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Follow the Follow-ons?

An exploratory study on the signalling of investors' follow-on decisions.

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Even though the field of venture investing has grown immensely in the latest decades, the empirical evidence on how to interpret signals from investors' follow-on decisions is limited. This explorative study seeks to take steps towards understanding how to value signalling in the context of follow-on decisions and staging dynamics. We test three hypotheses derived from earlier research in adjacent fields using a binary logistic regression. Our finding suggests that a professional investors' follow-on decision in an outside round increases the probability of a venture success, and could thus be regarded as a positive signal. We also provide evidence on the complex nature of inside rounds, finding that inside rounds decrease the probability of success. Our main contribution is our methodology for assessing ex-ante investment opportunities, and we hope it will serve as a valuable starting point for future research within the field.

Keywords: Venture Capital, Follow-on Investments, Inside Rounds

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1. Introduction

1.1 Overview

During the last fifteen years, early-stage investments by business angels and venture capital firms have had a major breakthrough. Today, the ventures backed by these types of investors have a major impact on the economy, so understanding the dynamics surrounding these types of ventures is an increasingly popular research field. (Da Rin, Hellmann et al. 2011)

Independent venture capital firms account for the majority of the investments made; they raise external money into venture capital funds, which they invest in promising ventures with the aim to make profitable exits. VC investments are accompanied by very high risks, thus demanding high returns. These funds' survival is contingent on finding successful ventures making up for other losses in the portfolio, which creates a large skewness in VC funds' returns, implying that the investments made can either make or break a VC fund (Da Rin, Hellmann et al. 2011, Berger, Udell 1998).

The young nature of the ventures makes the due diligence made prior to these investments often rely on signals and metrics outside the regular accounting reports. This process is associated with many uncertainties; therefore, finding empirical evidence for reliable signals and metrics could be valuable for anyone investing in ventures.

Since a venture usually goes through multiple funding rounds before the investors can make an exit, we want to find empirical evidence on how to interpret signals from investors' follow-on decisions since they might signal something about a venture's future prospects.

The existing literature on these dynamics shows emerging evidence that rounds without any new investors, inside rounds, are mainly used for 'rescue-financing' rather than for 'self-dealing' (Broughman, Fried 2012). This suggests that existing investors do not exploit potential information asymmetries by dealing promising rounds to themselves. The probable rationale for an existing investor to invite new investors to an outside round is provided by the broad consensus within the literature on the benefits of syndication and investor networks (Hochberg, Ljungqvist et al. 2007).

We are unable to find any studies looking into the signalling of a follow-on investment explicitly, so our study should be regarded as an exploratory step towards understanding these dynamics. To test the potential implications of these signals, we develop a method to analyse a dataset with ventures and their investors and investigate how exploited follow-on opportunities are affecting the probability of making a successful exit of a venture.

We analyse a sample containing 36,430 follow-on decisions for 2,012 US ventures that made over three funding rounds and where the first round was made between 1995 and 2010. In our analysis, we make distinctions between business angels and professional investors as well as between inside and outside rounds.

Our results show that professional investors' follow-on decisions have a positive effect on the probability of successfully exiting a venture. We find that for an increase of one standard deviation in follow-ons, the probability of successfully exiting a venture increases by 4.3 percentage points.

We find further evidence that inside rounds have a negative effect on the probability of successfully exiting a venture; for an increase of one standard deviation in insider rounds, the probability for success decreases by 3.6 percentage points.

This suggests that a follow-on decision from a professional investor in an outside round could be regarded as a positive signal of a venture's prospects. However, in the case of inside rounds, a follow-on decision is a negative signal; the signalling from outside investors not partaking should thus induce caution in an investor facing a follow-on decision in an inside round.

1.2 Purpose

We wish to contribute to the literature by combining earlier strands of venture capital research and take the first exploratory steps towards finding empirical results on what follow-on signalling actually means. However, this makes us unable to find benchmark studies for our methods. Thus, the chosen methodology should be regarded as exploratory in itself, and our methodological considerations could hopefully aid future researchers to refine our method.

Our main methodological contribution is the software created to identify follow-on decisions from a widely used database output format. We have published the application as an open-source project under an MIT license to further encourage future refinement of our method.

We accept the limitations of our study, so the ultimate purpose should be regarded as trying to inspire future research within the field of staging dynamics and the signalling of investment decisions. We do, however, hope that our findings will be regarded as valid and welcomed complements to professional investors' current decision-making processes.

1.3 Research Questions

The main question we wish to answer is

What useful signals can be extracted in the context of follow-on decisions and staging dynamics?

In order to take these first exploratory steps towards this, while staying connected to earlier strands of VC literature, our study answer the following questions:

If professional investors exploit follow-on opportunities in outside rounds, does that increase the probability of a venture's success?

If angel investors exploit follow-on opportunities in outside rounds, does that increase the probability of a venture's success? If so, do this effect differ from that of professional investors?

If a venture is making an inside round, does this lower the probability of a venture's success?

1.4 Limitations of the Study

We use the following definitions throughout our thesis:

i. A *venture* in this study is a young company with high growth potential whose investors finance the venture in pursuit of making a future exit.
ii. *Success* is when the venture is exited by an IPO or an M&A. Buy-backs are M&As where a minority of the shares are sold and management buyouts (MBO) are not considered as a success.
iii. A *funding round* is a deal when a venture raises development capital to support growth.
iv. The funding rounds can be done as either an outside or an inside round. *Outside rounds* include new investors (outsiders) whereas *inside rounds* are done exclusively with earlier investors (insiders) (Neher 1999).
v. An *exit round* is when investors are selling their equity shares through an IPO or a M&A. However, buy-backs, management buyouts (MBOs), and M&As where a minority of the shares are sold are not considered a success.

vi. A *staged investment* is a funding round where the terms are predetermined and the total investment amount is portioned out over numerous rounds.
vii. A *follow-on investment* is an exploited reinvestment opportunity for existing investors in an outside round.
viii. *Independent VCs* or simply *VC*s are defined as professional managers that raise money from capital providers into VC funds to invest in promising ventures.
ix. Bank-owned venture capital (BVC), corporate venture capital (CVC), and government venture capital (GVC) are referred to as *captive venture capital (captive VC)*.
x. *Professional investors* including both VCs and captive VCs.
xi. *Angels* are wealthy individuals who invest their personal money in promising ventures.
xii. The term *investors* for both professional investors and angels.

The following delimitations are made to narrow the scope of this thesis:

i. Our sample is limited to deals where the venture is registered in the US.
ii. We are only studying ventures that made their first development capital round between 1995 and 2010.
iii. We look at how staging dynamics affect the probability to exit a venture. Our study does not say anything about the effects on investment returns.
iv. We only consider data available through Bureau van Dijk's Zephyr database, thus not controlling variables that can be attained through niche VC databases.
v. We cannot prove causality, but rather show the relationships. We thus have to make explicit assumptions regarding the directions of the relationships based on existing theory. That is, we do not have empirical evidence proving that the dependent variable has no effect on the independent variables.

2. Background

2.1 The Nature of Venture Capital

2.1.1 Introduction to Venture Capital

Venture capital (VC) is an investment form where professional asset managers raise funds from accredited or institutional investors to invest in promising ventures and ideally exit them with a good return (Da Rin, Hellmann et al. 2011).

VC is a major force in the creation of new businesses. The VC industry has expanded rapidly since the 1980s, with investments growing from $610 million to $30 billion in 2010 (Da Rin, Hellmann et al. 2011). By focusing on emerging high-technology industries and increasing a venture's likelihood of doing a better exit, they are at the center of bringing innovations to markets and creating successful businesses(Berger, Udell 1998, Da Rin, Hellmann et al. 2011).

This has had a major impact on the US economy, even though only 1% to 2% of US firms receive VC funding(Berger, Udell 1998, Robb, Reedy et al. 2010). VC-backed ventures account for 5.3% to 7.3% of US employment and 35% of US IPOs between 1980 and 2010(Puri, Zarutskie 2011, Da Rin, Hellmann et al. 2011).

The growing impact of VC investing has inspired many researchers to better understand the field. The field is still relatively new and fast moving, and there are still much yet to be done, both in terms of findings and methodologies(Da Rin, Hellmann et al. 2011). This makes VC research a field with big potential going forward and numerous areas that could benefit from explorative studies such as ours.

2.1.2 The Organisational Structure of a Venture Capital Fund

A VC firm is made up of professional managers that raise money from capital providers into VC funds to invest in promising ventures (Da Rin, Hellmann et al. 2011).

The VC funds are generally structured as partnerships, with the VC firm as a general partner (GP) and capital providers, usually institutional investors and high-net-worth individuals, as limited partners (LPs), as illustrated in Appendix 1. The GPs are actively managing the fund’s investments, taking on unlimited liability whereas LPs become shielded from liability since they do not engage in the management of the fund (Da Rin, Hellmann et al. 2011).

GPs decide on the fund's portfolio composition and pick what ventures to invest in; also, often engage in 'value-adding activities' after the investments to further improve the chance of a venture's success. The goal of the GPs is to make profitable exits within the lifespan of a fund, usually between 8 to 10 years, in order to allocate the returns to the LPs. In return, GPs charge a fixed management fee and 'carried interest' based on fund performance (Da Rin, Hellmann et al. 2011).

The performance of a VC fund's investment decisions is best evaluated using gross returns, i.e., the return that the fund achieves before GPs extract their fees. The actual return to LPs is referred to as net returns and serves as a measure of how good LPs are at picking the right VC funds (Da Rin, Hellmann et al. 2011).

Any findings showing how to generate a high gross returns are of course very valuable to GPs; this is why our study's aim is to take exploratory steps towards finding out whether GPs could generate better gross returns by gauging their investment decisions against other investors' decisions.

2.1.3 The Venture Capital Industry

VC fulfils a special need in capital markets. By using equity and similar securities, they can, in contrast to banks, finance ventures with high risks and high returns without demanding collateral. The literature suggests that this is possible since VC firms are better than banks at screening companies and that the nature of the securities gives VCs some control over a venture's assets (Ueda 2004). VC funding is thus optimal for ventures choosing a strategy where the potential returns are big, albeit very risky, and where the liquidation value is very likely to be low (Winton, Yerramilli 2008, Da Rin, Hellmann et al. 2011).

