Many Cooks, Bitter Flavor? Venture Capital Syndicate Size and IPOs

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Dissertation written under the supervision of Professor Vítor Pereira

Dissertation submitted in partial fulfilment of requirements for the MSc in Finance, at the Universidade Católica Portuguesa, 05.01.2026.

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Abstract (PT)

Esta tese investiga se um maior número de sindicatos de venture capital (VC) está associado a uma maior ou menor duração experienciada por uma empresa até uma oferta pública inicial (IPO). Com foco no sector de saúde dos EUA, foram compilados dados sobre 18.292 rondas de financiamento de 6.019 empresas apoiadas por capital de risco observadas entre 1980 e 2024. A estratégia empírica baseia-se em modelos de sobrevivência ao nível da ronda de financiamento, em particular através do modelo de referência de riscos proporcionais. Os resultados base, suportados por análises de robustez, indicam consistentemente que um maior número de sindicatos está associado a IPOs mais rápidos. Em particular, o modelo base sugere que um VC adicional está associado a um aumento da taxa de risco de IPO de, aproximadamente, 13%. Este resultado mantém-se consistente quando considerados dois modelos que consideram a possibilidade heterogeneidade específica não observada. De forma a investigar a possibilidade de não linearidades na probabilidade de IPO, é também estimado um modelo profit quadrático. Os resultados mostram ainda uma relação em U invertido entre o tamanho do consórcio e a probabilidade de IPO, com um ponto de inflexão implícito em torno de 13 investidores.

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Palavras-chave: Capital de risco; Análise de sobrevivência; Sindicação; Tamanho do sindicato; Tempo até IPO; Modelo de riscos proporcionais de Cox

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Abstract (ENG)

This thesis investigates whether larger venture capital (VC) syndicates accelerate or impede a firm's path to an initial public offering (IPO). Focusing on the U.S. healthcare industry, data on 18,292 financing rounds from 6,019 venture-backed firms observed between 1980 and 2024 is compiled. The empirical strategy relies on round-level survival models that explicitly address right censoring, as many firms do not go public within the sample window. Across the baseline Cox proportional hazards model and additional robustness checks, the results consistently indicate that larger syndicates are associated with faster IPOs. In the Cox proportional hazards model, each additional VC is associated with an increase in the IPO hazard of about 13%. To assess sensitivity to modelling assumptions, the thesis examines an accelerated failure time model, accounts for firm-specific unobserved heterogeneity through a Heckman-Singer specification and captures environmental heterogeneity with a shared frailty Cox model. Across these extensions, the main result remains consistent. To examine nonlinearities in IPO likelihood (rather than timing), a quadratic probit model is estimated. The results indicate an inverted-U relationship between syndicate size and IPO likelihood, with an implied tipping point around 13 investors.

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Keywords: Venture capital; Survival analysis; Syndication; Syndicate size; IPO timing; Cox proportional hazards

Acknowledgements

I would like to express my deep gratitude to my parents and my brother for their constant encouragement and support throughout my studies and the completion of this thesis.

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List of Abbreviations

Abbreviation	Definition
AFT	Accelerated Failure Time
Cox PH	Cox Proportional Hazards
HR	Hazard Ratio
IPO	Initial Public Offering
KM	Kaplan-Meier
VC	Venture Capital

1. Introduction

Venture capital (VC) plays a central role in startup development as it provides more than just financing. Beyond risk capital, VC investors contribute experience, know-how, and access to networks. Young firms often lack these resources, even though they are critical for building and scaling a business. In addition, VC financing can mitigate information asymmetry. When a firm attracts VC funding early, it can serve as a credibility signal to the market, which can make it easier to attract further resources (Jeong et al., 2020). The relevance of VC is particularly pronounced in healthcare. The sector combines large financing needs with high uncertainty, which makes external risk capital highly valuable. Apart from that, it is characterized by R&D intensity, long development cycles and significant regulatory hurdles (Tarannum et al., 2025).

From an investor's perspective, healthcare has historically been seen as a defensive sector that tends to attract more capital during economic downturns because it is a comparably stable market. The rising importance of personalized medicine, telemedicine solutions and data-driven diagnostics, however, has shifted the sector's image from stable to high growth. This makes it an increasingly transformative space that attracts dedicated VC funds (Tarannum et al., 2025). Even despite the broader slowdown in venture markets in 2022, U.S. healthcare focused VC funds still managed to raise around $22 billion, signaling that investor demand for the sector remains robust (Gai et al., 2024). At the same time, recent work shows that U.S. healthcare startups attract the majority of global health-related VC. The U.S. is not only the world's biggest healthcare market but also a net importer of high-risk capital for healthcare innovation, with particularly strong inflows into biopharmaceuticals and healthcare technology (Ji & Kang, 2025).

A very common phenomenon in VC is the syndication of multiple investors in one financing round. A VC syndicate is an arrangement where two or more venture capitalists (VCs) jointly participate in financing the same venture (Brander et al., 2002). These syndicated deals account for roughly two-thirds of all VC deals (Das et al., 2011). The most common explanations for VC syndication in the literature are the selection and the value-add hypotheses (Brander et al., 2002). By joining forces, investors generally aim to achieve better investment outcomes. Out of these outcomes, IPOs are commonly described as the most successful and preferred exit route for VCs, which makes them the benchmark for venture success (Kim & Park, 2021).

Building on that idea, this thesis examines whether VC syndicate size affects how quickly venture-backed U.S. healthcare firms reach an IPO. Using round-level data, it measures the time from the start of an investment round to the IPO event. The empirical strategy relies on survival analysis, which is well-suited for modelling time-to-event outcomes and originated in medical research, where the event of interest often is time-to-death (Clark et al., 2003). A key advantage is that it naturally incorporates firms that do not go public within the observation window by treating them as right-censored observations rather than excluding them (Kleinbaum & Klein, 2012). The thesis then estimates hazard-based specifications to quantify how syndicate size is associated with IPO timing. Overall, the estimates indicate that larger syndicates are associated with a faster path to IPO. At the same time, the evidence suggests that the benefits of syndication do not grow indefinitely. Beyond a certain syndicate size, the IPO probability drops because the costs of syndication outweigh its benefits.

The remainder of the thesis is structured as follows. Section 2 reviews the literature on VC syndication, syndication size, and IPO outcomes. Section 3 describes the data, sample construction, and key variables. Sections 4 then sets out the empirical strategy, followed by the main results and robustness checks in Section 5. Lastly, section 6 concludes with implications for research and practice and outlines directions for future research.

2. Literature Review

Academic research does not tie VC syndication to a single purpose. Instead, it is typically described as a multi-motive arrangement that helps VCs cope with uncertainty and resource constraints in financing ventures. At the venture-level, these motivations are commonly sorted into three broad groups: risk sharing and diversification, information production through "second opinions" in screening, and value creation inside the venture by combining complementary skills, monitoring capacity, and networks across investors (Jääskeläinen, 2012).

2.1 Motivation behind Venture Capital Syndication

Within this broader taxonomy, Brander et al. (2002) focus on the two mechanisms that operate through screening and post-investment involvement. They then formalize them as competing hypotheses with opposite empirical predictions.

The selection hypothesis states that a lead investor can use syndication to bring additional VCs into the screening process before committing funds. Even after conducting its own due diligence, the lead VC may remain unsure about the venture's prospects and therefore seek additional partners. Because several independent investors compare their views and learn from each other's evaluations, they may be able to filter projects more effectively than a single VC acting alone. From this perspective, mainly borderline investments are syndicated, while obviously attractive investments are kept as solo deals. The selection hypothesis thus predicts lower average returns for syndicated investments compared to solo deals.

The value-added hypothesis, on the other hand, originates from the idea that VCs do more than just picking winners. By forming syndicates, investors expect the portfolio companies to become more valuable, as they can collectively improve how the venture is run. Each VC can bring value through their skills, monitoring and networks. The flip side is that the lead investor must give up part of the profit to its partners, so syndication will only be attractive when the anticipated extra value outweighs the cost of sharing the upside. If this reasoning holds, syndicated investments should, on average, earn higher financial returns than stand-alone deals.

