and 98 Europe syndicated VC-backed startups. The trading days is the number of days that is investigated. *Df* is the degrees of freedom (number of observations minus 2). The means of the returns are given for all the trading days of the syndicate U.S. and syndicate Europe VC-backed start-ups. The t-test is the t-statistic for the difference in means. The Wilcoxon Z score is the score for the Wilcoxon rank-sum test, difference in the medians. Panel A shows the initial returns measured with the underpricing formula. Panel B shows the cumulative abnormal returns with the CRSP equally weighted as the benchmark. Panel C shows the cumulative abnormal returns with the CRSP value weighted as the benchmark. Panel D shows the buy and hold abnormal returns with the CRSP equally weighted as the benchmark. Panel E shows the buy and hold abnormal returns with the CRSP value weighted as the benchmark. The asterisk; *,**,*** show if there is significance at the, respectively, 1%, 5% or 10% level.

Trading days	**Df**	**U.S.**	**Europe**	**t-test**	**Wilcoxon Z**
	Panel A: IR				
(0,1)	259	0.273	0.028	-2.76***	-6.277***
	Panel B: CAR EW				
(2,252)	247	0.039	0.126	0.86	-0.4
(2,504)	218	0.146	0.049	-0.58	-1.1
(2,756)	177	0.264	-0.134	-2.34**	-3.00***
	Panel C: CAR VW				
(2,252)	247	0.032	0.125	0.918	-0.3
(2,504)	218	0.163	0.071	-0.55	-1.1
(2,756)	177	0.316	-0.016	-1.94*	-2.63***
	Panel D: BHAR EW				
(2,252)	247	-0.016	0.238	1.78*	0.6
(2,504)	218	-0.045	0.228	1.20	0.495
(2,756)	177	0.104	-0.187	-1.13	-1.1
	Panel E: BHAR VW				
(2,252)	247	-0.022	0.239	1.81*	0.5
(2,504)	218	-0.036	0.244	1.22	0.4
(2,756)	177	0.144	-0.085	-0.90	-0.6

5.2 Multicollinearity

Before we run the regressions, we check whether the independent variables and control variables are correlated. The logarithm of the deal value is moderately correlated with the number of investors (0.58) and with the U.S. dummy (0.54). This is quite logical because if more investors participate in the funding of a start-up the deal value also becomes higher. As, the deal values in the U.S. are higher in comparison with Europe it is also logical that the logarithm of the deal value is moderately correlated with the U.S. dummy. We also find a moderate correlation between the Syndication dummy and the number of investors (0.55). However, we do not omit these control variables, the logarithm of the deal value and investors, as the correlation is moderate, and we cross-check with the variance inflation factor (VIF).[45] We find a very high positive correlation between VC number of deals and VC total companies invested in (0.97). This is very logical as the two variables increase if the other increases. Furthermore, we find a high negative correlation for the RDRT (research and development expenditures divided by the revenue) with ROS (-0.94) and for RDAT with ROA (-0.97). We solve this multicollinearity problem by omitting the variables, VC number of deals invested in, the RDRT

[45] We also check the multicollinearity issue by using the variance inflation factor (VIF) and we do not find reasons to exclude it. The VIF of the logarithm of the deal value is not high for the logarithm of the deal value (2.01) and not high for investors (1.65). A control variable is only troublesome for multicollinearity if the VIF is close to 10 or above 10.

variable and the RDAT variable. However, we still use the RDRT variable and the RDAT variable as dependent variables to check for the *Innovation* hypothesis and independent variables for the *Geographic operating performance* hypothesis.[46] The omission of the logarithm of the variable VC number of deals invested, the RDRT variable and the RDAT variable results in nearly the same coefficients, without omission, for other variables.[47]

5.3 Regressions

Table 14 shows the OLS regression for the total dataset U.S. and Europe combined. The dependent variable is the initial return of the VC-backed start-ups (IR). An explanation of all the dependent variables, independent variables and the control variables can be found in subsection 4.4. In model (1), (2), (3) and (4) the U.S. dummy has a positive significant coefficient. This means that if the start-up/VC is from the U.S. the initial return of the VC-backed start-up is higher (thus a greater underpricing). Furthermore, it is interesting that in model (2), (3) and (4) the Syndication dummy has a negative significant coefficient. This means that the underpricing effect is lower if the VC-backed start-up is syndicate. The underpricing is around 11% until 15% lower if the VC-backed start-up is syndicate. The coefficient of the constant in model (1) is very high in comparison with the other coefficients in model (1). The constant is positive significant, that means that if the other independent variables are zero the mean of the response is 4.846. However, this also has some explanatory values for the Syndication dummy. If the Syndication dummy is zero, then the VC-backed start-up is non-syndicate. Thus, apparently non-syndication VC-backed start-ups have a higher underpricing. In model (2), (3) and (4) the Pre-ROA variable has a positive significant coefficient. This means that for every unit increase in the Pre-ROA a 0.033 ~ 0.043 unit increase in the IR is predicted, holding all else equal. This provides a part of the answer for the *Value-added and Screening* hypothesis. Namely, syndicate VC-backed start-ups provide a lower underpricing (the Syndicate dummy is negative). Because we find a positive significant coefficient for the U.S. dummy the results are not in accordance with the (underpricing) *Geographic public market* hypothesis. Apparently, the U.S. VC-backed start-ups have a higher underpricing in comparison with the Europe start-ups.

