An Introduction to Hazard Rate Analysis
(and Its Application to Firm Survival)

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Hazard rate analysis: overview

- Hazard rate analysis
  - aka survival analysis; duration analysis; event history analysis
  - Handles duration data \( \rightarrow \) applicable in many economic contexts
  - Requires frequently repeated (better: continuous) observations of subjects
  - Uses maximum likelihood estimations
  - Is implemented in standard statistical software
What survival analysis originally WAS about:

- **Drug testing:**
  - 48 subjects in test
  - 28 take the drug to be tested; 20 take a placebo
  - Information at end of study:
    - Subject still alive?
    - If not, when did they die?

→ **Analysis of events**
  - Incidence of event (0/1)
  - Time \( t \) to event

- **Dependent variable: "risk" (hazard rate)**
  - Does drug affect hazard rate?

<table>
<thead>
<tr>
<th></th>
<th>Model1 (Cox Regression)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drug</td>
<td>-1.226*** (0.347)</td>
</tr>
<tr>
<td>Age</td>
<td>0.114*** (0.042)</td>
</tr>
<tr>
<td>Observations (Event = 1)</td>
<td>48 (31)</td>
</tr>
<tr>
<td>Log-Likelihood</td>
<td>-83.324</td>
</tr>
<tr>
<td>( P &gt; \chi^2 )</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Standard error in parentheses; *** \( p \leq 0.01 \); ** \( p \leq 0.05 \); * \( p \leq 0.10 \)

Hazard rate analysis: literature

- **Some introductory reading:**
  - Lecture notes on the web: Jenkins (2005)
    - [http://www.iser.essex.ac.uk/teaching/degree/stephenj/ec968/pdfs/ec968lnotesv6.pdf](http://www.iser.essex.ac.uk/teaching/degree/stephenj/ec968/pdfs/ec968lnotesv6.pdf)
  - Overview article:
    - Kiefer (JEL, 1988)
  - **How-to book on HRA using STATA:**
  - **Competing risks models:**
    - Lunn and McNeil (Biometrics, 1995)
Applications (1): Firm survival

- Widely used in empirical industry evolution / organization ecology literature
- Longevity as proxy for performance
- Analogous situation to drug testing example:
  - Firm still active at end of study?
  - If not, how long were they active?
  - Complication: exit for non-performance-related reasons (acquisition)
- Most frequently studied:
  - Time of entry and survival
  - Pre-entry experience and survival
  - “Density-dependence” (aggregate; local) → time-varying covariates

Example: Firm survival in 4 U.S. industries

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<thead>
<tr>
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<tbody>
<tr>
<td>Entry cohort 1</td>
<td>-0.478*** (.138)</td>
<td>-0.461*** (.152)</td>
<td>-1.173*** (.286)</td>
<td>-1.042*** (.337)</td>
</tr>
<tr>
<td>Entry cohort 2</td>
<td>-0.392*** (.115)</td>
<td>-0.529*** (.117)</td>
<td>-0.561*** (.182)</td>
<td></td>
</tr>
<tr>
<td>Entry cohort 3</td>
<td>-0.073 (.094)</td>
<td>-0.344*** (.102)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm age</td>
<td>-0.025*** (.005)</td>
<td>-0.041*** (.005)</td>
<td>-0.024** (.012)</td>
<td>-0.003 (.014)</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.619*** (.060)</td>
<td>-1.603*** (.069)</td>
<td>-1.676*** (.123)</td>
<td>-2.342*** (.215)</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-1948.312</td>
<td>-1773.015</td>
<td>-486.354</td>
<td>-178.674</td>
</tr>
</tbody>
</table>

Source: Klepper (RAND Journal, 2002)
The group of most recent entrants is the omitted control group in each model.
Gompertz specification; standard errors in parentheses; ***p ≤ 0.01; **p ≤ 0.05; *p ≤ 0.10
Applications (2): Labor economics

- **Probably the most prominent economic application of hazard models**
- **Unemployment:**
  - Duration of unemployment often more relevant than incidence
  - Policy evaluation → want to know whether labor market policies (e.g., training programs) affect duration of unemployment spells
  - Dependent variable: „Risk“ of finding a new job
  - Complication?

