

# Why Is Start-up Survival Lower Among Necessity Entrepreneurs? A Decomposition Approach

Marina Furdas\*, Karsten Kohn\*\*

Preliminary Version, April 2011

**Abstract:** Necessity entrepreneurs exhibit lower survival rates of their businesses than opportunity entrepreneurs. This paper analyzes the importance of person-related and business-related characteristics for explaining the observed gap. Using large-scale population-representative survey data, we estimate discrete-time hazard rate models with unobserved heterogeneity and apply non-linear Blinder-Oaxaca-type decompositions. As it turns out, both differences in characteristics and differences in the self-employment returns to those characteristics account for the lower survival rates of necessity compared to opportunity entrepreneurs.

**Keywords:** Entrepreneurship, Business Success, Start-up Survival, Decomposition Analysis, KfW Start-Up Monitor

---

\* Albert-Ludwigs University Freiburg. E-mail: marina.furdas@vwl.uni-freiburg.de.

\*\* KfW Frankfurt and IZA Bonn. Corresponding author: KfW, Department of Economics, Palmengartenstr. 5-9, 60325 Frankfurt, Germany. Tel. +49-69-7431-4473, Email: Karsten.Kohn@kfw.de.

Opinions expressed in this article reflect the personal views of the authors and not necessarily those of KfW. We thank seminar participants at Freiburg University for fruitful discussions. All errors are our sole responsibility.

# Contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
<b>2</b>	<b>Related Literature</b>	<b>2</b>
2.1	Opportunity-Necessity Dichotomy and Start-up Survival . . . . .	2
2.2	Other Determinants of Self-Employment Duration . . . . .	4
<b>3</b>	<b>Data</b>	<b>5</b>
3.1	KfW Start-Up Monitor . . . . .	6
3.2	Descriptive Statistics . . . . .	7
<b>4</b>	<b>Econometric Analysis</b>	<b>8</b>
4.1	Survival Functions: Kaplan-Meier Estimates . . . . .	9
4.2	Estimating A Discrete-Time Hazard Rate Model . . . . .	9
4.3	Decomposition Analysis . . . . .	14
<b>5</b>	<b>Concluding Remarks</b>	<b>18</b>
	<b>Literature</b>	<b>18</b>
	<b>Tables and Figures</b>	<b>21</b>
<b>A</b>	<b>Appendix</b>	<b>28</b>

# 1 Introduction

There is a great effort to support disadvantaged business starters and in particular starters from unemployment in many countries. However, ‘necessity’ entrepreneurs exhibit lower survival rates of their businesses as compared to ‘opportunity’ entrepreneurs (Caliendo and Kritikos (2009)). Empirical evidence on the reasons for this observation has so far been scarce. Is the lower survival rate driven by selection effects in the sense that necessity entrepreneurs have less favorable personal characteristics or start less promising projects? Or does the survival gap persist even beyond selection?

Our paper seeks to answer these questions by comparing opportunity entrepreneurs and necessity entrepreneurs using data from the KfW Start-up Monitor, a large-scale population survey on start-up activity in Germany. We first estimate discrete-time hazard rate models of start-up survival in the first 36 months of business existence, accounting for duration dependence and unobserved heterogeneity by means of random individual-specific effects. Second, the differential in survival rates between necessity and opportunity entrepreneurs is decomposed into a characteristics effect related to selection of individuals based on observable characteristics, and a coefficients effect capturing behavioral differences that exist even in case of equalized characteristics.

Our approach goes beyond related studies in several dimensions. We use population-representative sample of starters, not restricting our attention to starters from unemployment (as in Caliendo and Kritikos (2009)). Moreover, we are able to control for entrepreneur-related as well as project-related determinants of survival (unlike Block and Sandner (2009)). Most importantly, to our knowledge, decomposition techniques have so far not been applied in the context at hand. Investigating the influence of potential determinants on short-term survival of opportunity and necessity entrepreneurs in Germany, our study answers the following research questions. Is self-employment duration among opportunity and necessity entrepreneurs driven by different person-related and business-related characteristics? How large is the gap in estimated survival rates between those two groups? To what extent do differences in observed self-employment determinants account for the disparity in survival rates and how do the effects vary with elapsed time in self-employment?

Our findings suggest that business start-ups of necessity entrepreneurs in fact have lower survival rates than businesses started by opportunity entrepreneurs. We find a number of differences regarding the determinants of survival between the two groups. Unobserved heterogeneity plays a larger role among necessity entrepreneurs. The difference in predicted survival functions is growing over time. We find that irrespective

of the underlying counterfactual situation, the different survival rates for the two types of entrepreneurs are explained by both differences in characteristics and differences in the self-employment returns to those characteristics. The characteristics effect tends to be lower compared to the “unexplained” coefficients effect. This suggests different returns from self-employment activity, unobserved group differences in productivity, and behavioral differences are important drivers of the gap in survival rates.

The remainder of the paper proceeds as follows. Section 2 gives an overview of the literature on entrepreneurial survival among start-ups out of necessity and start-ups out of opportunity and discusses general self-employment determinants. Section 3 describes the data. Section 4 presents the econometric model and the decomposition technique for explaining differences in predicted survival rates. Section 5 concludes.

## 2 Related Literature

### 2.1 Opportunity-Necessity Dichotomy and Start-up Survival

The notion of opportunity and necessity entrepreneurs was introduced in the context of the Global Entrepreneurship Monitor (see Reynolds et al. (2001)) and adapted by other entrepreneurship-related surveys.<sup>1</sup> In spite of different concept measures<sup>2</sup>, the distinction between those two types of entrepreneurship captures mainly dissimilar motivational factors of the individual decision and the willingness to start-up a business. Whereas opportunity-driven entrepreneurship is often associated with pull factors, start-ups out of necessity are to a great extent related to push factors.<sup>3</sup> Previous entrepreneurship research suggest that pull and push motivations may come in a variety of forms.<sup>4</sup> Pull motivations include basically the perception and the exploitation of an innovative business idea or market opportunity, the need for independence, financial success and self-realization. On the other hand, escape from necessity (personal or for relatives) resulting from unemployment, low prospects for paid-employment due to, for instance, a lack of educational or language skills, or even job dissatisfaction with previous employment is classified as a traditional push factor.

Why does the distinction between opportunity-driven and necessity-driven entrepreneur-

---

<sup>1</sup>See, for instance, Kohn et al. (2010) for the KfW Start-up Monitor and Verheul et al. (2010) for the Flash Eurobarometer Survey on Entrepreneurship.

<sup>2</sup>Block and Wagner (2007), Caliendo and Kritikos (2009), Verheul et al. (2010).

<sup>3</sup>Recent studies highlight also the idea that some individuals decide to become self-employed based on both, pull and push motives (Caliendo and Kritikos (2009) and Verheul et al. (2010)).

<sup>4</sup>For an extended overview see Caliendo and Kritikos (2009) and Verheul et al. (2010) and the works cited there.

ship might be of a particular interest for entrepreneurial survival? Recent empirical studies provide several reasons for answering this question (see Verheul et al. (2010)). The most important one is that opportunity and necessity entrepreneurs may differ with respect to their individual-specific characteristics, their employment history prior to entry into self-employment and the characteristics of their businesses. Dissimilarity based on observable and/or unobservable characteristics might lead to different economic development of the start-up projects and might influence the length of self-employment duration for opportunity and for necessity entrepreneurs. For instance, because of their pull motivations opportunity entrepreneurs might exhibit higher entrepreneurial skills resulting from better preparation of their self-employment activity, which might improve their business success. On the other side, necessity entrepreneurs might lack the sufficient human capital in order to have higher chances in business performance and entrepreneurial survival.

There are only very few empirical studies that aim to explore the impact of different types of motivation on entrepreneurial survival. Block and Sandner (2009) use data from the German Socio-Economic Panel and find that, after controlling for education of the entrepreneur there is no difference in exiting self-employment between opportunity and necessity entrepreneurs. The authors conclude that observed hazard differences are due to selection in observable characteristics. Caliendo and Kritikos (2009) use data on business start-ups by unemployed West German males and investigate job creation and entrepreneurial survival among three types of motivational factors and entrepreneurs, respectively: push, pull, and push-pull motivations. Their study reveals that after controlling for socio-demographic and business-related characteristics and given the same duration of previous unemployment, start-ups out of opportunity and necessity have higher survival rates than start-ups out of necessity.

Though, there is little empirical evidence considering the fact that self-employment duration among opportunity and necessity entrepreneurs might be driven by different characteristics. To our knowledge there is only one study by Verheul et al. (2010) that allows the impacts of the explanatory variables to vary between different motivational types. Applying a multinomial logit model on the failure probability, the authors conclude that there exist some important differences between opportunity, necessity, and mixed-motivated entrepreneurs concerning their probability of exit out of self-employment. For example, their findings suggest that women exhibit lower survival rates but only for those who started their business out of necessity. On the other hand, having self-employed parents reduces the probability of failure for opportunity entrepreneurs but has no significant impact on necessity or mixed-motivated entrepreneurs.

## 2.2 Other Determinants of Self-Employment Duration

Millan et al. (2010) provide a recent overview of previous studies and findings on the determinants of self-employment survival. See also van Praag (2003) for a summary of historical lines of argument. In what follows, we discuss the impact of some covariates in our sample.

