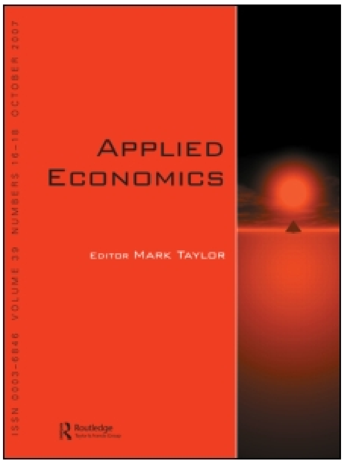

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Knowledge compensation in the German automobile industry

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Knowledge compensation in the German automobile industry

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In studies looking at firm survival over the industry life cycle knowledge is one of the most important determinants. Different kinds of knowledge, namely post-entry experience, pre-entry experience and knowledge acquired by innovative activity positively influence the survival chances. This article investigates how different kinds of knowledge are able to compensate each other. A statistical survival analysis is performed for the German automobile industry (1886–1939) which applies an estimation approach that links instrumental variables with the Cox regression. The results highlight that innovative activity is able to compensate for lacking post-entry experience, supporting Schumpeterian creative destruction.

I. Introduction

Knowledge is an important aspect of economic life, but has received only a crude treatment in economic analyses. This treatment frequently consists of the consideration of knowledge as an accumulable factor of production that contributes in the production function in addition to and just like labour, capital, materials, etc. by shifting the production function over time (Griliches, 1979). In the growth models of Romer (1990) and Aghion and Howitt (1992) microfoundations are provided that explain the aggregate effects of knowledge either by an increasing variety of intermediate products which are used to assemble the final product or by increasing the quality of these intermediate products.

In evolutionary economics knowledge acquired by agents in an cumulative process is conceived as incomplete. There are differences of the accumulated knowledge between the actors of an economy, so that they are heterogeneous. A detailed discussion of the role of knowledge in evolutionary economics can be found in Loasby (1999) who explored how the limitations of human knowledge create opportunities as well as problems in a modern economy. In general, knowledge can be divided in knowing that (knowledge of facts, relationships and theories) and knowing how (ability to perform appropriate actions to achieve a desired result). Loasby (1999) describes the evolution of knowledge as a path-dependent process in which the acquirement of new knowledge depends on the knowledge accumulated before. Furthermore, differences in knowledge arise from learning-by-doing in different activities as a result of the division of labour. In the following we restrict the notion knowledge to the knowing-how aspect.

In the present article we deal with this aspect of knowledge as a key determinant of firm survival in the German automobile industry. The life-cycle literature distinguishes between knowledge that is

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already available in the firm at the time of entry (pre-entry experience), the knowledge that is accumulated during the operation in the market since entry (post-entry experience) and the knowledge that is explicitly associated with innovative activities (innovative experience). In this article we build on the work of Klepper (1996, 2002a, b) who uses survival analyses for the investigation of the life cycle of various US industries, including the automobile industry. We use this approach and assess the role of knowledge over the life cycle of the German automobile industry during the period 1886–1939. Our earlier results reported in Cantner *et al.* (2006, 2009) show that each of the three types of knowledge has an independent effect on firm survival, even if all are included in the statistical analyses simultaneously.

To extend these results, the specific focus of this article is an investigation of whether and to which extent the three forms of know-how are able to compensate each other. In particular, we are interested in assessing whether an early entry in the industry which is associated with relatively more opportunities to accumulate post-entry experience is able to compensate for lacking pre-entry experience and likewise whether innovative experience since entry is able to compensate for lacking pre- or post-entry experience, respectively. Analyses of this type also appear in Klepper and Simons (2005) as part of their evaluation of the empirical validity of different theoretical explanations for industry shakeouts.

Following these introductory remarks we explain the three forms of compensation (pre-entry versus post-entry experience, pre-entry experience versus innovative experience and post-entry experience versus innovative experience) in Sections II–IV. A particularly illuminating interpretation in terms of Schumpeterian creative destruction is associated with the compensation of lacking post-entry experience as a result of late entry into the industry by innovative experience since entry. Section V concludes. Two appendices deal with the data sources, the definition of the variables and the solution to the simultaneity problem that arises in our econometric analysis.

II. Compensation I: Pre-entry Versus Post-entry Experience

Starting with the compensation of pre-entry and post-entry experience we divide the firms of our sample into four disjoint groups. It is assumed that pre-entry experience exists if a firm is either an experienced entrepreneur, a spinoff or a diversifying firm. Post-entry experience is assumed to be associated with the time of entry as quantified by the division of the firms into four entry cohorts. Firms that entered in the first (from 1886 to 1901) or second entry cohorts (from 1902 to 1906) are classified as early entrants and firms that entered in the third (from 1907 to 1922) or fourth cohorts (from 1923 to 1939) are classified as late entrants. Based on that we divide our sample of firms into the group of firms that entered early and are endowed with pre-entry experience (early experienced firms), the group of firms that entered late and are endowed with pre-entry experience (late experienced firms), the group of firms that entered early and are not endowed with pre-entry experience (early inexperienced firms) and finally, the group of firms that entered late and are not endowed with pre-entry experience (late inexperienced firms). Appendix A contains the relevant information about the data sources and the definition of the indicators for pre-entry and post-entry experience, as well as the indicator of innovative experience that will be required later.

