A General Test of the Industry Life Cycle – Evidence from Germany

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1. Introduction

The concept of industry life-cycles and the underlying theoretical framework are well established in the economic literature. As a simplifying generalisation the ILC has proven to be helpful for describing the evolution of industries from birth to maturity. A number of empirical studies of different industries and cases have adapted the ILC framework to explain industry evolution along several indicators (e.g., Bünstorf and Klepper 2009 (tires), Boschma and Wenting 2008, Cantner et al. 2004, Klepper 2002 (automobiles), and Stürz 2014 (piano industry)). Relative to this body of literature, however, the number of empirical work focussing on assessing the general validity and statistical properties of the ILC concept is underdeveloped. The industry life-cycle focusses on empirically rather intangible discrete stages, which complicates empirical tests of this simplifying concept. This paper follows a different approach by empirically exploring the statistical properties and potentially hidden regularities of various aspects in the context of industry life cycles.

First, we interpret the concept of the life cycle literally and develop a regression framework to test whether a broad set of industry level variables across a large set of industries actually follows a cyclical path. We are not aware of any other study that has attempted to explicitly test for this core feature of the ILC concept to date. Using this approach we are able to show for a given observation period how industries differ in their stage in the life-cycle as well as the speed of their development.

Second, we follow the classical approach of ILC analyses insofar as we also attempt to uncover serial correlations in the co-evolution of different industry level indicators, such as employment, qualification, innovation, and firm population. Especially we examine whether there are temporal relationships between the various aspects that are common for all or certain groups of industries.

Our empirical analysis exploits a rich industry level data set for (West-) Germany, covering industry evolution for 205 industries between the years 1975 and 2010. This period covers major technological changes, several major recessions and as a result of both also the rise and fall of major industries in Germany.

The core data set was derived from linked employer data of the Institute for Employment Research (IAB). We used micro data to compute a rich set of variables describing structural properties of German industries such as workforce composition, R&D intensity, entries and exits

as well as the industrial concentration across German regions during the analysed period. This data set was complemented with patent indicators computed from the Patstat database of the European Patent Office. Industry and patent data were matched using a novel industry-technology correspondence matrix. Several features such as the coverage of our data comprising also services and besides manufacturing industries, the long observation period and the possibility to combine industry and patent indicators, make our data set perfectly suited for the purpose of our empirical analysis.

We apply multivariate regression analyses to each industry separately in order to detect the cyclical pattern of the development of each variable and the temporal relationships between the variables. Indeed, we find that most variables follow in most industries a path that is well represented by a part of a cycle.

Furthermore, we find clear relationships between the variables, although some relationships differ strongly between industries, while other relationships are more universal across a larger set of industries.

The remainder of the paper is structured as follows: section two briefly reviews the related literature. Section three introduces the empirical approach and presents our database. This presentation is complemented with a set of descriptive statistics and an outline of our empirical methodology. In section four we present and discuss the results from the multivariate analyses. The final section concludes.

2. Related Literature

There is an extensive literature on the industry life cycle (ILC) that provides a stylized description of the evolution of an industry from its infancy to maturity (Gort and Klepper 1982, Klepper 1997). The concept of the ILC has its origin in the seminal work on product life cycles by Vernon (1966) and was later refined to a comprehensive theoretical framework about industries which are interpreted as some sort of product market (Utterback and Suarez 1993, Klepper 1996). A number of indicators such as market structure, firm dynamics, output, sales and innovation have been used by a number of now classical empirical studies to test the framework across a set of different industries and to elaborate on characteristics of the distinct life cycle stages.

Generally speaking, the young phase of a life cycle is characterized by a small number of firms

that produce non-standardized products, competition on product characteristics, many unexplored technological opportunities, high innovation dynamics and tapping of information from a wide range of industries for knowledge recombination (Gort and Klepper 1982). The spatial configuration of industries in these early stages favors urbanization economies which tend to be prevalent particularly in urban areas with a diversified pool of knowledge, knowledge dynamics and institutions that are supportive to a rather entrepreneurial or experimental industry (Neffke et al. 2011).

In more mature stages, a dominant product design has established and products become more homogeneous. Production has advanced from small batch series to standardized mass production exploiting economies of scale (Utterback and Suarez 1993). Firms in mature industries compete on prices, rather than on product features, and the focus of innovation has shifted from product to process innovations. Instead of knowledge recombination across different domains, access to specialized, industry-specific knowledge becomes more important. Industries therefore prefer a local environment that is tailored to their specific needs. The spatial structure of mature industries therefore favors agglomerations to exploit localization economies which enable firms in mature industries to benefit from labour market pooling effects, shared infrastructure or specialized institutions (Neffke et al. 2011). Besides this stylized description of the ILC[1], we review the literature on some variables and relationships that are of particular interest for our paper:

Industry structure

One of the most heavily studied aspects related to the ILC is the organisational structure of an industry. Usually industry structure is measured in the number of firms, which itself is closely linked to entries and exits of firms. Another aspect that has been raised in the ILC literature is the evolution of the firm size distribution within an industry and whether this distribution follows any statistical regularity. Attention on these indicators is well-deserved, because they are tied to the distribution of productivity, the heterogeneity of production technology, and the degree and type of competition within an industry.