- **Age:** Age of the entrepreneur is often considered as a proxy for general and specific knowledge, which is acquired over the individual life-time cycle. Compared to younger individuals older people have more experience as well as greater human, social and network capital. Thus, we would expect to find a positive impact of age on self-employment duration.
- **Education:** The results of previous studies of qualification on entrepreneurial survival are mixed. On the one hand, higher qualification measured by years of schooling or educational attainment is associated with more valuable human capital, which in general should have a positive effect on self-employment duration. On the other hand, individuals who expect lower average returns from a job in paid employment have less incentives to invest in their own education. In this case higher expected returns of investment in education would reflect higher opportunity costs of being self-employed.
- **Experience in paid employment:** Higher labor market experience is in line with more human capital, which should have a positive impact on survival rates. However, van Praag (2003) finds that experience in paid employment has no significant impact on exit from self-employment.
- **Self-employment experience:** Individuals with former self-employment experience (re-starters and serial entrepreneurs) are a particularly heterogeneous group because they might refer to either positive or negative entrepreneurial experience. Metzger (2008), for instance, argues that negative self-employment experience does involve selection and signalling effects for entrepreneurs, from which they can learn by increasing their human capital and improving their entrepreneurial skills. In case of positive entrepreneurial experience, Jovanovic's (1982) theory of industry evolution predicts positive returns due to accumulation of entrepreneurial skills over time.
- **Unemployment experience:** Previous unemployment experience is often regarded to be a strong negative predictor for self-employment duration. According to Carrasco (1999) this might be due to human capital depreciation during spells of unemployment, and the lower information quality of business opportunities. Taylor (1999)

argues that unemployment experience might also be related to lower entrepreneurial ability.

- **Firm size:** Firm size is intrinsically linked to the liability of smallness introduced by Freeman et al. (1983). This hypothesis argues that the larger the firm (as measured by the number of employees), the lower the business failure rate. Freeman et al. (1983) argue that the smallest organizations have the highest death rates due to low capital recourses particularly at the beginning of their self-employment spell. Additionally, an increasing firm size is associated with higher opportunity costs from exit out of entrepreneurship, which should reduce the failure rate.
- **Innovativeness:** In line with the classic view of new business formation, the entrepreneur herself is the driving force of her self-employment success. Classical economists like Schumpeter, Marshall, and Knight attributed entrepreneurs leading functions with respect to the economic processes and society (cp. van Praag, 2003). For instance, Schumpeter’s entrepreneur is defined as an “innovator” who discovers new markets and is willing to struggle with competitors. According to this view, we would expect the business failure rate to be lower among true entrepreneurs, i.e., among innovators. However, innovative start-up projects inherently take a larger risk that the new product or technology is not accepted on the market. Along this line of reasoning, innovativeness would be associated with higher failure rates.

We expect that the above explanatory variables may have different impacts on self-employment duration among opportunity than among necessity entrepreneurs. In addition, further unobserved factors (e.g. entrepreneurial ability) may also play an important role in explaining entrepreneurial survival rates.

### **3 Data**

We analyze determinants of entrepreneurial survival and the factors explaining survival rate differentials between necessity and opportunity entrepreneurs using data from the KfW Start-Up Monitor. We first describe the data and then report some summary statistics.

### 3.1 KfW Start-Up Monitor

The KfW Start-up Monitor is a representative computer-assisted telephone (CATI) survey on start-up activity in Germany.<sup>5</sup> Its yearly cross sections are conducted among 50.000 randomly selected inhabitants. Entrepreneurs are identified as those persons who started a new business or took over an established firm at some point within 36 months before the interview. The employed broad entrepreneurship concept includes industrial and commercial self-employment as well as freelances, and full-timers as well as part-timers. We use the pooled waves from 2007 to 2010 for empirical analysis.

Entrepreneurs are asked to provide information on month and year of their business start and – in case the start-up project has already been ended at the time of the interview – of the termination date. This information allows us to determine the length of self-employment duration for each respondent. The individual length of self-employment activity is observed at discrete time intervals and can range from 1 to 36 months. Since the analysis is based on flow sampling data (we observe self-employment entrants and self-employment drop-outs), self-employment duration might be either completed or right-censored. For right censored spells the time to termination exceeds the time of interview and data collection and only the beginning of self-employment activity is observed. In the case of completed spells (observed entry and exit), the respondents are also asked about the reason for giving-up the business.

The KfW Start-up monitor offers the unique advantage to provide information on both individual characteristics of the entrepreneur and business-related characteristics extensively describing the start-up project. Socio-economic background variables include, e.g., gender, age, educational attainment, and labor market status prior to entry into entrepreneurship. In the group of business-related characteristics we include the following explanatory variables: type of establishment, firm size, start-up capital, innovativeness as measured by the degree of novelty of the offered good or service, occupational categories, and an indicator for part-time self-employment. In addition, we take into account the industry structure to control for the start-up environment. All variables are grouped in categories and are treated as dummies in the estimation analysis. Table 2 in the Appendix provides definitions of included variables.

Regarding start-up motives, entrepreneurs are asked about their main reason for the decision to become self-employed. Similar to the GEM dichotomy, the choice is restricted to two different options: realizing one’s own business idea or lack of employment alternatives. Starters reporting the former motive are classified as ‘opportunity’ entrepreneurs,

---

<sup>5</sup>See Kohn et al. (2010) and Tchouvakhina and Hofmann (2003/04) for detailed descriptions of the data source.



whilst those reporting the latter reason are classified as ‘necessity’ entrepreneurs.

## 3.2 Descriptive Statistics

Our initial sample includes 4462 entrepreneurs of which 2180 are classified as necessity and 2282 as opportunity entrepreneurs, respectively. Overall, 778 entrepreneurs report an abandoned start-up business activity, which allows us to observe completed spells of self-employment in just 17.4% of cases. The remaining 3684 (82.6%) self-employment spells are right-censored at time of interview. Out of 2180 necessity entrepreneurs, 1701 continue to be self-employed (78.0% of the spells are censored) and only 479 report an exit (22%). The relative number of completed durations in the sample of opportunity entrepreneurs is relatively smaller (13.1%) and the censoring rate amounts to 86.9%. Table 3 in the Appendix shows the reasons for terminating self-employment for completed spells by type of entrepreneur. It turns out that the majority of completed spells in our sample are involuntary terminated, where a very large proportion (about 77% in the sample of necessity and 71% in the sample of opportunity entrepreneurs, respectively) of spells reveal termination because of liquidation. Table 3 shows also that on average opportunity entrepreneurs tend to report higher voluntary termination rate than necessity entrepreneurs, as measured by the the first two reasons for self-employment exits – “business being sold” and “business succession”.

Table 4 in the Appendix provides sample means of socio-economic characteristics and compares necessity with opportunity entrepreneurs in the group of self-employment drop-outs as well as in the group of self-employment survivors. Except for the previous employment status variable and gender we find relatively few significant differences in the group of self-employment drop-outs. For example, necessity and opportunity entrepreneurs do not differ with respect to educational attainment or migration background and show only marginal significant differences regarding age. On the contrary, depending on the start-up motive self-employment survivors differ strongly with respect to socio-economic characteristics. Table 4 shows that in the survivor sample opportunity entrepreneurs are on average better qualified than necessity entrepreneurs. On the other hand, regardless of the underlying population necessity entrepreneurs more often start a business from unemployment or from out of labor force and show on average significantly lower employment and/or self-employment experience. Also the female share is significantly higher among necessity than among opportunity entrepreneurs.

Table 5, also in the Appendix, compares business related characteristics of drop-outs and survivors by entrepreneurial motivation. Again, the survivor sample exhibits more significant differences than the drop-out sample. This suggests that self-selection into

entrepreneurship is larger for individuals that stated to continue to be self-employed at time of interview. The results in Table 5 reveal that on average the share of part-time self-employed is significantly higher among opportunity entrepreneurs than among necessity entrepreneurs. Regarding establishment type it turns out that most of the start-ups are new businesses (as compared to take-overs and joint ventures). This share is significantly higher among opportunity than among necessity entrepreneurs in the survivor population. In contrast, the share of joint ventures tends to be significantly lower for start-ups out of opportunity than start-ups out of necessity. Regarding firm size, the majority of entrepreneurs in our sample (almost 66% of cases) are solo business owners without any employees at time of start-up. This share is significantly higher among necessity (almost 73%) than among opportunity entrepreneurs (almost 59%). Start-ups out of opportunity are on average more often characterized by a larger size, whether in terms of additional partners or in terms of employees. Looking at the size of start-up capital we find that opportunity entrepreneurs tend to invest higher amounts in their business than necessity entrepreneurs do. The differences are strongly significant in the sample of self-employment survivors and show only partial significance in the sample of necessity entrepreneurs. With respect to the degree of innovation of the business we find that the highest share (more than 85% on average) form start-up projects without any market novelty. If the start-up project is described to be a regional, national-wide or world-wide novelty, then this applies more often to start-ups out of opportunity. Regarding industry structure, we observe that the majority of business start-ups take place in the service sector. Service shares are significantly higher among necessity than among opportunity entrepreneurs.

## 4 Econometric Analysis

We first show empirical hazards and survival rates for the two types of entrepreneurs and subsequently introduce a discrete-time hazard rate model used to explore the determinants of self-employment duration. We estimate the model separately for opportunity and necessity entrepreneurs. Finally, we decompose differences in estimated survival rates by means of a non-linear Blinder-Oaxaca-type decomposition. The idea of this decomposition analysis is to examine whether the differences in survival rates reflect dissimilar returns from self-employment to individual and business-related characteristics versus differences in terms of those characteristics.

## 4.1 Survival Functions: Kaplan-Meier Estimates

The empirical survival functions for the two groups of entrepreneurs are estimated by means of the Kaplan-Meier method and displayed in Figure 1. The Kaplan-Meier survival function gives the proportion of entrepreneurs of the corresponding population which has not experienced an exit out of self-employment until a particular time interval. Figure 1 shows strong survival rate divergence between opportunity and necessity entrepreneurs even in the early stage after establishment. As expected, start-ups out of opportunity experience significantly higher survival rates than start-ups out of necessity. A log-rank test for equality of survivor functions between the two groups proves to be rejected ( $\chi^2(1) = 50.21$ ).

