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REGIONAL DYNAMICS OF INNOVATION

INVESTIGATING THE CO-EVOLUTION OF PATENTS, R&D, AND EMPLOYMENT

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RTG 1411 – The Economics of Innovative Change

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Abstract. We investigate the lead-lag relationship between growth of patent applications, growth of R&D, and growth of total sectoral employment for 270 German labour market regions over the period 1999-2005. Our unique panel dataset includes information on four two-digit industries, namely Chemistry, Transport equipment, Medical & Optical Equipment as well as Electrics & Electronics. The results obtained from a vector autoregression model show that an increased innovative activity is associated with subsequent growth of employment in the Medical & Optical Equipment industry as well as in the Electrics & Electronics sector. With respect to the latter growth of patent applications is also associated with subsequent growth of R&D employees indicating either a 'success-breeds-success' story or benefits due to agglomeration economies at the level of the region. However we do not find those effects for the other industries due to their idiosyncratic innovation and patenting behaviour.

JEL codes: O18, R11,

Keywords: Innovation, Agglomeration, Employment

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I Introduction

Innovation is generally considered the most important source of long-term economic growth. However the public often shows a rather schizophrenic attitude towards technological change (e.g., Van Reenen, 1997). Especially for policy makers it is particular important to know about the interdependencies between technological advancement and growth. However this relationship is a rather complex one. While productivity gains may be accompanied by losses in jobs, innovation also has the potential to stimulate demand.

During the last two decades the regional dimension of innovation has gained importance in both, scientific debate and innovation policy (see, e.g., Audretsch, 1998; Feldman, 1994; Jaffe, 1989; Krugman, 1991). Particular attention was given to geographically bounded knowledge spillovers (e.g., Acs et al., 1992; Jaffe et al., 1993) and the spatial concentration of industries and innovative activity as such (e.g., Audretsch & Feldman, 1996; Brenner, 2004, 2006; Brenner & Gildner, 2006; Porter, 1990). The influence of local factors on regional innovativeness has been addressed by the concept of a geographically defined 'technological infrastructure' (Feldman and Florida, 1994). Moreover the effect of industrial concentration on regional innovative activity and growth has been subject to a heated debate, starting with the seminal work of Glaeser et al. (1992). The combination of the geographic dimension and the systemic nature of the innovation process itself led to the emergence of a new strand of research, viz. the regional innovation systems approach (e.g., Cooke, 2001; Doloreux, 2002). Such a system may be seen as an agglomeration or regional cluster but also encompasses the supportive institutions and organisations within those (Asheim & Gertler, 2006; Asheim & Isaksen, 2002).

With respect to the employment effects of innovation the regional dimension has been somewhat neglected in the literature though. The interdependencies between innovation and employment have been subject to research at the firm level (e.g. Smolny, 1998; Greenan & Guellec, 2000; Coad & Rao, 2007) as well as at the industry level (e.g. Antonucci & Pianta, 2002; Evangelista & Savona, 2003). However, very little is known about how the firm level relates to the regional level. Thus the focus of this paper is on the regional co-evolution of the three statistical series growth of employment, growth of R&D and growth of patent applications.

We trace the respective variables over time to reveal interdependencies. A unique panel dataset including information on total sectoral employment, R&D employees, and patent applications is used to gain new insights into the dynamics of innovation at a regional level. The dataset tracks the 270 German labour market regions over the period 1999-2005. In order to exploit this dataset properly we employ 'reduced-form' vector autoregressions (VAR), which has been successfully used in firm level studies (see Coad, 2007). In adopting this methodology in regional economics we intend to provide a description of the interrelated processes regarding the growth rates of the three variables. We aim at presenting evidence on how regions develop over time. Notice however that we do not claim to resolve any issues of causality.

The remainder of the paper is structured as follows. The next section provides the theoretical underpinnings for this study at both, the level of the firm and the regional level. Interdependencies between our variables are presented along with some propositions concerning their co-evolutionary dynamics. Section three highlights some particularities about the industries under consideration. The methodology of our empirical analysis is put forward in section four. Section five introduces the dataset we draw on. The results obtained by 'reduced form' vector autoregressions are presented and discussed in section 6. In section 7 we conclude the paper and offer some critical discussion.

II Theoretical considerations

Innovation at the firm level

In the analysis of the employment effects of innovation it is convenient and common practice to distinguish between product innovations and process innovations. The former basically influence the demand function. Instead process innovations focus on improvements of the production process itself, which yields a direct effect on factor productivity and unit costs. Accordingly the employment effects of both types of innovation are likely to go into different directions.

Product innovations are usually viewed as employment enhancing at the firm level since new products create new demand that is eventually associated with increasing labour. This effect will however be reduced if the new product substitutes other products of the firm (Harrison et al., 2005; Van Reenen, 1997), commonly known as cannibalisation. The matter becomes more complicated at the aggregate (regional) level as will be shown in the next section. Moreover, product innovations may also have productivity effects, if affecting production methods and input mix. This can lead to changes in the labour requirements as well. Nevertheless the positive compensation effects due to an increased demand are typically regarded the most important effects (Harrison et al., 2005). With respect to a single firm the impact of this effect is dependant on the nature of competition and the time competitors need to catch up (Harrison et al., 2005).

Regarding processes it is rather straightforward to assume that innovations will reduce the need for most of the required factors at a given output level, which includes labour. A first intuition therefore is that process innovations reduce employment. This is however conditional on the nature of the particular innovation, whether it is rather labour or capital augmenting, and on the competition the firm is exposed to. Furthermore a reduction in costs per unit eventually leads to a lower price, which in turn stimulates demand again inducing higher output and employment (Harrison et al., 2005). Other compensation mechanisms may gain importance as well. We refrain from a comprehensive discussion at this point but see Spiezia & Vivarelli (2000) for an overview.

Consequently the sign and magnitude of the firm level employment effects of innovations are not clear a priori and have to be determined empirically, which has stimulated a notable number of studies. Doms et al. (1995) explore survey data on U.S. manufacturing plants and find that the use of advanced manufacturing technologies (corresponding to process innovation) influences plant-level employment growth in a positive way. Hall (1987, p. 603) in analyzing panel data on the publicly traded firms in the US manufacturing sector observes that "a dollar of R & D expenditures is a more important predictor of growth in the immediate future than is a dollar of expenditure on physical capital". This finding proves to be robust across size classes. In contrast Coad & Rao (2007) by investigating patent data on four manufacturing industries report a rather small effect of innovation that is more positive for large firms compared to small ones. Evangelista & Savona (2003) instead provide evidence for a negative overall impact of innovation on employment in the Italian services sector.

