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Review Article

Trade Sale versus IPO as Exit Strategy - An Empirical Analysis of European and US VC Backed Biotechnology Companies

Gruener A* and Kutz R
School of Finance, University of St. Gallen, Switzerland

***Corresponding author:** Andreas Gruener, School of Finance, University of St. Gallen, Switzerland

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Abstract

This paper studies the influence factors that characterize a trade sale versus an IPO exit strategy of VC-backed biotechnology companies. Using a dataset of 142 European and US privately held companies, exiting between 2005 and the second quarter of 2014, this paper addresses VC investment structure variables as well as firm- and product-specific variables to examine the decision of VCs to either use the trade sale or the IPO strategy. It was found that the IPO exit strategy calls for higher investments, is financed by more investors, requires more financing rounds, and takes longer for VCs to exit. An interdependency of these four variables is shown. Additionally, firms with pre-clinical products show higher probabilities for trade sale exits, whereas firms with marketed products and/or revenues are more likely to go public. Furthermore, the size of a firm is positively related to the probability of an IPO exit. Finally, firms whose lead product belongs to the field of oncology or is biologic in nature, and/or firms with technology platforms do not show a higher probability to exit via one of the two exit strategies considered.

Keywords: Venture capital; Biotechnology; Exit strategies; IPO; Trade sale; Principal component analysis; Logistic regression

Introduction

The pharmaceutical industry was always strongly driven by innovation, but patent cliffs and cost pressure today has significantly influenced the environmental conditions [1]. As people still face a lot of unresolved medical needs, the emerging biotechnology industry will certainly play an important role in the future to preserve our living environment. Generally, new technology companies such as biotechnology firms often require substantial resources to fund early-stage and speculative development projects where revenues cannot be expected immediately [2].They require a lot of private capital to continue their Research and Development (R&D) activities. Moreover, the outcome of high technology is very uncertain and consequently bears high risk. However, high-technology industries provide large investment and return opportunities for Venture Capitalists (VCs), who specialize in providing capital in situations relating to high levels of risk and information asymmetry [3]. The VC cycle [3] describes all important VC principles and is defined by the topics of fundraising, investing and exiting. The concept of VC also encourages discussions on asymmetric information, conditions of relevant financial and product markets and the nature of firm's assets. Thus VCs introduce monitoring mechanism. It involves a lot of uncertainty but also provides many chances for investors [3].

Previously, VCs backed many of today's most successful high-technology companies such as Cisco Systems, Genentech, or Microsoft [4]. Medigene and Paion are two biotechnology top shots in the 1990s and early 2000s, financed by VCs. In those days the strategy of biotechnology firms was product-focused, while new and leaner business strategies (e.g., back to the basis of technology) are developing today [5]. New business strategies are driven by the aim to reduce the capital commitment of VCs, as their investment horizons tend to be shorter than the timeframe of typical drug development [5]. A successful exit is the desired target of most VCs and it is structured from the time of the first investment, together with the firms' managers. Many see an Initial Public Offering (IPO) as the most favored exit strategy. However, a recent Forbes article emphasizes the importance of trade sales as exit strategy for biotechnology companies. "IPOs are the apparent prize-winners in the eyes of many. But what often gets overlooked when talking about biotech exits is the important – and more frequent – role of the M&A exit in driving liquidity in biotech, even in the current marketplace" [6]. According to Booth (2014) both exit strategies provide equivalent return opportunities for VCs. Therefore, this should be verified.

Research in the area of VC is still emerging due to the very sensitive and limited amount of accessible data. Most publications in the field of VC analyze datasets from different industries and mainly focus on the US. However, some studies cover the pharmaceutical and/or biotechnology industry exclusively [2,7-11].

This paper focuses on the exiting process and deals as well with various investing aspects due to the high interconnectivity of investing and exiting. Additionally, company and product specific criteria are examined. It seems that only a few researchers directly analyze factors, thereby potentially explaining different exit strategies. Only Brau, Francis & Kohers [12], Cumming & Macintosh [13], Wang & Sim [14] and Lerner [15] apply logistic regression models to test for factors leading to a respective exit choice. Only Lerner [15] analyzes a biotechnology sample, all others investigate a sample of various

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Existing Studies	New Contribution
A: Time Frame	
- 1984-1998 *(Brau, Francis & Kohers, 2003)* - 1990-1998 *(Wang & Sim, 2001)* - 1992-1995 *(Cumming & Macintosh, 2003)* - 1978-1992 *(Lerner, 1994b)*	- 2005-2014, Q2
B: Research Focus; Industry	
- Trade sale vs. IPOs; various *(Brau, Francis & Kohers, 2003)* - IPO vs. others (trade sale, secondary sales, buyback, write-offs); various *(Wang & Sim, 2001)* - IPO vs. trade sale vs. secondary sales vs. buybacks, write-offs; various *(Cumming & Macintosh, 2003)* - IPO vs. remaining private; biotechnology *(Lerner, 1994b)*	- Trade Sale versus IPO; biotechnology
C: Independent Variables	
- Herfindahl index, technology dummy, financial service dummy, debt ratio, market-to-book ratio, IPO/mergers, market return, total assets, scaled transaction value, insider ownership after offer, liquidity, demand for funds, 3-month T-bill rate *(Brau, Francis & Kohers, 2003)* - Industry, sales, ROE, familiy owned dummy, age, number of rounds, total VC invested *(Wang & Sim, 2001)* - Market-to-book ratio, VC investment duration, technology dummy *(Cumming & Macintosh, 2003)* - Market timing, level of the biotechnology index, changes in equity prices, age of VC investor, age of firm, patents *(Lerner, 1994b)*	- Total VC invested, number of investors, number of rounds, VC investment duration - Employees, transaction value - Stage of development dummies, revenues - Therapeutic area dummy - Biologics dummy - Platform dummy

Table 1: Research gap.

industries. Yet, further elaboration is needed in this framework [13].

The goal of this paper is to directly compare the trade sale versus IPO exit strategy. Therefore, this paper elaborates how are VC investment structure variables, and firm- and product specific variables related to a trade sale versus an IPO exit strategy. This study integrates different factors forming the VC investment process (investment amount, number of investors, duration, and number of investment rounds) and playing a key role within the VC framework and especially with regard to exiting (see, e.g., Gompers & Lerner [16]; Stuart et al [2]. Furthermore, this paper adds several biotechnology firm-specific factors (product development stage, revenues, therapeutic area, biologics and technology platform) which explain the choice of one of the two exit strategies. Avery homogenous data sample of purely private VC-backed biotechnology companies has been used. The European and US markets form the framework of this paper.

The remainder of the paper is structured as follows: Chapter 2 builds a literature review. Based on the literature review, Chapter 3 develops the hypotheses for the empirical analyses. Chapter 4 describes the data sample and explains the econometric methodology applied for the regression analysis. Based on this methodology, the Chapter 5presents the results. Chapters 6 and 7provide a discussion of the results and a brief summary of the paper.

Research gap

The existing body of research provides some gaps with grateful potential for new contributions to the existing studies using logistic regression models on exit choices. First, no existing study covers a recent time period of the 21st century. Second, many studies cover data samples of various industries which provide the opportunity for greater data samples but the risk of a missing clear comparison of the data. Therefore, the field of research is widely open for new studies with focus on biotechnology companies. Third, no study analyses mutual dependencies of the tested independent variables within the exit prediction model. Especially variables which describe the investment process of a company, such as the total VC invested, number of investors, number of rounds invested, VC investment duration provide a presumption for being mutually explanatory. Furthermore, no existing study include product and biotechnology firm specific variables in their models. Finally, no paper includes European companies.

New contributions to the existing literature

The following (Table 1) provides a comparison of the existing studies using logistic regression models on exit choices and shows the new contributions of this paper. Section A compares the time frame, Section B compares the research focus and industry and Section C provides an overview of the applied independent variables used in the existing literature and the independent variables used in this paper to analyze the hypotheses. This paper complements the existing body of research in the field of exit strategy prediction models and contributes with regard to three points. First it covers a new time frame. It looks at the recent time period from 2005 to the second quarter of 2014. Second, it addresses exclusively the most common exit strategies, trade sale versus IPO, for a homogenous set of VC-backed private biotechnology companies. Except of the study from Lerner [15] all other papers are based on data from various industries. Third, it considers mutual interdependencies between the explanatory variables and identifies factors summarizing the underlying variables. Additionally, it newly adds product and biotechnology firm specific variables. This is a new contribution to the existing biotechnology study from Lerner [15], who analyzes different exit strategies against the background of macro-economic variables, such as the current market situation. Additionally, this paper includes European and US companies whereas the reference papers mainly focus on US firms.

Literature Review

The paper is related to the field of scientific research with regard to biotechnology and VC. The biotechnology and VC literature is reviewed with contents in relation to exit strategies. Against this back ground, it is crucial to investigate the investment as well as

exit processes as part of the VC cycle and the relation between the investment behavior of VCs and the chosen exit strategy. Therefore, the literature review first presents an overview of the literature with focus on exiting. Second, staging and syndication as part of the VC investing process are reviewed in order to derive differences in the VC investment structure of a company with regard to an IPO and trade sale exit.

The results of these papers under study are used to derive the influence factors that characterize a trade sale versus an IPO exit strategy.