2.2 Syndication and Investee Company Performance

The most common strategy to manage the risks and resource demands of VC investments is to form syndicates. Only around 5% of VCs never enter a syndicate, and those investors tend to be small firms (Bubna et al., 2020). After knowing that, the question that arises is whether the size of the syndicate has an influence on later IPO success. Previous literature on the relationship of syndication and time-to-IPO has already found significant results. Das et al. (2011) compare syndicated with non-syndicated investments. Their evidence indicates that syndicated ventures are more likely to achieve a successful exit and in survival models tend to exit faster overall. This finding strengthens the broader premise that collaboration among VCs can shape both the probability and timing of successful exits.

After knowing that syndicated investments perform better, the question arises whether the size of a syndicate influences the time-to-exit. Giot & Schwienbacher (2007) analyze this question by modelling exits via a competing risks survival framework comparing IPO, trade sale and liquidation. They find that the time-to-IPO decreases with a higher syndicate size. Based on their simulations for the exit timing, increasing the syndicate from two to four VC firms reduces the time-to-IPO by about 13%, and increasing it further from four to eight reduces it by about another 21%. They interpret this as evidence that additional syndicate partners contribute value-add and certification, e.g. by widening the network and helping to attract reputable underwriters. As a result, IPO exits in particular can be executed more quickly.

Gejadze et al. (2023) revisit VC exit dynamics with another competing-risks framework that allows key deal characteristics, such as syndication and funding patterns, to evolve over the investment's life. In their results, the shortest VC incubation periods occur when investments are both syndicated and completed in a single round, which suggests that speed is particularly pronounced when syndication coincides with a "one-shot" financing structure rather than protected staging. Surprisingly, a simple increase in syndicate size does not significantly change the time-to-IPO. This finding differs from the previous paper. Tian (2012) also links syndicate structure to exit outcomes via a logit model and reports that larger syndicates are associated with a higher likelihood of IPO exits. In his baseline estimates, adding one more VC to the syndicate increases the probability of an IPO by about 1.7%. Kim & Park (2021) nuance this further by arguing that the relationship is not necessarily linear. They propose that additional syndicate members bring more diverse resources but also rising coordination costs. This way the net effect can turn negative once the investor group becomes "too large." Empirically, their results are consistent with an inverted-U pattern in IPO likelihood, which peaks at around five to six VC firms.

Evidence from outside the U.S. suggests that institutional context can matter for how syndicate size translates into IPO-related outcomes. Using German Neuer Markt IPO data, Lehmann & Boschker (2003) analyze the post-IPO performance of standalone and syndicated investments. They do not find robust performance differences between the two groups across several post-IPO outcomes. Additionally, the probability of delisting is not meaningfully explained by whether one or multiple VCs financed the firm. By contrast, in a sample of Chinese VC investment events, Yang (2018) reports that a larger syndicate size is associated with a higher probability of IPO exit. In his competing risks model, he further shows that a larger syndicate is even linked to a lower likelihood of trade-sale exits. This suggests that bigger investor groups may tilt the exit route toward IPOs rather than Mergers & Acquisitions.

3. Data

This thesis combines information on deals, portfolio companies, and participating VC investors to examine how VC syndicate size relates to IPO timing. The data has been extracted from Refinitiv Eikon and covers the period from 01/01/1980 to 31/12/2024. The unit of observation is a firm financing round, meaning that one company can appear multiple times in the dataset, once for each investment round.

To arrive at the final sample, a series of sample restrictions is implemented. First, the analysis is restricted to the healthcare sector only, which is further split into "healthcare & equipment" and "pharmaceutical & medical research." Focusing on a single industry helps to reduce unobserved heterogeneity in factors such as regulation, technological dynamics and exit opportunities, and therefore makes firms more comparable for the analysis. The analysis then focusses strictly on IPOs, because they are commonly seen as the benchmark for venture success, as described before (Kim & Park, 2021). The sample is further cleaned to address data-quality issues. Negative durations are removed from the sample and the investee company status is restricted to "active" or "in registration" as only these firms remain at risk of an IPO within the survival framework.

3.1 Definition and Measurement of Variables

The final sample consists of 18,292 unique investment rounds from 6,019 venture-backed companies. Following Giot & Schwienbacher (2007), the financing rounds are described using two groups of variables: those associated with the entrepreneurial firms and those associated with the VC organizations. Table 1 summarizes the variables used in the empirical analysis.

Table 1: Variable Definitions

Variable	Definition
VC firm related	
Syndicate size	Number of VC firms investing in one investment round.
Age of oldest VC	Variable accounting for the experience of a VC. Age of the oldest VC firm in the syndicate (in years).
VC proximity	Dummy variable. Takes a value of one if at least one VC firm in the syndicate is in the same U.S. state as the entrepreneurial firm.
Round number	Indicates the financing round number.

Entrepreneurial firm related	
IPO exit	Dummy variable. Takes a value of one if the firm went public after a specific investment round.
Duration	Number of days elapsed between the date at which the round began and the exit date if there was an exit.
Stage of development	Dummy variables. Split into seed, early, expansion and later stage.
Stage advancement	Dummy variable. Takes a value of one if there was an advancement in the development stage from one investment round to the next (e.g. seed to early stage)
Geographical location	Dummy variables. West (California), Northeast (Massachusetts, New York and Pennsylvania), South (Texas), Midwest (Illinois and Ohio), and other.[1]
Log of total investment amount	Total amount of money received by the firm at the given round (in millions of USD).
Age of investee company	Variable accounting for firm maturity. Age of the investee company at time of investment (in years).
Macro related	
IPO activity	Measure of stock market liquidity. Number of IPOs in a given year on the most important U.S. stock exchanges (NASDAQ, NYSE and AMEX).[2]

Notes: Summary of the variables and their definitions used in the empirical study.

To isolate how VC syndicate size relates to IPO outcomes, the analysis models IPOs at financing-round level. Therefore, it needs variables that capture both the outcome of interest and the most important alternative drivers of IPO timing. The IPO exit indicator is included to identify whether a given round ultimately leads to a public listing, while duration measures the time from the start of that round until the IPO occurs. If there was no IPO, duration measures the time until the next investment round or the right censoring date. These are the key variables for a time-to-event analysis.

The core explanatory variable, syndicate size, captures the number of VC firms investing in the round. Apart from that, on the investor side, age of the oldest VC proxies for syndicate experience and reputation, capturing that more mature investors may bring stronger networks and a bigger value-add, but may also pursue different exit pacing than younger funds. Round number controls for where the round sits in the financing sequence, which matters because later rounds generally coincide with higher valuations and shorter remaining distance to IPO (Giot & Schwienbacher, 2007). To capture the role of informational frictions and hands-on monitoring, VC proximity indicates whether at least one syndicate member is located in the

[1] The classification follows Lerner et al. (2005).
[2] This data was obtained from Ray Ritter's web page.

same state as the portfolio company. This accounts for the possibility that local investors can monitor more closely and provide more operational support than distant investors.

Because IPO timing is strongly shaped by where a company stands in its lifecycle, the model controls for the stage of development (seed, early, expansion, later). This accounts for the fact that more mature firms are typically closer to commercialization, governance formalization, and the reporting standards expected in public markets (Lowry, 2023). Related to that, stage advancement indicates whether the firm moves up in stage from one round to the next. This helps to separate the effect of syndicate size from shifts in maturity and milestone completion that can independently change the likelihood and speed of an IPO. As a company evolves and moves up the stages of development, usually the deal scale becomes larger. To control for the intensity of funding associated with IPO readiness, the total investment amount at a given financing round is included. For the analysis the natural logarithm of the total amount is used to reduce skewness and allow a more interpretable proportional effect. Since venture outcomes and exit opportunities differ across U.S. regions due to talent pools, specialized investors, and local ecosystems, geographical location dummies are included to absorb persistent regional advantages. As a final firm-level control, the analysis includes the age of the investee company. Firm age captures an additional dimension of maturity that is not fully reflected by development stage alone. Companies can be in the same stage but differ substantially in how long they have been operating, which can affect, for instance, organizational readiness for public markets.

Finally, IPO activity is included as a macro control that reflects overall market liquidity and sentiment in a given year. This ensures that faster IPOs during hot markets are not mistakenly interpreted as an effect of syndicate composition rather than favorable exit conditions.