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[46] We omit RDRT as an independent variable if ROS is also an independent variable. We also omit RDAT as an independent variable if ROA is also an independent variable.
[47] The adjusted R^2 stays approximately the same

Table 14: Regression analysis with the total IR dataset

This table shows the results of a multivariate regression analysis. The sample consists of our combined U.S. and Europe dataset. The dependent variable is the initial return measured with the underpricing formula. The U.S. dummy is a dummy variable consisting of 1 if the start-up/VC is from the U.S. and 0 if the start-up/VC is from Europe. The Syndicate dummy is a dummy variable consisting of 1 if the start-up is syndicate and 0 if the start-up is non-syndicate. The Log of Deal Value is the logarithm of the Deal Value. The Pre-variables are the variables one year prior to the IPO. ROS is the EBITDA divided by the Revenue. ROA is the EBITDA divided by the Total Assets. See Table 8 and 9 for a description of the other explanatory variables. In Appendix C the coefficients and the t-statistics of the Industry Fixed effects is given. The t-statistics, based on robust standard errors, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
U.S. dummy	1.279*	0.199***	0.210***	0.183***
	(1.67)	(4.38)	(4.00)	(2.90)
Syndicate dummy	-1.331	-0.11*	-0.152**	-0.150*
	(-1.29)	(-1.89)	(-2.25)	(-1.92)
Age at IPO	-0.008	0.0001	-0.0001	-0.0002
	(-1.35)	(0.43)	(-0.39)	(-0.43)
Investors	0.020	0.010	0.006	0.011
	(0.15)	(1.57)	(0.76)	(1.30)
Log of Deal Value	-0.339	0.009	0.019	0.016
	(-1.19)	(0.53)	(1.06)	(0.77)
Pre-ROS		0.0001	0.002	0.0001
		(0.40)	(0.38)	(0.16)
Pre-ROA		0.042**	0.043**	0.033*
		(2.44)	(2.41)	(1.73)
VC Funds			0.001	0.002
			(0.66)	(1.02)
VC AUM			-0.000004	-0.00001
			(-1.11)	(-1.65)
VC Total known equity			0.00001	0.00005
			(-0.70)	(1.08)
VC Age			0.0003	0.0004
			(1.41)	(1.61)
VC Total investments			-0.0001	-0.0004
			(-0.68)	(-1.59)
Year fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	No	Yes
Constant	4.846**	-0.156	-0.264	-0.284
	(2.10)	(-0.59)	(-0.96)	(-0.74)
N	316	225	203	203
Adjusted R^2	0.016	0.183	0.183	0.113

Table 15 shows the OLS regression for the total dataset U.S. and Europe combined. The dependent variables are the post-IPO operational performance measures, ROS (1), ROS 1-year (2), ROS 2-year (3) and the ROS 3-year (4). The ROS stands for the EBITDA/Revenue. The dependent variable in model (1) is the average of the 1-year, 2-year and 3-year operational measure (ROS). An explanation of all the dependent variables, independent variables and the control variables can be found in subsection 4.4. In model (1) we find a high positive significant coefficient for our Syndication dummy (11.80). Apparently, if the VC-backed start-up is syndicate it has a positive outcome for the post-ROS. It is interesting that the coefficient for the Investors variable is negative. Apparently, if there are more than two Investors this does not lead to a unit increase in the ROS. We also find positive significant

coefficients for the Syndication dummy in models (2), (3) and (4). Where model (4) has the highest positive significant coefficient (19.69). In model (3) where the dependent variable is the ROS 2-year we find a positive significant coefficient for the U.S. dummy. If the syndicate VC-backed start-up is from the U.S., then it has a positive influence for the ROS 2-year performance measure. This is in accordance with the *Geographic operating performance* hypothesis. The long-term operating performance in the U.S. is greater in Europe due to syndication effects. As, the syndication dummy and the U.S. dummy both have significant positive coefficients. Furthermore, it is interesting that the Adjusted R^2 is very high in comparison with the other tables. We have tested for multicollinearity by looking for the correlation between the independent variables and with the variance influence factor (VIF). Thus, the model is apparently a good fit. It is possible that the Adjusted R^2 is very high because of the similarity between the dependent variable ROS (EBITDA/Revenue) and the independent variable RDRT (research and development expenditures/Revenue). This also shown by the very large t-statistic for the RDRT variable.

