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

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ABSTRACT

This paper examines the dynamics of exit options for US venture capital funds. Using a detailed sample of more than 20,000 investment rounds, we analyze the time to 'IPO', 'trade sale' and 'liquidation' for 6,000 venture-backed firms. We model these exit times using competing risks models, which allow for a joint analysis of exit type and exit timing as well as their dynamic interplay. 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 hazard rate 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. This sharply contrasts with exit options through a trade sale, where the hazard rate is less time-varying.

1. Introduction

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 be involved in their portfolio companies before cashing out. Besides the offer price, the exit decision therefore features two important dimensions. First, the type of exit route (the most important ones being IPO, trade sale and liquidation)[1] and secondly the actual timing of the exit. 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, Bergemann and Hege, 1998). Besides the disciplinary action that this procedure exerts on venture capital-backed firms, this stage financing also provides exit options to venture capitalists at all financing rounds. This allows the VCs to time their exit. In addition to stage finance, several studies document the widespread use of contractual arrangements that guarantee the venture capitalist explicit intervention rights, also regarding exit issues (Gompers, 1997, Cumming, 2002, and Kaplan and Stromberg, 2003). More generally, these rights allow the venture capitalist to force an exit. Thus, they can avoid being locked into holding the shares for an extended period of time should a disagreement with the entrepreneur occur. Moreover, the recent stock market developments witnessed over the last few years highlight the dependence of venture capital investments on prevailing exit conditions.

While IPO exits by VC funds have been researched quite extensively,[2] 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 as time flows. Moreover, little is known about the effect of the recent internet bubble on the relative importance of competing exit possibilities (especially trade sales compared to IPOs). 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 invest-

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

[2] See, among others, Lerner (1994), Gompers (1995, 1996), Black and Gilson (1998), Cumming and MacIntosh (2003), Cochrane (2005), Cumming (2002), Schwienbacher (2005), and Das, Jagannathan, and Sarin (2003).

ments as it requires jointly taking into account all potential exit routes. We also assess 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. This provides a better picture of the dynamics of exit options for venture capital funds.

In the last part the paper, we also tackle the issue as to whether the geographical location of the entrepreneurial firm affects the two dimensions of exit. For instance, does an investment in the Silicon Valley facilitate VC funds exits more than a similar investment in Texas or on Route 128?[3] If it does, the firm's cost of capital would be directly affected as VC funds would require a lower cost from firms in more favorable regions. Hence, this would lead to important implications for the clustering of entrepreneurial firms. Last, we examine how the internet bubble affected the exit conditions of venture-backed companies. More specifically, we look at whether investments made during the bubble period affected the times to exit and exit types as compared to similar deals made outside this period. The internet bubble period was said to be characterized by easy exits. Market conditions then changed dramatically in 2001 and 2002 as the NASDAQ and most stock indices crashed. Recent studies show that exit conditions are highly cyclical and strongly depend on the current or foreseen state of stock markets as well as other macro-economic factors (Lerner, 1994, Gompers and Lerner, 1998, Jeng and Wells, 2000, Bottazzi and Da Rin, 2001, and Cumming, Fleming, and Schwienbacher, 2003). Correspondingly, the exit from successful firms should have been easy. For unsuccessful ventures this may be attributed to the desire by venture capitalists to pull the plug more quickly and redirect their effort in new projects since they face a tradeoff between the number of portfolio companies and the time spent with each companies (Kanniainen and Keuschnigg, 2003). Some industries may also have been more affected than others during the bubble periods (Das, Jagannathan, and Sarin, 2003).[4]

Using a detailed sample 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. In the framework of survival analysis, we characterize and model the times to exit using competing risks models, which allow for a joint analysis of exit type and exit timing as well as their dynamic interplay. To our knowledge, this is the first application of such statistical models

[3]On the difference between Silicon Valley and Route 128, see Aoki (1999), Saxenian (1994), and Hellmann and Perotti (2004).

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

to venture capital investments.[5] The strength of our 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). In this framework, 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 or 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 increasing (as time goes by) IPO hazard rates during the first n years, and thereafter decreasing conditional probabilities 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 were funded during the internet bubble time period.

The empirical 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. Internet start-ups are quickly terminated if they don't achieve technological advancement fast enough. This effect is much less pronounced for biotech firms. Second, regarding the shape of the conditional probability (hazard) of IPO exit, a first sharply increasing hazard and then a slowly decreasing hazard are observed. 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. This pattern is the strongest for biotech and internet firms which tend to reach their plateau sooner than computer or semiconductor firms. We interpret this as evidence that IPO candidates tend to be selected relatively quickly. In contrast, if they do not achieve a public listing fast enough, their chances of doing so quickly decrease.

For trade sales, hazard functions reach their maximum much later and tend to decrease slowly thereafter. This is very much in line with the widespread notion that, in contrast to an

[5] Note that Gompers (1995) and Cumming and MacIntosh (2001) also use duration models, but these are not competing risks models.

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 startups (Lerner, 1994, Bascha and Walz, 2001, Cumming and MacIntosh, 2001, Schwienbacher, 2004). 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. The latter firm is thus ready to pay more than the liquidation value of the venture. This leads to a greater heterogeneity in the type of venture capital-backed firms doing a trade sale as compared to venture capital-backed firms going public.

Third, the geographical location of the entrepreneurial firm does not seem to impact the dynamics of the IPO process. In contrast, trade sales are significantly more likely (i.e. the hazard rate increases significantly) for firms based in California (Silicon Valley) and northeast states (Route 128). Similarly, liquidations are less likely in these regions. Since these are also the regions that feature the largest clustering of entrepreneurial firms and venture capitalists (and all other important players involved in venture capital finance), this may suggest that such a concentration facilitates the success of these firms as compared to firms in other US regions. Fourth, 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. Fifth, 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. Since an early-stage project is typically less developed than a project in the expansion stage and especially later stage, the time-to-exit for successful projects decreases with the development of the project. In particular, it is the largest for early stage and the shortest for later stage projects. Survival should therefore be greatest for ventures with more developed projects. The size of the syndicate of VC funds affects both dimensions of exit. Most interestingly, it accelerates exits through all routes. In early rounds, investments with larger syndicates tend to be divested more quickly (i.e., faster IPOs, trade sales and liquidations), which indicates gains from syndication.[6] In contrast, deals that are less syndicated are more likely to remain longer in the portfolios of VC funds.