A core finding of the ILC literature is that the numbers of firms comprising an industry evolves along a non-monotonic path (Agrawal 1998, Klepper and Simons 2000). The number of firms

[1] For a more comprehensive survey on industry life cycles see Klepper (1997).

increases rapidly from the birth of an industry until reaching a peak. Towards maturity, the number of firms declines through a phase of shakeout, before it continues to evolve at a rather stable level. This evolution in the number of firms is accompanied by an increasing level of output, whereas prices steadily reduce. This general finding is accompanied by a substantial shift in the firm size distribution of industries. Models of evolutionary change focus on technological change and interpret the implementation of new technologies in the production process as the main determinant for firm dynamics in terms of entries, exits and growth (Jovanovic and MacDonald 1994, Klepper 1996). The clear outcome of these models is that mean firm size should evolve along a monotonic path towards maturity of industries, whereas higher moments of the firm size distribution do not follow this rule. Increasing variance and standard deviations indicate selection processes of firms on the market that eventually lead to the stylized evolution of the number of firms. These regularities have been studied by a number of papers and have found support for the proposition of the ILC regarding the evolution in the number of firms and the size distribution of an industry over time (for a recent study see Dinlersoz and MacDonald 2009). The majority of studies however use output measures to determine firm size distributions. Dinlersoz and MacDonald (2009) show that the choice of the firm size distribution matters as industry structure determined from firm size classes in employment and output yield different results as evident from their empirics.

Innovation

The ILC theory argues that innovation intensity in industries as well as the type of innovative activity is primarily performed, are both closely linked to the stage of the industry life cycle. To this end, two stylised facts emerge from the theoretical framework of the ILC. First, the level of innovation tends to be high when an industry is young and the level of innovation decreases as an industry matures. Second, the type of innovation differs along the ILC: while in the early phase product innovations dominate, the relative importance of (cost-saving) process or organisational innovations in an industry substantially increase as the industry evolves over time. A number of papers have tested these hypotheses empirically. The results however, are rather mixed. Gort and Klepper (1982) as well as a successor study by Agarwal (1998) use patent counts mapped into industry level data as a measure of innovation in order to explain the life cycle patterns in prices, quantity and sales as a result of innovation intensity. Both studies show that patenting activity as approximated by their crude measure of patent counts

reveals a decline in technological activity in mature stages of the ILC. McGahan and Silverman (2001) also use patent output of 516 US industries and find in their life cycle stages framework that the general level of patenting activity is not lower in mature industries than in emerging industries. The expected shift from product to process innovation along the ILC stages is also not found. Two related studies by Filson (2001, 2002) of high-tech industries in the US also offer only mixed evidence. Only the automobile industry follows the conventional ILC patterns caused by of innovation with the highest innovation intensity in the young stage. Further high-tech industries in their sample exhibit a variety of patterns that do not conform to the stylised facts of the ILC, but which all have in common that they do not support the notion a relative increase in quality improvements or process innovations as the industry matures.

In a very recent paper, Bos et al. (2014) study 21 manufacturing industries across six European countries. Differently from earlier studies that used discrete life cycle stages, they employ a more flexible continuous measure of maturity and R&D indicators in their empirical approach to test the ILC propositions on innovation. Their findings support the two stylised notions of the ILC relating innovation activities to the evolution of an industry. According to their results, R&D is more productive in mature industries while, at the margin, the positive effect of R&D on technical change decreases as an industry matures.

Spatial structure of industries

The ILC allows formulating explicit hypothesis about the spatial structure of industries in different stages of their evolution. The evolutionary economic geography as well as models developed by economists suggests that whether agglomeration economies generate increasing returns or diminishing returns depends on time, and, therefore, might also be subject to the evolution of the ILC. The rationales for benefits of spatial clustering in the early stages of the ILC are provided by the presence of agglomeration externalities that might induce cost advantages and facilitate innovation. These externalities include localisation economies in the sense of the classical Marshall trinity, comprising benefits of labour market pooling, local knowledge spillovers and scale effects from localised resources such as specialised institutions or infrastructure. The nature of these effects is related to cost advantages. In terms of relative importance, the second type of agglomeration effects, urbanisation economies should play an even more important role from the life cycle perspective as these effects arise from the diversity properties of agglomerations. Diversity facilitates knowledge dynamics, recombination of knowledge and supports innovation. Both effects might play an important role along the stages of the ILC, however, their relative importance varies over the ILC. Due to the higher innovation intensity in the initial phase, urbanisation economies play a more important role in the early evolution. Due to the changing nature of production and innovation over time, localisation economies increase in their relative importance. However, as a result of path dependency, the positive effects of agglomerations might turn into a burden for growth and adaption of an industry to a changing environment in the mature stage of the ILC (Potter and Watts 2011). A set of studies have examined these theoretical propositions empirically and lend support to the fact that the life cycles of industries and agglomerations are indeed closely interrelated (Grabher 1993, Audretsch and Feldman 1996, Duranton and Puga 2001, Greunz 2004, Neffke et al. 2011)