– Figure 1 about here –

To give a closer look at the evolution of self-employment exits we report in Table 6 in the Appendix the empirical hazard functions and survival estimates for each period. For the first two years of process time we split the time axes into three-month intervals. The last year of observation after establishment, 25 to 36 months, is treated as one period.<sup>6</sup> The first three columns refer to the sample of necessity and the next three columns to the sample of opportunity entrepreneurs, respectively. The estimates show that about 90% of the population of opportunity and about 83% of the population of necessity entrepreneurs survive the first year after start-up. The two-year survival rate for opportunity entrepreneurs in self-employment amounts to 80% whereas only 71% of the necessity entrepreneurs survive this period of time. Finally, we detect that the survival rates for the two groups are intensely growing apart, with 73% of opportunity and solely 59% of necessity entrepreneurs, respectively lasting the first three years of self-employment. The last column in Table 6 reports the calculated difference in empirical survival rates. The observed survival rate gap is continuously increasing during the first 21 months of self-employment duration, decreases slightly at the end of the second year and starts to grow up again in the third year of self-employment duration.

## 4.2 Estimating A Discrete-Time Hazard Rate Model

We study business survival of opportunity and necessity entrepreneurs by applying a discrete-time hazard rate model for self-employment duration. Self-employment duration is treated as a grouped variable, since we have only monthly based information and

---

<sup>6</sup>The aggregation of self-employment duration into month intervals is particularly important for the implementation of the discrete-time hazard rate model. It ensures that there are enough exit events within each of the time intervals after conditioning on the set of explanatory variables.

the exact time span of self-employment activity is not observed. The grouped duration data approach for survival analysis allows us to take advantage of a simple binary choice model for transitions, since there are only two possible outcomes that we can observe – self-employment is terminated in a given discrete-time interval or not.<sup>7</sup>

Let  $T$  be the true duration of stay in the self-employment state and  $t_1, t_2, \dots, t_M$  the observed time intervals with  $m = 1, \dots, M$ . Further, we observe whether duration was censored in a particular interval and define a binary censoring indicator  $c_m$ , which takes the value of one if the duration is censored in the  $m$ th interval, and zero otherwise. In the same way, our outcome variable  $y_m$  is a binary indicator, equal to unity if self-employment duration ends in the interval  $[t_{m-1}, t_m)$ , and zero otherwise. We assume independence between true unobserved duration and censoring time after conditioning on a set of covariates  $\mathbf{x}_m$ .

For a particular time interval  $m$  the estimated discrete hazard rate  $h_m$  is the conditional probability of leaving the self-employment state in interval  $[t_{m-1}, t_m)$  given survival up to time  $t_m$ . More specifically,

$$(1) \quad \begin{aligned} h_m(\mathbf{x}_m, \tilde{\beta}) &= Pr(y_m = 1 \mid y_{m-1} = 0, \mathbf{x}_m) = Pr(t_{m-1} \leq T < t_m \mid T \geq t_{m-1}, \mathbf{x}_m) \\ &= \Phi(\tilde{\mathbf{x}}_m \tilde{\beta}) = \Phi(\alpha_m + \mathbf{x}_m \gamma), \end{aligned}$$

where  $\Phi$  is the standard normal cumulative distribution function. Thus, for identification of conditional discrete hazard rates we assume that interval durations are normally distributed and specify duration dependence nonparametrically by including in an additive manner a set of dummy variables  $\alpha_m$  that are specific to each time interval  $m$ . The specification of normally distributed interval hazards with flexible baseline hazards results in the estimation of a pooled probit model with period-specific constant parameters.<sup>8</sup> The period-specific constant parameters are estimated along with the coefficients of the explanatory variables by maximum likelihood. The corresponding log likelihood contribution for an individual with an observed exit in the  $m$ th interval may be written as

$$(2) \quad \sum_{s=1}^{m-1} \log[1 - \Phi(\alpha_s + \mathbf{x}_s \gamma)] + (1 - c_m) \cdot [\Phi(\alpha_m + \mathbf{x}_m \gamma)].$$

For censored spells no exit is observed and the second expression in (2) drops out.

---

<sup>7</sup>This approach goes back to the research of Prentice and Gloeckler (1978) and Kiefer (1988), as well as Meyer (1990), Jenkins (1995), and Sueyoshi (1995).

<sup>8</sup>In an alternative way one could assume that interval durations are being distributed according to the extreme value or the logistic cumulative function, which would involve the estimation of a complementary log-log or a logit model with time interval dummies, respectively (see Sueyoshi, 1995).

The corresponding survivor function summarizes the probabilities of having completed spell durations of different lengths (Jenkins, 1995). By definition of conditional probabilities, the survivor function in an arbitrary time interval  $m$  is given by

$$(3) \quad S(t_m, \mathbf{x}_m, \tilde{\beta}) = \prod_{s=1}^m h_m(\mathbf{x}_m, \tilde{\beta}).$$

The pooled probit specification with period specific terms does not take account of unobserved heterogeneity and this might lead to biased estimates and spurious duration dependence (Baker and Melino, 2000). The findings of Reize (2000) suggest also that not controlling for unobserved heterogeneity might result in downwards biased estimates of the baseline hazard rate. Thus, controlling for unobserved population heterogeneity is essential in the case of entrepreneurial survival. Unobserved factors might include, for example, individual entrepreneurial skills and skills acquired in informal learning processes, entrepreneurial ability, unobserved family related background characteristics, or unobserved market environments not being under control of the entrepreneur.

Unobserved heterogeneity is accounted for by including an individual specific term  $c_i$  in the hazard rate specification,  $h_m(\mathbf{x}_m, \tilde{\beta}) = \Phi(c_i + \tilde{\mathbf{x}}_m \tilde{\beta})$ . We assume that the unobserved individual-specific term is normally distributed with constant variance  $\sigma_c^2$  and independent of covariates and censoring time.<sup>9</sup> This specification involves estimating a random effects probit model where the unobserved heterogeneity component is integrated out from the likelihood function in order to obtain the distribution of the true self-employment duration (Wooldridge 2002).

Table 1 presents the results from the discrete-time hazard rate model described above. We report estimated coefficients on the probability of exit without controlling for unobserved heterogeneity (Probit) as well as with unobserved heterogeneity (RE Probit). A positive coefficient implies a positive impact on the hazard (exit probability) and a negative impact on self-employment duration, and vice versa. The first two columns display the results for the pooled sample of opportunity and necessity entrepreneurs. The next four columns contains the estimation results from the separate regressions, first for necessity and then for opportunity entrepreneurs. The separate estimations allow for different duration dependencies as well as the impacts of the covariates to vary between the two groups.

– Table 1 about here –

---

<sup>9</sup>In previous literature different choices for the behavioral assumption of the unobserved component were suggested. Meyer (1990), for example, assumes a Gamma distributed heterogeneity term in a proportional hazard specification. Alternatively, the heterogeneity component might be modeled without parametric restrictions (see Heckman and Singer (1984) and Reize (2000) for an application).

As expected, considering the pooled specification it turns out that after conditioning on socio-economic and business-related characteristics necessity entrepreneurs exhibit a significantly higher exit probability out of self-employment than opportunity entrepreneurs. This is consistent with Caliendo and Kritikos (2009), but unlike Block and Sandner (2009). The latter study finds that after controlling for education of the entrepreneur in the professional area the difference in hazard rates remains no longer significant. Our results suggest that those individuals who are pushed into self-employment because of no better labor market alternatives are at the same time less particularly suitable for entrepreneurship.

We discuss in the following the effects of several covariates on the hazard rate for the two groups separately. The results from the separate regressions suggest that in terms of significance different covariates have different impacts in explaining self-employment duration among necessity and opportunity entrepreneurs. There are only few categories of variables which have opposite sign effects in both groups, but they do not prove to be significant. Regarding the significance and the direction of estimated effects it should be noted that with some few exceptions the results without unobserved heterogeneity are generally the same as those with unobserved heterogeneity. Finally, we find significant unobserved heterogeneity in the pooled specification and for necessity entrepreneurs, but not for opportunity entrepreneurs. This result suggests a higher degree of heterogeneity among the latter group. When interpreting the results we concentrate on the RE probit estimates.

Considering the estimated coefficients of the baseline hazard rate the results in Table 1 confirm that not controlling for unobserved heterogeneity might result in downwards biased estimates. Additionally, the estimated parameters for the baseline hazard are only partly significant. For instance, except for the opportunity entrepreneurs and relative to the first three months in self-employment the hazard rate indicates a significant increase at the end of the first and second half of the first year and between 25 and 36 months of self-employment duration.

With respect to gender we find in line with previous studies that females *ceteris paribus* experience a lower self-employment duration than males. However, the gender difference is insignificant for opportunity entrepreneurs. This is in line with the findings by Verheul et al. (2010), despite the different motivational concepts and the methodology applied. Age proves to be a significant predictor for self-employment duration, but only at the low end of the age distribution in our sample. Thus, people entering self-employment at age between 18 and 24 years have a significantly higher exit rate than individuals aged between 35 and 44 years at the start of the spell. This result suggests, that young people might lack a sufficient, to the self-employment process specific knowledge due to

lower endowment of human, social and/or network capital. Our findings suggest also that compared to the reference category the 45 to 54 years old show a lower business failure rate, but the coefficients are no longer significant. Unlike the findings for Germany by Block and Sandner (2009) and Caliendo and Kritikos (2009) the qualification variable does not appear to be an important factor to determine self-employment duration. As argued by Taylor (1999) this might be explained by the so called signaling hypotheses associated with the lower need to enquire formal qualification because of lower expected returns from paid-employment. Our analysis confirms also that this hypothesis applies particularly to the sample of necessity entrepreneurs where the effect of a degree higher (lower) than vocational training increases (decreases) the hazard rate. Indeed, the effects are insignificant.

Our analysis confirms that employment status prior to self-employment entry has an impact on entrepreneurial survival. As before, the impacts of the different categories vary between the two samples. For instance, compared to individuals with previous paid-employee experience, re-starter out of necessity have a significantly lower hazard rate. The effect is insignificant for opportunity entrepreneurs, but still negative. Consistent with the Jovanovic's (1982) theory of "noisy selection" the negative coefficients indicate that entrepreneurs might learn from their previous self-employment experience, whether positive or negative, due to acquiring formal and informal business skills and knowledge over time. In line with expectations, previous unemployment experience *ceteris paribus* leads to a higher rate of business failure. The effect is significant and more pronounced among opportunity entrepreneurs while it is less striking among necessity entrepreneurs. As repeated status changes from unemployment to employment and vice versa are more likely for necessity entrepreneurs, the difference between those who started from an employment spell and those who started from out of unemployment is less pronounced. Finally, we find that a migrational background is negatively associated with staying in self-employment, but the effect is insignificant. This finding presumably indicates that migrants are more often pushed into self-employment because of possible disadvantages in dependent employment resulting from e.g missing language skills, lack of required educational attainments, or discrimination by potential employers.