Much of the past research on venture capital exits has dealt with IPOs only. Indeed, an IPO is deemed to be the most successful (hence preferred) venture capital exit. For example, Lerner (1994) examines 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), Schwienbacher (2004), and Das, Jagannathan, and Sarin (2003). These papers only look at the type of exit but do not examine the time-to-exit (the second dimension highlighted above). The contribution of our paper is to examine both dimensions at the same time, as well as their dynamic interaction.

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) also motivate 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 be available for new start-ups. Other papers show a positive link between company valuation and the likelihood of going public (Gompers, 1995, Cumming and MacIntosh, 2003, and Cochrane, 2005). 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. Finally, Ritter and Welch (2002) provide an extensive analysis of the overall IPO activities in the US, which documents the relation between the internet bubble and IPO volume.

[6] 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, Amit, and Antweiler, 2002, Lerner, 1994, and Hellmann, 2002). Some of these studies suggest that larger syndicates should make exits easier for successful start-ups as far as they increase 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.

The rest of the paper is structured as follows. After this introduction, we detail the data and variables used in the analysis. We next present the competing risks model in Section 3. The empirical application is split into 2 sections: Section 4 gives a detailed descriptive analysis, while we present all the estimation results in Section 5. Finally, Section 6 concludes.

2. 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. Observations cover the period from 1/1/1980 to 6/23/2003 (date at which the data has been collected). 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.[7] More than 97% (90%) of these screened firms were founded after 1970 (1980) and about 93% of the firms are established in the USA (firms incorporated in California and Massachusetts add up to a substantial proportion of the total US firms). Hence, our analysis mainly focuses on relatively recently established US firms. The complete descriptive analysis is provided in Section 4. To characterize the firms in our dataset and the stage financing they received 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 OTH-

[7] Note that we get the same qualitative results and conclude similarly when using non-filtered data. It is however well known that meaningless outliers can substantially affect the precision of the econometric estimations. We therefore focus on the filtered data.

ERIND (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. This latter route could include secondary sales or management buyouts (MBO).[8] This will yield right-censored durations in the statistical analysis (see below for the DURATION variable and Section 3).[9]

- On the geographical location of the entrepreneurial firm (dummy variable): WEST (California), NORTHEAST (Massachusetts, New York and Pennsylvania), SOUTH (Texas), and MIDWEST (Illinois and Ohio). Set to 1 (0) if the location matches (does not match) the description of the variable. For the classification of regions, we use the same definitions of Lerner, Schoar, and Wong (2005).

- 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.

[8]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.

[9]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.

- 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).[10] This variable is the main focus of our analysis as it characterizes the 'life' of the investment since a given round.

We thus have a total of 18 explicative variables, although many of these variable are pure dummy variables.[11] The full statistical model is detailed in Section 3. As an illustration, Table 1 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 the analysis will be detailed in Sections 4 and 5, 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). Besides these 18 variables, we also define a secondary variable, AMOUNTIND, for the total amount of money received by the firm (in millions of USD) in excess of the average amount of money received by firms in that industry (at the given round). This variable is used later in the analysis.

3. 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-

[10] This is characterized as a right-censored duration in the terminology of survival analysis. See Section 3.

[11] Note that to avoid multicollinearity problems in the statistical analysis of Section 5, 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.

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).

3.1. A simple competing risks model

The next sub-section presents the competing risks model used in the empirical analysis of Section 5. 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.[12] 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.[13] 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

[12]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.

[13]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.

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 $y_i = -1$.[14] 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.[15]

3.2. A competing risks model for venture capital exits

The competing risks model detailed in the previous sub-section can be used to model the exit times and types of exit of venture capital-backed investments provided that:

- we allow for multiple exits (IPO, trade sale and liquidation);
- we allow for right-censoring as many investments had not yet exited at the time of the analysis (i.e. they were 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 received the funding from the venture capitalist and the time of the analysis (June 23rd, 2003);

[14]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.

[15]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).

- 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 5, we use the generalized Gamma density distribution as pre-programmed in Stata. More specifically, the density distribution is specified as:

$$f(t,\kappa,\sigma,\mu) = \frac{\gamma^{\gamma}}{\sigma t\sqrt{\gamma}\Gamma(\gamma)} e^{(z\sqrt{\gamma}-u)} \tag{4}$$

if $\kappa \neq 0$, and

$$f(t,\kappa,\sigma,\mu) = \frac{1}{\sigma t\sqrt{2\pi}} e^{(-z^2/2)} \tag{5}$$

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 if all 18 explicative variables detailed in Section 2 are included in the model, this translates into 3 specifications for μ_j as we have 3 mutually exclusive exit possibilities:[16]

$$\mu_{j,IPO} = \beta_{1,IPO} INTERNET_j + \beta_{2,IPO} BIOTECH_j + \ldots + \beta_{18,IPO} BUYACQ, \tag{6}$$

$$\mu_{j,TS} = \beta_{1,TS} INTERNET_j + \beta_{2,TS} BIOTECH_j + \ldots + \beta_{18,TS} BUYACQ \tag{7}$$

[16] 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.

and

$$\mu_{j,LIQ} = \beta_{1,LIQ} INTERNET_j + \beta_{2,LIQ} BIOTECH_j + \ldots + \beta_{18,LIQ} BUYACQ. \qquad (8)$$

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. These time ratios can then be directly compared with each other, yielding relative time ratios. The latter are very easy to interpret as a relative time ratio indicates how fast/slowly the change of category impacts the (conditional) exit probability. For example, the relative time ratio (for the IPO exit) of the internet industry with respect to the biotech industry is equal to $e^{\beta_{1,IPO}}/e^{\beta_{2,IPO}}$.

4. 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 2 provides the frequency of exit routes for different types of investment stages, Table 3 gives a breakdown of key statistics by investment rounds, industries and stages of development. Finally, Table 4 gives information on the industry type and stages of development during the bubble period and outside that period.

Table 2 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 3, 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 the literature that conjectures a reduction in duration as the project is 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 decreases 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 3) 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 3) shows that the average internet firm was given 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 3), 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. 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 4 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![17] 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.

