IPOs, trade sales and liquidations: modelling venture capital exits using survival analysis

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ABSTRACT

Using a detailed sample made up of more than 20,000 investment rounds, we analyze the time to 'IPO', 'trade sale' and 'liquidation' for about 6,000 venture backed firms. We model these exit times using competing risks models. Biotech and internet firms have the fastest IPO exits. Internet firms are also the fastest to liquidate, while biotech firms are however the slowest. The conditional probability for IPOs are clearly non-monotonous with respect to time. As time flows, venture capital-backed firms first exhibit an increased likelihood of exiting to an IPO. However, after having reached a plateau, investments that have not yet exited have fewer and fewer possibilities of IPO exits as time increases. The bubble period from 1998 to 2000 was an 'easy money' period where venture capitalists gave much more money to firms, many of which did not offer outstanding growth potential as they tended to liquidate much faster than in normal times.

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The assessment of possible exit options is of paramount importance for venture capitalists prior to their investments in new ventures. Indeed, not only are they concerned about *how* they can cash out but also *how long* they need to stick with their portfolio companies before cashing out. The exit decision therefore has two main dimensions. First, the type of exit route (the most important being the IPO, trade sale and liquidation) and secondly the actual timing of the exit.[1] The existing academic literature on venture capital exits has shown that venture capitalists time their exits using stage financing split into several rounds (e.g., Gompers, 1995 and Bergemann and Hege, 1998): in each round, the entrepreneur gets the necessary financing to proceed to the next intermediate development phase, but the venture capitalists refrain from given more money than actually needed. Besides the disciplinary action that this procedure exerts on venture capital-backed firms, this stage financing also gives exit options to venture capitalists at every financing round. Because exit options for start-up companies are highly cyclical, venture capitalists aim at optimally timing their divestments. For instance, the internet bubble period was characterized by easy exits. Since venture-backed companies got a lot of public interest, going public was easy as investors stood ready to buy the newly issued equity of venture-backed companies when the IPO took place. Market conditions changed dramatically in 2001 and 2002 as the NASDAQ and most stock indices crashed. Next to the well documented stock market losses of individual and professional investors, the investors' appetite for newly issued shares waned considerably and the number of firms going public slowed to a trickle. Therefore venture capitalists had very few chances to divest their investments in recently funded start-up companies. This highlights the dependence of venture capital investments on prevailing exit conditions.

Much of the past research on venture capital exits has dealt with IPOs. Indeed, an IPO is deemed to be the most successful (hence preferred) venture capital exit. For example, Lerner (1994) examined the ability of venture capitalists to time IPOs in the biotechnology industry by going public when equity values are high, and using private financings when share prices are lower. Gompers (1996) shows that the building of a reputation affects the timing of going public. Less-experienced venture capitalists may not wait until the market is optimal to take firms public, because they need to signal their quality to potential investors in follow-on funds. Both papers only focus on the time dimension of exit and for IPOs only. A few recent papers have looked at the full range of exit routes, e.g. Cumming (2002) and Schwienbacher (2002).

These two papers only look at the type of exit but do not examine the timing of the exit nor the interaction between the timing and type of exits (the two dimensions highlighted above). Several other papers play up the crucial role of active stock markets and the importance of IPOs as exit routes for venture capitalists. Black and Gilson (1998) argue that active stock markets allow venture capitalists to exit more easily while leaving the entrepreneur in control of the firm. Michelacci and Suarez (2002) provide a further rationale for the link between stock markets and venture capital markets. They claim that the public markets allow venture capitalists to ‘recycle’ the financing invested in their successful investments so that new funds are available for new start-ups. Other papers show a positive link between company valuation and the likelihood of going public (Cochrane, 2001, Cumming and MacIntosh, 2000, Gompers, 1995, and Darby and Zucker, 2002). Das, Jagannathan, and Sarin (2002) provide an extensive analysis of exits by venture capitalists and Ritter and Welch (2002) one on IPO activities in the US. On a related topic, Kaplan and Stromberg (2003) show that venture capitalists include control rights and covenants in their contracts to keep their options open regarding exit possibilities.

While IPO exits have been researched quite extensively, a stock market listing is however only one out of several ways to exit private equity investments. Interestingly, the academic literature has not focused much on other types of exits such as trade sales and liquidations. Nor do we know how these various exit routes interact with each other over time. Moreover, little is known about the effect of the recent internet bubble on the relative importance (especially trade sales compared to IPOs) of competing exit possibilities. In this paper, we consider both dimensions (i.e. type and timing) of exit within a single framework of analysis. Thus, we explore the full range of exit routes, i.e. not only IPOs, but also trades sales and liquidations. This is particularly important when tackling the issue of ‘exit risk’ for venture capital investments as it requires jointly taking into account all potential exit routes. We also look at how exit conditions evolve when firms move up the ladder of financing rounds and compare these results with the prevailing conditions at the initial (first round) investment. Last, we further examine how the internet bubble affected the exit conditions of venture-backed companies.

More specifically, using a detailed sample made up of more than 20,000 investment rounds, we analyze the time to exit through IPO, trade sale and liquidation for about 6,000 venture-backed firms. Set in the framework of survival analysis, we characterize and model the times to exit using competing risks models. To our knowledge, this is the first application of such statistical models to venture capital investments.[2] The strength of this approach lies in the rigorous statistical modelling of exit times, and the possibility to fully parameterize the exit times with known covariates (i.e. explicative variables known at the time the investment round took place). As such, each type of exit exhibits its own dynamics and has its own dependence with respect to variables such as the industry type of the firm, the size of the syndicate, and the amount of venture capital received. Quite importantly, the use of the generalized Gamma density distribution as the underlying statistical distribution in the competing risks models allows for non-monotonous increasing/decreasing conditional probabilities of exits (also called hazard functions). For example, this allows for increased (as time goes by) conditional probabilities of exits to IPO during the first *n* years, and thereafter a decreasing conditional probability of exit. Because the dynamics of the times to exit depend on the selected explicative variables that pertain to the status of the firm or the characteristics of the investment round, we can highlight the pattern shown by firms that belong to a specified industry (e.g. internet firms vs biotech firms) or that got funded during the internet bubble time period.

The statistical analysis delivers key results which can be summarized as follows. First, biotech and internet firms have the fastest IPO exits. Internet firms are also the fastest to liquidate, while biotech firms are however the slowest. Secondly and regarding the shape of the conditional probability (hazard) of IPO exit, one has first a sharply increasing hazard and then a slowly decreasing hazard. Thus, as time flows, venture capital-backed firms first exhibit an increased likelihood of exiting to an IPO. However, after having reached a plateau, investments that have not yet exited have fewer and fewer possibilities of IPO exits as time increases. Note that this pattern is stronger for biotech and internet firms which tend to reach their plateau sooner than computer or semiconductor firms. This suggests that venture capitalists should not stick with ongoing investments that have an increased likelihood of being non-performing investments. Thirdly, the bubble period was an ‘easy money’ period where venture capitalists gave much more money to firms, many of which did not offer outstanding growth potential as they tended to liquidate much faster than in normal times. Moreover, the bubble period sped up the exit of investments already in the pipeline, i.e. investments who had been initiated some time ago and for which venture capitalists were eager to have a now accelerated exit. Fourthly, the bubble affected some industries more than others: the internet, computer and communication/media industries were strongly affected as firms in those industries exhibited significantly smaller exit times during the bubble. Finally and as expected, later (expansion) stage investments exit to IPO more quickly than expansion (early) stage investments.

The rest of the paper is structured as follows. After this introduction, we detail the data and variables in Section I. Section II gives a review of exit decisions and types of exits for venture capital-backed firms. It also provides a review of the empirical literature that deals with venture capital exits. We next present the competing risks model in Section III. The empirical application is split into 2 sections: Section IV gives a detailed descriptive analysis, while we present all the estimation results in Section V. Finally, Section VI concludes.

I. Data

The data used in this paper has been extracted from the VentureXpert database. Our database is made up of successive records, each record pertaining to 1 investment round in a given venture-backed firm. Note that whenever the firm was involved in more than one financing round, we therefore have as many observations (per firm) as investment rounds, see below for an example. The data was pre-filtered to remove all records where the times-to-exit (DURATION variable thereafter) are smaller than 14 days or larger than 20 years and we also removed all records for which the amount of money received (AMOUNT variable) by the firm is smaller than $10,000 or larger than $100,000,000. These observations are deemed to be meaningless outliers for which the recorded values do not belong to a plausible range. This pre-filtering leads us to discard very few records and gives us a sample made up of 22,042 investment rounds for 5,817 distinct venture-backed companies.[3]

To characterize the firms in our dataset and the stage financing they got from venture capitalists, we use the following variables:

- On the industry type (dummy variable): INTERNET (internet industry), BIOTECH (biotech industry), COMPUTER (computer industry), SEMIC (semiconductor industry), MEDICAL (medical industry), COMMEDIA (communication and media industry) and OTHERIND (other industries than those listed above). These variables are equal to 1 (0) if the given firm belongs (does not belong) to the specified industry.

- On the stage of development (dummy variable): EARLY (early stage financing), EXPANSION (expansion stage), LATER (later stage), BUYACQ (buy/acquisition stage), OTHERSTAGES (other stages than those listed above). Set to 1 (0) if the financing stage matches (does not match) the description of the variable.

- On the type of exit (dummy variable): IPO (IPO exit), TRADESALE (trade sale exit), LIQUID (liquidation exit). Set to 1 (0) if the firm exited (did not exit) according to the exit specified by the variable. Note that many firms are characterized by IPO = 0, TRADESALE = 0 and LIQUID = 0 as they are still 'active', i.e. venture capitalist have not yet exited, or have exited via a fourth exit route. These latter routes could include secondary sales or management buyouts (MBO).[4] This will yield right-censored durations in the statistical analysis (see below for the DURATION variable and Section III).[5]

- ROUND: ordinal round number of the investment. This indicates which financing round we are dealing with.

- SYNDSIZE: syndicate size, i.e. number of venture capital firms that participated in that financing round.

- AMOUNT: total amount of money received by the firm at the given round (in millions of USD).

- BUBBLE: dummy variable equal to 1 if the investment was made during the bubble time period from ranges from September 1, 1998 to April 30, 2000 (inclusive), and 0 otherwise.

- DURATION: number of days elapsed between the date at which the round began and the exit date if there was an exit. If the firm has not yet exited, this variable gives the number of days elapsed between the date at which the round began and the date of the analysis(June 23rd, 2003).[6] This variable is the main focus of our analysis as it characterizes the 'life' of the investment since a given round.

All in all we thus have a total of 14 explicative variables, although many of these variable are pure dummy variables.[7] The full statistical model is detailed in Section III. As an illustration, Table I presents the data structure and definition of variables for two venture-backed firms that made an IPO exit (Ask Jeeves and Brocade) and a third firm (InGenuity) that had not yet exited at the date of the analysis (June 23rd, 2003). Although this will be detailed in Sections IV and V, we can already see that Ask Jeeves, an internet firm, is characterized by a fast IPO exit (DURATION = 303 days since round 1, which was an early stage round).