3.2 Descriptive Analysis of the Dataset

Before going into the methodology and empirical results, the dataset is first examined through descriptive statistics. Table 2 summarizes the main characteristics of the sample and compares key variables between rounds that lead to an IPO and those that do not. It reports means for the full set of observations with standard deviations in parentheses.

Table 2: Main Descriptive Analysis

	All	IPO	Non-IPO
VC firm related			
Syndicate size	3.12	4.80	3.03
	(2.79)	(4.26)	(2.66)
Age of oldest VC	36.69	37.77	36.63
	(20.33)	(23.65)	(20.14)
VC proximity	0.47	0.46	0.47
	(0.50)	(0.50)	(0.50)
Round number	3.49	4.61	3.43
	(3.11)	(3.38)	(3.09)
Entrepreneurial firm related			
IPO exit	0.05		
	(0.22)		
Duration	1088	557	
	(1868)	(827)	
Seed	0.14	0.06	0.14
	(0.34)	(0.25)	(0.35)
Early	0.40	0.32	0.41
	(0.49)	(0.47)	(0.49)
Expansion	0.22	0.26	0.22
	(0.42)	(0.44)	(0.42)
Later	0.24	0.36	0.23
	(0.43)	(0.48)	(0.42)
Log-Amount	0.61	0.96	0.59
	(0.78)	(0.84)	(0.77)
Age of investee company	5.58	6.53	5.53
	(4.95)	(6.11)	(4.88)

Notes: This table reports mean values for all financing rounds and separately for rounds that lead to an IPO vs. those that do not. Standard deviations are shown in parentheses. Dummy variables are reported as shares. Duration is in days; age variables are in years; Log-Amount is the natural log of the round amount. All rounds: N = 18,292; IPO rounds: N = 934; Non-IPO rounds: N = 17,538.

These descriptive statistics provide a first overview of how IPO rounds differ from the rest of the sample. IPOs are rare at the round level with only about 5% of rounds achieving this exit. This fits a survival setting in which most observations are censored. Apart from having, on average, a shorter duration to exit, IPOs occur at greater maturity levels and round numbers. The main variable of interest shows a strong descriptive pattern. In IPO rounds, syndicates are substantially larger and are additionally funded with higher capital intensity. In contrast, VC proximity is almost identical across groups. This suggests that any proximity effect, if there is one, might be weaker than for the already discussed variables. Taken together, these patterns already point toward an intuitive mechanism for the later analysis. IPOs appear more likely in later, larger rounds with broader syndicates and favorable market conditions. It is also notable that, when the number of IPO exits in the dataset is compared with the total amount of U.S. IPOs over the sample period, healthcare firms account for around 10% of all IPOs. This provides additional context for the sector's presence in public market exits.

Table 3 provides a more detailed view of the main explanatory variable by reporting the distribution of syndicate size across financing rounds. This breakdown helps to understand how common different syndication sizes are in the dataset.

Table 3: Distribution of Financing Rounds along Syndicate Sizes

Syndicate size	Frequency	Percentage	Cum. Percentage
1	6,853	37.46%	37.46%
2	3,565	19.49%	56.95%
3	2,099	11.47%	68.43%
4	1,668	9.12%	77.55%
5	1,211	6.62%	84.17%

Notes: Frequency and percentage distribution of syndicate size. Cum. Percentage shows the cumulative share of observations up to and including each syndicate size category and sums up to 100%. Mean = 3.12; Median = 2; Min = 1; Max = 34.

The distribution indicates that a substantial share of rounds involves a single investor. At the same time, most rounds are syndicated with at least two investors. Overall, the mass of the distribution is concentrated in small syndicates, while very large syndicates occur only in a relatively small fraction of rounds.

4. Empirical Methodology

The previous chapter describes the sample, the construction of the main variables and explores some preliminary correlations that frame the upcoming empirical analysis. Building on that, this section lays out the empirical methodology used to analyze the time from the start of an investment round to an IPO of the portfolio company.

A key empirical challenge related to the study of durations from the start of an investment round to an IPO is that, within the sample period, not all firms go public. For these companies, the time-to-IPO is only partially observed, which creates censored survival-time data. This means that the true time-to-IPO is only known to be at least as large as the observed duration. As standard linear regression models can't deal with the latter issue, this empirical study employs survival analysis. It is designed for exactly this type of setting, where the variable of interest is the time until an event occurs and censoring is present (Kleinbaum & Klein, 2012).

4.1 Survival Analysis Framework

In line with Giot & Schwienbacher (2007), the survival analysis is conducted on a round-by-round basis. Rather than modelling time-to-exit from the first observed investment, each financing round serves as a new time origin. The outcome is defined as the remaining time-to-IPO measured from the start of that round until an IPO occurs. Otherwise, the observation is censored at the start of the subsequent round. This round-based design links the characteristics observed at at given funding round to the subsequent speed of exit from that point onward.

Let T denote the time from the start of a specific investment round to the IPO and t a specific value of time. In case the company did not go public in a specific round, T represents the time until the start of the new round. For firms that do not go public within the sample period, T is right censored at 31/12/2024.

Kleinbaum & Klein (2012) describe two core functions that summarize time-to-event data. On the one hand, the survivor function $S(t)$ gives the probability that the event time exceeds t, i.e. the probability of "surviving" beyond time t. The hazard function $h(t)$ on the other hand is defined as a limit of a conditional probability per unit time. The Cox model is built around the following hazard function:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t} \tag{1}$$

The above hazard function $h(t)$ can be interpreted as the instantaneous potential at time t that a firm goes public, given that it has not gone public before. It's important to note that the hazard is not a probability, has no upper bound, and depends on the unit in which time is measured (Kleinbaum & Klein, 2012).

Survival models can be organized into three broad groups that differ in how strongly they restrict the shape of the hazard over time: non-parametric, parametric and semi-parametric models. Jenkins (2004) discusses this taxonomy in terms of the functional form of the hazard and the amount of structure imposed on the baseline pattern of duration dependence. Non-parametric specifications estimate the survivor and hazard functions directly from the data without imposing any functional form (e.g. via Kaplan-Meier). These are mainly descriptive tools and serve as a benchmark for the empirical shape of the hazard. The second class are fully parametric models. Here, a specific distribution for survival times and thus a fully specified hazard function is assumed. Common examples are the Weibull and the Exponential models. Between these two extremes, there are semi-parametric approaches as well. They impose structure on how covariates enter the hazard but leave the baseline hazard over time unspecified. The best-known model in this group is the Cox proportional hazards (PH) model, which acts as baseline model in this thesis.

Beyond the degree of restrictions of the functional form, survival models also differ in the interpretation of covariate effects. The proportional hazards framework compares covariates through hazard ratios. On the other hand, many parametric models can be formulated as accelerated failure time (AFT) models, where covariates multiply the time scale. Characteristics accelerate or decelerate the time until the event, which is commonly summarized through time ratios rather than hazard ratios (Jenkins, 2004).

4.2 Cox Proportional Hazards Model Specification

This section introduces the baseline Cox PH model that is used for the analysis of time-to-IPO. The model is built around the hazard function conditional on the covariates X_i:

$$h_i(t \mid X_i) = \lim_{\Delta t \to 0} \frac{P(t \leq T_i < t + \Delta t \mid T_i \geq t, X_i)}{\Delta t} \tag{2}$$

This hazard describes the instantaneous conditional failure rate for firm i at time t, given that it has not gone public before t and conditional on X_i (Kleinbaum & Klein, 2012). The Cox PH model assumes that the hazard for firm i at time t can be written as:

$$h_i(t \mid X_i) = h_o(t) \exp(X_i' \beta) \tag{3}$$

where $h_o(t)$ is an unspecified baseline hazard common to all firms and $\exp(X_i' \beta)$ scales this baseline up or down according to the observed characteristics. The label "proportional hazards" reflects that the hazard ratio between any two sets of covariate values is constant over time. Put differently, the model assumes that the group with the higher hazard remains higher throughout the observation period. A central output of the Cox PH model is the hazard ratio (HR). In general, a HR compares the hazard for two different covariate values and is obtained by exponentiating the relevant linear combination of covariates. An HR of one indicates no association, whereas HRs greater than one indicate faster exits and HRs less than one slower exits (Kleinbaum & Klein, 2012).

