Darmstadt Discussion Papers in ECONOMICS

TECHNISCHE UNIVERSITÄT DARMSTADT

Survival Analysis in Product Life Cycle Investigations: An Assessment of Robustness for the German Automobile Industry

Jens J. Krüger

Nr. 223

Arbeitspapiere der
Volkswirtschaftlichen Fachgebiete der TU Darmstadt

ISSN: 1438-2733

Survival Analysis in Product Life Cycle Investigations: An Assessment of Robustness for the German Automobile Industry

January 2015

by

Jens J. Krüger

Darmstadt University of Technology
Department of Law and Economics
Hochschulstrasse 1, D-64289 Darmstadt, Germany
tel.: +49 6151 163 693, fax: +49 6151 163 897
e-mail: jjk@vwl.tu-darmstadt.de

Abstract

We apply various refinements of survival regression to assess the results of some basic specifications based on product life cycle theory for the case of a data set of the German automobile industry. The methods applied pay attention to biases in the coefficient estimates and the standard errors, the discrete nature of the duration data and the presence of unobserved heterogeneity. Robust estimation methods are also applied. We find that that the coefficient estimates and standard errors are not much affected by applying the refined estimators. The substantial results of a previous study with the same data are unchanged.

JEL classification: C41, C25, C14, L10, L62, O33

Keywords: firm survival, Cox regression, robustness assessment

1 Introduction

Research on the industry life cycle has generated many results about the specific pattern of the number of firms and the output from emergence to maturity of an industry and its drivers. This research, mainly associated with Steven Klepper, is documented in Gort and Klepper (1982), Klepper and Graddy (1990) and especially Klepper (1996, 2002). Of particular importance is the role of the knowledge of firms allowing them to survive longer and thus shaping the characteristic life cycle pattern. This knowledge could have been already existed before a firm is founded or could be acquired during its operation in the market. In particular, the theoretical model of Klepper (1996) highlights the role of knowledge accumulation by entering early in the life cycle (and thus having more time to accumulate knowledge in the form of learning-by-doing) as well as the role of relevant knowledge already existing at the time of entry in the industry (called pre-entry experience). The benefit of both forms of knowledge in terms of longer survival in the market is analyzed by Klepper (2002) for four US industries (including the automobile industry) using parametric survival regressions.

For the case of the German automobile industry in Cantner, Dreßler and Krüger (2006), CDK henceforth, we follow the line of research initiated by Klepper (2002) by first estimating parametric survival regressions based on the Gompertz distribution and then extending the analysis using the Cox regression with its semiparametric flavor not requiring to specify the complete distribution of the survival times. As Klepper (2002) we have a unique data set for the German automobile industry, following entering firms from the first automobile producers until the beginning of the Second World War, i.e. 1886-1939. These data are also used in Cantner et al. (2009, 2011), Krüger and von Rhein (2009) and von Rhein (2008).[1]

In this paper we undertake an assessment of the robustness of the results in CDK. In particular, we apply a batch of methods originating mainly from biostatistical applications. These methods offer the opportunity to investigate the influence of several specification issues on the results obtained by the ordinary Cox regression. Inter alia, this refers to the influence of the small-sample distribution on the standard errors of the coefficients (assessed by bootstrapping), the discreteness of the survival data at hand (already dealt with by Efron's ties breaking mechanism, but more directly assessed by a discrete time version of survival regression), the influence of unobserved heterogeneity (assessed by versions of mixed proportional hazards models or frailty terms), biases in the parameter estimates and the application of a robust version of the Cox regression.

The results of the robustness assessment documented in this paper show that the estimates of CDK are indeed remarkably robust. This holds for the numerical magnitudes of the coefficient estimates as well as for the associated standard errors. All substantive conclusions about the implications of the life cycle theory continue to hold when the refined estimators are applied. The conclusions are even strengthened in the cases where we observe differences to the previous findings of CDK.

The paper proceeds by reviewing the analysis of CDK in section 2, thereby also introducing data and variable definitions. Section 3 reviews the various refined versions of survival regression applied subsequently. The discussion of the results obtained and the comparison with the previous findings of CDK is the purpose of section 4. Finally, section 5 concludes with a brief summary of the main lessons learned.

2 Review of CDK, Data and Variables

The analysis of CDK is based on a comprehensive data set of the firms operating in the German automobile industry starting from 1886, the year where Daimler and Benz designed the first motorcars[2], and continuing until 1939 when the Second World War began. The data are obtained from various sources, mainly yearbooks, journals and books about veteran cars. Details can be found in the appendix of CDK. The data are collected only for automobile manufacturing firms, excluding suppliers or truck producers.