This classification into early and late as well as experienced and inexperienced firms is typically used in a statistical survival analysis to assess the impact of the different knowledge types on the survival rate or the exit hazard of the firms. The methods applied there consist of the nonparametric Kaplan–Meier estimator of survivor curves (Kaplan and Meier, 1958) and the semiparametric Cox regression for the hazard rate (Cox, 1972). Both the methods are able to take account for the right censored nature of the data. Since space considerations prevent a detailed discussion of these methods, we refer the interested reader to Kiefer (1988) or Lancaster (1990) for more general treatments of methods for survival analysis and references to economic applications.

For the case of pre-entry versus post-entry experience Fig. 1 depicts the survivor curves estimated by the Kaplan–Meier estimator on a logarithmic scale. In this exercise firms in the first two entry cohorts are considered as early entrants, whereas firms in the last two entry cohorts are considered as late entrants. As can be easily discerned from the figure, early experienced firms have the best survival chances since their survival curve is the flattest and is thus associated with the smallest hazard rate. Analogously, late inexperienced firms have the worst survival chances and the largest hazard rates. Most interesting is the comparison of the early inexperienced with the late experienced firms. The associated survivor curves suggest that late experienced firms have a smaller exit hazard than the early inexperienced firms. This implies that the existence of pre-entry experience is able to compensate for the disadvantages accruing from late entry into the market. The two survivor curves are not significantly different in a statistical sense, however, in contrast to the visual impression. Applying the family of tests described in Harrington and Fleming (1982), i.e. the variant associated with setting the parameter ρ equal to zero, gives a p-value of about 0.34 in that case. In contrast, all other survivor curves are indeed significantly different from each other with very low p-values.

More exact statements about the compensation of pre-entry and post-entry experience can be gained from an application of the Cox regression. The hazard rate of firm i out of a sample of n firms that survives for at least t_i years

$$h(t_i) = h_0(t_i) \cdot \exp(\mathbf{x}_i\boldsymbol{\beta}), \quad i = 1, \ldots, n$$

can be divided into the baseline hazard rate $h_0(t_i)$ depending exclusively on the duration of survival and a second part depending on the values of the explanatory variables for firm i, contained in the row vector $\mathbf{x}_i$, mediated by the exponential function. The method of partial maximum likelihood estimation allows to estimate the parameters in the vector $\boldsymbol{\beta}$ without requiring to estimate the baseline hazard rate which gives the whole procedure a distinct semiparametric flavour (see again Kiefer (1988) or Lancaster (1990) for the details).

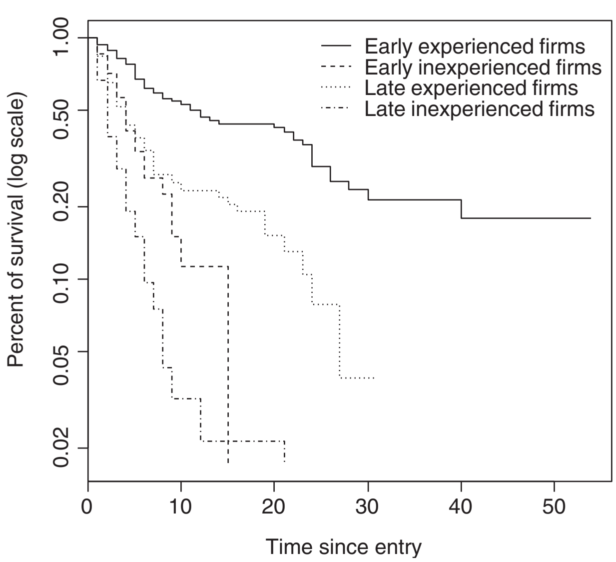

Fig. 1. Kaplan–Meier estimates for pre-entry versus post-entry experience

In the present case the vector $\mathbf{x}_i$ contains the three dummy variables indicating the affiliation to the groups of the early experienced, late experienced and late inexperienced firms, respectively. Since the four group classification of the firms is exhaustive, one category has to be omitted from the regressions. Here, this omitted category is the group of the early inexperienced firms so that the parameter estimates represent the differences of the hazard rates of the other groups relative to that reference group. All three possibilities to divide the firms in the four entry cohorts into early and late entrants are explored and the results for the Cox regressions are shown in the columns of Table 1. Accordingly, in model (A) the firms are divided between the first and the second entry cohorts, so that the firms of the first cohort are considered as the early entrants and the firms of the second, third and fourth cohorts are considered as the late entrants. Analogously, in model (B) the division is between the second and the third entry cohorts (as in Fig. 1) and in model (C) it is between the third and the fourth entry cohorts.