The 'value-adding activities' VC firms tend to engage in after making an investment make them unique as well, since they act both as capital and competence providers that accelerate the ventures road to exit (Jean-Etienne de Bettignies, Brander 2007, Da Rin, Hellmann et al. 2011).

There are numerous studies showing that the average net return of VC funds does not beat the market portfolio (Da Rin, Hellmann et al. 2011). However, for LPs in the top funds, the returns are substantial, while the worst funds yield returns far below the market. Some of the literature suggests that the dispersion of fund returns is persistent, where GPs having closed a top fund tend to sustain their high returns in following funds (Kaplan, Schoar 2005). However, these findings are nuanced by studies showing that this only holds true for the worst-performing funds, i.e., suggesting that there is persistence only in poor fund performance (Phalippou 2010).

This dispersion and return persistence shows that there are large negative consequences of not making the right investments and managing them correctly and that GPs doing this right have a large upside. Any research contributing to the understanding of the dynamics surrounding GPs' behaviour would be useful for understanding how to become a top performing GP.

2.1.4 The Staging of Investments

A venture is usually funded through multiple financing rounds before the exit. VCs' investments are thus usually done in stages, where staging is used as a way to lower the risk and enhance the learning in VCs' investment decisions; and the higher the risk of a venture, the more staging takes place(Da Rin, Hellmann et al. 2011, Bergemann, Hege et al. 2013). Instead of getting all the capital needed upfront, the venture either needs to raise additional funds in a future financing round or receives an additional capital injection when reaching a predetermined milestone(Da Rin, Hellmann et al. 2011, Bienz, Hirsch 2012). This creates a return structure similar to that of options and serves as a way to screen and learn about a venture's future without committing too much capital (Sahlman 1990, Da Rin, Hellmann et al. 2011, Dahiya, Ray 2012)

Staging dynamics can also be regarded as a device to create goal congruence and higher effort from portfolio ventures. By creating a point where the venture needs to raise additional funds, survival becomes conditional on working hard towards investors' goals and creates a competition for refinancing among a VC fund's portfolio ventures. This can also work in the opposite direction and potentially disincentivise a relatively uncompetitive venture in the portfolio since the VCs' bargaining power can be used to dilute the entrepreneurs of less well-performing ventures at the point of refinancing (Inderst, Mueller et al. 2007, Da Rin, Hellmann et al. 2011)

Milestone versus round-based financing

Staging can be done through round-based and milestone financing. In round-based financing, the terms and valuation are determined at the time of each round. Milestone financing gives existing investors the option to make a follow-on investment at a given price in the future, thus staging the deal at predetermined conditions. The literature shows evidence that milestone financing is most commonly used when the founder has a weak bargaining position stemming from a limited access to other outside investors (Da Rin, Hellmann et al. 2011, Bienz, Hirsch 2012).

Outside versus inside rounds

The financing rounds can be done as either an outside or an inside round. Outside rounds are inviting new investors (outsiders) to the table, whereas inside rounds are done exclusively with earlier investors (insiders).

The nature of outside rounds creates a possible source of conflict between insiders and outsiders, where insiders could potentially exploit information asymmetries at the expense of outsiders. The research made on the issue shows, however, that insiders do not act untruthfully when sharing information with outsiders indicating that there might be benefits in having good relationships to outside investors (Admati, Pfleiderer 1994, Da Rin, Hellmann et al. 2011).

This is further stressed when looking at insider rounds, where insiders could have the incentive to engage in 'self-dealing' and deal promising rounds to themselves by not inviting outsiders or use their bargaining power to dilute the entrepreneurs (Fluck, Garrison et al. 2005, Da Rin, Hellmann et al. 2011). The latest findings show evidence that this does not hold but that insider rounds are most commonly used for 'rescue financing', suggesting that insider rounds are mainly done when investors prefer to do an inside round at an artificially high valuation over doing an outside round at a lower valuation than the last round, a so-called down-round(Da Rin, Hellmann et al. 2011, Broughman, Fried 2012).

The different dimensions of staged investments are presented in Table 1. Understanding the behaviour in staging decisions by GPs could be useful since it could potentially signal an informed assessment about a venture's exit potential. Our study aims at taking explorative steps towards learning how to interpret these signals, even though they are mostly visible ex-post, something that could aid a GP's decision making at the point of an investment decision.

Table 1. Staging options

	Outside round	Inside round
Round-based financing	New investors Round date determined ex-post	Earlier investors Round date determined ex-post
Milestone financing	Including new investors Round date determined ex-ante	Earlier investors Round date determined ex-ante

2.1.5 The Dynamics of Follow-on Decisions Across Rounds

The amount of capital needed and the value-adding capabilities sought from investors change over a venture's funding rounds and lifetime. Optimally, the investment sizes should increase for each round, which makes smaller investors unable to partake in late-stage rounds (Da Rin, Hellmann et al. 2011, Dahiya, Ray 2012). In the early stages, investors with industry knowledge might have a competitive advantage, and as a venture approaches, an exit investor with better underwriter network might be more beneficial for the venture (Hochberg, Ljungqvist et al. 2007, Da Rin, Hellmann et al. 2011).

Partaking in multiple funding rounds is an explicit strategy pursued by some funds. For these funds, the follow-on decision becomes very important since they either gain or lose exponentially when following on. Many investors also have pro-rata rights, or the rights to make a follow-on investment to retain their ownership share as the valuation of a venture increases (Levine 2004).

One active VC goes as far as to say that 'it is how the follow-on decision is played that big money is either made or lost' (Ehrenberg 2011). The literature adds interesting evidence to this by showing that these follow-on decisions are problematic for less experienced GPs, who tend to invest more in loss-making ventures and thus exacerbates bad returns (Krohmer 2008).

When speaking to people in the VC industry, they stress the fact that there are reputational implications for a VC fund's follow-on decisions, where the VC firm faces a trade-off between putting more money into bad investments and potentially having a reputation of not supporting the entrepreneurs fully. There are no studies looking into this trade-off explicitly, but the proven importance of VC reputation and network centrality arguably underpins the potential importance of being regarded as a supportive VC ‘partner’ by entrepreneurs in order to ensure future deal-flow (Hochberg, Ljungqvist et al. 2007).

The decision regarding a follow-on investment is thus one that GPs commonly face and should be followed by thorough consideration and discipline. Any signals that could help a GP be disciplined and ‘kill their darlings’ without losing too much reputation would, in our opinion, be welcome.

2.1.6 Syndication of Venture Capital Investments

There are strong networks within the VC industry, and VC firms often co-invest in deals through syndication instead of investing on their own (Lerner 1994, Da Rin, Hellmann et al. 2011). Syndication comes with numerous benefits, and there is a strong relationship between a VC firm’s network position and its fund’s performance (Hochberg, Ljungqvist et al. 2007).

Having a strong position within a syndication network enhances access to good investment opportunities, the assessment of them, and the ability to add value to ventures(Hochberg, Ljungqvist et al. 2007). By inviting other VCs to an investment round, one can expect to be invited to their promising rounds in return, thus securing good deal-flow (Lerner 1994, Hochberg, Ljungqvist et al. 2007). When other investors are invited to the table, a VC firm’s investment decision gets benched towards numerous other professional investors’ opinions, arguably making the firm better informed regarding the risks and returns of a venture (Wilson 1968, Sah, Stiglitz 1986, Hochberg, Ljungqvist et al. 2007). The possibilities for value-adding activities are also expanded since multiple VC firms can leverage their respective resources and networks of lawyers, underwriters, etc., to increase the likelihood of successful exits (Bygrave 1988).

Taking part in syndicated deals is one of the few ways to successfully diversify a VC fund’s portfolio. Successful VC firms tend to specialise within certain industries and geographies; by syndicating with VCs specialising in other industries and geographies, one can diversify to domains where the fund is relatively uncompetitive (Sorenson, Stuart 2001, Hochberg, Ljungqvist et al. 2007)

Syndication not only leads to better deal flow and value-adding activities but also improves the probability of securing financing in follow-on rounds of portfolio ventures. By inviting other VCs to promising follow-on rounds, a VC can leverage an extended network of service providers such as bulge-bracket investment banks and headhunters when heading for the exit (Hochberg, Ljungqvist et al. 2007).

Follow-on decisions and the potential signalling need to be understood in the context of syndication, and there are still contributions to be made regarding the dynamics within syndicates and how syndicated ventures differ from each other.

2.1.7 Other Actors within Development Capital Investing

Apart from the 'independent' VC funds discussed above, there are numerous other types of investors active in the funding of a promising venture.

Captive Venture Capital

Bank-owned, corporate, and government venture capitals all take part in investments made in ventures and are in the literature referred to as captive venture capital. The investments strategies differ from independent VC, and this is why these ideally should be evaluated on their own (Da Rin, Hellmann et al. 2011).

Corporate venture capital (CVC) investments are often made with strategic considerations in mind, not only aiming for financial gains (Hellmann 2002, Da Rin, Hellmann et al. 2011). Learning about new technologies and potential synergies with portfolio companies is often the focus, which is why CVCs tend to invest in riskier ventures and in more R&D-intensive industries than independent VCs (Da Rin, Hellmann et al. 2011, Chemmanur, Loutskina et al. 2014). If a venture has a technology that serves as a complement to CVC's parent's core business, a CVC can add more value than an independent VC. However, if the venture cannibalises on the core business, the financial and strategic goals of the CVC are conflicting. In such a case, a venture will choose an independent VC who will provide more value to the venture than a CVC. The literature suggests that in the case of extremely strong cannibalisation, the deal is often syndicated between independent VCs and CVCs (Hellmann 2002, Da Rin, Hellmann et al. 2011).

Bank-owned venture capital (BVC) firms do not face the same strategic considerations as CVCs, but still differ from independent VCs. BVCs invest in later stages, usually accompanied by large syndicates. They tend to invest within industries that demand high leverage levels and add value by providing ventures with a lower cost of debt (Hellmann, Lindsey et al. 2008, Da Rin, Hellmann et al. 2011).