[1] Other empirical research in industrial organization also used methods of survival analysis, see Audretsch and Mahmood (1994, 1995), Agarwal and Audretsch (2001), Agarwal and Gort (2002), and Buddelmeyer et al. (2010) among many others. These papers investigate the determinants of firm survival over much shorter time spans, however. They are therefore only distantly related to investigations following the development of an industry from its birth to maturity which is at the heart of the industry life cycle literature on which we focus here. See Manjón-Antolín and Arauzo-Carod (2008) for a survey of this literature.

[2] Meaning a vehicle designed to be powered by an internal combustion engine as a predecessor of what we today understand as a car or an automobile.

Recorded are the year of entry into automobile production, the year of exit and a censoring indicator equal to unity when a firm was subject to a merger or an acquisition or if a firm survived beyond 1939.[3]

To capture post-entry experience originating from knowledge accumulated during the operation in die automobile industry (e.g. by innovating or just through learning by doing) the firms are grouped into entry cohorts using Klepper's 15-15 rule.[4] This leads to four entry cohorts, the first ranging from 1886 to 1901 (indicated by the dummy variable E_1 equal to unity), the second from 1902 to 1906 (indicated analogously by E_2), the third from 1907 to 1922 (indicated by E_3) and the fourth from 1923 to 1939 (indicated by E_4). Pre-entry experience is coded by the dummy variable P equal to unity if the founders of the firm were endowed with some form of technological experience or business experience available at the time of entry. This form of experience could originate from already having managed a firm before entering into the automobile industry, having diversified into the automobile industry, or being a spinoff of an automobile firm. All other firms are treated as inexperienced with P equal to zero.

Complete data including the information about pre-entry experience are available for $n = 333$ firms. Some descriptive statistics are reported in table 1. From the table we already see that the earlier entry cohorts E_1 and E_2 contain a lower number of entering firms which survive longer on average with a larger standard deviation compared to the later entry cohorts E_3 and E_4. Firms in the earlier cohorts are also more likely to be censored and more likely to have pre-entry experience, again compared to the firms in the later cohorts. Overall, about 15 percent of all firms are censored. 59 percent of all firms are endowed with some form of pre-entry experience.

Table 1: Descriptive Statistics

subsample	number of observations	fraction censored	mean duration	std. dev. duration	fraction with $P = 1$
total	333	0.147	7.036	8.751	0.589
$E_1 = 1$	54	0.259	13.741	13.874	0.778
$E_2 = 1$	51	0.216	10.039	9.425	0.686
$E_3 = 1$	123	0.106	6.187	6.361	0.512
$E_4 = 1$	105	0.105	3.124	3.480	0.533
$P = 1$	196	0.214	9.561	10.331	1.000

Note: Sample restricted to those firms for which complete information for all variables is available.

The analysis of CDK by means of the ordinary Cox regression leads to a number of findings which are consistent with the predictions of the industry life cycle literature, chiefly with the theoretical model of Klepper (1996). First, firms entering early in the life cycle (being member of an early entry cohort) face a significantly lower exit hazard and thus survive longer. Generally, the earlier a firm enters the lower is its exit hazard. More precisely, firms in the first entry cohort face a 75 percent lower exit hazard on average compared to firms in the fourth entry cohort (declining to 69 and 55 percent for the second and third entry cohorts, respectively, also compared to the fourth). This may be attributed to their greater opportunities to accumulate knowledge during their operation in the market. Second, firms with pre-entry experience have a sizable additional reduction of the exit hazard by 62 percent on average. Third, the additional reduction of the exit hazard from pre-entry experience is particularly pronounced in the case of the first and the fourth entry cohorts. Similar results are found by Klepper (2002) for the US and by Boschma and Wenting (2007) for the British automobile industries.

In the following two sections we first briefly introduce the refinements of the Cox regression applied subsequently and then turn to the assessment of the robustness of the findings of CDK just summarized.

[3] In the language of survival analysis we have single-spell duration data without left-truncation but with right-censoring, of course.

[4] This means that "where feasible, entry cohorts are defined so that they have at least 15 survivors to age 15" (Klepper 2002, p. 47).

3 Survival Regressions

Duration data have specific properties that require the application of special regression methods instead of OLS or NLS estimation. The first property is that durations are strictly positive since they represent the time passed until a certain event takes place and the duration ends. The second property is that duration data are frequently censored since a certain fraction of durations is ongoing at the time of the analysis so that one only knows that these durations are at least as large as recorded but may be much larger.

