Entry, Exit, Environment: Firm Mortality in Sweden, 1899-1999

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Abstract

Macro and micro perspectives of the behavior of firms should be viewed as complementary. Explanations that relate to structural and environmental phenomena often ignore or reduce the actions of entrepreneurs. Micro studies on entrepreneurship can explain why some firms are successful and others fail. Yet, these often disregard factors in the environment that limit, or increase, the possibilities for firms to grow and survive. In this paper we make these factors visible. In particular, we focus on the impact from environmental founding conditions and variations in the firms' environment over their life-course (current conditions). We employ a large longitudinal empirical dataset that covers complete birth cohorts, or entry cohorts, of Swedish joint-stock companies. The companies were founded in nine separate years between 1899 and 1992. We adopt semi-parametric complementary log-log model. Our results show that hazard function is skewed bell-shaped in the interval of first eight-year. Namely, the likelihood of exit increases with age first, peaks at the age of 6, and then decreases. Our result is also consistent to the previous finding that large start-up size, being manufacturing sector, and being established in booms would lower the hazard rates proportionally. At the same time, increases in GDP growth and nominal interest rate would push down the hazard rates. Inflation slightly increases the hazard rates.

This paper also attempts partially relaxing the assumption of proportionality. The first exercise is allowing the impact due to the factors listed above to be specified at the age of firm. We find that only result concerning the start-up size and industry is consistent to the proportional hazard model. For the rest of factors, we could not find clear cuts. It seems the impact is much more complicated than the simple model would suggest. The second exercise is grouping the sample and permitting non-proportionality across groups while maintaining proportionality within each group. We find that large start-up size would reduce the hazard rates similarly across two industries while significantly reduce more for the firms established in recessions. On the other hand, industry factor would be much effective in reducing hazard rates in the group of small start-up firms. The similar effect can be identified for the firms established in booms. Moreover, being established in recessions would increase the hazard of exit for the small start-up firms but would reduce the hazard for large start-up firms. It would increase the hazard rates in both industries, but more for manufacturing firms. It is also interestingly to observe that increases in inflation would increase hazard for small start-up firms but reduce the hazard for large start-up firms. At the same time, high inflation would reduce the hazard of exit for manufacturing firms but increase for other firms. Inflation has no significant impact for the firms established in booms but reduce hazard significantly for firms established in recessions. GDP growth and interest rate would reduce hazard rates for all kind of combinations but at different extents: GDP growth is in favor of firms established in recessions, and interest rate is in favor of firms with large start-up size, in manufacturing sector and being established in recessions.

Introduction

In empirical research on firm behavior (entry, growth, and exit), short observation periods and cross-sectional approaches have been common. (Gartner 1988; Landström and Lohrke 2010). Several scholars maintain that less attention has been given to the function of the context and environment in which firms enter, exist, perhaps grow, and exit. Research that specifically elaborates on temporal dimensions, and on transition and change, is relatively scant (e.g. Davidsson and Henrekson 2002; Caves 1998; Martinez et al., 2011). To be able to analyze changes in enterprising activity and environmental variation, empirical data with frequent observations over long intervals of time is of essence (Audretsch 1991; Caves 1998; Gartner and Shane, 1995; Manjón-Antolín and Arauzo-Carod 2008). The comparative paucity of such data may partly explain this relative unbalance in previous research (Fritsch et al. 2006). One way to evade the two problems of data scarcity and a-temporal research designs is to make use of alternative empirical sources. In the study, we analyze the survival of firms in Sweden over a very long period, 1899-1999. We use longitudinal data recorded at the firm-level that consists of several entry cohorts of firms. This data is largely collected from archives and historical sources. In the paper we employ a large, prospective longitudinal empirical dataset that covers complete entry cohorts, or birth cohorts, of Swedish joint-stock companies that were founded in nine separate years, 1899-1992. The dataset consists of first-eight-year observations of every new companies. Our dataset has been recorded both from historical, public archives and from exclusive data sources that provide detailed information at the firm level. This strategy for data collection helps to increase the possibilities for long-term analyses.

In essence, two major streams of research use demographic and quantitative approaches on the link between entrepreneurial activity and environmental conditions. On stream of research has analyzed moderately long periods, using aggregated country-level panels or data of a (repeated) cross-sectional design.[1] Another research stream uses micro level panel data on the entry, growth, survival and exit of firms. Overall, this stream of research is multidisciplinary – over the past several decades it has shown a substantial array of contributions from a number of disciplines. In this tradition, the effect from environmental variation – such as from the business cycle – has often been challenging to include and measure (Boeri and Bellmann 1995; Caves, 1998; Ejermo and Xiao 2014; Manjón-Antolín and Arauzo-Carod 2008; Martinez et al. 2011).[2] Relates to and hypothesize on theory and previous findings in Industrial Organization and in Organizational Ecology. These two literatures have generated a substantial amount of empirical research and they have developed established hypotheses and 'stylized facts' on organizational behavior (Brons 2004; Frech 2010). Our paper particularly relates to and hypothesize on theory and previous findings in these two literatures, both having developed established hypotheses and 'stylized facts' on organizational behavior.

[1] The Global Entrepreneurship Monitor, GEM, has produced global series from 1999 on attitudes towards entrepreneurship, entrepreneurial intentions, and on total early-stage entrepreneurial activity GEM is survey-based. Another international database is Compendia (COMParative ENtrepreneurship Data for International Analysis) which covers self-employment data for a large number of OECD economies from the 1970s and onwards.

[2] Some empirical research has used longitudinal data that consists of aggregate time-series on entrepreneurship, or on self-employment, for specific (individual) economies. This data is often measured over several decades or even longer (e.g., Lindh and Ohlsson 1998, Shane 1996, Steinmetz and Wright 1989).

Background and theory

In practice, several empirical populations are often incomplete or are measured at levels inadequate for the research problem at hand. This makes it difficult to operationalize and analyze transition and change over time, as well as challenging to study complementary and competing explanations to firm behavior (Aldrich and Ruef 2006; Carre and Thurik 2008; Davidsson and Wiklund 2001; Davidsson, 2008). Environmental variation has often remained absent in much past empirical research, or has often been problematical to operationalize (Manjón-Antolin and Arauzo-Carod 2008; Martinez et al. 2011). Our study uses demographic techniques for estimating rates of entries and exit for different populations of companies, for which we have built up data that span over long intervals of time. A substantial number of studies in the past several decades find that survival and mortality rates fluctuate with change and transition in the external economic, social and institutional environment. For the purpose of the present study, several contributions are found in the traditions of Industrial Organization (IO) and Organizational Ecology (OE). The IO and OE literatures differ substantially in several theoretical assumptions. Yet, the two literatures share common conceptions of a number of empirical regularities, including the perception that conditions at the industry or macro level, which are largely external to the individual firm, will affect its survival ability (Frech 2005; Geroski 2001).

At the *level of the firm*, established empirical regularities of age and size dependencies of survival imply that new and small firms generally have a higher probability to exit. Thus, there is at hand a liability of newness and a liability of smallness. These liabilities will diminish with increasing firm age and size (Evans, 1987; Carroll and Hannan, 2000; Thompson 2005). Several variants of this age dependency have been developed,[3] but the pervading idea is that firms and organizations, irrespective of time and place, are subjected to these liabilities (Carroll and Hannan, 2000).

Industry-level conditions are also considered to influence performance: IO maintains as a regularity that industries that are characterized by intense competition often have higher exit rates rates, and that manufacturing industries display higher survival rates compared to trade or service industries (Fritsch et al. 2006; Harhoff et al. 1998; Phillips and Kirchoff 1989). Furthermore, innovation rates, technological change and industry life-cycle effects will furthermore affect survival rates, both for incumbent firms and for new entrants (Agarwal and Audretsch 2001; Carlsson and Eliasson 2003; Klepper 1996, 2002; Klepper and Simons 2005). In contrast, OE displays a lesser general, theoretical interest in innovation and technology *per se.*

Theory in IO and economics as well as in OE assert that *macro-environmental conditions* play a considerable role for firm survival. One substantial difference between the two literatures is that the theory of OE holds that population density and changes in density over time in represents the principal and most influential environment for organizations.[4] On the other hand, the IO literature sets forth from economic theory and hypothesizes on the impact from both industry- and aggregate-level conditions and variation on survival (e.g., Bhattacharjee et al. 2002;

[3] Essentially, the liability of newness argument predicts that mortality rates monotonically decline with age. Other variants that have been developed is the 'liability of adolenscence' (initially increasing mortality followed by decreasing mortality), or the 'liability of obsolecence' (positive age dependence). See Carrol and Khessina (2005).