II. Exit decisions and type of exits for venture capital-backed firms

In this section, we present and motivate some research hypotheses that provide guidelines for the empirical analysis of Sections IV and V. These guidelines are motivated by recent developments in the empirical and theoretical literature on venture capital exit and financing.

First, it has been argued that, in contrast to an IPO, a trade sale is a more universal exit channel, i.e. a type of exit available to many firms and not only to the most successful start-ups. Venture capitalists do a trade sale for highly successful as well as less successful portfolio companies. Sometimes, venture capitalists even choose a trade sale for unprofitable ventures but for which a larger corporation is keen on acquiring the technology. This latter firm is thus ready to pay more than the liquidation value of the venture. This contrasts with the common wisdom that exit via an IPO is limited to high flyers only. Several papers have therefore concluded that an IPO tend to be the most preferred exit route for venture capitalists (Lerner, 1994, Bascha and Walz, 2001, Cumming and MacIntosh, 2001, Darby and Zucker, 2002, and Schwienbacher, 2002a). This leads us to expect a greater heterogeneity in the type of ventures doing a trade sale, which should also impact investment duration.

Hypothesis 1 ('High Flyers'): Times-to-exit for trade sales should exhibit a greater heterogeneity than times-to-exit for firms going public via an IPO.

Furthermore, most venture capital deals are syndicated and the size of the syndicate tends to become larger as the venture gets more developed. Many rationales have been suggested to explain the co-investment of such deals (Admati and Pfleiderer, 1994, Barry, Muscarella, Perry, and Vetsuypens, 1990, Megginson and Weiss, 1991, Brander et al., 2002, Lerner, 1994 and Hellmann, 2001). These studies suggest that larger syndicates should make exit easier for successful start-ups as far as it increases the pool of contacts required to make a trade sale possible. It may also improve the reputation of venture capitalists who succeed in bringing a firm public via an IPO. Moreover, one can expect increased performance through greater complementarities of skills between participating syndicate members.

Hypothesis 2 (Syndication): Larger syndicate sizes should increase the likelihood of exiting from a successful venture, either through a trade sale or an IPO.

Exit conditions are highly cyclical and largely depend on the current or foreseen state of stock markets as well as other macro-economic factors (Lerner, 1994, Gompers and Lerner, 1999, Bottazzi and Da Rin, 2001, and Cumming, Fleming, and Schwienbacher, 2003). In bubble periods as witnessed at the end of 1990s, the financial markets were very attractive and investors were keen on buying newly issued stock. Correspondingly, the exit from successful firms should have been easy. On the other hand, since the exit from unsuccessful companies is largely determined by bankruptcy rules, the latter type of companies should not have be affected. We also conjecture that some industries should have been more affected than others during the bubble periods. Indeed the height of the stock market craze saw many internet firms going public. Many of these firms had a rather dubious business and were highly unprofitable.[8]

Hypothesis 3 (Bubble Period): Exiting from successful ventures (trade sale and IPO) is expected to be more likely and quicker in bubble periods. There should be no effect on unsuccessful ventures. Sharp differences across industry types are to be expected.

Several papers have evidenced the use and optimality for venture capitalists of staging the financing in many rounds (Gompers, 1995, Bergemann and Hege, 1998, and Cornelli and Yosha, 2002). As such, entrepreneurs have strong incentives to be focused on their firm and they know that they have to deliver intermediate results to investors before getting additional funds. In other words, it also provides investors with the option to stop the project when predetermined benchmarks are not met (Bergemann and Hege, 2002). Practitioners typically distinguish between several stages of development, e.g. early stage, expansion stage and later stage.[9] Obviously, an early-stage project should be less developed than an project in the expansion stage and especially later stage. This is summarized in the next hypothesis.

Hypothesis 4 (Development stages and successful projects): The time-to-exit for successful projects decreases with the development of the project. In particular, it is greatest for early stage and shortest for later stage projects.

In the same vein, least developed projects are also the most risky ones. Survival should therefore be greatest for ventures with more developed projects. This is summarized in the next hypothesis where the development of a project is proxied by its development stage: early stage projects are typically riskier investments than projects in the expansion stage or later stage.

Hypothesis 5 (Development stages and unsuccessful projects): The likelihood of failure (exit through a liquidation) decreases with the development of the project.

A decision variable in any investment is the amount of funds supplied. More funds should increase investment durations for two reasons. First, a larger amount of committed money increases the likelihood of success as far as it provides management with better resources. And second, it allows entrepreneurs to pursue unsuccessful projects for a longer time period when obtaining more funds upfront.

Hypothesis 6A (Increased resources): A larger amount of committed money allows the entrepreneur to pursue inefficient projects for a longer time period, which increases investment duration for unsuccessful projects.

Hypothesis 6B (Rush to exit): More funds allow the entrepreneur to develop the project quicker. This decreases investment durations for successful and unsuccessful projects.

All these hypotheses will guide our empirical investigations in the next sections. Note that to control for project-specific characteristics, we also include in all estimated models industry dummies for the most important industry sectors.

III. Survival analysis and competing risks models

As briefly discussed in the introduction, our statistical analysis relies on survival analysis and competing risks models. Competing risks models are powerful statistical models tailored to model durations (also called time to failure) that end with multiple exits (also called multiple type of failure). They originate from the engineering sciences and have been extensively used in the medical sciences and in empirical studies of labor markets. In the first case, the duration (or time-to-exit in the venture capital terminology used above) is typically the number of days elapsed between the patient taking the given medicine and the possible failure (full recovery or death by several distinct causes of the patient for example). In the second case, the duration could be the length of time until an unemployed individual gets a job or quits searching. Recently competing risks models have also been used in the modelling of high-frequency stock market transaction data, where the duration is the time between a given price change and the exits are an increase or decrease in the stock price (Bauwens and Giot, 2003). In this section, we first detail a simple two-state competing risks model and then show how we plan to use a multi-state competing risks model in the venture capital exits framework. Additional information on survival analysis and/or competing risks models can be found in Crowder (2001), Kalbfleisch and Prentice (2002) and Lee and Wang (2003).

A. A simple competing risks model

The next sub-section presents the competing risks model used in the empirical analysis of Section V. We however first present a simple competing risks model with 2 exits to illustrate the general methodology. Let us consider a set of investments characterized by their durations (i.e. times until exit) and their exit types. In this introductory example, we assume that there are two exit possibilities (success and failure) and that the durations are not right censored.[10] We thus have a set of pairs (x_i, y_i), where x_i is the duration of the investment and y_i is a variable indicating the exit type. In this simplified example, there are only two possible exits characterized by mutually exclusive end states: $y_i = 1$ (success) or $y_i = -1$ (failure). For simplicity, let us assume that the hazard function is constant, which is equivalent to assume an exponential distribution for x_i.[11] The idea of the competing risks model is to let the hazard vary with the end state, in this case to have two hazards since y_i is binary. Thus we define λ_s (respectively λ_f) as the hazard of duration x_i when the end state is $y_i = 1$ (respectively -1). In most competing risks model, the hazards are made dependent on a set of covariates, which can thus be viewed as explicative variables which speed up/slow down the exits. For example, the exponential form $\lambda_s = e^{\beta_{s,0}+\beta_{s,1}X_1+\ldots+\beta_{s,k}X_k}$ (and correspondingly $\lambda_f = e^{\beta_{f,0}+\beta_{f,1}X_1+\ldots+\beta_{f,k}X_k}$), where $X_1, \ldots, X_k$ are the covariates, is widely used to ensure the positivity of the hazards. As in classical survival analysis, coefficients $\beta_{s,1}, \ldots, \beta_{s,k}, \beta_{f,1}, \ldots, \beta_{f,k}$ then allow an immediate assessment of the influence of the explicative variables on the exits. At the end of duration x_i, either state $y_i = 1$ (success) or state $y_i = -1$ (failure) is realized. In the framework of a competing risks model, the duration corresponding to the state that is not realized is truncated, since the observed duration is the minimum of two possible durations: the one which would realize if $y_i = 1$, and the one which would realize if $y_i = -1$.[12] This implies that the realized state will contribute to the likelihood function via its density function, while the truncated state contributes to the likelihood function via its survivor function.[13]

B. A competing risks model for venture capital exits

The competing risks model detailed in the previous sub-section can readily be used to model the exit times and types of exit (the two dimensions of our analysis discussed in the introduction) of venture capital-backed investments provided that:

- we allow for multiple exits (IPO, trade sale and liquidation in this study);
- we allow for right-censoring, as many investments have not yet exited at the time of the analysis (i.e. they are still categorized as 'active' investments by the venture capitalist);
- we allow for competing hazards that depend on a set of covariates (type of industry for the firm, amount of capital given to the firm, size of syndicate,...) that are known at the time of the investment;
- we estimate the competing risks models for a given round. This stems from the fact that a duration is defined herein as the time elapsed between the actual round date when the firm got the money from the venture capitalist and the time of the analysis (June 23rd, 2003);
- we allow for possible non-monotonously increasing or decreasing hazards, i.e. use density distributions such as the generalized Gamma density distribution for example. The choice of the 'right' density distribution can be tricky. Monotonously increasing or decreasing hazard functions are the simplest to use but imply that, as time flows, the likelihood of exiting gets either larger and larger or smaller and smaller. In our context, we could have a likelihood of instantaneous IPO exit that first gets larger and larger as the firm gets the funding, but then decreases once the firm does not deliver good results. After many trials and with the benefit of hindsight, we settle for the generalized Gamma

distribution, which is one of the most flexible density distributions available for survival analysis studies.

In the empirical analysis of Section V, we use the generalized Gamma density distribution as pre-programmed in Stata. More specifically, the density distribution is specified as:

$$f(t,\kappa,\sigma,\mu) = \frac{\gamma^{\gamma}}{\sigma t\sqrt{\gamma}\Gamma(\gamma)} e^{(z\sqrt{\gamma}-u)} \qquad (1)$$

if $\kappa \neq 0$, and

$$f(t,\kappa,\sigma,\mu) = \frac{1}{\sigma t\sqrt{2\pi}} e^{(-z^2/2)} \qquad (2)$$

if $\kappa = 0$, where $\gamma = |\kappa|^{-2}$, $z = sign(\kappa)\,(ln(t)-\mu)/\sigma$, $u = \gamma e^{(|\kappa| z)}$. The dependence with respect to the covariates is introduced through $\mu_j = X_j \beta$, where j is the observations' index. In the venture capital framework of this study (IPO, trade sale and liquidation exits) and with the 14 explicative variables detailed in Section I, this translates into 3 specifications for μ_j as we have 3 mutually exclusive exit possibilities:[14]

$$\mu_{j,IPO} = \beta_{1,IPO} INTERNET_j + \beta_{2,IPO} BIOTECH_j + \ldots + \beta_{14,IPO} BUYACQ, \qquad (3)$$

$$\mu_{j,TS} = \beta_{1,TS} INTERNET_j + \beta_{2,TS} BIOTECH_j + \ldots + \beta_{14,TS} BUYACQ \qquad (4)$$

and

$$\mu_{j,LIQ} = \beta_{1,LIQ} INTERNET_j + \beta_{2,LIQ} BIOTECH_j + \ldots + \beta_{14,LIQ} BUYACQ. \qquad (5)$$

In these specifications, the κ and σ parameters determine the general shape of the hazard function (monotonously increasing or decreasing, or more generally non-monotonous, as time increases) while the β parameters determine the 'time acceleration'. The j index refers to the available observations per round. A significantly negative value for any β parameter implies that an increase in the corresponding variable leads to a significantly faster exit. For example, a significantly negative $\beta_{8,IPO}$ (the coefficient of the SYNDSIZE variable in the specification of the IPO exit) would mean that, as the size of the syndicate grows, the time-to-exit for an IPO gets shorter. Note that, for dummy variables, exponentiated coefficients (i.e. $e^{\beta_{1,IPO}}$ for example) have an easy interpretation as 'time ratios'. Moreover, these exponentiated time ratios can be directly set against each other, which gives relative time ratios. For example, the relative time ratio (for the IPO exit) of the internet industry with respect to the biotech industry is equal to $e^{\beta_{1,IPO}}/e^{\beta_{2,IPO}}$.