Applications (3): Technology transfer

- **Example: commercialization of licensed university technology**
- **Issue: Characteristics of licensees**
  - Inventor startups more or less likely to commercialize than established firms?
  - Hazard rate analysis accounts for:
    - Time to commercialization
    - Non-commercialization at end of study ("censoring")
Message from applications

- Hazard rate analysis (HRA) has many applications
- „Survival“ need not be good; „risk“ need not be bad
- HRA measures both occurrence of event and time lapsed before the event…
- … and can account for artificially imposed end of duration („censoring“)

Key concepts (1)

- **Failure**
  - Event of interest (terminates period of risk for a given subject)
- **Conditional probability of failure**
  - Probability of failure conditional on not having failed before
- **Hazard rate \( \rightarrow \) instantaneous rate of failure**
  - Conditional failure (probability) over infinitesimally small time period
- **Origin**
  - Time at which risk begins \( \rightarrow \) often differs between subjects
- **Analysis time**
  - Time period during which subject is exposed to risk (\( \neq \) calendar time)
- **Spell**
  - Total time that a given subject is at risk
Calendar time vs. analysis time

Source: Cantner et al., 2004

Key concepts (2)

- **Some definitions:**
  - Spell length (duration of time to failure): $T$
  - Failure function (probability distribution of duration): $F(t) = Pr(T < t)$
    (density $f(t) = dF(t) / dt$)
  - Survivor function: $S(t) = 1 - F(t) = Pr(T \geq t)$
  - Hazard function: $h(t) = f(t) / S(t)$

- **Note: hazard rate = absolute slope of log survivor function:**

\[
h(t) = \frac{f(t)}{S(t)} = -\frac{f(t)}{1 - F(t)} = \frac{1}{1 - F(t)} \frac{d[1 - F(t)]}{dt} = \frac{d \ln[1 - F(t)]}{dt} = -\frac{d \ln S(t)}{dt}
\]
Why does HRA need special methods?

- **Reason 1: Characteristics of duration data**
  - Durations are never negative
  - Durations are frequently not normally distributed
    (→ "bathtub hazard" of human mortality)

- **Reason 2: Censoring of observations**
  - ("End-of-observation-for-reasons-other-than-what-we-are-interested-in")
  - Limitations of study design

Censoring (1)

- **Two causes of censored observations:**
  - **Exit for reasons unrelated to interest of study (see above)**
    - Industry evolution: exit by acquisition (Chrysler vs. Skype)
    - Labor economics: unemployment spell ends because individual reaches pension age (or is hit by train)
  - **Imperfections in study design / available data**
    - Right censoring (pervasive): not all individuals have exited at end of study
    - Left censoring: different definitions, not relevant here (Jenkins, 2005, 5f.)
    - Length-based censoring:
      - Entry and exit unobserved because both fall into same time span between two observations
      - Exit falls into interval between two observations
        (→ tied failures: order of individuals’ failures cannot be established)
Censoring (2)

- **Statistical treatment of (right) censored observations:**
  (intuition only, see Kiefer (JEL, 1988) for technical details)
  - Survival analysis based on maximum likelihood estimations
  - Uncensored exits contribute failure density \( f_i(t) \)
  - Censored exits contribute survivor function \( S_i(t) \)
  - Only information that they survived up to \( t \) enters the likelihood function

Truncation

- **Incomplete** information for some time period (censoring: no information)
- **Relevant for industry studies:** Left truncation (delayed entry):
  - Individual enters risk before first observation
  - For example, no systematic information may exist for first years of an industry, but founding dates of surviving firms are known
  - Observing the firm implies that no failure before beginning of study
  - Can be handled by STATA by distinguishing entry from origin
  - However, doing so means that we no longer study full population (some may have failed before first observation)
  - \( \Rightarrow \) needs to be reflected in interpreting results!
Continuous versus discrete-time methods

- **Historically, continuous-time models have been dominant**
  - Following exposition limited to continuous-time models

- **However, economic data are rarely continuous**
  - Daily / monthly / yearly data
  - Using continuous-time models for discrete-time data may be problematic:
    - Tied failures as artifacts of length-based censoring
  - Judgment needed whether continuous-time methods are adequate
    - Observation intervals vs. typical spell length → incidence of tied failure times

- **Discrete-time models (cf. Jenkins, 2005, for details)**
  - Complementary log-log model: discrete-time representation of cont.-time model with proportional hazards
    - Survival times divided into (observation) intervals
    - Parameters are estimated for (baseline) hazards in the individual intervals
    - Different functional forms for duration dependence can be specified