As for the geographical location (bottom of Table 4), about half of the entrepreneurial firms in our sample are located in California (WEST). The next largest region is NORTHEAST. About one third of the investments in our sample are from other regions, which also include all those outside the USA. This contrasts with the location of VC funds that are much more concentrated in the West and Northeast regions. Indeed, these latter two regions account for almost 80% of the VC funds located in the USA (Lerner, Schoar, and Wong, 2005).

5. Estimation results

The descriptive analysis of the previous section provided information on the dataset and on the exit characteristics. In this section we estimate the competing risks model to fully describe and analyze the exit process. We characterize extensively the estimation results for rounds 1

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

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 first estimate the model with all explanatory variables save for the geographical location variables included as covariates. We use the generalized Gamma density function as the distribution for the underlying error term.[18] In a later step, we will assess the impact of the geographical location by estimating an enhanced model that features 18 variables as covariates. We also allow for heterogeneity in our model.[19] 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 6 and for the third and fourth rounds in Table 7. 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 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 very good. As examples, we provide such plots in Figures 5 and 6 (IPO, trade sale and liquidation exits, rounds 1 and 2).[20]

[18] We avoid multicollinearity problems by not including the constant and the OTHERSTAGES dummy variable.

[19] 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.

[20] Note that the somewhat '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.

5.1. Round 1 (5,817 observations)

5.1.1. 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 is in accordance with the literature review provided in the Introduction. 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 the literature review on faster project realization, larger committed amounts also decrease exit times (significantly negative AMOUNT coefficient). This is also the case for the secondary variable AMOUNTIND, i.e. the amount of funds received in excess of the average firm in the same industry (note that because of collinearity problems, we estimate the models separately with the AMOUNT and AMOUNTIND variables).

The time ratio 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).

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.[21] 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.[22] 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, 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 (we delve more deeply on this issue below, as this coefficient gets significantly negative for rounds larger than 2).

5.1.2. 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

[21]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.

[22]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.

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 that candidates for a trade sale are less homogeneous than those for an IPO.

5.1.3. Exit to liquidation

There are some marked differences with respect to the successful exits (IPO and trade sale). First the coefficients for the EARLY, EXPANSION, LATER and BUYACQ variables are quite close and it is no longer true that coef(LATER) $<$ coef(EXPANSION) and coef(EXPANSION) $<$ coef(EARLY): the timing of the stage does not seem to hint at a faster/slower liquidation of the firm. 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 4 we showed that the amount of money raised (per funded firm) during bubble times was much larger than during normal times. This suggests 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 quickly reaches its plateau (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 5. 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 received first round financing during the internet bubble.

5.2. 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.

5.3. 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.

5.4. All rounds: summary of main results

The empirical 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 clearly matters 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. 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 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).

5.5. The internet bubble and the industry type

These estimation results 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.[23] 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 8. 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). In contrast, the bubble did not really impact the other industries as the corre-

[23] 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.

sponding dummy coefficients in Table 8 are not significant. These results strongly support the hypothesis that the bubble did not have an evenly impact on all venture capital financings.

5.6. The impact of the geographical location

Does the geographical location of the entrepreneurial firm affect the exit dynamics? To tackle this issue, we estimate an enhanced model that features all 18 explicative variables, i.e. the 14 original variables and the 4 geographical location dummy variables (WEST, NORTHEAST, SOUTH and MIDWEST). Estimation results for the first and second rounds are reported in Table 9. Regarding the IPO exit, there are few significative differences between the US regions, although firms in the Midwest area seem to exit much less frequently. In contrast, trade sale and liquidation exits are sharply different for, on the one hand, West and Northeast firms and, on the other hand, South and Midwest firms. Indeed, firms face much easier trade sale exits in the West and Northeast regions than for the other two regions. As far as liquidations are concerned, firms in the South and Midwest regions tend to liquidate much faster than firms in the West and Northeast. The difference is sharply significant, as shown by the time ratios which are almost halved when switching from a West firm to a Midwest firm (e.g. at round 2, the time ratio would be $e^{-0.707}/e^{-0.057} = 0.522$). To illustrate, Figure 7 presents the IPO, trade sale and liquidation hazard rates for an average firm hypothetically situated in the four US regions.

5.7. A brief discussion of related results

The analysis based on competing hazard models has provided a number of interesting results regarding the dynamics of the exit pattern for venture capital-backed firms. Some of these results are strongly related to previously reported findings in the literature on venture capital and exit strategies by venture capital-backed firms. We briefly discuss these here and stress the contribution of our analysis to this recent strand of the literature.

Exits occurred much more frequently during hot issue markets (here, the internet bubble is in line with observations provided by Lerner (1994)), which indicates that venture capital funds are able to time their IPO exits earlier when stock market valuations are highest (see also the survey in Jenkinson and Ljungqvist, 2001). While the study of Lerner (1994) only dealt with biotech firms, our analysis indicates that this also holds during the internet bubble period for firms in the internet, computers, communications and media sectors. Interestingly, these same industry sectors also had significantly quicker liquidations during the time of the internet bubble period. This highlights the fact that venture capitalists incurred a large risk when investing in companies that potentially had a great upside potential but also exhibited a high risk of failure. Gompers (1995) provides evidence that the degree of asymmetric information has a significant impact on the time-to-exit. This implies that early-stage investments require a longer lasting involvement of venture capital funds than later-stage investments, since asymmetric information decreases along with the reduction of technological risk. Our paper provides further evidence in line with this rationale.

Cumming and MacIntosh (2001) find that exits occur more quickly for early stages of development, which they interpret as the result of a selection process to sort out the bad from the good projects. Our study provides a somewhat different picture. While exits from later-stage investment are quicker than for early-stage investments (irrespective of the type of exit route) at the time of deal initiation, the results are mixed for later-round investments. Finally, Das, Jagannathan, and Sarin (2003) look at cumulative probabilities of exits. Among other things, they find that the likelihood of a trade sale increases with the stage of development ("this may be because many early-staged firms that were unable to make it to the IPO stage settled instead for a buyout"). They further show that successful companies in biotech and medical sectors exit more frequently. Our study goes a step further and looks at the time dimension of the exit process, how the exit probabilities evolve over time and how the dynamics of the exit process if affected by the actual outcome (IPO, trade sale or liquidation). In particular, the most striking feature is the difference between trade sales and IPOs (the main exit routes). While probabilities do not change that much in the first case, the probability of doing an IPO exhibits a strong, inverse U-shaped pattern; it increases very quickly and again decreases sharply right after it peaked. Successful companies that could not go public sufficiently quickly have to rely on other exit routes like trade sales.