Innovation and Employment

The employment effects of innovation and technological change are a classical topic in socio-economic research. However, employment is not as prominent represented among the core indicators of the ILC literature as other classical business variables. From a theoretical point of view, the effect of innovation on employment is generally ambiguous as two opposing effects of technological progress that occur along the evolution of an industry are at work. The first

effect is a straight forward labour-saving one. Following productivity gains realised from innovations and technological progress less labour is required to produce the same amount of products as before. The second effect points in the opposite direction, because prices decrease as a result of technological progress. Lower prices however boost product demand, so more labour is actually needed to produce a larger output. Whether this compensating effect outweighs the first labour-saving effect is essentially an empirical question. The core indicator in this framework is the elasticity of aggregate demand on the product market, which in the elastic case yields even in positive effects for labour demand. This theorem has been first formulated in a theoretical model by Appelbaum and Schettkat (1993, 1999), and was adapted and refined by e.g., Blien and Sanner (2006).

The basic concept outlined above also applies to a more complex and (certainly) realistic framework that accounts for different types of innovations and products. Generally, new products or product innovations increase the quality and variety of goods and may open up new markets, leading – as long as elasticity of aggregate demand is high enough – to greater production and employment. But new products can simply replace old ones, with limited economic effects, or be designed in order to simply reduce costs, with an impact similar to process innovations. These innovations, as a result of increasing productivity, tend to decrease employment since the same level of demand may be realised using fewer labour inputs.

The complex relationship between the employment quantity and innovation has been analysed in an extant body of literature. For Germany, Möller (2001) has shown that Germany is rather specialized on industries with relatively inelastic demand such as machinery or automobiles. This exposes the German labour market to a higher risk of negative employment shocks following innovations and unemployment. In empirical work presented in the survey of Pianta (2006), the results on the relationships between innovation and employment at the industry level are clear as they all document a generally negative effect of innovation on employment, (e.g., Meyer-Kramer 1992, Evangelista and Savona 2003). In fact, the labour saving effects of innovations and technological progress dominate. Some studies which are able to disentangle innovations into process and product innovations indeed document the expected employment effects according to the theory. Product innovations tend to increase employment while there is evidence that process innovations tend to reduce employment as has been shown by Evangelista and Savona (2003) for the service industries.

Another strand of literature assuming equilibrium on the labour market argues that the effects of innovations and technological progress show substantial heterogeneity in labour demand across different groups of workers. This heterogeneity is mainly caused by skill-technology complementarities. These complementarities result in a shift of labour demand from unskilled respectively groups of workers whose task profiles are less complementary to prevalent technologies, to skilled workers who realise superior productivity due to these complementarities. Studies in this realm use the theorem of skill biased technological change in order to describe the heterogeneous effects of technological change on the quality of employment (Acemoglu 2002). A number of empirical studies have documented evidence of skill biased technological change (see survey in Pianta 2006). The studies support the theorem of skill biased technological change as they document that the relative increase in skilled workers is driven by technological change and R&D intensity (Autor et al. 1998). Heterogeneity in tasks has also been studied (Wolff 1996, Autor et al. 2003). Results show that jobs with manual and routine tasks that are at risk of being substituted by technology indeed show a relative decline in labour demand. Since technological skills of workers are closely linked to the prevalent technology at the time when these workers entered the labour market or passed their vocational training, shifts in labour demand due to technological change are likely favour younger workers than older ones.

The outlined literature provides the background for our empirical analysis and allows us derive some basic expectations about the relationships between industry characteristics as industries evolve. The core hypothesis that we intend to test, however, is whether the proposed cyclical path of the life cycle is actually regularity across sectors and industry level indicators.

3. Empirical Approach

3.1. Data

Our data contains a comprehensive set of industry level variables that have been derived from administrative employment data and patent register data. We use linked employer-employee micro data (Employee History Data, for convenience “BeH”) available at Institute of Employment Research (IAB) to compute and aggregate employment and establishment related information at the industry level. The BeH is available between 1975 and 2010 and covers the

full population of employees and establishments[2] that employ at least one employee subject to social security contributions in Germany. The unchanged data collection method over the period of 36 consecutive years based on administrative processes and the population coverage of the data make the BeH a highly reliable data base for the longitudinal analysis of industries. The scope of the linked employer-employee data comprises a rich set of employee and job characteristics, unique establishment identifiers which remain unchanged over time, a location identifier for each establishment at the county level and an industry identifier in the NACE classification system reported annually by the establishment to the social security administration. Information on employees and establishments in our data base is recorded on the reference date June 30 in each year.

Due to changes in the industry classification systems over time, a major challenge for longitudinal analysis at the industry level is the generation of a time consistent industry classification. Before aggregating our linked employer-employee data at the industry level, we used the methodology described in Eberle et al. (2011) to create a time consistent industry classification for all establishments at the 3-digits level of the NACE Rev. 1 classification.