Continuous time methods: Three classes

- **Non-parametric analysis**
  - No assumptions on functional forms → "data speak for themselves"
  - Most important: Kaplan-Meier estimator

- **Semi-parametric analysis**
  - Functional form specified for:
    - effects of covariates on hazard rate

- **(Fully) parametric analysis**
  - Functional form specified for:
    - effects of covariates on hazard rate
    - duration dependence of hazard rate
Kaplan-Meier estimator (1)

- Non-parametric estimate of \( S(t) \)
  \[ \hat{S}(t) = \prod_{j|t_j \leq t} \left( \frac{n_j - d_j}{n_j} \right) \]

where

- \( t_j \) (\( j = 1..K \)): observed time of failures
- \( n_j \): number of individuals at risk at time \( j \)
- \( d_j \): number of failures at time \( j \)

Notes:

- Applicable only to categorical covariates
- Censoring: STATA convention: at time \( t \), failures occur before censoring (i.e., censored observations are in risk set at \( t \)) (\( \Rightarrow \) some authors do differently!)
- If survival probabilities on logarithmic scale: (absolute) slope = hazard rate

Kaplan-Meier estimator (2)

- Let’s do some practical econometrics – no computer required!

Approach:
1. Order cases by covariate values and survival times (shortest one first)
2. Calculate \( \frac{n_j - d_j}{n_j} \)
3. Calculate running product

Of course, Kaplan-Meier estimator also implemented in statistical software…
Kaplan-Meier estimator (3)

Kaplan-Meier survival estimates, by background

Kaplan-Meier estimator (4)

- **Hypothesis testing:**
  - Significant differences in survivor functions across groups?

- **Several nonparametric tests are available:**
  - Log-rank; Wilcoxon etc. → Cleves et al., 2002

- **Commonalities and differences:**
  - All test equality of entire survivor functions, not survival at specific times
  - \( H_0: \) survivor functions are equal → rejected?
  - At each observed failure time, expected and observed failures are compared for each group
  - Tests differ in how they weigh early versus late failure times
The proportional hazards assumption

- **Relevant to both semi-parametric and fully parametric models**
  - Separates influences of duration and covariates → covariates’ effect is to multiply hazard function by a scale factor
    \[ h(x, \beta, t, h_0) = h_0(t)\Phi(x, \beta) \]
    - \( h_0 \): “baseline hazard”
    - effect of explanatory variables does not depend on duration
    - baseline hazard has same shape for all values of covariates
    - quite heroic assumption in many applications!
  - Because of non-negativity constraints, exponential is normally used
    \[ h(x, \beta, t, h_0) = h_0(t)\exp(x'\beta) \]

- **Note:** for proportional models, \( \exp(\text{coeff. est}) \) → hazard ratio for unit difference in coefficient value

### Relationship proportionality / model classes

<table>
<thead>
<tr>
<th></th>
<th>Semi-parametric model (Cox)</th>
<th>Fully parametric model (e.g., Gompertz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Functional form: effect of covariates</td>
<td>specified</td>
<td>specified</td>
</tr>
<tr>
<td>Functional form: duration dependence of hazard rate</td>
<td>not specified</td>
<td>specified</td>
</tr>
<tr>
<td>Proportionality assumption</td>
<td>can be relaxed by stratification</td>
<td>can be given up interaction terms (covariates*duratin)</td>
</tr>
</tbody>
</table>
Testing the proportionality assumption

- **Simple check through visual inspection:**
  - If hazards are proportional, log-scale Kaplan-Meier graphs are parallel for different groups
    - Equivalent built-in STATA command: `stphplot, by(...)`
- **Better: Inspection of Schoenfeld residuals**
  - Schoenfeld residuals: difference (covariate value for failed individual j) – (weighted average of all covariate values at time of j’s failure)
  - Schoenfeld residuals are time-invariant under H₀ (proportionality)
  - Can be scaled so that proportionality assumption can be tested for individual covariates

Cox proportional hazards model (1)

