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# Regional Dynamics of Innovation: Investigating the Co-Evolution of Patents, R&D, and Employment

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Abstract. The paper investigates the lead-lag relationships between the growth rates of patents, R&D, and employment for German regions over the period 1999-2005. The panel dataset employed includes information on four two-digit industries. The results obtained from a vector autoregression model show that an increase in patents is associated with subsequent growth of employment in the Medical and Optical Equipment industry as well as in the Electrics and Electronics industry. With respect to the latter, growth of patents is also associated with subsequent growth of R&D. Neither of these effects can be found for the Chemicals and Transport equipment industries.

*JEL codes:* O18, O30, R11

*Keywords:* Regional Growth, VAR, Innovation, Patents

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Introduction

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) as well as to the spatial concentration of industries or the innovative activity as such (e.g., Audretsch and Feldman, 1996; Brenner, 2004, 2006; Brenner and 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 led to the emergence of a whole new strand of research, viz. the regional innovation systems approach (e.g., Cooke, 1992; Doloreux, 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 and Guellec, 2000; Coad and Rao, 2007) as well as at the industry level (e.g. Antonucci and Pianta, 2002; Evangelista and Savona, 2003). However, very little is known about how the observed effects relate to the regional level and which role agglomeration economies play in this respect. It is still unknown whether employment gains of innovative firms outweigh employment losses of non-innovative firms located in the same region.

Another unanswered question concerns differences in the impact of innovation in different types of regions. In terms of innovation policy is ‘picking the winners’ more or less effective than a levelling-out strategy? Are there differences in employment growth and innovation dynamics between specialized and diversified regions?

The paper aims at shedding light on these issues by exploring the co-evolution of three statistical series: growth of employment, growth of R&D and growth of patents at the regional level for four different industries.

A unique panel dataset 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 ‘reduced-form’ vector autoregressions (VAR) are utilised, which have been successfully used in firm level studies (see the survey in Coad, 2009 Chapter 5). The intention in adopting this methodology in regional economics is to provide a description of the interrelated processes regarding the growth rates of the three variables. New evidence shall be presented on how regions develop over time.

The remainder of the paper is structured as follows. In the following section, the theoretical underpinnings are presented at both, the level of the firm and the regional level. In the third section, the particularities of the industries under consideration are pointed out. In the subsequent section the methodology of the empirical analysis is explained. The dataset is introduced in the fifth section, followed by the presentation and a discussion of the results. Finally, the last section offers some concluding remarks along with a critical discussion.

## Theoretical Considerations

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*Innovation at the firm level*

In the analysis of employment effects of innovation it is convenient and common practice to distinguish between product innovations and process innovations. Both types of innovation are likely to exert different effects on employment.

At the firm level product innovations are usually viewed as employment enhancing since new products create new demand. This effect will however be reduced if new products substitute other products of the firm (Harrison et al., 2005; van Reenen, 1997), a pattern that is commonly known as cannibalisation. Moreover, product innovations may also have productivity effects if affecting production methods and the input mix. Nevertheless, the positive compensation effects due to an increased demand are typically regarded as being most important (Harrison et al., 2005).

Regarding process innovations it is rather straightforward to assume that innovations will reduce the need for most of the required factors at a given output level. A first intuition therefore is that process innovations reduce employment. This is however conditional on the nature of the particular innovation, i.e. if it is rather labour or capital augmenting, as well as on the competition the firm is exposed to. A reduction in costs per unit may eventually also lead to a lower price, which in turn stimulates demand (Harrison et al., 2005). Other compensation mechanisms may gain importance as well (see Spiezia and Vivarelli, 2000 for an overview).

Consequently the sign and magnitude of innovation's firm level employment effects 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 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”. Coad and 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 and 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. Their results reveal positive employment effects of innovation in general 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. Summarizing these findings one may conclude that the positive effects of product innovation seem to be clear while the results regarding new processes are less harmonious (see also Greenan and Guellec, 2000; Peters, 2004; Smolny, 2002).

