The Power of Syndicates: Evidence from Venture Capital Investments in the United States

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Abstract:

The way that Venture Capital is able to optimize its contribution towards the benefit of the venture has been debated for numerous years. Some authors show the competitive edge of the Corporate Venture Capital (CVC) with complementary assets while others suggest that Independent Venture Capital (IVC) offers other decisive attributes like strategy formulation and networking. Additionally, current literature also discusses the impact of creating a syndicate and of being within the same industry and location. Therefore, this dissertation studies the optimal setting a venture should have in regard to their investor in order to maximize its innovation output. Understanding what type of investor to have (CVC vs IVC) and the proximity to it in terms of industry and location, could play a paramount role. Based on the main sample of 1022 ventures between 1990 and 2019, there is strong evidence of an existing superiority of CVC compared to IVC. The syndicate can further boost the innovation output contribution when it is composed by more than twelve members. The regressions also show that having industry and geographical proximity augments the innovation output of the venture. To give additional support to the current findings, the sample was transformed into a Pre- and Post-IPO period. The results were similar to the ones before, except the geographic location that only is significant in a Post-IPO period. To solidify the conclusions, various regressions were done with different timeframes and different SIC restrictions. The findings were consistent with the original regressions.

Keywords: Innovation Output, Independent Venture Capital, Corporate Venture Capital, Syndicates, Public Ventures, R&D, Location Fit, Industry Fit

JEL Classification: G24, L21, O31

O Poder de Sindicatos: Evidência em Investimentos de Capital de Risco nos Estados Unidos

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Resumo:
Tem sido debatido durante vários anos qual o perfil ideal que os fundos de Capital de Risco têm de ter de forma a conseguirem maximizar a sua contribuição em termos de inovação para as startups. Certos autores mostram a vantagem competitiva do Capital de Risco Corporativo (CRC) com os ativos complementares, enquanto outros sugerem que o Capital de Risco Independente (CRI) oferece outros atributos decisivos, como formulação de estratégia e *networking*. Além disso, a literatura atual também discute o possível impacto da criação de um sindicato e de se encontrar dentro do mesmo setor e localização. Desta forma, esta dissertação estuda o cenário ideal que uma startup deve ter em relação ao seu investidor, a fim de maximizar o rendimento da sua inovação. Com base na amostra de 1022 startups entre 1990 e 2019, há fortes evidências de uma superioridade por parte da CRC em relação ao CRI em termos de inovação das startups. Adicionalmente, um sindicato, quando composto por mais de doze membros, aumenta ainda mais a contribuição para a inovação. As regressões também mostram que ter compatibilidade tecnológica e proximidade geográfica maximiza a produção de inovação do empreendimento. Para dar suporte adicional aos resultados, a amostra foi convertida em outras duas: Pré e Pós-IPO. Os resultados foram semelhantes aos anteriores, excepto a proximidade geográfica que só tem impacto relevante num período Pós-IPO. Estes resultados são robustos, o que significa que quando os períodos de tempo são alterados e/ou as restrições de SIC são diferentes, os resultados são idênticos.

Palavras-Chave: Rendimento da Inovação, Capital de Risco Independente (CRI), Capital de Risco Corporativo (CRC), Sindicatos, Empresas (Startups) Públicas, P&D, Proximidade Geográfica, Compatibilidade Tecnológica

Classificação JEL: G24, L21, O31

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Joakim Börrén Dias

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IV. List of Abbreviations

CVC – Corporate Venture Capital

EDGAR – Electronic Data Gathering, Analysis, and Retrieval system (SEC system)

IPO – Initial Public Offering

IVC – Independent Venture Capital

M&A – Mergers and Acquisitions

NVCA – National Venture Capital Association

R&D **–** Research and Development

RBV – Resource-Based View

ROA – Return on Assets

SEC – Securities and Exchange Commission

SIC **–** Standard Industry Classification

SVB – Silicon Valley Bank

US – United States of America

VC – Venture Capital

VCS – Venture Capital Syndicate

1. Introduction

A strive for invention and innovation (Maynard, 2019) drives the US economy more than ever, and these values are deeply embedded in many entrepreneurial companies (Lebret, 2015). Many entrepreneurial firms have the capability to be original and bring big disruptiveness to their industry.

Entrepreneurship is the seed for innovation and ambition in the current days and, once these innovative ideas start to move forward, opportunities arise. Research shows that start-ups account for 20% of the US gross job creation in terms of employment, while high-growth businesses account for 50% (Decker et al., 2014). Thanks to these outstanding characteristics, several entrepreneurial companies get the opportunity to take on the world's economy and reshape it with a whole new perspective.

For example, looking to the past couple of years, two companies have entirely transformed their industry: Uber & Airbnb (Appendix A). Uber has innovated in the way people travel and eat (Uber-eats). Due to its efficiency, Uber was able to snatch 70% US market share by December 2019 (Yeo, 2020). A similar path was followed by Airbnb that revolutionized the way people travel and live. It is estimated that in 2019 they accounted for roughly 20% of the entire US rental business (Molla, 2019). This simply shows that a fantastic innovative idea can upset outdated markets when supported financially and non-financially by the adequate Venture Capital (VC). A famous Nobel prize winner economist, Kenneth Arrow, once said in an interview to the Federal Reserve Bank of Minneapolis that:

> "Venture capital has done much more, I think, to improve efficiency than anything."
>
> Economist Kenneth Arrow

In the US, VC serves as a great mechanism that promotes development, risk-taking, networking, and rapid growth opportunities (Hartford, 2019; Startups, 2019). It has played many roles throughout the years, and it has helped develop several well-known companies such as Apple, Starbucks, and Tesla[1]. This has been a topic of interest by several researchers, and most of them agree that VC-backed companies offer more growth opportunities than those that are not (Colombo & Grilli, 2010; Puri & Zarutskie, 2011).

[1] Some other well-known ventures are WhatsApp, Facebook, Alibaba, Twitter, Zynga, Spotify, and Dropbox.

A typical depiction of Venture Capital is that it is a form of financing for innovative entrepreneurial firms. It is a sort of private equity that takes minority equity stakes and offers other non-financial support in order to help start-ups grow and establish their mark on the market. VC can be split into two major groups: Corporate Venture Capital (CVC) and Independent Venture Capital (IVC). The CVC is originated from a corporation, meaning investing in start-ups is not their primary business. Some well-known companies like Google, create branches (Google Ventures) to invest in innovative and strategically oriented ventures that meet their goals. IVC, on the other hand, is an independent entity with their core business being investing in start-ups[2]. Their focus is investing in ventures that will solely yield a financial outcome in the future. When investing, both of these investors can join forces and create a syndicate. This Venture Capital Syndicate (VCS) usually offers higher resource pooling, however, the managing of an investment can be more challenging (Lockett & Wright, 2001).

Current literature argues on what type of VCs offer the most value for these companies in terms of achieving an innovative high output. Some say that Corporate Venture Capital (CVC) offers an increased worth to their venture (Chemmanur et al., 2014; Alvarez-Garrido & Dushnitsky, 2016), while others state that CVCs just do not offer additional benefit compared to Independent Venture Capital (IVC) (Bertoni et al., 2013). Additionally, there are times when VCs are motivated to create a syndicate to achieve better future deal flow or diversification (Manigart et al., 2006).

With the help of Venture Capitalists (VCs), these start-ups can upscale their work and achieve astonishing results. When a Venture Capital firm enters a business, it usually has the capability to transform it using its industry experience, knowledge, and other resources (Gompers & Lerner, 2000; Alvarez-Garrido & Dushnitsky, 2016). It is estimated that when a VC firm invests, the entrepreneurial firms will consider approximately 100 potential opportunities (Gompers et al., 2020). For example, the Silicon Valley Bank made research finding that, from 2009 until 2018, 42% of FDA-approved drugs within the United States had some type of Venture Capital fundraising (SVB, 2019) which demonstrates both the strength and opportunity VC firms offer alongside the capacity to achieve results.

[2] Sections 1.1 and 1.2 further details the characteristics of each form of VC.

The 2020 Yearbook of PitchBook and NVCA (PitchBook & NVCA, 2020) shows that the popularity in Venture Capital is growing every year, with the deal amount in 2019 of $135.8 billion compared to the $27.5 billion in 2009 (figure 1). In 2019, 10,430 VC-backed deals were made, with 44% of them having +$100 million investment. Data confirms that Software and Biotech & Pharma are the sectors that registered the highest investment in 2019 ($61.5 billion).

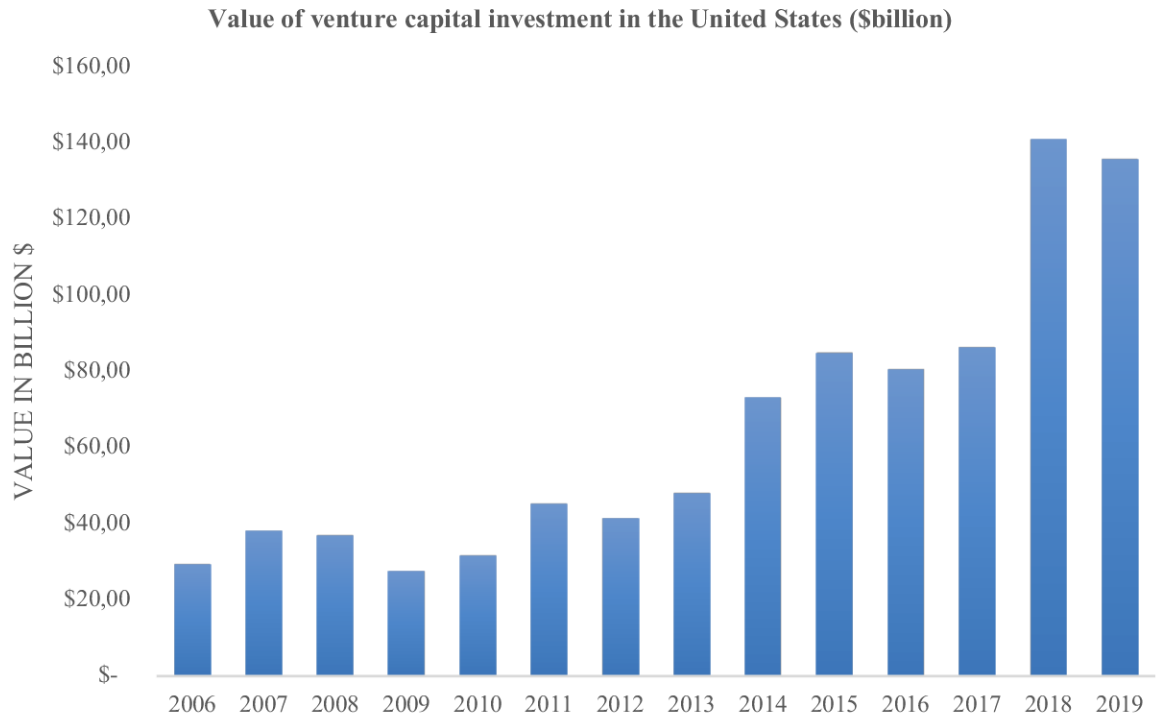

Figure 1: Deal amount between 2006-2019. Source: NVCA, CB Insights & PwC

These VCs have diverse options of exiting these investments[3] through an IPO, M&A or simply sell to another private equity buyer. In the case of the IPO's backed by VCs, they represented one-fifth of the market capitalization in 2015 and 44% of the R&D expense by US public companies (Gornall & Strebulaev, 2015), which is likely increasing. Some of the biggest and most famous IPO's in 2019 of venture-backed firms include Uber, Lyft, Zoom Video Communication, and Pinterest (PitchBook & NVCA, 2020)[4].

Having this in mind, the research aims to understand what the ideal investor setting is – Corporate VC, Independent VC, or VC Syndicate - that optimally nurtures innovation for

[3] Exit strategies are highly relevant to IVCs while CVCs sometimes consider keeping the investments for other purposes.
[4] Appendix A enumerates the top 10 IPOs made in 2019 within the US.

entrepreneurial companies while considering the geographical proximity to their ventures and their industry (sector) fit.
This research finds consistent support for the benefit of CVCs and syndicates. It also highlights the vastly positive impact that is created when investors and ventures operate within the same sector as well as location.

Finally, understanding the impact of VC on the innovation output of entrepreneurial companies is essential in the sense that it offers excellent insight for entrepreneurs and other institutions (e.g., Investment Banks) on how to proceed to achieve their highest potential. Entrepreneurial firms will have an idea of the most appropriate type of investor for them once they are able to understand what suits their technological and geographical needs best.
Taking a more in-depth look into both VC types, CVC and IVC, a more detailed understanding will be available below, including VCS.

1.1. Corporate Venture Capital (CVC) – Investor type

Corporate Venture Capital can be described as a structured subsidiary that aims to invest in entrepreneurial firms in an attempt to achieve both strategic benefits and financial returns (Gompers & Lerner, 2000). The funding is supplied by the parent corporations. The duration of the investments with the CVC does not usually have a predefined timeframe as some investments might be held for the long run (Guo et al., 2015).

The CVCs are associated with high innovation output and value creation (Dushnitsky & Lenox, 2006; Alvarez-Garrido & Dushnitsky, 2016), yet it achieves its utmost potential when it is within the appropriate temporal and sectorial factors (Dushnitsky & Lenox, 2006; Hill & Birkinshaw, 2014). There is evidence that suggests that this mechanism allows the corporations to be less reliant on R&D (Winters & Murfin, 1988), hence pursuing these types of venturing for financial reasons but also strategic ones. Additional studies suggest that strategic focused CVCs offer higher innovation outputs for entrepreneurial firms compared to the ones that are financially focused (Dushnitsky & Lenox, 2006).

In 2019, some of the most active CVCs globally were Google Ventures, Intel Capital, and Salesforce Ventures. As expected, these CVCs offer an extensive set of complementary assets and in-depth knowledge to their portfolio investments (Gompers & Lerner, 2000; Maula et al., 2005; Dushnitsky, 2012). The complementary assets can be diverse, but some have a unique

geographic proximity benefit (Alvarez-Garrido & Dushnitsky, 2016). This is especially true for the technological CVCs mentioned above but also to biotech/biopharma CVCs like Novartis Venture Fund, where they can offer both facilities and scientists to their ventures (Zucker et al., 1994).
Lastly, just like in R&D, innovation from entrepreneurial firms can come at substantial risk. Therefore, to promote an optimal environment, CVCs are usually much more tolerant to failure (Chemmanur et al., 2014; Tian & Wang, 2014).