Table 16 shows the OLS regression for the total dataset U.S. and Europe combined. The dependent variables are the post-IPO operational measures, ROA (1), ROA 1-year (2), ROA 2-year (3) and ROA 3-year (4). The dependent variable in model (1) is the average of the ROA 1-year, ROA 2-year and the ROA 3-year. The ROA stands for the EBITDA/Assets. In all the models we find a positive significant coefficient for our Syndication dummy. Apparently, if the VC-backed start-up is syndicate it has a positive outcome for the post-ROA. It is interesting that the coefficient for the Investors variable is significant negative in model (4). Apparently, if there are more than two Investors this does not lead to a unit increase in the ROA. In model (4) where the dependent variable is the ROA 3-year we find a positive significant coefficient for the U.S. dummy. If the syndicate VC-backed start-up is from the U.S., then it has a positive influence for the ROA 3-year performance measure it can lead to a unit increase of 14.4% ~ 21%. This is also in accordance with the *Geographic operating performance* hypothesis. Apparently, if the start-up is from the U.S. and the start-up is a syndicate VC-backed start-up it has a positive effect on the long-term operational performance. Furthermore, it is interesting that the Adjusted R^2 is very high in comparison with the other tables. We have tested for multicollinearity by looking for the correlation between the independent variables and with the variance influence factor (VIF). Thus, the model is apparently a good fit. It is possible that the Adjusted R^2 is very high because of the similarity between the dependent variable ROA (EBITDA/Assets) and the independent variable RDAT (research and development expenditures/Assets). This also shown by the large t-statistic for the RDAT variable. Furthermore, *Table 16* shows that the coefficient for the RDAT variable is significant negative. This means that per unit increase of the RDAT variable it leads to a unit decrease of the ROS variable. This is logically because the RDAT is the research and development expenditures divided by the revenue. Thus, these are costs if they increase the EBITDA decreases and therefore ROA decreases.

Table 15: Regression analysis with the total ROS dataset

This table shows the results of a multivariate regression analysis. The sample consists of our combined U.S. and Europe dataset. The dependent variable is the post- ROS (EBITDA divided by revenue). In model (1) the ROS is the averages of the 1-year, 2-year and 3-year ROS; this is also the case for the independent Post variables in model (1). Model (2), (3) and (4) are respectively the 1-year, 2-year and 3-year ROS and Post- independent variables. The U.S. dummy is a dummy variable consisting of 1 if the start-up/VC is from the U.S. and 0 if the start-up/VC is from Europe. The Syndicate dummy is a dummy variable consisting of 1 if the start-up is syndicate and 0 if the start-up is non-syndicate. See Table 8, 9 and 15 for a description of the other explanatory variables. In Appendix C the coefficients and the t-statistics of the Industry Fixed effects is given. The t-statistics, based on robust standard errors, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) ROS	(2) ROS-1	(3) ROS-2	(4) ROS-3
U.S. dummy	1.230	0.747	4.934**	0.309
	(0.33)	(0.48)	(2.17)	(0.04)
Syndicate dummy	11.805**	6.300***	8.402**	19.691***
	(2.16)	(2.81)	(2.56)	(2.05)
Age at IPO	0.038	-0.007	-0.021	0.088
	(1.32)	(-0.60)	(-0.11)	(1.38)
Investors	-1.034*	-0.290	-0.704***	-0.835
	(-1.93)	(-1.30)	(-2.14)	(-0.87)
Patents	0.022	0.007	0.006	0.022
	(1.01)	(0.79)	(0.45)	(0.67)
Post-ROA	5.562	8.440***	0.460	25.567**
	(1.63)	(3.79)	(0.18)	(2.37)
Post-RDRT	-1.316***	-1.193***	-1.348***	-1.347***
	(-55.86)	(-148.20)	(-87.81)	(-36.52)
VC Controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Constant	-16.743	-5.470	-21.386	12.04
	(-1.067)	(-0.53)	(-1.55)	(0.39)
N	183	168	146	116
Adjusted R^2	0.963	0.994	0.985	0.948