An interesting finding pertains to the effect of the type of establishment. We find that compared to new establishments, take overs and joint ventures are associated with higher business failure rates. This is rather counterintuitive as one might expect according to the liability of newness hypotheses (see for example, Freeman et al. (1983)) that new ventures lack specific sets of resources and capacities that more established firms accumulated over

time.<sup>10</sup> One possible explanation for our results might be that adverse selection occurs due to asymmetric information of the parties involved. For instance, in the case of business take overs the previous owner is better informed about the progress of the firm and about conceivable difficulties in the future and has in this way a clear information advantage over the new owner.

Concerning the firm size variable we find that *ceteris paribus* solo entrepreneurs with employees at the start of the spell are exposed to a lower hazard rate than solo entrepreneurs without employees. The effects are still for necessary entrepreneurs significant. The results suggest also that in the sample of necessity entrepreneurs team start-ups have a significantly higher probability of moving out of entrepreneurship than the reference category. This might be associated with conflicting incentives and different perceptions between team partners. The impacts of financial equipment as measured by the size of the start-up capital at the beginning of the self-employment spell yield a very clear picture. As expected, it turns out that a higher amount of start-up capital does reduce the probability of failure – again consistent with the liability-of-smallness hypothesis.

### 4.3 Decomposition Analysis

We apply decomposition techniques in order to explore whether differences in survival rates reflect dissimilar returns from self-employment to individual and business-related characteristics versus differences in terms of those characteristics. Since our outcome variable, exit or no exit from the state of self-employment, has a binary nature, we implement a modified, non-linear version of the decomposition technique introduced by Blinder (1973) and Oaxaca (1973).<sup>11</sup> For this purpose we rely on the estimates from the separate estimation of the discrete-time hazard rate models allowing for different baseline hazard rates and different impacts of explanatory variables between the group of opportunity (*OP*) and the group of necessity (*NE*) entrepreneurs. Based on the estimations we first predict for the two groups period-specific probabilities of an exit from self-employment and calculate for each time interval average predicted hazard rates in the corresponding sample of individuals. For example, within the *m*th interval the average predicted exit probability for either groups  $g \in \{OP, NE\}$  is given by

$$(4) \quad \widehat{h(\mathbf{x}_m^g, \beta^g)} = \frac{1}{N_{m,g}} \sum_{i=1}^{N_{m,g}} \Phi(\hat{c}_i + \hat{\alpha}_{m,g} + \mathbf{x}_{im,g} \hat{\gamma}_g),$$

---

<sup>10</sup>Morce et al. (2007) provide and discuss four explanatory mechanisms that might reinforce the liability of newness argument: the need to develop internal organizational systems, the need to incorporate trust relationships, as well as the formation of social and economic capital.

<sup>11</sup>See also Fairlie (1999, 2005).



where  $N_{m,g}$  denotes the number of individuals in interval  $m$  for group  $g$ . In the case of the random effects probit estimator we obtain the fitted values of the estimated nonlinear function at the average value of the unobserved heterogeneity component in the population,  $E(c) = 0$ . Based on the assumption that  $c_i$  and the vector of explanatory variables are independent and that  $c_i$  has a normal distribution, this approach implies multiplying the coefficients from the random effects probit estimation by the factor  $1/\sqrt{(1 + \sigma_c^2)}$ .

In what follows, we first take a look at the development of the average predicted hazard rates for the two types of entrepreneurs in order to understand how the different estimates from above influence the hazard function of leaving self-employment. The hazard functions are calculated as described in equation (4) and are displayed in Figure 2.<sup>12</sup> The solid line refers to the necessity and the dotted line to the opportunity entrepreneurs, respectively. The average hazard rate is predicted on the basis of the probit estimation (to the left) as well as by means of the random effects probit model (to the right). In line with expectations, the probability of leaving self-employment is higher for necessity than for opportunity entrepreneurs. Considering the two pictures in Figure (2) it turns out that controlling for unobserved heterogeneity components is essential. Accounting for unobserved heterogeneity in the model does shift the hazard rate curve of the necessity entrepreneurs upwards, especially in the first two years of self-employment. Considering the right hand panel in Figure (2), we observe more or less the same patterns of exit probabilities in the first two years of process time. Despite the different exit probability levels, hazard rate is low at the beginning of self-employment duration, increases slowly and reaches a maximum after one year and then decreases slightly. After two years in self-employment opportunity entrepreneurs experience almost the same hazard rate as at the end of the first year, but then the hazard rate declines dramatically and achieves the level at the beginning of the observation period. A something different picture emerges for the necessity entrepreneurs where its hazard is pushed upwards after two years of self-employment duration.

– Figure 2 about here –

Analogously to the prediction of interval hazard rates, we estimate the average predicted survivor functions according to equation (3). Figure 3 displays the predicted survival functions based on the probit estimation (top to the left) as well as on the basis of the

---

<sup>12</sup>Since we have specified duration dependence by including a set of period specific parameters and by this constrained the baseline hazard to be constant within a particular month interval, the predicted average hazard is a piecewise-constant function. To indicate the general shape of the predicted hazard rates we apply a Gaussian kernel-weighted local regression. The non-smoothed results are available from the authors upon request.

RE probit model (top to the right). As expected, start-ups by opportunity entrepreneurs experience higher survival rates, with 91.02% lasting the first one year and 80.58% surviving the first two years of self-employment duration. On the other hand, the one-year survival rate amounts to 79.86% and the the two-years survival rate to 57.22% among the projects of necessity entrepreneurs. The difference in predicted survival functions is growing over time as displayed by the picture to the left on the bottom of Figure 3. The difference in predicted survival rates amounts to 11.17 percentage points at the end of the first and 23.35 percentage points at the end of the second year of self-employment, respectively.

– Figure 3 about here –

In light of the observed divergency in simulated survival functions, the question arises whether it is due to differences in socio-economic variables and business related characteristics that we account for in the model, or it is due to different returns from self-employment activity that prevent necessity entrepreneurs having survival rates similar to that of opportunity entrepreneurs. At a particular time interval  $m$  the difference in predicted survival rates between the group of opportunity and the group of necessity entrepreneurs  $\Delta_m^S$  is decomposed into two parts as follows:

$$(5a) \quad \Delta_m^S = \underbrace{\widehat{S}(t_m, \mathbf{x}_m^{OP}, \tilde{\beta}^{OP}) - \widehat{S}(t_m, \mathbf{x}_m^{OP}, \tilde{\beta}^{NE})}_{\Delta_{m,\tilde{\beta}}^S} + \underbrace{\widehat{S}(t_m, \mathbf{x}_m^{OP}, \tilde{\beta}^{NE}) - \widehat{S}(t_m, \mathbf{x}_m^{NE}, \tilde{\beta}^{NE})}_{\Delta_{m,\mathbf{x}}^S}$$

$$(5b) \quad \Delta_m^S = \underbrace{\widehat{S}(t_m, \mathbf{x}_m^{OP}, \tilde{\beta}^{OP}) - \widehat{S}(t_m, \mathbf{x}_m^{NE}, \tilde{\beta}^{OP})}_{\Delta_{m,\mathbf{x}}^S} + \underbrace{\widehat{S}(t_m, \mathbf{x}_m^{NE}, \tilde{\beta}^{OP}) - \widehat{S}(t_m, \mathbf{x}_m^{NE}, \tilde{\beta}^{NE})}_{\Delta_{m,\tilde{\beta}}^S}.$$

The characteristics (or endowment) effect denoted by  $\Delta_{m,\mathbf{x}}^S$  captures the part of the gap in survival rates which is attributed to differences in the distribution of observed individual and business related characteristics at given estimated parameters. By contrast, the coefficients effect, which we denote with  $\Delta_{m,\tilde{\beta}}^S$ , encompasses differences in survival rates that are due to differences in the coefficients at given a distribution of characteristics.

It is well known that decompositions are not unambiguous with respect the chosen counterfactual. In the first case (equation (5a)) we predict the average survivor function for a hypothetical opportunity entrepreneurs facing the returns of a start-up out of necessity. In the second case, equation (5b) describes a counterfactual situation where the characteristics of a necessity and the coefficients of an opportunity entrepreneurs are used to decompose the gap in survival rates.

The results from the decomposition of survival rates into characteristics and coefficients effects are graphically presented in Figure 4. The two pictures at the top (to the left probit and to the right random effects probit) refer to equation (5a) where we consider a counterfactual generated for necessity entrepreneurs had they opportunity characteristics but had still gained self-employment returns according to the necessity coefficients. The two pictures at the bottom refer to equation (5b) with a hypothetical start-up having necessity characteristics and facing opportunity returns from self-employment. Unsmoothed results are also reported in Tables 7 and 8.

– Figure 4 about here –

Despite the fact that the results of the decomposition analysis reveal some sensitivity with respect to the chosen counterfactual, they qualitatively lead to the same conclusions. First, irrespective of the underlying counterfactual situation, the characteristic and the coefficients effect are positive. It means that differences in socio-economic and business-related characteristics as well as differences in the self-employment returns to those characteristics account both for the relatively lower survival rates of necessity than opportunity entrepreneurs. Therefore, the lower survival rates of necessity start-ups is driven by selection based on observable characteristics and by residual differences for given similar observables. Second, the share of the gap in survival rates explained by the characteristic effect tend to be lower compared to the share of the “unexplained” part. This suggests that the gap in survival rates is relatively more due to different returns from the self-employment activity as well as unobserved group differences in productivity and due to behavioral differences for given characteristics. Third, based on the estimates from the random effect probit we observe a decreasing share of the characteristic effect with process time. In the case where the unexplained component (differences in self-employment returns) is weighted by the characteristics of opportunity entrepreneurs (counterfactual (A)) the characteristic effect varies in the first two years of self-employment from 34% to 6%. Explaining the gap in survival rates on the basis of necessity characteristics and opportunity coefficients tend to increase the share of the characteristic effect to about 16% after the first and to about 15% after the second year of self-employment duration.