[4] Specifically, while organizational ecologists often include macroeconomic variables in empirical analyses, such as GDP growth or the interest rate level, the overall impression is that typical economic indicators generally are not considered to represent the most important (or the most theoretically interesting) environmental factors. For an exception, see Carroll and Delacroix (1982).

Boeri and Bellmann 1995; Geroski et al. 2010). Both literatures regard *founding conditions* – environmental conditions at the time of entry – as an important explanation to variation in survival and mortality rates in the short as well as the long term. The current characteristics of any entry cohort is revealed by both the internal and external historical conditions that prevailed at founding (Hannan and Freeman 1989; Swaminathan 1996). In a similar manner, scholars in IO have theorized that firms which enter an industry in distinctly dissimilar periods face different cyclical and macroeconomic conditions. As a consequence, firms and different entry cohorts may display different survival patterns both at young age and, possibly, over time. Fotopolous and Lori (2000) find distinct differences in survival between consecutively founded cohorts: firms (cohorts) established closer to an oncoming recession have lower survival rates. Huynh et al. (2010) make similar conclusions in their study following successive entry cohorts – external business conditions explain variance in survival between cohorts. Geroski et al. (2010) study ten consecutive entry cohorts and find that survival rates are higher in times in which the economy is growing, and slower in periods of decline. There is a distinct effect from of environmental founding conditions: firms born in a boom have nearly permanently high survival rates.

Furthermore, empirical studies in IO find that survival rates vary with *macro-environmental change over time*, and that this relationship holds for both large and established businesses (Goudie and Meeks 1991; Bhattacharjee et al. 2002), for fairly mature firms (Carreira and Texeira 2011), and for small and new firms. Several empirical studies in IO determine that varying macro environments affect new and small firms' survival rates: both Fritsch et al. (2006), Geroski et al. (2010), Huyhn et al. (2010), Mata et al. (1995), Strotmann (2007) and Wagner (1994) analyze entry cohorts and find that variations in macro variables are influential on survival over the firms' life course. Similarly, empirical results in OE reveal that organizational mortality varies with macro-environmental fluctuations. For example, Barron et al. (1994), Carroll et al. (1993), and Carroll et al. (1996), find long-term mortality effects from aggregate economic variation.

In this paper, we intend to these previously identified regularities on the case of Sweden. One first established regularity relates to the firm level, namely age and size of firms. Several theories and empirical results find that firm survival is positively related to age and to size. Second, we also test for industry or sectorial effects; several studies reveal that manufacturing industries systematically display higher survival rates. Third, theory and recent empirical results in both IO and OE suggest that macro-environmental conditions at founding, as well as environmental variation over the life course of firms and cohorts, explain variation in survival rates.

Methodology

In this paper, we employ the complementary log-log model to estimate hazard rates.

Complementary log-log model

Assume t to represent the age of firm in our consideration. T is a random variable for the timing of exit. T is continuous in nature but spell lengths are interval-censored that the values of T can only be observed on the calendar-year basis, namely in terms of the age of firms, t. Thus, the age with unit of calendar year can be used to establish non-overlapping intervals for our survival analysis. In this paper, we only consider first-eight-year of each cohort. That gives 8 intervals corresponding to the age of firm, t = 1, 2, …, 8.

The interval hazard rate h_t is a conditional probability that firm exits upon the condition that the firm has been survival until last interval:

$$h_t = \Pr(t-1 < T < t | T \geq t-1).$$

It says that the exit occurred in age t given the condition that the firm survived at least until t-1. By defining the survival function $S(t) = Pr(T \geq t)$, the interval hazard rate can be expressed as

$$h_t = \frac{S(t-1)-S(t)}{S(t-1)}. \tag{1}$$

To estimate the interval hazard rate h_t, we apply the complementary log-log model. Before giving the reason of adopting this approach, we first define the complementary log-log transformation or complementary log-log link function of the hazard, *cloglog* as:

$$cloglog = \log[-\log(h_t)].$$

The complementary log-log model specifies the link function *cloglog* as the dependent variable against a linear function of a set of covariates in explaining the departure of firm.

The complication of current study is that we include both time-varying and time-invariant covariates. The start-up size and type of industry are firm-specific but time-invariant. The states of economy in the first year of each cohort, recession or boom, is cohort specific. This variable is also time-invariant. We group these variables into one denoted by *X*. At the same time, we also consider inflation, GDP growth and interest rate, the time-varying variables that describe the concurrent economic state. They are cohort- but not firm specific. These variables, as the random variable *T*, are continuous but assumed to be observed once in a year. We use *Y* to represent this type of variable.

Define $\beta_X{}'X_i \equiv \beta_{X1}size_i + \beta_{X2}industry_i + \beta_{X3}se_i$, and, $\beta_Y{}'Y_{it} \equiv \beta_{Y1}inflatin_{it} + \beta_{Y2}GDPG_{it} + \beta_{Y3}rate_{it}$. Here, we unify the notation for cohorts and firms with i. Also note that there is no intercepts in both expressions. Basically $\beta_X{}'X_i$ contains the firm (cohort) specific but time-invariant variables, *size*, *industry*, and *se* (state of economy for each cohort). On the other hands, $\beta_Y{}'Y_{it}$ contains time-varying variables, *inflation*, *GDPR* (GDP growth), and *rate* (nominal interest rate). βs are coefficients representing slopes in the regression equation specified in the complementary log-log model:

$$\log\{-\log[1-h_t(X, Y_t)]\} = \beta_X{}'X + \beta_Y{}'Y_t + \alpha_t. \tag{2}$$

Note the notation of $h_t(X, Y_t)$ still represents interval hazard rate but with specification of a function of the variables of X and Y. Further note that intercept in (2) α_t is sensitive to the age of firm. α_t represents baseline hazard function which is defined as a hazard function without covariate and provides information concerning the impacts on firm's survival due to the age of firm. It determines the shape of hazard function. There are several ways to model the baseline hazard function. We adopt the semi-parametric approach by skipping parametric specification with any function form of αs. Since we only consider the survival of firms up to 8 years, we set up 8 piecewise constants. Due to the fact that these piecewise constants are baseline hazard rates under the framework of *cloglog* model, this gives rise a merit of using *cloglog* model in comparison with other alternatives, such as logit model in which proportional hazard assumption is based on logit rather on the hazard rate itself.

Furthermore, (2) is based on the setting that the hazard rate satisfies the PH (proportional hazard) assumption. This is in the line of Cox's proportional-hazard regression model Cox (1971). As the matter of fact, exponential of βs reflect hazard ratios.

To see this, we first take anti-log on (2) and rewrite it as

$$\log[1 - h_t(X,\, Y_t)] = -\exp(\beta_X{}'X + \beta_Y{}'Y_t + \alpha_t). \tag{3}$$

As an example, when X changed from X_1 to X_2, (3) gives

$$\frac{\log[1-h_t(X_2, Y_t)]}{\log[1-h_t(X_1, Y_t)]} = \exp[\beta_X(X_2 - X_1)]. \tag{4}$$

If the interval hazard function h_t is small enough, $\log(1 - h_t) \approx -h_t$, and the left hand side of (4) can be expressed as the ratio of hazard rates

$$\frac{h_t(X_2, Y_t)}{h_t(X_1, Y_t)} = \exp[\beta_X(X_2 - X_1)]. \tag{5}$$

For $X_2 - X_1 = 1$, the exponential of slope β_X offers information about proportional changes in hazard function when X changed one unit. $\beta_X > 0$ or equivalently $\exp(\beta_X) > 1$ indicates hazard would be higher when X changed from X_1 to X_2. On the other hand, $\beta_X < 0$ or equivalently $\exp(\beta_X) < 1$ indicates hazard would be lower when X changed from X_1 to X_2. This principle can also apply to the time-varying variables, Y. Namely β_Y offers the information proportional changes in hazard function when Y changes one unit (one percentage point).