6. 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.

Our empirical analysis delivers 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 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. While hazards for trade sale exits are also hump-shaped, our analysis suggests an exit order (IPO, and then possibly a trade sale) that is consistent with the fact that venture capitalists first target the IPO as the preferred way of cashing out on investments. Because the window of opportunity for trade sales extends for a considerable amount of time, trade sale exits are second-best choices available for an extended amount of time. This exit order reinforces the idea that the exit decision exhibits a considerable dynamics and that the monitoring of the investment durations and conditional probabilities of exits is of paramount importance for venture capitalists wishing to cash out on their initial investments.

Third, there seems to be little differences in terms of exit routes and timing between firms located in the Silicon Valley and on Route 128. On the other hand, there are significant differences between firm located in these two regions and the ones located in other regions of the US. Entrepreneurial firms in Silicon Valley and on Route 128 seem to provide a more favorable exit environment to VC funds. Last we also looked at the impact of the bubble period (1998-2000) on the exit dynamics and found that the exit of investments initiated earlier tended to be sped up as venture capitalists were probably eager to capitalize on better exit chances. As conjectured, the bubble affected some industries more than others since 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 1
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
WEST	1	1	1	1	1	1	1	1	1	1	1
NORTHEAST	0	0	0	0	0	0	0	0	0	0	0
SOUTH	0	0	0	0	0	0	0	0	0	0	0
MIDWEST	0	0	0	0	0	0	0	0	0	0	0
DURATION	303	242	101	1,423	1,148	899	537	143	1,755	1,412	1,117

This table details the 18 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 2
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 3

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 4

Summary statistics for investments 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%	33.3%	35.7%	
- Expansion stage	40.1%	38.9%	45.8%	
- Later stage	19.4%	20.3%	14.8%	
- Buyout/Acquisition	4.3%	4.6%	2.7%	
- Other stages	2.6%	2.9%	1%	
Geographical location of entrepreneurial firm:				
- West	43.6%	43.7%	43.5%	
- Northeast	17.3%	17.3%	17.3%	
- South	4.3%	3.8%	4.5%	
- Midwest	2.4%	2.2%	2.4%	
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 5

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 6
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 7
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 8
Impact of the 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 include the SYNDSIZE, AMOUNT, EARLY, EXPANSION, LATER and BUYACQ variables as in Tables 6 and 7. 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).

Table 9

Impact of the geographical location of the entrepreneurial firms.

	IPO		Trade sale		Liquidation	
Region	Round 1	Round 2	Round 1	Round 2	Round 1	Round 2
WEST	0.075 (0.250)	0.065 (0.424)	-0.116 (0.011)	-0.089 (0.110)	-0.009 (0.934)	-0.057 (0.667)
NORTHEAST	0.099 (0.233)	0.178 (0.084)	-0.149 (0.007)	-0.162 (0.018)	-0.095 (0.472)	-0.130 (0.469)
SOUTH	0.052 (0.707)	-0.026 (0.879)	0.096 (0.335)	0.219 (0.085)	-0.290 (0.222)	-0.186 (0.496)
MIDWEST	0.279 (0.142)	0.538 (0.030)	-0.015 (0.895)	0.037 (0.808)	-0.401 (0.335)	-0.707 (0.080)

Estimated coefficients (for the geographical location dummy variables only) for the competing risks model with 3 exits (IPO, trade sale, liquidation). Durations to exit start at round 1 and 2, 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 four geographical location dummy variables listed above, we include the INTERNET, BIOTECH, COMPUTER, SEMIC, MEDICAL, COMMEDIA, OTHERIND, SYNDSIZE, AMOUNT, EARLY, EXPANSION, LATER and BUYACQ variables. P-values for the null hypothesis that the coefficient is not different from zero are reported in parenthesis.