Table 16: Regression analysis with the total ROA dataset

This table shows the results of a multivariate regression analysis. The sample consists of our combined U.S. and Europe dataset. The dependent variable is the post- ROA (EBITDA divided by assets). In model (1) the ROA is the averages of the 1-year, 2-year and 3-year ROA; this is also the case for the independent Post variables in model (1). Model (2), (3) and (4) are respectively the 1-year, 2-year and 3-year ROA and Post- independent variables. The U.S. dummy is a dummy variable consisting of 1 if the start-up/VC is from the U.S. and 0 if the start-up/VC is from Europe. The Syndicate dummy is a dummy variable consisting of 1 if the start-up is syndicate and 0 if the start-up is non-syndicate. See Table 8, 9 and 15 for a description of the other explanatory variables. The t-statistics, based on robust standard errors, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) ROA	(2) ROA-1	(3) ROA-2	(4) ROA-3
U.S. dummy	0.046	0.053	0.072	0.144**
	(0.53)	(1.09)	(1.25)	(2.37)
Syndicate dummy	0.370***	0.174**	0.260***	0.210**
	(2.96)	(2.50)	(3.15)	(2.57)
Age at IPO	-0.0003	0.0002	0.0002	0.0004
	(-0.48)	(0.40)	(0.46)	(0.70)
Investors	-0.006	-0.008	-0.003	-0.018**
	(-0.46)	(-1.11)	(-0.37)	(-2.14)
Patents	0.0006	0.004	0.0004	0.0003
	(1.20)	(1.24)	(1.18)	(0.88)
Post-ROS	0.002***	0.0002	(0.0003)	0.0008***
	(4.67)	(0.68)	(1.17)	(3.62)
Post-RDAT	-0.797***	-1.054***	-1.066***	-0.607***
	(-4.45)	(-8.38)	(-12.03)	(-5.60)
VC Controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Constant	-0.641	-1.094***	-0.721**	-1.063***
	(-1.11)	(-3.46)	(-2.10)	(-4.42)
N	183	168	146	116
Adjusted R^2	0.631	0.673	0.937	0.950

Table 17 shows the OLS regression for the total dataset U.S. and Europe combined. The dependent variables are the post-IPO innovation measures, Number of Patents (1), RDRT (2) and RDAT (3). The Patents variable are the number of Patents issued by the firm until 2015. The RDRT dependent variable is the average of the post IPO 1-year, 2-year and 3-year RDRT. The RDAT dependent variable is the average of the post IPO 1-year, 2-year and 3-year RDAT. Model (1) shows that the U.S. dummy coefficient is very positive significant. Apparently, if the start-up is from the U.S. it is more likely that the number of issued Patents is higher. In model (2) we find a positive significance for the coefficient of the Syndication dummy. This means that if the VC-backed start-up is syndicate it leads to a unit increase of 12.2% of the RDAT innovation measure. In model (2) we also see a negative significant coefficient for the Post-ROA variable. This is similar to the negative relation *Table 16* shows. In model (3) we find a very high positive significant coefficient for the Syndication dummy.

Table 17: Regression analysis with the total Innovation dataset

This table shows the results of a multivariate regression analysis. The sample consists of our combined U.S. and Europe dataset. The dependent variable are the Patents (1), RDAT (2) and RDRT (3). In model (2) and model (3) the RDAT and the RDRT are the averages of the 1-year, 2-year and 3-year, respectively RDAT and RDRT. The Post- independent variables are also the averages of the 1-year, 2-year and 3-year independent variables (ROS and ROA). (1). The U.S. dummy is a dummy variable consisting of 1 if the start-up/VC is from the U.S. and 0 if the start-up/VC is from Europe. The Syndicate dummy is a dummy variable consisting of 1 if the start-up is syndicate and 0 if the start-up is non-syndicate. See Table 8, 9 and 15 for a description of the other explanatory variables. The t-statistics, based on robust standard errors, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Patents	(2) RDAT	(3) RDRT
U.S. dummy	37.90**	0.0328	1.350
	(3.18)	(0.85)	(0.49)
Syndicate dummy	4.761	0.122**	9.637**
	(0.27)	(2.17)	(2.38)
Age at IPO	0.030	-0.0001	0.024
	(0.30)	(-0.38)	(1.11)
Investors	0.464	-0.006	-0.803
	(0.25)	(-1.19)	(-2.02)
Post-ROS	0.048	-0.0002	-0.728***
	(0.79)	(-1.02)	(-55.86)
Post-ROA	10.731	-0.158***	1.522
	(1.02)	(-4.45)	(0.60)
VC Controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Constant	33.273	0.007	-12.448
	(0.36)	(0.03)	(-0.67)
N	215	183	183
Adjusted R^2	0.116	0.581	0.962