There is a wide range of methods for analyzing duration data, fully parametric as well as nonparametric and semiparametric. Therneau and Grambsch (2000) and van den Berg (2001) provide overviews of the literature of survival analysis. Out of these methods, the Cox regression, designed to estimate the proportional hazards specification, can be viewed as the 'workhorse' of survival analysis in economics and other disciplines such as biostatistics. This model specifies the hazards rate of firm i as

$$\lambda(y_i \,|\, \boldsymbol{x}_i) = \lambda_0(y_i) \cdot \exp(\boldsymbol{\beta}'\boldsymbol{x}_i), \tag{1}$$

where the hazard rate $\lambda(y_i \,|\, \boldsymbol{x}_i)$ is split multiplicatively into the baseline hazard rate $\lambda_0(y_i)$ which depends only on the duration of survival y_i and the part $\exp(\boldsymbol{\beta}'\boldsymbol{x}_i)$ which depends only on the explanatory variables, collected in the vector $\boldsymbol{x}_i$ (excluding the intercept). In this specification, the estimates of the parameters in the vector $\boldsymbol{\beta}$ can directly be interpreted as the rates of change of the hazard rate when the corresponding explanatory variable changes by one unit.

Original Cox regression was introduced by Cox (1972, 1975) with maximization of the partial likelihood function to eliminate the baseline hazard rate. For the case that all durations are completed (no censoring) and in the absence of ties the log-likelihood function for the unique ordered duration times $y_1 < y_2 < ... < y_n$ after canceling out the baseline hazard rate is

$$\ln L(\boldsymbol{\beta}) = \sum_{i=1}^{n} \left[\boldsymbol{\beta}'\boldsymbol{x}_i - \ln \left(\sum_{j \in R(y_i)} \exp(\boldsymbol{\beta}'\boldsymbol{x}_j) \right) \right], \tag{2}$$

with $R(y_i)$ as the set of observations which are at risk at survival time y_i (the so-called risk set). Censoring is handled by including the censored observations in the risk set but omitting them from the outer sum. Ties in the duration times are treated by the schemes of Breslow or Efron, where Efron's scheme (Efron 1977) is more efficient and is used as the default option in the R package 'survival'.

The first-order conditions (score function) are given by

$$\frac{\partial \ln L(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}} = \sum_{i=1}^{n} \left[\boldsymbol{x}_i - \frac{\sum_{j \in R(y_i)} \exp(\boldsymbol{\beta}'\boldsymbol{x}_j) \cdot \boldsymbol{x}_j}{\sum_{j \in R(y_i)} \exp(\boldsymbol{\beta}'\boldsymbol{x}_j)} \right] = \mathbf{0} \tag{3}$$

and can be solved numerically for the regression parameters $\boldsymbol{\beta}$, resulting in the Cox partial likelihood estimator (PLE) $\hat{\boldsymbol{\beta}}$.

The Cox proportional hazards model is attractive because of the possibility to estimate the $\boldsymbol{\beta}$ parameters by partial likelihood maximization without having to specify the whole distribution (i.e. not having to specify the baseline hazard rate) which gives it its semiparametric character. There are, however, several specific problems arising with this model and with this estimation approach:

- the assumption of proportional hazards (this assumption may also be violated because of the other problems listed next),
- the discrete measurement of the duration (the Cox model expects continuously measured duration data, but is able to deal with ties if there are not excessively many),
- unobserved heterogeneity (i.e. subgroups of observations with differing parameter values) and
- measurement errors and outliers.

The PLE is sensitive to these problems and departures from the underlying assumptions may cause parameter estimates to be biased towards zero and also leads to downward biases of the corresponding standard errors. To test the validity of the proportional hazards assumption we use the test of Grambsch and Therneau (1994). This test is applied to each regressor variable separately as well as to the whole specification. We also apply several refinements or alternatives to the ordinary Cox regression which are briefly discussed in the following paragraphs.

Cox regression with censored bootstrapping is used for implementing a bias correction and computing standard errors which are more valid in small samples. Davison and Hinkley (1997) describe the bootstrap for censored data in detail. Efron and Tibshirani (1986) propose to bootstrap the data directly together with the censoring indicator (resampling cases), claiming that standard errors are correctly estimated even in the case of violations of the supposed censoring mechanism. This approach is deemed to be quite robust to departures from the underlying model assumptions (see also Hjort (1992)).