Rather than specifying a parametric form for $h_o(t)$, the Cox PH model estimates β by maximizing a partial likelihood. It is called partial because it does not model the entire hazard function over time. Instead, it is constructed using the observed order of event times and focusses on contributions at observed failures. At each event time, the likelihood compares the covariates of the unit that experiences the event to the covariates of all units still at risk at that time. The set of firms under observation just before an IPO is the risk set $R(t)$, which shrinks as time progresses. Censored firms are treated as still being at risk until the censoring date (Lee & Wang, 2003).

5. Estimation Results

Table 4 summarizes the main estimates from the Cox PH model. A key modelling choice is that the regression is stratified by the investment round number. Stratification allows the baseline hazard $h_o(t)$ to differ across rounds, so that each round has its own underlying time pattern of IPO risk. At the same time, the estimated effects of the covariates are assumed to be the same across rounds. Because round number is used as a stratification variable, the model does not estimate a separate hazard ratio for it (Kleinbaum & Klein, 2012).

In line with the Cox framework, the model relates its covariates to the hazard of an IPO exit. Coefficients are reported as hazard ratios, which quantify how the hazard changes multiplicatively by increasing the syndicate size by one investor while holding other regressors constant. As multiple IPOs can occur at the same recorded time point, ties in event times are handled using the Breslow method. Standard errors are computed using robust variance estimates, which adjust inference when observations from the same firm may be correlated. The overall Wald test of the regression is highly significant, indicating that the covariates jointly explain a substantial part of the variation in IPO timing.[3]

Table 4: Estimation Results of the Cox Proportional Hazards Model

	Hazard ratio	95% confidence interval
VC firm related		
Syndicate size	1.13***	[1.10; 1.15]
Age of oldest VC	0.99***	[0.99; 1.00]
VC proximity	0.70***	[0.61; 0.82]
Entrepreneurial firm related		
Stage number 2 vs. 1	1.36**	[1.00; 1.82]
Stage number 3 vs. 1	1.32*	[0.95; 1.83]
Stage number 4 vs. 1	1.85***	[1.27; 2.72]
Stage advancement	0.77***	[0.65; 0.93]
West	1.46***	[1.24; 1.74]
Northeast	1.37***	[1.15; 1.64]
South	1.41*	[0.99; 1.99]
Midwest	0.87	[0.54; 1.40]
Log-Amount	1.21***	[1.38; 1.75]
Age of investee company	0.98	[0.96; 1.00]
Macro related		
IPO activity	1.00***	[1.00; 1.00]

*Notes: This table reports hazard ratios from the Cox PH model with IPO as the event. N = 18,292 financing rounds with 934 IPOs. Duration is measured in days from the start of each financing round until the next round or IPO; observations are right-censored at the end of the sample period. 95% confidence intervals are based on robust Huber-White standard errors. Model stratified by round number; no year, firm, or VC fixed effects included. Stage number 1 = Seed, 2 = Early, 3 = Expansion, 4 = Later. All values are rounded to two decimals. The stars ***, **, and * denote significance at 1%, 5%, and 10% levels.*

The central variable of interest is the syndicate size. The estimation suggests that, holding all other variables constant, adding one more VC to the syndicate raises the instantaneous probability of an IPO by about 13%. The effect becomes large when comparing higher changes in syndicate size, as hazard ratios are multiplicative. A syndicate with five investors instead of one has roughly $1.125^4 \approx 1.60$ times the IPO hazard, i.e. around 60% higher hazard. The controls behave largely as expected. Among the remaining VC related variables, the age of the oldest VC has a hazard ratio of 0.99, suggesting a small negative association. A one-year

[3] The Wald test evaluates whether the set of regression coefficients differs from zero as a group (Kleinbaum & Klein, 2012). Here, the p-value of the test is <0.001, which indicates strong evidence against the null and thus that the covariates are jointly significant.

increase is associated with about a 1% lower IPO hazard, keeping all else equal. One interpretation could be that older, more established investors pick safer but slower-exiting deals. VC proximity is associated with a hazard ratio of 0.70, which corresponds to a 30% lower IPO hazard compared to rounds without any VC investor in the same U.S. state. This result seems surprising as one might think that a geographically closer VC can give better support for the entrepreneurial companies.

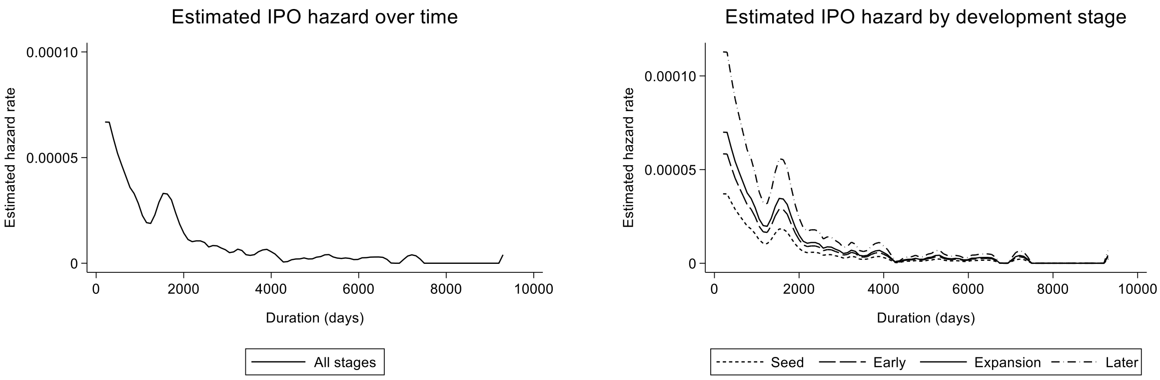
The stage indicators show strong differences in IPO timing across development stages. Firms that get financed at more advanced stages exit substantially faster than seed-stage firms. Relative to the seed stage, the hazard ratios are 1.36 for early stage, 1.32 for expansion stage and 1.85 for later stage. Put differently, later stage firms display substantially higher IPO hazards. This means that, conditional on survival up to time t, the event rate is considerably higher in these stages. This is consistent with the idea that they are closer to commercialization and therefore closer to being IPO-ready at the time of the investment round. The coefficient on the stage advancement indicator on the other hand is below one. This implies that rounds classified as advancing the company to a higher stage are associated with a lower IPO hazard relative to rounds that do not change the stage. This may reflect that stage-advancing rounds often occur in firms that are still building the capabilities needed for an IPO. The estimation result for the total amount of capital received in one round paints another interesting picture. The hazard ratio for log-amount is 1.21, meaning that a one-unit increase is associated with a 21% higher IPO hazard. This shows that bigger financing rounds shorten the time-to-IPO significantly. Because the amount is logged, a one-unit increase means the round size rises by a fixed percentage rather than by one extra dollar. Location also seems to play a role in the IPO likelihood. For instance, companies located in the West exhibit a hazard ratio of about 1.46 compared to any other region that is not listed. This implies a 46% higher hazard of going public. The hazard is also higher in the Northeast and South with 37% and 40%. In the Midwest, however, the coefficient is below one and statistically insignificant. Apart from that, the age of the portfolio company at the time of the financing round is statistically insignificant at standard significance levels as well, pointing to no clear difference in IPO speed.

Finally, IPO activity has a hazard ratio that is reported as 1.00 due to rounding. Using one more decimal place, the hazard ratio is 1.004 which indicates a slightly positive effect. IPO exits occur at a higher rate in years where the overall IPO market is more attractive, because the market conditions are favorable. For instance, an increase of 10 IPOs in a specific year corresponds to a $1.004^{10} \approx 1.04$, i.e. 4% higher IPO hazard.

5.1 IPO Hazard and Survival Over Time: Graphical Evidence

In the Cox PH model, the results are interpreted in terms of hazard ratios, meaning the relative change in the IPO hazard associated with a covariate. By contrast, Figure 1 shows estimated hazard rates, which describe the absolute level of IPO risk over time. Hazard rates therefore show when IPO exits tend to occur, while hazard ratios describe how covariates shift this hazard up or down (Kleinbaum & Klein, 2012). The hazard rates illustrated in Figure 1 are predicted at the sample means of the covariates, so they reflect the expected hazard for a representative round in the dataset. Generally, higher hazard rates are associated with a shorter survival time.