Venture capital exiting and investing

Many papers deal with different aspects of the VC cycle [3].This paper is related to a number of other papers which investigate exiting and investing. The investing aspect plays a crucial role with regard to an exit strategy and therefore staging and syndication are reviewed as important investment structure characteristics.

Exiting: The central elements of the literature review are the two exit possibilities IPO and trade sale. Once the investment decision is taken and VCs have structured their investments in accordance with their best knowledge, VCs need to manage the divestment of portfolio companies in the exiting stage [3]. However only few empirical studies focus on these two strategies exclusively. Most papers cover a broader range of different exit strategies. Going public is the most covered exit channel in the existing literature through which VC and entrepreneurs profitably unload their investments. According to many scholars, going public is the most desirable and/or valuable strategy [13,14,17-19]. This phenomenon is described as the "pecking-order of exit channels" [18,20]. VC-backed firms first aim for an IPO exit and afterward consider (or are forced to consider) trade sale exits [17]. However, in the past decade, new studies showed that going public has decreased by numbers and more VC-backed companies tend to exit via acquisitions [21,9]. Cumming and Macintosh [13] state that transaction synergies are a major factor that speaks on behalf of acquisition exits compared with IPOs.

Stuart et al. [2] add equity investors' prominence, and the number of patented products as driving going public factors. Black and Gilson [22] are undecided about whether IPOs or trade sales exit are the better option. A synergy gain speaks on behalf of a trade sale whereas IPOs might be more efficient and due to their high frequency in the US, Black and Gilson [22] see it as plausible that IPOs yield in higher valued exits. Bienz [18] explains the pecking order of IPO versus trade sale with a selection bias. Better-quality firms, measured by its profitability, exit via an IPO, while companies with less quality get sold. Brau et al. [12] apply a logistic regression model with the exit choice as a dependent variable and examine the impact of industry-related factors, market-timing factors, deal-specific factors, and demand for fund factors on the exit choice. Industry effects, described by the concentration of the industry and the high-tech indicator, the hotness of the IPO market relative to the private target takeover market, the current cost of debt, the percentage of insider ownership maintained in the firm, and the size of the firm are all positively related to the likelihood of an IPO. Furthermore, firms in high market-to-book industries, financial service firms, firms in high debt industries, and deals involving greater liquidity for selling insiders show a stronger probability for takeover.

Behnke and Hültenschmidt [9] focus only on biotechnology companies and give evidence that good-quality companies no longer get floated but sold. However, they provide descriptive results for the period of 1995–2005 only. They show a trend to the path to acquisition exits compared with the IPO alternative and observe higher returns on investment and a shorter time to exit for private biotech companies getting acquired. Behnke and Hültenschmidt [9] name higher hurdles for companies which like to go public as an explanation for this trend. Going public is more expensive, as it was decades ago. External investors are more cautious and expect technology revenue, major partnerships and Phase III clinical trials from a company going public [9]. They conclude that this requires more capital to get ready for an IPO and leads to lower valuations.

Cumming and Macintosh [13] investigate the quality of a firm (higher market-to-book value), investment duration, and the technology status of a firm as factors which may predict the choice of IPOs, acquisitions, secondary sales, buybacks, and write-offs. They apply a multinomial log it regression and show that high-quality US and Canadian firms have a higher probability for IPO exits compared with trade sales [13]. Furthermore, they do not find a significant relation between duration and exit choice. As a consequence, they assume a more complex relationship between the investment duration and exit strategy.

Gompers [16] shows that firms that go public receive more funding compared to the other exit strategies. This result is not influenced by the number-financing rounds. Generally, Gompers [16] shows that once VCs anticipate negative future returns, no further financing is provided and consequently VCs search for a corporate buyer. Firms without further potential get liquidated. Furthermore, companies with an IPO exit show higher number of funding rounds compared with all other alternatives.

Wang and Sim [14] apply a logistic regression and investigate different factors which may explain the choice for an IPO versus buybacks, trade sales, write-offs, and secondary sales. They show that high-technology companies are more likely to exit via an IPO. They relate this finding to the high R&D capital requirements and the successfulness of those companies. They find, that the age of the VC firm does not influence the exit choice significantly, which is against the grandstanding hypothesis developed by Gompers [23]. Furthermore, the number of financing rounds has no significant influence. Finally, firms with a higher total amount of VC financing show higher probabilities for an IPO.

Only a very few papers cover the present time windows [11]. Focusing on public biotech companies, Lawrence and Lahteenmaki [11] show in their descriptive study that 2013 was the year with the largest wave of IPOs since the stock market bubble in 2000-2001, which results in an increase of the NASDAQ Biotechnology Index (NBI) by 66 percent to 2,369.53 at the close of the year 2013, compared with 2012 when it closed at 1,430.81. Consequently, the NBI outperformed the gains made by other stock indices [11]. New public biotech listings were highly in demand in 2013 and offered VCs a wider exit window and provided them with share prices, which partly more than doubled since the IPO. In addition to the IPO height, biotech partnering and trade sale activity saw their aggregate value increasing in 2013. Tax strategies and strategic interests regarding

products and innovation are assumed to be the main drivers for trade sale [11]. However, they do not analyze the M&A market in detail, but give them a strong meaning to focus on. Additionally, by reviewing financing structures, Lawrence and Lahteenmaki [11] highlight the downside of debt and PIPEs in 2013, as they are more typically used in difficult markets when firms cannot take the advantage of straight equity vehicles. Finally, a recent report by Ernst and Young [5] discusses that platform companies are attractive for alliance contracts and subsequent IPOs, offering a sustainable model for short-term profits, profitable growth, and building up of a product portfolio based on own R&D. Additionally, they point out the risk in the context of an acquisition, as the comparative advantages from technology platforms might be quickly overrun by the fast developing technology industry.

Furthermore, within the exit literature, some authors go a step deeper and analyze biotechnology firm's value driver. They answer the question which characteristics lead to a more valuable exit. Following Black and Gilson [22], who state that IPOs are higher valued, the value drivers may steer a certain exit choice. Generally, it is shown that greater risk associated with revenue and profit translates into a lower valuation today [24]. A product's stage of development, the length of the revenue-generating phase, alliances/strategic partnerships, manufacturing, marketing, distribution capabilities, and the protection of Intellectual Property (IP) are factors with a positive impact on valuation [24]. Deeds, Decarolis, and Coombs [25] show that diversity of products in the pipeline has a positive influence on the market value of biotechnology companies. Stuart et al. [2] give evidence that the biotechnology company's firm age and the volumes of pre-IPO invested capital are proxies for the riskiness of a business and influence a company's valuation positively [2]. Guo, Lev, and Zhou [26] show that the stage of development, number of products under development, and legal protection of IP positively influence the value of a company. However, they show a negative impact on the valuation after the IPO, due to a too strong optimism of investors which has led to an overvaluation around the IPO. Nicholson et al. [8] show that higher prices are paid for biotechnology firms which develop non-biologics compared with biologics, as the latter are costlier to develop, more complex, and buyers have less experience with them. Furthermore, firms with products in Phases 2 and 3 get higher prices compared with companies having products in discovery or pre-clinical stages [8]. Ranade [10] show that IP rights such as patents add value to companies as they help them to retain the exclusive right to their products. Additionally, having different products and technologies add more value, compared with focusing on a single platform, due to the higher chance that one of several products finally will survive up to marketability. Finally, market opportunity and the therapeutic area are seen as the company's research focus that influences the value of a biotechnology company. Focusing on oncology research, for example, adds more value to a company as for example dermatology research, independent of the stage of development, caused by the popularity of the therapeutic area.

Finally, financing, based on the statement "cash is king," contributes to the value in a positive way [10]. Hand [7] pays special attention to the value elasticity of R&D expenditures. R&D spending adds more value to firms being in the early stages of the value chain. Those firms show greater growth rate of R&D spending. The effect diminishes as the development proceeds and the R&D spending decreases. He bases his analyses on the work of Cumming and Macintosh [13], which showed that early-stage Canadian biotech firms spend higher proportions of their expenditures on R&D compared with later-stage firms.

Staging and syndication as part of venture capital investing: The decision to invest is difficult because it is subject to asymmetric information and thus contains serious adverse selection risks. This makes project monitoring highly important. Several authors name staging of capital spending; and syndication of investments as main control mechanisms [3].

According to Sahlman [27], staging of capital investments is the most important control mechanism for VCs, as the performance of their invested capital strongly depends on the progress of the investment target. According to this, VCs stage their investments more frequently when the underlying investment situation contains more riskiness [3]. Based on the study of Sahlman [27], Gompers [16] observes high monitoring activities for early-stage companies and for firms in the high-tech industry, where a high level of information asymmetry exists. Consequently, he shows shorter investment durations for younger firms, early-stage companies, firms with fewer tangible assets, higher market-to-book ratios, and more R&D expenses. Furthermore, Gompers [16] observes a higher volume of VC financing for late-stage companies, firms with less tangible assets, higher market-to-book ratios, and more R&D activitie. In conclusion, less monitoring costs are related to longer durations and/or higher investment amounts. Gompers [16] also expects to observe an inter dependence between duration and investment volume but cannot confirm this assumption [16]. Similar results are shown for the number of financing rounds. Based on the same argumentation as above, more risk and information asymmetry is positively linked to the number of financing rounds [16]. Importantly, he presents a strong interdependence between the total VC financing volume and the number of financing rounds. By controlling for financing rounds, no further relation between VC financing, the tangibility of assets and R&D intensity is found. Nevertheless, firms in industries with high market-to-book ratios still obtain more capital infusions.