Lachenmaier and Rottmann (2007) draw on a panel data set of German manufacturing firms covering a period of more than 20 years. Their results reveal positive employment effects of innovation in general which are robust to several specifications with the impact of process innovation being higher than that of product innovation. The respective coefficients are significant mostly for the first or second lag. Similarly Smolny (1998) finds positive effects for both product and process innovation for West German manufacturing firms. While Van Reenen (1997) also reports positive effects of new products for UK manufacturing firms the coefficients for process innovations are insignificant and small (often negative). Regarding the manufacturing sector in four European countries Harrison et al. (2005) show that product innovation is associated with employment growth. Moreover they report that the tendency of process innovation to displace employment is partly counteracted by compensation mechanisms. At the same time the authors find less evidence of displacement effects in the service sector. Summarizing the findings from the literature we may conclude that while the positive effect of product innovation seems to be clear the results regarding new processes are less harmonious (see also Greenan & Guellec, 2000; Peters, 2004; Smolny, 2002).

Our innovation indicator (patent applications) captures mainly product innovation (see e.g. Arundel & Kabla, 1998). According to the above mentioned we assume an overall positive relationship between growth of patent applications and growth in total sectoral employment according to the respective firm level effects. Considering the results of Lachenmaier and Rottmann (2007) we reckon with significant coefficients for the first or second lag of growth of patent applications.

Though there is no need for firms to hire more R&D personnel in order to satisfy the additional demand created by new products there is still a firm level rationale for a positive correlation between growth of patent applications and subsequent R&D growth. If innovation leads to firm growth as described above firms may use parts of the profits to further invest in R&D. Firms might also try to keep the share of R&D employees on total employment stable because of various reasons, e.g. to ensure future growth or to keep an innovative image. In this case we expect to find a positive correlation between growth of patent applications and growth of R&D with a somewhat longer lead-lag relationship than between the former and growth of total employment. This corresponds to a 'success breeds success' hypothesis.

Straightforwardly we anticipate a positive correlation between growth in R&D employees and later growth in patent applications. In order to create innovations firms depend on creative minds. Accordingly R&D employees must be considered a necessary input into the process of knowledge generation (Henderson et al., 1995; Broekel & Brenner, 2007). We therefore regard them as the most important element within the innovative process and expect growth in this variable to be associated with subsequent growth of patent applications. Since the development of new products is a time consuming process we assume a rather long lead-lag relationship depending on sectoral specificities.

Dynamics in the region

Since the focus of this paper is the relationship between innovation, total employment, and R&D growth at the regional level, we need to relate the findings from the empirical literature presented above to the aggregate level. Of course we cannot get to the regional impact of innovation by simply multiplying the average firm level effect by the number of firms in a certain area (see, e.g., Harrison et al., 2005).

One reason is that while observing a positive effect for a single firm we cannot distinguish between an expanding market as a result of innovation on the one hand and simple market share stealing effects on the other hand. If the firm level effect is not based on a growing market but is the result of a market share gain on expense of less innovative firms then the aggregate effect will be much smaller compared to the effect at the firm level (see, e.g., Harrison et al., 2005).

In this case, the spatial distribution of innovating firms in relation to that of non-innovators gains importance. Most likely these distributions will overlap and the question remains, whether for each region the employment gains of innovative firms are greater or smaller than the reductions in non-innovative ones. In this respect also firm entry (stimulated by innovation) and exit (due to eroding market shares) becomes relevant (cf. Harrison et al., 2005; Pianta, 2005).

This refers lastly to an industry's degree of spatial concentration. In industries concentrated in a few regions most of the market stealing effects will be going on within the very same regions. In this case the regional employment effect of innovation will be smaller than the firm level effect. If on the contrary an industry is more or less uniformly distributed over space the employment gains in one region will cause employment losses in other regions and one would expect a clear correlation between innovation and employment at the regional level.

This relation is also impacted by agglomeration economies, which means that firms draw benefits from being located in spatial proximity to other firms. During the last two decades in regional science a huge body of empirical literature has been dedicated to investigate different types of agglomeration economies. This research is based on the seminal works of Marshall (1890), Arrow (1962), and Romer (1986) on the one hand and on that of Jacobs (1969) on the other hand. Thus the literature refers to the different notions of agglomeration economies as MAR and Jacobs externalities respectively.[1]

MAR-externalities refer to the spatial concentration of a single industry. In the respective literature we find mainly three driving forces giving explanatory power to this idea, viz. labour market pooling, specialised suppliers, and knowledge spillovers within the industry (see e.g. Rosenthal & Strange, 2001). These mechanisms allow for a more efficient production in specialised regions compared to less specialised areas. However advantages for firms with respect to innovation may derive mainly from intra-industry knowledge spillovers that become more likely the more knowledge is concentrated in the region.

While the former idea deals with a single industry and only indirectly considers other industries the second notion of agglomeration economies refers to local variety in industrial composition. Jacobs externalities are economies external to the firm deriving from the variety of industries in the region (Jacobs, 1969). It is argued to exert positive influence on the generation of innovations in two (similar) ways. First, the more important and radical innovations may be the result of a recombination of knowledge from different industries. Accordingly a large local variety of sectors increases the likelihood for such new combinations. Second, given that firms in different industries face similar problems the solutions developed in one industry might be suitable in another as well. Again, the larger the local knowledge base, the more opportunities for knowledge spillovers there will be (Frenken et al., 2007; Neffke et al., 2008). This idea stimulated the development of the concept of related variety. Its main argument is that it is not so much the quantity of contacts and intensity of knowledge exchanges that matters for firms' success, but rather the type of knowledge exchanged, i.e. the content of the knowledge exchanges, and how that matches the existing knowledge base of the firms. In this respect, cooperation is most fruitful when network partners have related, not similar knowledge bases (see, e.g., Boschma and Iammarino, 2007).

Recent research that attempts to analyze empirically the different types of externalities can be broadly classified into two streams. The first investigates the relationship between such externalities and regional economic growth (e.g., Glaeser et al., 1992; Henderson et al., 1995; Henderson, 1997; Combes, 2000; de Lucio et al., 2002). Studies belonging to the second stream analyze agglomeration externalities with respect to their influence on regional innovation activities (e.g., Feldman & Audretsch, 1999; Paci & Usai, 1999; Greunz, 2004; van der Panne & van Beers, 2006).

Both concepts, MAR and Jacobs externalities, emphasize the importance of knowledge spillovers either within or between industries. We regard a growth of patent applications as an indicator for an increased local knowledge base resulting in greater opportunities for knowledge spillovers within the industry[2] under consideration. Thus at the regional level there is a further reason to assume a positive relationship between growth of employment and previous growth of patent applications due to local knowledge spillovers.