Complementary log-log model is considered to take account of the discrete nature of the survival data. Cox regression principally expects continuous duration data but is principally able to deal with ties (here by Efron's (1977) procedure). Despite that Efron's procedure is considered to be quite robust even for moderately tied data (Broström/Lindkvist (2008, p. 681)), our data record the years of survival and are heavily tied with just 37 different survival times for a total of 333 observations. Thus, the application of a discrete time duration method, which is better suited when data are heavily tied and then also provides improved small sample properties, is strongly suggested as a further robustness check. Basically this amounts to create risk sets containing the observations which are at risk at the distinct survival times and transforming the duration of survival to a binary variable $y_{it_k} \in \{0,1\}$ equal to one when an event occurs for firm i at survival time t_k. Then a binary choice model with a complementary log-log link function $\Pr(y_{it_k} = 1 \,|\, \boldsymbol{x}_i) = 1 - \exp(-\exp(\boldsymbol{\beta}'\boldsymbol{x}_i + \lambda_{0k}))$, where λ_{0k} is the additive baseline hazard at t_k, is estimated. This corresponds to a discrete time analog to Cox's proportional hazards model. See Prentice and Gloeckler (1978) and Broström (2002) for details.[5] The complementary log-log model is used as implemented in the R package 'eha' (see Broström and Lindkvist (2008)).

Complementary log-log model with bootstrapping based bias correction and bootstrapped standard errors are used analogous to the Cox regression in the form of case resampling.

Mixed Cox regression can take account of unobserved heterogeneity (so-called frailty in the biostatistics literature). Neglecting unobserved heterogeneity potentially leads to biased parameter estimates and may also lead to a rejection of the proportional hazards assumption. We use three variants of a mixed effects model to introduce unobserved heterogeneity of the hazard rates. The first variant is the usual Gamma-distributed frailty term (γ-frailty) introduced by Lancaster (1979). Estimated is the model $\lambda(y_i \,|\, \boldsymbol{x}_i) = \lambda_0(y_i) \cdot \exp(\boldsymbol{\beta}'\boldsymbol{x}_i) \cdot \upsilon_i$ with $\upsilon_i \sim Gamma(\theta, \theta)$ independently, parameterized such that $\mathrm{E}(\upsilon_i) = 1$ and $\mathrm{Var}(\upsilon_i) = 1/\theta$. The parameter θ is estimated along with the other model parameters. The generality and robustness of the proportional Gamma-frailty is highlighted by Abbring and van den Berg (2007). The second variant is based on a penalized likelihood approach as described in Therneau et al. (2003) with a Gaussian frailty term. In that case the model estimated is $\lambda(y_i \,|\, \boldsymbol{x}_i) = \lambda_0(y_i) \cdot \exp(\boldsymbol{\beta}'\boldsymbol{x}_i + b_i)$ with $b_i \sim N(0, \sigma_b^2)$ representing the independently normally distributed random effects coefficients and σ_b^2 is a variance parameter to be estimated. The third variant consists of variable-specific normally distributed random effects. Its hazard rate is $\lambda(y_i \,|\, \boldsymbol{x}_i) = \lambda_0(y_i) \cdot \exp(\boldsymbol{\beta}'\boldsymbol{x}_i + \boldsymbol{b}_i'\boldsymbol{x}_i)$, where $\boldsymbol{b}_i$ now is a vector of random effects coefficients which is multivariate normally distributed with $\mathrm{E}(\boldsymbol{b}_i) = \boldsymbol{0}$ and covariance matrix $\mathrm{Var}(\boldsymbol{b}_i) = \boldsymbol{\Sigma}$. The implementation used here is based on the EM algorithm as outlined in Vaida and Xu (2000). Reported in the tables below are only the estimates of the fixed effects coefficients.

Cox regression with a bias correction is proposed in Heinze and Schemper (2001) adapting a general procedure proposed by Firth (1993). Cox regression can be subject to a problem called the problem of monotone likelihood.[6] Heinze and Schemper (2001) suggest a remedy against this problem to introduce a bias term into the score function of the Cox PLE to reduce the bias in $\hat{\boldsymbol{\beta}}$. This reduces the bias that may be caused by the monotone likelihood problem in Cox regressions. Since this problem arises more frequently with dummy explanatory variables, its correction is particularly relevant in the present application. The mathematical foundation for the general case of maximum likelihood estimation are

[5] In addition, Beck et al. (1998, pp. 1284f.) provide a nice derivation of this correspondence.

[6] The problem of monotone likelihood is described by Heinze and Schemper (2001, p. 114) as follows: "... during the iterative fitting process, the likelihood converges to a finite value while at least one parameter estimate diverges to $\pm\infty$. In general, one does not assume infinite parameter values in underlying populations. The problem of monotone likelihood is rather one of nonexistence of the maximum likelihood estimate under special conditions in a sample."

outlined by Firth (1993), while the computational details of the application to the Cox regression can be found in Heinze and Schemper (2001).