IV. Descriptive analysis

In this section, we provide a descriptive analysis of our dataset. Estimation results for the competing risks model are given in the next section. While Table II provides the frequency of exit routes for different types of investment stages, Table III gives a breakdown of key statistics by investment rounds, industries and stages of development. Finally, Table IV gives information on the industry type and stages of development during the bubble period and outside that time frame.

Table II shows that the proportion of exit types is quite similar across financing stages, except from the fact that there is a slight increase in trade sales with the increasing stage of development (and the decreasing likelihood of IPOs). In both panels, the ratio of trade sales over IPOs therefore tends to increase. Furthermore, this ratio is always greater than 1. For instance, there are about 50% more trade sales than IPOs for early-stage investments.

A breakdown of AMOUNT and SYNDSIZE by round number (Panel A of Table III, shown for up to round 5) shows that the AMOUNT variable increases steadily when going from round 1 to round 4. From round 3 onwards, it however stabilizes around $ 9 million. The fact that firms receive a much lower amount of money in their first round of financing is consistent with the literature: venture capitalists do not want to commit too many funds at the start of the venture capital process. Note although that there is a great standard deviation in all rounds. The SYNDSIZE variable also seems to be lower for the first rounds. For all types of exits, the duration decreases as the number of rounds increases, which is to be expected and is in line with Hypothesis 5 that conjectures a reduction in duration as the project gets more developed. For example (IPO exit), the mean duration goes from 1,620 days to 925 days as the representative firm goes from round 1 to round 5 (for trade sales, it goes down from 2,059 days to 1,506 days; for liquidations, it decreases to 981 days from 1,554 days). Again, there is a variability in the means for all the exit routes.

The breakdown of firms across industries (Panel B of Table III) shows that internet and computer companies attract the substantial part of the venture capital invested, while biotech companies are much less represented (in absolute number). Similarly, a breakdown of AMOUNT and SYNDSIZE by type of industry (Panel B of Table III) shows that the average internet firm got much more money (around $12.9 million) that the other types of firms. Communication/media firms rank second (mean of $9.5 million), while the other firms received on average around $6-9 millions. The mean of SYNDSIZE does not really change across industry types. Focusing on IPO exits only, it becomes obvious that internet firms had the fastest exit, with a mean of 670 days. Firms in the other industries needed much more time, the slowest being the semiconductor firms (mean duration of 1,725 days). When focusing on liquidations, it is also true that internet firms had the fastest exits (the representative internet firm exhibits a mean duration to liquidation of around 721 days).

Looking at the pattern of AMOUNT and SYNDSIZE for the different financing stages (Panel C of Table III), we see that buyouts/acquisitions provide the largest mean amount (around $14 million) and involve on average 3 venture capital firms. In contrast, early stage investments are characterized by an average amount of $5.1 million and an average of 3.5 venture capital firms. For IPO exits, a breakdown of DURATION per financing stage yields a mean of 1,581 days (early stage), and decreases as we go to the expansion and later stages. This supports Hypothesis 5 again. Furthermore, we observe similar patterns for trade sale and liquidation.

The BUBBLE variable characterizes investments that took place during the so-called bubble time period for the NASDAQ. Table IV provides summary statistics for investments during the internet bubble (BUBBLE = 1) as well as in ‘normal times’ (BUBBLE = 0). During the bubble period, internet type investments made up 39.2% of all investments, the computer industry being number 2 with 23.1%. Note that biotech investments made up only 4.1% of all investments during the bubble time period (against 7.2% in ‘normal times’). There are however no sharp differences between the stages of financing (early/expansion/later stages) regarding the bubble and normal time periods. Early and expansion (later) stage investments are somewhat less (more) frequent during bubble times. In contrast, there is a sharp difference in the amount of money given to firms when in normal or bubble times. Indeed the mean amount increases from $6.6 million to $13.4 million![15] Finally, the mean duration to exit (irrespective of the type) is only equal to 344 days in bubble times, while it is equal to 1,328 days in normal times. In this case the difference is also highly significant.

V. Estimation results

The descriptive analysis given in the previous section provided relevant information on the dataset and on the exit characteristics. In this section we estimate the competing risks model detailed above to fully describe and analyze the exit process. We characterize extensively the estimation results for rounds 1 and 2, but then lump together the comments for rounds larger than 2 as these estimations do not bring a lot of additional interesting results.

For all types of exits, we estimate the model with all explanatory variables (see Section I) included as covariates and we use the generalized Gamma density function as the distribution for the underlying error term.[16] We also allow for heterogeneity in the specified model.[17] Allowing for heterogeneity leads to somewhat less efficient estimators when dealing with small datasets. We however have a very large dataset and the minor loss of efficiency is irrelevant here. Note that we conclude similarly (from a qualitative point of view) with and without the frailty estimation option. When dealing with venture capital data, there is a strong case for suspecting that there is heterogeneity in the data. Indeed the quantitative information provided in the database is only part of the picture as the important ‘qualitative’ information (e.g. quality of the product developed by the firm, its degree of innovation, the current technological trends,...) about the venture-backed firm is not included. We present the estimation results for the first and second rounds in Table VI and for the third and fourth rounds in Table VII. Note that we analyze the residuals of the models after each estimation. As suggested by the literature on survival analysis (Engle and Russell, 1998, Kalbfleisch and Prentice, 2002), we focus on the so-called generalized Cox-Snell residuals (Cox and Snell, 1968): if the model fits the data well, then these residuals should be exponentially distributed. This can be checked by plotting their cumulative hazard function, along with the benchmark line with slope equal to 1. Anticipating on the estimation results given below, we can already claim that the fit of the models is quite good. As examples, we provide such plots in Figures 5 and 6 (IPO, trade sale and liquidation exits, rounds 1 and 2). Note that the quite 'erratic' line segments at the top right corner of some of the graphs refer to a couple of extreme residuals (outliers), while the hundreds of residuals cluster around the straight line with slope equal to 1.

A. Round 1 (5,817 observations)

A.1. Exit to IPO

All coefficients (except for the BUYACQ and SYNDSIZE variables) are significant at the 5% level and have the expected sign. In particular, later stage investments exit more quickly than expansion stage investments. This is also the case for expansion and later stage investments with respect to early stage investments, which supports the prediction of Hypothesis 4. This is confirmed by Wald statistical tests, according to which the null hypotheses coef(EARLY) $>$ coef(EXPANSION) and coef(EXPANSION) $>$ coef(LATER) are not rejected individually. From a statistical point of view, larger syndicate sizes somewhat increase the hazard for IPOs, and thus decrease exit times, as the SYNDSIZE coefficient is significant at the 6% level. This coefficient is however very small (-0.026) and therefore an increase in the syndicate size does not really impact the timing of the exit in a meaningful way. For example, an increase of the syndicate size from 4 to 8 implies a relative time ratio of only $e^{-0.026 \cdot 8}/e^{-0.026 \cdot 4} = 0.9$. In line with Hypothesis 6B on faster project realization, larger committed amounts also decrease exit times (significantly negative AMOUNT coefficient). The time ratio (or relative exponentiated coefficients) representation allows an easy comparison across industry classifications. Biotech firms have the fastest exits and are followed by internet firms. With respect to these firms, computer firms exhibit a relative time ratio of almost 1.5 (computed as $e^{8.886}/e^{8.476}$) while the other industries are in-between (not taking into account the 'other industries' category). Wald statistical tests indicate that the null hypothesis coef(INTERNET) = coef(BIOTECH) cannot be rejected, while the coefficients of the other industries are individually significantly different from the coefficients of the INTERNET and BIOTECH industries (for example the null hypothesis coef(INTERNET) = coef(COMPUTER) is rejected).

Quite importantly, the model rejects the null hypothesis of monotonously increasing or decreasing hazard. Hence, the generalized Gamma cannot be simplified into the Weibull density distribution for example. This is shown in Figure 1, where we plot the estimated hazard function for the first 4 industry classifications for a typical venture capital-backed firm that would receive (at the early stage and outside the bubble time frame) a $10 million funding provided by a syndicate of 4 venture capitalists, i.e. the covariates are fixed such as SYNDSIZE = 4, AMOUNT = 10, BUBBLE = 0 and EARLY = 1.[18] Regarding the shape of the hazard functions, one has first a sharply increasing hazard (to about 1,000 - 1,500 days) and then a slowly decreasing hazard. Thus, as time flows, venture capital-backed firms first exhibit an increased likelihood of exiting to an IPO. However, after having reached a plateau (around 1,000 - 1,500 days of existence, i.e. 2.75 - 4.0 years), investments that have not yet exited have fewer and fewer possibilities of exits as time increases. This suggests that venture capitalists should not hesitate to 'pull the plug' after a given number of years, rather than stick with potentially non-performing firms.[19] This pattern is stronger for biotech and internet firms which tend to reach their plateau sooner than computer or semiconductor firms (around 5 years (1,800 days) for these latter firms, around 3.3 years (1,200 days) for the former). In the top panel of Figure 4 we plot the hazard functions for an internet firm and the three financing stages, with SYNDSIZE = 4, AMOUNT = 10, BUBBLE = 0. As expected by Hypothesis 4 on stages of development, the maximum of the hazard functions shifts left as we go from early to expansion and finally later stage financing. We then repeat the exercise for a biotech and computer firm, and the results are given in the middle and bottom panels of Figure 4. Quite surprisingly, the BUBBLE coefficient is significantly positive, which leads to a time ratio greater than 1: investments made during the bubble period did not lead to faster IPO exits (more on this below, as this coefficient gets significantly negative for rounds larger than 2). We therefore find no support for Hypothesis 3 on quicker exits for first round investments during the bubble period.