Regarding the co-evolution of R&D and patenting one may think of two causal relationships. First and most intuitive, one anticipates a positive correlation between growth of R&D employment and later growth of patents. In order to create innovations firms depend on creative minds, which is why R&D employees are to be considered the



most important input into the process of knowledge generation (Henderson et al., 1995; Brenner and Broekel, 2009). Although there is indeed a positive relationship between R&D and innovation at the firm level (e.g. Mairesse and Mohnen, 2005) various studies indicate that there is no time lag between changes in R&D and patents (Ernst, 1998). As a consequence Griliches (1990) regards patents as an indicator of both inventive input and output. In this context it appears unlikely that the present study will reveal a lead lag relationship between R&D employment and patent growth.

On the other hand one can rightly argue that successful firms will make further R&D investments. If innovation leads to firm growth as described above firms may invest a fraction of their earnings in further R&D projects in order to maintain competitiveness. Indeed Gomory (1992, p.392) vividly describes how “R&D is often a fixed percent of sales” and Coad and Rao (2010) show that growth of employment and sales is associated with subsequent growth of R&D. Coad (2010) furthermore shows that employment growth precedes growth of sales, which in turn is followed by growth of profits. Hence the relationship between growth of patent applications and later growth of R&D seems to be mediated through the economic success of innovation. Accordingly a positive relationship is to be expected between growth of R&D and previous growth of patents and/or employment. This ultimately corresponds to a 'success breeds success' hypothesis at the firm level.

*Dynamics in the region*

Since the focus of this paper is the relationship between regional innovation, employment, and R&D, the firm level effects need to be related to the more aggregate regional level. Firms in a region are no isolated entities but may be embedded into the regional innovation system (e.g. Cooke, 2001). They interact, i.e. they compete,

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4 cooperate, and supply each other. Other actors in the region, such as universities or local  
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6 policy makers, also influence them. Regionally embedded firms exert influence on their  
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8 environment and are affected by it at the same time. All this has to be taken into account  
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10 when investigating the regional relationships between the aforementioned variables.  
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14 From a policy perspective the most interesting relationship is probably that between  
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16 employment and innovation in the region. Of course one cannot get to the regional  
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18 impact of innovation by simply multiplying the average firm level effect by the number  
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20 of firms in a certain area (see, e.g., Harrison et al., 2005).  
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24 One reason for why analyses treating firms as isolated fail in this context is that while  
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26 observing a positive effect for a single firm it is impossible to distinguish between an  
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28 expanding market as a result of innovation on the one hand, and simple market share  
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30 stealing effects on the other hand. If positive firm level effects are based on market  
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32 share gains at the expense of less innovative firms then the aggregate effect will be  
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34 much smaller (see, e.g., Harrison et al., 2005).  
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38 In this case, the spatial distribution of innovating firms in relation to that of non-  
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40 innovators gains importance. Most likely these distributions will overlap and the  
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42 question remains, whether for a particular region the employment gains of innovative  
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44 firms outweigh the reductions of non-innovative firms. In this respect also firm entry  
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46 (stimulated by innovation) and exit (due to eroding market shares) becomes relevant (cf.  
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48 Harrison et al., 2005; Pianta, 2005).  
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53 The direction of the regional effects depends among other things on an industry's  
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55 degree of spatial concentration and the spatial distribution of innovative and non-  
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57 innovative firms. In case of industries concentrated in few regions the market stealing  
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59 effects become effective in the same region in which the innovative firms are located  
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4 because this region is also a very likely location of non-innovative firms. Hence the  
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6 overall employment effects of innovation are smaller in this region than in the case  
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8 when the locations of less innovative and innovative firms fall apart. Such is more likely  
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10 to happen in industries rather uniformly distributed over space. In this case the  
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12 probability is higher that employment gains in one region cause employment losses in  
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14 other regions, which leads to a clear association between growth of innovation and  
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16 employment. Either way one can still expect a positive correlation between both  
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18 variables for which reason the first hypothesis to be tested is:  
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23 • Hypothesis 1: Growth of employment is  
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25 positively related to previous growth of patents.  
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29 The spatial distribution of an industry also refers to another concept in regional science,  
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31 namely agglomeration economies. During the last two decades in regional science a  
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33 large body of empirical literature has been dedicated to investigate different types of  
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35 agglomeration economies. This research is based on the seminal works of Marshall  
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37 (1890), Arrow (1962), and Romer (1986) on the one hand and on that of Jacobs (1970)  
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39 on the other hand. Therefore the literature refers to the different notions of  
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41 agglomeration economies as MAR and Jacobs externalities respectively (Glaeser et al.,  
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43 1992).  
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48 The notion of MAR-externalities addresses the spatial concentration of a single industry  
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50 (see, e.g., Rosenthal and Strange, 2001). An industry which is concentrated  
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52 disproportionately high in a region may benefit from labour market pooling, input-  
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54 output linkages, and intra-industry knowledge spillovers. Consequently the firms in  
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56 such specialised regions can produce more efficiently than elsewhere.  
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Jacobs externalities instead derive from the variety of industries in the region (see, e.g., Frenken et al., 2007; Neffke et al., 2008). In Jacobs' (1970) view the creation of new knowledge is based on spillovers between rather than within industries. Accordingly, only a large local variety of different industries allows for the beneficial exchange of complementary knowledge, which translates into a competitive advantage for firms in diversified regions over firms located in less diversified areas. While diversity is argued to directly impact innovation its effect on growth of employment is likely to be mediated through its effect on innovation.