Decomposition techniques raise typically the question about which counterfactual is more economically and policy relevant with respect of the underlying research question. From our point of view, the decomposition based on the hypothetical opportunity entrepreneurs facing the self-employment returns of a start-up out of necessity has a more meaningful explanation for the following reason. The characteristics of necessity entrepreneurs may be altered over time by policy interventions (e.g. advisory programs),

whereas the coefficients that account for behavioral differences and differences in unobserved determinants are more difficult to be influenced externally.

## 5 Concluding Remarks

Using a large-scale population survey data from the KfW Start-up monitor we investigate the impact of person-related and business-related characteristics on short-term entrepreneurial survival in Germany. Our analysis focusses on two particularly interesting groups – opportunity and necessity entrepreneurs. We find that different motives for engaging in entrepreneurship have an impact on self-employment duration, with start-ups out of opportunity exhibiting significantly higher survival rates than necessity entrepreneurs. In addition, our findings reveal some heterogeneity with respect to the impact of various explanatory variables on the probability of exit among the two groups of start-ups. In order to explore whether differences in predicted survival rates reflect dissimilar returns from self-employment activity to individual and business-related characteristics versus differences in terms of those characteristics we implement a non-linear decomposition technique. The results of the decompositions suggest that the lower survival rates observed by necessity entrepreneurs compared to opportunity entrepreneurs is relatively more due to different returns from the self-employment activity as well as unobserved group differences in productivity and due to behavioral differences for given characteristics. The characteristics effect, however, accounts for a maximum share of 20% in the early stage after start-up and becomes smaller with elapsed time in self-employment.

Future research building on the results at hand might analyze different routes of leaving self-employment by means of competing risks models. Termination of self-employment activity involves either a voluntary or an involuntary dissolution. For example, voluntary dissolution might result in face of a more superior labor market alternative for the entrepreneur which yields higher returns than self-employment. In this case exit out of self-employment does not imply business or even personal failure.

## Literature

- Baker, M. and A. Melino (2000). “Duration dependence and nonparametric heterogeneity: a Monte Carlo study.” *Journal of Econometrics* 96, 357–393.
- Blinder, A. S. (1973). “Wage discrimination: reduced form and structural estimates.” *Journal of Human Resources* 8, 436–455.

- Block, J. and P. Sandner (2009). “Necessity and opportunity entrepreneurs and their duration in self-employment: evidence from German micro data .” *Journal of Industry, Competition, and Trade* 9, 117–137.
- Caliendo, M. and A.S. Kritikos (2009). “‘A want to, but I also need to’: start-ups resulting from opportunity and necessity .” IZA Discussion Paper No. 4661.
- Carrasco, R. (1999). “Transition to and from self-employment in Spain: an empirical analysis.” *Oxford Bulletin of Economics and Statistics* 61, 315–341.
- Fairlie, R. W. (1999). “The absence of the African-American owned business: an analysis of the dynamics of self-employment.” *Journal of Labor Economic* 17, 80–108.
- Fairlie, R. W. (2005). “An extension of the Blinder-Oaxaca decomposition technique to logit and probit models.” *Journal of Economic and Social Measurement* 30, 305–316.
- Freeman, J., G. R. Carroll, and M. Hannan (1983). “The liability of newness: age dependence in organizational death rates.” *American Sociological Review* 48, 692–710.
- Heckman, J. J. and B. Singer (1984). “Econometric duration analysis.” *Journal of Econometrics* 24, 63–132.
- Jenkins, S. P. (1995). “Easy estimation methods for discrete-time duration models.” *Oxford Bulletin of Economics and Statistics* 57, 129–137.
- Jovanovic, B. (1982). “Selection and evolution of industry.” *Econometrica* 50, 649–670.
- Kiefer, N. M. (1988). “Analysis of grouped duration data.” *Contemporary Mathematics* 96(2), 357–393.
- Kohn, K., H. Spengler, and K. Ullrich (2010). “KfW-Gründungsmonitor 2010.” KfW Bankengruppe (ed.), Frankfurt.
- Metzger, G. (2008). “Habitual Entrepreneurs in Germany: an empirical investigation on restart incidence, restart performance, and restart financing.” Dissertation, Friedrich-Schiller-Universität Jena.
- Millan, J. M., E. Gongregado, and C. Roman (2010). “Determinants of self-employment duration in Europe.” *Small Business Economics* doi: 10.1007/s11187-010-9260-0.
- Meyer, B. D. (1990). “Unemployment insurance and unemployment spells.” *Econometrica* 96(2), 357–393.

- Morce, E. A., S. W. Fowler, and T. B. Lawrence (2007). “The impact of virtual embeddedness on new venture survival: overcoming the liability of newness.” *Entrepreneurship Theory and Practice* 31, 139–159.
- Oaxaca, R. (1973). “Male-female wage differentials in urban labor markets.” *International Economic Review* 14, 693–709.
- Prentiece, R. L. and L. A. Gloeckler (1978). “Regression analysis of grouped survival data with application to breast cancer data.” *Biometrics* 34, 57–67.
- Reize, F. (2000). “Leaving unemployment for self-employment: a discrete duration analysis of determinants and stability of self-employment among former unemployed.” ZEW Discussion Paper No. 00–26, Mannheim.
- Reynolds, P.D., S.M. Camp, W.D. Bygrave, E. Autio, and M. Hay (2001). “Global Entrepreneurship Monitor.” *Executive Report*.
- Sueyoshi, G. T. (1995). “A class of binary response models for grouped duration data.” *Journal of Applied Econometrics* 10, 411–431.
- Taylor, M. (1999). “Survival of the fittest? An analysis of self-employment duration in Britain.” *The economic journal* 109, 140–155.
- Tchouvakhina, M. and C. Hofmann (2003/04). “The KfW Start-Up Monitor – An Instrument for In-Depth Analysis of Start-up Activity in Germany.” *RWI: Mitteilungen. Quarterly* 54/55, 267–285.
- Van Praag, C. M. (2003). “Business survival and success of young small business owners.” *Small Business Economics* 21, 1–17.
- Verheul, I., R. Thurik, J. Hessels, and P. van der Zwan (2010). “Factors Influencing the Entrepreneurial Engagement of Opportunity and Necessity Entrepreneurs.” *EIM Research Reports* No. H201011.
- Wooldridge, J. M. (2002). “*Econometric analysis of cross-section and panel data*.” Cambridge (MA) and London (UK), MIT Press.

## Tables and Figures

Table 1: Estimated coefficients on probability of exit

VARIABLES	All		Necessity		Opportunity	
	Probit	RE Probit	Probit	RE Probit	Probit	RE Probit
Necessity	0.1641*** (0.0317)	0.2194*** (0.0504)				
<b>Baseline hazard</b> (Reference: 1-3 months)						
4–6 months	0.1265*** (0.0479)	0.2074*** (0.0723)	0.1885*** (0.0611)	0.3295*** (0.1047)	0.0394 (0.0769)	0.0395 (0.0782)
7–9 months	0.1535*** (0.0496)	0.2919*** (0.0967)	0.1622** (0.0653)	0.3877*** (0.1406)	0.1504** (0.0755)	0.1505* (0.0773)
10–12 months	0.1597*** (0.0525)	0.3406*** (0.1166)	0.1830*** (0.0688)	0.4760*** (0.1682)	0.1382* (0.0804)	0.1383* (0.0824)
13–15 months	0.2354*** (0.0540)	0.4687*** (0.1394)	0.2348*** (0.0717)	0.5947*** (0.1956)	0.2568*** (0.0815)	0.2569*** (0.0834)
16–18 months	0.1600*** (0.0611)	0.4199*** (0.1543)	0.1729** (0.0805)	0.5752*** (0.2161)	0.1590* (0.0928)	0.1591* (0.0943)
19–21 months	0.0611 (0.0699)	0.3411** (0.1679)	0.0409 (0.0952)	0.4669** (0.2331)	0.1130 (0.1029)	0.1131 (0.1049)
22–24 months	0.0984 (0.0745)	0.4040** (0.1801)	0.0431 (0.1038)	0.5033** (0.2491)	0.1872* (0.1066)	0.1874* (0.1086)
25–36 months	0.1082* (0.0577)	0.4685** (0.1945)	0.1844** (0.0729)	0.7303*** (0.2655)	0.0109 (0.0972)	0.0111 (0.0987)
<b>Female</b>	0.0387 (0.0318)	0.0455 (0.0431)	0.0308 (0.0433)	0.0315 (0.0643)	0.0488 (0.0482)	0.0488 (0.0479)
<b>Age</b> (Reference: 35-44 years old)						
18–24	0.3414*** (0.0585)	0.4934*** (0.1021)	0.3405*** (0.0817)	0.5651*** (0.1459)	0.3631*** (0.0836)	0.3632*** (0.0842)
25–34	0.0627* (0.0380)	0.0872 (0.0546)	0.1001** (0.0508)	0.1508* (0.0827)	0.0039 (0.0589)	0.0039 (0.0601)
45–54	-0.0328 (0.0415)	-0.0373 (0.0558)	-0.0475 (0.0549)	-0.0630 (0.0820)	-0.0152 (0.0648)	-0.0152 (0.0646)
55–67	0.0069 (0.0502)	0.0087 (0.0699)	-0.0243 (0.0661)	-0.0254 (0.1013)	0.0541 (0.0811)	0.0541 (0.0818)
<b>Education</b> (Reference: vocational training)						
university	-0.0280 (0.0409)	-0.0435 (0.0582)	0.0053 (0.0540)	0.0026 (0.0846)	-0.0654 (0.0656)	-0.0655 (0.0678)
technical college	-0.0297 (0.0456)	-0.0387 (0.0624)	-0.0212 (0.0628)	-0.0401 (0.0957)	-0.0132 (0.0687)	-0.0132 (0.0684)
technical school	-0.0196 (0.0704)	-0.0055 (0.0937)	0.0054 (0.0903)	0.0484 (0.1335)	-0.0284 (0.1153)	-0.0284 (0.1137)
no formal degree	-0.0026 (0.0491)	0.0067 (0.0656)	-0.0268 (0.0648)	-0.0444 (0.0961)	0.0613 (0.0761)	0.0613 (0.0749)
<b>Previous employment status</b> (Reference: paid-employee)						
self-employed	-0.1517** (0.0623)	-0.1954** (0.0823)	-0.1839** (0.0898)	-0.2543** (0.1297)	-0.1028 (0.0866)	-0.1028 (0.0845)
unemployed	0.0798** (0.0403)	0.1116** (0.0563)	0.0453 (0.0491)	0.0835 (0.0741)	0.1497** (0.0714)	0.1497** (0.0725)
out of labor force	-0.0484 (0.0403)	-0.0643 (0.0563)	-0.0645 (0.0546)	-0.0759 (0.0814)	-0.0422 (0.0625)	-0.0422 (0.0651)
<b>Foreigner</b>	0.0944** (0.0441)	0.1422** (0.0630)	0.0790 (0.0602)	0.1378 (0.0901)	0.1338** (0.0663)	0.1338** (0.0656)