We use the resulting linked employer-employee data to generate the following set of industry level variables:

- **Employment:** The number of employees is calculated as full time equivalents using part-time weights related to the (grouped) number of working hours for non-full time workers recorded in the IAB data.
- **Young employees:** Aggregate numbers of employees who belong to the age group: < 30 years.
- **R&D intensity (employees):** Aggregate number of employees with academic degree and who are reported by their employers to work in R&D occupations (science and engineering jobs).
- **Establishments:** Aggregate number of unique establishment identifiers in each industry in the IAB database.
- **Small firms (establishments):** Aggregate number of establishments with less than 50 employees.

[2] About 1.3 million establishments in 1975 (only West Germany incl. West Berlin) and more than 2.5 million establishments in 2010.

- **R&D firms (establishments):** Aggregate number of establishments with at least one R&D employee (see definition above).
- **Entries:** We use the emergence and disappearance of establishment identifiers[3] to identify entries and exits of establishments. Following Hethey-Maier and Schmieder (2013) entries are additionally classified using worker-flow data computed from the IAB micro data. This method is used to identify ID changes of establishments and separate them from the number of new establishments.
- **Exits:** See above (entries).
- **Concentration (spatial):** We use county codes ('Kreise, kreisfreie Städte') available for each establishment and their respective number of employees to compute a Herfindahl index of spatial concentration of employees for each industry in every year.

The above described data set does not any contain information on innovation activity, which is a main aspect in industry life cycles. To quantify innovation output for our analysis we follow earlier papers in the ILC literature (e.g., Gort and Klepper 1982) and make use of patent register data. Despite the critique on patents as indicators for innovation (Griliches 1991, Griliches 1994), patent data provide a number of advantages in our empirical framework. While they provide only a limited snapshot on innovative output, their biggest advantage for a study like ours is that patents are recorded for a long time, are available as population data and are, as a measure of output, correlated with R&D as the most important input for innovation.[4] We derive patent indicators from the Patstat Database provided by the European Patent Office (EPO) (de Rassenfosse et al. 2014). This database covers all patents that were filed with the EPO and national offices reporting to the EPO. We restrict our patent data sample to applications with at least one West-German inventor recorded in Patstat (Version October 2014) in application years (priority dates) between 1975 and 2010. From the rich set of information available from patent register data, we make use of technology codes from the International Patent Classification (IPC) reported on each patent. We use the aggregation of IPC classes into 34 technology areas[5] as proposed by Schmoch et al. 2003. If a patent contains several IPC

[3] Please note that establishments are only recorded in our data as long as they report at least one employee to the social security administration in any year. Disappearance does not necessarily imply that the establishment/firm is not operating any longer.
[4] Another frequently formulated critique is that the propensity to patent is contingent on an industry. We study industries separately, so that differences in patent propensity between industries do not matter.
[5] Please note that technological areas 21 and 22 in the original technology classification with 35 classes are

classifications and is, thus, assigned to several technology areas, fractional counting is applied. A major issue for the joint analysis of patent and industry data is the lack of a common identifier at the aggregate level. Industry-technology correspondence tables provide a link between the two data bases. Towards this objective, we make use of a novel correspondence table described by Dorner et al. (2015). This matrix has two major advantages: first, it draws industry information from high quality level establishment data of matched inventor-employer data while other correspondences are only restricted to company level data. Hence, the level of detail in the face of the multi-plant nature of patenting companies clearly outperforms correspondences derived from company data. Second, the table covers the full range of industries and not just manufacturing industries as in other correspondences (e.g. Schmoch et al 2003). This coverage advantage allows us to include both manufacturing industries as well services industries in the empirical analysis (18 of our 205 analysed industries have missing values because they do not appear in the correspondence table). To merge the indicators from patent data with our industry level data we employ the weights from the correspondence table and assign fractions of the patent counts to industries. The total patent activity shows tremendous dynamics within the last 40 years. Therefore we use a relative patent count:

- **Patents:** The share of (West-German) patents that are assigned to each industry according to the procedure explained above.

3.2. Descriptive Analysis

The coverage of our data enables us to analyse the dynamics of 205 industries in West Germany between 1975 and 2010. During this period, our data records the rise and fall of a number of industries in Germany and it covers four major recessions.

Both the average number of employees (full time equivalents) and establishments in all 205 industries of our sample increased over time (see Table A.1 in the appendix). For the subsample of 96 manufacturing industries, however, we see a decline in both indicators. A decrease in the average firm size in each industry is also found consistently for both the full sample and the manufacturing sample. The median of the industry growth rate for the full sample of industries is negative with an average decrease in employment from 1975-2010 of about -5.4 percent.

Hence, we have all kinds of industries in our sample: Growing, stagnating as well as declining.

aggregated.