Among other authors Frenken et al. (2007) distinguish an additional form of agglomeration economies, i.e. urbanisation economies. While the name is often used synonymously with Jacobs externalities the definition used here refers to it as being independent from a region's industrial structure. Urbanisation economies are rather seen as arising from urban size and population density per se. Urban centres not only host universities and extramural research facilities but also important social or cultural organisations. Frenken et al. (2007, p. 687) argue that "it is the dense presence of these organizations ... that supports the production and absorption of know-how, stimulating innovative behaviour, and which contributes to differential rates of interregional growth."

Research has been dedicated to analyze empirically the relationship between all kinds of externalities and regional economic growth on the one hand (e.g., Glaeser et al., 1992; Henderson et al., 1995; Henderson, 1997; Combes, 2000; de Lucio et al., 2002) and their influence on regional innovation activities on the other hand (e.g., Feldman and Audretsch, 1999; Paci and Usai, 1999; Greunz, 2004; van der Panne and van Beers, 2006). Positive evidence for all types of externalities has been found (see Beaudry and Schiffauerova, 2009 for an overview). In keeping with this literature the present study

explores the effects of agglomeration economies on the growth rates of employment, innovation as well as R&D and thus contributes to both strands in the literature. Which industry benefits from which type of agglomeration economies is unclear a priori. Therefore, the second hypothesis is put forward as:

- Hypothesis 2: Depending on the industry there is a positive relationship between some indicator of agglomeration economies and economic growth.

The aforementioned firm-level ‘success-breeds-success’ mechanisms as reflected in a lead-lag relationship between innovation and R&D and/or employment and R&D is likely to be observed at the regional level, too. However, the regional dimension adds an extra rationale for a positive relationship between the growth of innovation and subsequent growth of R&D.

A spinoff from an incumbent firm represents an important vehicle for regional knowledge transfer. A considerable number of research projects have been set up in order to explore the regularities of market entry by spinoffs. Klepper and Thompson (2005) summarize the findings from some of the most important studies concerning the semiconductor, automobile, hard drive, and biotech industry. With respect to these studies around 20% of all entrants can be considered spinoffs, which are markedly good performers. 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 (Klepper and Thompson, 2005; Klepper and Sleeper, 2005).

It may rather be the case that spinoffs and their well-educated personnel will contribute to a large degree to the category of R&D employees in the present study. An increase in

innovations also implies an increase in potential disagreements on how to pursue these innovations and thus raises the opportunities for potential entrepreneurs to start their own businesses. Both the decision to leave the old employer and start a new venture as well as the replacement of R&D personnel in the incumbent firm are very likely to require quite some time. It is thus plausible to anticipate a certain delay for the effects of a growing number of patent applications on growth of R&D employees.

Accordingly the last two hypotheses tested address the existence of ‘success-breeds-success’ mechanisms and spin-off effects in the region:

- Hypothesis 3: Growth of employment is succeeded by growth of R&D.
- Hypothesis 4: Growth of patents precedes growth of R&D.

### Industry Characteristics

The present study distinguishes between four different industries: Chemicals (CHEM), manufacturers of transport equipment (TRANS), Electrics and Electronics (ELEC), and manufacturers of medical, optical, and precision instruments (INSTR). These industries differ with respect to their spatial distribution, innovation modes, and production schemes.