These enormous relative advantages come at a cost, however. Managers are not as motivated as an IVC manager would be. CVC managers are softly incentivized as corporations usually have policies regarding pay uniformity (Block & A. Ornati, 1987; H. Chesbrough, 2000). These big corporations might also face more significant internal conflicts (Sykes, 1986; H. Chesbrough & L.Tucci, 2012) and information asymmetries (Gans & Stern, 2003).

1.2. Independent Venture Capital (IVC) – Investor type

Independent Venture Capital funds can usually be described as limited partnerships that raise funding from a third party to invest in entrepreneurial ventures to seek a purely financial return compared to the CVCs (Alvarez-Garrido & Dushnitsky, 2016). This type of investor usually makes investments aiming at a timeframe of around ten years (P. Gompers & Lerner, 1996), after which they exit the investment with the most common way being through an IPO, an acquisition, or a write-off (Guo et al., 2015). The objective is to dissolve the fund and capitalize on the gains. Besides the financial aspect, IVCs also add value with strategy formulation, personnel recruitment, and networking (Sapienza, 1992; Maula et al., 2005). Through its network, IVCs are usually more capable of obtaining additional alternative sources of financing as well as monitoring financial and operational performance (Gorman & A.Sahlman, 1989; Macmillan et al., 1988).

According to a BCG report (*How the Best Corporate Venturers Keep Getting Better*, 2020), IVC has always represented a more significant amount of the VC investment worldwide by representing 74% in 2017 yet fading yearly compared to CVC (IVC representing 80% in 2012). However, this value is purely on a percentage basis as global VC investments reached $147 billion in 2017 (being $109 billion for IVC) against the $50 billion in 2012 (being $40 billion for IVC), figure 2. A reason for such efficiency and outperformance within IVC could be that managers also have a performance-based compensation (Block & A. Ornati, 1987), alongside the other benefits mentioned above.

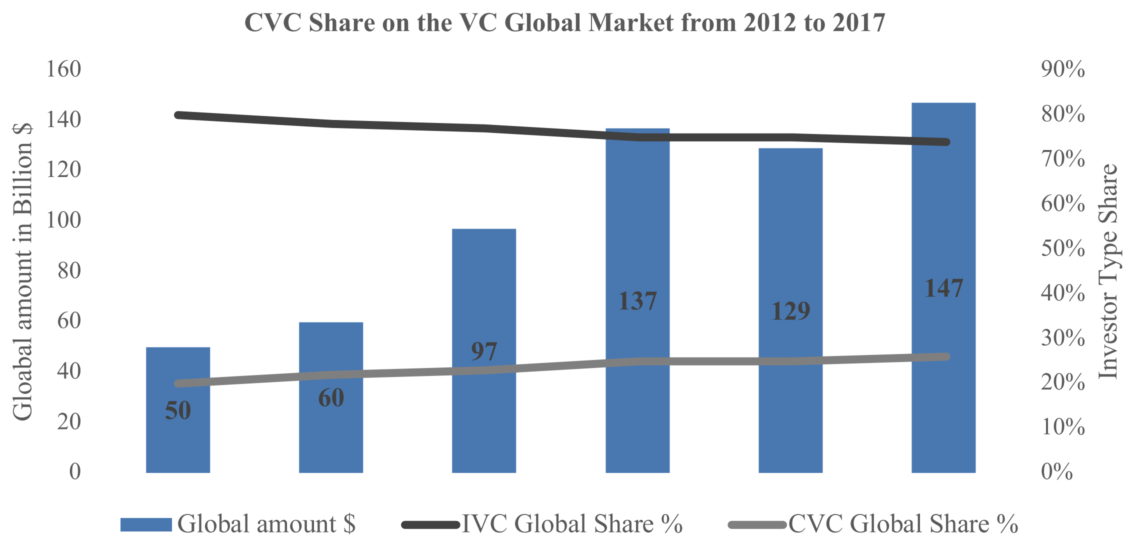

Figure 2: Global VC Market and Investor Type Share Source: BCG and Pitchbook

1.3. Venture Capital Syndicate (VCS) and comparison: CVC vs. IVC

It is clear that both types of investors' goals and objectives do not match entirely and that their added value to the entrepreneurial firms does neither (see appendix D). Therefore, this paper aims to understand how both CVCs and IVCs nurture and complement their ventures' innovativeness, which translates to value creation for the entrepreneurial firms (Chemmanur et al., 2014; Faria & Barbosa, 2014; Alvarez-Garrido & Dushnitsky, 2016).

Nevertheless, investors do not have to work by themselves with their skillset as a limitation. A business association between CVCs and IVCs can be created - Venture Capital Syndicate (VCS). This is a type of alliance (Wright & Lockett, 2003) where they will take a joint-equity stake in a venture and work together in an attempt to maximize their potential to try to create additional value/innovation for the venture as well as post-IPO operating performance (Tian, 2012). It allows the syndicate members to not only pool their resources (Ferrary, 2010) but also to diversify risk (De Clercq & Dimov, 2004).

According to Ferrary (2010), the motivations for creating a syndicate is two-fold. First, it is to diversify the risk during the seed stage, which is quite uncertain. Secondly, it is to create a heterogeneous community within that investment.
On the other side, however, the VCS may reveal some issues like the lack of dynamic stability or a dominant party within the decision making (Wright & Lockett, 2003). When the syndicate

is created, there is a lead investor that oversees the majority of the investment, with the rest of the investors being more passive (De Clercq & Dimov, 2004; Manigart et al., 2006). The lead investor is usually the investor that creates the original investment and invites others to join (Ferrary, 2010). Nevertheless, it is a potential issue to consider. With this paper, the path that nurtures most innovation and value creation will be apparent, whether in CVC, IVC, or VCS.

This thesis will be structured in the following manner. First, in section 2, there will be a literature review regarding past findings followed by the methodology in section 3, which explains the data collection and treatment process as well as the method used. Section 4 then expresses the results from this analysis which will, later on, be interpreted in the discussion, section 5. Lastly, there will be a conclusion of the research made and an insightful perspective on how to develop this idea further, section 6 and section 7.

2. Literature Review and Hypothesis

Nowadays, with the development of technology, the way people do business may have shifted from the early 2000s. In this research, the developed proposal states that the output of innovation for entrepreneurial firms is affected by the type of investor it uses and is sensitive to the geographical proximity and industry fit.

2.1. Impact of Investor Type on Ventures Outcome

Due to the heterogeneity of the type of investors, one can wonder how it will impact ventures with their different skill sets. This diversity is originated all from the complementary assets and know-how (Gompers & Lerner, 2000; Maula et al., 2005; Dushnitsky, 2012) to the managers' compensation (Block & A. Ornati, 1987; Gompers & Lerner, 2000) and strategy formulation (Sapienza, 1992; Maula et al., 2005; Luukkonen et al., 2013). Appendix B and C give an insight into the number of deals of the top investors, complementing the concept that experience from the investor gives not only reputation but also a unique skill set. Also essential to remember that whoever the entrepreneurial firms choose as their funding, it will affect the board of the firm itself as VC principals and representative take charge (Rosenstein et al., 1993).

For the past years, many studies have focused on this issue, and they have shown some outperformance from the CVC compared to the IVC (Maula, 2001; Chemmanur et al., 2014; Guo et al., 2015), raising a question of why they coexist and why the IVCs take up most of the

market. However, when controlling for selection, CVCs do not offer superior outcome (Bertoni et al., 2013). Bertoni (2010) argues that IVCs offer an increased growth compared to CVCs but only on a short-term post-investment period.
Therefore, considering the above literature, it is expected that, for the new time frame, CVC-backed ventures register higher innovation outputs.

> **Hypothesis 1a –** *The CVC-backed ventures display higher levels of innovation output compared to IVC-backed ventures*.

Usually, investors do not make the investments alone, so they create a syndicate to diversify risk (Manigart et al., 2006) and create a diverse community (De Clercq & Dimov, 2004; Ferrary, 2010). Moreover, the managerial concept of the resource-based view (RBV) is of paramount importance as well. The RBV (Lockett & Wright, 2001) shines another logical perspective into syndication, which benefits the alliances by understanding each member's strategic resources and pooling them together to achieve a competitive advantage.

There is usually a "lead" investor in a syndicate, which is the VC that invested first, likely in a seed stage. Once the leader is established, to achieve the benefits mentioned above, they look for partners to create the syndicate. As expected, syndicates offer more capital availability and increased future investment opportunities (Hochberg et al., 2007; Ferrary, 2010) due to the expansion of their networks. Some claim that the cooperation through syndicates and resource pooling of VCs can help find good investment targets and increase the value-added (Lockett & Wright, 2001; Brander et al., 2002).
Nonetheless, engaging in a syndicate, in the point of view of the lead investor, is not entirely straight-forward. Before considering creating a syndicate and its potential partners, VCs decision is dependent on their developed investment strategy and the intrinsic characteristics of the VC itself (De Clercq & Dimov, 2004).
Therefore, taking into consideration that syndications are supposed to boost the resources while reducing risk, it is hypothesized that, compared to IVCs, VCS-backed ventures experience higher innovation outputs.

> **Hypothesis 1b –***The VCS-backed ventures display higher levels of innovation output compared to IVC-backed ventures.*

2.2. Geographic Proximity

The existing distance between IVCs and CVCs from their ventures has been studied before. Most of the community agrees that this geographic proximity enables more interaction between the parties involved creating a more personal relationship, allowing a smoother due diligence process, operational assistance, and relationship nurturing (Sorenson & Stuart, 2001; Alvarez-Garrido & Dushnitsky, 2016). This geographic proximity has particular importance when it comes to the CVCs complementary assets. These complementary assets are any non-financial benefit a corporation can share with their investments. Using the example of Alvarez-Garrido & Dushnitsky (2016) while studying this effect on biotech ventures, both laboratories and scientists (Zucker et al., 1994) are complementary assets of paramount importance for these ventures. The need for R&D and other necessary facilities for the ventures are both expensive and scarce, giving a competitive advantage to the CVCs. The emphasis on the impact that complementary assets have on the output for innovation (Maula, 2001; Chemmanur et al., 2014) highlights the importance of proximity. Complementing the previous statement, the probability of a breakthrough for researchers is higher once the parties are neighboring each other (Catalini, 2018). The opposite is also true, however, where distant ventures access minimal resources, making the CVCs lose their main competitive advantage (Chemmanur et al., 2014).
Therefore, taking into consideration the potential boost of the CVCs, it is expected that geographic proximity will contribute to a higher innovation output for the CVCs.

> **Hypothesis 2a –** *The CVC-backed ventures display higher levels of innovation output compared to IVC-backed ventures, and it is sensitive to the geographic proximity between the VC and the venture.*

Still related to the hypothesis above, VCS is now taken into consideration. As mentioned in hypothesis 1b, a VCS consists of more than on VC and the involved VCs can be of both investor type – IVC or CVC. Therefore, following the related literature (Maula, 2001; Chemmanur et al., 2014), geographic proximity will still be analyzed. However, it is exclusive to the syndicate leader (Sorenson & Stuart, 2001; Ferrary, 2010). Meaning, while still measuring the syndicate's impact, the group leader will represent the geographic closeness to the venture. The leader within a syndicate is most likely the initial investor, which early on nurtures the relationships with the ventures. As the leader invites potential partners and establishes relationships with them, once the syndicate is closed, they get piquantly involved in the venture's management (Sapienza, 1992; Hellmann & Puri, 2002), attributing the location proximity to the leader.

Therefore, similarly to hypothesis 2a, it is expected that the geographic closeness will show an increased innovation output for VCS (leader).

> **Hypothesis 2b –** *The VCS-backed ventures display higher levels of innovation output compared to IVC-backed ventures, and it is sensitive to the geographic proximity between the VC and the venture*.

2.3. Industry Fit

The industry compatibility between the VCs and the ventures can impact the innovation output as they have specialized expertise (Gompers et al., 2009) like market knowledge and industry connections. Sometimes, parent corporations try to outsource their internal projects to increase the speed of innovation and competitive advantage (Fulghieri & Sevilir, 2009). Consequently, to accomplish this, they outsource through ventures with the same industry-specific goals. Compared with IVCs, they are sometimes focused on a specific industry to capture this beneficial innovation and compatibility.

There is opposing literature regarding who takes the most benefit from the industry fit. Due to the resources of the corporate parent, CVCs have access to a competitive advantage, which is industry-specific expertise (H. W. Chesbrough, 2002). In contrast, the efficient resource allocation, compensation schemes, and venturing experience with IVCs make them better at nurturing innovation (Gompers et al., 2009).

Therefore, despite opposing perspectives, it is expected that the CVC expertise will outperform the IVC in terms of innovation output for the ventures.

> **Hypothesis 3a –** *The CVC-backed ventures display higher levels of innovation output compared to IVC-backed ventures, and it is sensitive to the industry (sector) fit between the VC and the venture*.

The final hypothesis follows the rationale of hypothesis 2b in terms of syndicate leaders. As the syndicate leader is either an IVC or CVC, the proposition basis in hypothesis 3a still is applicable. Therefore, the aim is to see the impact industry-specific VCs can have on the innovation output. Moreover, as the syndicate is composed by a leader, that will be the benchmark point for this hypothesis.

Consequently, it is expected that the syndicate leader industry-specific expertise will be superior to the IVCs in terms of innovation output for the ventures.