Hence, potentially there are two contrary effects of agglomeration. On the one hand the positive employment effects of innovation might be smaller in an agglomerated industry (due to market stealing effects within the region). On the other hand a geographically concentrated industry may show larger employment effects if it benefits from agglomeration economies. Whether the one or the other effect is predominant in a certain industry or whether it is the pure firm level effect is unclear a priori.

One important vehicle for regional knowledge transfer is a spinoff from an incumbent firm. Research has been dedicated to explore the regularities of market entry by spinoffs. Klepper & Thompson (2005) summarize the findings from some of the most important studies concerning the semiconductor, automobile, hard drive, and bio tech industry. With respect to these studies around 20% of all entrants must be considered spinoffs, which are markedly good performers. The better the incubator firm the higher its spinoff rate and the better will be their spinoffs'

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[1] Following Glaeser et al. (1992)

performance. Spinoffs are typically formed by a few well educated employees whose prime reason for starting an own business has been identified in strategic disagreements with the incumbent firm's management, e.g. over what technologies shall be developed (Klepper & Thompson, 2005; Klepper & Sleeper, 2005).

It is quite likely that spinoffs with their well educated personnel will contribute to a large degree to the category of R&D employees in our study. Hence the regional dimension of innovation adds an additional rationale to assume a positive correlation between growth of R&D employees and previous growth of patent applications. The more knowledge is concentrated in a region the larger the opportunities will be for potential entrepreneurs to start their own business. Eventually this can also feed back on total employment if these firms grow above average.

Both, the decision to leave the old employer and start a new venture as well as the replacement of personnel in the incumbent firm are very likely to require quite some time. Therefore we expect a certain delay for the effects of a growing number of patent applications on growth of R&D employees and total employment if based on spinoff formation.

Summarising this section we hypothesise to find the same dynamics between our variables from a firm level as well as from a regional perspective. In detail we assume a positive correlation between growth of total sectoral employment and some lag of growth of patent applications. Moreover we expect to find a positive relationship between a growing number of patent applications and previous growth of R&D. In addition we expect growth of regional innovativeness to be associated with a subsequent increase in R&D employees.

III Industry characteristics

In the present paper we distinguish between four different industries, namely Chemistry (CHEM), Transport equipment (TRANS), Electrics & Electronics (ELEC), as well as Medical & Optical equipment (INSTR). As different industries exhibit very different innovation characteristics our results presumably will also differ significantly among the industries under consideration.

Innovations can be very heterogeneous in value for firms of different industries (Van Reenen, 1997). On the one hand this is because industries differ with respect to the importance of product and process innovation. In scale intensive industries, as transport equipment, process innovations are of outweighing importance (Arndt, 2000). On the other hand the degree to

[2] It is possible that we however capture in parts vertical knowledge spillovers since buyers and suppliers recruit mainly from within the industry at a two-digit level. In this case whether the phenomenon is to be labelled MAR or Jacobs externalities depends on the classification of the particular industry.

which innovations are captured by common innovation indicators varies between industries as well (see Arundel & Kabla, 1998).

Concerning Europe's largest firms in the 'automobiles' and 'other transport equipment' industry Arundel & Kabla (1998) report a sales-weighted patent propensity rate for process (product) innovations of only 17 % (30 %) and 10.9 % (31.2 %) respectively. The ratio for process (product) innovations for chemicals and pharmaceuticals is 39 % (57.3 %) and 45.6 % (80%) respectively. For the industries covered by ELEC the authors report ratios of slightly above 20 % for process innovations and of around 50 % for product innovations.

These differences in the innovation and patenting behaviour have to be kept in mind because our innovation indicator is based on patent applications, i.e. product innovations. Accordingly we are rather pessimistic about finding the relations specified above for the transport equipment industry (TRANS).

To judge an industry's degree of agglomeration we compute the location coefficient (see Table 4 in the Appendix). This index is defined as an industry's employment share in a region related to the same ratio at the national level (see, e.g., Feldman and Audretsch, 1999).

$$PS_{i,r} = \frac{X_{i,r} / \sum_{s=1}^{S} X_{s,r}}{\sum_{r=1}^{R} X_{i,r} / \sum_{r=1}^{R} \sum_{s=1}^{S} X_{s,r}}$$

$X_{s,r}$ is the employment of sector s in region r. We follow Laursen (1998) and make this index symmetric by estimating:

$$\frac{PS_{i,r} - 1}{PS_{i,r} + 1} + 1$$

The normalised location coefficient takes values between zero and two. A value of unity indicates that the regional employment share of the respective industry equals the industry's average employment share in Germany.

Regarding this index TRANS is the industry with the lowest mean value but also the one with the highest standard deviation. At the same time its 0.1 and 0.25-quantiles by far take the lowest values of all industries. For TRANS 10 % (25 %) of all regions exhibit a location coefficient below 0.0554 (0.157). In more than 75 % of all regions TRANS shows an employment share below the national average. For the other three industries the 0.75-quantile is larger than unity. The median for ELEC and INSTR is about 0.71 and 0.75 respectively. The one for CHEM even takes a value of about 0.85. In contrast the median for TRANS is about 0.46. Accordingly the Gini coefficient of inequality on TRANS's regional location coefficients is the highest of all four industries. In 1999 it shows a magnitude of about 0.45 for TRANS, 0.32 for ELEC, 0.26 for INSTR, and 0.23 for CHEM. Together those figures clearly show that TRANS is the industry with the highest degree of geographical concentration.[3]

As has been mentioned earlier in this paper the employment effects of innovation are likely to be smaller at the regional level if an industry is highly concentrated in geographical terms. But this effect might be set off in parts if the respective industry simultaneously benefits from agglomeration economies. The industry for which we expect these mechanisms to play the most significant role is TRANS. However, as mentioned above, we do not expect to find any correlations in this industry due to its idiosyncratic innovation and patenting behaviour.

Regarding the employment effects of innovation in the chemical sector we are again somewhat sceptical whether we can detect them in the data or not. Firms in this industry face rather long development times. For the pharmaceutical industry for example, which forms a part of the chemistry industry, Dranove & Meltzer (1994) report an average time from a drug's first patent application to its approval by the FDA of about 13.5 years. Only at this time the employment effects of the innovation may become visible. However our dataset does not allow for considering more than three one-year lags. Thus it is quite likely that our dataset does not allow for observing any co-evolutionary dynamics in this industry.

Malerba & Orsenigo (1995, p. 62) show 'that patterns of innovative activities differ systematically across technology classes'. In their study the authors identify two groups of technological classes, commonly known as 'Schumpeter Mark I' and 'Schumpeter Mark II'. Innovative activities within these groups follow very different rules. The first is characterized by a widening pattern, i.e. main innovative contributions stem from small firms and the entry of new innovators is high. The latter instead is dominated by large corporations representing a stable core of persistent innovators while the entry rate is low, which leads to some kind of deepening pattern. Malerba & Orsenigo (1996) identify large parts of our instruments industry as 'Schumpeter Mark I' whilst they classify chemicals and electronics into 'Schumpeter Mark II'.[4] Considering the study by Coad & Rao (2007) finding more positive effects for large compared to small firms we expect to find more clear-cut results for ELEC rather than for INSTR.