The most tremendously growing and declining industries are listed in Tables A.2 and A.3 (in the appendix). The most growing industry is Labour recruitment (745). Further industries with substantial increases in employment are Software consultancy (722) and Financial services (671). The industry “Dressing and dyeing of fur” (183) almost completely vanished after reducing its number of employees by almost 97 percent since 1975. Other tremendously decreasing industries are found in the sectors of textiles or coal mining.

Moreover, industries in Germany appear to follow global trends that characterise western industrial nations. These trends include the rise of the knowledge economy accompanied by an increasing importance of human capital and education as evident from the increasing (average) number of high-skilled and R&D workers in industries. Moreover, the number of firms employing at least on worker with these characteristics has also increased. Additionally, the demographic trend of an aging workforce is also reflected in the data by a decreasing share of workers younger than 30 years. Another trend in the data is the increasing importance of smaller (and presumable younger) establishments. Finally, in terms of spatial concentration, employment on average also deconcentrated between 1975 and 2010. Summary statistics of the used variables are given in **Table 1**. For some variables we have missing values. We analyse for each industry only those variables for which values are available for at least 30 out of the 36 years.

Table 1: Summary statistics full industry sample

Variable	Industries considered	Obs.	Mean	Std. Dev.	Min	Max
Employment	205	7380	92964.56	147355.4	294.8	1320686
R&D intensity	195	7217	1879.609	4755.909	0	58801.6
Young employees	205	7380	26995.72	49280.98	38.9	485085.3
Establishments	205	7380	7808.588	18014.26	20	169787
Small firms	205	7378	6858.479	16117.79	3	163118
R&D firms	192	7133	236.1567	851.7991	0	13205
Entries	193	7158	976.7366	6497.921	0	364951.4
Exits	179	7008	542.2149	1567.416	0	18998
Concentration	205	7380	0.043693	0.05107	0.004684	0.42418
Patents	187	6732				

Notes: Industry-year observations for 205 industries x 36 years at 3-digit level of time consistent NACE Rev.1 (N=7380). Variables may contain missing data cells due to data anonymisation of values N <=3. Variables on entries and exits rely on worker flow data using the previous year and therefore are only valid between 1976 and 2010. Employee figures are computed as full-time equivalents.

Source: IAB-BeH and Patstat (Version October 2014). Author’s own calculations

3.3. Methodology

The basic idea of our approach is that industries follow a life cycle. We take this literally, meaning that various variables that characterise an industry show a cyclical development. E.g. sales of a product or industry are usually assumed to increase from zero to a certain highest level and then, if the product or industry disappears, decrease to zero again. This would imply that the value of these sales runs through one complete cycle given by

$$sales = a + b \cdot \sin(t) \tag{1}$$

with t running from -π to +π.

In the real data we do not observe each industry from its beginning. Furthermore, time does not end, so that Equation (1) would imply that an industry rises again after it disappears. Therefore, we have to allow for an offset at time t=0 (in our case 1975) and for a decreasing speed. Hence, for each aspect a and each industry i the development of the respective variable $v_{i,a,t}$ is assumed to be given by

$$v_{i,a,t} = m_{i,a} + r_{i,a} \cdot \sin(o_{i,a} + d_{i,a,t}) \tag{2}$$

with $d_{i,a,0}$=0 and

$$d_{i,a,t+1} = d_{i,a,t} + s_{i,a} \cdot b_{i,a}^{t} \ . \tag{3}$$

$m_{i,a}$ is a parameter that reflects the mean value in the whole cycle, $r_{i,a}$ is a parameter representing the radius of the cycle, the parameter $o_{i,a}$ denotes the offset at time t=0, $s_{i,a}$ is a parameter representing the speed of the development at time t=0, and the parameter $b_{i,a}$ (<1) denotes the slowdown of the development with each year.

In order to find out whether a variable $v_{i,a,t}$ follows a cyclical path we estimate four regression models:

- Linear model: As a baseline the variable is linearly regressed against time.
- Quadratic model: In order to check that the development of a variable is not simply curved, we also estimate the quadratic model

$$v_{i,a,t} = a_{i,a} + b_{i,a} \cdot t + c_{i,a} \cdot t^2 + \varepsilon_t \ . \tag{4}$$

- Cyclic model: We also test the model above without a decreasing speed in the development, which is given by

$$v_{i,a,t} = m_{i,a} + r_{i,a} \cdot \sin(o_{i,a} + d_{i,a,t} \cdot t) + \varepsilon_t \ . \tag{5}$$

- Cyclic slowdown model: Finally the complete above model (Equations (2) and (3)) is estimated.

In all models the error term is assumed to be normally distributed. This assumption is tested by the Shapiro test, which finds deviations from this assumption in only a few of all cases. While the linear and quadratic models can be calculated directly, the cyclic and cyclic slowdown models represent non-linear regression. Using the R routine for non-linear regression does, especially in the case of the cyclic slowdown model, not converge for many variables. The usual gradient and mixed methods, such as Newton's method or the Levenberg–Marquardt algorithm are also not working well in most cases. Hence, we programmed a mixture of an evolutionary algorithm and Levenberg-Marquardt algorithm to fit the models.