Furthermore, approximately $\exp(\alpha_t)$, represents baseline hazard at t. Image that α_t is coefficient of a dummy variable, D_t, that takes value of 1 and otherwise 0 in interval t. When all covariates take value of 0, (3) and (4) imply that

$$h_{0t} = \exp(\alpha_t), \tag{6}$$

since exp(0)=1.

Non-proportionality

The proportionality is a very restricted assumption that only allows impacts from covariates to be proportional at each t. In other words, the hazard function would only be shifted proportionally according to various values of covariates. The implication is that if baseline hazard is higher the change would be also larger. It can be unrealistic. There are two basic approaches to overcome this weakness. The first approach is in the line of panel-data model in which heterogeneity is captured by setting up different intercepts. In our terminology, we may allow the baseline hazards, h_{0t}, to be a function of a strata, s. The cloglog model can be expressed as

$$\log[1 - h_t(X,\, Y_t)] = -\exp[\beta_Z'Z + \alpha_t + \alpha_t{}'(s * D_t)], \tag{7}$$

where Z contains all covariates but not s. D_t is time dummy taking value 1 at t but 0 otherwise. For instance when s is the start-up size. Z' contains now *industry*, *se* and all time varying variants, *inflation*, *GGDP*, and *rate*. The hazard function due to the firms with small size (*size* = 0) would be captured by the baseline hazard function, $\exp(\alpha_t)$. And $\alpha_t{}'$ seizes the possible impact on hazard rate related to the baseline hazard function due to the large start-up firms (*size* = 1). Since $\alpha_t{}'$ can be different across the age, the changes in hazard rates due to the *size* (from 0 to 1) are also age specific. To a large extent, the proportionality assumption is broken down. In this exercise we consider all variables in our consideration to be candidates of s. Namely, s={*size*, *industry*, *se, inflation, GGDP, rate*}. We estimate (7) with one element of s at time.

The second approach of capturing non-proportionality is in line of the Cox proportional model in which the baseline hazard function is assumed to be a constant across different strata s. It is referred as semi-proportional Cox model (Eide, Omenaas and Gulsvik, 1996, and Tveterås and

Eide, 1999). Interaction of s with rest of the variables provides information of possible non-proportional shifts associated with different s, although the hazards remain proportional within each strata. This approach is reasonable for setting up time invariant strata. In this paper we apply the idea of semi-proportional Cox model to complementary log-log model. The model is given by

$$\log[1 - h_t(X,\ Y_t)] = -h_{0t}\exp[\beta_{X'}' X' + \beta_Y' Y_t + s(\beta_s^* + \beta_{X'}^{*\prime} X' + \beta_Y^{*\prime} Y_t)]. \qquad (8)$$

where X' is a subset of X by excluding strata s. Note that the specification of (8) is different form the extension based on Cox model in terms of including $\exp(\beta_s^*)$ which is the "baseline" hazard ratio when s = 1 with all other covariates taking 0. It captures the pure effects due to s. $\exp(\beta_{X'}')$ and $\exp(\beta_Y')$ indicate proportional changes in the hazard function within the group classified with s = 0. However, the interpretation concerning $\exp(\beta_{X'}^{*\prime})$ and $\exp(\beta_Y^{*\prime})$ is complicated. We shall explain it by specifying the strata s.

We again use s=*size* to illustrate. Now X' contains merely *industry* and *se*. h_{0t} is still the baseline hazard rate at t for all covariates taking value of 0. $\exp(\beta_{size}^*)$ represents the hazard ratio of the large start-up non-manufacturing firms that were established in booms (*size*=1, *ind*=0, and *se*=0). For the group of small firms, $\exp(\beta_{ind}')$ shows the hazard ratio of manufacturing firms against service firms:

$$\frac{h_t(size{=}0\ \&\ ind{=}1)}{h_t(size{=}0\ \&\ ind{=}0)} = \frac{-h_{0t}exp(\beta_{ind}ind+\beta_{se}se+\beta_Y' Y_t)}{-h_{0t}exp(\beta_{se}se+\beta_Y' Y_t)} = \exp(\beta_{ind}). \qquad (9)$$

Equally, $\exp(\beta_{se})$ signifies the hazard ratio of small firms being established in recessions in comparison with that being established in booms. The slopes $\exp(\beta_Y')$ refer to hazard ratios of small firms with Y changed one unit.

Analogously, for the large firms, hazard ratio of manufacturing sector against service sector is given by:

$$\frac{h_t(size{=}1\ \&\ ind{=}1)}{h_t(size{=}1\ \&\ ind{=}0)} = \exp(\beta_{ind} + \beta_{ind}^*). \qquad (10)$$

Combining (9) and (10), we obtain that

$$\exp(\beta_{ind}^*) = \frac{h_t(size{=}1\ \&\ ind{=}1)}{h_t(size{=}1\ \&\ ind{=}0)} \Big/ \frac{h_t(size{=}0\ \&\ ind{=}1)}{h_t(size{=}0\ \&\ ind{=}0)}, \qquad (11)$$

in which the numerator is the hazard ratio of changing sector for large start-up firms and denominator is the ratio of changing sector for small start-up firms. If $\exp(\beta_{ind}^*) > 1$, the ratio $\frac{h_t(size=1\ \&\ ind=1)}{h_t(size=1\ \&\ ind=0)}$ for the large start-up firms would be bigger than that of small start-up firms, $\frac{h_t(size=0\ \&\ ind=1)}{h_t(size=0\ \&\ ind=0)}$. Since we know the ratio for small start-up firms $\frac{h_t(size=0\ \&\ ind=1)}{h_t(size=0\ \&\ ind=0)}$, we can calculate the ratio for large start-up firms $\frac{h_t(size=1\ \&\ ind=1)}{h_t(size=1\ \&\ ind=0)}$, according (11).

In addition, we can rewrite (11) as

$$\exp(\beta_{ind}^*) = \frac{h_t(size{=}1\ \&\ ind{=}1)}{h_t(size{=}0\ \&\ ind{=}1)} \Big/ \frac{h_t(size{=}1\ \&\ ind{=}0)}{h_t(size{=}0\ \&\ ind{=}0)}. \qquad (12)$$

This provides the relative hazard ratios of size in different sectors. This coefficient is comparable to the corresponding coefficient in the model when s=*industry*.

We may make the similar interpretations to the coefficients of $\exp(\beta_{se}^*)$ and $\exp(\beta_Y^{*\prime})$, although, for time-varying covariates Y, (12) seems not adequate. The latter would be naturally interpreted as relative changes in hazard rate due to Y in the large start-up group against that in the small start-up group.

Data

Our empirical datasets consists of birth cohorts of firms founded in nine different years, more specifically Swedish joint-stock companies established in 1899, 1909, 1912, 1921, 1930, 1942, 1950, 1987 and 1992. 37042 firms were established in these cohorts. All companies can be followed each year until their exit or, at most, until 1999. We have compiled this data from archival sources and from credit rating companies that have provided us with exclusive data (see Gratzer 1996 and Box 2005 for detailed descriptions).

Accordingly, 23761 firms, about 64%, failed. For the focus of this study, we only look at the period of first-eight-year since individual births. The firms survived beyond this period are treated as censored observations. This mainly because our last cohort, starting from 1992, contains only eight observations. It is also because, probably more importantly, that the early period of new firms is much crucial for the survival, due to the natural selection process. A high ratio of the failed firms were actually departured from business in this period. Our dataset shows that 69% or 16383 failures occurred within the first eight-year period. Thus, the exercise based on this particular period would provide us valuable information.