Hypothesis 3b – *The VCS-backed ventures display higher levels of innovation output compared to IVC-backed ventures, and it is sensitive to the industry (sector) fit between the VC and the venture.*

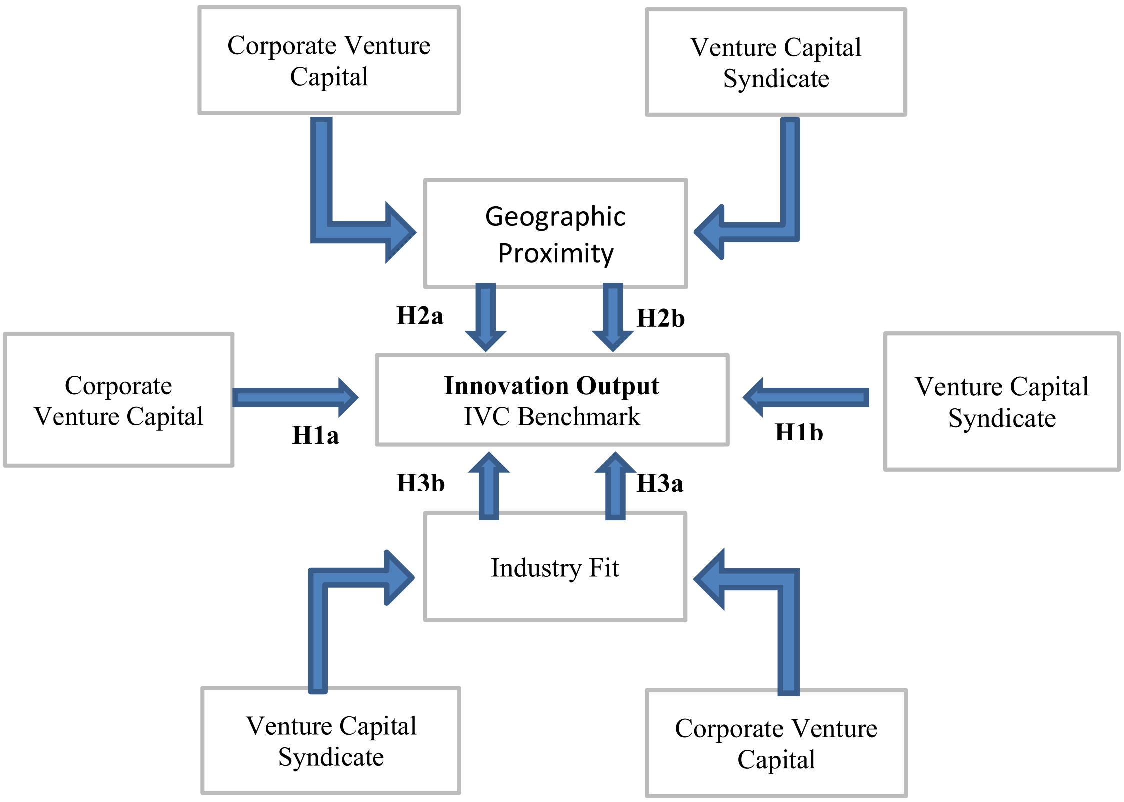

Figure 3: The following figure illustrates the different connections and viewpoints on the hypothesis.

3. Methodology

3.1. Data Collection and Treatment

The dataset collected features 1022 venture deals within the United States of America between 1990 and 2019. Appendix E details the location frequency of the ventures and investors within the USA. All the selected venture deals are of ventures that are public within the timeframe. From this entire dataset, 373 ventures have CVCs as their majority investor while 699 have IVCs. The first company to invest in a venture was a CVC for 18% of the time and, in the cases of syndicates, the 1st investor hardly ever maintained more than 10% (figure 4).

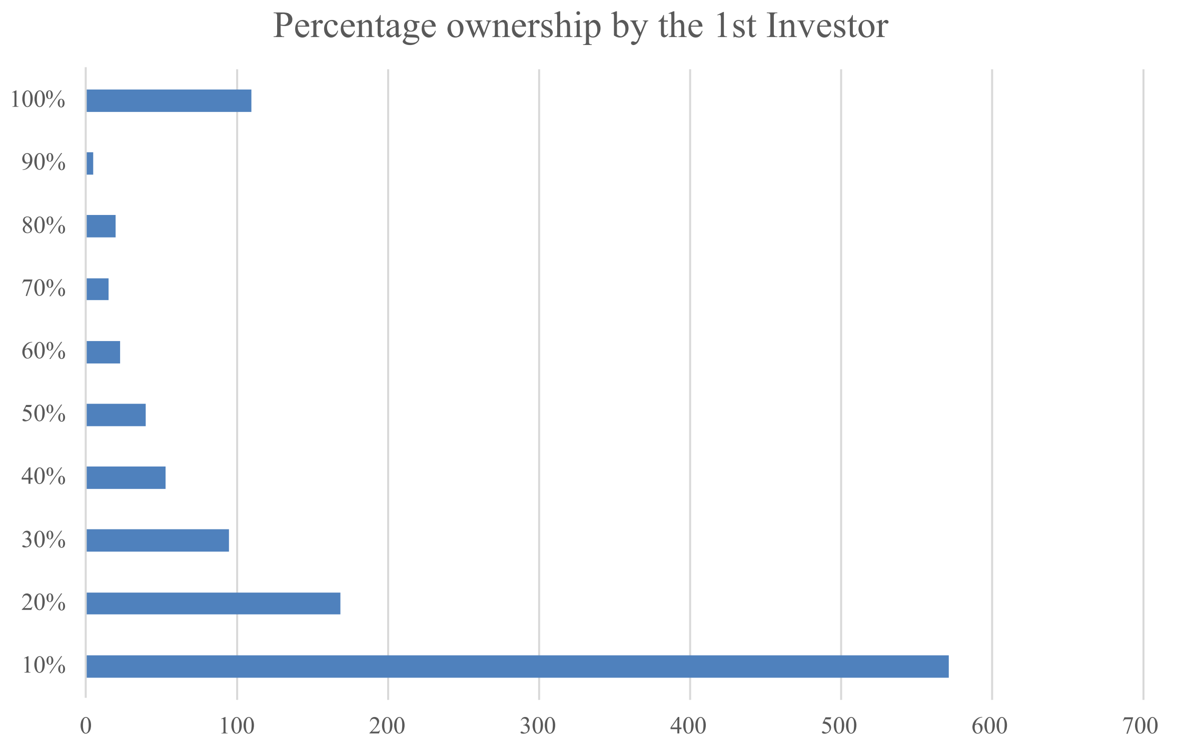

Figure 4: This figure represents the percentage of ownership the 1st investors end up with once the whole syndicate is formed. These values are related to the Last Value dataset. The ownership share could play an essential role in the decision-making process of the syndicates.

The collection of the raw data was done in four stages. The first stage consisted of extracting all the information available about the ventures through the Private Equity screener from Thomson Eikon. Whether public or not, all companies were extracted at this stage, reaching an amount of roughly 37,000 ventures within the timeframe. The only filters used was US-based ventures funded by CVC and IVC investors only. Due to data difficulties and inaccessibility to most private information, the 37,000 ventures were filtered. The filter consisted of only using ventures that had gone public sometime in their lifetime within the timeframe. The result left roughly 2,200 ventures.

The following stage was done on the same platform. However, the goal was to extract all the investments done during the 30-year timeframe regarding the ventures selected (very common to have several investments within the same venture). About 36,500 investments were made within this period on these 2,200 ventures. With this data, it was possible to identify the earliest investor in each venture as well as the amount of investment done, numbers deals and partners, and what was the majority VC present in the venture. Unfortunately, in an attempt to be conservative with the dataset and due to data unavailability, the dataset was reduced to 1434 ventures. The reduction was partially made by cross-matching venture information (street address, website, fax & phone number) between Eikon Screener and DataStream to get the corresponding Ticker code. This was a crucial step in order to have a dataset with ventures matching the DataStream ticker codes.

The third phase consisted of extracting all the financial data and venture SIC codes from the DataStream. Some of the financial variables consisted of the R&D and Assets, which were used as a dependent variable. As these values had to be present on all ventures, a further filter was applied in order to have the dependent variable present in all ventures, reducing the dataset from 1434 to 1103. Adding to this filter was the exclusion of companies that had either IPO dates outside the timeframe, were considered penny stocks[5] (Barnes, 2017) or had highly outlying values. The financials used as controls were extracted as a time-series within the timeframe.

Finally, as the last stage, the pillars of this thesis had to have accurate data. Meanwhile, the geographic location data for the investor and venture was a smooth process with the screener, that was not the case for the industry fit data, specifically the SIC codes. Similarly, to the geographic pillar, there were two sides to each deal: investor and venture. Beginning with the sic code for the venture, they were extracted quite swiftly from the DataStream database as all ventures were publicly traded, which means the data quality is higher and more obtainable.
However, in order to get the SIC code for the investor, which in many cases were private, it was a harsher process. To attain each investor SIC code, a two-phase process was employed. First, it was necessary to employ a web-scraping mechanism through some databases and SIC webpages to try to obtain the required codes. Secondly, as many firms did not have this code present, the Securities and Exchange Commission (SEC) was used to check the company fillings (e.g., 8-K, Acquisition Statements) through the EDGAR Company Fillings system. These official fillings usually have within them the SIC codes and operating industry. Lastly, would a firm's code not be found, it would be manually checked. When regressing with these codes, the CVC investors within the 6000-6799 (codes related to Finance, Insurance, and Real Estate) were excluded to avoid biased results. This reduced the observations from 1103 to final number 1022.

Once all the values for each deal done within this timeframe for the US were reached, three databases were created for analysis:

[5] This filter avoids microstructure issues since they are hard to trade. Some state that penny stocks are worth less than $1 while others less than $3 or $5. In this thesis, the middle ground was used of $3.

Last Value Database – Consists of all 1022 deals collected for the timeframe and utilizes the most current financial values available for each venture as well as the age of the venture when they went for IPO. This was used instead of the age of the venture since the values were not available.

Pre-IPO Database **–** Consists of 571 deals collected for the timeframe and utilizes the financials of the venture one year before it went for IPO. The venture's age one year before IPO was able to be used since IPO data was available. The database is derived from the Last Value database.

Post-IPO Database – Consists of 571 deals collected for the timeframe and utilizes the venture's financials one year after it went for IPO. The venture's age one year after IPO was able to be used since IPO data was available. The database is derived from the Last Value database.

The Pre and Post databases' size is not equal to the Last Value database due to the number of missing variables in the R&D variable extracted from DataStream one year before IPO (still private at this time, meaning sometimes it is not available the year before IPO). Additionally to this, it only uses ventures with IPO's between 1990 and 2018 in order to have the values one year after IPO. In the Pre-IPO case, the DataStream extracted values since 1988 to adapt to this situation to have values available by 1989.
Both investor (SIC and Location) and venture characteristics are taken into account alongside the financial metrics. Further, for the regression analysis, the OLS estimation method was used.

3.2. Dependent Variables

The baseline dependent variable used was the *R&D/ASSETS* that measures, in a financial way, the amount of innovation output a company is creating. This variable was based on an article by McKinsey, (2018)[6] mentioning R&D over Assets or Sales as a good proxy to measure innovation. In previous years, this metric was used however, the research community shifted to the use of patents. Unfortunately, the patent variable could not be used due to data limitations,

[6] This report mentions the procedures that McKinsey uses to measure innovation. They use as numerator either R&D Expense or New Product Sales. This value was limited therefore R&D was used.

therefore resourcing to the use of *R&D/ASSETS*. Both financial metrics were extracted on DataStream for the 1988-2019 period.

3.3. Independent Variables

With these variables, the aim is to understand its impact on the dependent variables based on the hypothesis. For the baseline regression, there were four different independent variables: *Type of Investor, Syndicate, Location Fit,* and *Industry Fit.*

Type of Investor: The variable *Type of Investor* is a dummy variable taking the value of one when the first investor in a venture is a CVC and zero otherwise (IVC). The objective with this variable is to analyze whether any extra impact is created depending on if it is a CVC or IVC. This information was gotten through the Private Equity screener while filtering for investments. The investment date and the investor were then used to determine who was the first investor and its type.

Syndicate dummy: Taking a more in-depth look into the Syndicate dummy, it consists of four different sub-variables: *VCS[2-4], VCS[5-7], VCS[8-11],* and *VCS[12+].* Each range of syndicates was based on each quartile of the *syndicate* in order to make an even distribution among all sub-variables. These variables are dummy, being one when the number of investors in the venture equals the range of the dummy, and zero otherwise. It is also relevant to keep in mind that when all the sub-dummies are zero, the venture only has a single investor. Similarly to the *Type of Investor*, this information was extracted from the Private Equity screener. These extracted values were sometimes inflated due to a double-counting error by the screener. Therefore, it was necessary to filter out all duplicate values from the list of investors to get the actual number. To be considered a duplicate value, it would require having the same fund investing the same amount at the same date. This would otherwise not add up in the total investment amount of the venture.

Location Fit: The purpose of the development of the *Location Fit* variable was to access the geographic aspect in order to understand if proximity fosters firms' innovation output. This variable is a dummy variable meaning it is one when the venture's geographic location matches the first investor's location and zero otherwise. Since some states are vast in the US, it was decided that this dummy would be developed using both parties' metropolitan locations. This way, the investor and the venture had to have their headquarters in the same city. This is most notable when looking to California, where several firms are based in San Jose or San Francisco. However, despite being in relative proximity, it would be considered as a different location. This information was extracted from the Private Equity screener filtering for investments (for investor's location) and company (for the venture's location).

Industry Fit: This variable was created to track the industry compatibility between the venture and the first investor. This variable was build based on the SIC codes of both parties. The SIC code is a 4-digit number that indicates the industry and business activity in which the company operates. The first two digits represent the major group the company works in while the first three digits represent the industry group, and the whole four digits combined represent their division. For the regressions used in this research, the three and the four digits SIC code would be considered. Because of insufficient relevant matches on the 4-digit code due to its specificity, the 3-digit SIC code was used instead as it took into account a broader number of firms and still translates that both parties work the same industry in the same manner.
The SIC codes for the ventures were taken from the DataStream. Simultaneously, for the investors, the information was extracted with web-scabbing mechanisms and the EDGAR system from the Securities and Exchange Commission (SEC).

3.4. Control Variables

Following the current literature on innovation and its impacts, the regressions have been controlled for financial metrics and other miscellaneous impacting variables.