Still we do not know whether large incubator firms or small businesses are more favourable to new firm formation (Dahlstrand, 1997). One might think that a positive correlation between patent growth and growth of R&D staff based on spinoff formation will be more likely in 'Schumpeter Mark I' industries due to higher entry rates. Following another line of reasoning

[3] The exhaustive statistics can be found in Table 4 in the Appendix.
[4] Note that our industries are defined broader than those in the mentioned literature.

technological change in these industries is rather the outcome of an overall high entry rate than the other way round. Large technology-based firms dominating in 'Schumpeter Mark II' industries encompass several technologies with a potential for innovation in other product areas. As large firms commonly do not spur such opportunities outside their own product areas spinoffs may take advantage of this neglected potential (Dahlstrand, 2005). However whether the effects of spinoff formation are more likely in the one or in the other industry is unclear.

Interestingly the R&D-employment ratio in three of the four industries under consideration is very high. In the Electrics and electronics industry almost 25% of all employees are classified as R&D staff. This number is quite high and we are a bit sceptical concerning misclassification. The ratio for transport is 19.3% and the one for instruments is 16.6%. Only the ratio for chemistry is much lower, viz. 5.6%. However, given the bias is systematic, general overestimation should not be much of a problem.

Summarising this section we expect to find the dynamics described in section II for ELEC and INSTR while we are more pessimistic to find the respective correlations in CHEM and TRANS. The scepticism with respect to the latter industries is based on substantial differences in the industries' idiosyncratic innovating and patenting characteristics. Instead effects stemming from an industry's degree of agglomeration should be more pronounced for TRANS.

IV Methodology

One of the main aims of this paper is to exploit a unique dataset that provides fresh insights into industrial dynamics at the regional level. We exploit a panel dataset that tracks a reasonably large number of regions over the period 1999-2005. In particular, we want to observe the co-evolutionary dynamics between the three statistical series – employment, R&D, and patenting activity. In recognition of the complex and endogenous nature of the growth of employment, R&D and patent applications, we apply a vector autoregression model.

The regression equation of interest is of the following form:

$$w_{it} = c + \beta w_{i,t-1} + \varepsilon_{it} \tag{1}$$

where w_{it} is an $m \times 1$ vector of random variables for region i at time t. β corresponds to an $m \times m$ matrix of slope coefficients that are to be estimated. In our particular case, m=3 and corresponds to the vector (Employment growth (i,t), R&D growth (i,t), growth of patent applications (i,t)). ε is an $m \times 1$ vector of disturbances.

In keeping with previous studies, our measure of growth rates is based on the differences of the logarithms of the respective variables. Let $X_i(t)$ represent the absolute value of total employment, R&D employees, or patent applications in region j at time t. Define the normalized (log) value of this variable as

$$x_j(t) = \log\left(X_j(t)\right) - \frac{1}{N}\sum_{j}^{N}\log\left(X_j(t)\right) \tag{2}$$

where N is the number of regions. In what follows we define growth rates as the first difference of normalized (log) values according to

$$g_j(t) = x_j(t) - x_j(t-1) \tag{3}$$

Thus common macroeconomic shocks are already controlled for because we have normalized to zero the growth rate distribution for each variable in each industry in each year.

We estimate equation (1) via 'reduced-form' VARs, which do not impose any a priori causal structure on the relationships between the variables, and are therefore suitable for the explorative nature of our analysis. These reduced-form VARs effectively correspond to a series of m individual OLS regressions (Stock and Watson, 2001).

One problem with OLS regressions in this particular case, however, is that the distribution of growth rates is typically exponentially distributed and has much heavier tails than the Gaussian. The heavy tailed nature of growth rate distributions has been observed for the growth of firms (Coad, 2007), industrial sectors (Castaldi and Sapio, 2006) as well as at the level of countries (Lee et al., 1998). Figure 1, Figure **2** and Figure **3** in the Appendix show that the growth rates distributions for our regional data also exhibit heavy tails. In this case OLS may provide unreliable results, and as a result we would prefer Least Absolute Deviation unconditional (LAD) estimation, which is better suited to the case of non-Gaussian residuals. We also base our inference upon standard errors obtained using the computationally intensive 'bootstrapping' resampling technique (see Efron and Gong (1983) for an introduction).

Since we are dealing with growth rates (i.e. differences rather than levels), we do not concern ourselves with the issue of unobserved heterogeneity in the form of time-invariant region-specific 'fixed effects'.

It is also worth emphasizing that we do not claim to resolve any issues of causality between growth of employment, R&D and patent applications.[5] Instead, we interpret our results merely in terms of the regularities that may be observed during the processes of industrial and regional

[5] One reason for this is that instrumental variable techniques are likely to perform poorly given that we have no suitable instruments. Taking lagged growth rates as instruments, for example, would not be suitable here because of the low persistence in the growth rate series (especially for R&D growth, and also for employment growth).

evolution. Indeed, much can be learned simply by considering the associations between the variables without mentioning issues of causality (see Moneta, 2005 for a discussion).

V The dataset

The 270 German labour market regions are chosen as unit of analysis, because they seem to best capture the regional dimension of innovation processes (Broekel and Binder, 2007) and have been used in similar studies (Combes, 2000, Broekel, 2008).[6]

The data on employment has been collected by the German Federal Institute of Labour. The dataset contains the number of employees for each of the four industries and each of the 270 labour market regions. As all other data used here it is available for the subsequent years from 1999 to 2005.

The data on patent applications is published by the Deutsches Patent- und Markenamt (German Patent Office) in Greif and Schmiedl (2002). The applications by public research institutes, such as universities and research societies (e.g. Max Planck Society) as well as the patent applications by private inventors are not included. The latter is because the corresponding R&D employment data covers only industrial R&D. Hence, only the innovations resulting from industrial R&D should be considered.

Data on R&D employees is obtained from the German labour market statistic. The R&D personnel is defined as the sum of the occupational groups agrarian engineers (032), engineers (60), physicists, chemists, mathematicians (61) and other natural scientists (883) (Bade, 1987, p. 194ff.).

An industry's total employment located in a region is defined as third variable. This data is taken from the German labor market statistic as well. For sound empirical estimations we subtract the number of R&D employees.