A.2. Exit to trade sale

Estimation results are somewhat similar to those presented above for the exit to IPO, although there are some differences. The coefficients for the AMOUNT and BUBBLE variables are no longer significant while the coefficient for the SYNDSIZE variable is now highly significant. The latter is in line with the idea that a larger syndicate increases the pool of corporate contacts required to find a buyer and thus do a trade sale. The relative time ratios between the different industries are not as dispersed and belong to a tighter range. The classification is also different as the internet, computer and communication/media firms have the fastest exit to a trade sale. The plots of hazard functions in the middle panel of Figure 1 tell the same story (same covariates as for the first figure of preceding sub-section). Note that in this case all hazard functions reach their maximum much later (around 2,500 - 4,000 days, i.e. 6.8 - 11 years) and decrease much more slowly thereafter. A comparison of hazard functions for exits to IPO and trade sale suggests that venture capital-backed firms first aim for an IPO exit and then consider (or are forced to consider) trade sale exits as their second choice. It also provides support for the notion pointed out in Hypothesis 1 that candidates for a trade sale are less homogeneous than those for an IPO.

A.3. Exit to liquidation

There are some marked differences with respect to the successful exits (IPO and trade sale) documented above. First the coefficients for the EARLY, EXPANSION, LATER and BUY-ACQ variables are quite close to each other and it is no longer true that coef(LATER) $<$ coef(EXPANSION) $<$ coef(EARLY): the timing of the stage does not seem to hint at a faster/slower liquidation of the firm, contradicting Hypothesis 5. In this case, the BUBBLE coefficient is strongly negative (with a time ratio of $e^{-0.704} = 0.49$), which suggests that firms that received venture capital money during bubble times have a much larger probability of quick liquidation. In Section IV we showed that the amount of money raised (per funded firm) during bubble times was much larger than during normal times. This clearly shows that the bubble period was an ‘easy money’ period where venture capitalists gave much more money to firms, many of which did not offer outstanding growth potential as they tended to liquidate much faster than in normal times. The relative time ratio of internet firms with respect to the other firms is also striking as it is between 1/3 and 1/4! This is clearly shown in the bottom panel of Figure 1 (same covariates as before) as there is a clear gap between the hazard functions of internet related firms and the other types of firms. Note also that the hazard function for internet firms reaches its plateau quite quickly (around 1,200 days) and strongly decreases thereafter. In contrast, biotech firms are the slowest to liquidate (largest relative time ratio, slowly increasing hazard function and delayed plateau). Lerner (1994) notes that “biotechnology firms [...] mature slowly and do not incur large up-front costs in building manufacturing facilities", which could explain why (in conjunction with the often lengthy Food and Drug Administration (FDA) approval process) these firms do not tend to liquidate quickly. In contrast, internet firms have been known to be gobbling up cash, which justifies their quick demise if they did not succeed in meeting their financial goals within a limited time frame.

These estimation results also concur with the descriptive analysis given in Table V. In this table, we present the number and type of exit for first round investments made during and outside the bubble period. A look at the left (bubble period) and right (outside the bubble period) parts of that table reveals that liquidations occurred much more frequently during the bubble period. While all industry sectors exhibit approximately the same pattern, results for the internet sector are particularly impressive as both periods (i.e. inside and outside the bubble period) are characterized by a large number of funded firms (164 vs 220). For some of the other industry sectors (biotech and medical for example), results are more difficult to interpret as few firms got first round financing during the internet bubble.

B. Round 2 (4,691 observations)

Because of the many similarities with the results of the first round, we highlight more particularly the results specific to round 2. Regarding the IPO exit, the results are similar to those presented for the first round, although many coefficients are no longer significant (they still have the expected sign though). Biotech and internet firms still have the lowest relative time ratios, but the internet firms are much closer to the other firms than in round 1. Biotech firms still exhibit an impressive halved time ratio with respect to most of the other firms. This is also shown in Figure 2, where we plot the estimated hazard function for the first 4 industry classifications with SYNDSIZE = 4, AMOUNT = 10, BUBBLE = 0 and EARLY = 1. Note that the hazard functions reach their maxima much earlier than for round 1 (around 700 days for biotech firms, around 900 - 1,200 days for the other firms). This is of course consistent with the fact that we now deal with the second financing round, which should thus be much closer to the IPO than the first round. Again the general shape is decisively first sharply increasing and then slowly decreasing as time goes by. This type of pattern is particulary striking for biotech firms. For exits to trade sales, results are very close to those given above for the first round:

the relative time ratios are much less dispersed and the hazard functions reach their maxima much later than for an IPO exit (around 2,000 days). Finally, for liquidation exits, results are also similar to those for the first round. In this case, the BUBBLE coefficient is again sharply negative, with a time ratio of 0.47 (i.e. $e^{-0.755}$). As for the first round, internet (biotech) firms have the lowest (largest) time ratio. See also the hazard functions plotted in the bottom panel of Figure 2. Note however that coef(LATER) $<$ coef(EXPANSION) $<$ coef(EARLY), but the coefficients are not significant.

C. Round 3 and above

Focusing on the results specific to these rounds we see that, for all rounds and all exits, the BUBBLE coefficient is now negative. The hazard functions (plotted in Figure 3) reach their maxima within a couple of months, and then sharply decrease. Round 3 biotech investments are particularly impressive.

D. All rounds: summary of main results

The descriptive and estimation results given above can be summarized as follows. Later stage investments exit to IPO more quickly than expansion stage investments. This is also the case for expansion and later stage investments with respect to early stage investments. The industry type matters in a big way as biotech and internet firms have the fastest IPO exits. Internet firms are the fastest to liquidate, while biotech firms are the slowest. Regarding trade sale exits, internet, computer and communication/media firms have the fastest exits. The model generally rejects the null hypothesis of monotonously increasing or decreasing hazards for all specifications. Regarding the shape of the hazard functions (exit to IPO), one has first a sharply increasing hazard and then a slowly decreasing hazard. Thus, as time flows, venture capital-backed firms first exhibit an increased likelihood of exiting to an IPO. However, after having reached a plateau (around 1,000 - 1,500 days of existence), investments that have not yet exited have fewer and fewer possibilities of IPO exits as time increases. Note that this pattern is stronger for biotech and internet firms which tend to reach their plateau sooner than computer or semiconductor firms (around 1,800 days for these latter firms, around 1,200 days for the former). This motivates and supports the 'limited partnership' structure of VC firms where VC investment funds automatically dissolve after a given number of years (rather than sticking with ongoing investments). The bubble period was an 'easy money' period as venture capital-backed firms were awash with funds but many of these firms tended to liquidate much faster than in normal times. Furthermore the bubble period led to significantly decreased exit times for investments made at round 3 or above. This suggests that the bubble period sped up the exit of investments already in the pipeline, i.e. investments who had been initiated some time ago and for which venture capitalists were eager to have a now accelerated exit. Broadly speaking, we conclude similarly for all rounds. Of course, as the round number increases, hazard functions tend to shift leftwards, as one get closer and closer to the exit (particulary true for the IPO exit).

E. The internet bubble and the industry type

The estimation results given above suggest that exits were sped up during the internet bubble. Indeed the evidence is conclusive for the IPO and trade sale exits (starting at round 3) and strongly conclusive for the liquidation exit (all rounds). It can however be argued that the internet bubble has affected some firms more than others. We conjecture that the bubble has sped up the exits for specific industries, while it has hardly affected others.[20] This hypothesis can be tested with our dataset and within the framework of the competing risks model. To do this, we remove the INTERNET dummy variable from the model and include 7 additional industry type dummy variables. These new industry type variables (INTERNET_B, BIOTECH_B, COMPUTER_B, SEMIC_B, MEDICAL_B, COMMEDIA_B and OTHERIND_B) are dummy variables that are equal to 1 when the firm is in the given industry AND the given financing round took place during the bubble. We then estimate the competing risks model with the 13+7 variables hence defined. Estimation results are given in Table VIII. Note that we only report results for the 7 new internet bubble related variables as the estimated coefficients of the 13 previous variables do not really change. A bird's eye view of that table ascertains that 3 of the 7 industries were strongly affected by the bubble: the internet, computer and communication/media industries. For these industries, the bubble sped up the liquidations (all rounds) and the IPOs (round 3 and above). On the contrary, the bubble did not really impact the other industries as the corresponding dummy coefficients in Table VIII are not significant. These results strongly support the hypothesis that the bubble did not have an evenly impact on all venture capital financings.

VI. Conclusion and outlook

For venture capitalists, the decision to exit has two main dimensions, the type and the timing of the exit. This paper has examined both dimensions of exit simultaneously in the framework of competing risks models and survival analysis. Besides the rigorous statistical modelling of exits times, this approach allows the computation of the instantaneous probabilities (hazards) of the different exit routes, conditional on the time already elapsed and on covariates (type of industry, stage of development, syndicate size,. . .) included in the model.

We put forward a series of interesting results. First, the type of industry matters as the biotech and internet firms have the fastest IPO exits. Regarding the least favorable exit (the liquidation of the firm), internet firms are also the fastest to liquidate, while biotech firms are however the slowest. Second, the instantaneous conditional probabilities (or hazards) for IPO exits are clearly non-monotonous. As time flows, venture capital-backed firms first exhibit an increased likelihood of exiting to an IPO. However, these upward sloping hazards then reach a plateau and start to decrease: investments that have not yet exited have fewer and fewer possibilities of IPO exits as time increases. Third, the bubble period from 1998 to 2000 was an 'easy money' period where venture capitalists gave much more money to firms, many of which did not offer outstanding growth potential as they tended to liquidate much faster than in normal times. It also sped up the exit of investments initiated earlier as venture capitalists wanted to capitalize on better exit chances. As conjectured, the bubble affected some industries more than others. More precisely, the internet, computer and communication/media industries were strongly affected as firms in those industries exhibited significantly decreased exit times during the bubble. More generally, our results thus shed light on the competing exit possibilities for venture capitalists and on the dynamics of the time-to-exit for the IPO, trade sale and liquidation exits.

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Table I
Data structure and explicative variables.

NAME	Ask Jeeves	Ask Jeeves	Ask Jeeves	Brocade	Brocade	Brocade	Brocade	Brocade	InGenuity	InGenuity	InGenuity
INTERNET	1	1	1	0	0	0	0	0	0	0	0
BIOTECH	0	0	0	0	0	0	0	0	1	1	1
COMPUTER	0	0	0	0	0	0	0	0	0	0	0
SEMIC	0	0	0	0	0	0	0	0	0	0	0
MEDICAL	0	0	0	0	0	0	0	0	0	0	0
COMMEDIA	0	0	0	1	1	1	1	1	0	0	0
OTHERIND	0	0	0	0	0	0	0	0	0	0	0
ROUND	1	2	3	1	2	3	4	5	1	2	3
SYNDSIZE	7	10	9	2	4	6	12	2	4	3	10
AMOUNT	1,350	7,653	25,000	1,425	3,300	10,000	21,160	700	1,025	5,000	50,000
EARLY	1	0	0	1	0	0	0	0	1	0	0
EXPANSION	0	1	1	0	1	0	0	0	0	1	0
LATER	0	0	0	0	0	1	1	1	0	0	1
BUYACQ	0	0	0	0	0	0	0	0	0	0	0
OTHERSTAGES	0	0	0	0	0	0	0	0	0	0	0
IPO	1	1	1	1	1	1	1	1	0	0	0
TRADESALE	0	0	0	0	0	0	0	0	0	0	0
LIQUID	0	0	0	0	0	0	0	0	0	0	0
BUBBLE	0	1	1	0	0	0	0	0	1	1	0
DURATION	303	242	101	1,423	1,148	899	537	143	1,755	1,412	1,117

This table details the 14 explicative variables and shows how they are defined for two venture capital-backed firms that went public (Ask Jeeves and Brocade) and a firm that has not yet exited (InGenuity). AMOUNT is expressed in \$1,000s and DURATION is in days.