Following the variables used by Chemmanur et al. (2014) and Dushnitsky & Lenox (2006), while considering its impact on the results, it was relevant to control the effects of these types of financial metrics. Therefore, in order to replicate this validity, some of the variables were considered in this research: *REVENUES/ASSETS, Ln(LEVERAGE), ROA, and CAPEX/ASSETS*. Purposely, all the variables are on a percentage basis, and the leverage variable had to be normalized. Additionally, the *GROSS MARGIN* variable was also considered, following McKinsey's report (McKinsey, 2018). All financial variables were extracted in the same way using DataStream time-series to extract the values for the 1988-2019 period.

Furthermore, as literature has shown, including Chemmanur et al. (2014) and Alvarez-Garrido & Dushnitsky, (2016), the venture's age also plays a significant role in their outcome and growth. This variable assumes three somewhat interchangeable and mutually exclusive forms:

Ln(Age of the Firm)$_{PRE}$, Ln(Age of the Firm)$_{POST}$, and Ln(Age at IPO)$_{LAST\ VALUE}$. The first couple forms represent the venture's age one-year before IPO and one-year after IPO, respectively. By having the founding and IPO date available, this was straight forward to compute. This approach was not possible for the Last Value Database due to a lack of data on the year certain ventures either got acquired or diluted, hence not computing the venture's age when their last value was available. Therefore, in order to employ an unbiased approach towards all ventures in the Last Value regressions, the variable consists instead of the age of the venture in the year they went for IPO. All the dates were extracted from the Private Equity screener while filtering for company.

Lastly, as a control variable, there is the *Average Equity Per Firm in Total (USD).* Knowing that the amount of investment ventures get is correlated with the amount of money they can spend on R&D (Gompers et al., 2020), it would be of paramount importance controlling for it. Despite having more investment in R&D, it does not mean it is more efficiently employed compared to ventures with lower access. Companies with higher restraints on capital will be more meticulous about how their money is used in order to maximize their output. Similarly to the variable above, this information was also extracted from the Private Equity screener filtering for company.

4. Empirical Results

This research aims to compare how the ventures' innovation output is impacted depending on their type of investor and their industry and location compatibility. It starts by analyzing the summary statistics of the dataset, section 4.1, then the baseline database results of the Last Value database, section 4.2, moving towards the comparison between the Pre-IPO and Post-IPO performance, section 4.3 and 4.4 respectively.

4.1 Summary Statistics

Table 1 below describes the summary statistics of the Last Value database. This is the baseline database, which incorporates all the values that are within the Pre- and Post-IPO databases.

On panel A, 323 (31,6%) ventures had CVC as their majority investor, however, only 116 (11,4%) ventures had CVCs as their first investor. From the 1022 ventures, only 43 of them had a match of at least three-digit SIC codes with their investor, meaning they operate in the same

Table 1 **Summary Statistics - Last Value Database**

Panel A: Last Value - Venture Innovation Output based on the last value reported

	Mean	**SD**	**P25**	**Median**	**P75**	**N**
1. R&D/ASSETS	0,20	0,01	0,06	0,14	0,28	1022
2.Revenues/Assets	0,74	0,02	0,34	0,65	1,00	1022
3. Gross Margin	0,37	0,04	0,31	0,55	0,74	1022
4. Leverage	0,27	0,03	0,00	0,05	0,37	1022
5. ROA	-0,23	0,01	-0,39	-0,11	0,03	1022
6. CAPEX/Assets	0,03	0,00	0,01	0,02	0,04	1022
7. Avg Equity Per Firm ($M)	15,90	1,20	3,72	8,16	15,00	1022
8. Age at IPO	12,95	0,27	5,00	13,00	20,00	1022
9. Industry Fit[a]	-	-	-	-	-	43
10. Location Fit[a]	-	-	-	-	-	284
11. 1st Investor Type[a,b]						
CVC Firms	-	-	-	-	-	116
R&D/ASSETS	0,25	0,02	0,09	0,16	0,32	116
Age at IPO	12,47	0,80	4,25	13,00	20,00	116
Industry Fit	-	-	-	-	-	24
Location Fit	-	-	-	-	-	22
IVC Firms	-	-	-	-	-	906
R&D/ASSETS	0,19	0,25	0,06	0,14	0,27	906
Age at IPO	13,01	8,55	5,00	13,00	20,00	906
Industry Fit	-	-	-	-	-	19
Location Fit	-	-	-	-	-	262
12. Majority Syndicate Investor						
CVC Firms	-	-	-	-	-	323
IVC Firms	-	-	-	-	-	699

Panel B: Correlation - Last Value Database

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
2	-0,06**									
3	-0,11***	0,05*								
4	0,04	0,09***	0,02							
5	-0,77***	0,09***	0,20**	-0,10***						
6	-0,14***	0,18***	0,00	0,02	0,04					
7	-0,08***	0,03	0,00	0,03	0,05	0,04				
8	-0,17***	0,21***	-0,01	0,02	0,20***	0,16**	-0,18***			
9	0,10***	-0,04	-0,03	-0,03	-0,04	-0,04	-0,03	0,03		
10	0,03	-0,08**	0,00	-0,03	0,01	0,02	-0,04	-0,04	0,01	
11	0,07**	0,01	0,00	-0,04	-0,03	0,03	-0,01	-0,02	0,29***	-0,07**
N	1022									

This table represents the descriptive statistics of the Last Value database (Panel A) and the variables' correlation matrix (Panel B). Panel A describes the entire dataset but also separated into CVC and IVC backed ventures. All these values are based on the most recent value reported by DataStream. In Panel B, the significance level for 1%, 5% and 10% are ***, **, and *. [a]Dummy variable, [b]while this variable, is split in Panel A, on Panel B the variable is a CVC due to the dummy.

industry group. Out of these 43 matching ventures, 24 (55,8%) were from ventures with the first investor as a CVC. This means that 20,7% of CVC-backed ventures had a matching three-digit SIC code while IVC-backed ventures only had it 2,1% of the time.
Regarding geographic proximity, 284 ventures were located in the same metropolitan area as their first investor. The IVC-backed ventures were registered at a frequency of 28,9%, while CVC-backed ventures at 18,9%, within their groups.

Regarding the dependent variable, R&D/ASSETS, which measures the innovation output, registers an average amount of 20%. This value is above the median of 14%, suggesting that this variable has some extreme values on the higher quartiles. Separating the results per investor type, it is notable that CVC-backed ventures present higher innovation outputs (25%), on average, compared to IVC-backed venture (19%), which goes on par with Chemmanur et al., 2014. Regarding the venture's age, once it goes to IPO, it is quite similar between IVC and CVC-backed ventures.

Taking into consideration the correlation matrix, it is clear that R&D/ASSETS has a significant negative relationship with most of the financial variables, but specially ROA (-77%). This is very understandable as companies use part of their capital to invest in R&D, reducing their profitability (Jen Huang & Ju Liu, 2005)[7]. It has a significant positive correlation with industry fit and the type of investor (CVC), suggesting it could impact the output innovation just like Alvarez-Garrido & Dushnitsky, (2016).
From the perspective of the first investor type (CVC), there is a significant positive correlation with the industry fit with 29%. Interestingly, when the investor type is a CVC, it shows a significant negative correlation with the geographical proximity (-7%), which is not usual among other authors like Alvarez-Garrido & Dushnitsky, (2016), but in accordance with Wang et al. (2019).

4.2 Baseline Findings: Last Value Database

Table 2 reports the ordinary least squares (OLS) regression results for the Last Value innovation output for CVC and IVC-backed ventures. This regression is, therefore, based on the most recent value each venture has available. In this regression, the dependent variable is the financial metric that measures innovation: R&D/ASSETS. Notice that the tables have been

[7] Jen, Huang & Ju, Liu (2005) also considers IT expenditure relationship to ROA.

Table 2 – Last Value D.V. R&D/ASSETS	Model 2.1	Model 2.2	Model 2.3	Model 2.4	Model 2.5	Model 2.6	Model 2.7	Model 2.8
1st Investor CVC		0.0387**	0.0330**	0.0408***	0.0274*	0.0350**	0.0214	0.0236
		(0.0151)	(0.0152)	(0.0151)	(0.0158)	(0.0152)	(0.0158)	(0.0159)
Syndicate								
VCS [2-4]			0.0018			0.0018	-0.0005	-0.0005
			(0.0237)			(0.0237)	(0.0237)	(0.0237)
VCS [5-7]			0.0217			0.0212	0.0209	0.0204
			(0.0233)			(0.0233)	(0.0233)	(0.0233)
VCS [8-11]			0.0417*			0.0413*	0.0401*	0.0397*
			(0.0234)			(0.0234)	(0.0234)	(0.0234)
VCS [12+]			0.0577**			0.0564**	0.0569**	0.0557**
			(0.0234)			(0.0233)	(0.0233)	(0.0233)
Location Fit				0.0210*		0.0189*		0.0180*
				(0.0107)		(0.0107)		(0.0107)
Industry Fit					0.0600**		0.0622**	0.0607**
					(0.0250)		(0.0248)	(0.0248)
Revenues/Assets	0.0122	0.0119	0.0150*	0.0131	0.0126	0.0160*	0.0157*	0.0166**
	(0.0085)	(0.0085)	(0.0085)	(0.0085)	(0.0085)	(0.0085)	(0.0084)	(0.0085)
Gross Margin	0.0092**	0.0092**	0.0095**	0.0092**	0.0093**	0.0095**	0.0097**	0.0097***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)
LN(Leverage)	0.0038	0.0038	0.0038	0.0038	0.0039	0.0038	0.0039	0.0039
	(0.0026)	(0.0026)	(0.0025)	(0.0026)	(0.0026)	(0.0025)	(0.0025)	(0.0025)
ROA	-0.4001***	-0.3995***	-0.3948***	-0.4000***	-0.3986***	-0.3953***	-0.3938***	-0.3943***
	(0.0105)	(0.0105)	(0.0105)	(0.0105)	(0.0105)	(0.0105)	(0.0104)	(0.0104)
CAPEX/Assets	-0.6072***	-0.6178***	-0.6023***	-0.6277***	-0.6041***	-0.6114***	-0.5878***	-0.5968***
	(0.1109)	(0.1107)	(0.1100)	(0.1106)	(0.1105)	(0.1100)	(0.1099)	(0.1099)
LN(Age at IPO)	-0.0027	-0.0021	0.0024	-0.0017	-0.0027	0.0027	0.0018	0.0022
	(0.0051)	(0.0051)	(0.0052)	(0.0051)	(0.0051)	(0.0052)	(0.0051)	(0.0051)
Avg Equity Per Firm in Total (Million USD)	-0.0003**	-0.0003**	-0.0002*	-0.0003**	-0.0003**	-0.0002	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Cons	0.1325***	0.1274***	0.0831***	0.1194***	0.1267***	0.0767***	0.0835***	0.0774***
	(0.0143)	(0.0144)	(0.0266)	(0.0149)	(0.0144)	(0.0268)	(0.0265)	(0.0268)
N	1022	1022	1022	1022	1022	1022	1022	1022
R2	0.62	0.62	0.63	0.62	0.62	0.63	0.63	0.63

This table presents the results of the Last Value innovation output database OLS regression. All these values are in regard to a 30-year timeframe of companies that have gone public. The dependent variable is a financial metric for innovation. The main focus variables are the Investor Type dummy, all the Syndicate dummies, Location Fit dummy, and Industry Fit dummy. As financial controls, there is Revenues/Assets, Gross Margin, logarithm of leverage, Return on Assets (ROA), and CapEx/Assets. As deal size control, the Average Equity Per Firm in Total variable. As age, the natural logarithm of the age of the venture at IPO. Lastly, N represents the sample size. For more detail on each variable, check appendix F. The values in parentheses represent the standard deviation. For *, ** and *** represent a significance level of 10%, 5% and 1% respectively.

constructed to isolate each effect of the variables to give a more comprehensive understanding and conclusions on the hypothesis developed.

Throughout the regressions, the control variables are the same to isolate the impact that certain variables create on the innovation output studied by other authors. That can be seen in model 2.1, which focuses solely on controls.
Once the first independent variable is introduced in model 2.2, Investor Type, the coefficient is positive and significant, supporting the research from Chemmanur et al., 2014 and Alvarez-Garrido & Dushnitsky, 2016 that CVCs promotes innovation more effectively than IVCs. This is the case of most models, except models 2.7 and 2.8, where, despite being positive, it is not significant.

Model 2.3 introduces the syndicate concept. This variable was divided into their respective quartiles to determine the effect better. The regression suggests that large VCSs stimulate innovation at higher rates than a single investor or even smaller VCSs.
Moving on to models 2.4 and 2.5, they address the Location Fit and Industry Fit, respectively. Both these variables in both these models are positive and significant, which goes accordingly with Alvarez-Garrido & Dushnitsky, (2016) and H. W. Chesbrough, (2002), respectively.

Following model 2.6 and 2.7 that combine both the syndicate with each individual industry and location variables, the coefficients still maintain positively significant. Comparing 2.6 to other models, both the location and the syndicate variable slightly lose influence on the innovation output. Meanwhile for 2.7, while the smaller syndicates also lose influence, that is not the case for the industry compatibility nor big syndicates.

Lastly, model 2.8 aggregates all the variables to access how and if these variables combined still create significant results. As mentioned above, the Investor Type dummy, despite being positive it is not significant. Nevertheless, all other variables that were significant in previous models remain positive and significant.

4.3 Findings: Pre-IPO Database

In this section, Table 3 reports the ordinary least squares (OLS) regression results for the Pre-IPO innovation output for CVC- and IVC-backed ventures. The reasoning is similar to the one in section 4.2 as well as in the next section.