Government-aided venture capital (GVC) usually works towards broader societal policy goals rather than just achieving financial returns(Da Rin, Hellmann et al. 2011). The literature shows evidence that ventures backed by GVCs only exhibit significantly lower performance; this does not hold for ventures backed by both GVCs and independent VCs, implying that GVCs should be regarded as a welcome complement to independent VCs (Da Rin, Hellmann et al. 2011, Brander, Du et al. 2015).

The literature's findings suggest that ventures where captive VCs have syndicated with independent VCs are not too different from ventures only backed by independent VCs, and this is why we will regard all these types of VCs as professional investors.

Angels

Angels are wealthy individuals who invest in early-stage financing rounds. They often have significant industry experience and networks that could add value in the early stages (Da Rin, Hellmann et al. 2011). Even though it has been questioned, the latest literature shows evidence that angels can add value in the same way as VCs, but the main difference from VCs is that angels lack the ability to refinance a company(Schwienbacher 2009, Da Rin, Hellmann et al. 2011). The lack of refinancing ability makes angels put in more effort than individual VCs in attracting new investors for future rounds; a venture with angel financing thus needs greater investor effort and a higher refinancing risk (Schwienbacher 2007, Da Rin, Hellmann et al. 2011). The literature shows that this trade-off is often beneficial, where angel-backing strongly correlates with a venture’s survival (Da Rin, Hellmann et al. 2011, Kerr, Lerner et al. 2014). Since angels do not face the same considerations as professional investors, the literature suggests studying angel investing separately (Da Rin, Hellmann et al. 2011).

Given the literature’s suggested dynamics surrounding angels, especially in the context of follow-on rounds, we believe that there is a need to deepen the understanding of whether an angel’s follow-on could signal something different from professional investors’ follow-ons. By making this distinction, we can hopefully contribute to the emerging field of angel investment research.

2.2 The Nature of Venture Capital Research

The field of venture capital research is still comparatively new, and there are lots of factors slowing down research. One of the major issues is the private nature of the data (Da Rin, Hellmann et al. 2011). VC fund returns, distributions, and investments are not publicly available, and individual deal terms, such as valuation and equity stakes, are often undisclosed (Da Rin, Hellmann et al. 2011). The young and private nature of the ventures invested in also limits the accounting data available in the databases covering them. Niche VC databases such as ThompsonOne, VentureSource, and Cepres, together with researchers, are collecting return data, so the data availability is slowly growing. However, there are severe reporting biases in all of these databases since VC firms and LPs have an incentive to report only successful investments (Da Rin, Hellmann et al. 2011). The literature finds strong evidence for this by showing that funds that do not voluntarily report cash flows to ThompsonOne have a five percentage point lower exit rate than funds that do report cash flows (Phalippou, Gottschalg 2009, Da Rin, Hellmann et al. 2011).

Caution is thus advised when trying to calculate fund returns; this is why many researchers use exit rates rather than explicit returns in terms of IRR on deals made or net returns to LPs. Bureau van Dijk's Zephyr is regarded as one of the most accurate databases on deal-specific data and has verified exits containing both IPOs and M&As. The reason that researchers are not using Zephyr is that it does not include comprehensive data on returns and valuation for each round. This limited access to data means many of the easy findings to be done have already been made (Da Rin, Hellmann et al. 2011). In this environment, any new findings most probably come from creative augmentations of existing databases or manually collected data(Da Rin, Hellmann et al. 2011).

3. Hypothesis Development

Our main purpose is to aid professional investors' decision making by investigating whether follow-on decisions can be used as a signal of a venture's exit prospects. We hypothesise the following relationships between follow-on decisions and the probability for a ventures exit, as summarised in Figure 1.

Figure 1. Summary of hypotheses

	Professional investor follow-on	**Angel follow-on**
Outside round	H_{1A}= Higher probability of success	H_{1B}= Higher probability of success, but lower than for VCs
Inside round	H_2= Lower probability of success	

3.1 The Signalling of Exploited Follow-on Opportunities

The literature shows that there are benefits both from staging and syndicating investments, but the dynamics of staging behaviour within investor networks are still to be better understood. When having a syndicated round or any kind of round that includes new investors, we believe it is evident that both the deal-picking and the value-adding activities are enhanced. A successfully syndicated round thus raises the likelihood of exit, but what if the syndicates follows on in the next round? Is that reflecting a stronger consensus regarding the probability to exit and a stronger commitment to engage in value-adding activities? Given this, would the extent that a group of existing investors choose to reinvest themselves in an outside round not increase the likelihood of the firm's success? Based on this, we hypothesise that:

H_{1A}= The more professional investors exploiting their follow-on opportunities in outside rounds, the higher the probability of a venture's success.

There has been little research conducted on angel financing, which is why we want to look further into follow-on dynamics within angel financing as well. What are the effects of the suggested lack of refinancing abilities vis-a-vis a VC, and why would such a capital-constrained investor choose to invest even more capital into the same venture instead of diversifying away risk by investing in new ventures? Could an angel follow-on signal a relative lack of outside capital, but be a promising enough venture to invite outside investors?

The better the exit prospects of a venture, the bigger valuation difference between rounds. This makes us believe that an angel follow-on might signal a relatively lower access to outside capital, based on a lower probability to exit. The higher the probability of a good exit, the higher the valuation; the higher the valuation, the more promising trajectory for the venture, which decreases the need for an angel to take on more idiosyncratic risk. This reasoning leads us to believe that ventures where angels are participating in follow-on rounds have a relatively lower exit rate than VC follow-ons.

H_{1B} = The more angel investors exploiting their follow-on opportunities in outside rounds, the higher the probability of a venture's success, but to a lesser degree than for professional investors.

3.2 The Impact of Inside Rounds

Why do investors make rounds on their own when the literature suggests that there are such strong benefits of syndicating? The dynamics of inside rounds are interesting since they could question the value of inviting new investors to the table. The two conflicting hypotheses of 'self-dealing' and 'rescue financing' raise the question of whether inside rounds are done when investors believe that they can achieve higher returns by refinancing by themselves, or when outside investors are not convinced of the firm's exit potential. If investors believe that they can achieve higher returns on their own, the syndication benefits are questioned; on the other hand, inside rounds could be done when new investors within a network chooses not to invest, or the existing investors know that they will not, supporting the evidence that inside rounds are mainly used for 'rescue financing'. If inside rounds have lower success rates, it also adds to the earlier evidence of insiders not exploiting information asymmetries. This suggests that either there could be a 'continuation bias' among investors, since they choose to reinvest even though outsider investors will not, or the insiders value reputational gains from supporting entrepreneurs higher than the cost of exacerbating the loss.

Given the literature's broad consensus on the benefits of syndicating deals, and that the latest literature shows evidence towards 'rescue financing', we hypothesise that inside rounds are primarily done when an exit is less likely to occur, thus potentially suggesting a continuation bias or reputational concerns among insiders rather than exploited information asymmetries.

H_2 = The more inside rounds a venture makes, the lower the probability of a venture's success.

4. Method

Because of to the relatively young nature of VC research and the exploratory nature of this study's research question, we were not able to find any benchmark studies with well-defined methods for answering our specific research questions. What follows is our best effort of combining methods from earlier VC research and applying established statistical methods to answer our questions. We acknowledge the fact that constructing one's own method is usually outside the scope of a bachelor's thesis and that there's probably severe limitations in our method. As such, a caution is advised, and any critique of our method is welcomed and could lead to valuable contributions in understanding how to evaluate follow-on signalling.

4.1 Definition of Variables

4.1.1 Response variable - Success

As a proxy for a successful investment, we look at whether a venture has made an exit through an IPO or M&A, something that is commonly used by researchers (Da Rin, Hellmann et al. 2011). Our response variable is constructed as a binary variable that assumes the value 1 for exits and 0 for non-exits. Of course, gross returns would be a better measure of an investor's success, but the returns are hard to obtain or model since the valuation and the equity shares of funding rounds are usually undisclosed (Da Rin, Hellmann et al. 2011).

Early VC research has mainly used IPO as a proxy for success. However, we choose to augment this measure by adding exits through M&A as well, in line with Hochberg (2007). Within the US data used by Hochberg (2007) there is a correlation of 0.41 between a fund's exit rate and its gross returns, which shows that it is still not a perfect measure but it is one of the best proxies, given the limited availability of data. Figure 2 provides an overview of proxies previously used.

Figure 2. Success proxies used as described by Hochberg (2007)

	IPO	IPO or M&A
Studies	Gompers and Lerner (1998, 2000) Brander et al. (2002) Sorensen (2005)	Hochberg (2007)

Classifying all M&As regardless as successful exits would potentially overweight the proxy. In an effort to be prudent we only regard M&As where at least a majority of the shares are sold as a success. We also exclude all management buyouts since these are usually done due to bad performance of a venture (Hochberg, Ljungqvist et al. 2007).

The limitations of the constructed success variable are evident, but we argue that it is the best we could achieve given the scope of this thesis and the fact that it is based on a solid ground of previous research.

4.1.2 Explanatory Variables

Degree of Follow-on (FO)

We construct a linear index between 0 and 100% for the extent that investors have exploited follow-on opportunities for each venture's outside funding rounds:

Formula 1. Degree of exploited follow-on opportunities for a venture

$$\beta_{FO} = \frac{exploited\ follow - on\ opportunities}{total\ follow - on\ opportunities} = \frac{1}{R} \cdot \sum_{r=1}^{R} \frac{(investors_r \mid investors_{r-1})}{investors_{r-1}}$$

where: R = number of outside rounds the venture have completed
investors = sum of professional investors who invested in the venture at round number r
$investors_{r-1}$ = sum of professional investors who invested in the ventures at the preceding round

If all investors in a venture exploited every direct follow-on opportunity, the venture receives the highest value, 100%. If none of the investors chooses to exploit their follow-on opportunity, the value equals 0%.