Considering the first two rows of the table which show the parameter estimates for the experienced firms, we observe that all parameter estimates have a negative sign. The parameter estimates for the group of early experienced firms are largest in absolute magnitude and statistically different from zero (as is evident from the p-values in parentheses). This implies that the early experienced firms have the lowest exit

Table 1. Cox regressions for pre-entry versus post-entry experience

	Model (A)	Model (B)	Model (C)
	Cohort 1 versus Cohorts 2–4	Cohorts 1 and 2 versus Cohorts 3 and 4	Cohorts 1–3 versus Cohort 4
(1) Early experienced firms	−1.163 (0.000)	−1.044 (0.000)	−0.999 (0.000)
(2) Late experienced firms	−0.385 (0.087)	−0.211 (0.280)	−0.041 (0.840)
(3) Late inexperienced firms	0.501 (0.029)	0.603 (0.001)	1.055 (0.000)
R^2	0.202	0.234	0.278
n	333	333	333
t-statistic for (1) − (2)	−3.570 (0.000)	−4.716 (0.000)	−4.544 (0.000)
t-statistic for (2) − (3)	−6.772 (0.000)	−5.644 (0.000)	−4.375 (0.000)

Note: p-values are given in parentheses.

hazards of all groups. This finding holds irrespective of where the division into early and late entrants has been implemented. Opposed to that, all parameter estimates for the late inexperienced firms are consistently positive and significantly different from zero (on 5% level or lower), implying the highest exit hazards and the worst survival chances for the firms in this group.

For the group of late experienced firms the reduction of the hazard rate that is associated with negative parameter estimates which are, however, only significant on a 10% level in the case of model (A). Accepting this higher error probability, one can state that the firms with pre-entry experience that entered late into the market are faced with a lower exit risk compared to the firms of the reference group that entered early but were not endowed with pre-entry experience if earliness means membership in the first entry cohort. In this case pre-entry experience is able to compensate for the disadvantages of late entry. Unfortunately, this form of compensation is only weakly supported by the data because it is found only in the case of model (A) and there only at a 10% level of significance, but not in the cases of models (B) and (C).

Further results reported in the table concern the differences of the exit hazards within the group of experienced firms (comparing the parameter estimates in rows (1) and (2)) and within the group of late entrants (comparing the parameter estimates in rows (2) and (3)). The associated results for the *t*-statistics of the differences of the parameter estimates show that the parameter estimates are significantly different with essentially zero *p*-values. This confirms our findings in Cantner *et al.* (2006) that pre-entry experience and post-entry experience play their own role in reducing the exit hazard. Related findings are reported in Klepper (2002a) for the US automobile industry. The overall fit of the regressions can be judged from the row R^2 and appears to be quite reasonable in all the three regressions.

III. Compensation II: Pre-entry Experience Versus Innovative Experience

We now turn to the investigation of the relation of the pre-entry experience and innovative experience. Innovative experience is assumed to be associated with patenting (see, e.g. Griliches, 1990). Specifically, innovative experience is quantified by a dummy variable that is equal to unity if a firm got granted at least one patent since it entered the automobile industry. Combining this variable with information about pre-entry experience we can again divide the firms of our sample into four exhaustive groups. We distinguish firms that are endowed with pre-entry experience and have been innovative since market entry (experienced innovators), firms that are not endowed with pre-entry experience and have been innovative since market entry (inexperienced innovators), firms that are endowed with pre-entry experience but have not been innovative since market entry (experienced noninnovators) and finally firms that are not endowed with pre-entry experience and have not been innovative since market entry (inexperienced noninnovators).

The graphical analysis of the survival chances of these four groups is shown in Fig. 2. The survivor curves are again estimated by the Kaplan–Meier estimator. The figure clearly shows that the experienced innovators have by far the best survival chances, whereas the inexperienced noninnovators have the highest exit hazards. The survivor curves of the inexperienced innovators and the experienced noninnovators are rather close and the test of Harrington and Fleming (1982) does not reject the equality of these two survivor curves. Besides this exception all other survivor curves are statistically significantly different from each other.