Conducting industry specific analyses requires a definition of industries that, in the context here, covers all three variables: patent applications, R&D employees, and total employment. In the case of R&D employees and total employment this is easy. Both are organized according to the German Industry Classification ('Deutsche Wirtschaftskzweig Klassifikation') which is the German equivalent to the international NACE classification. However, the patent applications are classified according to 31 technological fields (TF) defined by Greif and Schmiedl (2002).

[6] Note that we use the up-to-date definition of labour market regions in contrast to the older definition used in Greif and Schmiedl (2002).

We use the concordance between these two classifications developed by Broekel (2007), which adapts the concordance by Schmoch et al. (2003) to our data. We concentrate on four industries as defined in Broekel (2007): Chemistry (CHEM), Transport equipment (TRANS), Electrics & Electronics (ELEC), and Medical & Optical equipment (INSTR). Its definition in terms of included technological fields and industries is presented in **Table 3**.

For most of these industries patenting represents an important property rights protection mechanism (Arundel and Kabla, 1998). This ensures that the patent applications capture most, or at least a significant share of innovations in these industries.

In order to obtain a single variable representing an industry's innovations, the number of patent applications of the technological fields that are assigned to this industry is added up. Similarly, sums of the R&D employees and total employment numbers of the corresponding 2-digit NACE-industries define the other two variables.

Table 1 presents some summary statistics for our dataset. We observe that the sizes of the four industries vary considerably across the regions. We also obtain a few null values in some cases for each of the variables. This leads us to drop some observations in the subsequent analysis based on growth rates. In addition, data constraints limit our study to no more than three lags because of a sharp decline in observations afterwards.

	Mean	Std Dev	10%	25%	median	75%	90%	Min	Max	Obs
TRANS										
Empl	3014.722	8894.129	30	137	563	1663	7379.5	0	99320	270
R&D	553.537	1994.839	0	5	60	265	1315.5	0	25986	270
Patents	16.63185	64.96559	0	1.3	4.5	12	32.5	0	951.1	270
Chem										
Empl	2793.189	4875.299	323	644	1319	2658	6069	38	49218	270
R&D	146.9296	402.6852	5.5	14	40.5	112	304.5	0	4408	270
Patents	12.37148	38.8693	0	0.6	1.9	6.2	27.75	0	382	270
INSTR										
Empl	1544.874	2729.405	123.5	244	614.5	1593	3517	11	18124	270
R&D	254.2074	541.8255	2	11	64	193	703.5	0	3731	270
Patents	11.50037	28.14851	0	1	3.3	11.1	26.25	0	272.3	270
ELEC										
Empl	2421.804	5024.096	107	275	836	2476	5623.5	1	55861	270
R&D	610.8185	1405.686	7	42	165	591	1555.5	0	16548	270
Patents	22.24037	73.18004	0	1.8	6.15	16.8	42.15	0	956.2	270

Table 1: Summary statistics for the four industries in 1999. The statistics refer to absolute numbers of total employment, R&D employees and patent applications.

In order to check for spatial autocorrelation we estimated Moran's I on the regions' average growth rates, see **Table 5** in the Appendix. We use average growth rates because they reflect the fundamental relations between the regions in contrast to fluctuating yearly growth rates. While most of the growth rates show significant spatial autocorrelation the correlation coefficient is very low. Therefore this should not bias our estimations. This is even more so as we do not use standard OLS but rather LAD estimation techniques.

VI Results

As the growth rates of our variables do not follow a normal distribution we prefer the bootstrapped LAD estimation to simple OLS. We will only present the respective coefficients in the following. However results obtained with OLS regression and LAD without 'bootstrapping' re-sampling technique are very similar.[7] Table 2 shows the results with 1000 bootstrap replications.

Autocorrelation series

To begin with we shall give some information on the observed autocorrelation of our variables. First of all R&D growth does not appear to be persistent. The respective coefficients are mostly negative but insignificant except for CHEM where the third lag is negative and highly significant. Total sectoral employment instead seems to have small positive persistence. In fact the coefficients are always positive though mostly insignificant.

By contrast what turns out to be consistent over all industries is a negative autocorrelation of the patent growth variable, which corresponds to decreasing coefficients for larger lags. The coefficients are negative and highly significant for all lags and all industries. We ascribe this result to erratic growth dynamics since the innovative process always encompasses chance as such. Fortuity deriving from the non-deterministic nature of human creativity is always an inherent part of the innovative activity. However, the regularity of this pattern is surprisingly strong for which reason future research should investigate this in more detail.

Patent applications and total employment

With respect to the transport equipment industry we do not find any significant correlation between the growth rate of patent applications and subsequent growth of total sectoral employment. This is in line with our expectations concerning the industry's low patent propensity rate. Patent data captures less than 20 % of all process innovations in the transport sector (Arundel & Kabla, 1998), which are particularly important in such scale intensive industries (Arndt, 2000). Moreover this industry is the most agglomerated of all four industries

[7] They can be obtained from the authors upon request.