Figure 1: Baseline Hazard for IPO Exit Overall and by Development Stage



(a) (b)

Figure 1. a) plots the estimated baseline hazard for IPO exits over the duration since the first VC investment across all development stages whereas Figure 1. b) splits it up in the different stages. In Figure 1. a) the hazard is highest early in the life of the investment and then declines sharply. After the clear spike in the beginning, there is a second bump after roughly five years. Beyond that point the hazard remains low and fairly flat, with only minor fluctuations. This suggests that if a venture-backed firm has not gone public within the first several years after funding, the probability that it will go public in any subsequent interval becomes very small. Figure 1. b) investigates the same hazard profile separately by stage at the time of investment. The general shape is similar across stages, but the levels differ. Later stage companies have the highest hazards, while seed stage companies have the lowest hazard at every point in time.

Figure 2: Kaplan-Meier Survival Curves for Chosen Syndicate Sizes

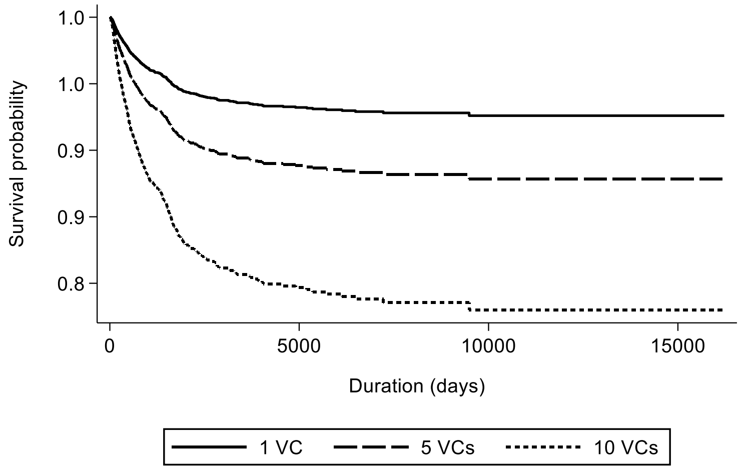


Figure 2 presents the Kaplan-Meier (KM) survival curves for different syndicate sizes. The KM method is a non-parametric approach to estimate and graph survival functions from right-censored data. Theoretically, a survivor function is a smooth, decreasing curve that goes from S(0) = 1 to S(∞) = 0. In practice, the estimated survival curve is typically a step function, which may not reach zero by the end of the study, if not everyone experiences the event. Censored observations contribute information up to the time they are censored, which allows KM curves to use incomplete data appropriately (Kleinbaum & Klein, 2012). In this application, survival means that an IPO has not occurred yet, so lower survival curves correspond to faster IPO exits.

To illustrate the differences in survival across syndicate sizes, Figure 2 shows three different examples that underline the results of the baseline model. The survival probability of companies, that are backed by a syndicate of 10 VCs drops more quickly and lower than the other two groups. This implies that firms backed by 10 VCs experience exits at a faster rate. After the steep decline at first, the curve flattens out and stays at the same survival probability, as no further IPO events are observed in the remaining follow-up period. The KM estimate then stays consistent at its last value. Firms with five VCs lie in the middle, while those backed by a single VC show the slowest decline in their survival rate. These non-parametric survival curves line up with the regression result that each additional syndicate member increases the IPO hazard by about 13%.

5.2 Extensions and Robustness Models

As show in the baseline Cox PH model, larger VC syndicates are associated with faster IPO exits. This section assesses whether this result is sensitive to alternative modelling choices. Therefore, two dimensions are considered.

First, an alternative survival framework is introduced by estimating an AFT model. This approach shifts the interpretation from proportional changes in the hazard, captured by hazard ratios, to proportional changes in the expected time-to-IPO.

Second, the analysis accounts for unobserved heterogeneity, because IPO timing may also be shaped by persistent factors that are not captured by the covariates. To address this, two further robustness models are estimated: A Heckman-Singer specification that approximates unobserved heterogeneity through discrete latent classes, and a Cox PH model with shared gamma frailty. The Heckman-Singer model addresses unobserved heterogeneity by approximating it with a small number of discrete mass points. This effectively assigns firms to latent types that differ in their baseline hazard. The Cox PH model with shared gamma frailty takes a different approach. It extends the baseline PH framework by adding a multiplicative random effect that captures persistent differences in IPO speed across groups. Using two different robustness models is helpful because they both address the same concern but impose different structures on unobserved heterogeneity.

5.2.1 Parametric Accelerated Failure Time (AFT) Model

To test whether the baseline finding from the Cox PH model still holds in a parametric specification, the time-to-IPO relationship is re-estimated using a parametric AFT model based on the generalized gamma distribution. In an AFT setting, the coefficients are interpreted in terms of time ratios. Negative coefficients indicate that the expected time until an IPO becomes shorter, while positive coefficients imply longer expected times to exit (Jenkins, 2004). Table 5 reports the estimated time ratios of the variables of interest.

Table 5: Estimation Results of the AFT Model

	Time ratio	95% confidence interval
VC firm related		
Syndicate size	0.77***	[0.73; 0.80]
Age of oldest VC	1.01***	[1.00; 1.02]
VC proximity	1.75***	[1.42; 2.17]
Entrepreneurial firm related		
Stage number 2 vs. 1	0.66***	[0.49; 0.89]
Stage number 3 vs. 1	0.49***	[0.34; 0.70]
Stage number 4 vs. 1	0.18***	[0.12; 0.28]
Stage advancement	1.35**	[1.04; 1.75]
West	0.62***	[0.49; 0.79]
Northeast	0.65***	[0.51; 0.82]
South	0.55**	[0.34; 0.91]
Midwest	1.14	[0.65; 2.01]
Log-Amount	0.53***	[0.45; 0.63]
Age of investee company	1.02*	[1.00; 1.04]
Macro related		
IPO activity	0.99***	[0.99; 0.99]

*Notes: This table reports time ratios from a generalized gamma AFT model with IPO as the event. N = 18,292 financing rounds with 934 IPOs. Duration is measured in days from the start of each financing round until the next round or IPO; observations are right-censored at the end of the sample period. 95% confidence intervals are based on standard errors clustered at firm level. Stage number 1 = Seed, 2 = Early, 3 = Expansion, 4 = Later. All values are rounded to two decimals. The stars ***, **, and * denote significance at 1%, 5%, and 10% levels.*

The central result remains consistent with the baseline model. Syndicate size is negative and highly significant with a time ratio of 0.77. The interpretation of time ratios is intuitive. The predicted time-to-IPO is multiplied by 0.77 when there is one more investor in the syndicate. This means that, keeping all else equal, adding one additional VC reduces the expected time-to-IPO by approximately 23%. This suggests that larger syndicates are associated with faster IPO exits. Because time ratios compound multiplicatively, the implied effect becomes economically larger for bigger changes in syndicate size. For example, an increase by four investors would correspond to a factor of $0.77^4 \approx 0.35$, i.e. approximately 65% shorter expected time-to-IPO under the model's assumptions.

Both the Cox and the AFT model indicate that larger syndicates are associated with faster IPOs. However, the Cox model reports proportional changes in the instantaneous IPO hazard, whereas the AFT model reports proportional changes in the time scale itself. Therefore, while the direction of the effect is directly comparable, the magnitudes do not translate one-to-one.

The remaining covariates largely reinforce the baseline patterns. The strongest effect can be seen on later stage firms, which are associated with substantially shorter times to IPO. This is consistent with the idea that more mature firms are closer to IPO readiness. VC proximity shows the same result as before, indicating that this result is robust even though it is counterintuitive. For the amount received in an investment round, the AFT model shows a larger effect than the Cox PH model. This suggests that larger rounds coincide with accelerated scaling and preparation for public markets.