Robust estimation of the Cox regression as proposed in Bednarski (1993) and Minder and Bednarski (1996) amounts to modifying the score function by introducing trimming using a kind of weights to reduce the influence of large values of $\exp(\boldsymbol{\beta}'\boldsymbol{x}_i)$. The weight function is chosen to smooth the estimator with respect to the data. Monte-Carlo results show that the downward biases (towards zero) of the parameter estimates and their standard errors caused by unobserved heterogeneity, omitted variables or measurement errors are smaller when the robust Cox estimator is applied (see Bednarski (1993) and Minder and Bednarski (1996) for the details).

These refinements of the Cox regression are implemented in several packages for the R programming environment (Chambers (2008)). Used for generating the estimation results discussed in the following section are the packages 'survival' (for the original Cox regression, the test of proportional hazards and the Gamma-fraily model), 'boot' (for the bootstraps), 'eha' (for the conditional log-log model), 'coxme' and 'phmm' (for the models with unobserved heterogeneity), 'coxphf' (for the bias correction), and 'coxrobust' (for the robust Cox regression estimates).

4 Results and Robustness

For our robustness assessment we focus on models 3 and 4 of CDK where both pre-entry and post-entry experience are considered. We first turn to the tests of the proportional hazards assumption. Recall that, as defined above, abbreviations used in the tables are E_1, E_2, E_3 and E_4 for the dummy variables indicating membership in the first to fourth entry cohort, respectively, and P is a dummy variable indicating the presence of some form of pre-entry experience.

Table 2 shows the p-values of the proportional hazards tests. We see that for model 3, which includes the cohort dummy variables E_1, E_2 and E_3 (the dummy E_4 serves as the omitted reference category) and the pre-entry experience dummy P, the proportional hazards assumption is generally rejected. For the original Cox regression the rejection holds for the cohort dummies as well as globally. The exception is the dummy for pre-entry experience. When we incorporate γ-frailty the rejections become weaker (the p-values are higher) and now we find no rejections for the variables E_1 and P. The picture changes when we turn to model 4, where the pre-entry experience is interacted with the entry-cohort dummies. Now we find no rejection of the proportional hazards assumption with the single exception of the global test for the original Cox regression, but this rejection is rather weak with a p-value close to 0.05. Thus, we see here that the tests of the proportional hazards assumption appear also to have power against model misspecification in general which is a more general insight of the literature concerned with specification testing (see e.g. MacKinnon (1992) and more specifically Therneau and Grambsch (2000, ch. 6)).

Table 2: Proportional Hazards Tests

	Model 3		Model 4	
model variables	original Cox regression	γ-frailty Cox regression	original Cox regression	γ-frailty Cox regression
E_1	0.039	0.258	0.249	0.330
E_2	0.002	0.019	0.187	0.238
E_3	0.000	0.004	0.105	0.122
P	0.512	0.324		
$E_1 \cdot P$			0.644	0.538
$E_2 \cdot P$			0.991	0.906
$E_3 \cdot P$			0.932	0.864
$E_4 \cdot P$			0.191	0.329
global	0.005	0.020	0.048	0.136

Note: Reported are p-values of the tests of Grambsch and Therneau (1994).

The comparison of the survival regression results focuses on the coefficient estimates and their standard errors (reported in parentheses). Table 3 collects the whole set of results for model 3. The first column shows the results of CDK for the original Cox regression as summarized above in section 2.[7] We see that all coefficient estimates are negative and highly significant. The next column shows that these results are robust to the application of the bootstrap. This holds for the magnitude of the now bias-corrected coefficient estimates as well as for the standard errors which are all numerically close to that of the original Cox regression. Hence, no biases or underestimation of standard errors can the detected in this way.

In column three we find the estimates of the complementary log-log model for taking better account of the discreteness of the duration data. Compared to the original Cox regression we see that the coefficient estimates for the early entry cohorts (E_1 and E_2) are more negative while the coefficient estimate for the later entry cohort (E_3) is less negative. Thus, the differences in the survival chances of the earlier and later entrants appear more pronounced when using this estimator. The coefficient estimate of the pre-entry experience is slightly more negative, also showing that pre-entry experience is here even more important for reducing the exit hazard. The standard errors are a bit larger but give no reason to change any conclusion about the significant influence of the variables. The application of the bootstrap to the complementary log-log model results in minor changes of the coefficient estimates which are far too small to change any conclusions. The standard errors are further increased somewhat.