If an investor only invests in round A, the model only considers round B an opportunity, not rounds C, D and so on. Indeed, the investor has insider information and potentially the opportunity to invest in rounds C and D too. However, since the literature shows that there are generally large differences in size and aim of each round, and that pro-rata rights usually only covers the right to invest in the next following round, we argue that few investors have the ability or wish to make follow-ons in non-adjacent rounds.

Research on staging behaviours faces one key issue: how to identify ex-ante intentions of staging; more follow-on investments could be both a result of a promising venture and a consequence of milestone financing (Da Rin, Hellmann et al. 2011). Our method for solving this is to calculate the degree of follow-on based on opportunities in outside rounds. By doing so, we exclude both deliberately staged investments, where the actual follow-on decision was made in advance, and inside rounds, where no outside investors had the opportunity to invest. Including inside rounds would also severely skew the follow-on measure since milestone financing would be regarded as 100% exploited follow-on opportunities.

To fully understand whether investors truly has an ex-ante reinvestment opportunity or intentions is very hard and one way to further refine our method is to control for further variables, such as funds' remaining life-times and investment pool, but the limited access to data makes these variables unobservable.

Our aim with this variable is to capture the exploited reinvestment opportunities for unique ventures. Even though there are some limitations to it, we hope that this measure could at least serve as an exploratory step towards future contributions to methodologies used when looking at staging dynamics within VC research.

Number of inside rounds (IR)

If a funding round only includes existing investors, it is categorised as an inside round, and each venture is assigned the count of inside rounds made before exit.

Apart from being useful as a classification when excluding them from the calculation of the degree of follow-on variable, we also want to look at this variable on its own. The theory suggests that the dynamics of inside rounds differ from that of outside rounds, so we construct this variable in order to capture how many inside rounds a venture has made and see how it affects a the probability to exit.

Data limitations and the proprietary nature of deal terms make us unable to distinguish further between deliberately staged deals, such as milestone financing, and round-based financing where insiders are choosing, or are forced to, make an inside round.

The obvious limitation of this measurement, thus, is that we are unable to say anything about why an inside round is made. However, given the literature's evidence of different reasons for doing inside rounds, we argue that the common denominator among these reasons is that inside rounds are used primarily when ventures face high uncertainty, and this holds true across all investor types.

This makes us believe that this somewhat noisy variable will have an effect on the dependent variable's success and hopefully provide some guidance on how investors should interpret the signals from inside rounds.

4.1.3 Additional Predictors Used as Control Variables

We choose to control for the variables we suspect to exert influence on the relation between success and the follow-on decisions and we were able to retrieve from Zephyr. We control for *Average time between funding rounds (TBG), Number of funding rounds (FR), Region (REG)* and *Industry (IND)*. To categorise the ventures into industries, we use the first two digits in the primary SIC-code. These two digits determine which major group the venture belongs to.

Ideally, we should have incorporated more known determinants of a venture's exit, controlling for investor characteristics, firm-specific factors, stock market environment, etc. We were unable to get access to more niched VC databases in order to augment our data set with these control variables based on fund and investor characteristics. Accounting data is widely available in commercial databases; however, we realised that incorporating reliable accounting figures would both limit our dataset due to the young nature of many the ventures analysed, but mostly create a severe survivorship bias. The accounting measures could of course have been obtained by manually collecting them or modelling them based on stock market peers, but we decided that this would take a considerable amount of time without knowing the actual contribution of the effort.

4.1.4 Split Test for Professional and Angel Investors

Angel Investors

The literature suggests that angels differ in nature from professional investors (Rin, 14), which is why we choose to examine the effect of follow-on decisions for VC firms and angels separately.

Most of the angels are easy to identify since the investor-name fields in our data set begins with MR., MRS., or MS. To further refine the selection, we also include investors whose SIC-codes are classified as 'other actors' in Zephyr.

Separating out angels this way is a bit problematic since some angel investments could be done through private investment companies. Ideally, one would have an exhaustive list of active angel investors, but even if we were able attain such list, we argue that it would probably be biased towards successful or well-known business angels. Our data limitations thus force us to make the somewhat bold assumption that angels operating through investment companies are relatively more professionalized and therefore can be regarded as professional investors.

Professional Investors

The residual after separating out angels contains independent VC-firms, captive VC firms, and, to a small extent, angel investment companies.

This definition of a professional investor is somewhat noisy and contingent on assumptions we need to do because of the data limitations. Apart from sorting out the angels above, we tried to distinguish between different captive VCs and independent VCs. One common way to go about this is relying on an investor's industry classification within the used database. This, however, did not hold when using Zephyr; we did a manual check of the classifications and found that misplaced investors within all categories.

We are thus forced to make the distinction between professional investors and angels, rather than the more beneficial one between angels and all different subsets of VC types. We argue that our classification is still useful since we make the distinction between inside rounds and outside rounds, and only calculate the degree of follow-on based on outside rounds. By doing so, we are not distorting our results with ventures including only GVC-, BVC- or CVC-backed companies. As the literature suggests that captive and individual VCs are complementary when syndicating deals, we make the assumption that for outside rounds the different investor types work in parallel, so our classification of professional investors is still useful.

Ideally, we should have gained access to niche VC databases that provide these classifications, and further research on the subject is advised to take this into account and further refine this method.

4.3 Statistical Methods

4.3.1 Data Restructuring to Cross-Sectional Data

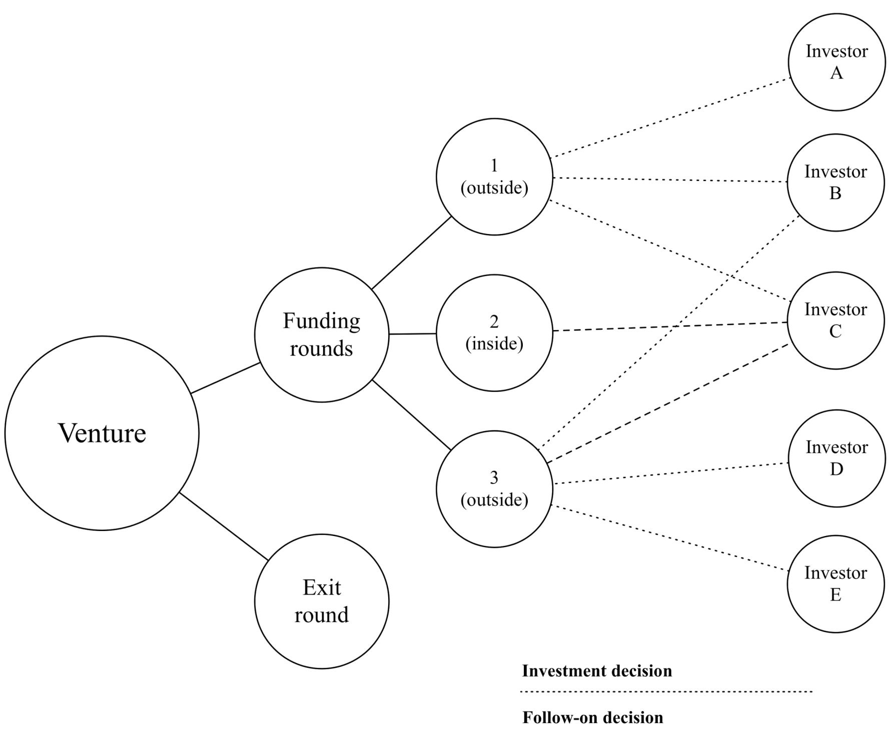
Our raw data from Zephyr is a panel dataset of deals made in ventures. The list of deals are processed and rearranged to a new dataset, with a list of ventures and information about each company's *success* and *degree of follow-on*. This final cross-sectional dataset will be used in the analysis. The initial dataset from Zephyr includes information on each deal as shown in Table 2:

Table 2. Structure of the raw data

Columns	**Description or reason for inclusion**
ID of round	To group all deals into rounds
Completed day	To make sure each round in the *degree of success* is analysed in the correct order, and to apply a scope of time
Deal type	The simply the classification of funding and exit rounds
Name of venture	To group all rounds to the same venture
Investor	The name of the investor
Vendor	The name of the investors selling their shares. This is empty if it is a funding round.

In order to retrieve the variables success, degree of follow-ons (FO), inside rounds (IR), funding rounds (FR), and average time between rounds (TBG) the data is rearranged into a new structure, as shown in Figure 3:

Figure 3. New structure of the data



Worthy of note in Figure 3 is the 'many-to-many relationship' between the funding rounds and the investors (Oracle 2005). This structure cannot be obtained using one single table, such as a sheet in Excel. To solve this issue, we create a database architecture including four tables:

ventures, funding rounds, investors, and *investors' decisions*. An overview of the steps from the panel data to the cross-sectional data can be seen in Appendix 2.

We remove ventures whose first deals are made outside the selected time-scope (1995-2010). To ensure that the measure of the degree of follow-on does not get skewed, we exclude ventures with less than three funding rounds, investment decisions in inside rounds, and business angels' decisions. Finally, we remove ventures with less than three observable investment opportunities. This gives us a solid ground to calculate the degree of follow-ons*,* in a balanced way. A summary of the adjustments is presented in Table 3:

Table 3. Adjustments made to the initial dataset

Step	Adjustment
1.	Ventures with their first development capital round 1995 - 2010
2.	Ventures with at least three rounds
3.	Exclude inside rounds
4.	Remove angels
5.	Remove companies with to few data points in the degree of follow-on

When restructuring the data set, the information on whether an exit round has occurred is stored as a Boolean in the information about the venture, which we use as the dependent variable Success.

By looping through each venture, its rounds and each round's investors, all input is given to calculate the sought variables. The new variables are stored in the final cross-sectional dataset including each *venture's legal name, degree of follow-on, inside rounds, success,* and *control variables.* In Figure 4, the columns of the new dataset is presented:

Figure 4. Variables in the final dataset

Venture's legal name	Degree of follow-on (FO)	Inside rounds (IR)	Success	Region (REG)	…	Industry (IND)

In order to arrange our data-set including over 100,000 investments into this new structure in an efficient way, we use a PHP application built specifically for this study. By using Zephyr's data in this novel way, we hope to contribute to the methodologies used for researching follow-on dynamics. We publish our application on GitHub[1] as an open-source project under an MIT-licence, so that future researchers can easily point out flaws and use our software for developing the methodologies even further.