Furthermore, we find in model (3) a negative significant coefficient for the ROS variable. Apparently, a unit decrease in the ROS variable leads to a unit increase in the RDRT variable. This is logically because the ROS variable is defined as the EBITDA/Revenue whereas the RDRT variable is defined as the research and development expenditures/Revenue. If the costs (research and development expenditures) increases the EBITDA decreases. Model (3) also shows a very high Adjusted R^2. We believe the reason for this is the very high negative correlation between the RDRT and the ROS variable. *Table 17* is in accordance with the *Innovation* hypothesis. Namely, the syndicate VC-backed start-ups appear to have a higher RDAT and RDRT measure. This means that the syndicate VC-backed start-ups have a higher innovation level than the non-syndicated VC-backed start-ups.

Table 18 shows the OLS regression for the total dataset U.S. and Europe combined. The dependent variables are the CAR 1-year (1), the CAR 2-years (2) and the CAR 3-years (3). We find a positive significant coefficient for the U.S. dummy in model (3) with the CAR 3-year as dependent variable. Apparently, the long-term performance on the public market is higher in the U.S. than in Europe for VC-backed start-ups. *Table 18* also shows that the Age at IPO variable has a negative significant coefficient. Apparently, the age of the start-up has a negative effect on the 1-year performance of the start-up on the public market. Because the Syndication dummy is not significant we cannot provide any information if the differences on the long-term performance on the public market are due to syndication effects. This does not provide an answer for the *Geographic public market* hypothesis. But with the results of *Table 13* we know that syndicate VC-backed start-ups in the U.S. outperform the syndicate VC-backed start-ups in Europe. In combination with the results of *Table 18* we can say that the higher long-term performance in the U.S. for the 3-year CAR is mainly due to a higher 3-year Post ROA.

Table 18: Regression analysis with CAR

This table shows the results of a multivariate regression analysis. The sample consists of our combined U.S. and Europe dataset. The dependent variables are the 1-year CAR, 2-year CAR and the 3-year CAR with the CRSP Value weighted as the benchmark. The U.S. dummy is a dummy variable consisting of 1 if the start-up/VC is from the U.S. and 0 if the start-up/VC is from Europe. The Syndicate dummy is a dummy variable consisting of 1 if the start-up is syndicate and 0 if the start-up is non-syndicate. The Post-variables are the variables 1-year, 2-years and 3-years after the IPO. See Table 8 and 9 for a description of the other explanatory variables. The t-statistics, based on robust standard errors, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) CAR-1	(2) CAR-2	(3) CAR-3
U.S. dummy	-0.074	0.170	0.728**
	(-0.47)	(0.58)	(2.70)
Syndicate dummy	0.181	0.226	-0.135
	(0.88)	(0.59)	(-0.44)
Age at IPO	-0.003***	-0.001	-0.0009
	(-2.66)	(-0.44)	(-0.45)
Investors	-0.029	-0.43	0.028
	(-1.09)	(-1.06)	(0.84)
Log of Deal Value	0.066	0.014	-0.020
	(1.10)	(0.12)	(-0.22)
Post-ROS	-0.010	0.013	-0.002*
	(-1.49)	(0.94)	(-1.81)
Post-ROA	0.042	0.092	0.949***
	(0.23)	(0.50)	(2.78)
VC Controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Constant	-1.856*	-0.202	2.38*
	(-1.75)	(-0.11)	(1.82)
N	206	175	139
Adjusted R^2	0.220	0.155	0.243

Table 19 shows the OLS regression for the total dataset U.S. and Europe combined. The table is given in Appendix C. The dependent variables are the BHAR 1-year (1), the BHAR 2-years (2) and the BHAR 3-years (3). We do not find any significant coefficients for the independent variables U.S. dummy and the Syndication dummy. There appears to be no relation between the BHAR and the fact that the start-up is syndicate or non-syndicate VC-backed. In model (1) the Age of the VC-backed start-up has a negative significant coefficient. This means that for every unit increase in the Age of the start-up it results in a unit decrease in the BHAR. The 3-year post ROA and the 3-year post ROS are both significant in model (3). Interesting is that the coefficients of the 3-year post ROS and the 3-year post ROA have a different direction. The coefficient of the 3-year post ROA is negative whereas the coefficient of the 3-year post ROS is positive. Furthermore, we find for the BHAR 1-year and the BHAR 2-year a positive significance for the year fixed effect dummy 1999. This means that if the IPO is done in 1999 it has a positive outcome for the long-term buy and hold abnormal return.