Figure 1 provides some basic facts concerning the failure and survival. The north-west panel shows the numbers of exit in the order of age of firm. It is easy to note that the number of failure increases first towards its peak occurred at the age of 6. Thereafter, the numbers of exit fall and reach to quite low level at the age of 8. The rest of panels in Figure 1 shows decomposed numbers according to various start-up conditions. It can be observed that numbers of exit of the large firms are unambiguous small than that of the small firms. This is also true for manufacturing firms in comparison with other firms. However, it is not so clear for the case of economic states, boom or recession, in the start-up years. A special attention should be given, however, at the age of 8, no exit for the firms established in booms and survived until then. This observation may cause a problem for the estimation and we are cautious for the interpretations related to this phenomenon.

In this paper, we also consider concurrent economic conditions, such as GDP growth, inflation, and nominal interest rate. All these variables are measured at a unit of percentage. They are all time-varying but cohort-specific. This means for all firms that belong to the same cohort would face the same value of each variables although they are different at ages of firm.

Results

Preliminary estimates

Figure 2 plots estimated hazard functions. The north-west panel shows the hazard functions according to each cohort. What we can notice immediately is that hazard functions share similar shapes, skewed bell shapes: increasing towards the peaks and falling thereafter. But it seems having considerable heterogeneities across cohorts. It might not be necessarily true, since what plotted here are sensitive to values of the concurrent macroeconomic variables, which may different considerably across the cohorts. Thus it would be misleading to simply judge that the heterogeneity would impose a problem for estimating an integrated hazard function.

Other panels in Figure 2 illustrate the estimated hazard functions for the groups according to various start-up conditions. Using the start-up size to group the firms in consideration, the hazard function of large firms is much lower than that of small firms. The hazard function of manufacturing firms, similarly, locates far below the one of non-manufacturing firms. Furthermore, the firms established in the booms would have low risk to fail in comparison with the ones established in the recessions. The last panel provides a better understanding than the corresponding panel in Figure 1, which is based on the absolute numbers. This fact might suggest that aggregate demands seem playing a great role for the survivals.

We start our estimations by integrating all firms into one group according to (3), referring as BASE model. The first column of Table 1 reports the result. The 8 piecewise intercepts, representing baseline hazard rates, are all statistically significant. The baseline hazard rates started roughly at level of 1.16% when new firms aged 1 and rise steadily towards the topmost, about 26%, when the age reached 6. Thereafter the hazard rates decline quickly to 2.89% at age of 8. In other words, risks for exit of the firm intensify year by year until year 6th and drops afterwards. This result reveals the important role played by the age of young firm. The firms survived beyond their 6th year would face low risk to exit. This result is consistent to the previous studies such as Holmes, Hunt, and Stone (2010) which finds the clear evidence of positive duration dependence followed by negative duration dependence.

In this BASE model, all slopes are significant at 1%, except one associated with the inflation which is at 5%. The slopes of *size* and *industry* are less than 1 indicating that hazard rates of large start-up firms would decline 87% (1-0.13) of that for small ones. This is consistent to the previous finding for manufacturing firms in north-east UK (Holmes, Hunt and Stone, 2010) and for Portuguese new firm between 1982 to 1995 (Geroski, Mata and Portugal, 2010). And the hazard rates of manufacturing firms is only 35% of that of the service firms. Our result here confirms the finding from Fritsch et al. (2006), Harhoff et al. (1998), and Phillips and Kirchoff (1989). The slope of *se*, 1.70, is larger than 1, thus, indicates that the firms established during recessions would increase hazard rate by 70% in comparison with the ones established in booms. This is in the line of Fotopolous and Lori (2000) and Huynh et al. (2010). Note that all changes discussed above are irrelevant to the age. This implies hazard functions would be proportionally.

The BASE model reported in Table 1 also reveals how concurrent economic conditions would affect the hazard function. The slope coefficient of *inflation* is 1.009 (significant at 5%). This means 1% increases in inflation is likely to increase the hazard function by 0.9%, a very marginal rise. The coefficients for both *GGDP*, 0.95, and *rate*, 0.97, on the other hand, are less 1. This indicates the baseline hazard function would be shifted downwards. Quantitatively, 1% increases in *GGDP* would likely make the hazard rates 5% less. Analogously, 1% rise in *rate* would cause a reduction of the hazard rates by 3%. This result is interesting, since the common believe is the importance of the credit condition for young firms: Higher the interest rate, the though condition that the firms are facing. However our result here indicates the opposite. What is the implication of this result? It is reasonable to believe that, in long run perspective, the nominal interest rate usually reflects the state of economy. High interest rates are often accompanied with strong aggregate demands. Thus, it would be nature to consider the result here as an evidence of the aggregate demand as a key determination of young firms' survival.

The rest of columns in Table 1 report the estimations based on various groups. SIZE_0 and SIZE_1 models base on group of large and small start-up size firms, respectively. In contrast to the model BASE, these two models require no restriction that parameters across two groups should be the same. The similar approach can be found in Andreta and Mata (1995). Thus the models estimate the hazard rates separately in corresponding panel in Figure 2. The similar approach can be found in Audretsch and Mahmood (1994) and Mata et al (1995). Interesting to note that baseline hazard rates are not necessarily lower for the larger start-up firms, although as hinted in Figure 2 that the hazard function locates below. It must be true that the hazard function is affected more by the start-up conditions and/or concurrent macroeconomic conditions for larger start-up firms. The estimates of the rest of parameters in models confirm this guess. All slopes in the exponential form, except one for *industry*, in SIZE_1 are smaller than the ones in SIZE_0. So the GDP growth, interest rate, and start-up state of economy would reduce further the risks of failure. Increases in inflation, surprisingly, decreases the risk. This is contrast to the small start-up firms, in which the impact of inflation is similar to that in the BASE model: increasing risk. The exception is the industry. The manufacturing firms seem increase more risk to fail in the group of the larger start-up firms than the one of small firms.

The results concerning groups with *industry* are named as IND_0 and IND_1, respectively. Similar to previous case, baseline hazard rates are higher for the manufacturing firms than the service firms. Since estimated hazard functions show lower risks in general faced by the manufacturing firms, one or more slopes should be smaller than the corresponding ones with service firms in order to make this to happen. In details, inflation, GDP growth, and interest rate would reduce the risks further in the manufacturing group than in the service group. However, two start-up conditions, *size* and *se*, would make manufacturing firms even more risk to failure.

The study on groups with *se* summarizes in the models of SE_0 and SE_1. Note that in the year of age 8, all firms established during the booms and survived until year of age 7, survived. So hazard rate is 0. In terms of estimation, these observations are perfectly collinear. The piecewise intercept for year of age 8 will not be estimated. Apart from that, we observe the similar trend that baseline hazard rates are all higher (excepting year of age 5) for the firms established during the recessions. Recall that the estimated hazard function is indeed located above the one with established in booms. It should be less restricted in terms of reactions towards other covariates. But we still observe the same that majority of the covariates would actually make risk of failure lower for the firms established during the recessions. Inflation and *size* would reduce the risk more. GDP growth and interest rate make no significant reductions for the firms established in recessions, while for the firms established in booms the risk of failure would be actually increased. This implies that the credit condition seems more important for the firms established in booms. The manufacturing and other firms established in recessions would have no difference in terms of risk for failure. On the other hand, the manufacturing firms established in booms would have much lower risk in comparison with the other firms.

Overall, we do find variance in parameters across various groups by estimating separated equations. However, the problem of this approach is that it is hard to judge whether the differences are statistically significant. Another potential problem is that dividing the sample into subsample might lead to too few observations in particular groups. To overcome the problem, we use "semi" integrated models by relaxing one proportional restriction at time from the BASE model.

Decompose the influences on the base of age of firm

Table 2 reports the estimations based on various grouping criteria in line of the strata model (7). We start with the model SIZE in which s=*size*. The possible impacts due to *size* are now decomposed at each years of age. This means that no proportionality is required concerning the changes in start-up size. The result shows the similarity of parameters other than *size* in SIZE and BASE models. Focusing on coefficients of $\exp(size * D_i)$, which explicitly give the hazard ratios of the large start-up firms against the small ones at each years of age, we find that except the one at 8th year, which is significant only at 10% and larger than 1, all other coefficients are significant and less than 1. This implies that the large start-up firms would have lower risk to exit in comparison with small ones in general. And differences seem getting bigger by time. In the first year, the reduction is about 31% (1-0.69). The reduction increases to 96% (1-0.04) at the age 7.