4.3.2 Data Analysis

Since the dependent variable Success is a binary variable, a linear regression cannot be used since it assumes a continuous variable. Therefore, we use a binary logistic regression model, which is a generalised linear model that allows us to regress the probability of the binary outcome of success (Hedman, Sandberg et al. 2014). By linearising the function using logit transformation, we can specify the full regression model:

Formula 2. Regression

$$\begin{aligned}\ln\left(\frac{p}{1-p}\right) &= a_0 + \beta_{i,1} \times FO_i + \beta_{i,2} \times IR_i \\ &+\beta_{i,3} \times FR_i \ + \ \beta_{i,4} \times TBF_i \\ &+\beta_{i,region1} \times REG_{region1;i} + \ldots + \beta_{i,regionN} \times REG_{regionN;i} \\ &+\beta_{i,industry1} \times IND_{industry1;i} + \ldots + \beta_{i,industryN} \times INDy_{industryN;i} \\ &+\varepsilon_i\end{aligned}$$

where:

(i) p = The probability of success,
(i) a_0 = The intercept,
(ii) FO = Degree of follow-ons,
(iii) FR = Number of funding rounds,
(iv) IR = Number of inside rounds,
(v) TBG = Average time between funding rounds,
(vi) REG_n = Dummy variable if the company is registered in the region *n*
(vii) IND_n = Dummy variable if the company is operating in the industry *n*

To determine whether the right-hand side variables are significant and have an explanatory value, each variable is analysed before running the final binary logistic regression. First, we analyse potential relationships between the numerical predictors and success. Afterwards, to test whether the mean values of the numerical predictors are *significantly* different across the two categories of success, a two-tailed independent samples t-test is performed. The null hypothesis

[1] http://www.github.com/jarnheimer/fohlin-ons

for the t-test is that ‘there is no significant difference between the mean values of predictors across Success categories’. Variables where the null hypothesis is not rejected will be eliminated. Variables whose null hypothesis is rejected by the t-test are further investigated in a logistic regression to see if the explanatory value is relevant enough to include in the final regression. If a variable has a very low prediction, it will be eliminated.

Regarding the categorical predictors *industry* and *region,* it is not reasonable to include a high number of categories, since some categories have a low frequency (Tabachnick, Fidell 2013). Therefore, only industries and regions with a high frequency should be included to attain significance. A chi-squared test is used to determine if the selected categories are significant and become a part in the final regression.

The final regression used is a binary logistic regression including the variables that we found to be significant and have an explanatory effect on the dependent variable success.

4.4 Multicollinearity

Since four of our independent variables are indirectly derived from investment decisions, we control for multicollinearity among these. Our biggest concern is the correlation between number of funding rounds and inside rounds, since no external investors need to be convinced in an inside round, and that an inside round is potentially done to reach more future funding rounds. We examine this by looking at the variance inflation factor (VIF) and ensure it does not exceed the threshold of 2.50, which we regard as an aggressive rule of thumb(Allison 2012)

4.5 Industry reality-checks

Due to our method’s limitations and the explorative nature of our study, we did our best to control that our conclusions made sense to active professional investors. To reach beyond our own extended network we use the online community Quora.com to ask for input on our findings and conclusions. Numerous active investors responded with valuable insights and confirmed that we were not off track in our conclusions. One VC went as far as saying that that the our subject was of utmost importance and that he appreciated to have his own theories from a long career within venture capital confirmed by our data.

5. Data

5.1 Initial Data Set

Data on all completed deals is obtained through the database Zephyr, provided by Bureau van Dijk. We use Zephyr since it is commonly used by VC researchers to validate other databases, and our method distils new findings from this reliable database by restructuring it.

We only export deals where the venture invested in is located in the US, and the deal is categorised either as development capital or an exit; thus, we rely on Zephyr being correct in its classifications. We feel confident doing this because of the literature's wide adoption of this database. Each entry includes information about the involved parties in the deal. The geographical scope is chosen because the US is the most developed country when it comes to VC investing, and previous research within the same geography gives us some descriptive benchmarks to ensure the quality of our data(Da Rin, Hellmann et al. 2011).

We have considered only looking at California; however, this gives us too small of a sample. The current scope enables us to collect a sample of adequate size without it being too heterogeneous. Worth mentioning is the initial absence of time restrictions when we export the deals from Zephyr. We wish to filter ventures based on their first funding round, but we need to make sure all the ventures' deals are exported, hence ventures that are too young to have had the possibility to exit successfully or make follow-on rounds are excluded at a later stage.

Table 3. Deal observations

	Filter	**Observed deals**
1.	Completed deals	1,047,202
2.	Ventures within US	198,549
3.	Funding categorised as Development capital or Exit	48,581

As shown in Table 3, the initial data set includes 49,394 rounds from 28,487 ventures.

5.2 Adjustments to Initial Data Set

To be able to perform the analysis, a series of adjustments are done. In Table 4, the adjustments made to analyse professional investors are summarised:

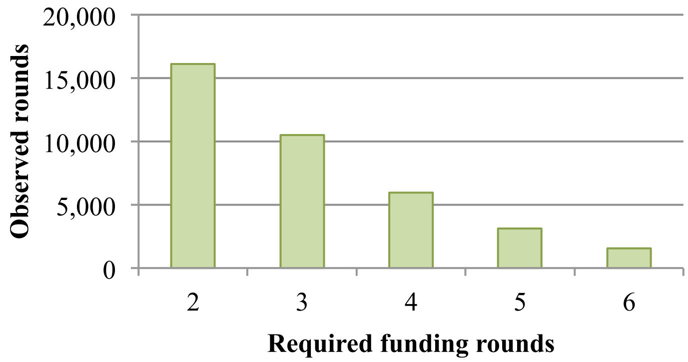
Table 4. Change in Number of Observations Due to Adjustments to Initial Data Set

	Adjustment	Target companies	Funding rounds	Investment decisions
	Initial dataset	28,600	40,397	114,112
1.	Ventures with their first development capital round 1995 - 2010	13,821	26,004	77,138
2.	Ventures with at least three rounds	2,769	10,502	36,430
3.	Exclude inside rounds	2,769	9,028	33,281
4.	Remove angels	2,769	9,028	31,909
5.	Remove ventures with too few datapoints in the degree of follow-on	2,012	7,226	28,458

The adjustments are done as follows:

1. *Ventures with their first development capital round 1995-2010*
   Only ventures with their first round between 1995 and 2010 are considered. An additional filtering of young companies is made when the requirement of funding rounds is applied. The aim is to eliminate ventures that have not been able to make an exit yet.
2. *Ventures with at least three rounds*
   There is a trade-off between the quality of the measurement *degree of follow-on* and the number of observed ventures. As the number of rounds increases for any given target, the measure includes more data points regarding the investors' follow-on decisions. That is, the number of observable follow-on opportunities per venture increases for each performed funding round. We require at least three rounds, which we consider is the highest amount without losing too many observations. As shown in Figure 5, the number of ventures in our sample falls drastically when we increase the requirement of rounds:

Figure 5. The trade-off between number of rounds and observations



3. *Exclude inside rounds*

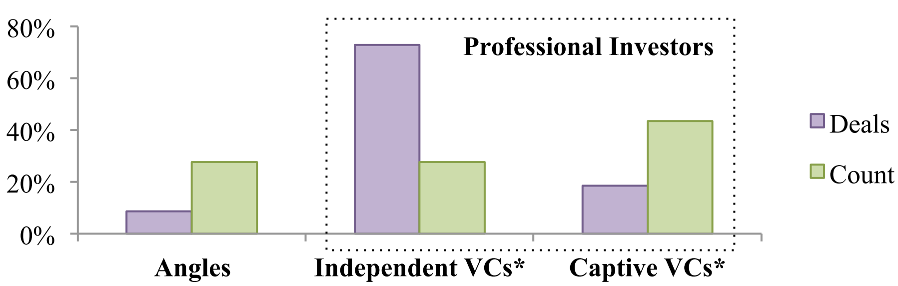
   If a funding round only includes existing investors, it is classified as an inside round and treated in a separate column in the analysis. In our sample, 21.4% of all rounds are classified as inside rounds and therefore excluded in the calculations of the degree of follow-on variable.

4. *Split test for angels and professional investors*

   A split test is made to analyse the data for angels and professional investors separately. In our sample 9% of the deals are made by angels and 91% are done by professional investors.

Even though we regard the categorisation of captive VCs based on industry SIC-codes too unreliable for including in our analysis, it gives us a rough estimate of the proportion of captive VCs within the professional investors category. As shown in Figure 6, captive VCs account for approximately 18% of the deals.

Figure 6. Distribution of investors and their number of deals



**The proportion between independent VCs and captive VCs is approximative*

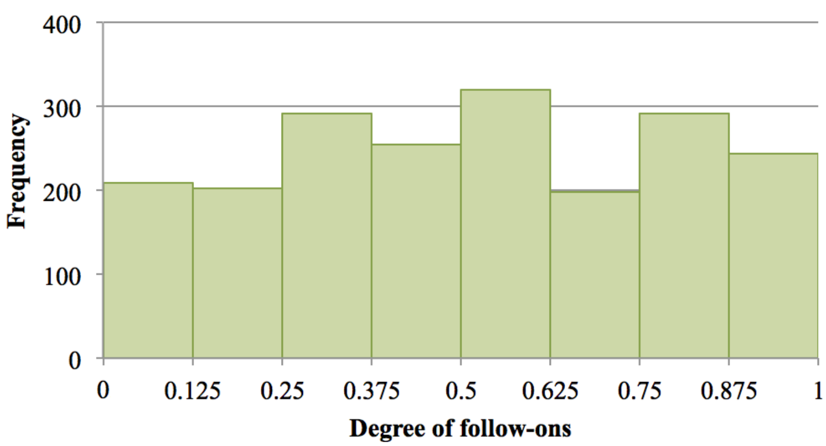
5. *Remove ventures with too few data points in the degree of follow-on*

   After making the above adjustments, a portion of the ventures have not had more than three reinvestment opportunities. To ensure a good quality of the degree of follow-ons variable, ventures with less than four possible follow-on opportunities are eliminated.