Table 3 – Pre-IPO D.V. R&D/ASSETS	Model 3.1	Model 3.2	Model 3.3	Model 3.4	Model 3.5	Model 3.6	Model 3.7	Model 3.8
1st Investor CVC		0.1087***	0.1047***	0.1090***	0.0924***	0.1047***	0.0882**	0.0882**
		(0.0349)	(0.0350)	(0.0350)	(0.0357)	(0.0351)	(0.0358)	(0.0359)
Syndicate								
VCS [2-4]			0.0545			0.0545	0.0501	0.0501
			(0.0475)			(0.0475)	(0.0474)	(0.0474)
VCS [5-7]			0.0678			0.0678	0.0630	0.0630
			(0.0450)			(0.0450)	(0.0449)	(0.0449)
VCS [8-11]			0.0487			0.0487	0.0438	0.0439
			(0.0465)			(0.0466)	(0.0465)	(0.0465)
VCS [12+]			0.1074**			0.1074**	0.1056**	0.1057**
			(0.0446)			(0.0447)	(0.0445)	(0.0446)
Location Fit				0.0037		0.0001		-0.0004
				(0.0246)		(0.0246)		(0.0245)
Industry Fit					0.1316**		0.1341**	0.1341**
					(0.0644)		(0.0643)	(0.0644)
Revenues/Assets	0.0457***	0.0431***	0.0462***	0.0433***	0.0425***	0.0462***	0.0457***	0.0457***
	(0.0125)	(0.0124)	(0.0125)	(0.0125)	(0.0124)	(0.0125)	(0.0124)	(0.0125)
Gross Margin	0.0011	0.0008	0.0006	0.0008	0.0004	0.0006	0.0001	0.0001
	(0.0058)	(0.0057)	(0.0057)	(0.0058)	(0.0057)	(0.0057)	(0.0057)	(0.0057)
LN(Leverage)	0.0146**	0.0149**	0.0145**	0.0149**	0.0148**	0.0145**	0.0144**	0.0144**
	(0.0063)	(0.0063)	(0.0063)	(0.0063)	(0.0062)	(0.0063)	(0.0062)	(0.0063)
ROA	-0.1795***	-0.1693***	-0.1679***	-0.1691***	-0.1690***	-0.1679***	-0.1676***	-0.1676***
	(0.0186)	(0.0188)	(0.0187)	(0.0188)	(0.0187)	(0.0188)	(0.0187)	(0.0187)
CAPEX/Assets	0.2464	0.2488	0.2148	0.2474	0.2572	0.2147	0.2238	0.2239
	(0.1797)	(0.1783)	(0.1791)	(0.1787)	(0.1778)	(0.1794)	(0.1786)	(0.1790)
LN(Age of the Firm)	-0.0793***	-0.0800***	-0.0770***	-0.0798***	-0.0790***	-0.0770***	-0.0759***	-0.0759***
	(0.0132)	(0.0131)	(0.0134)	(0.0132)	(0.0131)	(0.0134)	(0.0133)	(0.0134)
Avg Equity Per Firm in Total (Million USD)	-0.0014***	-0.0014***	-0.0012***	-0.0014***	-0.0014***	-0.0012***	-0.0012***	-0.0012***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Cons	0.3282***	0.3214***	0.2448***	0.3198***	0.3170***	0.2448***	0.2433***	0.2434***
	(0.0341)	(0.0339)	(0.0511)	(0.0355)	(0.0339)	(0.0520)	(0.0510)	(0.0519)
N	571	571	571	571	571	571	571	571
R2	0.27	0.28	0.29	0.28	0.29	0.29	0.30	0.30

This table presents the results of the Pre-IPO innovation output database OLS regression. All these values are in regard to a 30-year timeframe of companies that have gone public. The dependent variable is a financial metric for innovation. The main focus variables are the Investor Type dummy, all the Syndicate dummies, Location Fit dummy and Industry Fit dummy. As financial controls, there is Revenues/Assets, Gross Margin, logarithm of leverage, Return on Assets (ROA), and CapEx/Assets. As deal size control, the Average Equity Per Firm in Total variable was used. As age, the logarithm of the age of the venture at IPO. Lastly, N represents the sample size. For more detail on each variable check appendix F. The values in parentheses represent the standard deviation. For *, ** and *** represent a significance level of 10%, 5% and 1% respectively.

This regression focuses on the values that the ventures displayed one-year before their IPO launch and also utilized R&D/ASSETS as its dependent variable. There could be some implicit bias by utilizing the one-year prior values as some of the ventures may be preparing for the IPO launch, making certain variables, such as financials, misleading. Unfortunately, this procedure had to be used due to limited data availability of the ventures financials before going public.

Throughout all the Table 3 models, the 1st Investor type dummy coefficient is positive and very much significant, meaning CVC impacts in a positive way the innovation yield. In this regression, the coefficients are relatively high when comparing with the other couple regressions.

When taking into consideration the syndicate, model 3.2, it appears that the size of the syndicate, VCS[12+], plays an important role being positive and significant. Once again, the regression suggests that higher syndicates bring considerable higher innovation output, previously suggest by other authors like Ferrary, (2010). This significance level maintains throughout model 3.6, 3.7 and 3.8.

On the regressions with the Location Fit as a variable, models 3.3, 3.6 and 3.8, the coefficient is never significant. This is not the case for the Industry Fit variable, however. That variable in models 3.4, 3.7 and 3.8, is positively significant, supporting H. W. Chesbrough, (2002) research.

4.4 Findings: Post-IPO Database

Table 4 features the ordinary least squares (OLS) regression results for the Post-IPO innovation output for CVC- and IVC-backed ventures. Using R&D/ASSETS as a dependent variable, this regression mirrors the one in section 4.3, although now aiming at the values that the ventures displayed one-year after to their IPO. This regression follows the same bias mentioned about the Pre-IPO values since companies, once public, they register some fluctuation and uncertainty. Chemmanur et al., (2014), when using this Pre vs. Post IPO method, uses a sum of the following four years to the IPO launch. Despite being a more comprehensive and less bias tactic, the one-year after approach had to be used to avoid high data loss.

In Table 4, the variable 1st investor is positive and significant throughout the board, keeping the notion that CVC is superior when promoting innovation previously mentioned.

Table 4 – Post-IPO D.V. R&D/ASSETS	Model 4.1	Model 4.2	Model 4.3	Model 4.4	Model 4.5	Model 4.6	Model 4.7	Model 4.8
1st Investor CVC		0.0683***	0.0634***	0.0712***	0.0499**	0.0664***	0.0450**	0.0480**
		(0.0210)	(0.0210)	(0.0209)	(0.0213)	(0.0210)	(0.0213)	(0.0213)
Syndicate								
VCS [2-4]			0.0261			0.0261	0.0210	0.0209
			(0.0288)			(0.0287)	(0.0285)	(0.0284)
VCS [5-7]			0.0219			0.0217	0.0168	0.0166
			(0.0274)			(0.0273)	(0.0271)	(0.0270)
VCS [8-11]			0.0539*			0.0514*	0.0486*	0.0461
			(0.0285)			(0.0284)	(0.0282)	(0.0281)
VCS [12+]			0.0550**			0.0519*	0.0534**	0.0503*
			(0.0273)			(0.0272)	(0.0269)	(0.0269)
Location Fit				0.0358**		0.0328**		0.0326**
				(0.0149)		(0.0149)		(0.0147)
Industry Fit					0.1485***		0.1496***	0.1493***
					(0.0389)		(0.0389)	(0.0388)
Revenues/Assets	0.0103	0.0106	0.0123	0.0131	0.0108	0.0144	0.0127	0.0148
	(0.0139)	(0.0138)	(0.0138)	(0.0137)	(0.0136)	(0.0138)	(0.0136)	(0.0136)
Gross Margin	0.0092***	0.0091***	0.0088***	0.0087***	0.0088***	0.0085***	0.0085***	0.0082***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0031)	(0.0032)	(0.0031)	(0.0031)
LN(Leverage)	0.0000	0.0001	0.0000	0.0004	0.0008	0.0003	0.0007	0.0010
	(0.0032)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
ROA	-0.3247***	-0.3211***	-0.3144***	-0.3182***	-0.3202***	-0.3124***	-0.3131***	-0.3111***
	(0.0247)	(0.0245)	(0.0247)	(0.0245)	(0.0243)	(0.0246)	(0.0244)	(0.0243)
CAPEX/Assets	-0.0385	-0.0307	-0.0486	-0.0272	-0.0311	-0.0442	-0.0487	-0.0444
	(0.0732)	(0.0726)	(0.0728)	(0.0723)	(0.0717)	(0.0726)	(0.0719)	(0.0717)
LN(Age of the Firm)	-0.0479***	-0.0478***	-0.0439***	-0.0462***	-0.0458***	-0.0427***	-0.0416***	-0.0405***
	(0.0104)	(0.0103)	(0.0104)	(0.0102)	(0.0102)	(0.0104)	(0.0103)	(0.0103)
Avg Equity Per Firm in Total (Million USD)	-0.0005*	-0.0005*	-0.0004	-0.0005*	-0.0005*	-0.0004	-0.0004	-0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Cons	0.2212***	0.2130***	0.1673***	0.1962***	0.2066***	0.1542***	0.1641***	0.1511***
	(0.0285)	(0.0284)	(0.0372)	(0.0291)	(0.0281)	(0.0375)	(0.0367)	(0.0371)
N	571	571	571	571	571	571	571	571
R2	0.31	0.33	0.33	0.33	0.34	0.34	0.35	0.36

This table presents the results of the Post-IPO innovation output database OLS regression. All these values are in regard to a 30-year timeframe of companies that have gone public. The dependent variable is a financial metric for innovation. The main focus variables are the Investor Type dummy, all the Syndicate dummies, Location Fit dummy and Industry Fit dummy. As financial controls, there is Revenues/Assets, Gross Margin, logarithm of leverage, Return on Assets (ROA), and CapEx/Assets. As deal size control, the Average Equity Per Firm in Total variable. As age, the logarithm of the age of the venture at IPO. Lastly, N represents the sample size. For more detail on each variable check appendix F. The values in parentheses represent the standard deviation. For *, ** and *** represent a significance level of 10%, 5% and 1% respectively.

When taking into account the performance of the syndicate in model 4.3, it conveys similar results as the Last Value regression, where the high quartiles display positive and significant results. This positive significance remains within models 4.6 and 4.7 as well.
Regarding the models 4.4 and 4.5, both reveal positive significant coefficients regarding Location and Industry Fit while maintaining positive significance coefficients towards the 1st investor.

When taking into account model 4.6, there are consistent positive results between the top syndicates and the metropolitan location. Similar observations can be found in model 4.7, where the results are positively significant for big syndicates and industry fit. In this model, the industry compatibility variable yields the best innovation outcome amongst all other models.

Finally, once all the variables are combined, the significance of each result in previous models maintain except for the syndicate quartile of VCS[8-11]. Interestingly, the strength of the syndicate weakens throughout model 4.8, where not only does VCS[8-11] lose its significance, but VCS[12+] becomes less significant at 10% confidence level (from 5%).

5. Discussion

The analysis of these ventures brings some insightful perspectives on the hypothesis. Consequently, in order to dissect the results, the discussion will first proceed individually by each regression. The findings will, therefore, be compared both with the previous literature and with the stipulated hypothesis.

Beginning with Table 2, model 2.2 results suggest that when the investor is a CVC, the innovation output will increase by 0,0387. This complements previous literature that mentioned the benefit of CVC compared to IVC (Maula, 2001; Chemmanur et al., 2014; Guo et al., 2015) and supports the hypothesis 1a (H1a). This furthers the findings of Sapienza, 1992 and P. A. Gompers & Lerner, 2000 regarding the positive benefits of complementary assets and strategy formulation.

Moving onwards to model 2.3, evidence is found that cooperation in these ventures is advantageous. According to the results shown, the syndicate creation fosters innovation more often than not. Possibly due to risk diversification and network expansion mentioned by De

Clercq & Dimov, (2004) and Manigart et al., (2006). Findings illustrate that syndicates with more than eight investors boost the innovation output by 0,0417, and when the syndicate is composed of a group superior to twelve members, this is augmented to 0,0577. The analysis of this model is consistent with hypothesis 1b (H1b). These results could even foresee a somewhat proportional relationship between the numbers of investor and their innovation output. It could give further support to the research developed by Lockett & Wright, (2001) regarding the resource-based theory (RBV) whereas the number of investor increase, the bigger their competitive edge and resource amount.

The main diversity pillars had some stimulating results. First, the geographic proximity between ventures and their investor is proven as beneficial relating to the stimulation of innovation. Model 2.4 indicates that when both parties are within the same metropolitan area, the ventures innovation output is increased by 0,0210. This backs the theory developed by Maula, (2001) and Alvarez-Garrido & Dushnitsky, (2016) regarding all the perks within complementary assets such as operational assistance and facilities, for example. Additionally, matching the findings by Catalini, (2018), regarding the positive impact of proximity, it is possible to conclude that these results support the hypothesis 2a (H2a).

Complementing with the technological pillar, model 2.5 demonstrates that when both the venture and the investor share the same industry sector, it enhances the innovation output by 0,0600. This industry-specific expertise, like market experience and connections, gives an additional edge for the CVCs (Gompers et al., 2009). Once again, this proves to be consistent with the postulated hypothesis 3a (H3a). Finally, it gives a somewhat interesting perspective that the ventures and investors should focus more on working within the same industry, rather the same location as the benefit is more significant (0,0600 vs. 0,0210).

Combining the syndicates with the location proximity, it presents evidence that when syndicates are created, the geographical location plays a paramount role in the innovation output of the venture. Despite contributing less to the innovation yield, model 2.6 shows that the geographic location provides an increase of 0,0189 (vs. $0{,}0210_{M2.4}$). This suggests that in terms of innovation productivity, single investors have a higher yield in innovation that syndicate groups. Regardless, this provides enough evidence to be consistent with hypothesis 2b (H2b).

On model 2.7, results are consistent with hypothesis 3b (H3b). Using both the syndicate and industry fit as independent variables, the findings give the highest innovation contribution values amongst the models in the industry fit (0,0622 vs. $0{,}0600_{M2.2}$ vs. $0{,}607_{M2.8}$) and big syndicates [12+]. However, this model does not have significance for the 1st investor variable. Despite this, model 2.7 indicates that the industry fit benefit is maximized when in a syndicate. Similarly to model 2.3, this gives further support for the RBV theory developed by Lockett & Wright (2001).