The IND model sets s=*industry*. The baseline hazard function as well as the coefficients other than that of *industry* are similar to BASE and SIZE models. However, coefficients of $\exp(ind{*}D_i)$ seem having no clear cut as that in SIZE model. But if we look closely, it turns out that all coefficients with values above 1, are statistically insignificant. All significant coefficients are actually less than 1. This indicates that hazard rates of manufacturing firms are generally not larger than that of the other firms.

When s=*se*, the model SE shows hazard ratios at each years of age for firms established during recessions against that during booms. Note that the coefficient at age 8 is 0. This is probably due to multicollinarity that we discussed previously. Other coefficients are significant, at least at 5%. They are larger than 1, except first and fifth years. Roughly, we may conclude that the firms established during recessions would have higher risk of failure in comparison with that established during booms in the majority of the period in our considerations.

Table 3 studies changes in hazard rates due to the time-varying covariates at each years of age. Surprising, inflation would in general not increase the hazard risks significantly in the most years except age 5 in which the hazard rate will be increased by 9% when inflation rose 1%. It seems when inflation is allowed to influence the hazard rates at basis of firms' age, inflation replaces growth and nominal interest rate to represent aggregated demands. Interestingly, growth and interest rate in this model would actually increase the hazard rates proportionally. When we allow growth to influence hazard rates year by year, the model GROWTH suggests that inflation would proportionally decrease the hazard rates but interest rate would increase the rates. At the same time, influence due to growth is divided: in the, 6th and 8th years, hazard rates are increased due to increases in growth. However, in the rest of years, hazard rates are declined when growth increased. In the model in which interest rate is allowed to influence hazard rate at year bases, inflation reduces the hazard rates but growth increases the rates although it is only significant at 10%. Interest rate makes hazard rates in the most of years increased or no change except the first and last years. As a summary of the studies associated with time-varying covariates, proportionality assumption plays a crucial role here. When we relax this assumption with the time-varying covariates, inflation in general increases the hazard rates and growth and interest rate reduce the rates. The year by year influences are mixed and hard to find a trend. In this sense, the setting of piecewise intercepts seems a suitable framework to study failure of firms based on our dataset.

Grouping according to start-up conditions

Our next exercise is to estimate (8). Table 4 reports estimations when s=*size*, *industry*, and *se*, respectively. The model SIZE_S corresponds to s=*size*. The coefficients of *industry*, *se*, *inflation*, *gdp_growth*, and *interestrate* provide information of hazard ratios for small start-up firms. For instance, $\exp(\beta'_{ind})$ is 0.62 meaning that the small manufacturing firms reduces the risk of failure of other small firms by 38%. What is new here is the coefficient of $\exp(\beta^*_{ind})$, which is denoted by *size_ind* in the result table, providing information about the ratio of the hazard ratio due to changes in industry in large start-up group against that in small start-up group. This value is 1.23 meaning that the hazard ratio due to changes in industry in large start-up group is 23% more than that in small start-up group. Since we know the hazard ratio in small start-up group, 0.65, we may calculate the hazard ratio of the large manufacturing firms against the other large firms by 1.23*0.62= 0.76. So the large manufacturing firms reduces the risk of failure of other large firms by only 24%. (12) provides an alternative interpretation of $\exp(\beta^*_{ind})$ that 1.23 means that hazard ratio of larger against small start-up manufacturing firms is 23% larger than that of other firms.

Analogically, the coefficient of *size_se*, $\exp(\beta^*_{se})$, is 0.30, indicates that the hazard ratio of large start-up firms established in recessions against the one established in booms is 70% less than that of small firms. Again since we know hazard ratio for small start-up firms, $\exp(\beta'_{se})$ = 1.87 (the hazard risk for small start-up firms established in recessions would be 87% higher than that established in booms), we can calculate the hazard ratio for large start-up firms: 1.87*0.30 = 0.56. This means that the hazard rate for large start-up firms established in recessions would be 44% less than that established in booms. In other words, the firms established in recessions and that in booms would change the hazard ratios in different directions according to their start-up sizes. This result shows the impacts due to initial states of economy could be different across firms at different start-up size. This result would not be captured by a model which allows only proportional changes.

As implied in (12), $\exp(\beta^*_{se})$ also informs the relative hazard ratios of the ratio that large start-up firms established in recessions to that established in booms against to the ratio that with small start-up firms.

The coefficients of time varying covariates share the same interpretation: increasing 1% inflation would rise the risk of small start-up firms' failure by 1.2%. At the same time, 1% increases in growth and interest rate would reduce the risk of small start-up firms' failure by 5% and 2%, respectively. Impacts of inflation on large start-up firms are given by 1.012*0.97=0.98: increasing 1% inflation would reduce the risk of large start-up firms' failure by 2%. 1% increases in growth and interest rate would reduce the risk of large start-up firms' failure by 7% (=1-0.95*0.98) and 26% (=1-0.98*0.92), respectively. Inflation is particularly harmful for small start-up firms while large start-up firms seem benefiting from the developments.

In addition, the coefficient of *size*, 0.5364, reflects 46% decreases in hazard rates for the large against the small start-up non-manufacturing firms established in booms.

The third column in Table 4 studies the model IND_S, when s=*industry*. Being the non-manufacturing firms, large start-up size could reduce hazard rates by 87% (with the coefficient of 0.13). Being the manufacturing firms, large start-up ones could reduce the hazard by 85% (with coefficient of 0.15=0.13*1.16). Since $\exp(\beta^*_{size})$ is only significant at 10%, impacts due to size would not be significant different across manufacturing and non-manufacturing firms. This result is a bit different to the one suggested by $\exp(\beta^*_{ind})$ in the model SIZE_S. (12) suggests that two are referring the same relative ratios. But based on different models, the estimates are slightly different. The main reason is due to the way of modeling. In the model SIZE_S, we allow non-proportionality across different start-up sizes but proportionality remains valid within the groups. On the other hand, the model IND_S allows non-proportionality across different sectors. The proportionality is still valid within the sectors. Thus, although $\exp(\beta^*_{ind})$ in the model SIZE_S and $\exp(\beta^*_{size})$ in the model IND_S refer the same relative hazard ratios, they are estimated based on different specifications. The variance in the point estimates is somehow no surprising.

Move to the result concerning founding condition, *se*: Being established recessions would increase the hazard rates by 68% for non-manufacturing firms and by 95% (1.95=1.68*1.16) for manufacturing firms. This is a surprising result. Although manufacturing firms face lower hazard rate, the result here shows that manufacturing firms established in recessions would have higher hazard rate in comparison with other firms established in the same state of economy. The initial states of economy seems having crucial influence on manufacturing firms than other ones.

1.9% (according to the coefficient of *inflation* 1.0185) increases in hazard rates for non-manufacturing firms with 1% increases in inflation. The coefficient of *ind_infl*, an abbreviation of *industry*inflation*, 0.9015, refers 1% increases in inflation would lead to 8% (=1-0.9015*1.0185) fall in hazard rates for manufacturing firms. There is no significant reduction of hazard rates by GDP growth for manufacturing firms. But the impact on non-manufacturing firms is significant. 4% of drop in hazard rates of 1% GDP growth. The interest rate has roughly similar impacts on both type firms: 1% rises in interest rate lead 4% reductions for manufacturing firms and 2% reductions for other firms.

The last column in Table 4 provides the result from the model SE_S, where $s=se$, by grouping firms due to founding states of the economy. The hazard ratio of large start-up firms related to small ones established during the booms is given by $\exp(\beta_{size})=0.21$. It is significant and indicating that the hazard rates would be reduced by 79%. That hazard ratio would be further reduced by 56% for the firms established in recessions. The hazard ratio is then 0.09 (=0.21*0.44). This means that the large start-up firms would reduce hazard rates by 91% compared with the small ones established in recessions. Note that $\exp(\beta^*_{size})$ also provide the relative impact of initial state of economy in groups due to the size. The initial state of economy could reduce the hazard rate more for the firms established in recessions than that established in booms. This is consistent to the result from the model SIZE_S: $\exp(\beta^*_{se})$ is about 0.30. Again the difference of the coefficients is due to the specifications of proportionality.