Table II
Frequency of exit route for different types of investment stage.

Stage of investment	Nbr. obs.	Exit route				Ratio TS-IPO
		IPO	Trade sale	Liquidation	Other routes	
Panel A: first investment round (ROUND = 1)						
Early stage	1,839	33.8%	53.0%	9.8%	3.4%	1.57
Expansion stage	472	38.4%	50.4%	8.7%	2.5%	1.31
Later stage	141	34.8%	55.3%	5.0%	5.0%	1.59
Buyout/Acquisition	218	28.4%	56.0%	8.3%	7.3%	1.97
Other stages	54	31.5%	64.8%	1.9%	1.9%	2.06
Panel B: all investment rounds						
Early stage	3,957	35.1%	52.4%	8.4%	4.0%	1.49
Expansion stage	4,397	33.6%	52.8%	9.1%	4.5%	1.57
Later stage	2,692	30.0%	56.2%	8.3%	5.5%	1.87
Buyout/Acquisition	407	26.3%	57.7%	10.1%	5.9%	2.20
Other stages	249	30.1%	62.7%	5.2%	2.0%	2.08

Panel A gives the exit routes frequencies by stage of investment for the first investment round (by focusing on the first round only, we make sure that each exited company is represented once). Panel B provides similar summary statistics for all investment rounds of exited companies. Column 2 gives the number of observations per stage of investment for which an exit already occurred. The last column gives the ratio of trade sales over IPOs. Since we exclude yet-to-exit investments, the total number of observations is 2,724 for Panel A and 11,702 for Panel B.

Table III

Summary statistics for the investment rounds, industries and stages of development.

Variable	Nbr. Obs.	AMOUNT	SYNDSIZE	DURATION (in days)			
				IPO	TS	IPO and TS	Liquidation
Panel A: Breakdown by investment rounds							
All rounds	22,042	7.7	3.9	1,219	1,666	1,496	1,203
		(12.0)	(3.3)	(1,066)	(1,335)	(1,259)	(1,035)
1st round	5,817	6.5	2.9	1,620	2,059	1,887	1,554
		(10.7)	(2.1)	(1,148)	(1,447)	(1,355)	(1,168)
2nd round	4,691	8.1	3.8	1,350	1,739	1,586	1,286
		(11.7)	(3.0)	(1,093)	(1,355)	(1,273)	(1,049)
3rd round	3,562	9.4	4.5	1,125	1,603	1,414	1,087
		(13.0)	(3.6)	(995)	(1,331)	(1,232)	(960)
4th round	2,548	9.7	4.7	956	1,514	1,290	996
		(14.1)	(4.0)	(977)	(1,277)	(1,197)	(852)
5th round	1,765	8.6	4.6	925	1,506	1,286	981
		(13.2)	(4.0)	(954)	(1,294)	(1,210)	(845)
Panel B: Breakdown by industries							
INTERNET	3502	12.9	3.9	670	991	852	721
		(15.5)	(3.1)	(566)	(826)	(742)	(519)
BIOTECH	1468	6.9	4.1	1,097	2,062	1,523	1,354
		(10.0)	(3.5)	(860)	(1,370)	(1,212)	(868)
COMPUTER	6352	5.9	4.0	1,251	1,599	1,486	1,254
		(9.0)	(3.4)	(1,071)	(1,325)	(1,259)	(997)
SEMIC	1793	7.2	4.3	1,725	1,835	1,787	1,562
		(11.4)	(4.0)	(1,376)	(1,387)	(1,383)	(977)
MEDICAL	2673	5.5	3.9	1,162	1,792	1,542	1,684
		(7.9)	(3.2)	(890)	(1,249)	(1,162)	(1,407)
COMMEDIA	3169	9.5	4.3	1,206	1,683	1,526	1,291
		(14.5)	(3.6)	(1,029)	(1,438)	(1,337)	(901)
OTHERIND	3085	6.3	2.9	1,504	1,943	1,794	1,624
		(12.0)	(2.7)	(1,274)	(1,351)	(1,341)	(1,525)
Panel C: Breakdown by stage of development							
Early stage	7,427	5.1	3.5	1,581	1,907	1,776	1,470
		(7.7)	(2.8)	(1,073)	(1,377)	(1,274)	(1,000)
Expansion stage	8,827	9.3	4.2	1,106	1,530	1,366	1,000
		(12.9)	(3.5)	(1,038)	(1,294)	(1,219)	(932)
Later stage	4,273	8.1	4.3	776	1,400	1,183	985
		(13.3)	(3.8)	(840)	(1,161)	(1,101)	(835)
Buyout/Acquisition	936	13.7	3.0	1,237	1,790	1,617	2,127
		(18.0)	(2.3)	(1,134)	(1,268)	(1,253)	(1,763)
Other stages	579	3.8	2.5	1,464	2,870	2,414	1,453
		(10.9)	(2.6)	(1,281)	(1,796)	(1,771)	(1,761)

Key statistics for different investment rounds, industries and stages of development. AMOUNT is expressed in $1,000,000s and gives the amount of money received by the firm. SYNDSIZE is the size of the syndicate. Standard deviations are reported below each value in brackets.

Table IV
Summary statistics for investment during and outside the bubble period.

Variables	Full sample	Period of observation		Test of diff.
		$BUBBLE = 1$	$BUBBLE = 0$	P-value
Industry sector:				
- INTERNET	15.9%	39.2%	11.3%	
- BIOTECH	6.7%	4.1%	7.2%	
- COMPUTER	8.1%	5.0%	8.8%	
- MEDICAL	28.8%	23.1%	30.0%	
- SEMIC	12.1%	8.4%	12.9%	
-COMMEDIA	14.4%	13.1%	14.6%	
- OTHERIND	14.0%	7.2%	15.4%	
Stages of development:				
- Early stage	33.7%	33.30%	35.68%	
- Expansion stage	40.1%	38.91%	45.79%	
- Later stage	19.4%	20.29%	14.80%	
- Buyout/Acquisition	4.3%	4.55%	2.72%	
- Other stages	2.6%	2.95%	1.02%	
Mean amount (in $1,000,000s)	7.7	13.4	6.6	0.00
Mean syndicate size	3.9	3.96	3.88	0.15
Mean duration to IPO (in days)	1,219	344	1,328	0.00

The variable BUBBLE equals 1 (0) if the investment took place during (outside) the internet bubble period that ranges from September 1998 to April 2000. The number of observations for BUBBLE = 1 (BUBBLE = 0) is 3,643 (18,399), which makes a total of 22,042.

Table V

Type of exit during and outside the bubble period.

	$BUBBLE = 1$					$BUBBLE = 0$				
	N	IPO	Trade sale	Liquidation	Other routes	N	IPO	Trade sale	Liquidation	Other routes
All industries	287	16%	49.8%	32.8%	1.4%	2,437	36.3%	53.5%	6.3%	3.9%
INTERNET sector	164	15.9%	45.7%	36.6%	1.8%	220	44.6%	40.0%	14.5%	0.9%
BIOTECH sector	5	40.0%	40.0%	20%	0%	183	56.8%	37.7%	2.2%	3.3%
COMPUTER sector	33	12.1%	57.6%	30.3%	0%	767	31.2%	60.6%	3.9%	4.3%
SEMIC sector	17	17.6%	70.6%	11.8%	0%	216	44.4%	48.6%	5.1%	1.9%
MEDICAL sector	6	83.3%	0%	16.7%	0%	282	38.6%	50.7%	5.0%	5.7%
COMMEDIA sector	46	6.5%	56.5%	37.0%	0%	366	32.2%	56.8%	9.3%	1.7%
OTHERIND sector	16	18.7%	56.2%	18.8%	6.3%	403	29.8%	56.3%	6.9%	7.0%

Total number of exits (N) and type of exit (IPO, trade sale, liquidation or other exit routes) for first round investments made during and outside the bubble period that ranges from September 1998 to April 2000. The top row gives the information for all industries lumped together, while the other rows break up the data according to the industry the firm belongs to.

Table VI
Estimation results for the competing risks model (rounds 1 and 2).

	Round 1			Round 2		
Coefficient	IPO	Trade sale	Liquidation	IPO	Trade sale	Liquidation
INTERNET	8.532 (0)	8.785 (0)	9.463 (0)	8.038 (0)	8.127 (0)	8.927 (0)
BIOTECH	8.476 (0)	9.137 (0)	10.769 (0)	7.710 (0)	8.426 (0)	9.993 (0)
COMPUTER	8.886 (0)	8.769 (0)	10.354 (0)	8.350 (0)	8.080 (0)	9.758 (0)
SEMIC	8.830 (0)	8.959 (0)	10.398 (0)	8.206 (0)	8.224 (0)	9.676 (0)
MEDICAL	8.841 (0)	9.123 (0)	10.481 (0)	8.236 (0)	8.457 (0)	9.876 (0)
COMMEDIA	8.885 (0)	8.722 (0)	9.909 (0)	8.133 (0)	7.974 (0)	9.202 (0)
OTHERIND	9.484 (0)	9.313 (0)	10.545 (0)	8.807 (0)	8.716 (0)	9.767 (0)
SYNDSIZE	-0.026 (0.052)	-0.037 (0)	-0.055 (0.008)	-0.012 (0.288)	-0.012 (0.110)	0.010 (0.618)
AMOUNT	-0.016 (0)	-0.003 (0.198)	-0.011 (0.036)	0.004 (0.324)	-0.002 (0.486)	-0.022 (0)
BUBBLE	0.770 (0)	-0.004 (0.953)	-0.704 (0)	0.291 (0.009)	-0.030 (0.669)	-0.755 (0)
EARLY	-0.455 (0.016)	-0.427 (0)	-0.975 (0.040)	0.082 (0.785)	0.087 (0.584)	-0.143 (0.716)
EXPANSION	-0.702 (0)	-0.377 (0.003)	-0.901 (0.061)	-0.122 (0.679)	-0.058 (0.716)	-0.295 (0.454)
LATER	-1.377 (0)	-0.732 (0)	-1.039 (0.046)	-0.556 (0.072)	-0.174 (0.310)	-0.601 (0.157)
BUYACQ	-0.284 (0.180)	-0.300 (0.027)	-0.609 (0.218)	0.109 (0.765)	-0.084 (0.681)	0.118 (0.805)

Estimated coefficients for the competing risks model with 3 exits (IPO, trade sale, liquidation). Durations to exit start at round 1 (left panel) and 2 (right panel), and end when there is an exit or are right-censored at the date of the analysis. The underlying density distribution is the generalized Gamma density distribution and we allow for heterogeneity (frailty). P-values for the null hypothesis that the coefficient is not different from zero are reported in parenthesis.