When aggregating all the variables together, all hypothesis stand except for hypothesis 1a (H1a) since the 1st investor variable is no longer significant. Interestingly, meanwhile, all coefficients in model 2.8 decrease compared to the models 2.2 to 2.5, that is not the case for the industry fit (0,0600 vs. 0,0607). This further contributes to the emphasizes of the importance of technological compatibility between parties.

Having understood the benefits from the Last Value regression, it would be interesting to take a more profound analysis into this dataset, therefore focusing on the derived Pre- and Post-IPO period datasets. To enhance the interpretation of the findings from the Pre- and Post-IPO dataset, they will be analyzed jointly for comparison purposes.
Just like mentioned by several authors (Block & A. Ornati, 1987; P. A. Gompers & Lerner, 2000; Luukkonen et al., 2013), CVCs offer practical value through knowledge, strategy formulation and complementary assets. Evidence from model 3.2 (Pre-IPO) and model 4.2 (Post-IPO) support this claim, proposing that when a CVC invests in a venture, its innovation output is set to increase 0,1087 and 0,0683, respectively.
Interestingly, in the period previous to the IPO, ventures benefit significantly more from having CVC as their 1st investor. This could possibly be justified by the idea that investors have a more impactful role in the beginning years before the IPO as well as the fact that in the years following the IPO, the investor has a less meaningful role and influence on the venture. This applies to all models when comparing the 1st Investor Type between Table 3 (Pre-IPO) and Table 4 (Post-IPO), as on average they benefit an additional 40,44% increase in innovation output in the year previous to the IPO. Regardless of this observation, these findings also support hypothesis 1a (H1a).

Proceeding to model 3.3 (Pre-IPO) and model 4.3 (Post-IPO) regarding the syndicates, the comments are slightly different. While both models show consistent results with hypothesis 1b

(H1b), Pre-IPO data only finds this right when the syndicate has 12 or more members (VCS[12+] – 0,1074). However, when looking at Post-IPO results, eight members or above is already enough to show strong support for the hypothesis (VCS[8-11] – 0,0539; VCS[12+] – 0,0550). While being consistent with the hypothesis and previous literature (Manigart et al., 2006; Ferrary, 2010), the same observation as before can be seen. In the Pre-IPO regression, the contribution to the innovation output of the venture in superior to the one in the Post-IPO (VCS[12+] – $0{,}1074_{pre}$ vs. $0{,}0550_{post}$), which would imply the same conclusion that syndicates have a more significant impact prior to IPOs. Nonetheless, this can be overstepped by the fact that in a Post-IPO period, not only does syndicates with more than twelve members offer positive output but so do syndicates with 8 to 11 members, hence making the overall benefit larger (VCS[8-11] – 0,0539).

The geographic proximity contrast between the Pre-IPO and the Post-IPO regressions have some peculiarities and cannot be adequately compared. Therefore, starting with the Pre-IPO database, the findings do not indicate that there is any added innovation output of having the venture and the 1st investor in the same metropolitan area. Therefore, it can be assumed that these results are not in par with authors like Maula, (2001) and Alvarez-Garrido & Dushnitsky, (2016), nor is it consistent with hypothesis 2a (H2a). This conclusion is derived from model 3.4 (Pre-IPO), where the Industry Fit coefficient, despite being positive, it is not significant (0,0037).
Opposing these findings is model 4.4 from the Post-IPO regression. In this case, there is a clear benefit from neighboring parties. Having an increase of 0,0358 would confirm previous literature as well as hypothesis 2a (H2a) in a similar way model 2.4 did.
In model 3.6 (Pre-IPO) and 4. 6. (Post-IPO), the exact same situation occurs. Model 3.6 (Pre-IPO) shows a non-significant location coefficient of 0,0001 but with a syndicate [12+] significant. Therefore, in a Pre-IPO situation, there is not enough evidence coherent with hypothesis 2b (H2b). However, relating to a Post-IPO period, the model 4.6 has both the syndicate (0,0519) and the location fit (0,0328) positively significant, which is steady with hypothesis 2b (H2b).
Comparing the situation in a Pre-IPO era against one in a Post-IPO, it could suggest that ventures have more use of their 1st investor's complementary assets (e.g. facilities) once they have had additional funding through the public market. Additionally, the investor might increase its access and priority towards a venture once it has reached major relevant milestones such as IPOs.

Model 3.5 (Pre-IPO) and 4.5 (Post-IPO) show the levels of industry compatibility between parties. Maintaining the findings from other authors (Gompers et al., 2009), these results are able to prove hypothesis 3a (H3a). From model 3.5 in a Pre-IPO period, there is good evidence that when both the venture and its 1st investor operate within the same industry sector, the innovation output is magnified by 0,1316. Improving on this, once the venture has launched for an IPO, the Industry Fit coefficient increases up to 0,1485, giving it even more influence on the innovation output for the ventures. Therefore, and while confirming this competitive edge through industry-specific expertise and market knowledge (Fulghieri & Sevilir, 2009), the evidence align with the formulated hypothesis 3a (H3a).
Similar findings can be seen with models 3.7 (Pre-IPO) and 4.7 (Post-IPO) where the significance of the results remain from both models above. Notably, comparing these two models with their peer regressions, the industry fit coefficients reach the highest value within all models. In the case of model 3.7 (Pre-IPO), the industry coefficient is of 0,1341 compared with 0,1316 and 0,1341 from models 3.5 (Pre-IPO) and 3.8 (Pre-IPO). In the case of model 4.7 (Post-IPO), the coefficient is of 0,1496 (vs. $0{,}1485_{M4.5}$ vs. $0{,}1493_{M4.9}$).
With these regressions, it is possible to conclude that, in order to maximize the innovation output, ideally the venture should have an investor syndicate in a Post-IPO period to maximize the contribution of the industry fit to their output.

Lastly, when aggregating the variables together, all hypothesis conclusions regarding both databases still hold true. When analyzing model 3.8 (Pre-IPO), it is notable that while the syndicate and 1st Investor variable are still positively significant, only the industry Fit variable increases in absolute terms (0,1316 vs. 0,1341). Similarly to model 4.8 (Post-IPO), the Industry Fit variable also increases in terms of innovation output compared to models from 4.2 to 4.5 (0,1485 vs. 0,1493). It is also relevant to mention that the syndicate quartile VCS[8-11] losses its significance when combined with the other variables, leaving only VCS[12+] variable significant (0,0503).

To give an additional robustness to these findings, further regressions have been developed by changing the timeframe and the SIC filter[8]. Also segmented in the three databases, most of the results are consistent. When using the smaller timeframe (1999-2010), the Last Value

[8] Appendix G to O show the tables. Appendix G, H, and I do not have the SIC filter applied. Appendix J, K, and L also have no SIC filter and focuses on 1999-2010. Appendix M, N, and O focuses 1999-2010.

regression losses some of it strengthen, however the Post-IPO regression gives stability to the previous results. Interestingly, in a Pre-IPO situation between 1999 and 2010, the syndicate only had to consist of 5 or more members to give significant results. Overall, and despite of not being very strong, the results show the results as somewhat rubust.

6. Conclusion

This paper aims at understanding how CVCs and IVCs impact the innovation output for the ventures while taking into consideration syndicates, geographic proximity and technological compatibility. There is evidence that CVC offers additional value compared to IVC. This can be augmented by created by syndicates (usually more than 12 members).

The impact that the geographic closeness between parties reveals as an excellent feature to have regarding boosting its innovation output. This benefit is evident in both types of investors.

A similar conclusion can be drawn from the technological fit, as results show strong evidence that parties with matching industry have high cooperation benefits.

Interestingly, when comparing a period prior to IPO with a post IPO launch, the geographic proximity only reaches relevant results once it is in a Post-IPO period. Notably, the effect of the industry fit on the innovation output is increased in a Post-IPO era.

This research gives further support on the critical role that geographic proximity and technological fit play on the innovation outcome of ventures. Additionally, this paper gives further support to the benefit of syndicate creation with evidence that the bigger the syndicate, the more relevant the innovation output is (RBV theory).

7. Limitations and Future Research

This research had to overcome some issues throughout the process. The first limitation was the inability to use patents. Nowadays, it is a must more likely measure of innovation. Several authors like Chemmanur et al., (2014) and Alvarez-Garrido & Dushnitsky, (2016) used this method. However, the second-best solution was the use of R&D.

Another issue was access to inconsistent and information lacking databases. The authors above used VentureXpert as their database. Despite the Private Equity screener using similar data, the later database is not entirely complete making some values biased. Also, VentureXpert has within its database the SIC codes, which would make the SIC collection method in this research risk-free of possible mismatch.

To make also the Pre and the Post-IPO database for robust, one can extend the cumulative timespan. Instead of solely using one-year, the approach of Chemmanur et al., (2014) can be used where Pre-IPO accounts for the cumulative three years before IPO and Post-IPO account for four years onwards. A selection effect could also play a significant role, therefore controlling for it like Bertoni et al. (2013), would also enhance the results.

Further research could take into account all the limitations to achieve more effective results. Additionally, it would add a different perspective to take into account the knowledge that the investor has prior to making a particular investment and to measure its reputation.

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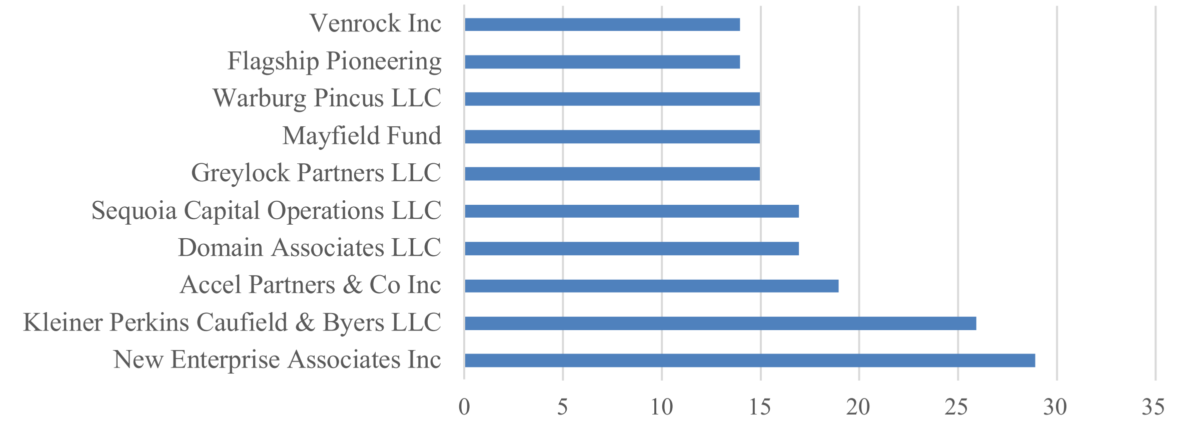
9. Appendix

Appendix A: Top 10 US VC-Backed IPOs in 2019

Venture	Exit Size ($M)
Uber	67 613,50 USD
Slack	25 250,00 USD
Lyft	21 660,00 USD
Zoom Video Communications	8 873,20 USD
Pinterest	8 632,50 USD
Datadog	7 177,50 USD
Peloton	6 942,30 USD
CrowdStrike	6 075,40 USD
Cloudflare	3 875,20 USD
10x Genomics	3 270,10 USD

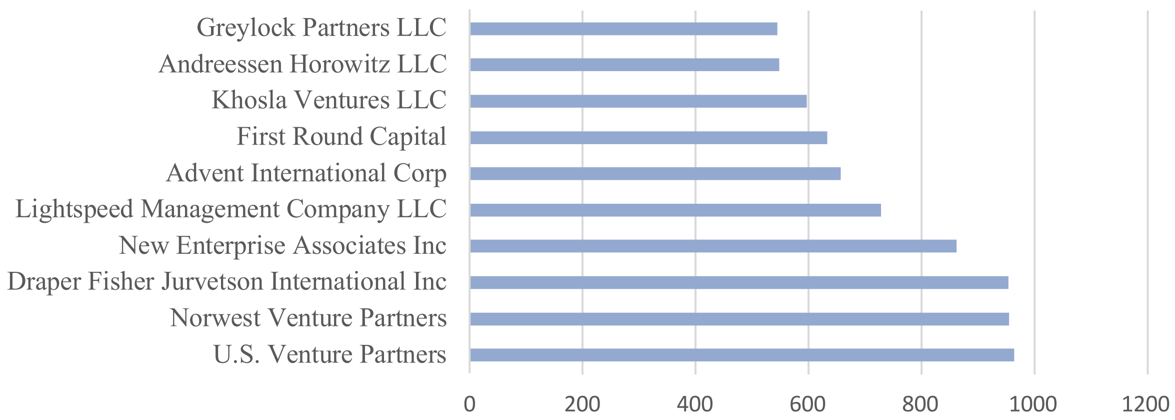
This table enumerates the top 10 IPOs made in 2019 within the US. Alongside to the venture is the exit amount of each company. Notably, Uber had slightly more than 2,5x the amount of the second-largest IPO exit. The source of this information is the 2020 Pitchbook & NVCA report.

Appendix B: Top 10 Most Common 1st Investors by 2019



This figure represents the frequency that investors were the first investor in the venture. Many of these investors are Independent Capital Ventures. These values are exclusively form the dataset. Also relevant that these firms engage in many more ventures either as non-1st investors or in ventures that have not gone public hence not in this dataset.

Appendix C: Top 10 Most Deals Made Ever by 1st Investors by 2019



This figure represents which investors have done the most deals. Many of these investors are Independent Capital Ventures. These values are related to the firms' entire existence, not exclusive to the timeframe. These deals include every type of deal in any type of venture, meaning it is not restricted to public firms only.