6. Conclusion

Earlier empirical literature has investigated the differences between VC-backed start-ups in the U.S. and in Europe. However, to our understanding, there is no earlier empirical research on the effect of syndication on VC-backed start-ups in the U.S. versus in Europe. In this paper we investigate whether the public market performance and the operating performance are higher in the U.S. than in Europe due to syndication effects. Like Tian (2012) and Brander et al. (2002), we find that syndicate VC-backed start-ups perform better on the public market in comparison with non-syndicate VC-backed start-ups. Similarly to Chahine et al. (2012), we also find that start-ups from the U.S. have a higher level of underpricing. In line with the *Value-added and Screening* hypothesis, we find that syndicate VC-backed start-ups experience a lower underpricing compared to non-syndicate VC-backed start-ups in our combined dataset (Europe and U.S.). The initial return of syndicate VC-backed start-ups is lower in comparison with non-syndicate VC-backed start-ups. This is in accordance with Tian (2012). This effect seems to be more present in the U.S. than in Europe based on our t-statistics and Wilcoxon rank-sum test. However, we also find, based on our initial return regression, that there is a greater underpricing effect in the U.S. than in Europe. This difference in underpricing is not due to higher syndication levels but there are other variables that play a prominent role. For the underpricing effect, we find evidence that the *Pre-ROA* variable has a positive significant effect on the initial return of the start-up. The underpricing *Geographic public market* hypothesis states that the underpricing effect is lower in the U.S. in comparison with Europe because there are more syndicate VC-backed start-ups in the U.S. Thus, for the underpricing effect we do not find evidence for the *Geographic public market* hypothesis. As, we do not find that the underpricing effect is lower in the U.S. in comparison with Europe. Furthermore, we control for VC reputation controls, IPO year fixed effect dummies and Industry fixed effects dummies. For the underpricing effect these control variables do not appear to have a significant influence on the initial return of the start-up on the first trading-day.

In accordance with the *Innovation* hypothesis, we find that syndicate VC-backed start-ups have a higher innovation level in comparison with non-syndicate VC-backed start-ups. We find for the innovation measures, *RDAT* and *RDRT*, evidence that syndicate VC-backed start-ups have a positive significant influence. Furthermore, we also find that VC-backed start-ups from the U.S. have a positive significant influence on the number of issued patents.

In accordance with the long-term *Value-added and Screening* hypothesis, we find that syndicate VC-backed start-ups perform better in the long-run than non-syndicate VC-backed start-ups for the Europe dataset, based on the results of the t-statistics and the Wilcoxon rank-sum test. However, we do not find evidence for the long-term *Value-added and Screening* hypothesis in our U.S. dataset. We find a higher long-term performance on the public market with the BHAR and the CAR method for non-syndicate VC-backed start-ups. However, as stated earlier, this is due to two start-ups in our non-syndicate VC-backed dataset in the U.S. These certain start-ups in our non-syndicate VC-backed U.S. dataset have a huge increase in the stock price (up to a 900% increase in one year) this results in a higher long-term performance on the public market for our non-syndicate VC-backed start-ups in the U.S. As, stated earlier we do not treat these as an outlier because it can be quite common for start-ups that they have a huge increase on the public market return. Based on the regressions we run with either the CAR and the BHAR as the dependent variable we do not find evidence for the long-term *Value-added and Screening* hypothesis nor for the long-term *Geographic public market* hypothesis. We find that in the case a VC-backed start-up is from the U.S. it has a positive influence on the 3-year cumulative abnormal return. We find that the 3-year post-IPO *ROA* is the main driver for the positive performance of VC-backed start-ups from the U.S. As, the syndicate dummy that we include in the CAR and BHAR regressions, is not significant we cannot provide any information if the better long-term public market performance in the U.S. is due to syndication effects. We do not find evidence for the *Geographic public market* hypothesis due to data availability. Although, we only have listed start-ups in our dataset it is common that the IPO was in late 2015 or late 2016 and therefore we cannot measure the long-term public performance.