Addressing duration as time to exit, Giot and Schwienbacher [17] show that high-tech companies, led by internet firms and followed by biotechnology firms, show the shortest time to IPO. With regard to trade sale exits, internet firms still exit in the fastest manner, while the opposite is true for biotechnology companies [17]. Additionally, the likelihood to exit via an IPO decreases as time flows. They show a hump-shaped relation between the total investment duration and the likelihood for an IPO exit. Biotech firms reach this plateau sooner compared with others. Cumming and Macintosh [13] say that the exit timing of VCs depends on the relation of the marginal value, which means that VCs exit as soon as marginal costs of the investment start to outnumber the value added.

Additionally, syndication plays an important role as control mechanism. Syndication helps investors to minimize information problems [15]. On the one hand, syndication helps to spread risk, while, on the other hand, it helps to share information. Both points are especially relevant for investment in high-technology firms [20].

Brander et al. [28] show that syndication is value adding compared with standalone investments, as they lead to higher rates of returns. Next, in line with the risk mitigation assumption, syndicated investments show a higher return volatility [28].Giot and Schwienbacher [17] show that more investors are involved when measuring the size of a company by the number of employees, while fewer investors exist in the financing process of companies with higher sales per employee ratios. Additionally, they show that a larger syndicate raises the likelihood for a trade sale, as larger syndicates increase the pool of corporate contact required to find a buyer [17]. Hopp and Rieder show that especially young and riskier firms syndicate [29]. Additionally, they show weak evidence that the size of a company, measured by the number of employees, calls for syndication.

Hypothesis

The paper examines the trade sale versus IPO exit decision by focusing on certain factors that are related to one of both exit strategies. For the trade sale versus IPO exit strategy analysis, a logistic regression model is used to estimate the importance of each variable on the trade sale versus IPO choice. To elaborate different hypotheses, this paper focuses on VC-investing factors as well as firm and product-specific factors. The methodological approach is based on the studies of Brau et al. [12] as well as Wang and Sim [14]. However, with regard to the hypotheses development, only the firm size hypothesis of Brau et al. [12] can be used as a basis. All other hypotheses in this paper refer to various studies, allowing all assumptions presented below. Finally, the influence of 14 factors, including two control variables, is tested for their prediction of a trade sale exit. The analysis first controls for the years 2008 and 2009, having negative effects on general stock market activities. The period between 2008 and 2009 is named "Lehman Years"throughout the study and characterized as Lehman Dummy for the analysis performed. Also, the models are adjusted for a US dummy as US firms are overrepresented in the sample.

Stage of development

As outlined, VCs face high information asymmetries when investing in young and risky projects. VCs can mitigate this problem by intense screening and monitoring activities. Outside investors face similar problems while deciding whether or not to invest in a particular company. Especially in the context of privately held biotechnology firms, very limited information is available for outside investors. Additionally, most of them have no deep industry knowledge to assess a company's valuation. Following the statement of Bratic et al. [24]-"greater risk associated with revenues leads into less value today" (p. 3)-it can be assumed that outside investors heavily base their investment decisions on the riskiness of a business to evaluate a firm's value. "Outside investors expect technology revenues (…) and Phase III clinical trials from a company going public" [9]. Indeed, several authors show a positive impact of revenues [24] and products in advanced development stages [24,26,8] on companies' valuation. Based on these findings it might be assumed that biotechnology firms with marketed product and/or revenues would rather go public than getting acquired. Furthermore, it can be assumed that strategic buyers are more skilled to evaluate high-technology companies [13] and therefore may even buy a company with products in less developed stages. They may assess future product potential much better and at an earlier stage, and may expect synergy gains caused by the transaction. Hence, this paper assumes a negative relation between the stage of development and the probability for a trade sale exit. The variables used to test this hypothesis are a dummy for pre-clinical products, a dummy for marketed products and revenues.

Hypothesis 1: Stage of Development-Firms with less developed products shows a positive relation to the probability that VCs will exit via a trade sale.

Given this hypothesis it might be assumed on the one hand that firms with products in advanced stages have more total cash spending due to the length and capital intensity of the whole drug development process. On the other hand, firms with many pre-clinic products may spend the same amount as companies with one or very few marketed products. The latter may even have more need for capital due to higher R&D activities associated with early-stage companies [16,7,13].

VC investment variables

Generally, different authors [2,10] show a positive relation between the investing volume and a biotechnology company's valuation. They follow the assumption "cash is king" and see expenditures as necessary to drive a company's R&D activities, which, in turn, reduce risks [2]. Furthermore, Gompers [16] presents higher volumes of VC financing for late-stage companies and firms with less tangible assets, and argues with less monitoring costs [16]. In addition to VC financing, Gompers [16] discusses duration and the number of financing rounds in the context of information asymmetries and agency theory. VCs use shorter durations and more financing rounds to minimize asymmetric information problems and to mitigate risk. Consequently, Gompers [16] assumes a relation between the variables VC financing, duration and number of financing rounds. However, no significant relation is found between VC financing and the duration of investment rounds, while the numbers of rounds are positively related to VC financing. Furthermore, syndication addresses the riskiness of a business as well [20,28,29] and/or is value adding [28]. Positive relations have been proved between the demand for capital and number of investors involved in a syndicate [17,29].

Turning to the context of exiting, VC financing, duration, number of investment rounds and syndication are frequently discussed. First, larger investment amounts are applicable for firms that go public [16,14]. They assume that going public is the preferred exit outcome and that once VCs have enough favorable information about the investee firm and it has potential for an IPO, VCs would provide higher financing amounts. Behnke and Hültenschmidt [9] correlate higher costs with IPOs in the context of the biotechnology industry, which may require more VC financing. Also, longer investment durations are shown for firms with IPO exits [21,13]. However, Cumming and Macintosh [13] as well as Achleitner et al. [21] do not find statistically significant results. Consequently, they assume that there are other variables that may describe the relation between duration and the exit choice than only the mitigation of information asymmetries between company insiders and VCs. Further, IPOs have more financing rounds [16]. Wang and Sim [14] assume more frequent VC financing for IPOs as well, underlying the same assumptions as for the financing volume above. However, no significant result is shown. Finally, Giot and Schwienbacher [17] show that larger syndicates lead to trade sales as they may provide easy access to corporate contacts [17].

Based on these findings and the above-made assumptions, this paper assumes that biotechnology companies which exit via an IPO need more cash due to the associated higher costs that require more VC financing. Consequently, based on the findings of Gompers [16], a higher number of financing rounds is assumed for IPOs. Additionally, as firms going public face higher hurdles compared with firms getting acquired, this paper assumes longer investment durations for those companies to fulfill all requirements. Finally, contrary to what was illustrated by Giot and Schwienbacher [17], this paper associates more investors for IPOs based on the aim to share risk and diversify investments, as IPOs are assumed to be more capital-intensive. Only a small number of investors might be willing to carry those amounts. Therefore, this hypothesis adds to the existing literature [13,14] by assuming interdependencies between the VC investment structure variables VC financing, duration, the number of financing rounds, and the number of investors involved and assumes that those variables are described by one factor. Consequently, the following hypothesis is made.

Hypothesis 2: VC Investment Factor-Firms with lower indexed Investment Factor show a positive relation to the probability that VCs will exit via a trade sale.

This in turn proposes that IPOs are associated with over all higher values of the VC investment structure variables.

Firm size

Based on the size hypothesis employed by Brau et al. [12], larger companies are assumed to be more successful to compete as an independent publicly traded firm. Additionally, larger firms may be better equipped to stem the higher costs associated with IPOs. This relationship is presented in Hypothesis 3.

Hypothesis 3: Size-Smaller companies show a positive relation to the probability that VCs will exit via a trade sale.

The employed variables are the transaction value [12] and the number of employees [28].

Therapeutic area

Ranade [10] states that market opportunity and the therapeutic area influence biotechnology companies' market value. He especially points out high valuation opportunities of oncology research due to its associated popularity, independent of the stage of development. Therefore, the following hypothesis is made.

Hypothesis 4: Therapeutic Area-Firms whose lead product belongs to the field of oncology show a lower probability that VCs will exit via a trade sale.

This paper assumes that firms with lead products in the oncology area may send out positive valuation signals to outside investors and consequently may force their willingness to invest in development of cancer products.

Biologics

Furthermore, Nicholson et al. [8] show that acquirers pay more for firms that develop non-biologics than biologics. More costs, higher complexity, and less experience with biologics have been stated as reasons which lead to the buyer's smaller willingness to pay high prices. Based on this information the following hypothesis is build.

Hypothesis 5: Biologics-Firms whose lead product is biologic in nature show a positive relation to the probability that VCs will exit via a trade sale.

In accordance with the information divergence between outside investors and strategic buyers, Hypothesis 5 assumes a positive relation between firms whose lead product is biologic in nature and the probability of a trade sale.