- **Semi-parametric model: no assumptions on functional form of baseline hazard (duration dependence)**
- **Cox model is analogous to sequence of conditional logits**
  - Data ordered by times of failures (similar to Kaplan-Meier)
  - Coefficients are estimated such that at each time of failure tᵢ, the likelihood is maximized that the failing individual is the one that actually failed (among the individuals still at risk at tᵢ)
- **Coefficient estimates driven by order of failure (ties are handled by specific procedures)**
- **Proportionality assumption may be problematic**
Cox proportional hazards model (2)

- **Shortcoming**: information of time intervals between the failures is not used
  - Likely to affect outcomes if intervals differ strongly
  - Also: inefficient because not all information in data is used

Extension: stratified Cox model

- **Stratified Cox model** → baseline hazards allowed to differ
  - Each group (stratum) can have different shape of baseline hazard
  - Baseline hazard still remains unspecified → semiparametric model
  - Coefficients of covariates constrained to be equal across strata
  - Group-specific baseline hazards; identical coefficient estimates
  - Medical example: treatment equally effective for men/women, but gender-specific baseline hazard

- **Alternative**: groups entered as control variables
  - Disadvantage:
    - Assumes that group variable shifts hazard proportionally over the entire time period at risk
Fully parametric proportional hazards models (1)

- **Key difference to Cox model:**
  - Assumptions on functional form of baseline hazard $h_0$

- **Crucial issue:**
  - Reasonable priors on duration dependence of hazards? ($\rightarrow$ theory)

- **Firm survival:**
  - "liability of newness"; "liability of senescence"
    - decreasing or U-shaped duration-dependence

- **Most commonly used distributions:**
  - Exponential: $h_0(t) = \exp(\alpha)$ $\rightarrow$ constant baseline hazard
  - Weibull: $h_0(t) = \alpha t^{\alpha-1} \exp(\alpha)$ $\rightarrow$ reduces to exponential for $\alpha=1$
  - Gompertz: $h_0(t) = \exp(\alpha) \exp(\gamma t)$

Fully parametric proportional hazards models (2)

*Chapter 2. Describing the distribution of failure times*

Figure 2.1: Examples of hazard functions obtained from various parametric survival models
Example: survival, entry time, and innovation

**IE models assume:**
- Technological determinants of industry evolution
- Innovative success drives firm performance

**Tests for 3 industries:**
- Control group: early non-innovators
- Early entry enhances performance even when controlling for innovation
- Early non-innovators perform less well than late innovators

<table>
<thead>
<tr>
<th></th>
<th>Automobiles</th>
<th>Tires</th>
<th>TVs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innovator in first cohort</td>
<td>-2.19*** (0.46)</td>
<td>-1.11*** (0.36)</td>
<td>-2.41** (1.04)</td>
</tr>
<tr>
<td>Innovator in second cohort</td>
<td>-1.32** (0.59)</td>
<td>-0.12 (0.33)</td>
<td>-0.71 (0.65)</td>
</tr>
<tr>
<td>Non-innovator in second cohort</td>
<td>0.64*** (0.13)</td>
<td>0.39 (0.34)</td>
<td>0.22 (0.33)</td>
</tr>
<tr>
<td>Constant</td>
<td>-2.32*** (0.11)</td>
<td>-2.10*** (0.28)</td>
<td>-2.43*** (0.30)</td>
</tr>
<tr>
<td>Number of firms (exits)</td>
<td>299 (265)</td>
<td>154 (91)</td>
<td>91 (73)</td>
</tr>
<tr>
<td>Log-Likelihood</td>
<td>-197.43</td>
<td>-131.88</td>
<td>-74.58</td>
</tr>
</tbody>
</table>

Source: Klepper and Simons, IJIO 2005

*Exponential specification; standard errors in parentheses;***p≤.01; **p≤.05; *p≤.10

Relaxing the proportional hazards assumption

**Is straightforward for fully parametric estimators**

**Example:**
- Different duration-dependent effects for different entry cohorts; backgrounds
- Interpretation: dynamics of firm performance may differ between groups
- Possible explanation: selection effects: composition of cohorts varies over time, as lesser performers are weeded out

**Baseline hazard of fully parameterized Gompertz model:**

\[ h_0(t) = \exp[(\gamma_0 + \gamma_2 t)] \]
Example: Diversifiers in U.S. tractor industry

Non-proportional models and stratified models

- **Tractor model:**
  - Cohort effects were assumed to shift hazards proportionally
  - Background effects were allowed to affect hazards differently at different ages