To provide an answer if VC-backed start-ups in the U.S. perform better in comparison with VC-backed start-ups in Europe we investigate the long-term operating performance. We find in accordance with the *Geographic operating performance* hypothesis that VC-backed start-ups in the U.S. have a higher operating performance in comparison with VC-backed start-ups in Europe, due to syndication effects. We find evidence that syndicate VC-backed start-ups and VC-backed start-ups from the U.S. have a positive influence on the 2-year *ROS* (EBITDA/Revenue). We find a high significant positive coefficient for our syndication dummy. This means that the operating performance is higher for syndicate VC-backed start-ups in comparison with non-syndicate VC-backed start-ups. A syndicate VC-backed start-up has a better operating performance because the VCs can select a better start-up together and the combined VCs provide more value-added services. Furthermore, we also find a positive significant relation between our U.S. dummies and syndication dummies for our 3-year *ROA* variable (EBITDA/Assets). This means that the U.S. VC-backed start-ups have a higher operating performance in comparison with our Europe VC-backed start-ups due to syndication effects. For both regressions, *ROS* and *ROA*, we find a significant negative coefficient for the *Investors* variable. Apparently, more VCs providing funding for a start-up does not necessarily result in a better operating performance.

This paper provides an answer to the research question: *"To what extent is the difference in performance of VC-backed start-ups in Europe and the U.S. due to syndication effects?"* We do not find evidence that the long-term public performance of VC-backed start-ups in the U.S. is better in comparison with the long-term public performance of VC-backed start-ups in Europe, due to syndication effects. We believe that we do not find a positive relation between syndication and public performance due to data availability. Although, we only have listed start-ups in our dataset it is common that the IPO was in late 2015 or late 2016 and therefore we cannot measure the long-term public performance. Furthermore, we exclude all start-ups that have received investments from non-U.S. (for our U.S. dataset) and we exclude all start-ups that have received investments from non-Europe VCs (for our Europe dataset). This also leads to a smaller selective sample. However, we do find evidence that the operating performance of VC-backed start-ups in the U.S. is better in comparison with the operating performance of VC-backed start-ups in Europe, due to syndication effects. This paper is of added value in comparison with earlier empirical research because we show that syndicate VC-backed start-ups in the U.S. perform better than syndicate VC-backed start-ups in Europe, due to syndication effects. However, the better performance is not visible on the public market, underpricing or long-term, but it is visible for the operating measures of the VC-backed start-ups. The reason that syndicate VC-backed start-ups in the U.S. have a better performance than syndicate VC-backed start-ups in Europe is because syndication is more active in the U.S. and therefore VCs in the U.S. provide better connections and can better select a start-up.

One of the limitations of this paper is that we only use one measure for syndication. We do not use the measure that a syndicate VC-backed start-up is syndicate if there are two or more VCs funding in a certain funding round. The measure that we use for syndication is, that a start-up is syndicate if there are at least two VCs in all the funding rounds combined. We use this measure because we believe that a VC, of a previous funding round, will still have an impact on the next funding round. Because, the previous VC will likely have an effect on selecting the next VC and thus provides added-value for the start-up. Another possible limitation is that we use the CRSP benchmark for our European VC-backed start-ups. However, we include IPO year fixed effects that can be used to control for certain events in Europe. Data limitation is also one of the limitations for this paper. We do not have all the data for our variables. For the European and the U.S. dataset we do not have all the offer prices and we also do not have all the long-term performance measures. We also have the limitation that we compare a country with a continent namely U.S. with Europe. We do not investigate if there are any differences among the countries within Europe. Another limitation in this paper is that we do not use either the syndicate dummy or the U.S. dummy as a dependent variable in the regressions. Furthermore, we do not have regressions of the U.S. and Europe separately.

For further research it is interesting to investigate if there are differences between the two different syndicate measures among VC-backed start-ups. In this paper we only focus on one syndicate measure. Furthermore, for future research it also recommended to have more data availability among the variables. For further research, it can be interesting to investigate if certain countries in Europe perform better than the U.S.. Furthermore, it can also be interesting to investigate the effects of syndicate VC-backed start-ups in another continent, like Asia. For further research it is also recommended that the benchmark for the public long-term performance of VC-backed start-ups in Europe and in the U.S., is appropriate.