The next three columns consider the mixed proportional hazard models with the consideration of unobserved heterogeneity in three different ways. Here, the magnitude of the coefficient estimates lies in between those of the Cox regression and the complementary log-log model. When they are outside of this range, then not by far. The sole exception are the coefficient estimates of the cohort dummy E_3 which are much more negative than in the estimates discussed before. They are, however, not larger in absolute magnitude than those of the other cohort dummies and thus do not overrule the substantial conclusion about the benefit of entering early in the life cycle. The standard errors are overall similar in magnitude to showing the robustness of estimation precision to the allowance of unobserved heterogeneity. The variances of the random effects (not reported) are generally rather small and the effects themselves are not significant. This outcome of modest effects of accounting for unobserved heterogeneity is also reported in the survey of Manjón-Antolín and Arauzo-Carod (2008).[8]

In the final two columns we find the bias-corrected and robust Cox regression estimates. Besides minor exceptions the coefficient estimates are in the range of those computed by the other estimation methods. Here, the standard errors are among the lowest for the bias-corrected estimator while they are among the largest for the robust estimator. But even in the latter case, they are not nearly as large as would be required to overrule any previous findings of statistical significance. All conclusions drawn by CDK therefore also hold for these refinements of the Cox regression.

Model 4 examines the differences of the effect of pre-entry experience for the entry cohorts in more detail. Therefore, the regressor P is divided into four interaction terms of the cohort dummies and the dummy for pre-entry experience (now the dummy E_4 for the fourth entry cohort interacted with P is also included, of course). The corresponding results are collected in table 4. With our objective to assess the robustness of the results we first find again all coefficient estimates to be negative and all standard error to be much smaller than necessary to safely reject the null hypothesis of no influence of a particular variable. Thus, again both pre-entry experience and post-entry experience significantly reduce the exit hazard.

As regards coefficient magnitudes we are able to confirm the two essential results from this specification across all estimation methods. First, the coefficient estimates of the first two entry cohorts (E_1 and E_2) are throughout considerably larger in absolute magnitude than the coefficient estimates for the third entry cohort (E_3). In most cases we also have a larger absolute coefficient magnitude of E_1 compared to E_2. This reveals again the advantages from entering in the market early. Second, with minor exceptions the coefficient estimates of the interaction terms of the first and the fourth entry cohort dummies with the pre-entry experience dummy ($E_1 \cdot P$ and $E_4 \cdot P$) are considerably larger in absolute magnitude than the coefficient estimates of the interaction terms of the second and third entry cohort dummies with the pre-entry experience dummy ($E_2 \cdot P$ and $E_3 \cdot P$), thereby generating an $\cup$-shaped effect. Hence, we can again conclude that the substantial conclusions drawn by CDK from this specification are also robust to the different refinements of the Cox regression applied here.

[7] The interpretation is as outlined above. As an example, the coefficient estimate of P is -0.964, implying a reduction of the hazard rate to $e^{-0.964} \approx 0.38$, meaning a reduction of the hazard rate by 62 percent.

[8] See also Strotmann (2007).

Table 3: Robustness Assessment of Model 3

	original Cox regression	Cox boot	conditional log-log	conditional log-log boot	mixed ph (γ-frailty)	mixed ph (coxme)	mixed ph (phmm)	Cox bias corrected	robust Cox regression
E_1	-1.387	-1.365	-1.567	-1.679	-1.547	-1.520	-1.399	-1.225	-1.692
	(0.213)	(0.220)	(0.274)	(0.325)	(0.222)	(0.220)	(0.204)	(0.204)	(0.304)
E_2	-1.159	-1.144	-1.263	-1.311	-1.302	-1.278	-1.163	-1.013	-1.463
	(0.202)	(0.205)	(0.257)	(0.269)	(0.215)	(0.212)	(0.196)	(0.197)	(0.227)
E_3	-0.804	-0.793	-0.648	-0.653	-0.911	-0.892	-0.810	-0.677	-1.079
	(0.159)	(0.162)	(0.168)	(0.187)	(0.162)	(0.159)	(0.145)	(0.146)	(0.174)
P	-0.964	-0.952	-1.042	-1.011	-1.023	-1.017	-0.946	-0.852	-0.923
	(0.127)	(0.130)	(0.130)	(0.140)	(0.143)	(0.141)	(0.130)	(0.130)	(0.161)

Note: Standard errors are reported in parentheses below the coefficient estimates.