w_t	β_{t-1}			β_{t-2}			β_{t-3}				
	Empl. gr.	Pat. gr.	R&D gr.	Empl. gr.	Pat. gr.	R&D gr.	Empl. gr.	Pat. gr.	R&D gr.	R^2	obs
TRANS											
Empl. gr.	0.0437	-0.0020	-0.0030	0.0339	-0.0019	-0.0122	0.0571	0.0068	-0.0102	0.0107	586
t-stat	1.34	-0.32	-0.18	1.75	-0.30	-0.77	1.50	1.14	-0.87		
p-value	0.182	0.749	0.860	0.081	0.768	0.443	0.134	0.253	0.384		
Pat. gr.	-0.0818	**-0.5204**	-0.0283	-0.0734	**-0.3495**	0.1448	0.0437	**-0.2513**	-0.0369	0.1448	582
t-stat	-0.85	**-8.48**	-0.34	-0.69	**-4.42**	1.22	0.35	**-3.71**	-0.52		
p-value	0.395	**0.000**	0.738	0.491	**0.000**	0.221	0.727	**0.000**	0.607		
R&D gr.	0.0677	0.0002	-0.0040	0.0268	-0.0154	0.0043	**0.1009**	-0.0047	-0.0109	0.0086	585
t-stat	1.02	0.03	-0.13	0.61	-1.74	0.14	**2.06**	-0.74	-0.56		
p-value	0.309	0.975	0.899	0.543	0.083	0.892	**0.040**	0.459	0.577		
CHEM											
Empl. gr.	0.0475	-0.0072	0.0091	0.0884	-0.0014	-0.0194	0.0685	0.0009	-0.0337	0.0167	562
t-stat	1.22	-1.69	0.61	1.49	-0.29	-0.89	1.2	0.18	-1.41		
p-value	0.223	0.092	0.542	0.138	0.772	0.376	0.229	0.858	0.161		
Pat. gr.	0.4327	**-0.5760**	0.0171	0.3824	**-0.3120**	0.0852	-0.2978	**-0.1327**	0.3108	0.1272	547
t-stat	1.04	**-8.66**	0.1	0.7	**-4.63**	0.41	-0.55	**-2.27**	1.44		
p-value	0.299	**0.000**	0.922	0.483	**0.000**	0.681	0.582	**0.023**	0.149		
R&D gr.	0.1352	-0.0080	-0.0374	0.0473	0.0011	-0.0356	0.1227	-0.0021	**-0.1545**	0.0154	562
t-stat	1.31	-0.99	-0.82	0.42	0.11	-0.65	1.42	-0.23	**-2.75**		
p-value	0.191	0.323	0.414	0.672	0.911	0.513	0.156	0.822	**0.006**		
INSTR											
Empl. gr.	0.0506	0.0038	-0.0087	0.0111	0.0096	-0.0071	0.0663	0.0080	-0.0030	0.0107	638
t-stat	1.14	0.70	-0.34	0.45	1.81	-0.62	1.21	1.73	-0.26		
p-value	0.253	0.482	0.732	0.650	0.072	0.537	0.225	0.083	0.793		
Pat. gr.	-0.0895	**-0.5914**	0.1260	-0.2198	**-0.2409**	0.0629	0.2343	**-0.1371**	-0.1198	0.1600	634
t-stat	-0.28	**-12.37**	0.96	-0.76	**-4.64**	0.51	0.64	**-3.04**	-0.91		
p-value	0.777	**0.000**	0.338	0.449	**0.000**	0.613	0.520	**0.002**	0.365		
R&D gr.	0.0861	0.0009	0.0084	0.0376	0.0020	0.0233	0.0262	-0.0019	-0.0225	0.0058	637
t-stat	1.65	0.13	0.39	0.88	0.29	0.70	0.44	-0.30	-1.00		
p-value	0.100	0.898	0.696	0.378	0.769	0.486	0.663	0.765	0.319		
ELEC											
Empl. gr.	0.0433	**0.0176**	-0.0056	0.0379	**0.0183**	0.0132	0.0598	0.0136	-0.0056	0.0205	675
t-stat	0.74	**2.42**	-0.21	0.99	**2.14**	0.69	1.57	1.58	-0.22		
p-value	0.461	**0.016**	0.833	0.323	**0.033**	0.491	0.118	0.115	0.828		
Pat. gr.	0.1012	**-0.4184**	-0.0755	-0.1667	**-0.2186**	0.1994	0.1244	**-0.1456**	-0.1955	0.0803	665
t-stat	0.52	**-7.00**	-0.56	-0.77	**-3.15**	1.51	0.74	**-3.27**	-1.16		
p-value	0.605	**0.000**	0.578	0.444	**0.002**	0.132	0.460	**0.001**	0.245		
R&D gr.	0.0708	0.0105	-0.0012	-0.0183	**0.0209**	-0.0021	0.0270	**0.0224**	-0.0096	0.0078	672
t-stat	0.95	1.10	-0.03	-0.32	**2.06**	-0.05	0.48	**2.26**	-0.37		
p-value	0.344	0.272	0.979	0.751	**0.040**	0.960	0.631	**0.024**	0.709		

Table 2: LAD estimation of equation (1) where m=3 and corresponds to the vector (Empl. growth (i,t), growth of patent applications (i,t), R&D growth (i,t)). Standard errors (and hence t-statistics) obtained from 1000 bootstrap replications.

considered here and our results very likely encompass market-stealing effects within the regions. Such may hide the ‘real’ relationship between these variables at the regional level. Whether or not the industry simultaneously benefits from agglomeration economies which are covered by market stealing effects or which are simply not reflected in patent applications can not be inferred from the data.

Concerning the Chemical industry the first lag of growth of patent applications is significant but at the 10 % level. The coefficient is small and negative. However we refrain from overrating this correlation. A possible explanation could be market-stealing effects within the region which we doubt because of the industry’s comparatively low regional concentration and its long development times. All other lags of growth of patent applications are small as well and anything but significant. As in the transport equipment industry this supports our expectations about the industry’s innovation characteristics. With the long development times in this industry it is rather unlikely that patent applications show an immediate effect upon employment growth in the region. Since time to market is long it is plausible to assume a longer lag structure between the growth rates of the two variables.

In the medical & optical equipment industry we find positive coefficients for the second and the third lag, both being significant but at the 10 % level. Whether this low significance level is due to market share stealing within the regions or whether it is based on rather small innovation effects at the firm level we cannot infer from the model. Nevertheless growth of patent applications is somewhat associated with subsequent growth of total employment. The low significance level might as well be owed to the lower number of observations in the three-lag model in which we face roughly 230 observations less compared to a two-lag specification.

Regarding the electrics & electronics industry instead growth of patent applications is associated with subsequent growth of total employment. We observe exactly the lag structure we expected. The coefficients are positive and significant for the first and second lag of growth of patent applications. This result coincides with the findings by Lachenmaier and Rottmann (2007) who report positive effects for the first and second lag at the level of the firm. Though our methodology does not allow for resolving issues of causality our results at least suggest that in this case (i) there are positive compensation effects of innovations at the regional level and (ii) the employment gains of innovative firms are higher than the losses of less innovative firms in the region. Likewise it possible that there are agglomeration economies in terms of knowledge spillovers working in the region which benefit those firms that exhibit sufficient absorptive capacities. In this context one should remember that ELEC shows the second highest degree of agglomeration out of the four industries considered here. However, the data at hand do not allow for distinguishing between aggregate firm level and pure regional effects.

Those results also confirm our expectations based on the findings by Coad & Rao (2007). We also find the strongest employment effects of innovation in an industry (ELEC) which is, according to Malerba & Orsenigo (1996) dominated by large innovator firms. On the other hand those effects seem to be less pronounced in INSTR, an industry for which Malerba & Orsenigo (1996) report that in large parts of it small firms act as the main innovators.

Patent applications and R&D employees

Interestingly we do not observe any correlation between growth of R&D employees and subsequent growth of patent applications as we expected to do. One can think of different reasons for this result. On the one hand the true lead-lag structure between the two variables could be larger than the three lags considered in our model. Maybe an increase in R&D employees first pays off after more than three years in the industries considered here. This is especially probable in industries with long development times as, for example, CHEM.

On the other hand any additional lag we consider in the VAR comes along with a sharp decline in observations. This may render some coefficient insignificant. Indeed when we include but two lags in the analysis we observe a positive coefficient for the second lag of R&D growth with respect to growth of patent applications in INSTR. This coefficient is then significant at the 10 % level. In this case we run the VAR with about 230 additional observations. Lastly, it is known that the innovation activities are subject to decreasing returns to scale at the regional level (see, e.g., Bode, 2004), which may also lower the correlations.