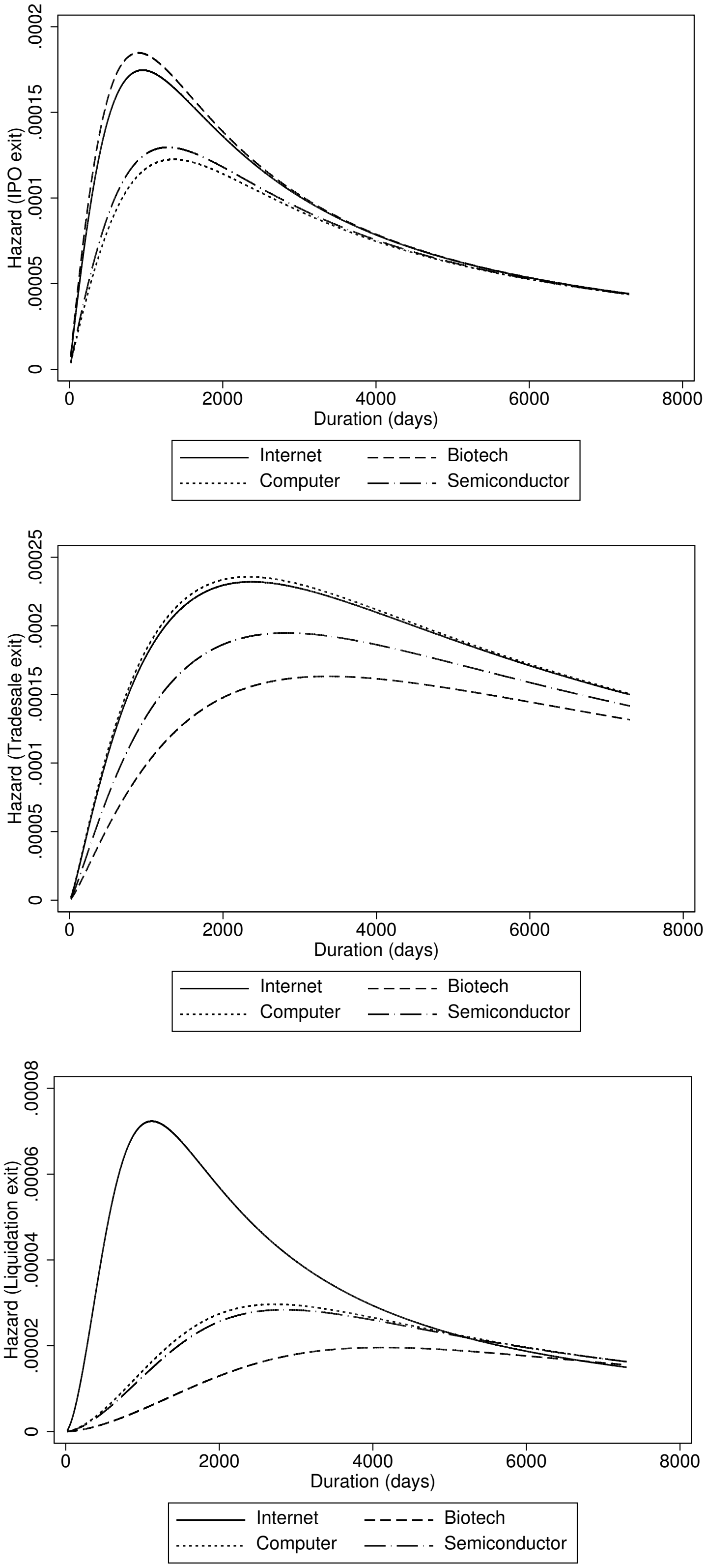

Figure 1. Hazard functions for the IPO, trade sale and liquidation exits as a function of industry type; durations start at round 1. Besides the industry type, the covariates are AMOUNT=10, SYNDSIZE=4, EARLY=1 and BUBBLE=0.

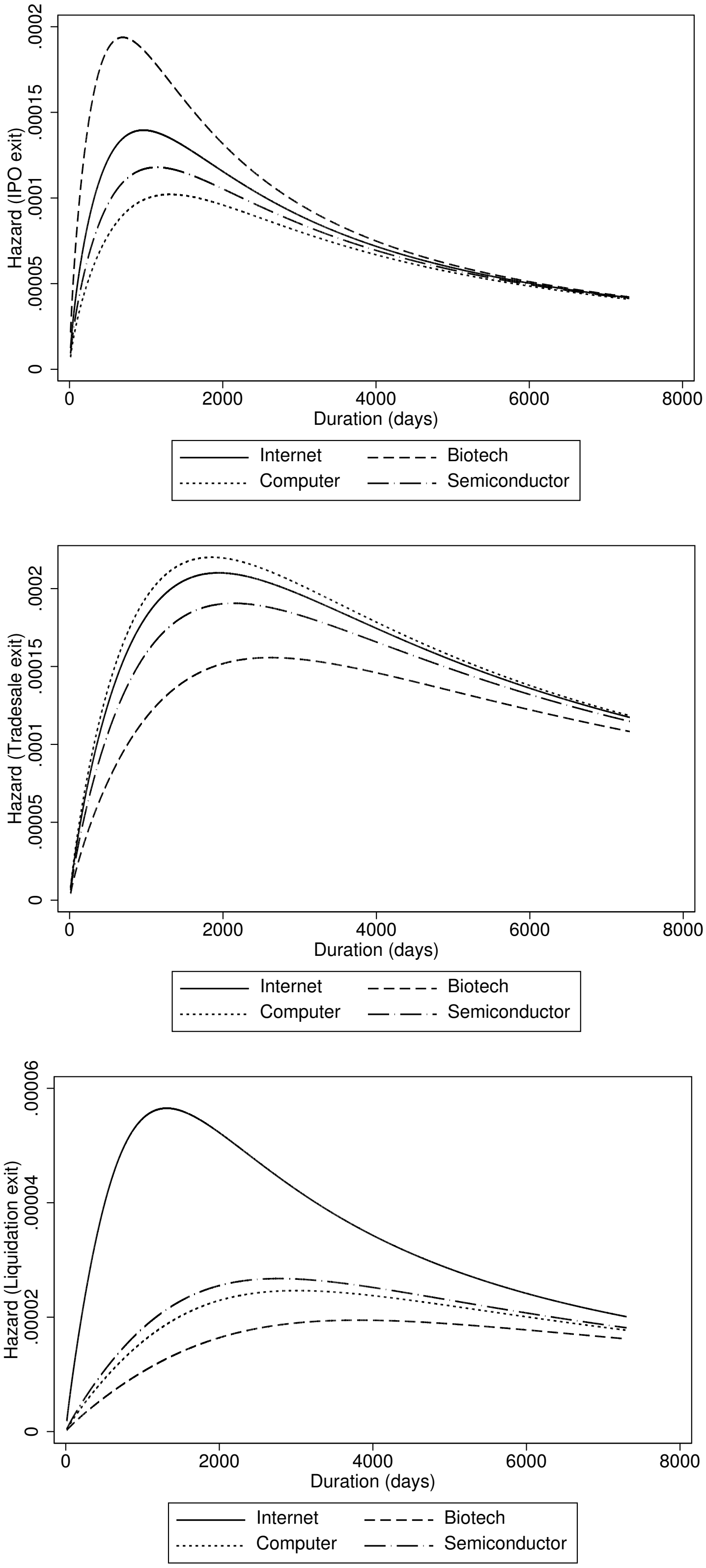

Figure 2. Hazard functions for the IPO, trade sale and liquidation exits as a function of industry type; durations start at round 2. Besides the industry type, the covariates are AMOUNT=10, SYNDSIZE=4, EARLY=1 and BUBBLE=0.