Appendix D:	**Comparison: IVC & CVC**	
Type	**Independent VC (IVC)**	**Corporate VC (CVC)**
Definition	This type of investor aims at acquiring equity portions of ventures.	This investor undertakes investments in ventures as a representative of a corporation.
Funding	Funds are raised by third-party investors, expressly limited partners.	The funds are given by the corporate parent.
Investor style	Exclusive financial experts, aiming at financial gains.	Usually, a corporation that creates a branch dedicated to this type of investments. There are financial experts, however, their objective is not totally financial.
Scope	Investments are the core business of this entity with the objective to capitalize on gains while supplying as much assistance as possible to increase its value.	The primary purpose is not as an investment firm instead develop suitable investments with foreseeable integration and strategy opportunities.
Structure	Consists of a Limited Liability Partnership (LLP).	Structured as a subsidiary where the corporate parent supplies capital, R&D, and the required assets to complement the proper function of the branch.
Managers	Performance-based compensation. Usually highly motivated to archive results.	Poorly motivated due to pay uniformity policies. Also, more susceptible to information asymmetries.
Assets & Resources	Well-structured investment team fully dedicated to managing the investors' money as well as possible.	The ventures get access to their complementary assets which include their R&D, facilities, networking, etc. Allows for both parties to create some synergies and cut costs.
Timeframe	Around ten years or earlier to exit.	Not specified. There is a possibility to integrate the venture if it strategically makes sense.
Main Benefits	Network, strategy formulation, and personnel recruitment.	Complementary assets like networking, facilities, know-how, experience, and R&D.
Risk tolerance	A very pragmatic approach towards assessing risk to mitigate is as much as possible.	Increased tolerance to failure.
Objective	Purely financial returns.	Both strategic and financial objectives.
Future/Exit	Exit by IPO, write-off or acquisition to capitalize on their gains.	If it aligns with their corporate parent, they could hold on to the investments, otherwise, they exit like an IVC.
	Venture Capital Syndicate (VCS)	
Definition	The VCS is a combination of more than one investor to undertake investments in ventures. It can be considered as an alliance where they unite their assets to maximize the results. Therefore, a syndicate could have all the features of an IVC and/or a CVC.	
Pros	Resource pooling, allows risk diversification and creates a heterogenous group of investors.	
Cons	Increase dynamic instability and possible risk that the dominant investor of the syndicate makes the majority of the decision making hence creating possible friction.	

This table summarizes the information regarding the IVC vs CVC and also VCS. This table highlights the main characteristics of each investor type. The table is based on Alvarez-Garrido & Dushnitsky, 2016 paper.

Appendix E: How do the Ventures and Investors Distribute throughout the US

These values are based on the Last Value database. As seen in all panels, the states of CA, NY and MA are the ones that have the highest incidence of ventures and investors. Within the 1st Investor group, it is clear that Independent VC (IVC) have much higher dispersion throughout the US compared with Corporate VC (CVC).

The state of California registers the highest amount of ventures by almost three times the second state, which is Massachusetts. In California, San Jose and San Francisco are the metropolitan areas that contribute the most. In Massachusetts, it is Boston. The third state with most ventures is New York state, more specifically the New York metropolitan area. From these ventures, 105 did not have a specified state.

The state of California registers the highest amount of investors by almost two times the second state, which is New York. In California, San Jose and San Francisco are the metropolitan areas that contribute the most. In New York, it is the New York metropolitan area. The third state with most ventures is in the US is Massachusetts, more specifically Boston. Out of this dataset, 69 investors are not based in the US, and 27 other investors do not have a specified location.

The state of California registers the highest amount of investors by almost one and a half times the second state, which is New York. In California, San Jose and San Francisco are the metropolitan areas that contribute the most. In New York, it is the New York metropolitan area. The third state with most ventures is Massachusetts, more specifically Boston. Out of this dataset, 28 investors are not based in the US, and five other investors do not have a specified location.

The state of California registers the highest amount of investors by almost two times the second state, which is New York. In California, San Jose and San Francisco are the metropolitan areas that contribute the most. In New York, it is the New York metropolitan area. The third state with most ventures is Massachusetts, more specifically Boston. Out of this dataset, 41 investors are not based in the US, and 22 other investors do not have a specified location. For the IVCs, there is a much higher state distribution than the CVCs mostly due to their higher existence and due to the fact that CVC has their Corporate Parent as the location headquarter.

Appendix F: Variable Description

Variable	Description	Sources	Type
R&D/ASSETS	R&D divided by Assets. It represents a financial metric that measures innovation.	Eikon DataStream (1988-2019)	Dependent
Type of Investor (Dummy)	The value is 1 when the 1stinvestorr is a CVC and 0 if it is IVC.	Private Equity screener (1988-2019)	Independent
Syndicate (Dummy)	This variable is divided by quartile ranges. It is 1 when the syndicate is within range, 0 otherwise.	Private Equity screener (1988-2019)	Independent
Location Fit (Dummy)	This variable is 1 when the 1stinvestorr and the venture have the same location, 0 otherwise.	Private Equity screener (1988-2019)	Independent
Industry Fit (Dummy)	This variable is 1 when the 1stinvestorr and the venture have the same SIC code, 0 otherwise.	Venture - Eikon DataStream. Investor - EDGAR system (SEC) and web-scraping.	Independent
REVENUES/ASSETS	Revenues divided by Assets. Represents the asset turnover of the ventures at a specific year.	Eikon DataStream (1988-2019)	Control
Ln(LEVERAGE)	The logarithm of Debt divided by Equity. It represents the ability of the ventures to meet their obligations.	Eikon DataStream (1988-2019)	Control
ROA	Net Income divided by Assets. Gives an idea of how well the assets are being managed.	Eikon DataStream (1988-2019)	Control
CAPEX/ASSETS	CapEx divided by Assets. It suggests how much capital was used as a part of assets.	Eikon DataStream (1988-2019)	Control
GROSS MARGIN	Net Revenues minus COGS divided by Revenues. It represents the profit per each dollar employed.	Eikon DataStream (1988-2019)	Control
Ln(Age at IPO)	The logarithm of the ventures' age at the IPO date.	Private Equity screener (1988-2019)	Control
Ln(Age of the Firm)	The logarithm of the ventures' age at a specific year.	Private Equity screener (1988-2019)	Control
Average Equity Per Firm in Total	Equity invested divided by the number of investors.	Private Equity screener (1988-2019)	Control

This table describes all the used variables as well as their source and their variable type. In the description, it explains how the variable is computed and if necessary, its purpose.

Appendix G **Last Value (no SIC filter) Regression D.V: R&D/Assets**

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
1st Investor CVC		0.0339**	0.0321**	0.0390***	0.0277**	0.0369***	0.0261*	0.0310**
		(0.0138)	(0.0139)	(0.0139)	(0.0141)	(0.0140)	(0.0142)	(0.0143)
Syndicate								
VCS [2-4]			0.0122			0.0120	0.0101	0.0100
			(0.0269)			(0.0269)	(0.0269)	(0.0268)
VCS [5-7]			0.0116			0.0106	0.0108	0.0099
			(0.0265)			(0.0265)	(0.0265)	(0.0264)
VCS [8-11]			0.0335			0.0329	0.0314	0.0310
			(0.0265)			(0.0265)	(0.0265)	(0.0264)
VCS [12+]			0.0540**			0.0519**	0.0529**	0.0509*
			(0.0265)			(0.0265)	(0.0265)	(0.0264)
Location Fit				0.0324***		0.0308**		0.0296**
				(0.0120)		(0.0120)		(0.0120)
Industry Fit					0.0597**		0.0592**	0.0560**
					(0.0277)		(0.0276)	(0.0276)
Cons	0.1395***	0.1308***	0.0928***	0.1192***	0.1306***	0.0831***	0.0940***	0.0847***
	(0.0154)	(0.0157)	(0.0299)	(0.0163)	(0.0157)	(0.0300)	(0.0298)	(0.0300)
Financial Controls	yes	yes	yes	yes	yes	yes	yes	yes
Size Control	yes	yes	yes	yes	yes	yes	yes	yes
Age Control	yes	yes	yes	yes	yes	yes	yes	yes
N	1103	1103	1103	1103	1103	1103	1103	1103
R2	0.57	0.58	0.58	0.58	0.58	0.58	0.58	0.59

This table presents the results of the Last Value innovation output database OLS regression. However, this sample does not have the SIC code filter that the table above have. These values are in regard to a 30-year timeframe of companies that have gone public. The dependent variable is a financial metric for innovation. The main variables are the Investor Type dummy, all the Syndicate dummies, Location Fit dummy and Industry Fit dummy. As financial controls, there is Revenues/Assets, Gross Margin, logarithm of leverage, Return on Assets (ROA), and CapEx/Assets. As deal size control, the Average Equity Per Firm in Total variable. As age, the logarithm of the age of the venture at IPO. Lastly, N is the sample size. For more details check appendix F. The values in parentheses is the standard deviation. The *, ** and *** equal a significance level of 10%, 5% and 1% respectively.

Appendix H **Pre-IPO (no SIC filter) Regression D.V: R&D/Assets**

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
1st Investor CVC		0.0761***	0.0761***	0.0771***	0.0662**	0.0766***	0.0663**	0.0665**
		(0.0284)	(0.0285)	(0.0287)	(0.0286)	(0.0288)	(0.0287)	(0.0290)
Syndicate								
VCS [2-4]			0.0317			0.0317	0.0275	0.0275
			(0.0461)			(0.0461)	(0.0459)	(0.0460)
VCS [5-7]			0.0389			0.0388	0.0336	0.0336
			(0.0437)			(0.0437)	(0.0436)	(0.0436)
VCS [8-11]			0.0159			0.0157	0.0100	0.0099
			(0.0451)			(0.0451)	(0.0450)	(0.0450)
VCS [12+]			0.0758*			0.0756*	0.0732*	0.0731*
			(0.0433)			(0.0434)	(0.0431)	(0.0432)
Location Fit				0.0058		0.0027		0.0012
				(0.0243)		(0.0244)		(0.0243)
Industry Fit					0.1458**		0.1488**	0.1487**
					(0.0634)		(0.0635)	(0.0635)
Cons	0.3233***	0.3106***	0.2633***	0.3082***	0.3069***	0.2624***	0.2634***	0.2630***
	(0.0327)	(0.0329)	(0.0495)	(0.0343)	(0.0328)	(0.0502)	(0.0493)	(0.0500)
Financial Controls	yes	yes	yes	yes	yes	yes	yes	yes
Size Control	yes	yes	yes	yes	yes	yes	yes	yes
Age Control	yes	yes	yes	yes	yes	yes	yes	yes
N	615	615	615	615	615	615	615	615
R2	0.27	0.28	0.29	0.28	0.29	0.29	0.29	0.29

This table presents the results of the Pre-IPO innovation output database OLS regression. However, this sample does not have the SIC code filter that the table above have. These values are in regard to a 30-year timeframe of companies that have gone public. The dependent variable is a financial metric for innovation. The main variables are the Investor Type dummy, all the Syndicate dummies, Location Fit dummy and Industry Fit dummy. As financial controls, there is Revenues/Assets, Gross Margin, logarithm of leverage, Return on Assets (ROA), and CapEx/Assets. As deal size control, the Average Equity Per Firm in Total variable. As age, the logarithm of the age of the venture at IPO. Lastly, N is the sample size. For more details check appendix F. The values in parentheses is the standard deviation. The *, ** and *** equal a significance level of 10%, 5% and 1% respectively.

Appendix I **Post-IPO (no SIC filter) Regression D.V: R&D/Assets**

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
1st Investor CVC		0.0522***	0.0500***	0.0574***	0.0419**	0.0549***	0.0400**	0.0447**
		(0.0181)	(0.0181)	(0.0182)	(0.0181)	(0.0183)	(0.0181)	(0.0183)
Syndicate								
VCS [2-4]			0.0312			0.0312	0.0266	0.0267
			(0.0295)			(0.0294)	(0.0292)	(0.0292)
VCS [5-7]			0.0176			0.0172	0.0123	0.0120
			(0.0280)			(0.0280)	(0.0278)	(0.0277)
VCS [8-11]			0.0485*			0.0461	0.0426	0.0404
			(0.0291)			(0.0290)	(0.0288)	(0.0288)
VCS [12+]			0.0557**			0.0527*	0.0532*	0.0504*
			(0.0279)			(0.0279)	(0.0276)	(0.0276)
Location Fit				0.0313**		0.0281*		0.0268*
				(0.0155)		(0.0156)		(0.0154)
Industry Fit					0.1517***		0.1520***	0.1504***
					(0.0406)		(0.0406)	(0.0405)
Cons	0.2386***	0.2272***	0.1840***	0.2136***	0.2214***	0.1740***	0.1821***	0.1726***
	(0.0288)	(0.0289)	(0.0378)	(0.0296)	(0.0286)	(0.0381)	(0.0374)	(0.0377)
Financial Controls	yes	yes	yes	yes	yes	yes	yes	yes
Size Control	yes	yes	yes	yes	yes	yes	yes	yes
Age Control	yes	yes	yes	yes	yes	yes	yes	yes
N	615	615	615	615	615	615	615	615
R2	0.32	0.33	0.34	0.33	0.34	0.34	0.35	0.35

This table presents the results of the Post-IPO innovation output database OLS regression. However, this sample does not have the SIC code filter that the table above have. These values are in regard to a 30-year timeframe of companies that have gone public. The dependent variable is a financial metric for innovation. The main variables are the Investor Type dummy, all the Syndicate dummies, Location Fit dummy and Industry Fit dummy. As financial controls, there is Revenues/Assets, Gross Margin, logarithm of leverage, Return on Assets (ROA), and CapEx/Assets. As deal size control, the Average Equity Per Firm in Total variable. As age, the logarithm of the age of the venture at IPO. Lastly, N is the sample size. For more details check appendix F. The values in parentheses is the standard deviation. The *, ** and *** equal a significance level of 10%, 5% and 1% respectively.