Unfortunately, since we are unable to increase the number of observations and cannot include longer lags we can test neither the one nor the other hypothesis.

Regarding correlations between patent growth and subsequent growth of R&D employees there is no evidence for a 'success breeds success' story or spinoff effects at the regional level for CHEM, INSTR, or TRANS. The coefficients often change the sign between the different lags and are always far from being significant. Regarding CHEM and TRANS this again might be owed to the industries' innovation characteristics.

The expected correlations are found in the electrics & electronics industry, though. While the first lag of growth of patents is positive but insignificant the second and the third lag are positive as well and significant at the 5 % level. Hence growth of patent applications is associated with subsequent growth of R&D employees. This is again in line with our argumentation in section II. Accordingly our results basically suggest two things. Either there is (i) a 'success-breeds-success' mechanism at work and/or, since the industry shows the second highest degree of agglomeration, (ii) an increase in the local knowledge stock raises the likelihood for opportunity spinoffs.

However we have to emphasise again that while we observe positive correlations that are in line with our theoretical considerations we cannot resolve any issues of causality.

Total employment and R&D employees

In the first place there is no reason to anticipate any kind of lead-lag relationship between the growth rates of total employment and R&D employees. An increase in total employment is very likely to preserve the R&D-employment ratio. Accordingly both variables will change at the same time. This assumption is confirmed by our results with respect to CHEM, INSTR, and ELEC. None of the coefficients of lagged growth rates of R&D employees and total sectoral employment is significant at a reasonable level.

However we find a lead-lag relationship between those variables in the transport equipment industry. Here the coefficient for the third lag of growth of total employment with respect to growth of R&D is positive and significant at the 5 % level. Hence growth of employment is associated with subsequent growth of R&D employees, or put differently a downturn in total employment is followed by a later reduction of R&D employees. The most plausible explanation refers to the latter more pessimistic point of view. R&D is one of a firm's most important strategic resources. If the firms in a region are forced to reduce employment they may keep their R&D staff at first and only in the long run lay them off as well. Accordingly the correlation found for the transport equipment industry is most likely to reflect the importance of R&D personnel in this industry.

VII Conclusions

We investigated the co-evolutionary dynamics, i.e. the lead-lag relationship between growth of patent applications, growth of R&D, and growth of employment for German labour market regions over a period of seven years. The unique panel dataset we employed comprises the Chemistry, Transport equipment, Medical & Optical equipment as well as Electrics & Electronics industry. Because of the complex and endogenous nature of the respective growth rates, we applied 'reduced form' vector autoregressions. The introduction of this methodology into regional innovation literature yields new insights into the development of regions. It allows us to describe the interdependencies between growth of employment, R&D, and innovation. We further relied on Least Absolute Deviation estimation for the distributions of the growth rates show much heavier tails than the Gaussian.

We did not find much evidence for any co-evolutionary dynamics in the transport equipment and chemistry industry which we ascribe to their innovation and patenting characteristics. For the Medical & Optical equipment industry, however, we find a slightly positive correlation between growth of patent applications and subsequent growth of total sectoral employment. While the coefficients are positive for all lags they are significant at the 10 % level for the second and the third lag. The results for the Electrics & Electronics industry instead clearly reflect the expected relationships. In this industry an increased patenting activity is associated with subsequent growth of both total sectoral employment and R&D. Explanations for both effects can be found at the firm level as well as at the level of the region.

We further should mention the limitations of our results. First of all we do not claim to resolve any issues of causality. We rather interpret our results as a description of the interrelated processes concerning the growth rates of our variables as may be observed during industrial and regional evolution. Nevertheless the results match very well our expectations based on the theoretical and empirical literature on the topic.

Regarding our data we have to admit that patent data is not equally suited as innovation indicator for all industries. In the case of the transport equipment industry our results support our previous concerns regarding this industry's characteristics. It seems as patent applications do not depict the industry's innovative activity properly. The patent propensity rate in this sector is much too low to allow for the usage of this kind of innovation indicator. Accordingly we fail in detecting the expected correlations between the growth rates of the three variables.

With respect to the chemical industry this concern does not hold. However our panel dataset seems to be too short in order to detect any co-evolutionary dynamics between the variables. To do so we would need longer time series to account for the very long time to market in this industry. However our dataset is confined to a seven year period restricting us to at most three lags in order to build on a sufficiently high number of observations.

Moreover, since we take labour market regions as observational units, we cannot distinguish between aggregate firm level effects and regional effects when agglomeration economies are present. A comparison of our results with those obtained by a firm level analysis of the same variables and the same industries would thus be enlightening.

Appendix

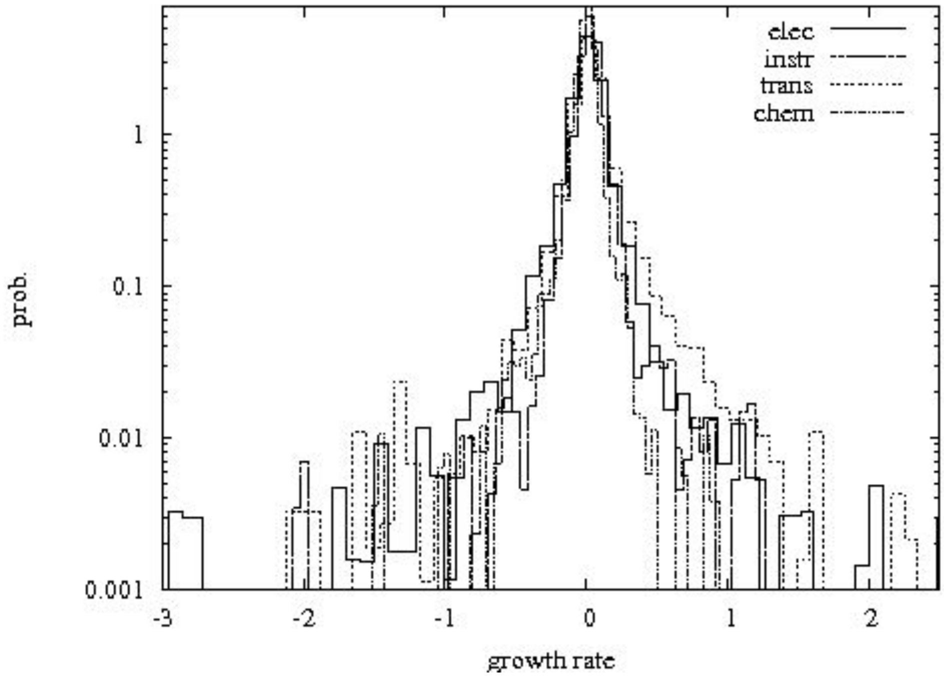

Figure 1: Distribution of employment growth rates across regions, for the four sectors. Growth rates are normalized around zero for each year, and then the years are pooled together.