Platform

The last hypothesis addresses the two most common business models of biotechnology companies-the product and platform model. It has been shown that product diversity [10,26] leads to higher valuations compared with single products or single platforms [10]. However, being a platform company does not necessarily limit a company to one product. Platform firms may offer sustainable models to develop different products and to generate a product portfolio based on own R&D [5]. Additionally, they may have a much broader risk diversification potential by being attractive for an IPO, as platform firms are not dependent on one single product/indication. They offer the advantage of back-up products, in case the lead products fail. In contrast, acquirers may fear that the technology platform becomes obsolete by new technologies and therefore do not provide a long-lasting comparative advantage [5]. Furthermore, according to Gompers [30], early-stage investors like to protect their IPs which they would transfer in case of an acquisition. Based on these facts, this paper assumes that firms developing platforms are more likely to go public. Hence, the following final hypothesis.

Hypothesis 6: Platform - Firms with a platform show a smaller probability that VCs will exit via a trade sale.

Research Method

To analyze different factors that predict and/or describe, either the trade sale or IPO as an exit strategy for European and US VC-backed biotechnology companies a logistic regression analysis was performed. This chapter first provides the process behind the construction of the data sample. Next, it describes how and which data has been collected. Finally, the methodology applied in the empirical analysis is explained. The results of this empirical analysis are illustrated in Chapter 5.

Data Sample

An initial dataset, made available by the HBM Partners AG (HBM), was used as the basis for constructing the final dataset used for all analyses, which was created in two steps.

The HBM dataset covers all completed trade sales and IPOs of US, Canadian, and European biotechnology, pharmacy, generics, Over-The-Counter (OTC) and health nutrition companies from 2005 up to the end of 2013. It contains 741 trade sale exits and 326 IPO exits. Additionally, data such as region, founding date, and exit date, total investments made by VCs, upfront and milestone transaction values, volume of IPO raised, new shares raised, and the development stage of a company's lead product was provided. However, some information was missing. Therefore, the dataset provided by HBM was double-checked and manually complemented. Next, we added all trade sale and IPO exits for the first and second quarters (Q1, Q2) of 2014 to the HBM dataset. Press releases with the completed trade sales and IPOs

Variable	Measurement
Dependent Variables	
ExitDummy *(TS Dummy; IPODummy)*	Coded 1 if a company exited via a trade sale and 0 if the firm went public
Independet Variables	
A. VC Investment Factor	
Total Investment *(LNIn)*	LN of the cumulated cash inflows (All individual VC investments are added); Government grants are excluded, debt investments included
Number of Investors *(Investors)*	Addition of number of investors involved in each financing round
Number of Financing Rounds *(Rounds)*	Addition of all individual financing rounds
Duration *(Duration)*	Time between the exit date and the date of the first funding (Assumption of 360d/y)
B. Size	
Employees *(LNEmp)*	Number of employees
Capital Outflow *(LNOut)*	Trade sale: Total cash outflow to the VCs (upfront value); IPO: Value of a firm at IPO = (subscription price at IPO x total number of shares outstanding - subscription price at IPO x number of newly shares offered)
C. Stage of Development	
Pre-clinical stage; Marketed Products *(PreDummy; MarketDummy)*	PreDummy: Coded 1 for pre-clinical stage products and 0 otherwise MarketDummy: Coded 1 for clinical phase IV, market products, and profitable products and 0 otherwise.
Revenues *(LNRev)*	Addition of the individual revenues per year from foundation to exit
D. Therapeutic Area	
Cancer *(CancerDummy)*	Coded 1 if the product belongs to the therapeutic area "oncology" and 0 otherwise
E. Biologics	
Biologics *(BioDummy)*	Coded as 1 if the company develops biologics and 0 otherwise
F. Platform	
Platform *(PlatDummy)*	Coded as 1 if a company is developing a platform or has a platform and 0 otherwise
Control Variables	
G. Lehman Years	
Lehman Years *(LehmDummy)*	Coded 1 if the exit was during the Lehman time period from 2008 to 2009 and 0 otherwise
H. US Firms	
Region *(USDummy)*	Coded 1 for firms with headquarters in US and 0 for firms with headquarters in Europe

Table 2: Variable definitions.

in 2014, Q1 and Q2, were provided by HBM. Hence, 55 trade sales and 58 IPOs were added, which led to a dataset of 794 trade sales and 384 IPOs for the period of 2005 to 2014, Q2. This defines the "starting dataset" used to obtain the final dataset for all analyses performed in this study.

The second step describes the approach to obtain the final dataset used for all empirical analyses. Thus, the whole sample of 1,178 firms was limited to a homogenous data sample of European and US VC-backed biotechnology companies. The aim of this limitation is to mitigate any biases in the empirical analyses, which may arise due to differences in firm structures caused by different sub-industries. To apply a consequent method, whether or not a company can be called a biotechnology company, all firms were classified in accordance with the sub-industry classification "biotechnology" from Bloomberg. Furthermore, the acquisition of divisions and reverse mergers were excluded, whereby the buyer's shareholders receive the majority share of the target. This procedure resulted in a reduced dataset of 217 firms (128 (entire) trade sales and 89 IPOs).

Thereafter, additional variables were collected described in the current VC literature, which are relevant within the VC framework and may impact the trade sale versus IPO strategy for all 218 firms. Again, data with missing values were eliminated. This resulted in a sample of 67 trade sales and 75 IPOs. Finally, for all remaining 142 firms, product specific variables were collected.

The aggregated final data sample consists of a trade sale subsample and an IPO subsample. A major part of the data was obtained from the Venture Source database, provided by HBM. The independent variables were selected to test the six hypotheses regarding reasons for trade sale versus IPOs.

Variables

All the variables are defined in (Table 2). The dependent variable is the Exit Dummy, defined as a binary variable coded as 1 if a company exited via a trade sale and 0 if the firm went public. Furthermore, two control variables are added.

Methodology

The data sample of VC-backed biotechnology companies includes firms that either follows the trade sale or the IPO exit strategy. By focusing on specific factors, as it is examined how they influence the trade sale versus IPO strategy. By following Brau et al. [12] and Wang and Sim [14], this paper uses a logistic regression model to determine a relationship between the financing structure, firm and product variables and the likelihood of a trade sale or IPO. Compared with an Ordinary Least Square (OLS) regression, the dependent variable in a logistic regression model is binary or dichotomous [31]. The binary dependent variable "Exit Dummy" equals 1 for trade sales (TS Dummy) and 0 for IPOs (IPO Dummy). Therefore, the logistic regression model predicts the probability that an observation belongs either to a trade sale or an IPO [32].

At first, parametric t-tests and a non-parametric Wilcoxon ranks tests were used to test for the mean differences in the two samples. This provides a first analysis of the hypotheses based on a univariate model. Additionally, to reduce the issue of multicolinearity between the independent variables in the subsequent logistic regression, a correlation analysis and a factor analysis are applied. For all analyses but the t-tests/Wilcoxon rank tests, all data were rescaled by

Region	Trade Sale		IPO		Total	
	No.	*Percent*	No.	*Percent*	No.	*Percent*
EU	29	43.28	20	26.67	49	34.51
US	38	56.72	55	73.33	93	65.49
Total	**67**	**100.00**	**75**	**100.00**	**142**	**100.00**

Table 3: Sample composition.

calculating the natural logarithm of the variables [LN(1 + "value")] to mitigate the impact of extreme positive outliers. As normality of independent variables is not compulsory for logistic regression, it normally improves the model fit [33]. Additionally, all variables were standardized. Thus, all variables have a mean=0 and variance=1, which allows a better comparison and interpretation of the variables [34].

The t-tests provide a first indication if the six hypotheses can be confirmed. The two independent samples x (trade sales with n1 = 67) and y (IPOs with n2 = 75) are tested for their significant differences in means. Therefore, H0: $\pi x = \pi y$ is tested against H1: $\pi x \neq \pi y$ [35]. The variances of both samples ($\delta 1$ and $\delta 1$) are unknown, but assumed to be equal. The common variance is estimated by the pooled sample variance

$$S^2=((n_1-1)\ S^2\ X+(n_2-1)\ S^2\ Y)/(n_1+n_2-2), \quad (1)$$

and the test value is calculated as

$$T(X,Y)=(X^{-}-Y^{-})/S\ \sqrt{([n_1\times n]_2/[n_1\square(+)\ n]_2)}\ . \quad (2)$$

The test value shows a Student t-distribution with n1 + n2 □ 2 degrees of freedom [35]. In addition to the parametric t-tests, Wilcoxon rank sum (WRS) tests provide an alternative test of the differences in means, as the tested variables can be assumed to be non-parametric. H0: P = 0.5 is tested against H1: P ≠ 0.5, whereas P is the probability that an observation from the first population X exceeds any value from population Y [35]. Subsequently, the data is ranked to produce two rank totals (R1+ and R2+), one for each condition. The Mann-Whitney-U, necessary to calculate the test statistic Z as n1, n2 ≥ 8, is described by the smaller value of U1, U2:

$$U_1=n_1\times n_2\ (n_1\ (n_1-1))/2-R_(1+), \quad (3)$$

$$U_2=n_1\times n_2\ (n_2\ (n_2-1))/2-R_(2+). \quad (4)$$

The test value, adjusted for ties, is calculated as

$$Z=\ (U-(n_1\times n_2)/2)/(\sqrt{([(n_1\ [\times n]_2)/n(n-1)\ ][(n^3-n)/12-\Sigma_(t=1)^R(T_i^3-T_i)/12)]})\ \sim N(0,1). \quad (5)$$

R is the random variable "number of ties" and Ti is the random variable "Number of equal values at tie i" [35]

A correlation matrix for all variables is calculated to look at the connection of the different variables. The correlation matrix combines the trade sale and IPO data samples. Based upon the correlations, we further decided to run a principal component analysis (PCA).