Appendix J **Last Value (no SIC filter – 1999 to 2010) Regression D.V: R&D/Assets**

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
1st Investor CVC		-0.0040	-0.0040	0.0038	-0.0047	0.0032	-0.0049	0.0024
		(0.0213)	(0.0212)	(0.0217)	(0.0214)	(0.0216)	(0.0214)	(0.0218)
Syndicate								
VCS [2-4]			0.0454			0.0488	0.0456	0.0489
			(0.0551)			(0.0550)	(0.0552)	(0.0551)
VCS [5-7]			0.0615			0.0658	0.0609	0.0653
			(0.0528)			(0.0527)	(0.0529)	(0.0528)
VCS [8-11]			0.0591			0.0632	0.0586	0.0628
			(0.0522)			(0.0521)	(0.0522)	(0.0522)
VCS [12+]			0.1057**			0.1077**	0.1057**	0.1077**
			(0.0524)			(0.0523)	(0.0525)	(0.0523)
Location Fit				0.0324*		0.0304*		0.0301*
				(0.0180)		(0.0179)		(0.0180)
Industry Fit					0.0131		0.0187	0.0147
					(0.0474)		(0.0473)	(0.0472)
Cons	0.1204***	0.1212***	0.0383	0.1078***	0.1208***	0.0225	0.0379	0.0224
	(0.0232)	(0.0237)	(0.0565)	(0.0248)	(0.0238)	(0.0571)	(0.0565)	(0.0572)
Financial Controls	yes	yes	yes	yes	yes	yes	yes	yes
Size Control	yes	yes	yes	yes	yes	yes	yes	yes
Age Control	yes	yes	yes	yes	yes	yes	yes	yes
N	413	413	413	413	413	413	413	413
R2	0.72	0.72	0.72	0.72	0.72	0.73	0.72	0.73

This table presents the results of the Last Value innovation output database OLS regression. However, this sample does not have the SIC code filter that the table above have. These values are related to a period from 1999-2010 timeframe of companies that have gone public. The dependent variable is a financial metric for innovation. The main variables are the Investor Type dummy, all the Syndicate dummies, Location Fit dummy and Industry Fit dummy. As financial controls, there is Revenues/Assets, Gross Margin, logarithm of leverage, Return on Assets (ROA), and CapEx/Assets. As deal size control, the Average Equity Per Firm in Total variable. As age, the logarithm of the age of the venture at IPO. Lastly, N is the sample size. For more details check appendix F. The values in parentheses is the standard deviation. The *, ** and *** equal a significance level of 10%, 5% and 1% respectively.

Appendix K **Pre-IPO (no SIC filter – 1999 to 2010) Regression D.V: R&D/Assets**

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
1st Investor CVC		0.0291	0.0263	0.0261	0.0168	0.0214	0.0147	0.0090
		(0.0474)	(0.0474)	(0.0484)	(0.0476)	(0.0485)	(0.0476)	(0.0487)
Syndicate								
VCS [2-4]			0.0409			0.0414	0.0401	0.0407
			(0.0828)			(0.0829)	(0.0824)	(0.0825)
VCS [5-7]			0.1083			0.1097	0.0974	0.0988
			(0.0767)			(0.0769)	(0.0766)	(0.0768)
VCS [8-11]			0.0914			0.0936	0.0785	0.0808
			(0.0762)			(0.0764)	(0.0761)	(0.0763)
VCS [12+]			0.1268*			0.1297*	0.1224	0.1257*
			(0.0750)			(0.0754)	(0.0748)	(0.0751)
Location Fit				-0.0118		-0.0191		-0.0219
				(0.0390)		(0.0392)		(0.0390)
Industry Fit					0.1795*		0.1724*	0.1744*
					(0.0921)		(0.0931)	(0.0933)
Cons	0.2872***	0.2823***	0.1747**	0.2878***	0.2773***	0.1814**	0.1777**	0.1854**
	(0.0565)	(0.0572)	(0.0870)	(0.0602)	(0.0569)	(0.0882)	(0.0866)	(0.0878)
Financial Controls	yes	yes	yes	yes	yes	yes	yes	yes
Size Control	yes	yes	yes	yes	yes	yes	yes	yes
Age Control	yes	yes	yes	yes	yes	yes	yes	yes
N	285	285	285	285	285	285	285	285
R2	0.30	0.30	0.31	0.30	0.31	0.31	0.32	0.32

This table presents the results of the Pre-IPO innovation output database OLS regression. However, this sample does not have the SIC code filter that the table above have. These values are related to a period from 1999-2010 timeframe of companies that have gone public. The dependent variable is a financial metric for innovation. The main variables are the Investor Type dummy, all the Syndicate dummies, Location Fit dummy and Industry Fit dummy. As financial controls, there is Revenues/Assets, Gross Margin, logarithm of leverage, Return on Assets (ROA), and CapEx/Assets. As deal size control, the Average Equity Per Firm in Total variable. As age, the logarithm of the age of the venture at IPO. Lastly, N is the sample size. For more details check appendix F. The values in parentheses is the standard deviation. The *, ** and *** equal a significance level of 10%, 5% and 1% respectively.

Appendix L **Post-IPO (no SIC filter – 1999 to 2010) Regression D.V: R&D/Assets**

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
1st Investor CVC		0.0680**	0.0660**	0.0792***	0.0471*	0.0765***	0.0455	0.0551*
		(0.0289)	(0.0289)	(0.0293)	(0.0279)	(0.0294)	(0.0279)	(0.0284)
Syndicate								
VCS [2-4]			0.0282			0.0276	0.0241	0.0236
			(0.0516)			(0.0514)	(0.0493)	(0.0492)
VCS [5-7]			0.0657			0.0626	0.0481	0.0456
			(0.0472)			(0.0470)	(0.0453)	(0.0451)
VCS [8-11]			0.0666			0.0623	0.0447	0.0412
			(0.0474)			(0.0472)	(0.0455)	(0.0454)
VCS [12+]			0.0778*			0.0712	0.0708	0.0650
			(0.0464)			(0.0464)	(0.0444)	(0.0444)
Location Fit				0.0474**		0.0434*		0.0386*
				(0.0239)		(0.0241)		(0.0231)
Industry Fit					0.2879***		0.2862***	0.2824***
					(0.0550)		(0.0556)	(0.0555)
Cons	0.1821***	0.1645***	0.0984	0.1412***	0.1390***	0.0819	0.0845	0.0700
	(0.0484)	(0.0486)	(0.0621)	(0.0497)	(0.0466)	(0.0626)	(0.0595)	(0.0599)
Financial Controls	yes	yes	yes	yes	yes	yes	yes	yes
Size Control	yes	yes	yes	yes	yes	yes	yes	yes
Age Control	yes	yes	yes	yes	yes	yes	yes	yes
N	285	285	285	285	285	285	285	285
R2	0.33	0.35	0.36	0.36	0.41	0.36	0.41	0.42

This table presents the results of the Post-IPO innovation output database OLS regression. However, this sample does not have the SIC code filter that the table above have. These values are related to a period from 1999-2010 timeframe of companies that have gone public. The dependent variable is a financial metric for innovation. The main variables are the Investor Type dummy, all the Syndicate dummies, Location Fit dummy and Industry Fit dummy. As financial controls, there is Revenues/Assets, Gross Margin, logarithm of leverage, Return on Assets (ROA), and CapEx/Assets. As deal size control, the Average Equity Per Firm in Total variable. As age, the logarithm of the age of the venture at IPO. Lastly, N is the sample size. For more details check appendix F. The values in parentheses is the standard deviation. The *, ** and *** equal a significance level of 10%, 5% and 1% respectively.

Appendix M **Last Value (1999 to 2010) Regression D.V: R&D/Assets**

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
1st Investor CVC		0.0099	0.0068	0.0144	0.0102	0.0112	0.0064	0.0113
		(0.0300)	(0.0301)	(0.0300)	(0.0308)	(0.0301)	(0.0310)	(0.0310)
Syndicate								
VCS [2-4]			0.0464			0.0498	0.0464	0.0498
			(0.0541)			(0.0540)	(0.0542)	(0.0541)
VCS [5-7]			0.0631			0.0673	0.0630	0.0673
			(0.0517)			(0.0516)	(0.0518)	(0.0517)
VCS [8-11]			0.0552			0.0593	0.0551	0.0593
			(0.0510)			(0.0510)	(0.0511)	(0.0510)
VCS [12+]			0.0957*			0.0978*	0.0957*	0.0978*
			(0.0512)			(0.0511)	(0.0513)	(0.0511)
Location Fit				0.0314*		0.0302*		0.0303*
				(0.0175)		(0.0175)		(0.0176)
Industry Fit					-0.0025		0.0025	-0.0006
					(0.0473)		(0.0475)	(0.0474)
Cons	0.1277***	0.1264***	0.0489	0.1135***	0.1265***	0.0334	0.0489	0.0334
	(0.0236)	(0.0239)	(0.0555)	(0.0249)	(0.0240)	(0.0561)	(0.0556)	(0.0562)
Financial Controls	yes	yes	yes	yes	yes	yes	yes	yes
Size Control	yes	yes	yes	yes	yes	yes	yes	yes
Age Control	yes	yes	yes	yes	yes	yes	yes	yes
N	373	373	373	373	373	373	373	373
R2	0.74	0.74	0.75	0.75	0.74	0.75	0.75	0.75

This table presents the results of the Last Value innovation output database OLS regression. These values are related to a period from 1999-2010 timeframe of companies that have gone public. The dependent variable is a financial metric for innovation. The main variables are the Investor Type dummy, all the Syndicate dummies, Location Fit dummy and Industry Fit dummy. As financial controls, there is Revenues/Assets, Gross Margin, logarithm of leverage, Return on Assets (ROA), and CapEx/Assets. As deal size control, the Average Equity Per Firm in Total variable. As age, the logarithm of the age of the venture at IPO. Lastly, N is the sample size. For more details check appendix F. The values in parentheses is the standard deviation. The *, ** and *** equal a significance level of 10%, 5% and 1% respectively.

Appendix N **Pre-IPO (1999 to 2010) Regression D.V: R&D/Assets**

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
1st Investor CVC		0.1702***	0.1529**	0.1667**	0.1494**	0.1473**	0.1337**	0.1276*
		(0.0647)	(0.0647)	(0.0650)	(0.0665)	(0.0650)	(0.0665)	(0.0669)
Syndicate								
VCS [2-4]			0.0577			0.0582	0.0575	0.0580
			(0.0829)			(0.0830)	(0.0829)	(0.0829)
VCS [5-7]			0.1666**			0.1676**	0.1596**	0.1605**
			(0.0777)			(0.0777)	(0.0779)	(0.0779)
VCS [8-11]			0.1400*			0.1436*	0.1314*	0.1350*
			(0.0781)			(0.0783)	(0.0784)	(0.0785)
VCS [12+]			0.1797**			0.1848**	0.1786**	0.1838**
			(0.0757)			(0.0759)	(0.0756)	(0.0759)
Location Fit				-0.0251		-0.0342		-0.0351
				(0.0382)		(0.0381)		(0.0381)
Industry Fit					0.1316		0.1200	0.1219
					(0.0988)		(0.0993)	(0.0993)
Cons	0.3283***	0.3152***	0.1590*	0.3262***	0.3112***	0.1702*	0.1595*	0.1711*
	(0.0588)	(0.0584)	(0.0881)	(0.0608)	(0.0584)	(0.0891)	(0.0881)	(0.0890)
Financial Controls	yes	yes	yes	yes	yes	yes	yes	yes
Size Control	yes	yes	yes	yes	yes	yes	yes	yes
Age Control	yes	yes	yes	yes	yes	yes	yes	yes
N	296	296	296	296	296	296	296	296
R2	0.22	0.24	0.26	0.24	0.25	0.27	0.27	0.27

This table presents the results of the Pre-IPO innovation output database OLS regression. These values are related to a period from 1999-2010 timeframe of companies that have gone public. The dependent variable is a financial metric for innovation. The main variables are the Investor Type dummy, all the Syndicate dummies, Location Fit dummy and Industry Fit dummy. As financial controls, there is Revenues/Assets, Gross Margin, logarithm of leverage, Return on Assets (ROA), and CapEx/Assets. As deal size control, the Average Equity Per Firm in Total variable. As age, the logarithm of the age of the venture at IPO. Lastly, N is the sample size. For more details check appendix F. The values in parentheses is the standard deviation. The *, ** and *** equal a significance level of 10%, 5% and 1% respectively.

Appendix O **Post-IPO (1999 to 2010) Regression D.V: R&D/Assets**

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
1st Investor CVC		0.1524***	0.1467***	0.1564***	0.1111***	0.1509***	0.1047***	0.1089***
		(0.0368)	(0.0371)	(0.0369)	(0.0368)	(0.0372)	(0.0371)	(0.0372)
Syndicate								
VCS [2-4]			0.0080			0.0080	0.0060	0.0061
			(0.0489)			(0.0488)	(0.0473)	(0.0473)
VCS [5-7]			0.0565			0.0556	0.0432	0.0425
			(0.0455)			(0.0454)	(0.0441)	(0.0440)
VCS [8-11]			0.0453			0.0424	0.0278	0.0252
			(0.0460)			(0.0460)	(0.0447)	(0.0447)
VCS [12+]			0.0581			0.0537	0.0562	0.0523
			(0.0447)			(0.0447)	(0.0432)	(0.0433)
Location Fit				0.0317		0.0289		0.0265
				(0.0222)		(0.0224)		(0.0216)
Industry Fit					0.2555***		0.2561***	0.2544***
					(0.0560)		(0.0567)	(0.0567)
Cons	0.1749***	0.1482***	0.0990*	0.1351***	0.1271***	0.0899	0.0851	0.0769
	(0.0471)	(0.0463)	(0.0599)	(0.0471)	(0.0450)	(0.0602)	(0.0580)	(0.0583)
Financial Controls	yes	yes	yes	yes	yes	yes	yes	yes
Size Control	yes	yes	yes	yes	yes	yes	yes	yes
Age Control	yes	yes	yes	yes	yes	yes	yes	yes
N	296	296	296	296	296	296	296	296
R2	0.34	0.38	0.38	0.38	0.42	0.39	0.42	0.43

This table presents the results of the Post-IPO innovation output database OLS regression. These values are related to a period from 1999-2010 timeframe of companies that have gone public. The dependent variable is a financial metric for innovation. The main variables are the Investor Type dummy, all the Syndicate dummies, Location Fit dummy and Industry Fit dummy. As financial controls, there is Revenues/Assets, Gross Margin, logarithm of leverage, Return on Assets (ROA), and CapEx/Assets. As deal size control, the Average Equity Per Firm in Total variable. As age, the logarithm of the age of the venture at IPO. Lastly, N is the sample size. For more details check appendix F. The values in parentheses is the standard deviation. The *, ** and *** equal a significance level of 10%, 5% and 1% respectively.