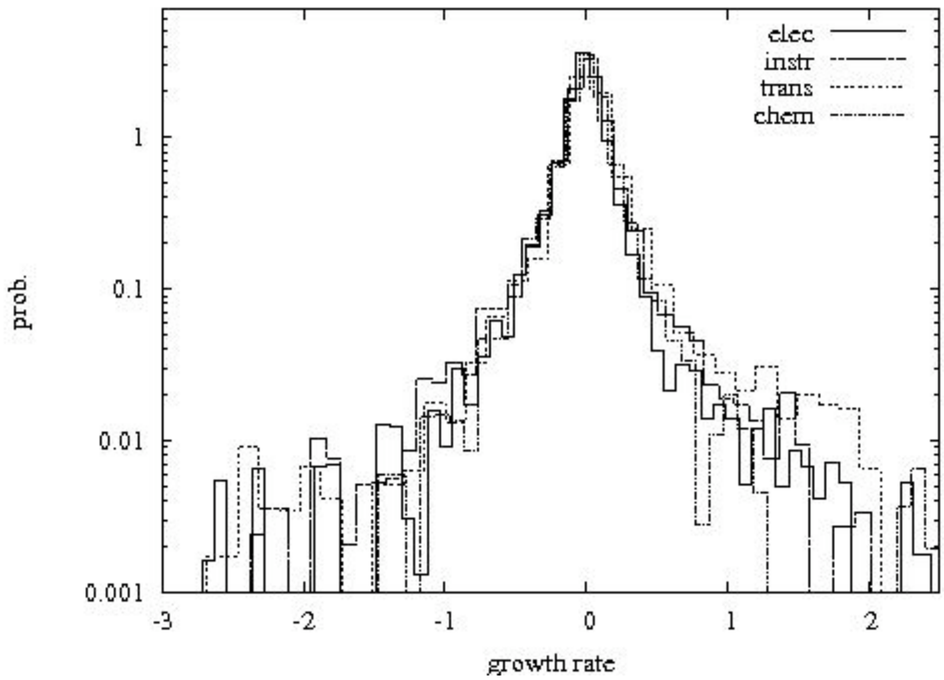

Figure 2: Distribution of R&D growth rates across regions, for the four sectors. Growth rates are normalized around zero for each year, and then the years are pooled together.

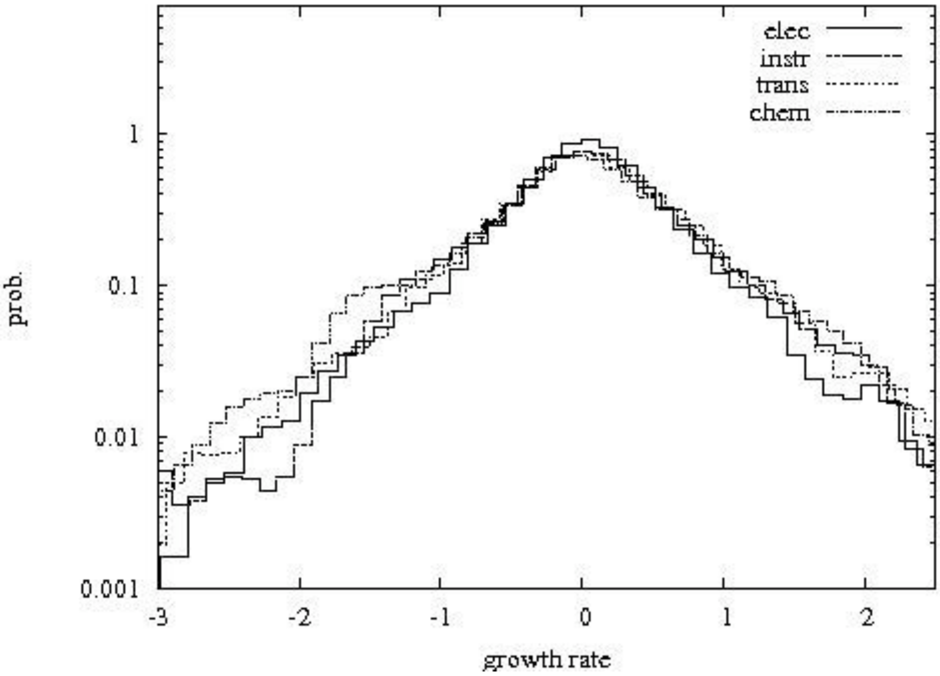

Figure 3: Distribution of growth rates of patent applications across regions, for the four sectors. Growth rates are normalized around zero for each year, and then the years are pooled together.

Industry	Technological fields*	Industries**	Control***
Chemistry	TF5, TF12, TF13, TF14, TF15	DG24, DI26	TF6 ,TF20, DF23
Transport equipment	TF10, TF22	DM34, DM35	TF23, TF20
Electrics & electronics	TF27, TF28, TF29, TF30, TF31	DL30, DL31, DL32	DL33
Medical & optical equipment	TF4, TF16, TF26	DL33, DF23	TF6, TF15, DL30

* As defined in Greif & Schmiedel (2002); ** According to the GIC DESTATIS (2002);
*** Technological fields of industries which have to be controlled for

Table 3: Overview technological fields.

	CHEM	TRANS	ELEC	INSTR
Mean	0.8759	0.5714	0.7541	0.7977
Std Dev	0.3609	0.4735	0.4271	0.3667
0.10-Quantile	0.4055	0.0554	0.1950	0.3784
0.25-Quantile	0.6227	0.1570	0.4271	0.5131
median	0.8499	0.4568	0.7084	0.7493
0.75-Quantile	1.1234	0.8585	1.0599	1.0495
0.90-Quantile	1.3788	1.2722	1.3940	1.3039
Min	0.0954	0.0000	0.0051	0.0840
Max	1.8801	1.8972	1.7628	1.8346
Gini*	0.2342	0.4518	0.3245	0.2607
obs	270	270	270	270

* Gini coefficients obtained from 100 bootstrap replications and multiplied by n/(n-1) to get unbiased estimates (cf. Dixon, 1987)

Table 4: Location coefficients in 1999, normalised as in Laursen (1998).

Moran's I	CHEM	TRANS	ELEC	INSTR
R&D	-0.0178	0.0621***	-0.0018	0.0.03*
Pat	0.058**	0.0313*	0.0114**	0.103***
Empl	-0.002	0.085***	0.0065	0.005

* p-value based on Monto-Carlo simulation.

Table 5: Check for spatial autocorrelation.

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