The PCA serves to identify a meaningful number of unobserved variables. For example, it is possible that variations in the 12 observed independent variables (excluding the two control variables) mainly reflect variation in three unobserved variables. "The goal of the PCA is to identify a new set of a few variables, called principal components, that explains all (or nearly all) of this total variance" [36]. The number of principal components is selected in accordance with the Kaiser's stopping rule, which is to drop all PCs with Eigen values less than one. Furthermore, different types of rotations are useful to apply in order to interpret the identified PCs in a far easier manner [36]. This thesis uses the orthogonal varimax rotation keeping the PCs uncorrelated while increasing their interpretation [36]. Finally, the Kaiser-Meyer-Olkin measure assesses the qualification of the particular indicators for their sampling adequacy. Values ≥ 0.5 are assumed to be valid [36].

To address the Hypotheses outlines in Chapter 3, a logistic regression model is applied. It is described by the binary output variable Y, which takes only two values (trade sale and IPO). The interpretation of the parameters in a logistic regression is not as trivial as in a linear model. However, the sign of the coefficient of an independent variable explains whether the probability of a trade sale is increasing (positive sign) or decreasing (negative sign) [37]. By using odds, a more intuitive understanding of the probabilities is given (Behnke, 2015, p.26):

$$\text{Odds}\ (\pi)=\pi/(1-\pi)=P(Y=1)/(1-P(Y=1))=P(Y=1)/P(Y=0) \quad (6)$$

Odds build the relation between the probability y = 1 and its counter probability y = 0. For example, an odd of 1 imply a 50 percent probability of a trade sale, an odds higher than 1 indicates a probability of a trade sale higher than of an IPO. The opposite is true for values smaller than 1. One option to obtain a linear relationship is by transforming Equation (6) to log odds (Behnke, 2015, p. 26):

$$\text{Logit}(\pi)=\ln\ [\text{Odds}(\pi)]=\ln\ [\pi/(1-\pi)]=\omega=\beta_0+\beta_1\ x. \quad (7)$$

The odds ratio, defined as OR = eβ1, represents the ratio of two odds. It is useful because it does not depend on the corresponding regressor (Behnke, 2015, p. 34). Finally, by transforming Equation (7), the basic logistic regression model for the probability itself is obtained (Behnke, 2015, p. 35):

$$P(Y=1)=\pi=\pi(x)=e^(\beta_0+\beta_1\ x)/(1+e^(\beta_0+\beta_1\ x)). \quad (8)$$

Formula (8) is an example to predict the probability of a trade sale based on one independent variable. For the analysis in Chapter 5, a multiple logistic regression model is used. Hereby, Statauses maximum likelihood estimation, as this achieves more efficient results for a logistic regression compared with the OLS method [34].

Furthermore, as the R2-measure may not be an appropriate measure for logistic regressions, this paper relies on a combination of the Pearson statistic, χ^2, which indicates the goodness-of-fit of a logistic model [38] and the Akaike Information Criterion (AIC). The AIC is used to compare the relative validity of different models. It penalizes a model for having more parameters than are useful for getting a good prediction. The model with the lowest AIC has the best fit [38]. According to Behnke [39], it is calculated as AIC = 2ln(L) + 2k, where k is the number of used predictor variables, L is the likelihood, and the term 2ln(L) is called deviance [39].

Empirical results

First the descriptive results are presented, including a sample composition, descriptive statistics and difference tests between the trade sale and IPO sample. Second the hypotheses developed in Chapter 3 are analyzed through the results of the logistical regression.

	No. of obs.	Mean	St.dev	Min.	Max
Lehman Years 2008/2009					
LehmDummy	67	20.90%	40.96%	0	1
Region					
USDummy	67	56.72%	49.92%	0	1
VC Investment Factor					
Capital Inflow (m)	67	51.92	36.91	0.80	166.22
Investors	67	14.97	9.49	1.00	43.00
Rounds	67	3.63	1.77	1.00	10.00
Duration (years)	67	5.90	2.87	1.09	12.65
Size					
Employees	67	32.73	22.75	2.00	90.00
Capital Outflow (m)	67	136.69	146.20	0.50	610.00
Early Stage					
PreDummy	67	28.36%	45.41%	0	1
Late Stage					
MarketDummy	67	2.99%	17.15%	0	1
Revenues (m)	67	2.97	10.81	0.00	83.21
Therapeutic Area					
Cancer	67	31.34%	46.74%	0	1
Biologic					
BioDummy	67	43.28%	49.92%	0	1
Platform					
PlatformDummy	67	43.28%	49.92%	0	1
Total Inv./Upfront Trans. Value					
Multiple	67	3.38	3.94	0.01	19.79

Table 4: Trade sale - descriptive statistics.

	No. of obs.	Mean	St.dev	Min.	Max
Lehman Years 2008/2009					
LehmDummy	75	1.33%	11.55%	0	1
Region					
USDummy	75	73.33%	44.52%	0	1
VC Investment Factor					
Capital Inflow (m)	75	102.34	79.26	2.64	504.31
Investors	75	21.31	13.95	1.00	68.00
Rounds	75	4.60	2.03	1.00	11.00
Duration (years)	75	7.19	3.60	1.19	20.71
Size					
Employees	75	58.05	46.90	2.00	243.00
Capital Outflow (m)	75	176.70	181.58	2.20	1,393.7
Early Stage					
PreDummy	75	2.67%	16.22%	0	1
Late Stage					
MarketDummy	75	22.67%	42.15%	0	1
Revenues (m)	75	14.92	26.00	0.00	121.04
Therapeutic Area					
Cancer	75	33.33%	47.46%	0	1
Biologic					
BioDummy	75	42.67%	49.79%	0	1
Platform					
PlatformDummy	75	42.67%	49.79%	0	1
Total Inv./Market Value					
Multiple	75	2.32	2.19	0.10	11.20

Table 5: IPO - Descriptive statistics.

Descriptive results

Sample composition: The final dataset consists of 142 biotechnology companies which either exited via a trade sale or an IPO. (Table 3) shows a more detailed composition of the sample. Accounting for roughly 65 percent of the exits, US firms are overweighed in the data sample. Apart from that, however, the two exit strategies trade sale and IPO are well balanced across the sample. From a geographic perspective, European firms exit more frequently via trade sale (n=29) than an IPO (n=20), whereas in the US more companies go public (n=55) than being acquired (n=38).By looking at both regions separately, each higher probability counts for roughly 59 percent.

	IPO Sample Mean N=75	Trade Sale Sample Mean N=67	Differences in Mean	Parametric p-value	Wilcoxon p-value
Lehman Years 2008/2009					
LehmDummy	1.33%	20.90%	-19.56%	0.0001 ***	0.0002 ***
Region					
USDummy	73.33%	56.72%	16.62%	0.0189 **	0.0383 **
VC Investment Factor					
Capital Inflow (USD m)	102.34	51.92	50.43	0.0000 ***	0.0000 ***
Investors	21.31	14.97	6.34	0.0011 ***	0.0063 ***
Rounds	4.60	3.63	0.97	0.0015 ***	0.0031 ***
Duration (years)	7.19	5.90	1.29	0.0105 ***	0.0327 **
Size					
Employees	58.05	32.73	25.32	0.0000 ***	0.0003 ***
Capital Outflow (USD m)	176.70	136.69	40.00	0.0768 *	0.0126 ***
Early Stage					
PreDummy	2.67%	28.36%	-25.69%	0.0000 ***	0.0000 ***
Late Stage					
MarketDummy	22.67%	2.99%	19.68%	0.0002 ***	0.0006 ***
Revenues (USD m)	14.92	2.97	11.95	0.0003 ***	0.0000 ***
Therapeutic Area					
CancerDummy	33.33%	31.34%	1.99%	0.4010	0.8010
Biologic					
BioDummy	42.67%	43.28%	-0.62%	0.4707	0.9411
Platform					
PlatformDummy	42.67%	43.28%	-0.62%	0.4707	0.9411
Total Inv./Upfront Trans. Value					
Multiple	2.32	3.38	-1.05	0.0240 **	0.4173

Table 6: Parametric and nonparametric t-tests for difference in means. Significance (sig.) codes 0.01 '***', 0.05 '**' and 0.1 '*'.

Descriptive statistics: Table 4 and Table 5 present the complete descriptive statistics for the trade sale and IPO sample for each of the variables used in the regression. Additionally, for information purposes only, the multiple is shown as well. However, as it is a combination of capital outflow and inflow, it would make no sense to include it in the logistic regression model, as the variable inevitably correlates with the other two variables mentioned previously. All variables are presented with the mean, standard deviation, minimum and maximum amount over all years, and all companies. From the particular standard deviations, and minimums and maximums, it can be shown that the variables vary a lot for both samples.