Table 4: Robustness Assessment of Model 4

	original Cox regression	Cox boot	conditional log-log	conditional log-log boot	mixed ph (γ-frailty)	mixed ph (coxme)	mixed ph (phmm)	Cox bias corrected	robust Cox regression
E_1	-1.264	-1.259	-1.304	-1.259	-1.270	-1.369	-1.291	-0.995	-1.551
	(0.292)	(0.316)	(0.410)	(0.316)	(0.331)	(0.357)	(0.330)	(0.327)	(0.401)
E_2	-1.263	-1.249	-1.238	-1.249	-1.268	-1.357	-1.270	-1.012	-1.427
	(0.311)	(0.329)	(0.388)	(0.329)	(0.318)	(0.338)	(0.317)	(0.315)	(0.350)
E_3	-0.963	-0.942	-0.694	-0.942	-0.967	-1.041	-0.976	-0.774	-1.132
	(0.212)	(0.219)	(0.221)	(0.219)	(0.202)	(0.219)	(0.202)	(0.202)	(0.242)
$E_1 \cdot P$	-1.244	-1.196	-1.364	-1.196	-1.247	-1.296	-1.215	-1.207	-1.117
	(0.300)	(0.328)	(0.355)	(0.328)	(0.358)	(0.381)	(0.358)	(0.353)	(0.489)
$E_2 \cdot P$	-0.924	-0.893	-1.051	-0.893	-0.927	-0.978	-0.907	-0.891	-0.979
	(0.322)	(0.345)	(0.351)	(0.345)	(0.346)	(0.365)	(0.345)	(0.343)	(0.373)
$E_3 \cdot P$	-0.780	-0.767	-0.947	-0.767	-0.782	-0.820	-0.756	-0.706	-0.826
	(0.171)	(0.175)	(0.196)	(0.175)	(0.195)	(0.208)	(0.195)	(0.195)	(0.224)
$E_4 \cdot P$	-1.106	-1.086	-1.046	-1.086	-1.109	-1.152	-1.096	-0.908	-0.945
	(0.253)	(0.260)	(0.220)	(0.260)	(0.214)	(0.230)	(0.213)	(0.213)	(0.245)

Note: Standard errors are reported in parentheses below the coefficient estimates.

5 Conclusions

The results reported above show that the various assumptions involved in the usually applied ordinary version of the Cox regression appear not to be critical for the results of the application of survival analysis in industry life cycle investigations of the sort considered here. This is demonstrated in the present paper for the case of the German automobile industry over the period 1886-1939 from its foundation until maturity. It can be expected that this finding holds for related samples, too, although this needs deeper investigation. The possible specification errors investigated here are the assumption of proportional hazards, the discrete measurement of the durations leading to excessively many ties, the neglection of unobserved heterogeneity of the firms and the existence of measurement errors and outliers in the data.

The robustness of the results found previously in a study of CDK is established by using various refinements of the Cox regression mainly developed in the biostatistics literature. All previous results concerning the benefits of early entry in the life cycle, providing more opportunities to accumulate experience after entry and of the existence of technological or business experience already before entry can be confirmed and in some cases even strengthened. Moreover, not only the qualitative pattern of the coefficient estimates regarding sign and significance can be confirmed, but we also observe remarkable stability of the coefficient estimates and their standard errors across the different estimation methods.

By that, our results reinforce the results of the empirical analyses of CDK for the German automobile industry and indirectly also those of related studies such as Klepper (2002) for the US automobile industry and other US industries. The findings are also in agreement with the predictions of the theoretical life cycle model of Klepper (1996) concerning the role of knowledge in different forms for shaping the characteristic pattern of firm survival.

Acknowledgment

I am grateful to Reinhard Hujer for in some way accidentally suggesting the topic of this paper. Therefore, it is particularly clear that he is not responsible for my interpretation and implementation of his comments in this paper.

References

[1] Abbring, J.H., van den Berg, G.J. (2007), The Unobserved Heterogeneity Distribution in Duration Analysis, Biometrika 94, 87–99.

[2] Agarwal, R., Audretsch, D.B. (2001), Does Entry Size Matter? The Impact of the Life Cycle and Technology on Firm Survival, Journal of Industrial Economics 49, 21-43.

[3] Agarwal, R., Gort, M. (2002), Firm and Product Life Cycles and Firm Survival, American Economic Review, Papers and Proceedings 92, 184-190.

[4] Audretsch, D.B., Mahmood, T. (1994), Firm Selection and Industry Evolution: The Post-Entry Performance of New Firms, Journal of Evolutionary Economics 4, 243-260.

[5] Audretsch, D.B., Mahmood, T. (1995), New Firm Survival: New Results Using a Hazard Function, Review of Economics and Statistics 77, 97-103.

[6] Beck, N., Katz, J.N., Tucker, R. (1998), Taking Time Seriously: Time-Series-Cross-Section Analysis with a Binary Dependent Variable, American Journal of Political Science 42, 1260-1288.

[7] Bednarski, T. (1993), Robust Estimation in Cox's Regression Model, Scandinavian Journal of Statistics 20, 213-225.

[8] Boschma, R.A., Wenting, R. (2007), The Spatial Evolution of the British Automobile Industry: Does Location Matter?, Industrial and Corporate Change 16, 213-238.

[9] Broström, G. (2002), Cox Regression; Ties without Tears, Communications in Statistics: Theory and Methods 31, 285-297.

[10] Broström, G., Lindkvist, M. (2008), Partial Partial Likelihood, Communications in Statistics: Simulation and Computation 37, 679-686.