5.2.2 Unobserved Heterogeneity

A central challenge in duration analysis is that firms differ in IPO readiness in ways that are not fully observable, like for instance quality of the product, founder ability or governance maturity. As a result, two firms can look similar in the measured covariates, but still have systematically different underlying chances of reaching an IPO. In survival analysis, this unobserved heterogeneity is often referred to as frailty. If frailty is not accounted for, the model effectively treats firms as more similar than they really are, which can bias coefficient estimates (Balan & Putter, 2020).

5.2.2.1 Heckman-Singer (Firm-Level)

At the start of the observation window, the sample contains a mix of high-quality and low-quality firms. This goes back to the selection hypothesis which is one of the reasons why VCs syndicate. Over time, firms with a higher propensity are more likely to exit the risk set earlier, while firms with a low propensity remain under observation for longer. This pattern does not necessarily imply that time itself makes IPOs less likely. Instead, it reflects that the remaining firms are increasingly those with a lower underlying likelihood of going public.

If unobserved firm quality is correlated with syndicate size, then part of the estimated syndicate size effect may reflect latent quality. Heckman and Singer's (1984) approach addresses this concern. Conceptually, it assumes that firms belong to a small number of latent types, each with its own baseline hazard. These types are derived from an estimated mixing distribution for the unobserved heterogeneity term. When the likelihood is maximized, this mixing distribution takes a discrete form with a finite number of mass points. Each mass point corresponds to one latent type and represents a particular value of the unobserved component that shifts the baseline hazard up or down.

The estimates suggest that the sample consists of two latent types of portfolio companies with different IPO processes. In both types, larger syndicates are associated with a significantly higher IPO hazard, which reinforces the main result from the Cox and AFT models. The first type follows a more conventional and maturity-driven path to IPO, where later development stages and later funding rounds are associated with higher IPO hazards. This first type represents around 41% of the companies in the dataset. The second type captures fast-track companies that go public rapidly even from seed and early stages. This type represents about 59% of all companies. For both types, the IPO hazard is highest shortly after an investment round and then declines with time since that round, which is consistent with the baseline Cox PH model. The early post-investment phase is even more pronounced for the second type.[4]

Table 6: Estimation Results of the Heckman & Singer Model

	Type 1 Hazard ratio "Conventional"	***Type 2*** Hazard ratio "Fast-track"
VC firm related		
Syndicate size	1.10*	1.17***
Age of oldest VC	0.97***	1.02***
VC proximity	0.53***	1.16
Round number	1.12***	1.12***
Entrepreneurial firm related		
Stage number 1 vs. 4	0.12***	4.99*
Stage number 2 vs. 4	0.18***	5.08**
Stage number 3 vs. 4	0.45***	0.85
Stage advancement	0.79*	0.86
West	1.45**	1.33
Northeast	1.18	1.50
South	1.08	3.77***
Midwest	0.88	0.91
Log-Amount	1.19*	5.77***
Age of investee company	0.99***	1.01***
Macro related		
IPO activity	1.01***	1.00*

*Notes: This table reports type-specific hazard ratios from a Heckman-Singer finite-mixture survival model with IPO as the event. N = 18,292 financing rounds with 934 IPOs. Duration is measured in days from the start of each financing round until the next round or IPO; observations are right-censored at the end of the sample period. 95% confidence intervals are based on robust Huber-White standard errors. No year, firm, or VC fixed effects included. Stage number 1 = Seed, 2 = Early, 3 = Expansion, 4 = Later. All values are rounded to two decimals. The stars ***, **, and * denote significance at 1%, 5%, and 10% levels.*

[4] This pattern is supported by the Weibull shape parameter in the Heckman-Singer estimates. In both types p is below 1. This implies a hazard that is highest shortly after a financing round and then declines. This decline is slightly stronger for the first type because its estimated p is lower than for the second type (0.83 vs. 0.88).

Table 6 reports the results of this two-class model. For the main variable of interest, syndicate size, each additional VC increases the IPO hazard by around 10% for the lower pace type and by about 17% for the fast-track type. This indicates that the association between syndicate size and IPO timing is stronger for firms in the fast-track group.

Stage effects also differ across the two types. For the conventional type, later stage firms are more likely to go public sooner than seed, early, or expansion stage firms. To make this comparison explicit, later stage is used as the baseline category in this specification. For the fast-track type, the pattern is reversed. Here, seed and early stage firms show much higher hazards relative to later stage, which is consistent with this type capturing unusually high momentum firms that reach public markets despite being at an early development stage. The value-add related controls show additional differences across types. Age of the oldest VC and VC proximity seem to matter more for the fast-track type. In the conventional type, both variables have hazard ratios below one, which mirrors the baseline model. In the fast-track type, the age of the oldest VC is positively associated with the IPO hazard, while VC proximity shows no statistically significant effect. For both types, higher round numbers are associated with about a 12% higher IPO hazard.

The Heckman & Singer model thus indicates that the positive association between syndicate size and IPO timing is not driven by a single homogeneous process. Instead, it holds across distinct latent groups of firms.

5.2.2.2 Shared Frailty Model (Environmental-Level)

The baseline Cox PH model already suggests that environmental heterogeneity matters. The estimated hazard ratios for the regional indicators differ substantially, which indicates that IPO timing is not only shaped by firm and deal characteristics, but also by broader location-specific conditions such as ecosystem depth, local capital supply, or networks. This motivates a specification that does not treat all remaining unobserved influences as purely firm-specific noise, but also allows for shared heterogeneity across firms operating in similar environments. After estimating the Heckman-Singer model to capture firm-level unobserved heterogeneity, now a Cox PH model with shared frailty is used to address unobserved environmental factors that can be common across firms within the same setting.

Balan & Putter (2020) define frailty models as survival models that introduce unobserved heterogeneity as a multiplicative random effect on the hazard. In the standard Cox PH model, the estimated hazard is interpreted as the IPO risk conditional on the observed covariates. In practice, however, it is rarely possible to include every determinant of IPO timing. As a result, the estimated hazard is not the hazard of a single fully observed firm type, but rather an average over firms that share the same observed covariates but still differ in unobserved conditions. The frailty approach adds structure by capturing the missing determinants with a latent random term that scales the hazard up or down.

Building on that, the shared frailty extension applies this idea to clustered data. Instead of assigning a separate frailty term to each financing round, all observations within a cluster share the same latent factor. Balan & Putter (2020) describe the shared frailty model as adding one hidden factor for each cluster. Although this component is not observed, it can be interpreted as a cluster-specific multiplier of the baseline hazard. Conditional on this multiplier and the observed covariates, financing rounds within the same cluster are treated as independent. Once the shared environmental effect is captured, there is no remaining systematic reason for IPO timing to be correlated within clusters.

In this specification, the frailty clusters are defined as "state by cohort." State refers to the location of the entrepreneurial company in the U.S., and cohort denotes the year of the firm's first observed investment. Cohorts are grouped into five-year bins. This choice reflects the idea that clusters should capture units that plausibly share persistent, unobserved conditions. States proxy differences in local innovation and financing ecosystems, while entry cohorts capture the starting conditions at the beginning of a firm's VC lifecycle that can shape its subsequent trajectory. The five-year grouping also reflects that financing and ecosystem conditions often evolve in multi-year regimes. Apart from that, it avoids splitting the data into very small cohorts.

To account for unobserved heterogeneity, a Cox PH model with gamma shared frailty is estimated using the Breslow method to handle ties. The shared frailty term allows unobserved factors to shift the baseline hazard for all firms within the same "state by cohort" cluster. This is important when IPO timing may be affected by common shocks or shared characteristics that are not fully captured by the observed covariates. Because this model implementation does not allow shared frailty together with round-level stratification, round number is included as a covariate in this specification.

Table 7: Main Estimation Result from the Shared Frailty Model

	Hazard ratio	95% confidence interval
VC firm related		
Syndicate size	1.11***	[1.09; 1.13]

Notes: This table reports the main hazard ratio from the Cox shared frailty model with IPO as the event. N = 18,292 financing rounds with 934 IPOs. Duration is measured in days from the start of each financing round until the next round or IPO; observations are right-censored at the end of the sample period. The estimated frailty variance is $\theta \approx 0.73$ (LR test of $\theta = 0$: $p < 0.001$).