5.3 Sample Distribution

The distribution of the main predictor degree of follow-on follows a uniform distribution as presented in Figure 7. Worth noting is that by incorporating the implications of inside rounds and angel investments, we are able to create this, in our opinion, balanced measure of exploited reinvestment opportunities.

Figure 7. Distribution of reinvestment degree across ventures



The distribution of the binary dependent variable success shows that approximately 22% of all ventures have made an exit, which is close to Hochberg (2007). The distribution of the two categories of Success is visualized in Appendix 3.

Furthermore, there are two control variables that needs further manipulation: *region* and *industry*. Both are categorical variables. Their distributions are listed in Appendix 4 and Appendix 5. As shown in the appendices, both variables have skewed distributions. Three of four ventures are located in one of the top five states[2], and the top four industries[3] include 85% of all

[2] California, Massachusetts, New York, Texas and Washington

[3] (1) Business Service, (2) Accounting, Research, Management, And Related Services, (3) Electronic And Other Electrical Equipment And Components, Except Computer Equipment, (4) Measuring, Analyzing, And Controlling Instruments; Photographic, Medical And Optical Goods; Watches And Clocks

ventures. Only this selection is used since it covers most of the ventures. A category with few entries will never get significance. The new recoded variables only include the top 5 regions and the top 4 industries. All other regions and industries will not add information to the estimation.

6. Empirical Results and Analysis

6.1 Empirical Results

Our key findings give answer to two of three questions about whether investor decisions can be used as a predictor of success. The strongest predictor is the degree of follow-on decisions made by professional investors in an outside round. The number of inside rounds has a negative impact on success. There was not enough data to determine the impact of angels' investment decisions. The findings are summarised in Figure 8:

Figure 8. Summary of findings

<table>
<tr><th></th><th>Professional investor follow-on</th><th>Angel follow-on</th></tr>
<tr><td>Outside round</td><td>Higher probability of success</td><td>No significance</td></tr>
<tr><td>Inside round</td><td colspan="2">Lower probability of success</td></tr>
</table>

6.1.1 Professional Investors

First, we analyse the largest sample, professional investors. Potential correlations between numerical predictors and the dependent variable success are analysed using the following descriptive statistics as shown in Appendix 7. By only looking at the descriptive statistics, we can see that the degree of follow-on has a positive correlation. Inside rounds, funding rounds and average time between funding rounds have a negative correlation. To determine if there is a *significant* difference in means for the independent variables between the success categories, a t-test is performed for each variable separately, as shown in Table 5.

Table 5. Independent Sample T-Test of Success Variables

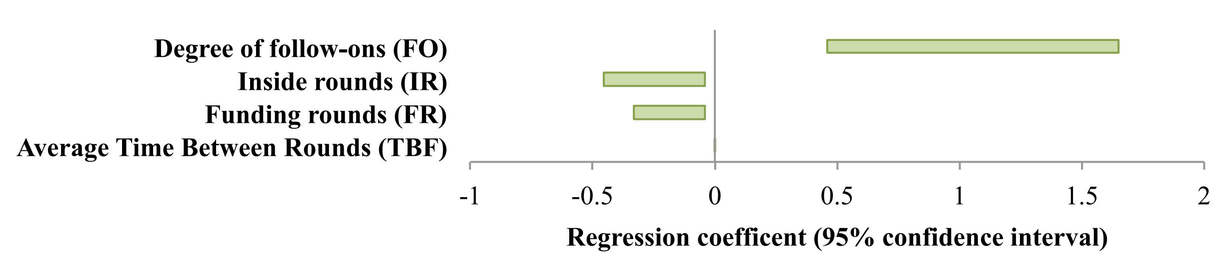
		Levene's Test for Equality of Variances		t-test for Equality of Means		
		F	**Sig,**	**t**	**df**	**Sig, (2-tailed)**
Degree of follow-ons (FO)	Equal variances assumed	1.65	0.20	-4.85	2010	0.00
	Equal variances not assumed			-4.78	692	0.00
Inside rounds (IR)	Equal variances assumed	22.54	0.00	2.57	2010	0.01
	Equal variances not assumed			2.87	839	0.00
Funding rounds (FR)	Equal variances assumed	5.84	0.02	3.06	2010	0.00
	Equal variances not assumed			3.23	766	0.00
Average time between Rounds (TBF)	Equal variances assumed	1.64	0.20	1.95	2010	0.05
	Equal variances not assumed			1.99	728	0.05

Looking at the last column in Table 5, we can conclude that there *is* a significant difference of the mean values for all predictors between the success categories. To summarise the findings:

- The mean *degree of follow-ons* is significantly higher for succeeded ventures (positive correlation).
- The mean *inside rounds* is significantly lower for succeeded ventures (negative correlation).
- The mean *funding rounds* is significantly lower for succeeded ventures (negative correlation).
- The mean *average time between rounds* is significantly lower for succeeded ventures (negative correlation). However, this predictor is close to not being significant and needs further investigation.

Furthermore, we estimate the impact from each numerical predictor. This is determined using a binary logistic regression. The entire output of the regression is shown in detail in Appendix 8, and a visual summary of the regression coefficients is shown below in Figure 9:

Figure 9. Independent numerical variables impact on success



As visualised, all independent variables but *average time between rounds* has a significant impact on the success. Therefore, this variable will be excluded in the following regressions and tests. The two previous steps are run again without *average time between rounds*. See Appendix 9 for the new slightly changed result.

Furthermore, the categorical variables: *region* and *industry* are added. These recoded variables, including the top 5 and the top 4 categories, are tested with a chi-square test to find whether there is a significant difference in success rates among the categories. The result, as presented in detail in Appendix 10 and Appendix 11, shows significance of both tests. We can reject the null hypothesis and conclude that the success rate is not the same across all observed industries and regions.

These two categorical variables will be included in the logistic regression with the numerical independent variables in order to improve the regression even more. The final result is shown in Appendix 12. The results of the regression are presented below in Table 6:

Table 6. Transformed coefficient of all independent variables

Success	Coef.	Std. Err.	P>|z|	95% Conf. Interval	
Degree of follow-on (FO)	0.78	0.24	0.00	0.31	1.25
Inside rounds (IR)	-0.34	0.12	0.01	-0.59	-0.10
Funding rounds (FR)	-0.25	0.77	0.00	-0.40	-0.10
Region (recoded) REG *					
$REG_{Massachusetts}$	0.22	0.18	0.22	-0.14	0.59
$REG_{New\ York}$	-0.54	0.29	0.06	-1.11	0.03
REG_{Texas}	0.34	0.28	0.23	-0.21	1.00
$REG_{Washington}$	0.68	0.31	0.03	0.07	1.28
Industry (recoded) IND **					
$IND_{SIC\ 87}$ - Engineering…	-0.76	0.23	0.00	-1.11	-0.31
$IND_{SIC\ 36}$ - Electronic…	0.13	0.19	0.50	-0.24	0.50
$IND_{SIC\ 38}$ - Measuring…	-0.53	0.28	0.06	-1.08	0.02
Constant (a_0)	-0.60	0.34	0.07	-1.26	0.06

The transformed coefficient of the main predictor FO is 0.69, which means that for a one percentage point increase in the degree of follow-ons the probability of success *increases* by 0.69 percentage points.

The transformed coefficient of IR is 0.42. For each extra inside round, the probability of success *decreases* by 0.42 percentage points.

The transformed coefficient of FR is 0.44, meaning that for each extra funding round, the probability of success decreases by 0.44 percentage points.

When controlling multicollinearity, we can conclude this is not an issue. The results of the tests are shown in Appendix 6.

We have constructed a couple of examples to make it easier to interpret the coefficients. A Texas based venture active within Electronics (SIC 36) is about to make its fourth round (Round D) and have four insiders from round C. In Case 1, three of the four investors follow-on. In Case 2 no follow-ons are made.

Table 7. Case 1 - Three follow-ons

	Inside round	Exploited follow-on opportunities	Follow-on opportunities
Round A			
Round B	FALSE	0	2
Round C	FALSE	1	4
Round D	FALSE	0	4
Total		**1**	**10**
Degree of follow-ons			**10%**

Table 8. Case 2 - No follow-ons

	Inside round	Exploited follow-on opportunities	Follow-on opportunities
Round A			
Round B	FALSE	0	2
Round C	FALSE	1	4
Round D	FALSE	0	4
Total		**1**	**10**
Degree of follow-ons			**10%**

The degree of follow-on differ by 30 percentage points. The estimated probability of success in case 1 and 2 are 30.4% and 25.7% correspondingly. In the next examples, we increase the number inside round by one, keeping the degree of follow-ons fixed. In Case 3, with no inside rounds, the probability of success is 30.4%. In Case 4, with one inside round, the probability is 23.6%. See Appendix 13 for all calculations.

6.1.2 Angel Investors

When repeating the analysis with business angels, the coefficient for degree of follow-ons could differ from the above. First, when looking at potential correlations, we found a slightly higher mean for degree of follow-ons in the case of success:

Table 9. Descriptive analysis for categories of success when only looking at angels

	Success	N	Mean	Std. Deviation
Degree of follow-ons (FO)	No	307	0.12	0.25
	Yes	76	0.15	0.29
Inside rounds (IR)	No	307	0.39	0.76
	Yes	76	0.33	0.76
Funding rounds (FR)	No	307	4.04	1.27
	Yes	76	3.92	1.27

However, in this case we have considerably fewer data points; thus, our results are not significant. In Table 10, the closest outcome is given. Even when relaxing the requirement of three possible follow-on opportunities, there are only 1,391 investment decisions from angels, compared to 35,042 made by professional investors. In addition to this, only 13% of all angels makes a follow-up investment, compared to 49% among the professional investors, which makes the sample weak. The significance is 0.30, far away from a 95% significance (0.05).