For all variables (all aspects and all industries) the four models are estimated. The Akaike Information Criterion (AIC) is used to decide about the best fitting model. In those cases in which either the cyclic or the cyclic slowdown model is the best fitting model we conclude that the variable shows a cyclical development.

3.4. Method for detecting common development

The second aim of this paper is to identify whether different variables characterising an industry develop according to a common life cycle. A common life cycle means that we find cyclical dynamics that adequately describes all variables. Of course, there might be variables that run in front, while others might follow. Hence, a common cyclical behaviour is given if each variable *a* for an industry *i* can be described by

$$v_{i,a,t} = m_{i,a} + r_{i,a} \cdot \sin\left(o_{i,a} + d_{i,t}\right) \qquad (6)$$

with $d_{i,0}$=0 and

$$d_{i,t+1} = d_{i,t} + s_i \cdot b_i^t \,. \qquad (7)$$

While each variable has its own average $m_{i,a}$ and radius $r_{i,a}$ as well as its own offset $o_{i,a}$ for the cyclical development, the dynamics within the cycle are the same for all variables. The offsets of the various variables show which variables are leading and which variables are following.

In order to test whether there is a common cyclical development, we estimate Equations (6) and (7) for all variables together. Then we compare the resulting likelihood value with the likelihood values for the individual models (Equations (2) and (3)). The individual models contain more parameters (individual parameters $s_{i,a}$ and $b_{i,a}$), so that we use the likelihood ratio

test to check whether these additional parameters are justified. If the additional parameters are not justified the model based on a common cyclical development describes the variables also adequately, if not better. In case that the individual model is significantly better in terms of model fit, we eliminate the variable that deviates most from the common development and repeat the analysis. We repeat this step until either a common cyclical development is identified or less than two variables remain.

The above procedure provides us for each industry with a list of those variables that show a common cyclical behaviour, if there are any. Hence, we obtain results about whether the various aspects characterising an industry develop in a common life cycle and which aspects develop together.

4. Results

4.1. Cyclical dynamics

Our first intention is to detect whether the various variables show a cyclical behavior that is adequately described by Equations (2) and (3). To this end, we compare the cyclical model with the linear and quadratic model. We distinguish three cases. First, if the AIC is highest for either the linear or the quadrat model, we do not find evidence for cyclical dynamics. Second, if the AIC is highest for the cyclical model, the variable seems to show a cyclical behaviour. Third, to prove the cyclical behaviour a likelihood ratio test is applied between the cyclical model and the two alternative models.

Table 2: Adequateness of the cyclical model for the various variables

Variable	No. of industries	AIC higher for lin./quad. model	AIC higher for cyclical model	AIC sign. higher for cyclical model
Employment	205	21	184	177
R&D intensity	195	33	162	159
Young employees	205	9	196	194
Establishments	205	19	186	181
Small firms	205	12	193	191
R&D firms	192	19	173	171
Entries	193	8	185	185
Exits	179	84	95	83
Concentration	205	8	197	190
Patents	187	17	170	158

Table 2 presents the results of the AIC comparison. It can be clearly seen that in most cases the cyclical model represents the development of the variables significantly better than the linear or quadratic model. There is only one variable for which the results are more mixed: In the case of exits we do find cyclical dynamics only in around half of the studied industries. For all other variables cyclical dynamics are a common feature.

The same holds for industries. Table 3 lists the number of industries for which a certain number of variables is better described (higher AIC) by the cyclical model. For more than half of the industries the cyclical model is the adequate model for all variables. There are only three industries in which the cyclical model fits less than half of the variables best. These are the industries with the highest growth rate (see Table A.2 in the appendix) – 745 (labour recruitment) and 722 (software consultancy) – and the industry 642 (telecommunications). In these cases the quadratic form with an increasing positive development fits most variables very well. It seems as if in these industries is far from reaching its top, so that the cyclical development is not yet visible.

Table 3: Adequateness of the cyclical model for the various industries

Number of variables adequately described by the cyclical model	No. of industries
2	1
4	2
5	4
6	12
7	21
8	41
9	13
10	112

Considering the results for all 205 industries and all ten variables together, we find a clear confirmation of cyclical behaviour. The only exception is the number of exits. For the exit numbers the maximum likelihood values for the various variables are quite similar in most cases and the optimal model varies. This shows that the structure of the development is less clear in the case of exits.

4.2. Common industry cycles

Our second aim was to study whether the different variables follow the same cyclical dynamics for each industry. To this end, for each industry those variables that can be described by a common cycle are identified. For each industry only those variables that have been found to show cyclical behaviour in the first step are considered in the check for joint development. Industries with less than seven variables with cyclical dynamics are excluded completely. Hence, we study 186 industries in this second step.