The hazard ratio of manufacturing firms related to non-manufacturing ones established during the booms is given by $\exp(\beta_{ind})=0.31$. It is significant and indicates that being in manufacturing sector would significantly reduce the hazard rates by 69% in comparison with the non-manufacturing firms established in booms. Since $\exp(\beta_{ind})* \exp(\beta^*_{ind})=0.31*3.17=0.98$. The reduction would only be 2% for firms established in the recessions. $\exp(\beta^*_{ind})= 3.17$ means that being established in recessions would increase hazard rate more in manufacturing sector than that in non-manufacturing sector. This is consistent to the result we obtained from the model IND_D, although the values of coefficients are quite different due to the specifications of proportionality.

Inflation and interest rate have no significant impacts on hazard rates for the firms established during the booms. For the firms established in the recessions, the hazard rates would be increased by 17% (1.17=0.99*1.18) when inflation rises 1%. The hazard rates would be reduced by 17% (0.83=0.996*0.83) instead when interest rate rises 1%. 1% GDP growth can reduce the hazard rate by 5% for the firms established in booms and reduce by 15% (0.85=0.95*0.89).

Concluding remarks

The theory and previous empirical studies demonstrate the importance of age of firm, start-up size, the sector that firm belongs to, and initial states of economy, as well as time-varying concurrent macroeconomic conditions on determination of firms' survival. This paper attempts to identify similar evidences based on Swedish observations. We employ the semi-parametric complementary log-log model to estimate hazard rates. Our results here are largely consistent to the previous finding that the age plays a crucial role for selecting survival. We also observe the positive duration dependence followed by negative duration dependence. At the same time, a large start-up size, being in manufacturing sector, being established in booms and strong aggregated demands would in general push down the hazard rates.

This paper moves further to investigate two issues which have not been generally focused by previous studies. First, we looked at possible impacts from the factors listed above at each age of firm. We find that the impacts due to start-up size and sector are largely consistent to the integrated model. But it lucks the consistence for other factors. Our study here shows that impacts on hazard rates could be much more complicated if we allow the non-proportionality across age of firm.

The second distinguished issue is to allow the non-proportionality across various groups. When we grouped the firms according to the start-up size, we find that the reduction of hazard rates due to industry sector is much less for larger start-up firms than that of small firms. In other words, industry sector as a factor to influence the hazard rates would be much effective in the group of small start-up firms. More interestingly, impacts due to initial states of economy are more sensitive to the group. Established in recessions would increase the hazard of exit for the small start-up firms but would reduce the hazard for large start-up firms. This result poses different picture to the model in which the non-proportionality is not allowed. Furthermore, we also observe the similar impacts due to inflation: Increases in inflation would increase hazard for small start-up firms but reduce the hazard for large start-up firms. However, both growth and interest rate would reduce the hazard rates for all start-up sizes while at different extents: 5% and 2% reductions for small start-up firms in comparison with the reductions of 7% and 26%, respectively for large start-up firms. In other words, more effective reductions in the group for large start-up firms.

When criterion is industry sector for grouping firms, our result shows that impacts due to start-up size would not be significantly different across different industries. This is inconsistent to the one obtained based on grouping according to size. The main reason is probably because that the proportionalities are specified differently. When we group according to start-up size, the non-proportionality is allowed with large and small start-up firms. On the other hand, grouping according to industry sector implies the allowance of non-proportionality across manufacturing and non-manufacturing firms. For the impacts due to initial states of economy, we find that the hazard rates would be increased for both sectors. But it would increase more, 95%, for manufacturing firms in comparison with 68% for other firms. Inflation, again, impacts two sector in different directions: High inflation would reduce, by 10%, the hazard of exit for manufacturing firms but increase, by 1.9%, for other firms. GDP growth displays no significant difference across two sectors: 4.5% reductions for both sectors. At the same time, interest rate reduces the hazard rate by 4% and 2%, respectively, for manufacturing and other firms.

This paper also looks at groups divided according to the initial states of economy. The start-up size would reduce hazard rates for both firms established in booms and recessions, by 79% and 91%, respectively. On the other hand, manufacturing firms would reduce hazard by 69% for that established in booms in comparison with only 2% for that established in recessions. Inflation and interest rate have no particular impacts on hazard rates for firms established during the booms but have significant impact on firms established in recessions. Hazard rates would be increased by17% due to 1% increases in inflation but be reduced by17% due to 1% increases in interest rate. GDP growth would reduce both hazard rates by 5% for firms established in booms and by 15% for firms established in recessions.

Our study here provides a rich picture about the hazard function for young firms. As note previously, some of the results might not be consistent. We believe it is largely due to the restriction of proportionality, although we do attempt to relax the assumption to some extent. A future study might be needed to adopt more general framework in order to overcome the inconsistency here.

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Appendix
In this appendix, we show how to derive of (2).

First of all, by denoting the time-varying and time-invariant variables as *X* and Y_t, respectively and define the interval hazard rate as

$$h_t(X,\ Y_t) = \Pr(t-1 < T < t | T \geq t-1). \qquad \text{(A1)}$$

Express the interval hazard rate as a function of discrete survival function

$$\begin{aligned} h_t(X,\ Y_t) &= \frac{S(t-1, X, Y_{t-1}) - S(t, X, Y_t)}{S(t-1, X, Y_{t-1})} \\ &= 1 - \frac{S(t, X, Y_t)}{S(t-1, X, Y_{t-1})} \end{aligned}. \qquad \text{(A2)}$$

Note that the survivor function at time *t* in (A2) is given by

$$S(t, X,\ Y_t) \ = \ \exp[-\textstyle\int_0^t \theta(u, X, Y_u) du] \qquad \text{(A3)}$$

where continuous hazard rate, $\theta(t, X, Y_t)$, satisfies the PH assumption:

$$\theta(t, X, Y_t) = \theta_0(t)\gamma\lambda_t, \qquad \text{(A4)}$$

with $\gamma = \exp(\beta_X{}'X)$ and $\lambda_t = \exp(\beta_Y{}'Y_t)$.
Replacing $\theta(t, X, Y_t)$ in (A3) with (A4), we obtain

$$\begin{aligned} S(t, X,\ Y_t) &= \exp[-\int_0^t \theta(u, X, Y_u) du] \\ &= \exp\left[-\int_0^t \theta_0(u)\gamma\lambda_u\, du\right] \\ &= \exp\left[-\gamma\int_0^t \theta_0(u)\lambda_u\, du\right] \end{aligned}$$

Furthermore, if we consider individual intervals where the time-varying variables, *Y*, remain unchanged, we have

$$\begin{aligned} \int_0^t \theta_0(u)\lambda_u\, du &= \int_0^1 \theta_0(u)\, \lambda_u du + \int_1^2 \theta_0(u)\lambda_u\, du + \cdots + \int_{t-1}^t \theta_0(u)\lambda_u\, du \\ &= \lambda_1 \int_0^1 \theta_0(u)\, du + \lambda_2 \int_1^2 \theta_0(u)\, du + \cdots + \lambda_t \int_{t-1}^t \theta_0(u)\, du. \end{aligned}$$

By define the integrated hazard function $H_t = \int_0^t \theta_0(u)\, du$, we can rewrite the expression above as

$$\begin{aligned} \int_0^t \theta_0(u)\lambda_u\, du &= \lambda_1 \int_0^1 \theta_0(u)\, du + \lambda_2 \int_1^2 \theta_0(u)\, du + \cdots + \lambda_t \int_{t-1}^t \theta_0(u)\, du \\ &= \lambda_1 H_1 + \lambda_2(H_2 - H_1) + \cdots + \lambda_t(H_t - H_{t-1}). \end{aligned}$$