(continued)



Table 1 continued: Estimated coefficients on probability of exit

VARIABLES	All		Necessity		Opportunity	
	Probit	RE Probit	Probit	RE Probit	Probit	RE Probit
<b>Part-time</b>	0.0580*	0.0945**	0.0383	0.0655	0.0852	0.0852*
	(0.0343)	(0.0473)	(0.0465)	(0.0650)	(0.0542)	(0.0502)
<b>Establishment type</b> (Reference: new establishment)						
take over	0.0951	0.1508*	-0.0687	-0.0666	0.3081***	0.3081***
	(0.0653)	(0.0889)	(0.0971)	(0.1359)	(0.0868)	(0.0872)
joint venture	0.2660***	0.3689***	0.2435***	0.3745***	0.3039***	0.3040***
	(0.0358)	(0.0694)	(0.0472)	(0.0922)	(0.0580)	(0.0590)
<b>Firm size</b> (Reference: solo/without)						
solo/with	-0.0703	-0.0975	-0.1416**	-0.2193**	0.0065	0.0065
	(0.0461)	(0.0627)	(0.0670)	(0.1042)	(0.0647)	(0.0646)
team/without	0.0952*	0.1117	0.1343*	0.1946*	0.0413	0.0413
	(0.0497)	(0.0708)	(0.0705)	(0.1105)	(0.0739)	(0.0771)
team/with	0.0112	-0.0123	0.0574	0.0302	-0.0513	-0.0513
	(0.0534)	(0.0759)	(0.0798)	(0.1254)	(0.0784)	(0.0781)
<b>Start-up capital</b> (Reference: 1–10.000 €)						
0 €	0.1008*	0.1579**	0.0983	0.1662*	0.1548	0.1548
	(0.0529)	(0.0751)	(0.0637)	(0.0969)	(0.0999)	(0.0969)
10.000–25.000 €	-0.0836*	-0.1006*	-0.1106*	-0.1689*	-0.0372	-0.0372
	(0.0433)	(0.0591)	(0.0585)	(0.0923)	(0.0655)	(0.0643)
> 25.000 €	-0.1541***	-0.1910***	-0.1342*	-0.1886*	-0.1762**	-0.1762**
	(0.0509)	(0.0686)	(0.0702)	(0.1068)	(0.0759)	(0.0721)
<b>Degree of innovation</b> (Reference: no market novelty)						
regional novelty	0.1908***	0.2548***	0.1922***	0.2729**	0.1809***	0.1809***
	(0.0456)	(0.0704)	(0.0658)	(0.1104)	(0.0650)	(0.0640)
national-wide novelty	0.1265	0.1663	0.1174	0.1955	0.1563	0.1563
	(0.0791)	(0.1107)	(0.1437)	(0.2200)	(0.0989)	(0.0974)
world-wide novelty	0.0308	0.0597	0.0081	0.0306	0.0742	0.0742
	(0.0929)	(0.1263)	(0.1412)	(0.2221)	(0.1266)	(0.1217)
<b>Constant</b>	-2.4951***	-2.9464***	-2.2866***	-2.8166***	-2.6141***	-2.6143***
	(0.0680)	(0.2442)	(0.0869)	(0.2813)	(0.1068)	(0.1106)
Observations	67036	67036	32839	32839	34197	34197
Number of id	4462	4462	2180	2180	2282	2282
Log Likelihood	-4021.23	-4017.57	-2367.75	-2363.43	-1624.14	-1624.14

Notes: Clustered standard errors in parentheses. Control variables: region and city size dummies, industry and occupation dummies, dummies for missing values. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Figure 1: Kaplan-Meier survival function