Table 4: Identified common cyclical development

Variable	Number of industries			Share of common development
	with data	with cyclical development	with common cyclical development	
Employment	205	160	107	67%
R&D intensity	195	139	55	40%
Young employees	205	169	72	43%
Establishments	205	166	101	61%
Small firms	205	169	104	62%
R&D firms	192	149	72	48%
Entries	193	164	104	63%
Exits	179	88	33	38%
Concentration	205	166	58	35%
Patents	187	144	58	40%

Table 4 presents the results of the identification of common cyclical industrial development. In general the results are mixed. Of all checked industries and variables slightly more than 50% show a common cyclical development. However, clear difference between the variables are found. A clear tendency for joint development is found for the variables employment, establishments, small firms and entries. Table 5 goes into more detail and presents the links between the variables.

Table 5: Joint cyclical development between variables (ordered according to frequency for frequencies above 25%)

Variable1	Variable2	Number of industries		Share of common development
		with cyclical development	with common cyclical development	
Establishments	**Small firms**	163	88	54%
Establishments	**Entries**	157	71	45%

Small firms	**Entries**	160	72	45%
Employment	**Entries**	151	67	44%
Employment	**Establishments**	157	68	43%
Employment	**Small firms**	155	67	43%
R&D firms	**Entries**	141	55	39%
Establishments	**R&D firms**	142	48	34%
Small firms	**R&D firms**	145	46	32%
Employment	**R&D firms**	136	42	31%
Employment	**Young employees**	157	45	29%
Entries	**Exits**	88	25	28%
Entries	**Patents**	137	38	28%
Young employees	**Small firms**	165	43	26%
Employment	**R&D intensity**	128	33	26%
Small firms	**Patents**	141	36	26%
Establishments	**Exits**	83	21	25%

Table 5 clearly shows that the three aspects, Establishments, Small firms and Entries, are most related. Somewhat less, but still strongly related to these three aspects is the aspect of Employment. Hence, we confirm the arguments that the industry life-cycle is strongly connected with the industry dynamics represented by the firm and entry numbers as well as the size of the industry (represented by total employment).

The aspect of spatial concentration is the one that shows the lowest integration into joint development. Hence, we find little evidence for a link between the industry life-cycle and the industry's spatial distribution. However, it might be that the development of the spatial concentration comes to an end earlier than the other aspects, so that it does not fit the same model. Further research into this would be necessary to obtain a clearer picture.

We are also able to identify the temporal order of the variables. If we take the number of establishments as baseline, the number of small firms runs on average by 0.191 in front (see Figure 1), meaning that the number of firms picks up and decreases again slightly earlier than the number of establishments. As expected, the number of entries runs much in front, while the employment number runs behind. Similarly, patents also run clearly in front compared to establishments, while we do not find significant results for the other variables.

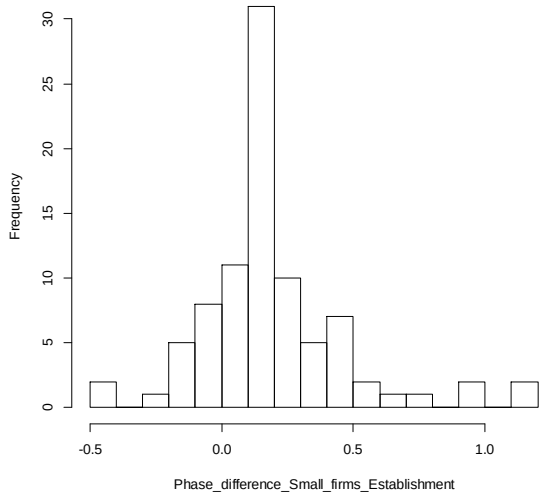

Figure 1: Phase difference between the variables Establishment and Small firms.

5. Conclusions

Kommentiert [MD1]: Ergänzen

The purpose of the paper was to test whether industry variables actually exhibit a cycle pattern as hypothesised by the life cycle theory. Moreover we analyse how different industry properties are interrelated along the industry life cycle. We employ a unique longitudinal industry level data set originating from register data comprising 205 industries that were complemented with information from patent register data. The simultaneous analysis of ten different variables, ranging from employment and entry and exits to patents, in a longitudinal framework is the main contribution of the paper to the literature.

The analysis revealed that indeed most industry variables follow a cyclical development, as suggested by the industry life-cycle literature. We also found that the cyclical developments of the various industry characteristics show some relationships. Especially, the number of establishments, the number of small firms, the number of entries and the employment numbers develop together in many industries. We are able to prove also the usually assumed temporal

order of entries running in front, followed by the number of small firms and establishments and finally the number of employees, at least on average.

This study has a number of caveats that are mainly data related issues. First, due to data restrictions we were not able to complement our longitudinal data with industry level information on output, sales or products, as usually done in the in the ILC literature. Hence, we are not able to test these classical variables against our rich set of variables. In fact, this makes our study less comparable with existing ILC studies. Moreover, we are aware of the limitations associated with the use of patent data as an indicator for innovation (Griliches 1991). Moreover, for the sake of space and focus of our paper, we keep the discussion of “life cycle” properties of industries brief. This is because of the lack of classical indicators and because we think that these measures would actually require a much greater disaggregation and even longer time spans for the analysis as the classical papers show (Klepper 1997).