Minimum numbers of investor indicate that the dataset includes standalone investment as well. However, a look at the raw data shows that only four companies (two trade sale and two IPO exits) got financed by a single investor. Thus, the dataset is generally characterized by syndicated investment. IPOs show higher average capital outflow values (USD 176.7 million) compared to trade sales (USD 136.7 million), whereas trade sales have higher exit multiples (3.4x) compared to IPOs (2.3x).

Before analyzing the six hypotheses by logistic regressions the paper previously conducts a parametric and non-parametric univariate mean test, followed by a correlations analysis and two PCAs. The process serves to identify the optimal set of components for the final regression analysis.

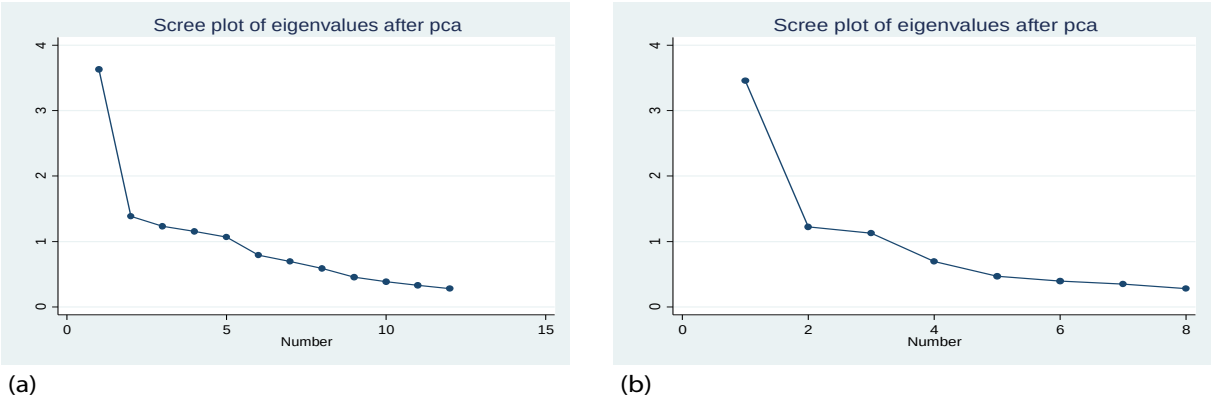
The difference tests between the trade sale and IPO sample are shown in (Table 6). Parametric t-tests and Wilcoxon rank difference tests are performed. Additionally, the results for the multiple are shown. The results show significant differences for most variables. The corresponding p-values are below 0.01, 0.05 or 0.1.

The result for the Lehman Years 2008 and 2009, described by the LehmDummy, confirms the moderating effect of the general financial distress on IPO activities. Additionally, the result for the US Dummy indicates significantly more IPOs in the US, compared to trade sales. Yielding of more than 50 percent in both samples represents the overweight of US firms in the final dataset. The VC investment structure variables, Capital Inflow, Investors, Rounds and Duration show all higher means for the IPO sample and provide support for the prediction of more distinct investment activities for IPOs compared to trade sales. Turning to the company-specific factor size, approximated by the number of employees and the transaction value, described as capital outflow to investors, are both significantly larger for IPOs than for trade sales. Furthermore, the results for the stage of development of a firm's lead product, described by the Presume, Market Dummy, and Revenues, show that firms with an IPO exit have significantly more products in later stages and/or are generating revenues. Acquired companies show significantly more firms with lead products in the preclinical phase of development. For the Cancer Dummy, Bio Dummy, and Platform Dummy, no statistically significant differences for the whole sample can be found. Finally, trade sales have significantly higher multiples. However only statistically significant results are provided by the parametric t-test.

Correlation matrix: Table 7 presents the pairwise correlations between all centered independent variables used in the logistic regression. It shows whether two independent variables are correlated and thus might cause multicollinearity problems in the logistic regression. As a consequence, the logistic regression model performed later most probably would not give valid results for the individual variables. The correlation matrix below shows correlations at a statistically significant level of 5 percent for roughly 24 percent of the pairwise correlations. Some correlation coefficients are quite high with values around 0.6. Strongest interdependences are found between the variables Investors and Rounds, between the Investors and LNIn, and between Duration and Rounds. This provides a first confirmation of the assumption laid out in the hypotheses

	Lehm-Dummy	US-Dummy	LNIn	Investors	Rounds	Duration	LNEmp	LNOut	Pre-Dummy	Market-Dummy	LNRev	Cancer-Dummy	Bio-Dummy	Platform-Dummy
LehmDummy	1.0000													
USDummy	0.1049	1.0000												
LNIn	-0.1406	0.3560*	1.0000											
Investors	-0.1328	0.2542*	0.5572*	1.0000										
Rounds	-0.1182	0.1505	0.5459*	0.6460*	1.0000									
Duration	-0.0831	0.0327	0.4180*	0.5183*	0.5728*	1.0000								
LNEmp	-0.2256*	-0.0690	0.5300*	0.4171*	0.3509*	0.3362*	1.0000							
LNOut	-0.0980	0.1101	0.4661*	0.2637*	0.1487	0.0126	0.5069*	1.0000						
PreDummy	-0.0505	0.1149	-0.2242*	-0.1132	-0.0907	-0.1223	-0.2440*	-0.1961*	1.0000					
MarketDummy	-0.0678	-0.0628	0.1080	-0.0669	0.1618	0.1720*	0.2706*	0.0342	-0.1637	1.0000				
LNRev	-0.1294	0.0995	0.3815*	0.3177*	0.2773*	0.3304*	0.3958*	0.1995*	-0.1430	0.2377*	1.0000			
CancerDummy	0.0069	0.0910	0.1165	0.1634	0.1346	0.0692	0.0959	-0.0126	0.0084	-0.0953	0.2081*	1.0000		
BioDummy	0.0257	0.0613	0.0191	0.1329	0.0538	0.1076	0.0287	0.1400	0.1194	-0.0486	0.0373	-0.1447	1.0000	
PlatformDummy	0.0257	0.0613	0.1206	0.1467	0.1264	0.2017*	0.1694*	0.0324	0.0392	0.0350	0.2250*	0.0985	0.1666*	1.0000

Table 7: Correlation matrix.
Significance (sig.) codes 0.01 '***', 0.05 '**' and 0.1 '*'.



(a) (b)

Figure 1: Scree plots for (a) 12 Independent variables and (b) eight selected Independent Variables from PCA.

development, where a relation between the variables Inflow, Investors, Rounds, and Duration is assumed. Additionally, (Table 7) presents positive interdependencies between the variables LNRev and Market Dummy and a negative correlation between LNRev and Pre Dummy. However, the latter is not statistically significant proved. Finally, as expected interdependence between LNEmp and LNOut is found, indicating that both variables may speak for the size of a company.

In conclusion, the results of the correlation matrix make it reasonable to apply for a PCA to eventually extract some PCs that describe the underlying variables and to solve the problem of multicollinearity.

Principal component analysis: The identification of the most meaningful set of components is achieved in two different PCAs. In the first step, the PCA was run with all 12 independent variables relevant for the six hypotheses. The control variables LehmDummy and US Dummy are not included. The corresponding scree plot (a) for the first PCA is given in (Figure 1). The PCA yields five PCs with Eigen values greater than one, whereas the first explains by far most of the variance, which can be seen by the distinct bends after the first PC. A look at the rotated data (Appendix A1) shows that the first three components are solely described by the nine variables LNIn, Investors, Rounds Duration, LNEmp, LNOut, Pre Dummy, Market Dummy, and LNRev. The assignment of the remaining variables to the last two PCs is theoretically not plausible and does not provide a concise description of the data. Additionally, enhancing this argumentation, the variables Cancer Dummy, Bio Dummy, and Platform Dummy show very few and weak significant correlations between themselves and to all other variables (Table 7). Therefore, this paper conducts a second PCA including only eight variables, as described by the first three PCs. For the second PCA, the variable PreDummy is excluded as well as this leads to a better interpretation of the third PC. The scree plot (b) for the second PCA can be found in the right part of (Figure 1). For the selected group of variables, three PCs with Eigen value larger than one are obtained. Based on these analyses, the eight variables are joined into three PCs.

1. VC Investment Structure Component (PC1), characterized in decreasing order by Rounds, Duration, Investors and LNIn, and

2. Size Component (PC2), characterized in decreasing order by LNOut, LNEmp, and LNIn and

3. Late Stage Component (PC3), characterized mainly by Market Dummy and less by LNRev.

Finally, three PCs, four additional independent variables, and two control variables are stepwise tested in the logistic regression model.