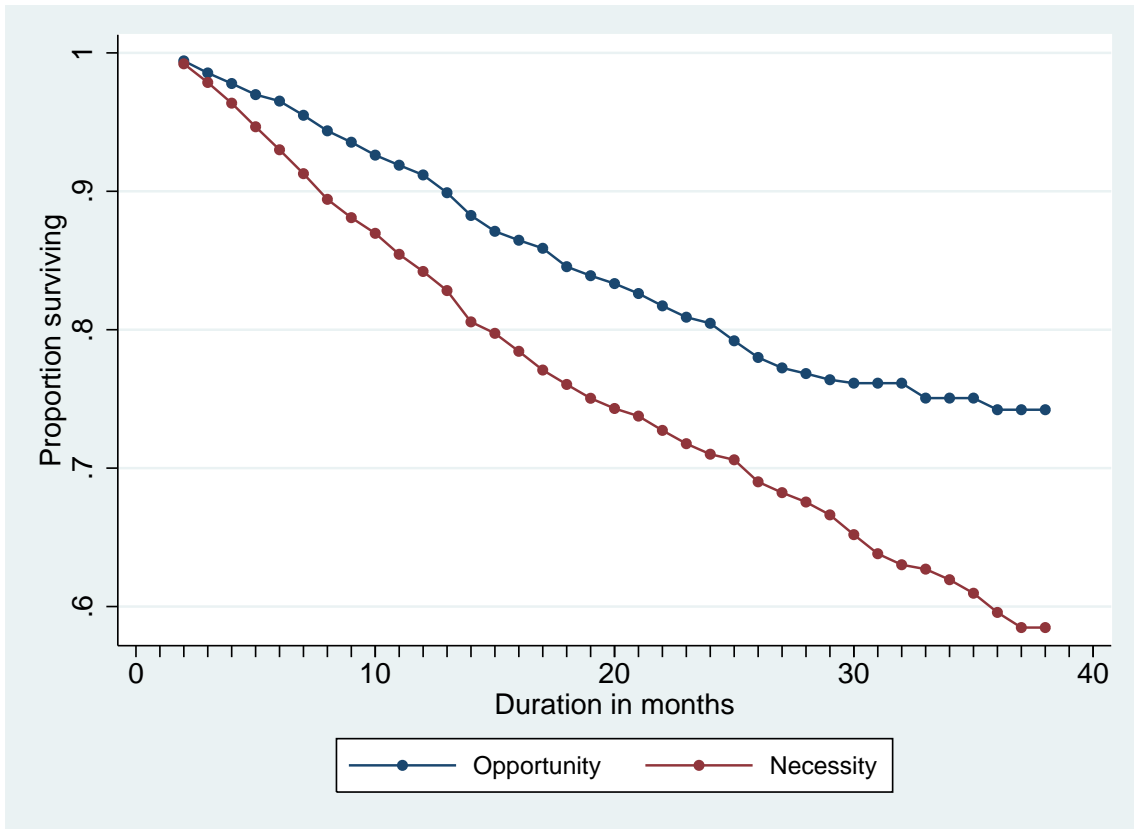


Figure 2: Average predicted hazard rates

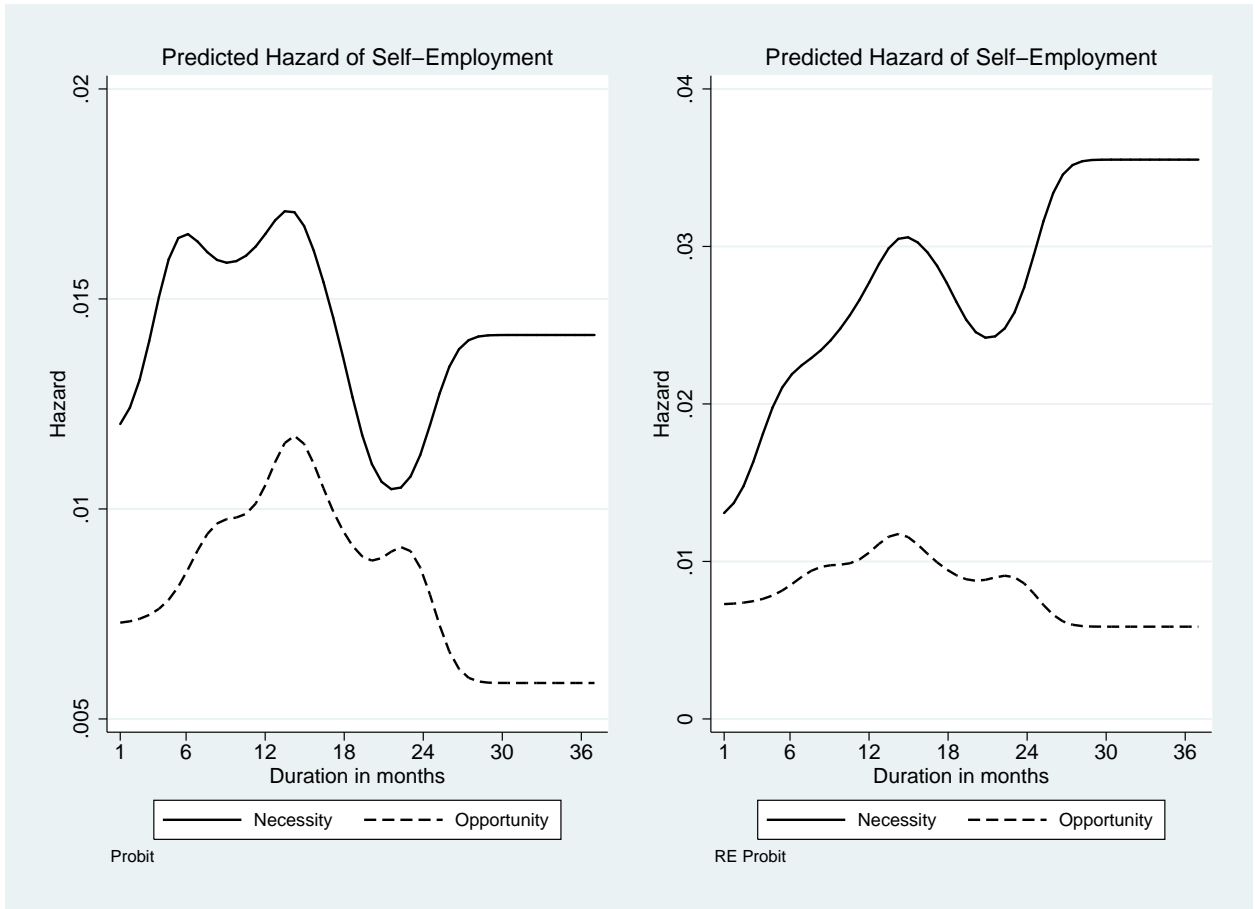


Figure 3: Simulated survival functions

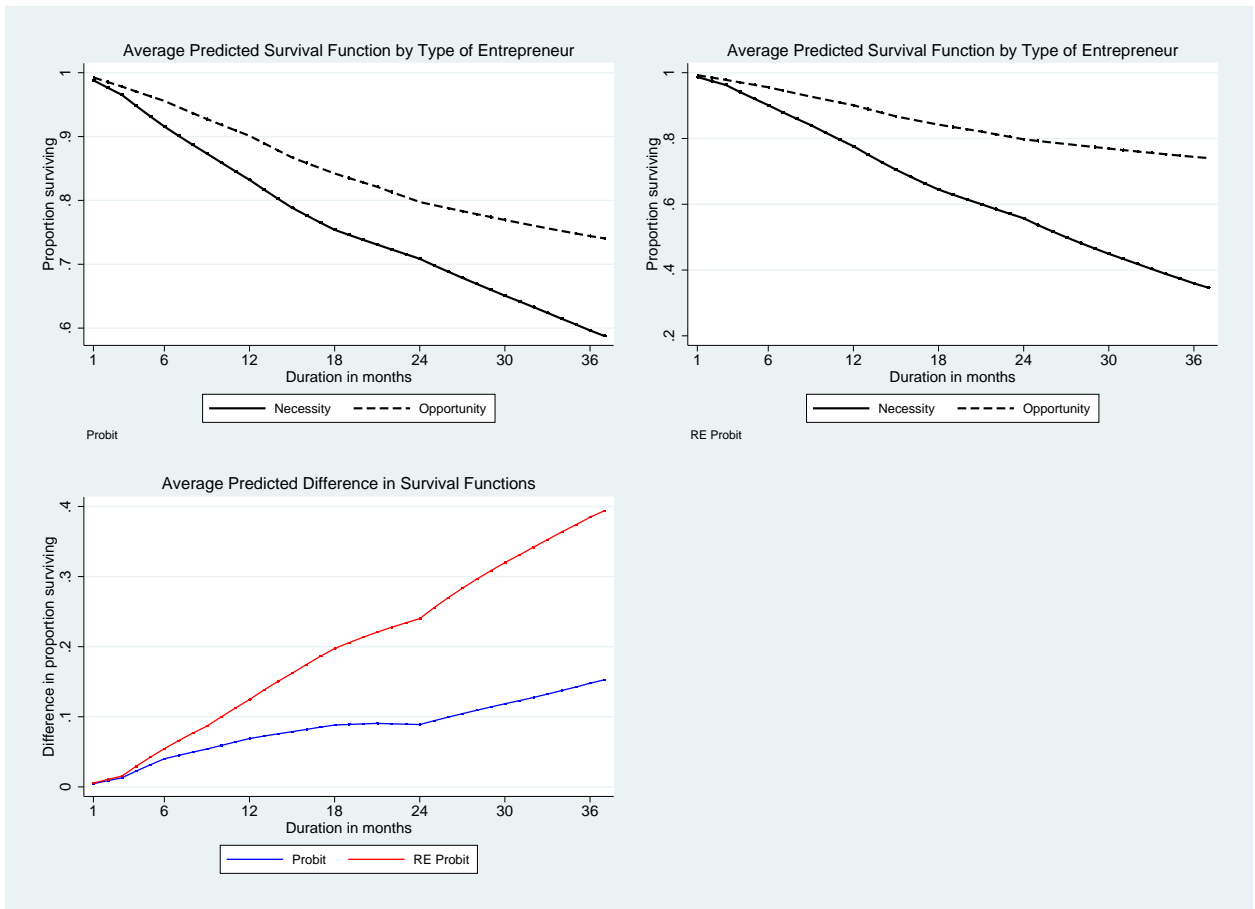
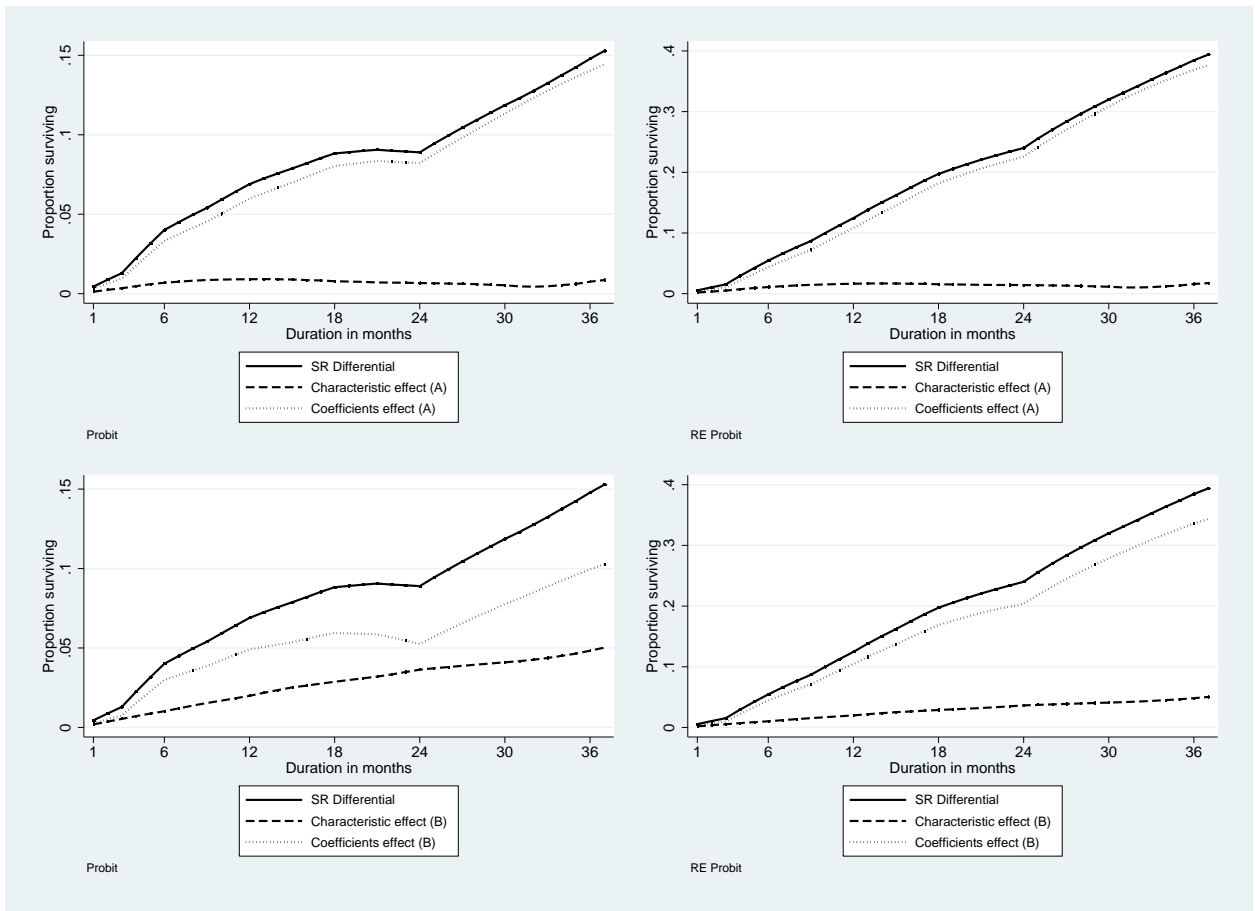


Figure 4: Decomposition of simulated survival functions



# A Appendix

Table 2: Definition of variables

Variable	Definition
<i>Socio-economic background of the entrepreneur</i>	
Necessity [1]	dummy with 1 = start-up out of necessity
Female [1]	dummy with 1 = female
Age [5]	dummies for age groups: 18–24, 25–34, 35–44, 45–54, 55–67
Education [5]	dummies for educational attainment: university degree, technical college degree (Fachhochschulabschluss), technical school graduation (Fachschule/Meisterschule), vocational training degree (Lehrabschluss), no formal degree
Previous employment [4]	dummies for employment status prior to start-up: employee, self-employed, unemployed, out of labor force
Foreigner [1]	dummy with 1 = origin in foreign country
Region [1]	dummy with 1 = living in Eastern Germany
City size [5]	dummies for: up to 5.000, > 5.000–20.000, > 20.000–100.000, > 100.000–500.000, > 500.000 inhabitants
<i>Business-related characteristics</i>	
Part-time <sup>a)</sup> [1]	dummy with 1 = part-time self-employment
Establishment type [3]	dummies for: new establishment, take over, joint venture
Firm size [4]	dummies for: solo entrepreneur without employees (solo/without), solo entrepreneur with employees (solo/with), team entrepreneur without employees (team/without), team entrepreneur with employees (team/with)
Start-up capital [4]	dummies for: 0 €, 1–10.000 €, 10.000–25.000 €, > 25.000 €
Degree of innovation [4]	dummies for: no market novelty, regional novelty, national-wide novelty, world-wide novelty
Occupational category [3]	dummies for: free lances, craftsman's establishment, miscellaneous
Industry [6]	dummies for: manufacturing, construction, retail trade, economic services, personal services, others

Notes: Number of regressors in brackets. <sup>a)</sup>Information is available at time of the start-up and at time of the interview. The time-varying information is exploited in the empirical analysis.