Table 10. Independent sample T-test for angels

		Levene's Test for Equality of Variances		t-test for Equality of Means		
		F	**Sig,**	**t**	**df**	**Sig, (2-tailed)**
Degree of follow-ons (FO)	Equal variances assumed	3.93	0.05	-1.04	381	0.30
	Equal variances not assumed			-0.95	104	0.35
Inside rounds (IR)	Equal variances assumed	0.54	0.46	0.67	381	0.50
	Equal variances not assumed			0.67	115	0.50
Funding rounds (FR)	Equal variances assumed	0.05	0.82	0.71	381	0.48
	Equal variances not assumed			0.71	115	0.48

7. Conclusion

The purpose of this study is to take exploratory steps towards understanding how to interpret the signalling of follow-on investment decisions.

In order to analyse this, we use a binary logistic regression to examine the relationship between follow-on dynamics and a portfolio venture's probability to exit. By reconstructing an extensive data set of investors in 2,012 US ventures that made over three funding rounds, we are able to extract 36,430 follow-on opportunities and construct a variable capturing to what extent investors have exploited their follow-on opportunities for each venture. We control for other known implications from staging dynamics and find significant results for how to interpret the signals from the professional investors' follow-on opportunities. To the best of our knowledge, no other studies have looked at this particular relationship between exploited follow-on opportunities and a venture's success.

We find that exploited follow-on opportunities generally have a positive impact on a venture's success. The more professional investors exploiting their follow-on opportunities in outside rounds, the higher the probability for a venture to make a successful exit. No conclusions can be made regarding angels' follow-on decisions. Furthermore, inside rounds have a negative impact on the probability for success.

A follow-on decision from an existing professional investor should thus be regarded as a positive signal as long as there are new outside investors involved in the deal, but if no new investors are involved, the follow-on decision's signalling is a bit more problematic.

These findings are in line with the literature's evidence on the benefits of syndicating investments. While our study does not answer the underlying reasons explicitly, we can speculate based on the literature that the more investors choosing to make a follow-on, the stronger the commitment to add value to the company, combined with a less biased assessment of a venture's prospects.

Based on this, we suggest that investors facing a follow-on decision should be cautious when considering making a follow-on through an inside round. By not inviting external investors, one misses out on their external assessment and 'value-adding activities', but more importantly the existing investors should take into account the strong negative signalling from outsiders choosing not to invest.

When faced with a follow-on decision, our recommendation is to take outside and inside investors' investment decisions into account. The ability to identify these signals ex-ante a deal is made adds to the literature's earlier findings about the benefits of being a well-networked investor. We argue that such ex-ante signals most probably are credible since there are strong disincentives to untruthfully signal, since it most probably will be followed by negative repercussions within an investment network.

Our findings and the literature's evidence of the negative implications of inside rounds raises the question of why our findings shows that inside rounds are made to such a great extent. The literature makes us inclined to believe that the underlying reasons for making inside rounds could be twofold. First, in line with the 'rescue financing' hypothesis, we believe that investors tend to overvalue the turnaround option; in such a case, our findings suggest that there is a continuation bias among professional investors. Secondly, we believe that there are potentially reputational concerns at play when making an inside round, thus nuancing the 'rescue financing' hypothesis by suggesting that professional investors are valuing the reputational concerns higher than the incremental financial loss of doing a follow-on. We see it as an interesting field of future research to investigate whether this trade-off is considered and whether the net effect of the follow-on is beneficial in the long run. If not, the current findings on inside rounds suggest that there would be severe behavioural biases even among professional investors.

We welcome future studies to look into the methodologies we developed for evaluating ex-ante follow-on opportunities, and manually collecting data on deal terms including pro-rata rights would be one way to go about this.

Future studies could also look into the different subsets of professional investors and try to find more data to reach significance for angel investments. This could potentially tell us something about how to interpret the signalling from different actors and whether investor types exhibit different levels of behavioural biases in the context of inside rounds.

A limitation of our study is that we do not evaluate the returns achieved by looking at these signals, but rather the implications for exiting a venture; the more investors that are willing to invest, the higher the valuation. Therefore, our findings should be regarded as a complement to the current myriad of signals and considerations going into the due diligence that investors engage in.

We hope our findings can inspire future research on the subject of follow-on signalling and how investors can be disciplined in their follow-on considerations. They have already spurred numerous interesting discussions online and we hope more researchers follow-on.

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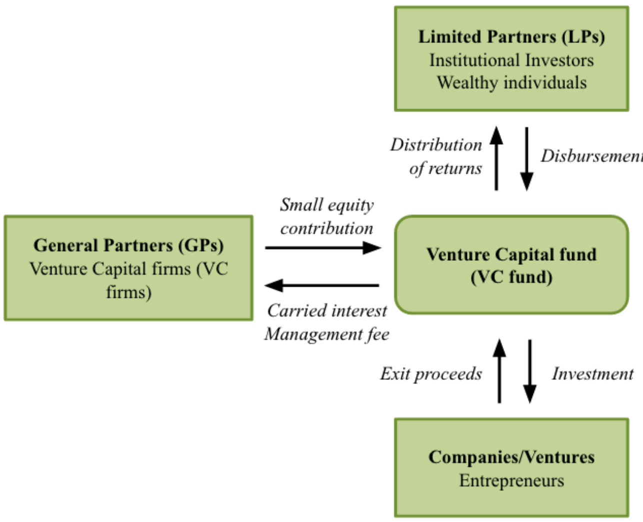
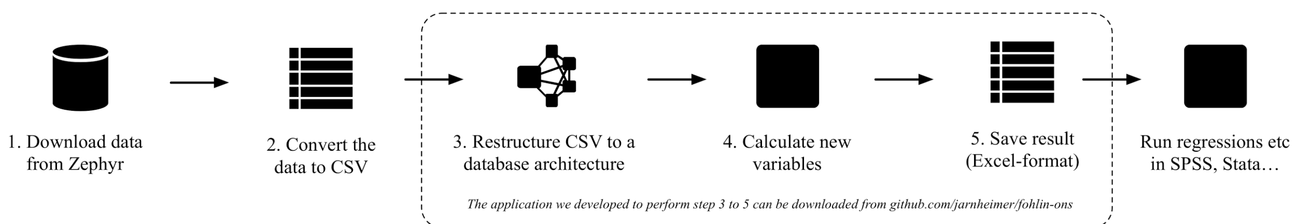
Appendices

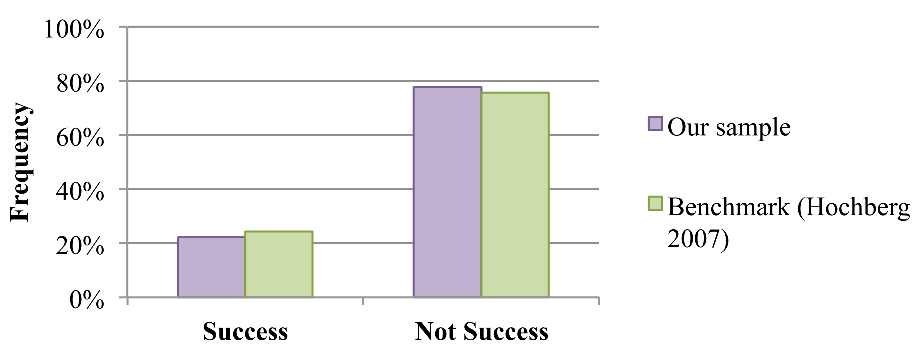
Appendix 1. The Organisational Structure of a Venture Capital Fund (Da Rin, Hellmann et al. 2011).



Appendix 2. Our Data Restructuring Process



Appendix 3. Distribution of Success



Appendix 4. Distribution of Regions

Region	Freq.	%	Cum. %
California	941	46.9%	46.9%
Massachusetts	251	12.5%	59.4%
New York	135	6.7%	66.1%
Texas	86	4.3%	70.4%
Washington	68	3.4%	73.8%
Pennsylvania	54	2.7%	76.5%
New Jersey	49	2.4%	78.9%
Colorado	47	2.3%	81.3%
Maryland	36	1.8%	83.1%
Georgia	34	1.7%	84.8%
North Carolina	33	1.6%	86.4%
Illinois	29	1.4%	87.8%
Virginia	28	1.4%	89.2%
Connecticut	26	1.3%	90.5%
Florida	24	1.2%	91.7%
Minnesota	21	1.0%	92.8%
Oregon	19	0.9%	93.7%
Arizona	18	0.9%	94.6%
Ohio	18	0.9%	95.5%
Utah	14	0.7%	96.2%
Michigan	12	0.6%	96.8%
New Hamshire	9	0.4%	97.3%
Wisconsin	7	0.3%	97.6%
New Mexico	6	0.3%	97.9%
Tennessee	6	0.3%	98.2%
Rhode Island	5	0.2%	98.5%
Indiana	5	0.2%	98.7%
Missouri	5	0.2%	99.0%
South Carolina	4	0.2%	99.2%
Idaho	3	0.1%	99.3%
District of Columbia	2	0.1%	99.4%
Delaware	2	0.1%	99.5%
Alabama	1	0.0%	99.6%
Louisiana	1	0.0%	99.6%
Vermont	1	0.0%	99.7%
Mississippi	1	0.0%	99.7%
Wyoming	1	0.0%	99.8%
West Virginia	1	0.0%	99.8%
Hawaii	1	0.0%	99.9%
Nevada	1	0.0%	99.9%
Arkansas	1	0.0%	100.0%
Kentucky	1	0.0%	100.0%
All regions	**2007**		