[11] Buddelmeyer, H., Jensen, P.H., Webster, E. (2010), Innovation and the Determinants of Company Survival, Oxford Economic Papers 62, 261-285.

[12] Cantner, U., Dreßler, K., Krüger, J.J. (2006), Firm Survival in the German Automobile Industry, Empirica 33, 49-60.

[13] Cantner, U., Krüger, J.J., von Rhein, K. (2009), Knowledge and Creative Destruction over the Industry Life Cycle: The Case of the German Automobile Industry, Economica 76, 132-148.

[14] Cantner, U., Krüger, J.J., von Rhein, K. (2011), Knowledge Compensation in the German Automobile Industry, Applied Economics 43, 2941-2951.

[15] Chambers, J.M. (2008), Software for Data Analysis: Programming with R, New York: Springer.

[16] Cox, D.R. (1972), Regression Models and Life Tables, Journal of the Royal Statistical Society Series B 34, 187-220.

[17] Cox, D.R. (1975), Partial Likelihood, Biometrika 62, 269-276.

[18] Davison, A.C., Hinkley, D.V. (1997), Bootstrap Methods and their Application, Cambridge (Mass.): Cambridge University Press.

[19] Efron, B. (1977), Efficiency of Cox's Likelihood Function for Censored Data, Journal of the American Statistical Association 72, 557-565.

[20] Efron, B., Tibshirani, R.J. (1986), Bootstrap Methods for Standard Errors, Confidence Intervals, and other Measures of Statistical Accuracy, Statistical Science 1, 54-77.

[21] Firth, D. (1993), Bias Reduction of Maximum Likelihood Estimates, Biometrika 80, 27-38.

[22] Gort, M., Klepper, S. (1982), Time Paths in the Diffusion of Product Innovations, Economic Journal 92, 630-653.

[23] Grambsch, P.M., Therneau, T.M. (1994), Proportional Hazards Tests and Diagnostics Based on Weighted Residuals, Biometrika 81, 515-526.

[24] Heinze, G., Schemper, M. (2001), A Solution to the Problem of Monotone Likelihood in Cox Regression, Biometrics 57, 114-119.

[25] Hjort, N.L. (1992), On Inference in Parametric Survival Data Models, International Statistical Review 60, 355-387.

[26] Klepper, S. (1996), Entry, Exit, Growth, and Innovation over the Product Life Cycle, American Economic Review 86, 562-583.

[27] Klepper, S. (2002), Firm Survival and the Evolution of Oligopoly, Rand Journal of Economics 33, 37-61.

[28] Klepper, S., Graddy, E. (1990), The Evolution of New Industries and the Determinants of Market Structure, Rand Journal of Economics 21, 27-44.

[29] Krüger, J.J., von Rhein, K. (2009), Knowledge, Profitability and Exit of German Car Manufacturing Firms, Economics of Innovation and New Technology 18, 107-122.

[30] Lancaster, T. (1979), Econometric Methods for the Duration of Unemployment, Econometrica 47, 939-956.

[31] MacKinnon, J.G. (1992), Model Specification Tests and Artificial Regressions, Journal of Economic Literature 30, 102-146.

[32] Manjón-Antolín, M.C., Arauzo-Carod, J.-M. (2008), Firm Survival: Methods and Evidence, Empirica 35, 1-24.

[33] Minder, C.E., Bednarski, T. (1996), A Robust Method for Proportional Hazards Regression, Statistics in Medicine 15, 1033-1047.

[34] Prentice, R.L., Gloeckler, L.A. (1978), Regression Analysis of Grouped Survival Data with Applications to Breast Cancer Data, Biometrics 34, 57-67.

[35] Strotmann, H. (2007), Entrepreneurial Survival, Small Business Economics 28, 87-104.

[36] Therneau, T.M., Grambsch, P.M. (2000), Modeling Survival Data: Extending the Cox Model, New York: Springer.

[37] Therneau, T.M., Grambsch, P.M., Pankratz, V.S. (2003), Penalized Survival Models and Frailty, Journal of Computational and Graphical Statistics 12, 156-175.

[38] Vaida, F., Xu, R. (2000), Proportional Hazards Model with Random Effects, Statistics in Medicine 19, 3309-3324.

[39] van den Berg, G.J. (2001), Duration Models: Specification, Identification and Multiple Durations, in: J.J. Heckman, E. Leamer (eds.), Handbook of Econometrics, vol. 5, ch. 55, pp. 3381-3460.

[40] von Rhein, K. (2008), Heritage and Firm Survival: An Analysis of German Automobile Spinoffs 1886-1939, Economics Bulletin 12, 1-8.