Table 7 reports the shared frailty estimates. The central result remains intact, as syndicate size is positively associated with IPO hazard. Adding one VC to the syndicate is associated with roughly an 11% increase in the instantaneous IPO hazard ratio, holding all other covariates constant. Compared to the baseline Cox PH model, this is a modest decrease in the estimated syndication size effect, which is consistent with the idea that part of the baseline effect reflects shared environmental differences. The relationship nevertheless remains strong and precisely estimated at standard significance levels. The estimated frailty variance parameter and the likelihood ratio (LR) test also indicate that the frailty component is relevant. This implies that the "state by cohort" clusters differ meaningfully in their underlying IPO hazards beyond what is explained by the observed covariates.

5.3 Tipping Point via Probit Model

The previous findings from the Cox PH model suggest that larger syndicates are associated with a faster IPO exit. A natural follow-up question is whether this positive association continues to increase with syndicate size, or whether there is a point at which adding further VCs may become detrimental. Prior literature findings have already shown the negative effects of larger syndicates, like coordination frictions or conflicting investor objectives (Kim & Park, 2021).

Importantly, the baseline Cox PH specification with a linear syndicate size term does not estimate an optimal syndicate size. It imposes a linear effect of syndicate size, meaning that each additional investor shifts the IPO hazard by the same proportional amount. This is a timing framework, since it explains when an IPO occurs rather than whether it occurs at all. To explicitly examine potential nonlinearity in the likelihood that an IPO occurs rather than when it occurs, a probit model is estimated. For this purpose, the dependent variable is redefined so that it equals one if a firm ever goes public during the same period, not only in a specific round.

This design follows Kim & Park (2021), who also model IPO likelihood with a probit specification that includes both a linear and a quadratic syndicate-size term.

Table 8: Main Estimation Result from the Probit Model

	Coefficient	95% confidence interval
VC firm related		
Syndicate size	0.16***	[0.13; 0.18]
(Syndicate size)^2	-0.01***	[-0.01; -0.00]

*Notes: This table reports coefficients from a probit model where the dependent variable equals one if a firm ever went public. N = 18,292 financing rounds with 934 IPOs. The squared term captures potential nonlinearity in the effect of syndicate size. 95% confidence intervals are based on standard errors clustered at firm level. All values are rounded to two decimals. The stars ***, **, and * denote significance at 1%, 5%, and 10% levels.*

To allow for a nonlinear relationship, the probit model includes both a linear and a quadratic term of syndicate size. As seen in the estimation results in Table 8, the linear syndicate size coefficient is positive and the quadratic term is negative. This combination implies an inverted-U shaped pattern. Following Wooldridge (2002), the tipping point of this shape is the syndicate size at which the predicted IPO probability reaches its maximum and is calculated as:

$$syndsize^{*} = -\frac{\beta_1}{2\beta_2} \tag{4}$$

Using the estimated coefficients before rounding, a tipping point of approximately 13 investors can be derived. Intuitively, predicted IPO probability increases with syndicate size up to this level and then declines for larger syndicates. This tipping point refers to the peak of the predicted probability curve in the probit model. It is not the point where the Cox hazard ratio changes sign, since the Cox PH model does not estimate this type of turning point.

Figure 2: Inverted-U Shape of Syndicate Size

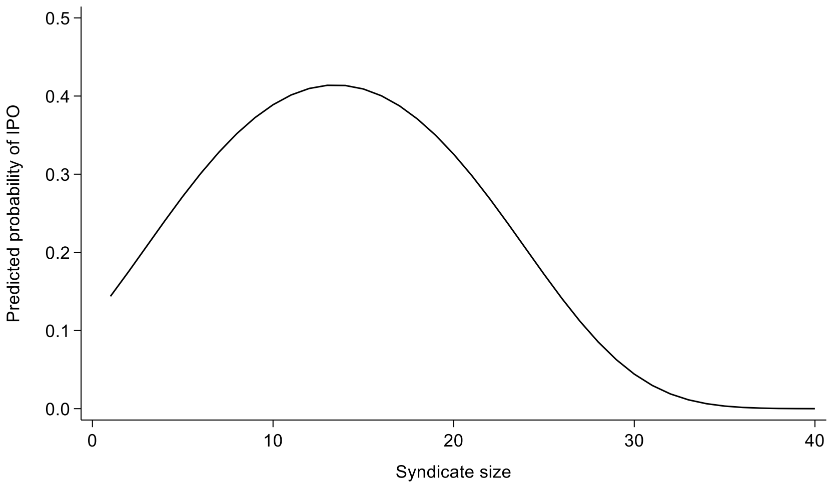


Figure 2 visualizes the inverted-U relationship by plotting predicted IPO probabilities across syndication sizes while holding the remaining covariates constant. The predicted IPO probability starts at around 0.14 for a single-investor round and then increases steadily with syndicate size. It reaches its maximum at around 13 investors, where the fitted probability is about 0.41 and declines thereafter as more investors are added. This decline does not imply that IPO probability becomes exactly zero at a specific syndicate size. Instead, the fitted index becomes increasingly negative at very large syndicates, so the probit prediction approaches zero. The curve is estimated most precisely where syndicate sizes are common, while uncertainty increases at very large syndicates because there are fewer observations in that range.

Compared to previous literature findings, the estimated tipping point is relatively high. Kim & Park (2021), for instance, report a substantially smaller inflection point of around five to six in their study with focus on the information and communications technology sector. This suggests that the balance between the benefits and the costs of additional investors may differ across sectors and sample periods.

To assess whether the estimated turning point is driven by a small number of large syndicates, the quadratic probit model is re-estimated after excluding observations above the 99th percentile of the syndicate size distribution.[5] The sample is therefore restricted to rounds with syndicate sizes of up to 14 investors. Under this restriction, the implied tipping point shifts only slightly,

[5] This is based on how frequently each size occurs. As the baseline tipping point is at 13.45, syndicate sizes of 14 are also included, which are at the 99.30th percentile.

from 13.45 to 12.66 investors. This indicates that the relatively high turning point is not driven by a handful of extremely large and rare syndicates, but reflects the broader pattern in the healthcare sample. The high tipping point is consistent with the sector context discussed earlier. Healthcare ventures often face high financing needs and long development cycles, which can increase the value of bringing in additional investors over an extended period (Tarannum et al., 2025).

6. Conclusion

6.1 Main Findings and Contributions

This thesis investigates whether VC syndicate size helps venture-backed U.S. healthcare companies reach an IPO more quickly. Using round-level data, the empirical strategy treats IPO exit as a time-to-event outcome and explicitly accounts for right-censoring. This is essential as most ventures do not go public within the sample window.

Across the baseline Cox PH model and multiple robustness specifications, the results consistently point in the same direction. Larger syndicates are associated with faster IPO exits. In the baseline Cox PH model, each additional VC is linked to a higher IPO hazard of about 13%, implying a faster transition to IPO, conditional on the firm still being at risk. This core association remains intact when switching to a parametric AFT framework, where an additional syndicate member is associated with a shorter expected time-to-IPO. Also, after accounting for unobserved heterogeneity through a Heckman-Singer specification and an environmental frailty model this result holds.

Taken together, these findings support the view that syndicates can accelerate the IPO path because additional investors expand the pool of resources available to the firm, such as sector expertise, networks, and certification toward external stakeholders. These factors facilitate scaling and capital-market readiness. At the same time, the evidence suggests that these benefits do not increase indefinitely. A complementary probit analysis that focusses on the probability of observing an IPO within the sample window indicates an inverted-U pattern in IPO likelihood, with a turning point of around 13 investors. This does not translate one-to-one into the Cox estimates, which capture timing rather than likelihood. However, it is consistent with the broader interpretation that beyond a certain size additional syndicate members may bring rising coordination and bargaining costs, weaker monitoring incentives, and more complex decision-making, which can offset earlier gains.

Overall, the thesis contributes to the syndication literature by showing that in healthcare, syndicate expansion is, on average, strongly linked to IPO speed, yet there are indicators that very large syndicates are not necessarily associated with further improvements. For practitioners, the result suggests that syndication can be beneficial as a mechanism to mobilize complementary resources and accelerate the path to public markets, but that more investors is not automatically better in all cases.