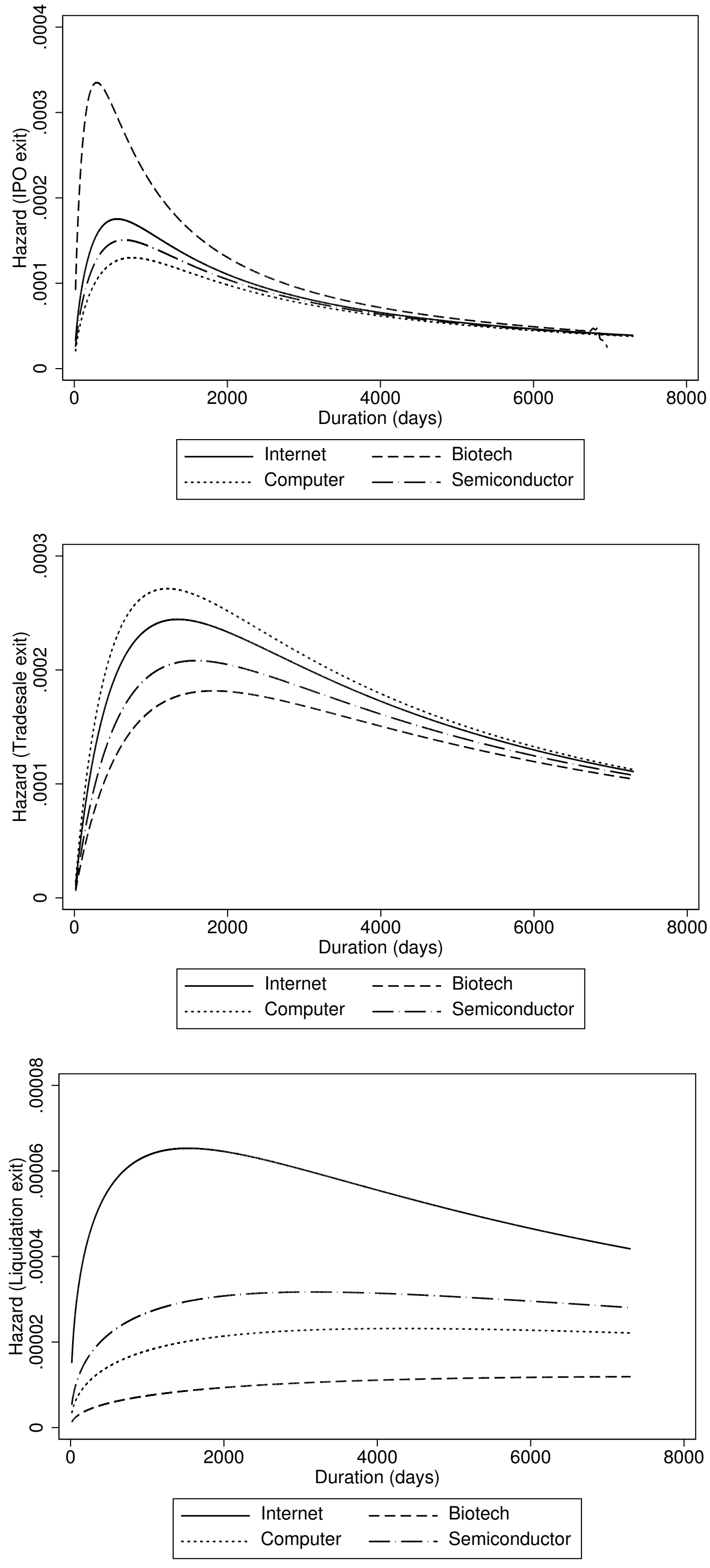

Figure 3. Hazard functions for the IPO, trade sale and liquidation exits as a function of industry type; durations start at round 3. Besides the industry type, the covariates are AMOUNT=10, SYNDSIZE=4, EXPANSION=1 and BUBBLE=0.

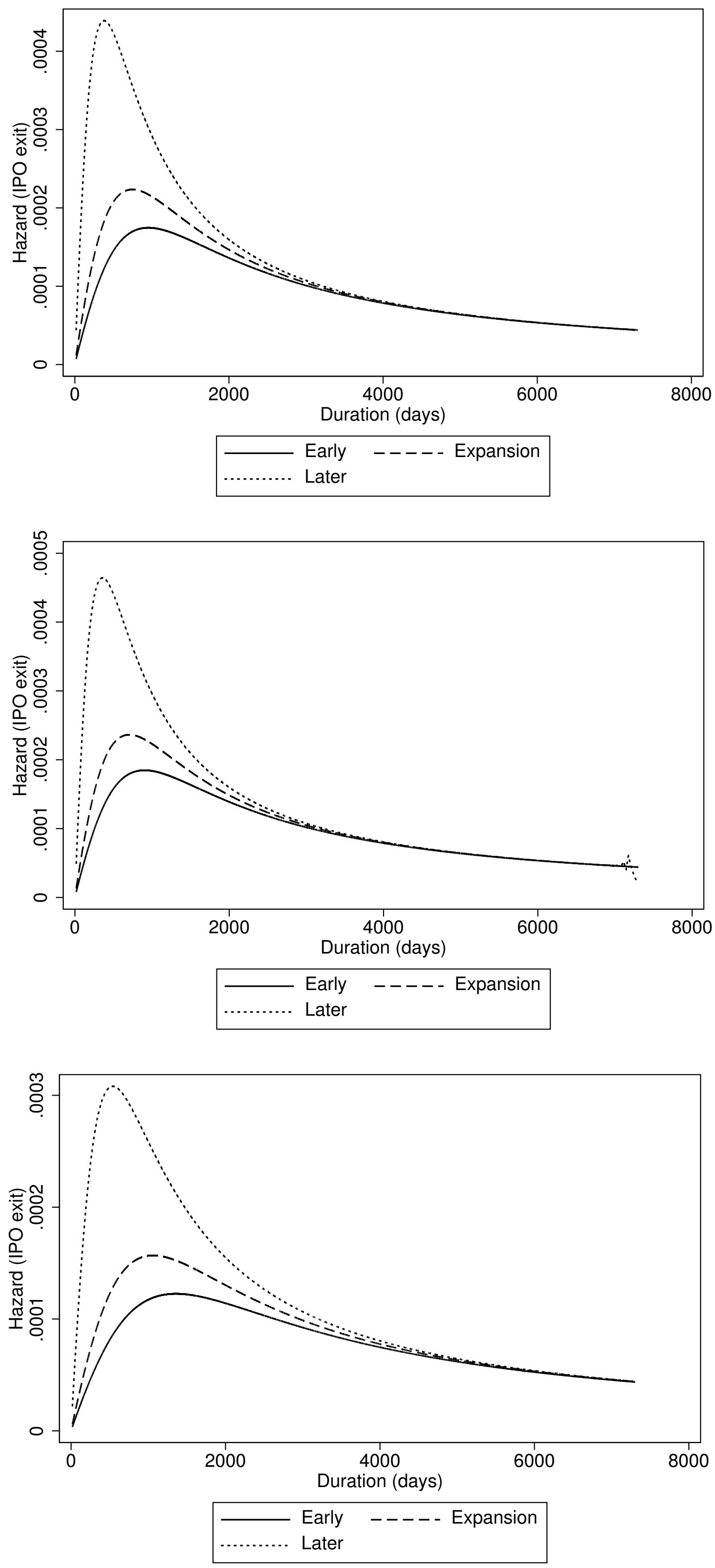

Figure 4. Hazard functions (IPO exit) for the internet (top), biotech (middle) and computer (bottom) industries as a function of the type of stage; durations start at round 1. Besides the industry and stage types, the covariates are AMOUNT=10, SYNDSIZE=4 and BUBBLE=0.