Table VII
Estimation results for the competing risks model (rounds 3 and 4).

	Round 3			Round 4		
Coefficient	IPO	Trade sale	Liquidation	IPO	Trade sale	Liquidation
INTERNET	8.097 (0)	8.281 (0)	10.539 (0)	7.478 (0)	8.470 (0)	9.693 (0)
BIOTECH	7.450 (0)	8.578 (0)	12.238 (0)	6.993 (0)	8.822 (0)	11.517 (0)
COMPUTER	8.397 (0)	8.176 (0)	11.576 (0)	7.909 (0)	8.392 (0)	10.917 (0)
SEMIC	8.249 (0)	8.441 (0)	11.262 (0)	7.778 (0)	8.640 (0)	10.658 (0)
MEDICAL	8.324 (0)	8.689 (0)	11.503 (0)	7.520 (0)	8.849 (0)	10.923 (0)
COMMEDIA	8.293 (0)	8.128 (0)	10.932 (0)	7.627 (0)	8.406 (0)	10.011 (0)
OTHERIND	9.006 (0)	8.873 (0)	11.653 (0)	8.536 (0)	9.141 (0)	10.940 (0)
SYNDSIZE	-0.016 (0.147)	0.011 (0.190)	0.048 (0.035)	-0.007 (0.663)	0.005 (0.587)	0.061 (0.018)
AMOUNT	-0.005 (0.257)	-0.003 (0.266)	-0.029 (0)	-0.006 (0.207)	0.005 (0.121)	-0.032 (0)
BUBBLE	-0.362 (0.007)	-0.184 (0.021)	-0.788 (0)	-0.719 (0)	-0.234 (0.020)	-0.459 (0.034)
EARLY	-0.130 (0.696)	-0.274 (0.145)	-1.061 (0.173)	0.694 (0.114)	-0.317 (0.242)	-0.065 (0.925)
EXPANSION	-0.300 (0.364)	-0.286 (0.123)	-1.150 (0.137)	0.238 (0.574)	-0.523 (0.046)	0.171 (0.800)
LATER	-0.616 (0.068)	-0.415 (0.029)	-1.467 (0.061)	-0.051 (0.906)	-0.677 (0.010)	-0.304 (0.653)
BUYACQ	0.025 (0.957)	-0.417 (0.103)	-1.484 (0.081)	0.267 (0.641)	-0.364 (0.289)	0.081 (0.921)

Estimated coefficients for the competing risks model with 3 exits (IPO, trade sale, liquidation). Durations to exit start at round 3 (left panel) and 4 (right panel), and end when there is an exit or are right-censored at the date of the analysis. The underlying density distribution is the generalized Gamma density distribution and we allow for heterogeneity (frailty). P-values for the null hypothesis that the coefficient is not different from zero are reported in parenthesis.

Table VIII
Impact of internet bubble on IPOs and liquidations.

IPO					
Coefficient	Round 1	Round 2	Round 3	Round 4	Round 5
INTERNET_B	0.808 (0)	0.443 (0.015)	-0.732 (0.001)	-0.954 (0.002)	-1.407 (0)
BIOTECH_B	0.458 (0.347)	0.377 (0.405)	-0.652 (0.225)	-0.017 (0.975)	-0.282 (0.567)
COMPUTER_B	1.166 (0)	0.317 (0.152)	-0.247 (0.313)	-1.274 (0)	-1.530 (0)
SEMIC_B	0.198 (0.605)	0.106 (0.821)	0.140 (0.773)	-0.557 (0.371)	-0.179 (0.781)
MEDICAL_B	0.272 (0.384)	0.367 (0.304)	0.543 (0.194)	0.945 (0.039)	0.188 (0.783)
COMMEDIA_B	1.091 (0.001)	-0.044 (0.865)	-0.983 (0.001)	-1.293 (0.001)	-1.696 (0)
OTHERIND_B	0.301 (0.402)	0.139 (0.736)	-	-	-
Liquidation					
Coefficient	Round 1	Round 2	Round 3	Round 4	Round 5
INTERNET_B	-0.592 (0)	-0.823 (0)	-0.668 (0.006)	-0.166 (0.598)	0.132 (0.815)
BIOTECH_B	-0.764 (0.224)	-1.043 (0.090)	-2.179 (0.030)	-	-
COMPUTER_B	-0.853 (0)	-0.765 (0.006)	-0.675 (0.059)	-1.169 (0.006)	-0.502 (0.459)
SEMIC_B	-0.693 (0.123)	-1.072 (0.055)	-0.827 (0.149)	-1.064 (0.158)	-
MEDICAL_B	-0.366 (0.459)	8.926 (0.997)	0.085 (0.916)	-	-
COMMEDIA_B	-0.718 (0.001)	-0.739 (0.014)	-0.945 (0.011)	-0.587 (0.183)	-1.351 (0.059)
OTHERIND_B	-0.992 (0.004)	-0.697 (0.112)	-1.591 (0.003)	-1.194 (0.106)	-

Estimated coefficients (for the internet bubble industry dummy variables only) for the competing risks model with 3 exits (IPO, trade sale, liquidation). Durations to exit start at round 1, 2, 3, 4 and 5, and end when there is an exit or are right-censored at the date of the analysis. The underlying density distribution is the generalized Gamma density distribution and we allow for heterogeneity (frailty). Besides the seven internet bubble industry dummy variables listed above, we included the SYNDSIZE, AMOUNT, EARLY, EXPANSION, LATER and BUYACQ variables as in Tables VI and VII. P-values for the null hypothesis that the coefficient is not different from zero are reported in parenthesis. A $-$ indicates that the coefficient could not be estimated because of a lack of observations for that industry in the internet bubble period (in that case, the model was estimated without that dummy variable).

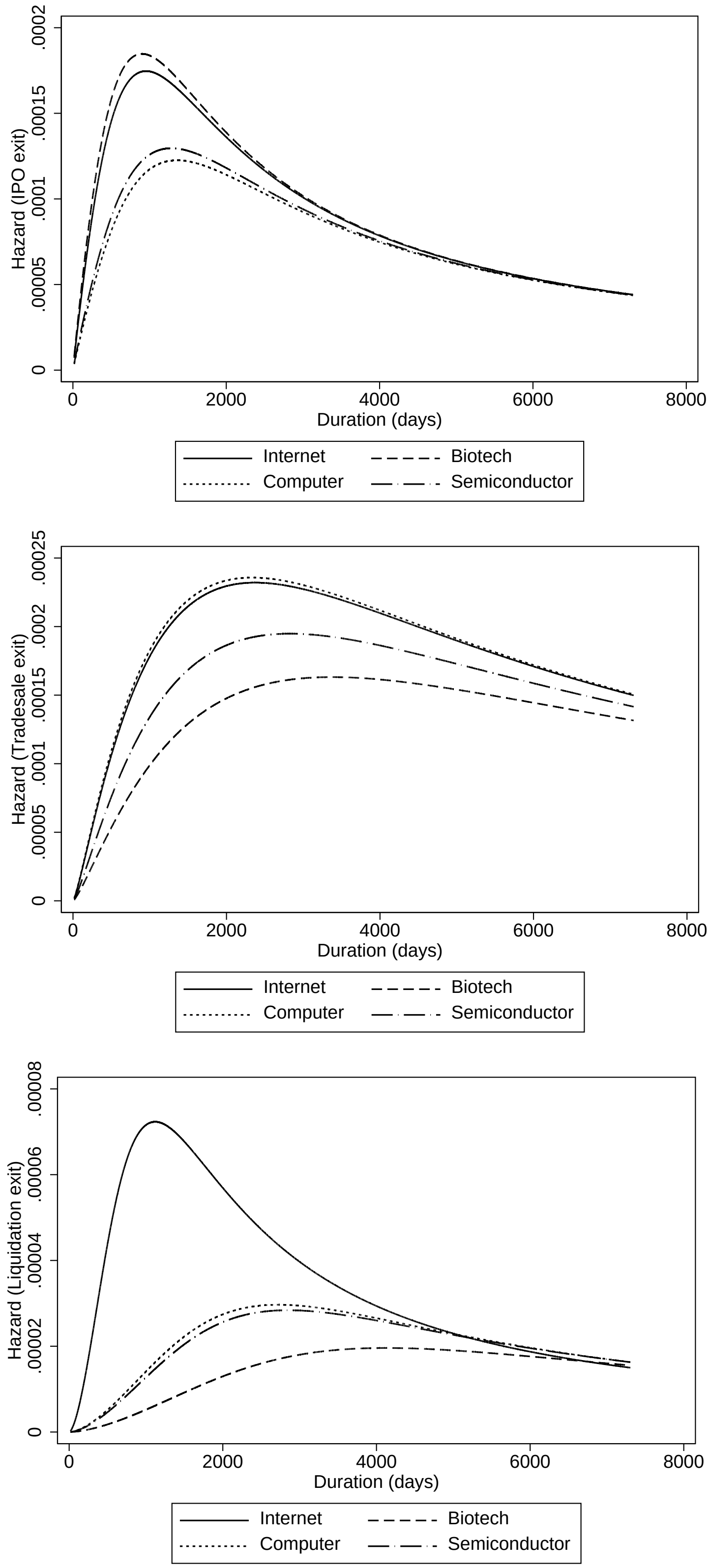

Figure 1. Hazard functions for the IPO, trade sale and liquidation exits as a function of industry type; durations start at round 1. Besides the industry type, the covariates are AMOUNT=10, SYNDSIZE=4, EARLY=1 and BUBBLE=0.