Recalling the survival function, we now can express the function in terms of *H*s:

$$S(t, X,\ Y_t) = \exp\{-\gamma[\lambda_1 H_1 + \lambda_2(H_2 - H_1) + \cdots + \lambda_t(H_j - H_{t-1})]\}.$$

This further leads to a simplification of the interval hazard function:

$$\begin{aligned} h_t(X,\ Y_t) &= 1 - \frac{S(t, X,\ Y_t)}{S(t-1, X,\ Y_{t-1})} \\ &= 1 - \exp[-\gamma\lambda_t(H_t - H_{t-1})]. \end{aligned}$$

This implies that the cloglog transform is a linear function of the variables, *X* and Y_t:

$$\log\{-\log[1 - h_t(X,\ Y_t)]\} = \beta_X{}'X + \beta_Y{}'Y_t + \log(H_t - H_{t-1}). \qquad \text{(A5)}$$

The last term in (A5) corresponds to the interval baseline hazard rate for the year t, h_{0t}. In our study, we shall not fit these terms with a function form. Instead, we adopt the semi-parametric specification to estimate these piecewise constants. To carry out this approach, we simply assume $\alpha_t = \log(H_t - H_{t-1})$ and rewrite the cloglog model as

$$\log\{-\log[1 - h_t(X, Y_t)]\} = \beta_X{}'X + \beta_Y{}'Y_t + \alpha_t. \quad \text{(A6)}$$

The interval hazard function is then

$$h_t(X, Y_t) = 1 - \exp[\exp(\beta_X{}'X + \beta_Y{}'Y_t + \alpha_t)]. \quad \text{(A7)}$$