Appendix 5. Distribution of Industries

SIC Code	SIC Description	Freq.	%	Cum. %
73	Business Services	1003	0.50	0.50
87	Engineering, Accounting, Research, Management, And Related Services…	285	0.14	0.64
36	Equipment And Components, Except…	250	0.12	0.76
38	Instruments; Photographic, Medical…	164	0.08	0.85
35	Industrial And Commercial Machinery And Computer Equipment	65	0.03	0.88
28	Chemicals And Allied Products	58	0.03	0.91
48	Communications	40	0.02	0.93
89	Miscellaneous Services	30	0.01	0.94
80	Health Services	14	0.01	0.95
27	Printing, Industries	13	0.01	0.96
59	Miscellaneous Retail	11	0.01	0.96
49	Electric, Gas, And Sanitary Services	10	0.00	0.97
60	Depository Institutions	6	0.00	0.97
37	Transportation Equipment	6	0.00	0.97
50	Wholesale Trade-durable Goods	5	0.00	0.97
56	Apparel And Accessory Stores	5	0.00	0.98
20	Food And Kindred Products	4	0.00	0.98
63	Insurance Carriers	4	0.00	0.98
39	Miscellaneous Manufacturing Industries	3	0.00	0.98
47	Transportation Services	3	0.00	0.98
13	Oil And Gas Extraction	2	0.00	0.98
78	Motion Pictures	2	0.00	0.99
16	Heavy Construction Other Than Building Construction Contractors…	2	0.00	0.99
62	Dealers, Exchanges, And Services	2	0.00	0.99
79	Amusement And Recreation Services	2	0.00	0.99
45	Transportation By Air	2	0.00	0.99
82	Educational Services	2	0.00	0.99
57	Home Furniture, Furnishings, And Equipment Stores	2	0.00	0.99
61	Non-depository Credit Institutions	2	0.00	0.99
30	Rubber And Miscellaneous Plastics Products	2	0.00	0.99
65	Real Estate	2	0.00	0.99
86	Membership Organizations	1	0.00	1.00
72	Personal Services	1	0.00	1.00
67	Holding And Other Investment Offices	1	0.00	1.00
32	Stone, Clay, Glass, And Concrete Products	1	0.00	1.00
15	Building Construction General Contractors And Operative Builders	1	0.00	1.00
75	Automotive Repair, Services, And Parking	1	0.00	1.00
58	Eating And Drinking Places	1	0.00	1.00
17	Construction Special…	1	0.00	1.00
95	Administration Of Environmental Quality And Housing Programs	1	0.00	1.00
55	Automotive Dealers And Gasoline Service Stations	1	0.00	1.00
11	Agriculture	1	0.00	1.00
All industries		**2012**		

Appendix 6. Multicollinearity Analysis

Multicollinearity analysis for number of inside rounds

Model	Collinearity Statistics	
	Tolerance	VIF
Degree of follow-ons	0.98	1.02
Funding rounds	0.93	1.07
Average Time Between Rounds	0.92	1.08

Multicollinearity analysis for degree of follow-ons

Model	Collinearity Statistics	
	Tolerance	VIF
Degree of follow-ons	0.94	1.07
Funding rounds	0.91	1.10
Average Time Between Rounds	0.97	1.03

Comment: The Variance Inflation Factor (VIF) has a lower bound of 1, which all correlations are close to. As an upper threshold, we used 2.5 for all variables.

Appendix 7. Descriptive Analysis of Numerical Predictors

	Success	N	Mean	Std. Deviation	Std. Error Mean
Degree of follow-ons (FO)	No	1571	0.48	0.29	0.01
	Yes	441	0.56	0.30	0.01
Inside rounds (IR)	No	1571	0.37	0.68	0.02
	Yes	441	0.28	0.56	0.03
Funding rounds (FR)	No	1571	3.63	1.00	0.03
	Yes	441	3.46	0.91	0.04
Average time between Rounds (TBF)	No	1571	727.88	364.17	9.19
	Yes	441	689.92	350.82	16.71

Appendix 8. Estimation of Impact of Numerical Predictors

	Coeff.	Std. Error.	Wald	Sig	Exp(B)	95% C.I. For EXP(B)	
						Lower	Upper
Degree of follow-ons (FO)	0.78	0.12	17.26	0.00	2.19	1.51	3.16
Inside rounds (IR)	-0.20	0.10	4.31	0.04	0.82	0.68	0.99
Funding rounds (FR)	-0.20	0.06	9.98	0.00	0.82	0.73	0.93
Average Time Between Rounds (TBF)	0.00	0.00	3.24	0.07	1.00	1.00	1.00
Constant (a_0)	-0.71	0.31	5.33	0.02	0.49		

Appendix 9. Estimation of Numerical Predictors' Impact

Excluding average time between funding rounds

	Coeff.	Std. Error.	Wald	Sig	Exp(B)	95% C.I. For EXP(B) Lower	Upper
Degree of follow-ons (FO)	0.83	0.19	19.54	0.00	2.29	1.59	3.30
Inside rounds (IR)	-0.23	0.09	5.78	0.04	0.80	0.66	0.96
Funding rounds (FR)	-0.17	0.06	7.95	0.00	0.84	0.75	0.96
Constant (a_0)	-1.02	0.25	16.56	0.02	0.36		

To easily interpret the regression coefficient, it is made into a transformed coefficient.

Independent numerical variables impact on success

	Regression coefficients	Transformed coefficients
	ln(p/(1-p))	*p*
Degree of follow-ons (FO)	0.827	0.70
Inside rounds (IR)	-0.226	0.44
Funding rounds (FR)	-0.171	0.46

Appendix 10. Analysis of the Recoded Variable Region

			Success		
		Count	**No**	**Yes**	**Total**
Region (recoded) REG_n	**California ($REG_{California}$)**	Count	625	175	800
		%	78.1%	21.9%	100.0%
	Massachusetts ($REG_{Mass.}$)	Count	174	53	227
		%	76.7%	23.3%	100.0%
	New York ($REG_{New York}$)	Count	96	16	112
		%	85.7%	14.3%	100.0%
	Texas (REG_{Texas})	Count	51	21	72
		%	70.8%	29.2%	100.0%
	Washington ($REG_{Washington}$)	Count	38	18	56
		%	67.9%	32.1%	100.0%
Total		Count	984	283	1267
		%	77.7%	22.3%	100.0%

Chi Square test

	Value	df	Asymp. Sig. (2-sided)
Person Chi-Square	9.547	4	0.05
Likelihood Ratio	9.527	4	0.49
Linear-by-Linear Ass.	1.593	1	0.21
N of Valid Cases	1267		

Appendix 11. Analysis of the Recoded Variable Industry

			Success		Total
		Count	**No**	**Yes**	
Industry (recoded) IND_n	**SIC 73 (IND_{73})**	Count	600	188	788
		% within Industry (recoded)	76.1%	23.9%	100.0 %
	SIC 87 (IND_{87})	Count	155	27	182
		% within Industry (recoded)	85.2%	14.8%	100.0 %
	SIC 36 (IND_{36})	Count	141	51	192
		% within Industry (recoded)	73.4%	26.6%	100.0 %
	SIC 38 (IND_{38})	Count	88	17	105
		% within Industry (recoded)	83.8%	16.2%	100.0 %
Total		Count	884	283	1267
		% within Industry (recoded)	69.8%	22.3%	92.1%

Chi Square test

	Value	df	Asymp. ig. (2-sided)
Person Chi-Square	11.2	3	0.01
Likelihood Ratio	11.9	3	0.01
Linear-by-Linear Ass.	1.3	1	0.26
N of Valid Cases	1267		

Appendix 12. Summary of Logistic Regression Including All Independent Variables

Success	**Coef.**	**Std. Err.**	**P>|z|**	**95% Conf. Interval**	
Degree of follow-on (FO)	0.78	0.24	0.00	0.31	1.25
Inside rounds (IR)	-0.34	0.12	0.01	-0.59	-0.10
Funding rounds (FR)	-0.25	0.77	0.00	-0.40	-0.10
Region (recoded) REG *					
$REG_{Massachusetts}$	0.22	0.18	0.22	-0.14	0.59
$REG_{New\ York}$	-0.54	0.29	0.06	-1.11	0.03
REG_{Texas}	0.34	0.28	0.23	-0.21	1.00
$REG_{Washington}$	0.68	0.31	0.03	0.07	1.28
Industry (recoded) IND **					
$IND_{SIC\ 87}$ - Engineering…	-0.76	0.23	0.00	-1.11	-0.31
$IND_{SIC\ 36}$ - Electronic…	0.13	0.19	0.50	-0.24	0.50
$IND_{SIC\ 38}$ - Measuring…	-0.53	0.28	0.06	-1.08	0.02
Constant (a_0)	-0.60	0.34	0.07	-1.26	0.06

* The reference category for region is California

** The reference category for industry is SIC 73,Business Services

Appendix 13. Calculations for Examples

Case 1. Degree of follow-ons 40%

	Value	B
Degree of follow-ons (FO)	0.400	0.78
Inside rounds (IR)	0	-0.34
Funding rounds (FR)	4	-0.25
Region REG_n **	Texas	0.34
Industry IND_n **	SIC 36	0.13
Contant a_0		-0.60
Probability of success*		**30.4%**

Case 2. Degree of follow-ons 10%

	Value	B
Degree of follow-ons (FO)	0.100	0.78
Inside rounds (IR)	0	-0.34
Funding rounds (FR)	4	-0.25
Region REG_n **	Texas	0.34
Industry IND_n **	SIC 36	0.13
Contant a_0		-0.60
Probability of success*		**25.7%**

Case 3. Default case - Degree of follow-ons 40%, no inside-rounds

	Value	B
Degree of follow-ons (FO)	0.400	0.78
Inside rounds (IR)	0	-0.34
Funding rounds (FR)	4	-0.25
Region REG_n **	Texas	0.34
Industry IND_n **	SIC 36	0.13
Contant a_0		-0.60
Probability of success*		**30.4%**

Case 4. One inside-rounds

	Value	B
Degree of follow-ons (FO)	0.400	0.78
Inside rounds (IR)	1	-0.34
Funding rounds (FR)	4	-0.25
Region REG_n **	Texas	0.34
Industry IND_n **	SIC 36	0.13
Contant a_0		-0.60
Probability of success*		**23.6%**

* Based on the formula

$$u = a_0 + \beta_{FO} \times \mathrm{FO} + \beta_{IR} \times IR$$
$$+\beta_{FR} \times FR_i + \beta_{TBF} \times TBF$$
$$+\beta_{REG} \times REG$$
$$+\beta_{IND} \times IND$$

$$\hat{p} = \frac{e^u}{1 + e^u}$$

**The categorical variables are multiple dummy variables in the regression. Therefore will the coefficient (B) for Region and Industry change when changing the value.