The inference based on the Kaplan–Meier estimates may, however, be flawed since the assessment of the effect of a firm's innovative experience since entry on its hazard rate and therefore on its duration of survival may be associated with a simultaneity problem. The reason is that the longer the duration of survival of a firm, the higher is the probability of receiving at least one patent grant (and the higher

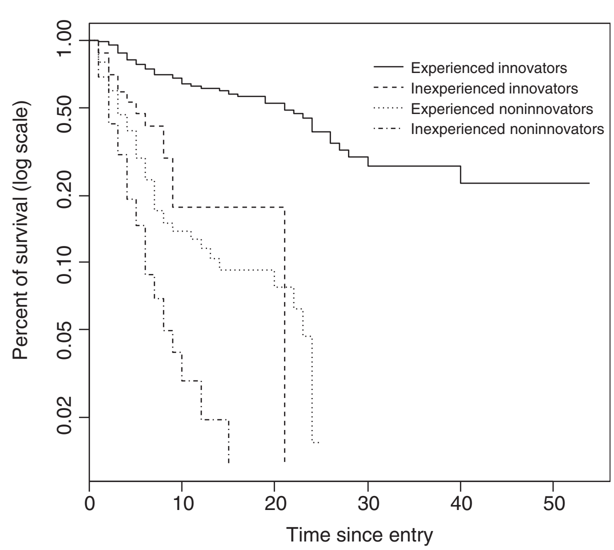

Fig. 2. Kaplan–Meier estimates for pre-entry experience versus innovative experience

is also the expected number of patents granted). Thus, the patent variable is likely to be jointly determined with the duration. This implies that using any information contained in the patent data that refers to the period in which a firm actually operates possibly leads to inconsistent coefficient estimates. In econometrics, methods of instrumental variables estimation (also referred to as two-stage least squares) have been developed in order to achieve consistent estimates in such situations. To solve the simultaneity problem we combine the idea of instrumental variables estimation with the Cox regression and apply the bootstrap for computing correct SEs (see Appendix B for a detailed description of the approach taken).

For the instrumental variable estimates of the Cox regression reported in Table 2 (model (D)) the set of instruments consists of variables that are fixed at the time of entry and can therefore not be affected by the subsequent events. In particular, as instruments used are the dummy variables for the first three entry cohorts, the dummy variables for the type of pre-entry experience, a dummy variable indicating innovative experience prior to market entry (equal to unity if patents are granted to the founder before the firm enters the automobile industry), the number of patents granted before market entry and its square as well as several interactions of the patent variables with the cohort dummies and the dummies for the type of pre-entry experience.

The results show that the parameter estimates for both groups of innovators are negative, irrespective of their pre-entry experience. Although the estimates are only in the case of the experienced innovators statistically significant on 5% level, the magnitude of both parameter estimates is quite similar. Thus, with respect to the omitted reference group of the experienced noninnovators, innovating firms generally tend to have systematically better survival chances. This further supports our findings reported in Cantner *et al.* (2009). As expected, the inexperienced noninnovators are faced with the highest exit hazard, even higher than that of the reference group and statistically significant on 5% level.

Table 2. Cox regression for pre-entry experience versus innovative experience

	Model (D)
(1) Experienced innovators	−1.763 (0.000)
(2) Inexperienced innovators	−1.645 (0.104)
(3) Inexperienced noninnovators	0.575 (0.027)
R^2	0.226
n	333
t-statistic for (1) − (2)	0.117 (0.906)
t-statistic for (2) − (3)	−2.022 (0.043)

Note: The p-values are given parentheses which are based on bootstrapped SEs as explained in Appendix B.

Based on these estimates we have to be a bit cautious with our conclusions regarding the compensation of pre-entry experience by innovative experience. The parameter that is associated with the dummy variable for the inexperienced innovators and that reflects the difference of the hazard rate to the experienced noninnovators has a p-value slightly above 0.1. Given that this parameter estimate is indeed negative, this would imply that inexperienced innovators have a lower exit hazard than experienced noninnovators. In that case, the disadvantages accruing from lacking experience before market entry can be compensated by innovative experience since the time of entry.

In addition to these results the differences within the group of innovating firms (comparing (1) and (2)) and the differences within the group of inexperienced firms (comparing (2) and (3)) are also tested. The reported t-statistics show that the differences within the group of innovating firms are not statistically significant on conventional levels, but the differences within the group of inexperienced firms are. Thus, for innovating firms the existence of experience before market entry or the lack of that form of knowledge does not make a difference for their exit hazards. This may be explained to some extent by the depreciation of pre-entry experience (analogous to Carroll *et al.* (1996)) and further supports the assertion that innovative experience can compensate lacking pre-entry experience. In contrast, for the inexperienced firms it is very important to be innovative for achieving improvements of their survival chances.

IV. Compensation III: Post-entry Experience Versus Innovative Experience

The final compensation relationship we want to investigate is that between the post-entry experience and the innovative experience since market entry. Therefore, we again construct four groups of firms: firms that entered early and were innovative since entry (early innovators), firms that entered late and were innovative since entry (late innovators), firms that entered early but were not innovative since entry (early noninnovators) and finally firms that entered late and were not innovative since entry (late noninnovators). Again, all three different possibilities to define early and late entry provided by the four cohorts are explored, see Section II.