Figure 1. The facts about the exits

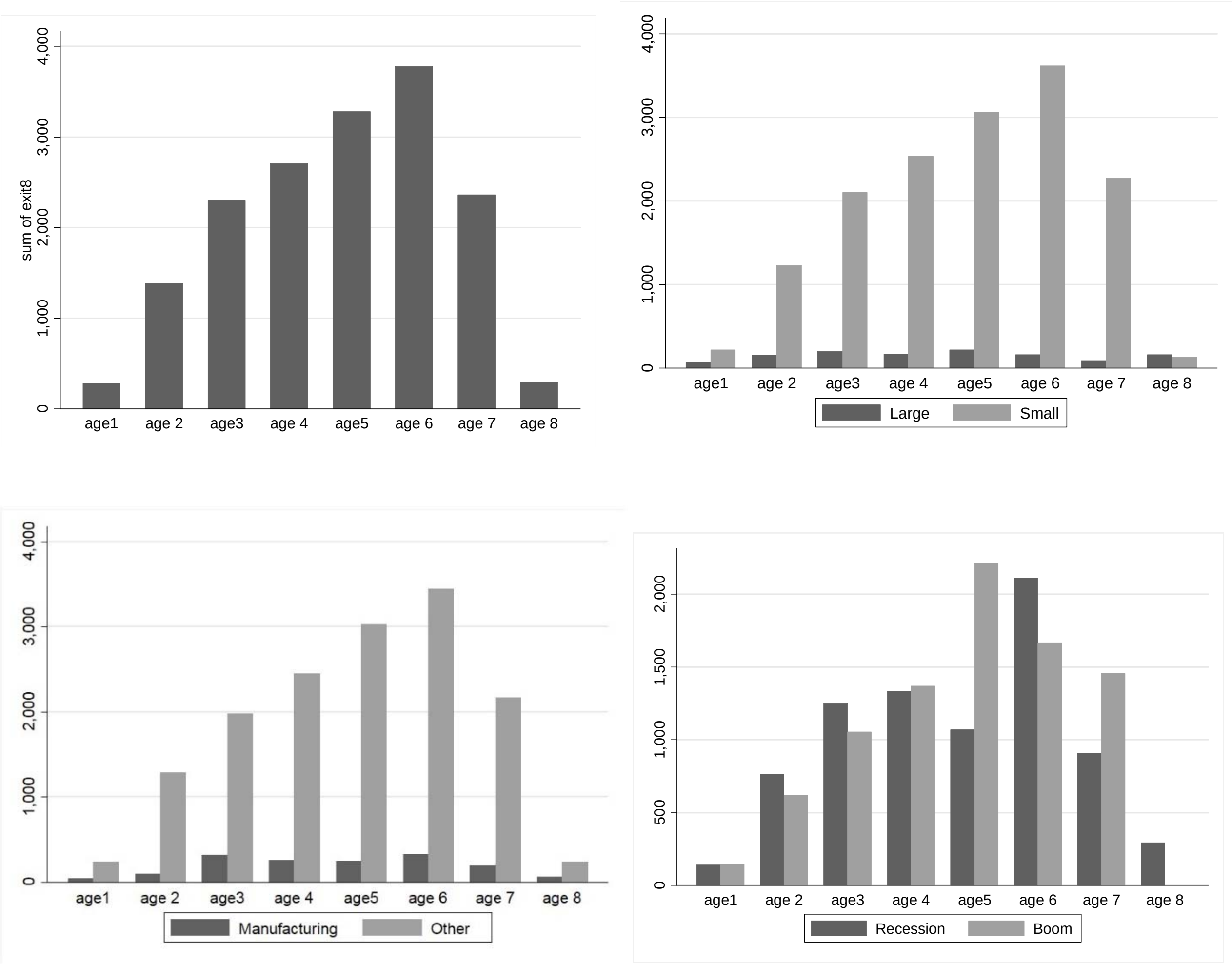

Figure 2. Estimated hazard rates

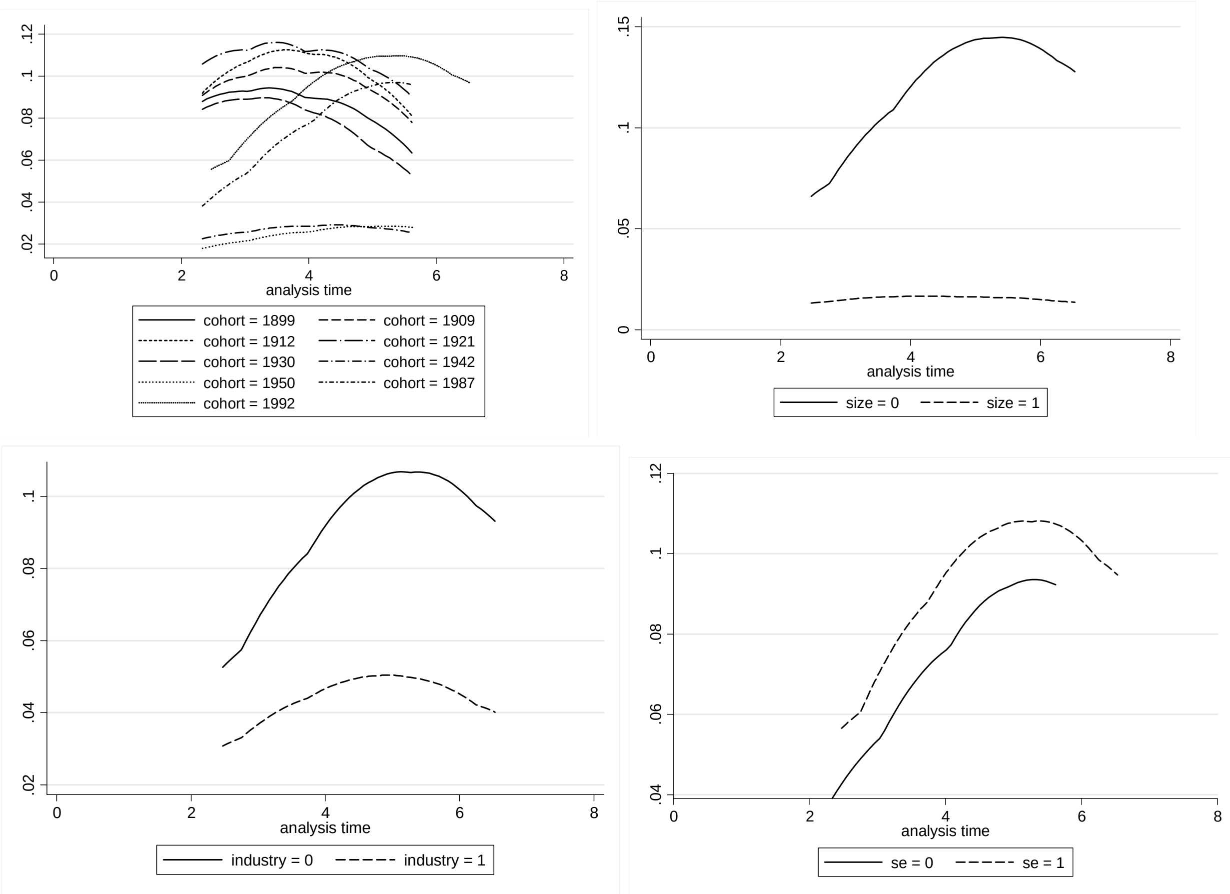

Table 1: Hazard functions in various groups according to the start-up conditions

Variable	BASE	SIZE_0	SIZE_1	IND_0	IND_1	SE_0	SE_1
d1	0.0116***	0.0067***	0.0488***	0.0076***	0.0522***	0.0049***	0.0082***
d2	0.0610***	0.0402***	0.1262***	0.0438***	0.0970***	0.0245***	0.0973***
d3	0.1062***	0.0743***	0.1511***	0.0725***	0.3004***	0.0430***	0.1356***
d4	0.1285***	0.0908***	0.1426***	0.0883***	0.3164***	0.0727***	0.1570***
d5	0.1741***	0.1302***	0.1366***	0.1306***	0.2362***	0.1469***	0.1285***
d6	0.2626***	0.2101***	0.0956***	0.2046***	0.3133***	0.0509***	0.3704***
d7	0.2167***	0.1774***	0.0572***	0.1720***	0.2101***	0.1157***	0.1959***
d8	0.0289***	0.0115***	0.0846***	0.0213***	0.0555***	(omitted)	0.0842***
inflation	1.0090**	1.0221***	0.9434***	1.0269***	0.9196***	0.9041***	0.8588***
gdp_growth	0.9517***	0.9663***	0.8727***	0.9652***	0.9460***	1.0085	0.9794
interestrate	0.9734***	0.9904*	0.8739***	0.9940	0.8618***	1.1068***	1.0519*
size	0.1303***			0.1256***	0.1573***	0.2044***	0.0887***
industry	0.6488***	0.6243***	0.7549***			0.3134***	0.9958
se	1.7019***	2.0038***	0.5396***	1.8060***	2.1985***		
aic	102784	89173	12548	91310	10676	55065	45848
bic	102929	89303	12669	91442	10789	55183	45972
ll	-51378	-44574	-6261	-45641	-5323	-27520	-22911

legend: * p<.1; ** p<.05; *** p<.01

Table 2. Hazard functions with identical slopes within groups

Variable	BASE	SIZE	IND	SE
d1	0.0116***	0.0097***	0.0106***	0.0066***
d2	0.0610***	0.0584***	0.0616***	0.0329***
d3	0.1062***	0.1051***	0.0995***	0.0564***
d4	0.1285***	0.1322***	0.1267***	0.0927***
d5	0.1741***	0.1787***	0.1758***	0.1754***
d6	0.2626***	0.2815***	0.2648***	0.0626***
d7	0.2167***	0.2365***	0.2212***	0.1545***
d8	0.0289***	0.0148***	0.0261***	0.0000
inflation	1.0090**	1.0086**	1.0096**	0.8995***
gdp_growth	0.9517***	0.9531***	0.9533***	0.9725***
interestrate	0.9734***	0.9716***	0.9738***	1.0863***
size	0.1303***		0.1305***	0.1287***
industry	0.6488***	0.6477***		0.6532***
se	1.7019***	1.6794***	1.6973***	
sized1		0.6886***		
sized2		0.2907***		
sized3		0.2055***		
sized4		0.1326***		
sized5		0.1257***		
sized6		0.0616***		
sized7		0.0427***		
sized8		1.2229*		
industryd1			1.3034	
industryd2			0.5082***	
industryd3			1.0870	
industryd4			0.7073***	
industryd5			0.5358***	
industryd6			0.5631***	
industryd7			0.4733***	
industryd8			1.2101	
sed1				0.7264**
sed2				1.9803***
sed3				1.8412***
sed4				1.2080***
sed5				0.6213***
sed6				5.2864***
sed7				1.1573***
sed8				1.99e+08
aic	102784	102004	102660	101486
bic	102929	102223	102879	101705
ll	-51378	-50981	-51309	-50722

legend: * p<.1; ** p<.05; *** p<.01

Table 3. Piecewise effects due to time-varying covariates

Variable	BASE	INFLATION	GROWTH	RATE
d1	0.0116***	0.0074***	0.0038***	0.0508***
d2	0.0610***	0.0419***	0.0421***	0.0485***
d3	0.1062***	0.0736***	0.0582***	0.0575***
d4	0.1285***	0.0716***	0.0797***	0.0318***
d5	0.1741***	0.0678***	0.1213***	0.0165***
d6	0.2626***	0.1994***	0.1109***	0.1906***
d7	0.2167***	0.1136***	0.7110	0.0490***
d8	0.0289***	0.2622***	0.0010***	0.9312
size	0.1303***	0.1288***	0.1301***	0.1294***
industry	0.6488***	0.6475***	0.6520***	0.6527***
se	1.7019***	1.7557***	1.9642***	1.8156***
inflation	1.0090**		0.9386***	0.9176***
gdp_growth	0.9517***	1.0168		1.0226*
interestrate	0.9734***	1.0297***	1.0534***	
inflationd1		0.8487***		
inflationd2		0.9348***		
inflationd3		0.9285***		
inflationd4		0.9998		
inflationd5		1.0874***		
inflationd6		0.7968***		
inflationd7		1.0119*		
inflationd8		0.0198***		
growthd1			1.2511***	
growthd2			0.9280***	
growthd3			0.9897	
growthd4			0.9141***	
growthd5			0.8103***	
growthd6			1.1012***	
growthd7			0.6398***	
growthd8			2.0490***	
rated1				0.8590***
rated2				1.0173
rated3				1.0600***
rated4				1.1626***
rated5				1.3253***
rated6				1.0102
rated7				1.2085***
rated8				0.3574***
aic	102784	101355	101874	101364
bic	102929	101573	102092	101582
ll	-51378	-50657	-50916	-50660

legend: * p<.1; ** p<.05; *** p<.01

Table 4. Relative hazard ratios

Variable	BASE	SIZE_S	IND_S	SE_S
d1	0.0116***	0.0102***	0.0103***	0.0137***
d2	0.0610***	0.0542***	0.0539***	0.0512***
d3	0.1062***	0.0948***	0.0939***	0.0954***
d4	0.1285***	0.1143***	0.1122***	0.1131***
d5	0.1741***	0.1558***	0.1537***	0.1579***
d6	0.2626***	0.2361***	0.2341***	0.1977***
d7	0.2167***	0.1944***	0.1936***	0.1929***
d8	0.0289***	0.0257***	0.0261***	0.0218***
size	0.1303***	0.5364***	0.1264***	0.2061***
industry	0.6488***	0.6239***	0.9978	0.3129***
se	1.7019***	1.8731***	1.6837***	6.4225***
inflation	1.0090**	1.0122***	1.0185***	0.9945
gdp_growth	0.9517***	0.9530***	0.9554***	0.9545***
interestrate	0.9734***	0.9795***	0.9828***	0.9955
size_ind		1.2291***	1.1565*	
size_se		0.2981***		0.4365***
size_infl		0.9729**		
size_growth		0.9791		
size_rate		0.9199***		
se_ind			1.5464***	3.1664***
ind_infl			0.9015***	
ind_growth			1.0078	
ind_rate			0.9368***	
se_infl				1.1804***
se_growth				0.8919***
se_rate				0.8262***
aic	102784	102580	102226	102106
bic	102929	102778	102424	102304
ll	-51378	-51271	-51094	-51034

legend: * p<.1; ** p<.05; *** p<.01