Regression analysis

Model assumptions: The trade sale and IPO sample described

	Model1 (n=142)	Model2 (n=142)	Model3 (n=142)	Model4 (n=142)	Model5 (n=142)
Lehman Years 2008/2009					
LehmDummy	3.20 ***	3.12 ***	3.12 ***	3.12 ***	3.10 ***
	(1.06)	(1.16)	(1.16)	(1.16)	(1.13)
Geographic Dummy					
USDummy	-0.97 ***	-0.99 **	-0.99 **	-0.99 **	-0.97 **
	(0.38)	(0.48)	(0.48)	(0.48)	(0.47)
VC Investment Factor					
PC1		-0.60 ***	-0.60 ***	-0.60 ***	-0.54 ***
		(0.18)	(0.18)	(0.18)	(0.16)
Size					
PC2		-0.45 **	-0.45 **	-0.45 **	-0.46 **
		(0.21)	(0.21)	(0.21)	(0.21)
Early Stage Dummy					
PreDummy		1.98 **	1.98 **	1.98 **	2.02 ***
		(0.82)	(0.81)	(0.81)	(0.81)
Late Stage					
PC3		-0.56 **	-0.56 **	-0.56 **	-0.51 **
		(0.28)	(0.27)	(0.27)	(0.26)
Therapeutic Area					
CancerDummy		0.05	0.05		
		(0.49)	(0.47)		
Biologics Dummy					
BioDummy		0.00			
		(0.47)			
Platform Dummy					
PlatformDummy		0.55	0.55	0.55	
		(0.48)	(0.47)	(0.47)	
LR χ^2	23.220 ***	64.900 ***	64.900 ***	64.890 ***	63.490 ***
AIC	177.179	149.501	147.500	145.511	144.917

Table 8: Logistic regression on trade sale versus ipo sample.
Significance (sig.) codes 0.01 '***', 0.05 '**' and 0.1 '*'.

above are used to examine the relation of those variables to trade sale and IPO exit strategies. Due to the bivariate nature of the dependent variable, this paper employs a logistic regression methodology. Before applying the logistic regression model, this section presents five assumptions, based on Wright [32], underlying the methodology used and elaborates whether they are fulfilled for this paper. This procedure ensures the validity of the logistic regression results [32]. The first assumption requests the binary design of the dependent variable. Based on the dataset used for the regression analysis, the first assumption can be confirmed. The dichotomous variable takes the value 1 for firms which exit via a trade sale and 0 for companies which go public. The second assumption requires the outcome to be statistically independent. According to Wright [32], this means that a single case can be represented in the dataset only once. No firm is allowed to show more than one outcome. Undoubtedly, this assumption is met as all companies either exits via trade sale or via an IPO. As all firms in the data sample were private before exiting, no firm in the trade sale sample was listed previously. Also, the applied model must contain all relevant data and no irrelevant predictors. The omission of theoretically important variables as well as the inclusion of irrelevant predictors may lead to incorrect estimates of coefficients for variables in the model. Based on a thoroughly performed hypotheses development and variables selection, the inclusion of irrelevant data can be denied. In contrast, the condition to cover all relevant data in the model cannot be ensured completely. In practice, however, this assumption is rarely met [32]. Furthermore, to prove the goodness of fit- for-all regression models, this paper consults χ^2 and AIC. The fourth assumption requires that the dependent variables "must be mutually exclusive and collectively exhausting" [32]. As a firm can either get acquired or go public but cannot do both at the same time, the dependent variable can be assumed to be mutually exclusive. Furthermore, it is collectively exhausting, as every company in the sample exited through one of both strategies. Finally, the application of the logistic regression model requires a sufficient large sample, even larger than for a linear regression analysis. This is because standard errors for maximum likelihood coefficients are large-sample estimates. According to Aldrich and Nelson [40], a minimum of 50 cases per predictor variable is assumed to be sufficient. As this paper is based on a final dataset of 142 companies, each predictor variable has 142 cases. Consequently, the fifth assumption can be approved.

Following the model assumption guideline presented by Wright [32], the data structure used in this paper satisfies the conditions to apply a logistic regression model to analyze the hypotheses.

Results of the logistic regression

To test the six hypotheses, five different logistic regression models are used to compare the quality of different regression models and to find the model with the highest explanatory power. The following logistic regression model, corresponding to Model 2 (Table 8), was estimated and tested in a step-wise approach:

[0 if IPO or 1 if trade sale]=α_9+β_1 LehmDummy+β_2 USDummy+β_3 PC1+β_4 PC2+[β]_5 PreDummy+β_6 PC3+β_7 CancerDummy+β_8 BioDummy+β_9 PlatDummy+ε_9. (9)

The five logistic regression models are provided in (Table 8). The models are adjusted for two control dummies—first, for a Lehman

Number	Hypothesis	Supposed Influence Factors pre PCA	Tested Influence Factors post PCA	Result
1	Firms with less developed products show a positive relation to the probability that VCs will exit via a trade sale.	- *PreDummy:* Positive - *MarketDummy:* Negative - *LNRev:* Negative	- *PreDummy* : Positive Late Stage Compnent (PC3) - *MarketDummy* : Negative - *LNRev* : Negative	Proven
2	Firms with a lower indexed VC investment factor show a positive relation to the probability that VCs will exit via a trade sale.	- *LNIn:* Negative - *Investors:* Negative - *Rounds:* Negative - *Duration:* Negative	VC Investment Structure Component (PC1) - *LNIn* : Negative - *Investors* : Negative - *Rounds* : Negative - *Duration* : Negative	Proven
3	Smaller companies show a positive relation to the probability that VCs will exit via a trade sale.	- *LNEmp:* Negative - *LNOut:* Negative	Size Component (PC2) - *LNEmp:* Negative - *TLNOut* : Negative - *LNIn* : Negative	Proven
4	Firms whose lead product belongs to the field of oncology show a smaller probability that VCs will exit via a trade sale.	- *CancerDummy:* Negative	- *CancerDummy:* n/a	Not proven
5	Firms whose lead product is biologic in nature show a positive relation to the probability that VCs will exit via a trade sale.	- *BioDummy:* Positive	- *BioDummy:* n/a	Not proven
6	Firms with a platform show a smaller probability that VCs will exit via a trade sale.	- *PlatformDummy:* Negative	- *PlatformDummy:* n/a	Not proven

Table 9: Summary of hypotheses for trade sales vs. ipo strategies.

dummy, due to the significant impact of the financial crisis on overall IPO activities; and second, for a US dummy due to the larger size of US exits in the sample.

The first model includes just the two control variables, LehmDummy and US Dummy, not related to any of the six hypotheses. This model was mainly included to test the improvement over the first model while adding the other independent variables relevant for the hypotheses. It can be seen from (Table 8) that the first model has rather low explanatory power compared to the following four models, when including the other more relevant independent variables. Also, a full model, named as model 2, was employed to estimate the effect of all variables on the probability of a trade sale. The subsequent models 3, 4, and 5 follow a step-wise approach and removes variables with coefficients that are not significant different from zero at the 90 percent level and improve the models most by being removed. Each model is evaluated with χ^2 and AIC. The provided coefficients cannot be interpreted directly as they are logit coefficients.

Compared to the first model, the second model has an improved goodness of fit as the AIC is much lower. Based on Model2, the VC investment structure component (PC1), the size component (PC2), the early stage dummy (Pre Dummy), and finally, the late-stage component (PC3) show coefficients being significantly different from 0. The coefficients for the therapeutic area (Cancer Dummy), biologics dummy (Bio Dummy), and for the Platform Dummy (Plat Dummy) are not significantly different. As multicollinearity is no issue within the logistic regression analysis due to the previously conducted PCA, Model2 could be applied for analyzing the six hypotheses. However, a steady improvement of the models is observed by removing the most insignificant variables throughout the models 3 and 4. This leads finally to Model5 with the lowest AIC, which will be used to evaluate all particular hypotheses. As all five models show significant χ^2, this calls for an overall good fit of all five models.

Model5 shows that companies that exited within the years 2008 and 2009 have higher probabilities for a trade sale. The coefficient of the US Dummy indicates a negative relation to the probability for a trade sale. Turning now to the more relevant variables to evaluate the hypotheses indicates a confirmation of the VC investment structure hypothesis, the size hypothesis, and the stage of development hypothesis. First, the VC investment structure component shows that more intense investment activities-described by LNIn, Rounds, Duration and Investors—are related to the higher probability that VCs exit via an IPO. Also, the size component shows that larger transactions are more likely to be IPOs. Based on the results of the PCA, it can be assumed that the volume of VC capital invested relates to the size component as well. Therefore, firms which have more employees show larger transaction values and additionally got more venture capital-hence, they are more likely to go public. Further, firms which have more developed products and already show revenues are more likely to go public. In contrast, companies whose lead product is still in the pre-clinical phase show a positive probability to get acquired and are less likely to go public. The variables for the therapeutic area hypothesis and the biologics hypothesis show coefficients around zero, which do not provide a clear tendency for one of the two exit strategies. Furthermore, both coefficients are insignificant. Finally, the platform hypothesis presents a positive coefficient, indicating that firms with platforms are more likely to get acquired. However, the coefficient is not significant as well.

Summary of Results

Summing up the results from the above subchapters, three out of the six developed hypotheses could be confirmed. Biotechnology companies that follow a trade sale exit strategy show a lower indexed VC investment structure. They receive capital in fewer rounds, show a shorter time to exit, include fewer investors in the investment process, and finally, receive less total VC. Additionally, acquired companies are smaller and measured by the number of employees as well as the transaction value. Based on a PCA performed before the logistic regression analysis, it is shown that the volume of total

capital invested also explains some variance of the size component. Therefore, it can be assumed that larger companies are more capital-intensive. The last confirmed hypothesis has shown that firms with pre-clinical lead products rather get acquired and firms with marketed lead products show a higher probability for the IPO exit strategy. As assumed, pre-clinical products are negatively and marketed products are positively related to the revenues generated. (Table 9) provides a summary of the results.

The next chapter will discuss the results in the context of the literature review provided in Chapter 2. Additionally, it will discuss the implication of these findings for practitioners and will present the implications of this study.