Figure 3 shows the Kaplan–Meier estimates of the survivor curves for all four groups, where again the firms in the first two entry cohorts are treated as early entrants and the firms in the last two entry cohorts are treated as late entrants. This figure provides a clear ranking of the four groups with respect to the survival chances of their member firms. The early innovators have the best survival chances, followed by the late innovators. Compared to that, noninnovating firms have larger exit hazards, with the early noninnovators being more successful than the late noninnovators. Application of the Harrington–Fleming test shows that the differences between all the four survivor curves are statistically significant with very low p-values (all below 0.0025).

Especially the statistically significant difference between the survivor curves of the late innovators and the early noninnovators opens up a very appealing economic interpretation. This difference shows that firms that are faced with the disadvantage of being late in the market but are innovative once entered have better survival chances than firms that have the advantage of entering early but are not innovative since their entry. Thus, the disadvantages of late entry can be compensated by innovative experience which implies that young innovative firms tend to replace old, but noninnovative, firms. This pattern resembles exactly the process that Schumpeter (1942) had in mind when he coined the notion of 'creative destruction', which he described as revolutionizing 'the economic structure *from within*, incessantly destroying the old one, incessantly creating a new one' (Schumpeter, 1942, p. 83; emphasis in the original).

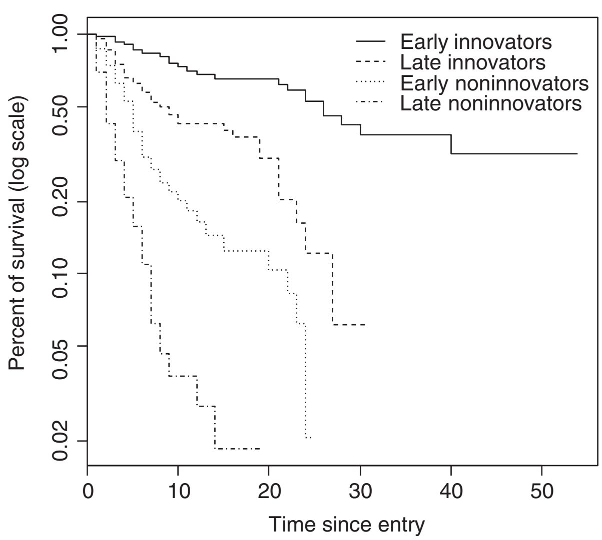

Fig. 3. Kaplan–Meier estimates for post-entry experience versus innovative experience

A possible source of bias that may render the Kaplan–Meier estimates erroneous is the simultaneity problem already discussed in the previous section. To safeguard against this possibility, we again apply the instrumental variable Cox regression to this form of compensation. The set of instrumental variables is the same as that used in the previous section. Table 3 shows the corresponding results for three regressions with the three alternative divisions of the firms into early and late entrants. In model (E) only the firms of the first entry cohort are considered as early entrants, whereas in model (F) the firms of the first two cohorts and in model (G) the firms of the first three cohorts are considered as early entrants. It is important to note first that all parameter estimates are significantly different from zero, the sole exception being the parameter estimate pertaining to the late noninnovators in model (E). Recall that the parameter estimates in rows (1), (2) and (3) of Table 3 again represent the deviations from the hazard rate of the omitted reference group of the early noninnovators.

Table 3. Cox regressions for post-entry experience versus innovative experience

	Model (E)	Model (F)	Model (G)
	Cohort 1 versus Cohorts 2–4	Cohorts 1 and 2 versus Cohorts 3 and 4	Cohorts 1–3 versus Cohort 4
(1) Early innovators	−2.224 (0.002)	−1.956 (0.001)	−2.170 (0.000)
(2) Late innovators	−2.197 (0.000)	−1.588 (0.000)	−1.547 (0.004)
(3) Late noninnovators	0.333 (0.399)	0.739 (0.008)	0.760 (0.000)
R^2	0.206	0.250	0.264
n	333	333	333
t-statistic for (1) − (2)	−0.051 (0.959)	−0.730 (0.465)	−1.082 (0.279)
t-statistic for (2) − (3)	−4.891 (0.000)	−4.965 (0.000)	−3.743 (0.000)

Note: The p-values given in parentheses are based on bootstrapped SEs as explained in Appendix B.