Data source: KfW Start-Up Monitor, 2007–2010.

Table 3: Reasons for exiting self-employment

Reason for exit	Necessity	Opportunity
Business being sold	3.35	5.98
Business succession	7.99	12.35
Liquidation	76.55	71.31
Bankruptcy/Insolvency	3.61	7.17
Temporary start-up project	8.51	3.19

*Notes:* Numbers are shares, population-weighted.



Table 4: Socio-demographic characteristics of drop-outs and survivors, by type of entrepreneurs

Variable	Drop-out			Survival		
	(1) Necessity	(2) Opportunity	Diff.	(1) Necessity	(2) Opportunity	Diff.
<b>Female</b>	0.530	0.464	*	0.504	0.402	***
<b>Age</b>						
18–24	0.142	0.157		0.071	0.069	
25–34	0.294	0.241	***	0.238	0.265	
35–44	0.267	0.324	**	0.306	0.337	***
45–54	0.188	0.181		0.252	0.218	***
55–67	0.109	0.097		0.132	0.111	***
<b>Educational attainment</b>						
university	0.223	0.171	*	0.205	0.243	***
technical college	0.115	0.137		0.134	0.171	***
technical school	0.050	0.040		0.063	0.057	
vocational training	0.447	0.482		0.465	0.424	
no formal degree	0.165	0.171		0.132	0.105	***
<b>Professional status</b>						
employee	0.408	0.601	***	0.422	0.594	***
self-employed	0.052	0.077		0.090	0.126	***
unemployed	0.281	0.136	***	0.287	0.109	***
out of labor force	0.258	0.185	**	0.200	0.171	
<b>Foreigner</b>	0.146	0.171	*	0.118	0.098	***
<b>Region</b>	0.190	0.147	*	0.228	0.167	**
<b>City size</b>						
up to 5.000	0.104	0.114		0.159	0.169	
> 5.000–20.000	0.225	0.268		0.232	0.250	
> 20.000–100.000	0.257	0.268	**	0.246	0.252	
> 100.000–500.000	0.184	0.171		0.154	0.147	
> 500.000	0.230	0.181	*	0.209	0.183	**
Obs. (Min/Max)	(458/479)	(286/299)		(1618/1701)	(1892/1983)	

Notes: Numbers are shares, population-weighted. The significance refers to test of equal proportions in the variables between the two groups. \*, \*\*, \*\*\* significant at 10%, 5%, 1% level.

Table 5: Business-related characteristics of drop-outs and survivors, by type of entrepreneurs

Variable	Drop-out			Survival		
	Necessity (1)	Opportunity (2)	Diff.	Necessity (1)	Opportunity (2)	Diff.
<b>Part-time</b> ‡	0.497	0.636	***	0.428	0.551	***
<b>Establishment type</b>						
new establishment	0.586	0.639		0.730	0.816	***
take over	0.045	0.090	***	0.072	0.056	
joint venture	0.368	0.271	***	0.198	0.128	***
<b>Firm size</b>						
solo/without	0.724	0.581	***	0.728	0.592	***
solo/with	0.091	0.176	***	0.156	0.193	***
team/without	0.111	0.118		0.056	0.094	*
team/with	0.073	0.125	***	0.060	0.121	***
<b>Start-up capital</b>						
0 €	0.171	0.083	***	0.114	0.048	***
1–10.000 €	0.575	0.563	*	0.558	0.475	***
10.000–25.000 €	0.149	0.202		0.188	0.215	*
> 25.000 €	0.105	0.151	**	0.140	0.262	***
<b>Degree of innovation</b>						
no market novelty	0.836	0.730	***	0.908	0.808	***
regional novelty	0.099	0.169	***	0.059	0.116	***
national-wide novelty	0.019	0.064	**	0.016	0.044	***
world-wide novelty	0.019	0.037		0.017	0.031	***
<b>Occupational category</b>						
free lances	0.279	0.233		0.320	0.309	
craft	0.103	0.118		0.195	0.133	***
miscellaneous	0.618	0.649		0.485	0.557	***
<b>Industry</b>						
manufacturing	0.020	0.043		0.030	0.055	***
construction	0.047	0.029	**	0.088	0.041	***
retail trade	0.208	0.308	***	0.161	0.200	***
economic services	0.438	0.319	***	0.379	0.377	
personal services	0.277	0.272		0.320	0.259	**
others	0.011	0.029	***	0.023	0.068	***
Obs. (Min/Max)	(409/475)	(252/296)		(1440/1649)	(1611/1943)	

Notes: Numbers are shares, population-weighted. The significance refers to test of equal proportions in the variables between the two groups. ‡ Reported at the time of start-up. \*, \*\*, \*\*\* significant at 10%, 5%, 1% level.

Table 6: Kaplan-Meier estimator

Duration	Necessity			Opportunity			Difference in survival rates
	At risk	Survival	Hazard	At risk	Survival	Hazard	
1-3 months	2180	0.9639	0.0122	2282	0.9778	0.0075	1.40
4-6 months	1902	0.9131	0.0180	2001	0.9551	0.0078	4.20
7-9 months	1610	0.8697	0.0162	1736	0.9261	0.0103	5.64
10-12 months	1348	0.8282	0.0163	1442	0.8993	0.0098	7.11
13-15 months	1104	0.7844	0.0181	1146	0.8650	0.0129	8.06
16-18 months	886	0.7502	0.0149	916	0.8395	0.0100	8.93
19-21 months	730	0.7273	0.0104	751	0.8177	0.0087	9.04
22-24 months	622	0.7057	0.0100	621	0.7929	0.0103	8.72
25-36 months	508	0.5816	0.0148	480	0.7294	0.0064	14.78

*Notes:* The difference in survival rates (last column) is calculated as the cumulative proportion of opportunity entrepreneurs surviving minus the cumulative proportion of necessity entrepreneurs surviving up to the respective time interval. The difference is expressed in percentage points.

Table 7: Decomposition results on survival rates (Probit estimation)

Time interval	Diff.	Counterfactual (A)		Counterfactual (B)	
		Char. effect (%)	Coeff. effect (%)	Char. effect (%)	Coeff. effect (%)
1–3 months	0.0086	0.0023 (27.6)	0.0063 (72.4)	0.0036 (42.0)	0.0050 (58.0)
4–6 months	0.0310	0.0058 (19.2)	0.0252 (80.8)	0.0086 (28.4)	0.0224 (71.6)
7–9 months	0.0493	0.0081 (16.4)	0.0412 (83.6)	0.0137 (27.6)	0.0357 (72.4)
10–12 months	0.0638	0.0089 (14.1)	0.0548 (85.9)	0.0183 (28.7)	0.0455 (71.3)
13–15 months	0.0755	0.0091 (12.0)	0.0664 (88.0)	0.0234 (31.0)	0.0520 (69.0)
16–18 months	0.0850	0.0083 (9.7)	0.0768 (90.3)	0.0275 (32.3)	0.0575 (67.7)
19–21 months	0.0898	0.0074 (8.2)	0.0824 (91.8)	0.0309 (34.4)	0.0589 (65.6)
22–24 months	0.0895	0.0069 (7.7)	0.0826 (92.3)	0.0348 (38.9)	0.0547 (61.1)
25–36 months	0.1135	0.0058 (5.2)	0.1077 (94.8)	0.0405 (35.9)	0.0731 (64.1)

*Notes:* Counterfactual (A) refers to equation (5a): opportunity characteristics and necessity coefficients. Counterfactual (B) refers to equation (5b): necessity characteristics and opportunity coefficients.

Table 8: Decomposition results on survival rates (RE Probit estimation)

Time interval	Diff.	Counterfactual (A)		Counterfactual (B)	
		Char. effect (%)	Coeff. effect (%)	Char. effect (%)	Coeff. effect (%)
1–3 months	0.0103	0.0035 (34.1)	0.0068 (65.9)	0.0036 (35.1)	0.0067 (64.9)
4–6 months	0.0415	0.0092 (22.5)	0.0324 (77.5)	0.0086 (21.4)	0.0329 (78.6)
7–9 months	0.0760	0.0135 (17.8)	0.0626 (82.2)	0.0137 (20.0)	0.0624 (82.0)
10–12 months	0.1117	0.0158 (14.3)	0.0958 (85.7)	0.0183 (16.4)	0.0934 (83.6)
13–15 months	0.1495	0.0169 (11.3)	0.1327 (88.7)	0.0234 (15.7)	0.1261 (84.3)
16–18 months	0.1855	0.0160 (8.7)	0.1695 (91.3)	0.0275 (14.8)	0.1580 (85.2)
19–21 months	0.2130	0.0149 (7.0)	0.1980 (93.0)	0.0309 (14.5)	0.1821 (85.5)
22–24 months	0.2335	0.0143 (6.1)	0.2192 (93.9)	0.0348 (14.9)	0.1987 (85.1)
25–36 months	0.3055	0.0126 (4.2)	0.2929 (95.8)	0.0405 (13.3)	0.2651 (86.7)

*Notes:* Counterfactual (A) refers to equation (5a): opportunity characteristics and necessity coefficients. Counterfactual (B) refers to equation (5b): necessity characteristics and opportunity coefficients.