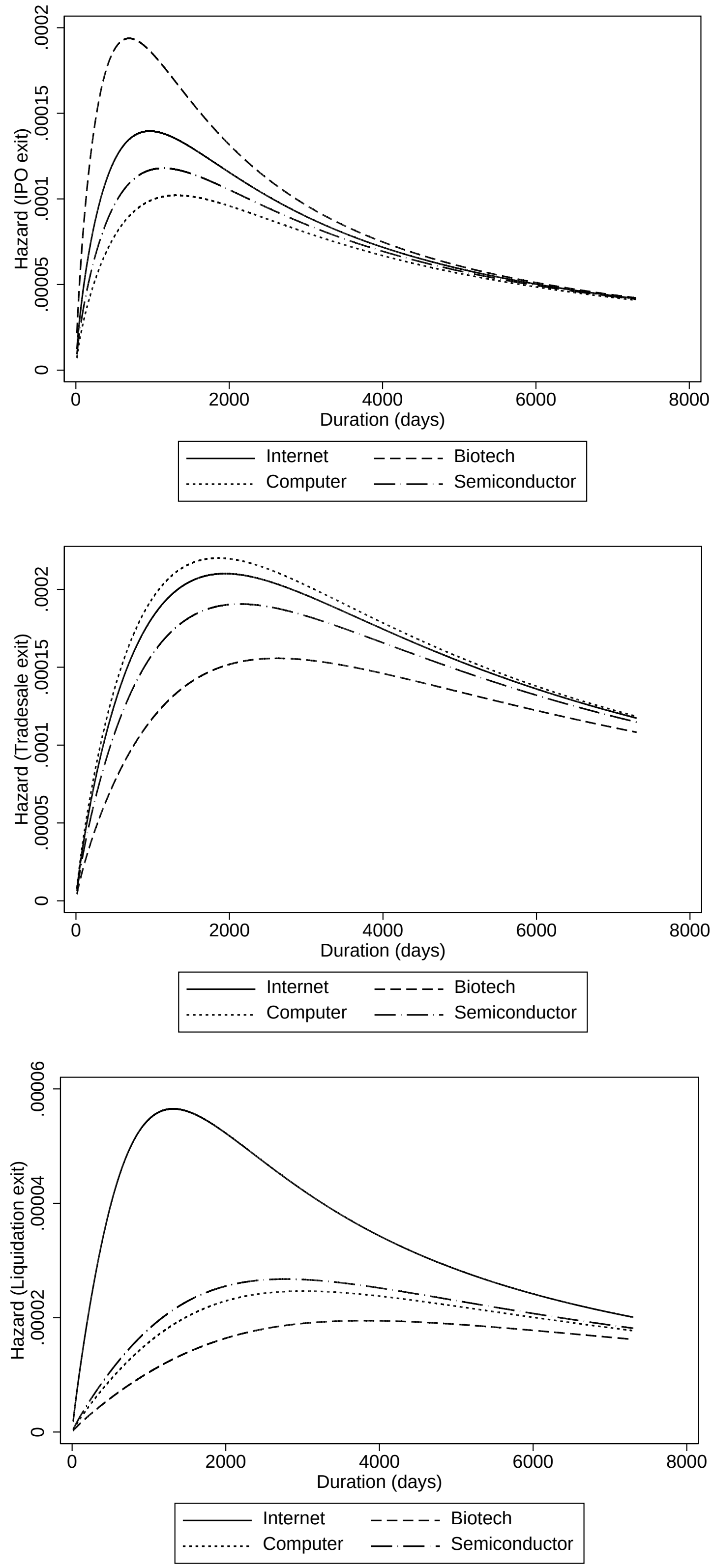

Figure 2. Hazard functions for the IPO, trade sale and liquidation exits as a function of industry type; durations start at round 2. Besides the industry type, the covariates are AMOUNT=10, SYNDSIZE=4, EARLY=1 and BUBBLE=0.

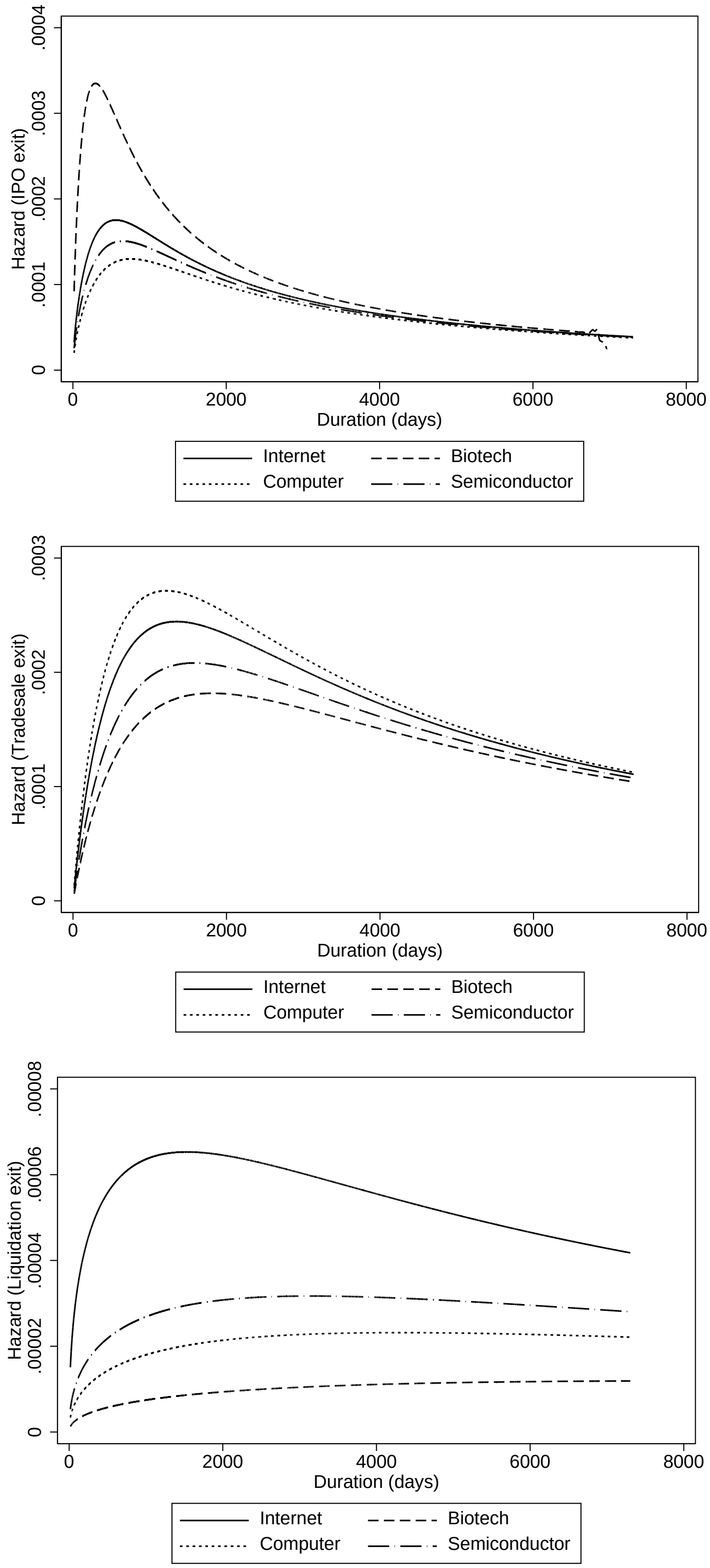

Figure 3. Hazard functions for the IPO, trade sale and liquidation exits as a function of industry type; durations start at round 3. Besides the industry type, the covariates are AMOUNT=10, SYNDSIZE=4, EXPANSION=1 and BUBBLE=0.

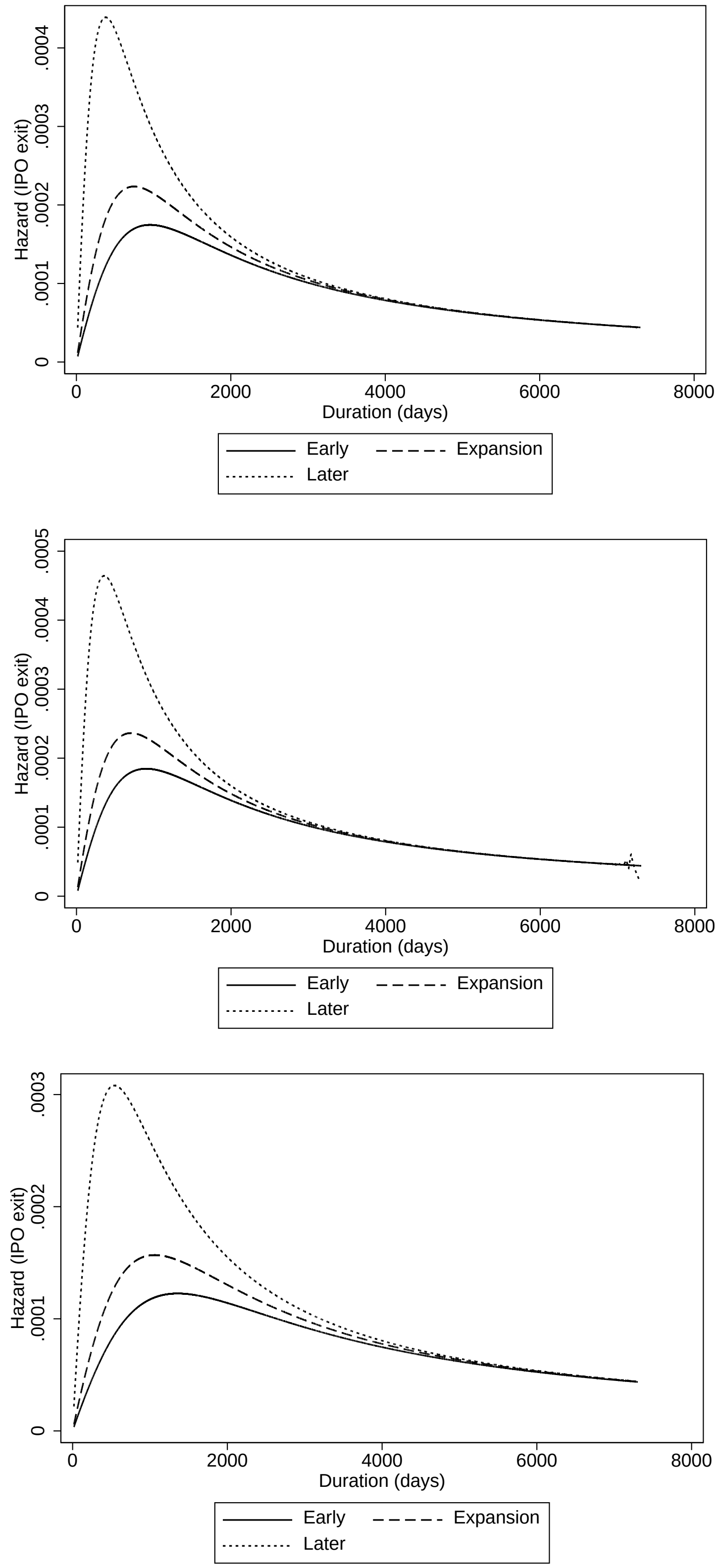

Figure 4. Hazard functions (IPO exit) for the internet (top), biotech (middle) and computer (bottom) industries as a function of the type of stage; durations start at round 1. Besides the industry and stage types, the covariates are AMOUNT=10, SYNDSIZE=4 and BUBBLE=0.