Discussion

This chapter critically assesses the empirical results presented in Chapter 5.It firstly discusses the results of this study in the context of the most relevant studies and secondly it will address limitations of this thesis and give suggestions for future research.

Discussion of results

First, this section deals with the results of the two control variables, LehmDummy and US Dummy, before the focus is placed on the discussion of the six hypotheses.

The results indicate that during the years 2008 and 2009, which were highly characterized by the Lehman Brothers bankruptcy, a significantly small number of firms went public. While roughly 21 percent of the 142 analyzed firms were acquired, just around 1.5 percent of the firms exited via an IPO (Table 3). This result is in line with several studies [12,2,41-43], which shows that firms go public when markets are hot and prefer other exit alternatives when the overall market conditions are rather weak. Accordingly, this paper shows that the biotechnology industry is not immune to economic distress. Although acquisitions profit from overall good market conditions, they can benefit from low costs of capital, which makes acquisitions less costly.

The second aspect gives evidence that US firms show a higher probability for IPOs, whereas European firms prefer the trade sale exit. This is in line with the findings of Hege et al. [19] showing that a trade sale is the preferred exit route in Europe as well as Black and Gilson [22], who state that going public is the most frequent exit route in the US due to the better stock market environment. Furthermore, the fact that US firms are more strongly represented in both data samples indicates that the VC industry is still more active in the US. An addition explanation is that the US has a stronger biotechnology industry per se, which might explain the higher demand for VC. Consequently, the higher number of US exits would be a natural consequence of the higher number of existing biotechnology firms in the US. However, it has to be mentioned that many firms had to be dropped due to missing values, which may bias the geographical representation as well as distribution of exits in the sample.

The results of Hypothesis 1 have shown that firms with pre-clinical products rather get acquired, while companies generating revenues and/or having marketed products tend to go public. Arguing in the light of asymmetric information and risk mitigation confirms that outside investors expect revenues and Clinical Phase III products from firms going public [9]. Furthermore, it can be proved that buyers are more willing to acquire earlier-stage firms with the associated risks. This indicates that strategic buyers have a deeper understanding of biotechnology products and accordingly are better skilled to detect early-stage top shots. Furthermore, they might be looking for specific products to complete and enhance their own pipeline, and therefore are interested to buy a small biotechnology company. Additionally, it has been shown that biotechnology firms with less developed products have lower valuations [24,26], which makes these targets more attractive to buy.

The results of Hypothesis 2 of this study address differences in the VC investment structure. The results show that trade sale targets receive less capital from less investors in less rounds and in a shorter time compared with firms that go public. This is in line with different authors, who show that IPOs receive more financing [14,16] and have more financing rounds [16]. However, it does not provide evidence for the result of Giot and Schwienbacher [17], who show that larger syndicates raise the likelihood for a trade sale due to the advantage of a broader network. Importantly, this study confirms significant interdependencies between the four variables. This addresses weaknesses of other studies [13,14,16,21] that test some of those four factors independently. Therefore, it can be assumed that the insignificant results for the number of financing rounds provided by Wang and Sim [14], and the duration presented by Cumming and Macintosh (2003) as well as Achleitner et al. [21], are caused by multicollinearity problems.

One explanation for the positive relationship between the VC investment structure factor and the probability for an IPO is purely based on asymmetric information on the agency theory as well as on the pecking order theory [17-20]. Following these approaches means that VCs monitor intensively. So, staging allows VCs to identify companies of high quality. Consequently, they inject more capital as monitoring costs decreases [16] and more investors get involved to spread their investment exposure [39]. Finally, in line with the duration hypothesis of Cumming and Macintosh [13], the process to mitigate information symmetry, and to identify high-quality targets takes time and results in longer durations.

An alternative explanation for the higher indexed VC investment factor of IPO candidates is in line with the fact provided by Behnke and Hültenschmidt [9]. They show that biotechnology firms going public have to fulfill more requirements that are more costly. Therefore, this paper mainly argues that VCs who like to make a company public simply need more capital and more time due to the requirement to show products in advanced clinical stages and/or revenues. It can take up to roughly 20 years to bring a product to the market. In line with the first argumentation, VCs like to diversify their capital exposure, which requires more investors and additional staging to monitor particular milestones.

Hypothesis 3 shows that larger firms go public. This confirms the results of Brau et al. [12], and supports the argumentation that size indicates that a private firm can successfully survive as an independent company. Additionally, as going public is more costly, it is likely that small firms have too few resources to support the listing.

The therapeutic area and biologics hypotheses do not provide

statistically significant results. Furthermore, as the coefficients are around zero (Table 8), no interpretation in favor of one of the two exit strategies can be made. One explanation for this result is that this study exclusively focuses on a company's lead product and not on the whole portfolio. This might implicate that the diversification of a product portfolio could play a more dominant role in the trade sale versus IPO decision framework than the therapeutic area, or the existence of products which are biologic in nature. Alternatively, it might be that patent losses drive large pharmaceutical companies to search for smaller biotechnology companies to gain access to new products. Accordingly, to counteract patent cliffs [1], they are looking for a product fitting its strategy and therefore are indifferent between different therapeutic areas or whether a firm produces biologics. Finally, it might be that biologics are comparably attractive for both strategies as they are more immune against biosimilars compared to chemical drugs [1]. Therefore, firms with drugs which are biologic in nature are less exposed to competitors, being an advantage for both exit strategies.

With regard to technology platforms, Hypothesis 6 does not provide significant results as well. However, the positive coefficients in Models 2, 3, and 4 indicate a higher probability for trade sales, which is in contrast to Hypothesis 6. A possible explanation could be that large pharmaceutical companies might be strongly interested in the strong IP background of platform technologies. Hence, this effect overweighs the argument by Gompers [30], who mentions that biotechnology companies would like to protect their IPs.

Limitations

This paper includes two main limitations. The first belongs to the third point of the model assumption in accordance with Wright [32], as laid out in Chapter 5.2.1. The second limitation addresses the data sample size.

According to Wright [32] the applied model must contain all relevant data to mitigate incorrect estimates of coefficients for variables included in the model. Since the regression results of all five performed models (Table 8) show a statistically significant goodness of fit, it indicates that the results of the regression models are very solid. Additionally, as the coefficients of the particular variables and components employed do not vary much between the different models, problems of multicollinearity can be excluded. Furthermore, the research on possible independent variables prior to this paper was very comprehensive, and many different variables were gathered to enable the inclusion of as many variables as possible. Also, the existing literature has shown that other variables are important for the prediction of a trade sale versus IPO strategy [12-15]. However, it can be assumed that the inclusion of those broad market factors would have improved the overall goodness of fit for all models, but not altered the coefficients significantly. Due to the diversity of biotechnology companies, however, the inclusion of more product-, firm- and acquirer-specific variables would have provided additional interesting results. However, larger data samples would be required to get meaningful results. This directly leads to the second limitation of this paper.

This paper includes 142 firms, which, according to the model assumptions laid out in, is enough to provide solid results and represents a fairly representative sample size. However, as mentioned above, a larger sample would have allowed investigation of even more variables. To achieve a larger data set a longer period of time could have been used and/or the missing data could have been interpolated. The extension of the time period would have exceeded the scope of this paper. Additionally, no interpolation was performed as the characteristics and structures of the different biotechnology companies are diverse. Therefore, interpolation is assumed to bias the whole dataset, instead of improving it by making the dataset representative.

Different areas are interesting for future research. In particular, the profitability of exit strategies. Accordingly, it would be of interest for future researchers to analyze valuation drivers for biotechnology firms. Different authors [2,7,8,10,24,25,26] have already addressed biotechnology valuation drivers. Analyzing for more recent time periods and further variables (especially firm- and product-specific factors) would be of high interest. Additionally, investigations of post-exit performances of IPOs and trade sales provide space for further investigation to provide a more detailed picture with regard to the profitability of VC exits. To better compare IPO and trade sale exit returns, it would make sense to consider the lock-up period as well as dilution while calculating IPO exit returns along with the exact percent of milestones payment paid out to VCs in a trade sale.

Conclusion

The paper analyzed factors addressing VC investment structure variables as well as firm- and product-specific factors. In contrast to the existing studies, except the paper of Lerner [15], the paper analyzes a homogenous dataset of biotechnology companies, which makes the inclusion of financing as well as firm- and product-focused factors more meaningful. The paper analyzed 142 European and US privately VC-backed companies which exited between 2005 and the second quarter of 2014 via a trade sale or an IPO. By referring to the research question of which factors are responsible for a higher probability that VCs exit via a trade sale than an IPO, a logistic regression model was applied. A sample of 67 trade sales and 75 IPOs was used to estimate an exit model. Based on the available data and results presented in the existing body of research, six hypotheses were formulated.

The results confirm that firms with pre-clinical products have a positive influence on the trade sale probability. Firms with marketed products and/or revenues show higher probabilities for an IPO. Additionally, companies that exit via a trade sale have a lower indexed VC investment factor. This means they get lower amounts of VC, involve fewer investors, show fewer financing rounds, and finally, have a shorter time to exit. Furthermore, it has shown in line with Brau et al. [12] that the larger firms rather go public. The remaining Hypotheses 4, 5, and 6, addressing the therapeutic area, biologics and technologic platforms, did not deliver statistically significant results.

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