- **This is equivalent to stratification by type of entrant:**
  - Stratified parametric models: baseline hazard functions allowed to differ between strata, but assumed to have same type of distribution
  - In above model, both parameters of Gompertz distribution were estimated separately for entry groups \( \rightarrow \) amounts to stratification

### Table

| Implement div. | -.967*** (.000) | -.121*** (.000) |
| Engine div. | -.417** (.043) | -.575** (.033) |
| Auto/truck div. | -.230 (.337) | -.005 (.986) |
| Other div. | -.055 (.809) | -.709* (.051) |
| Spin-off | -.391 (.233) | -.184 (.661) |
| Cohort 1 | -.040 (.927) | -.046 (.916) |
| Cohort 2 | .675* (.083) | .637 (.104) |
| Cohort 3 | .627 (.121) | .638 (.117) |
| Constant | -2.393*** (.000) | -2.332*** (.000) |
| Impl. div. * age | .011 (.475) |
| Engine div. * age | .015 (.276) |
| Auto/tr. div. * age | -.020 (.372) |
| Other div. * age | -.122*** (.005) |
| Spinoff * age | -.038 (.485) |
| Age | -.023*** (.000) | -.029*** (.003) |
| No. of firms | 319 | 319 |
| Log-likelihood | -444.403 | -438.985 |
| P>chi² | .000 | .000 |

p-values in parentheses; ***p ≤ .01; **p ≤ .05; *p ≤ .10

Source: Buenstorf in Elsner/Hanappi (eds.), forthcoming
Extensions

- **Time-varying covariates**
  - Spells are broken into shorter time periods (e.g., years)
  - STATA can handle multiple observations per subject
  - Current values of covariates are used for each individual observation

- **Competing risks**
  - Allows analysis of two (or more) kinds of events (e.g., bankruptcy vs. acquisition)
  - Implementation is straightforward (Bogges, 2004)

- **Unobserved heterogeneity: (unshared) frailty (cf. Jenkins, 2005)**
  - Allows for indiv. differences in propensity to experience event (e.g., capability)
  - random var. with unit mean and specified variance included in hazard fct.
  - Relevance: negative duration dependence may be artifact of selection effect
    (least capable exit first)

**Pre-entry experience and firm survival**
Pre-entry experience effects: why bother?

- **Pragmatic interest**: link to entrepreneurship research: what kind of entrants are more likely to succeed?

- **Theoretical interest:**
  - Experience effects indicative of heterogeneity in firm capabilities
  - Experience effects indicative of processes of knowledge transfer
    - Between industries → related diversification
    - Between firms → spin-offs
    - Puzzles for organizational theories

- **Implications for geography (→ tomorrow)**

How to measure experience and performance?

- **Data on full firm populations**

- **Experience measures:**
  - Mostly based on industry-specific data sources (trade registers; trade publications etc.) → selection of industries tends to be opportunistic
  - Census data: new firms versus new plants
  - In some countries (Denmark, Portugal, recently also Germany), individuals can be traced across their employment spells → indicative of spin-offs
Evidence: related diversification

Diversification and performance

- **Related diversifiers superior in various different samples**
  - U.S. census data (20 years, 4-digit SIC): diversification is pervasive, diversifiers are larger and survive longer than *de novo* entrants (Dunne et al., RAND 1988)
  - Autos: diversifiers survive longer (Carroll et al., SMJ 1996)
  - TV receivers: diversifying radio producers enter earlier, are more innovative, and persistently have lower hazard of exit (Klepper and Simons, SMJ 2000)
  - Iron and steel shipbuilding: diversifiers persistently have lower hazard of exit (Thompson, RES Stat 2005)

- **Note: In some industries (e.g., disk drives), prior experience appears to have been detrimental**
  - Theoretical approaches to explain negative experience effects:
    - Architectural innovations (Henderson/Clark, ASQ 1990)
    - Value network effects (Christensen/Rosenbloom, RP 1995)
    - Generality of negative experience effects?
What makes diversifiers superior? (1)

- **“Proximity” of experience:**
  - Experience effects indicative of heterogeneity in firm capabilities
  - Some indication that not (primarily) technological capabilities are at work
    - Autos: carriage and bicycle firms performed better than engine firms (Carroll et al., 1996)
    - Farm tractors: implement producers more successful than auto or engine producers (Buenstorf, forthcoming)
    - TVs: diversification largely limited to home radio producers (Klepper and Simons, 2000)
  - Suggests role of market knowledge
  - Transferability of capabilities across industries may explain role of diversifiers versus spin-offs (TVs versus autos, tires)