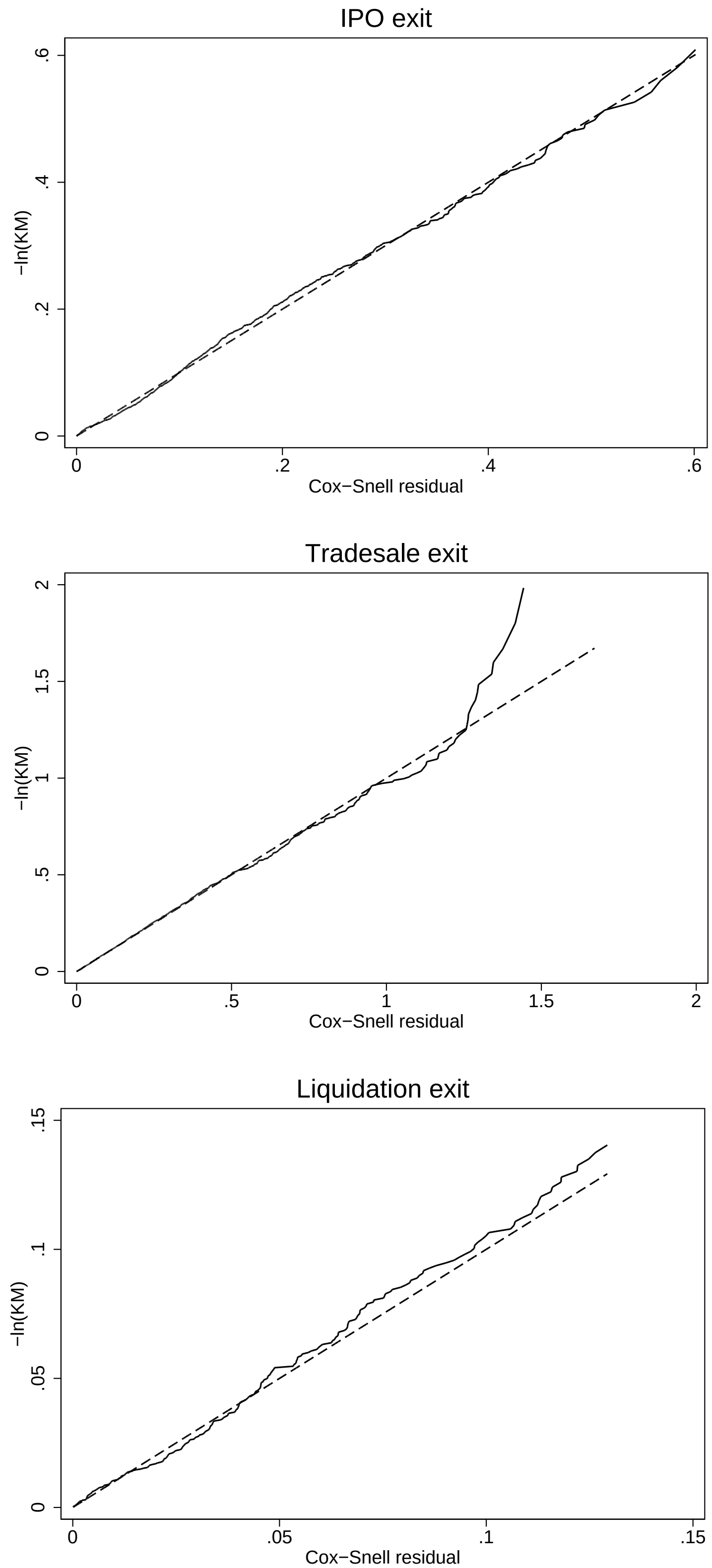

Figure 5. Cumulative hazard functions of Cox-Snell residuals for the IPO, trade sale and liquidation exits; durations start at round 1. We also plot the benchmark line whose slope is equal to 1.

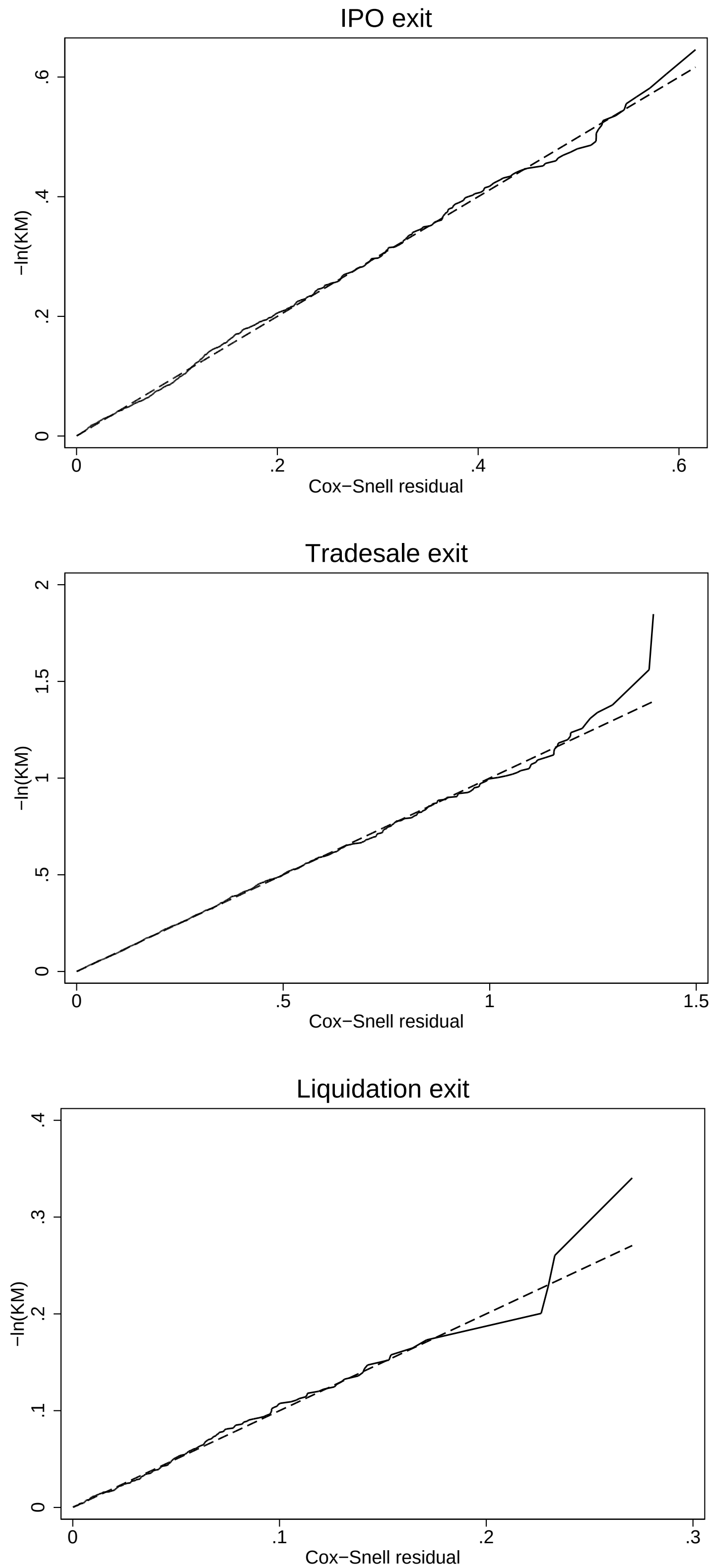

Figure 6. Cumulative hazard functions of Cox-Snell residuals for the IPO, trade sale and liquidation exits; durations start at round 2. We also plot the benchmark line whose slope is equal to 1.

Notes

[1]Note that we also use the word ‘trade sales’ for so-called acquisitions.

[2]Note that Gompers (1995) also uses duration models, but these are not competing risks models.

[3]Note that we get the same qualitative results and conclude similarly when using non-filtered data.

[4]Because of the structure of the competing risks model used in the statistical analysis, the fact that we do not model explicitly these other types of exit routes does not lead to any bias in our estimations for the IPO, trade sale and liquidation exits.

[5]Note that if a company had more than one financing round, we consider the exit type at the very end of the financing cycle (i.e. the exit route chosen at the end of the last round). In other words, for a given firm, this variable takes the same value for all financing rounds. See the examples given below.

[6]This is characterized as a right-censored duration in the terminology of survival analysis. See Section III.

[7]Note that to avoid multicolinearity problems in the statistical analysis of Section V, we do not include a constant and we have to drop one of the dummy variables (as the industry type and stage of development type variables sum to 1 separately): we do not include the OTHESTAGES dummy variable.

[8]See Cassidy (2002) for a lively account of the internet bubble.

[9]For a more detailed categorization of investment stages, see e.g. the EVCA or NVCA websites.

[10]In competing risks models, durations are said to be right-censored if the corresponding individual or firm at risk has not yet exited at the time of the analysis. Right-censoring is discussed below.

[11] In survival analysis, the hazard function gives at all times the conditional instantaneous probability of exit given that the subject at risk has not yet exited at that time. For example, in a medical science context, the hazard of death by heart attack at time t for a patient is the instantaneous probability of dying of a heart attack at time t given that the patient is still alive 'just' before time t.

[12] As indicated in Lee and Wang (2003): "This is perhaps the most important concept in competing risks analysis. It is because the basic assumption for a competing risks model is that the occurrence of one type of event removes the person from risk of all other types of events and the person will no longer contribute to the successive risk set.

[13] Assuming independence (conditionally on the past state) between the durations ending at states $y_i = 1$ and $y_i = -1$, the joint 'density' of duration x_i and state y_i in our simplified examples is then equal to

$$f(x_i, y_i) = (\lambda_s)^{I_i^+} e^{-\lambda_s x_i} (\lambda_f)^{I_i^-} e^{-\lambda_f x_i}. \tag{1}$$

where

$$I_i^+ = \begin{cases} 1 & \text{if} \quad y_i = 1 \\ 0 & \text{if} \quad y_i = -1, \end{cases} \tag{2}$$

$$I_i^- = 1 - I_i^+. \tag{3}$$

For example, if state $y_i = 1$ is observed ($I_i^+ = 1$ and $I_i^- = 0$), x_i contributes to the likelihood function via the density function $\lambda_s e^{-\lambda_s x_i}$ and via the survivor function $e^{-\lambda_f x_i}$. Details regarding the construction of likelihood functions of competing risks models are available in Kalbfleisch and Prentice (2002).

[14] Note that in practice more than 3 exit types are observed. This is also the case in our sample. We focus however on the IPO, trade sale and liquidation exits as these are the most important exists and are the real focus of our analysis. Because of the multiplicative nature of the likelihood function for competing risks models (see Equation (1)), not modelling explicitly the other (few) types of exits does not lead to any bias.

[15]Statistical tests clearly reject the null hypothesis that the two means are equal.

[16]As indicated previously, we avoid multicolinearity problems by not including the constant and the OTHERSTAGES dummy variable.

[17]We do this by estimating the model with the ‘frailty’ option provided in Stata. Details are available in Kalbfleisch and Prentice (2002) and in the “Survival analysis and epidemiological tables” Stata reference guide.

[18]To ensure a good readability of the graphs, we do not plot all 7 types of industries on the same graph. Full page color graphs for all industries are available on request.

[19]Note that this is similar to what is observed in the labor market regarding individuals seeking jobs. Individuals who have been searching jobs for extended periods of time often have less and less chances of actually getting a job as time goes by.

[20]Of course the name ‘internet bubble’ by itself indicates that the worst excesses of the stock market bubble witnessed at the end of the 1990s were to be found in the internet industry.