The results confirm that innovating firms have consistently lower exit hazards than noninnovating firms, irrespective of their time of entry. Among the noninnovating firms, those classified as late noninnovators have higher exit hazards than the reference group of the early noninnovators (this finding, however, is not significant in the case of model (E)). Late innovators have substantially better survival chances compared to late noninnovators, as the respective t-statistics for the coefficient difference $(2)-(3)$ show. The hazard rates the early innovators are slightly lower than that of the late innovators, but this difference is not statistically significant as the respective t-statistics for $(1)-(2)$ show. These findings parallel the analogous results of Klepper and Simons (2005, Table 4) for the US automobile industry regarding sign as well as significance and actually roughly resemble the magnitude of the parameter estimates.

Most important is the significantly negative parameter estimate for the late innovators showing that firms that entered late but are innovative afterwards are faced with lower exit hazards compared to the reference group of the early noninnovators. The finding that innovative experience is able to compensate for the disadvantages of late entry supports the conclusions from the Kaplan–Meier estimates. Moreover, this compensation consistently holds across all definitions of late and early entrants with respect to statistical significance and is also of considerable magnitude. The hazard rate of late innovators is about 78 to 89% lower than that of the early noninnovators. All this strongly suggests that the force of Schumpeterian creative destruction appears to be a very robust and quantitatively important finding in the German automobile industry.

V. Summary and Conclusion

Summarizing the findings, it can be concluded that firms with pre-entry experience tend to be better off than inexperienced firms, that early entrants tend to be better off than late entrants and that innovative firms (with at least one patent since entry) tend to be better off than noninnovative firms, always expressed in terms of survival chances. Moreover, each of the three knowledge components has a separate effect on the exit hazard as found by Cantner *et al*. (2009). This article adds value to the detailed examination of the possibility that one knowledge component dominates another knowledge component in that it is able to compensate for the lack of the other knowledge component, again expressed in terms of survival chances. These results are not restricted to the German automobile industry; the already mentioned article of Klepper and Simons (2005) reports similar results for several US industries.

Regarding this compensation issue the results give a rather weak indication for the compensation of post-entry knowledge by pre-entry knowledge, a marginally significant indication of compensation of pre-entry knowledge by innovative experience and a strongly significant indication of compensation of post-entry knowledge by innovative experience. Thus, the relation of the three knowledge components satisfies transitivity with innovative knowledge weakly dominating pre-entry knowledge and pre-entry knowledge weakly dominating post-entry knowledge. Furthermore, the results reported above establish that knowledge accumulated by innovative experience is able to compensate for lacking pre-entry and post-entry experience. This gives rise to the conclusion that knowledge accumulated by innovative experience is the most important type of knowledge for long-run firm survival.

This finding is so important because the decision to innovate can be made by the firm itself, whereas pre-entry experience and time of entry are fixed once a firm enters the market. So firms are able to improve their survival chances by engaging in innovative activity, but they cannot influence their pre-entry experience or their time of entry. Thus, the survival chances of firms are not fixed at the time of entry because of their founding characteristics, instead they can be actively influenced by their decision about innovative activity. This is another lesson taught by Schumpeter and his successors.

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Appendix A: Data Sources and Variable Definitions

The basis of the statistical analyses performed in this article is a data set of German firms which produced automobiles during the period 1886 to 1939,[1] their experience before they entered into the market and the patents they hold. The data set is the same as used in Cantner *et al*. (2009). We have collected data only for automobile manufacturing firms, excluding their suppliers and trucks producers. The data we gathered pertain to the year of entry (start of the automobile production) and the year of exit (due to the stop of the automobile production and mergers or acquisitions). Relevant for the survival analysis is the number of years a firm was actually producing automobiles and not the number of years in which the firm merely existed. We further collected data regarding the type of entry (explained below).

The data are assembled from a multitude of different sources, such as yearbooks, historical and statistical journals and books about veteran cars. The most important sources are Doyle and Georgano (1963), Flik (2001), Köhler (1966), Kubisch (1983), Oswald (1996), Schrader (2002), von Fersen (1967, 1968) and von Seherr-Thoss (1979). From these sources we identified 441 firms that produced automobiles at some time during 1886 to 1939. The data are censored at 1939 after which the German economy became increasingly regulated and adapted to war production. As in Köhler (1966) we assign 1915 as the year of exit to those firms that exit the market

[1] The history of the German automobile industry started in 1886 with the inventions of Gottlieb Daimler and Karl Benz, who worked independent of each other.

as a cause of World War I. The peak of the number of firms is reached in 1924 with 139 firms. Thereafter, the German automobile industry experienced the typical shakeout and the number of firms declined to 26 by the year 1939.

(1) Pre-entry experience

The classification of the type of entry is implemented according to Klepper (2002b). He distinguishes experienced firms (firms that diversify into the production of automobiles originating from other industries), experienced entrepreneurs (de novo firms whose founder headed and typically owned a part of another firm before), spinoffs (de novo firms whose founder worked in the automobile industry before) and inexperienced firms. Firms that produced automobiles, were forced to exit and later on produced automobiles again are treated as different firms and are classified as spinoffs when they enter the market for the second time.