What makes diversifiers superior? (2)

- **Performance in earlier activities:**
  - Superior performance in origin industry → superior performance in target industry?
  - Evidence on TVs (Klepper and Simons, 2000):
    - Larger and more experienced radio producers more likely diversifiers
    - Size and experience also translated into earlier entry
    - Larger radio producers had lower hazard of exit in TVs
Evidence: Spin-offs

A typology of spin-offs (1)

- **Firm spin-offs versus university spin-offs**
  (below: only firm spin-offs considered)

- **Involuntary spin-offs versus voluntary spin-offs**
  - Involuntary spin-offs (employee spin-offs; entrepreneurial spin-offs; spin-outs): Founding impetus provided by employee(s), not by parent firm leadership
  - Voluntary spin-offs (parent spin-offs): Founding impetus provided by parent firm management
    - Management buy-outs, serial entrepreneurship as special cases

- **Note: Industry evolution literature focuses on**
  - involuntary/entrepreneurial
  - firm

  spin-offs
Theoretical accounts of the spin-off process

- **Opportunism / principal-agent approaches (???)**
- **Employee frustration / strategy conflicts**
  - Formal model: Klepper and Thompson (working paper)
- **Employee learning**
  - Incumbent firms as (involuntary) training grounds
    - Capabilities embedded in individual employees
    - Obscure and changing market niches (Æ submarkets)
- **Spin-offs due to parent firm inertia?**
  - Klepper and Sleeper (Management Science, 2005): Incumbents may choose not to preclude all opportunities for spin-off entry
  - Agarwal et. al (AoMJ, 2005): Less spin-offs in firms that are both technological leaders and market pioneers

The performance of spin-offs

- **Spin-offs among top performers in variety of industries**
  - Autos: Spin-offs outperform other de novo entrants; are similar to diversifiers in performance (Klepper, ICC 2002)
  - Lasers (Germany): Spin-offs more successful than university start-ups (Buenstorf, RIO 2007)
- **Better incumbents have better spin-offs**
  - Autos: Spin-offs of leading firm in industry outperform diversifiers (Klepper, ICC 2002)
  - Tires: Only spin-offs from top and second-tier firms perform above average (Buenstorff and Klepper, forthcoming)
  - **Consistent with learning-based spin-off theories**
Determinants of the spin-off process

- **Better incumbents have more spin-offs**
  - Tires (Buenstorf and Klepper, forthcoming)
  - Lasers (Germany) (Buenstorf, RIO 2007)

- **Spin-offs draw on specific capabilities**
  - Lasers (U.S. / Germany): Parent firm experience in specific submarket, but not general experience in lasers, explains spin-off rate

- **Spin-offs may be triggered by events at the incumbent firm**
  - Lasers:
    - Firms that exit through acquisition have more spin-offs
    - Spin-offs more likely at time of parent firm exit (Germany)
  → Consistent with role of frustration / “necessity spin-offs”

Spin-off emergence in the German laser industry

<table>
<thead>
<tr>
<th>Explained variable</th>
<th>All spin-offs</th>
<th>Spin-offs by laser type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total years (industry)</td>
<td>0.134*** (0.033)</td>
<td>0.038 (0.024)</td>
</tr>
<tr>
<td>Total years (laser type)</td>
<td>0.117*** (0.026)</td>
<td></td>
</tr>
<tr>
<td>Diversifier</td>
<td>-0.974 (0.686)</td>
<td>-0.921 (0.392)</td>
</tr>
<tr>
<td>Allspins</td>
<td>-0.299 (0.564)</td>
<td>-0.313 (0.393)</td>
</tr>
<tr>
<td>Exit by acquisition</td>
<td>1.674*** (0.557)</td>
<td>0.761** (0.373)</td>
</tr>
<tr>
<td>No of observ.</td>
<td>142</td>
<td>1136</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>0.146</td>
<td>0.157</td>
</tr>
</tbody>
</table>

Ordered logits; standard errors in par.; ***p ≤ 0.01; **p ≤ 0.05; *p ≤ 0.10
Source: Buenstorf, RIO 2007