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Appendix

Table A.1: Summary statistics of employment growth rates in Germany (1975-2010)

		Full Industry Sample	Only manufacturing industries
Number of employees (means in industry)	1975	90332.64	77874.15
	2010	93502.85	53699.61
Number of establishments (means in industry)	1975	6070.58	2162.52
	2010	9973.61	1838.19
Avg. size of establishments (means in industry)	1975	81.00	118.67
	2010	39.67	59.74
Employment growth (%) 1975-2010	Mean	104.32	-31.63
	Std. dev.	486.40	41.10
	min	-96.80	-96.80
	median	-5.84	-41.74
	max	5011.86	119.95
Number of industries (NACE Rev. 1, 3-digits level)		**205**	**96**

Note: Number of employees measured in full time equivalents.

Source: IAB-BeH. Author's own calculations.

Table A.2: Employment growth rates of industries in Germany (1975-2010).

Rank	Industry (NACE Rev. 1, 3-digit level)	Employment Growth (%) 1975-2010	Employees		Establishments		Avg. size	
			1975	2010	1975	2010	1975	2010
1	745 Labour recruitment and provision of personnel	5011.86	10,162	519,451	397	9,566	25.6	54.3
2	722 Software consultancy and supply	3595.41	6,346	234,522	228	19,709	27.83	11.9
3	671 Activities auxiliary to financial intermediation	1935.82	1,188	24,192	156	6,102	7.62	3.96
4	372 Recycling of non-metal waste and scrap	1515.23	1,273	20,560	65	1,379	19.58	14.91
5	712 Renting of other transport equipment	1140.26	295	3,656	59	780	5	4.69
6	555 Canteens and catering	800.63	6,773	60,998	398	10,552	17.02	5.78
7	371 Recycling of metal waste and scrap	777.38	598	5,244	57	585	10.49	8.96
8	723 Data processing	744.18	6,155	51,956	252	2,640	24.42	19.68
9	455 Renting of construction or demolition equipment	641.62	508	3,764	54	420	9.4	8.96
10	554 Bars	518.63	3,619	22,386	1,306	17,141	2.77	1.31
196	103 Extraction and agglomeration of peat	-84.73	8,688	1,326	269	83	32.3	15.98
197	323 Manufacture of television and radio receivers...	-85.51	114,792	16,630	719	400	159.66	41.57
198	335 Manufacture of watches and clocks	-85.74	18,654	2,661	446	128	41.82	20.79
199	192 Manufacture of luggage, handbags and the like	-86.19	31,139	4,301	1,555	518	20.03	8.3
200	172 Textile weaving	-86.71	71,951	9,564	872	266	82.51	35.95
201	101 Mining and agglomeration of hard coal	-88.67	181,061	20,517	135	43	1341.19	477.14
202	182 Manufacture of other wearing apparel and accessories	-89.74	258,144	26,489	9,342	2,053	27.63	12.9
203	171 Preparation and spinning of textile fibres	-91.07	76,699	6,848	519	141	147.78	48.57
204	176 Manufacture of knitted and crocheted fabrics	-93.98	84,914	5,112	2,579	270	32.93	18.93
205	183 Dressing and dyeing of fur; manufacture of art..	-96.8	10,907	349	1,598	161	6.83	2.17

Note: Employment measured in full time equivalents.

Source: IAB-BeH. Author's own calculations.

Table A.3: Top-10 employment growth rates of manufacturing industries in Germany (1975-2010).

Rank	Industry (NACE Rev. 1, 3-digit level)	Employment Growth (%) 1975-2010	Employees		Establishments		Avg. size	
			1975	2010	1975	2010	1975	2010
1	355 Manufacture of other transport equipment n.e.c.	119.95	2,621	5,765	179	247	14.64	23.34
2	157 Manufacture of prepared animal feeds	78.24	5,562	9,914	106	294	52.47	33.72
3	203 Manufacture of builders' carpentry and joinery	71.8	27,623	47,457	3,841	6,796	7.19	6.98
4	333 Manufacture of industrial process control equi…	61.32	11,209	18,082	53	991	211.48	18.25
5	353 Manufacture of aircraft and spacecraft	54.73	45,310	70,109	121	327	374.47	214.4
6	321 Manufacture of electronic valves and tubes and...	42.3	44,199	62,894	175	1,236	252.56	50.89
7	273 Other first processing of iron and steel and p…	38.51	34,145	47,294	518	1,096	65.92	43.15
8	316 Manufacture of electrical equipment n.e.c.	30.91	76,561	100,227	848	1,544	90.28	64.91
9	291 Manufacture of machinery for the production an…	24.69	157,611	196,531	1,019	2,115	154.67	92.92
10	285 Treatment and coating of metals; general mecha…	22.88	130,695	160,604	14,086	15,960	9.28	10.06

Note: Only manufacturing industries (N= 96). Employment measured in full time equivalents.

Source: IAB-BeH. Author’s own calculations.