(2) Post-entry experience

The classification of the entry cohorts is based on Klepper (2002a). He defines the cohorts so that there are at least 15 firms in each cohort which survived for at least 15 years. This procedure results in four entry cohorts, the first with 56 firms ranging from 1886 to 1901, the second with 52 firms from 1902 to 1906, the third with 126 firms from 1907 to 1922 and the fourth with 115 firms from 1923 to 1939. In the fourth cohort there are 11 firms that survived for at least 15 years. Together with the information about the pre-entry experience, a total of 333 observations is available for the survival analysis.

(3) Innovative experience

The data about a firm's innovative experience are based on the patent grants of these firms. The search procedure is described in detail by Cantner *et al.* (2009). Since this procedure is based on the patent documents it is evident that patent grants are used, but recorded in the data set is the year of the application. The reason is that although there is a time lag between the application and the grant (see Griliches, 1990), the knowledge represented by the innovation is available for the firm at least since the date of application. Some patents were applied together by two or more automobile firms. These patents were assigned to all the applying firms, justified by the argument of Romer (1990) that the firms can use the associated know-how simultaneously. In the case of mergers and acquisitions, the patents of the merged (respectively acquired) firms were assigned to the new firm. As an example, after the merger of Wanderer, DKW, Horch and Audi to Auto-Union in 1932 (recorded in the data set as DKW), all patents that were applied for by Wanderer, Horch or Audi were assigned to DKW as the continuing firm.

All the results reported in this article are based on the sample of the 333 firms for which all required data are available. Mergers and acquisitions are treated as in Klepper (2002a, p. 42). In the cases of mergers the firm with the same name as the new group or the largest firm (if the new group has a new name) is treated as continuing, the others are treated as censored exits. In the case of acquisitions, the absorbing firm is treated as continuing if it produces automobiles and the acquired firm is treated as a censored exit. If the absorbing firm does not produce automobiles, the acquired firm is treated as continuing.

Appendix B: Cox Regression with Instrumental Variables

Our estimation methodology relies on three basic building blocks. It combines (1) the idea of Generalized Instrumental Variables Estimation (GIVE) with (2) the semiparametric Cox regression. Since the SEs (and therefore t-statistics and p-values) of the regression coefficients obtained from this procedure does not adequately reflect the additional estimation uncertainty that is introduced by the construction of the instrumental variables, corrected SEs are computed by (3) the design matrix variant of the bootstrap.

(1) Instrumental variables

In this procedure the endogenous regressors are projected on to the space spanned by the exogenous regressors and the instruments in the first step, which are chosen to assure their uncorrelatedness with the error terms. Considered as instrumental variables are only those variables that represent characteristics of the firms which are fixed once and for all before their entry into the automobile industry. The idea is that such predetermined variables represent information that may have an effect on the duration of survival but are by construction not affected by the duration themselves. Among the data series available, the cohort dummies, the classification of pre-entry experience and the number of patent grants before the recorded time of entry are valid candidates for instrumental variables.

Let n denote the sample size and k the number of explanatory regressors on the right hand side of the regression equation and define $\mathbf{X}$ as the $n \times k$ matrix of all (exogenous and endogenous) regressors and $\mathbf{W}$ as the $n \times l$ matrix (with $l \geq k$) containing both exogenous regressors and instruments. Both matrices are assumed to contain a column of ones representing the intercept. Then the linear projection of $\mathbf{X}$ on to $\mathbf{W}$ is equivalent to the matrix operation $\hat{\mathbf{X}} = \mathbf{W}(\mathbf{W}'\mathbf{W})^{-1}\mathbf{W}'\mathbf{X}$ where the prime denotes matrix transposition. This amounts to the calculation of the fitted values of a linear regression of the columns of $\mathbf{X}$ on $\mathbf{W}$. Accordingly, since the exogenous regressors are contained in $\mathbf{W}$ this operation does not affect the columns of the exogenous regressors but expresses the endogenous regressors as optimal (in the least squares sense) linear combinations of the variables in $\mathbf{W}$. Since all variables in $\mathbf{W}$ are predetermined by assumption, the variables in the resulting matrix $\hat{\mathbf{X}}$ are exogenous as well by the properties of orthogonal projections (see Davidson and MacKinnon (2003, pp. 57ff.) for more details on the geometry of orthogonal projections). The matrix $\mathbf{X}$ of the original regressors is subsequently replaced by $\hat{\mathbf{X}}$ in the estimation of the Cox regression in the second step.