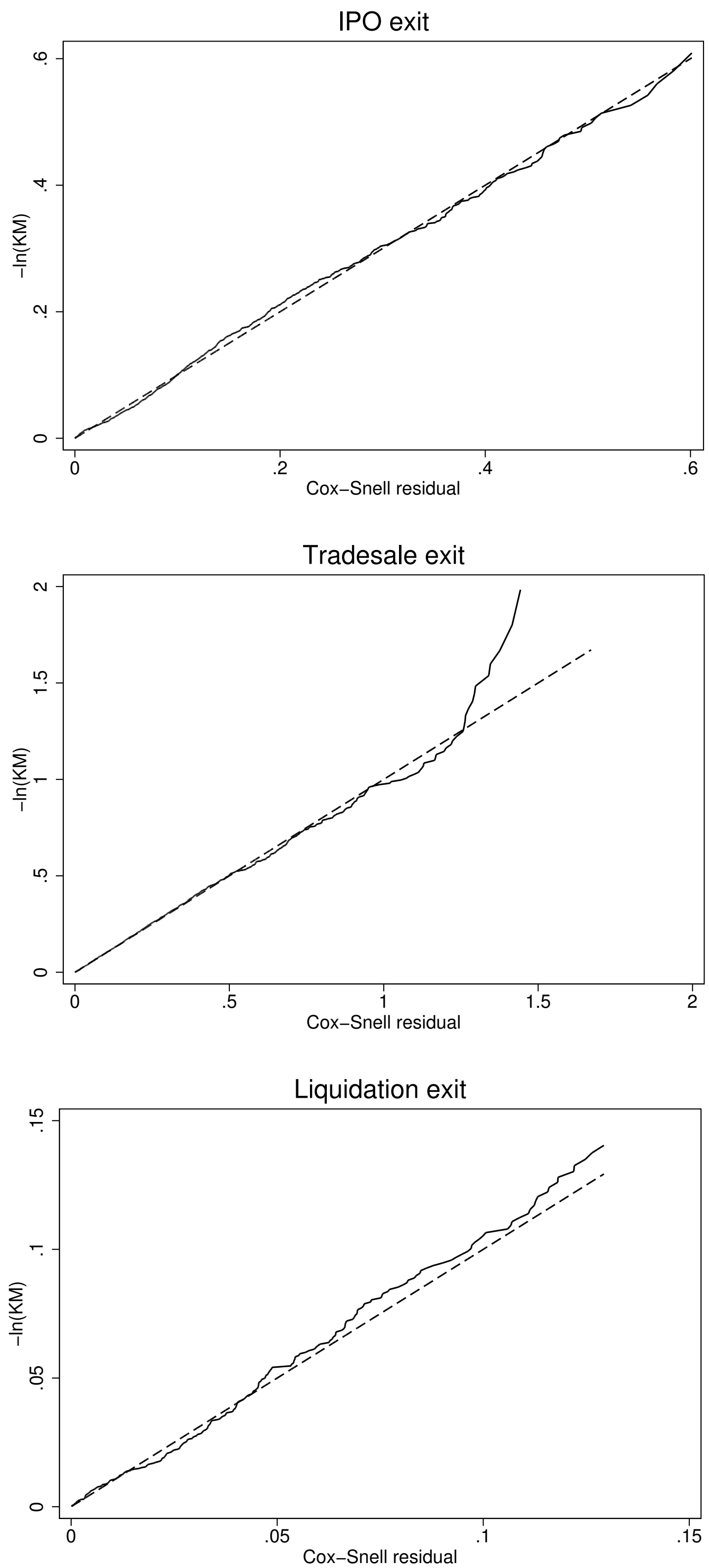

Figure 5. Cumulative hazard functions of Cox-Snell residuals for the IPO, trade sale and liquidation exits; durations start at round 1. We also plot the benchmark line whose slope is equal to 1.