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Appendix

Appendix A

Table 19: Regression analysis with the total BHARVW dataset

This table shows the results of a multivariate regression analysis. The sample consists of our combined U.S. and Europe dataset. The dependent variable is the 1-year BHAR with the CRSP Value weighted as the benchmark. The U.S. dummy is a dummy variable consisting of 1 if the start-up/VC is from the U.S. and 0 if the start-up/VC is from Europe. The Syndicate dummy is a dummy variable consisting of 1 if the start-up is syndicate and 0 if the start-up is non-syndicate. The Log of Deal Value is the logarithm of the Deal Value. The Post-variables are the variables one year (1), two years (2) and three years (3) after the IPO. ROS is the EBITDA divided by the Revenue. ROA is the EBITDA divided by the Total Assets. RDRT is the Research and development expenditures divided by the Revenue. RDAT is the Research and development expenditures divided by the Total Assets. See Table 8 and 9 for a description of the other explanatory variables. In Appendix C the coefficients and the t-statistics of the Industry Fixed effects is given. The t-statistics, based on robust standard errors, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) BHAR-1	(2) BHAR-2	(3) BHAR-3
U.S. dummy	-0.120	0.010	0.270
	(-0.82)	(0.02)	(1.11)
Syndicate dummy	0.200	0.751	-0.286
	(1.02)	(1.22)	(-0.94)
Age at IPO	-0.003**	-.0001	-0.001
	(-2.82)	(-0.03)	(-0.50)
Investors	-0.025	-0.064	0.041
	(-1.20)	(-0.98)	(1.25)
Log of Deal Value	0.047	-0.239	-0.020
	(0.83)	(-1.28)	(-0.22)
Post-ROS	-.009	0.001	-0.002**
	(-1.48)	(0.67)	(-2.00)
Post-ROA	0.017	0.304	0.919***
	(0.10)	(1.03)	(2.69)
VC Controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Constant	-1.521	0.175	0.4
	(-1.54)	(0.06)	(0.30)
N	206	175	139
R^2	0.726	0.160	0.409

Appendix B

Table 19: 2-digit SIC Codes Sector description

This table provides the sector description with the matched 2-digit SIC Codes. SIC Codes are the "Standard Industrial Classification" codes

SIC Code	Industry description	SIC Code	Industry description
01	Agricultural Production - Crops	49	Electric, Gas and Sanitary Services
02	Agricultural Production - Livestock and Animal Specialties	50	Wholesale Trade - Durable Goods
07	Agricultural Services	51	Wholesale Trade - Nondurable Goods
08	Forestry	52	Building Materials, Hardware, Garden Supplies & Mobile Homes
09	Fishing, Hunting and Trapping	53	General Merchandise Stores
10	Metal Mining	54	Food Stores
12	Coal Mining	55	Automotive Dealers and Gasoline Service Stations
13	Oil and Gas Extraction	56	Apparel and Accessory Stores
14	Mining and Quarrying of Nonmetallic Minerals, Except Fuels	57	Home Furniture, Furnishings and Equipment Stores
15	Construction - General Contractors & Operative Builders	58	Eating and Drinking Places
16	Heamy Construction, Except Building Construction, Contractor	59	Miscellaneous Retail
17	Construction - Special Trade Contractors	60	Depository Institutions
20	Food and Kindred Products	61	Nondepository Credit Institutions
21	Tobacco Products	62	Security & Commodity Brokers, Dealers, Exchanges & Services
22	Textile Mill Products	63	Insurance Carriers
23	Apparel, Finished Products from Fabrics & Similar Materials	64	Insurance Agents, Brokers and Service
24	Lumber and Wood Products, Except Furniture	65	Real Estate
25	Furniture and Fixtures	67	Holding and Other Investment Offices
26	Paper and Allied Products	70	Hotels, Rooming Houses, Camps, and Other Lodging Places
27	Printing, Publishing and Allied Industries	72	Personal Services
28	Chemicals and Allied Products	73	Business Services
29	Petroleum Refining and Related Industries	75	Automotive Repair, Services and Parking
30	Rubber and Miscellaneous Plastic Products	76	Miscellaneous Repair Services
31	Leather and Leather Products	78	Motion Pictures
32	Stone, Clay, Glass, and Concrete Products	79	Amusement and Recreation Services
33	Primary Metal Industries	80	Health Services
34	Fabricated Metal Products	81	Legal Services
35	Industrial and Commercial Machinery and Computer Equipment	82	Educational Services
36	Electronic & Other Electrical Equipment & Components	83	Social Services
37	Transportation Equipment	84	Museums, Art Galleries and Botanical and Zoological Gardens
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	86	Membership Organizations
39	Miscellaneous Manufacturing Industries	87	Engineering, Accounting, Research, and Management Services
40	Railroad Transportation	88	Private Households
41	Local & Suburban Transit & Interurban Highway Transportation	89	Services, Not Elsewhere Classified
42	Motor Freight Transportation	91	Executive, Legislative & General Government, Except Finance
43	United States Postal Service	92	Justice, Public Order and Safety
44	Water Transportation	93	Public Finance, Taxation and Monetary Policy
45	Transportation by Air	94	Administration of Human Resource Programs
46	Pipelines, Except Natural Gas	95	Administration of Environmental Quality and Housing Programs
47	Transportation Services	96	Administration of Economic Programs
48	Communications	97	National Security and International Affairs