(2) Cox regression

In this second step the semiparametric Cox regression (Cox, 1972) is executed in order to estimate the parameters $\boldsymbol{\beta}$ of the hazard rate

$$h(t_i) = h_0(t_i) \cdot \exp(\hat{\mathbf{x}}_i \boldsymbol{\beta})$$

specified in proportional hazards form, where $h_0(t_i)$ denotes the baseline hazard rate that exclusively depends on the duration of firm i, t_i, and $\hat{\mathbf{x}}_i$ denotes the i-th row of $\hat{\mathbf{X}}$, $i = 1, \ldots, n$. The parameters are estimated by maximizing the so-called partial likelihood function, which allows us to estimate $\boldsymbol{\beta}$ independent of the specific functional form of the baseline hazard rate, simultaneously accounting for the effects of censoring. In practice, numerical and tractability considerations lead to the maximization of the partial likelihood function. The ability of the Cox regression to estimate $\boldsymbol{\beta}$ without requiring the specification of the functional form of the baseline hazard rate underscores the semiparametric character of the procedure. The resulting estimate is denoted by $\hat{\boldsymbol{\beta}}$. A brief and illuminating exposition of the reasoning underlying the partial likelihood estimation is given by Kiefer (1988).[2]

(3) Design matrix bootstrap

The preceding two steps of our approach will produce consistent estimates of the parameters, but the raw combination of these two methods will result in flawed statistical inference since the regressors used are generated by the projection operation in the first step. To obtain SEs that are corrected for these biases, the design matrix variant of the bootstrap (alternatively called bootstrapping cases or bootstrapping pairs) is used (see Davison and Hinkley (1997) for a general reference on bootstrapping). According to Davison and Hinkley (1997, p. 87) this procedure is also justified in the present case of censored data if the censoring information is included in the process of repeated sample drawing.

The p-values that are reported jointly with the coefficient estimates of the instrumental variables variant of the Cox regression are throughout computed with the aid of the design matrix bootstrap. This approach usually performs well even if some forms of heteroskedasticity are present. The design matrix bootstrap is based on randomly drawn samples (with replacement), each of size n from the rows of the original data $(\mathbf{y}, \mathbf{d}, \mathbf{X}, \mathbf{W})$, where $\mathbf{y}$ contains the duration data, i.e. $\mathbf{y} = (t_1, \ldots, t_n)'$. Note that the data also include the instrumental variables as well as the censoring information in the $n \times 1$ dummy vector $\mathbf{d}$. The resulting bootstrap samples are denoted by $(\mathbf{y}^*, \mathbf{d}^*, \mathbf{X}^*, \mathbf{W}^*)$. Repeating this procedure B times and conducting the first two steps for each bootstrap sample results in B different bootstrap estimates for the Cox regression coefficients, denoted by $\hat{\boldsymbol{\beta}}_1^*, \ldots, \hat{\boldsymbol{\beta}}_B^*$. From these the bootstrap estimate of the covariance matrix of the coefficients is computed by

$$\hat{\mathbf{V}}^* = (B-1)^{-1} \cdot \sum\nolimits_{b=1}^{B} (\hat{\boldsymbol{\beta}}_b^* - \bar{\boldsymbol{\beta}}^*)(\hat{\boldsymbol{\beta}}_b^* - \bar{\boldsymbol{\beta}}^*)',$$

where $\bar{\boldsymbol{\beta}}^* = B^{-1} \cdot \Sigma_{b=1}^{B} \hat{\boldsymbol{\beta}}_b^*$. The p-values for the null hypothesis H_0: $\beta_j = 0$ for the j-th coefficient is then based on the t-statistic $\tau_j = \hat{\boldsymbol{\beta}}_j \cdot (\hat{v}_{jj}^*)^{-1/2}$ which is distributed as standard normal asymptotically. In this

[2] A further problem may be suspected in the application of the linear projections of the first stage to dummy variables since the result of the projection operation is unlikely to be a dummy variable itself. However, results reported in Angrist (2001) justify our procedure. Even more forcefully Angrist and Krueger (2001, p. 80) argue that 'using a linear regression for the first-stage estimates generates consistent second-stage estimates even with a dummy endogenous variable. Moreover, using a nonlinear first stage to generate fitted values that are plugged directly into the second-stage equation does not generate consistent estimates unless the nonlinear model happens to be exactly right, a result which makes the dangers of misspecification high'.

formula $\hat{v}^*_{jj}$ denotes the j-th diagonal element of the bootstrap covariance matrix $\hat{\mathbf{V}}^*$ and is thus a correct estimate for the variance of the j-th regression coefficient, $j \in \{1, \ldots, k\}$. Since the test is two-tailed, the p-values can be explicitly computed by $\hat{p}_j = 2(1 - \Phi(|\tau_j|))$, where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function.

All p-values that are reported in this article are based on $B = 1000$ bootstrap replications. This is much more than actually necessary to satisfy the rule of thumb recommending that 'seldom are more than $B = 200$ replications needed for estimating a standard error' (Efron and Tibshirani, 1993, p. 52).