6.2 Limitations and Outlook to Future Research

Several limitations qualify the interpretation of the results. First, the empirical analysis identifies robust associations rather than strict causal effects. Syndicate formation is likely endogenous to unobserved deal quality, strategic choices, and other market conditions that were not accounted for. Second, the focus on IPO exits diverts the attention from other major exit routes such as acquisitions, which may respond differently to syndicate structure. Third, the probit-based tipping point relies on the IPO outcome within the observed window and therefore does not account for firms that may exit later.

Future research could build on these findings by applying alternative empirical designs that explicitly model selection into syndicates or exploit settings where syndicate formation is plausibly shaped by external variation like institutional constraints or market-level shocks. It would also be valuable to broaden the outcome space to competing exits within a unified duration framework. Finally, moving beyond syndicate size alone, future work could examine syndicate composition, such as lead-investor characteristics or distribution of experience characteristics within the investor group. This could identify which forms of syndication are most closely associated with timely and successful exits.

Appendix

Appendix 1: Full descriptive analysis

	All	IPO	Non-IPO
VC firm related			
Syndicate size	3.12	4.80	3.03
	(2.79)	(4.26)	(2.66)
Age of oldest VC	36.69	37.77	36.63
	(20.33)	(23.65)	(20.14)
VC proximity	0.47	0.46	0.47
	(0.50)	(0.50)	(0.50)
Round number	3.49	4.61	3.43
	(3.11)	(3.38)	(3.09)
Entrepreneurial firm related			
IPO exit	0.05		
	(0.22)		
Duration	1088	557	
	(1868)	(827)	
Seed	0.14	0.06	0.14
	(0.34)	(0.25)	(0.35)
Early	0.40	0.32	0.41
	(0.49)	(0.47)	(0.49)
Expansion	0.22	0.26	0.22
	(0.42)	(0.44)	(0.42)
Later	0.24	0.36	0.23
	(0.43)	(0.48)	(0.42)
Stage advancement	0.19	0.21	0.18
	(0.39)	(0.41)	(0.39)
Total investment log amount	0.61	0.96	0.59
	(0.78)	(0.84)	(0.77)
West	0.33	0.38	0.33
	(0.47)	(0.49)	(0.47)
Northeast	0.26	0.28	0.26
	(0.44)	(0.45)	(0.44)
South	0.04	0.04	0.04
	(0.19)	(0.20)	(0.19)
Midwest	0.03	0.02	0.03
	(0.18)	(0.14)	(0.18)
Other location	0.33	0.28	0.34
	(0.47)	(0.45)	(0.47)
Age of investee company	5.58	6.53	5.53
	(4.95)	(6.11)	(4.88)
Macro related			
IPO activity	146	227	142
	(117)	(158)	(112)

Notes: All rounds: N = 18,292. IPO rounds: N = 934. Non-IPO rounds: N = 17,538. Values are reported as means; standard deviations are reported below each value in parentheses (if applicable). Units: Duration in days; log amount in million dollars; age of oldest VC in years.

Appendix 2: Distribution of Financing Rounds along Syndicate Sizes

Syndicate size	Frequency	Percentage	Cum. Percentage
1	6,853	37.46%	37.46%
2	3,565	19.49%	56.95%
3	2,099	11.47%	68.43%
4	1,668	9.12%	77.55%
5	1,211	6.62%	84.17%
6	869	4.75%	88.92%
7	636	3.48%	92.40%
8	434	2.37%	94.77%
9	277	1.51%	96.28%
10	194	1.06%	97.34%
11	131	0.72%	98.06%
12	98	0.54%	98.60%
13	83	0.45%	99.05%
14	46	0.25%	99.30%
15	40	0.22%	99.52%
16	27	0.15%	99.67%
17	12	0.07%	99.73%
18	21	0.11%	99.85%
19	8	0.04%	99.89%
20	6	0.03%	99.92%
21	6	0.03%	99.96%
22	6	0.03%	99.99%
24	1	0.01%	99.99%
34	1	0.01%	100.00%

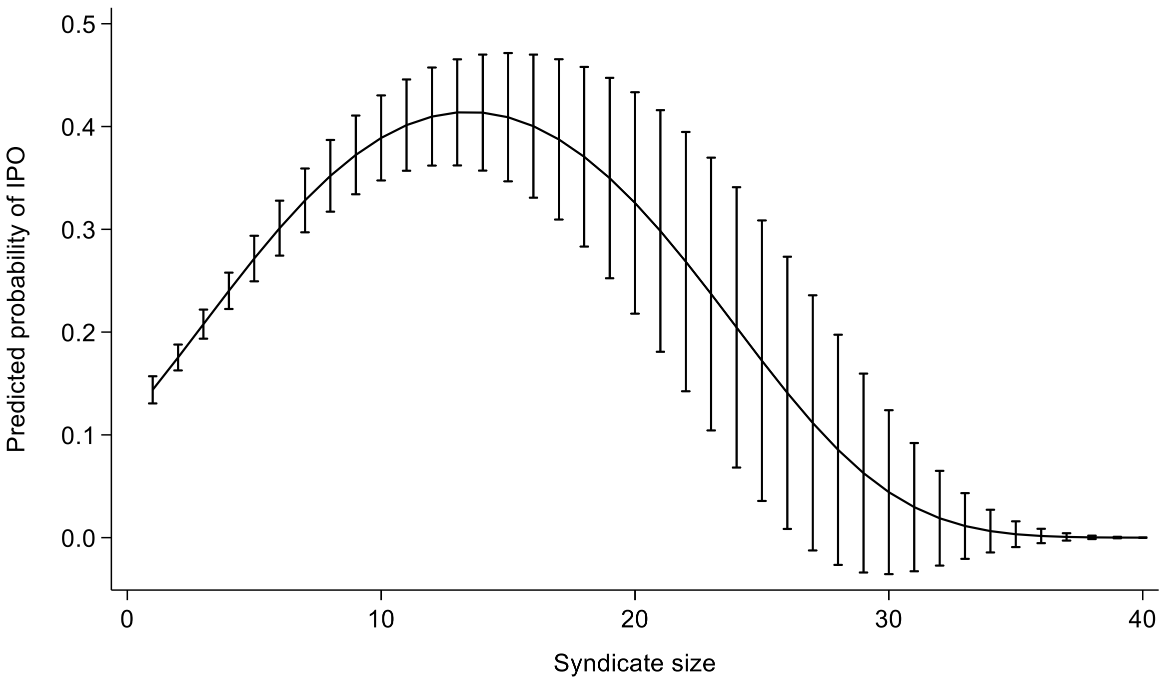
Notes: Notes: Frequency and percentage distribution of syndicate size. Cum. Percentage shows the cumulative share of observations up to and including each syndicate size category and sums up to 100%. Mean = 3.12; Median = 2; Min = 1; Max = 34.

Appendix 3: Full Estimation Results from the Shared Frailty Model

	Hazard ratio	95% confidence interval
VC firm related		
Syndicate size	1.11***	[1.09; 1.13]
Age of oldest VC	1.00	[0.99; 1.00]
VC proximity	0.71***	[0.61; 0.82]
Entrepreneurial firm related		
Early vs. seed stage	1.93***	[1.45; 2.57]
Expansions vs. seed stage	1.84***	[1.36; 2.51]
Later vs. seed stage	2.78***	[1.98; 3.89]
Stage advancement	0.71***	[0.60; 0.84]
Log-Amount	2.01***	[1.78; 2.28]
West	1.97**	[1.06; 3.66]
Northeast	1.67**	[1.07; 2.61]
South	2.13*	[0.97; 4.67]
Midwest	0.90	[0.45; 1.82]
Age of investee company	1.00	[1.00; 1.00]
Macro related		
IPO activity	1.00***	[1.00; 1.00]

Notes: This table reports the hazard ratios from the Cox shared frailty model with IPO as the event. N = 18,292 financing rounds with 934 IPOs. Duration is measured in days from the start of each financing round until the next round or IPO; observations are right-censored at the end of the sample period. The estimated frailty variance is $\theta \approx 0.73$ *(LR test of* $\theta = 0$: $p < 0.001$*).*

Appendix 4: Inverted-U Shape of Syndicate Size incl. 95% Confidence Intervals



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