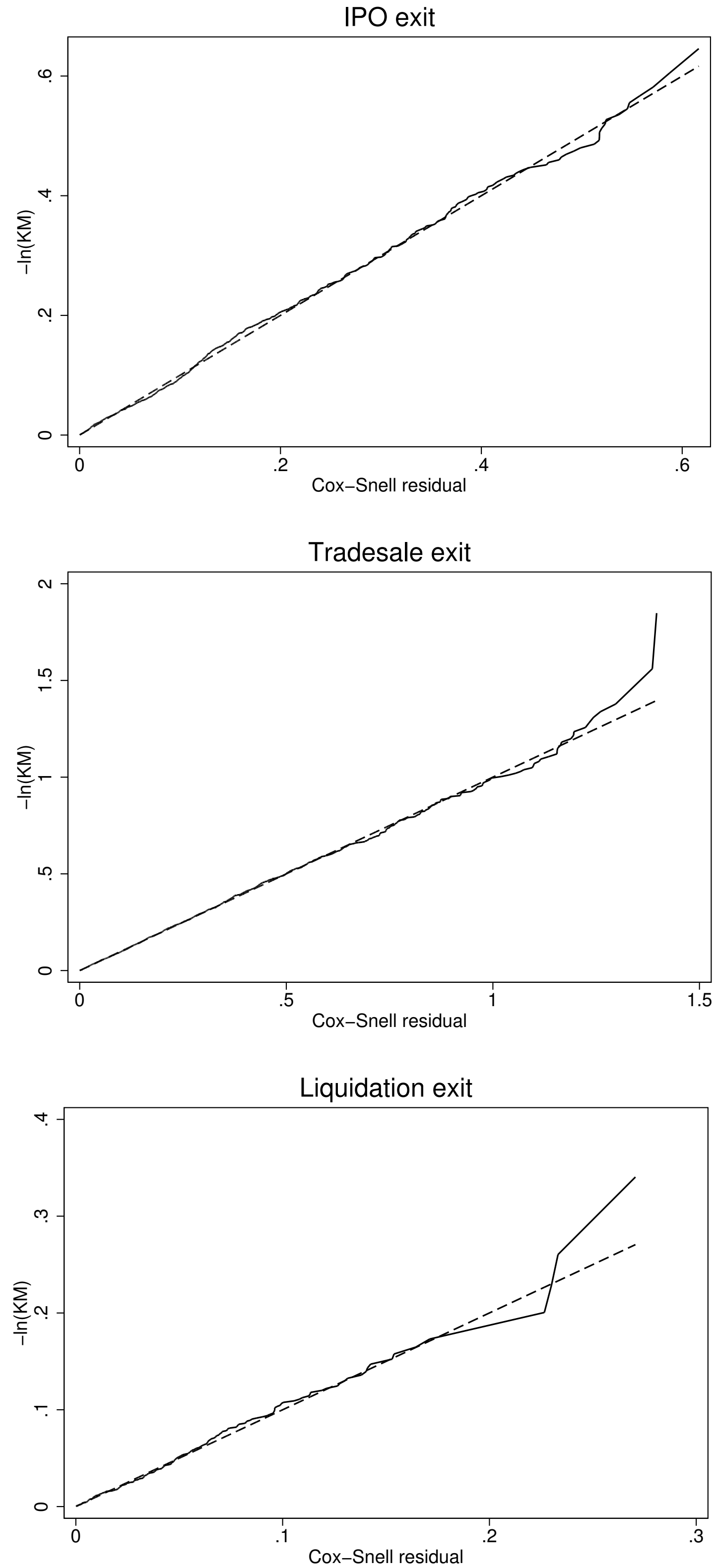

Figure 6. Cumulative hazard functions of Cox-Snell residuals for the IPO, trade sale and liquidation exits; durations start at round 2. We also plot the benchmark line whose slope is equal to 1.

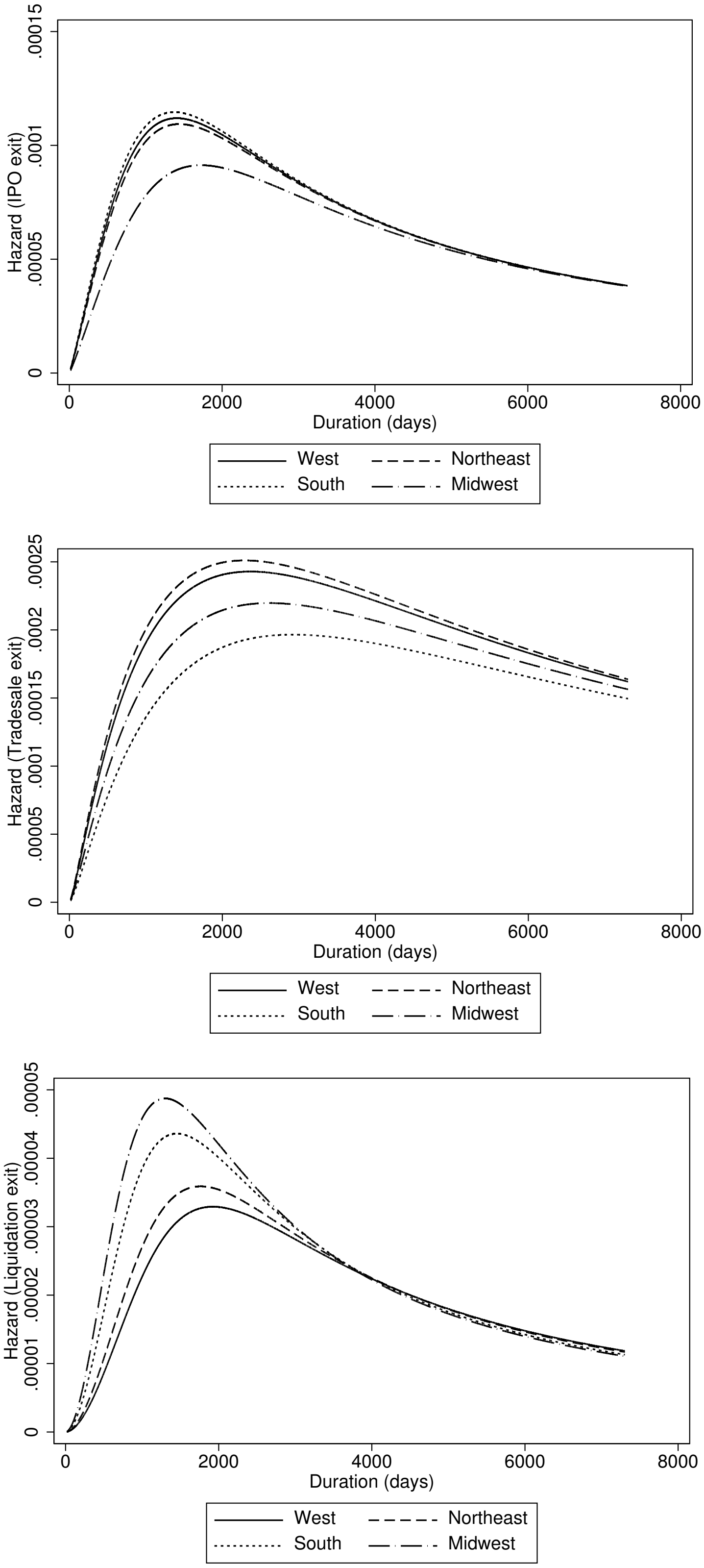

Figure 7. Hazard functions for the IPO, trade sale and liquidation exits as a function of the geographical location of the firm; durations start at round 1. Besides the geographical location, the covariates are COMPUTER=1, AMOUNT=10, SYNDSIZE=4 and EARLY=1.