For instance innovations can be very heterogeneous in value for firms of different industries (Van Reenen, 1997). In scale intensive industries, such as transport equipment, process innovations are of outweighing importance (Arndt, 2000), whereas the firms in the instruments industries focus on product innovations (Pavitt, 1984). Also

the degree to which innovations are captured by common innovation indicators varies between industries (Arundel and Kabla, 1998; Cohen et al., 2000).

Concerning Europe’s largest firms in the ‘manufacturers of automobiles’ and ‘manufacturers of other transport equipment’ industry Arundel and Kabla (1998) report a sales-weighted patent propensity rate for process (product) innovations of only 17 % (30 %) and 10.9 % (31.2 %) respectively. In contrast, the ratio for process (product) innovations for chemicals and pharmaceuticals in the same study 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. For precision instruments the reported ratios for both kinds of innovations are about 50 %. Cohen et al. (2000) arrive at similar results for U.S. manufacturing firms.<sup>1</sup>

These differences have to be kept in mind as the present study relies on patent data as an innovation indicator. Scepticism arises about finding the relations specified in hypotheses 1 and 4 for the manufacturers of transport equipment (TRANS). The patent propensity rate in this industry is extremely low, most notably for new processes which are however eminently important in this sector.

Regarding the Chemicals industry there is another reason to be pessimistic about the detection of innovation dynamics in the present data. Firms in this industry face a rather long time-to-market for new products. For the pharmaceutical industry, e.g., Dranove and Meltzer (1994) report an average time from a drug's first patent application to its approval by the FDA of about thirteen years. Only at this time the employment effects of innovation may become visible. However, the data at hand do not allow for considering more than three one-year lags. Thus it is rather questionable whether the

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4 expected co-evolutionary dynamics concerning patents (hypotheses 1 and 4) can be  
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6 detected in this industry. Moreover, the employed classification does not allow  
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8 disaggregating the chemicals industry into organic and inorganic chemistry as well as  
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10 pharmaceuticals. These branches might however be characterized by varying co-evolution  
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12 patterns, which can lead to insignificant results at the higher level of aggregation used in  
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18 Malerba and Orsenigo (1995, p. 62) show 'that patterns of innovative activities differ  
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20 systematically across technology classes'. In their study the authors identify two groups  
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22 of technological classes, commonly known as 'Schumpeter Mark I' and 'Schumpeter  
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24 Mark II'. Innovative activities within these groups follow very different rules. The first  
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26 is characterized by a widening pattern, i.e. main innovative contributions stem from  
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28 small firms and the entry of new innovators is high. The latter instead is dominated by  
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30 large corporations representing a stable core of persistent innovators. Malerba and  
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32 Orsenigo (1996) identify large parts of the instruments industry as 'Schumpeter Mark I'  
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34 whilst they classify Chemicals and Electronics into 'Schumpeter Mark II'. Considering  
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36 the study by Coad and Rao (2007) finding more positive effects for large compared to  
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38 small firms one must expect to find more explicit evidence for hypothesis 1 in the  
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40 electrics and electronics industry.<sup>2</sup>  
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48 It has been argued above that industries may differ as to the extent to which they benefit  
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50 from different types of agglomeration economies. Pavitt (1984) offers a way to classify  
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52 industries according to their innovation characteristics; a taxonomy which has been  
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54 validated in recent studies (e.g. Archibugi, 2001; de Jong and Marsili, 2006). According  
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56 to this taxonomy CHEM and ELEC are to be considered science based industries in  
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58 which innovation mainly originates from the firms' own R&D activities based on the  
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60 underlying sciences. The firms concentrate on their principal sector which can hardly be



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4 entered by firms outside the industry because of the sophisticated technologies applied  
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6 (Pavitt, 1984). Given this sophistication one would expect these industries to benefit  
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8 rather from MAR as opposed to Jacobs externalities.  
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11 The same holds for scale-intensive producers which Pavitt (1984) identifies in the motor  
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13 vehicles industry. There “innovative firms produce a relatively high proportion of their  
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15 own process technology” and “make a relatively big contribution to all the innovations  
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17 produced in their principal sectors of activity” (Pavitt, 1984 p.359). Accordingly it is  
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19 rather straightforward to presume a less important role of Jacobs externalities compared  
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21 to MAR externalities for TRANS.  
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26 For INSTR instead Jacobs externalities might be more relevant than in other industries.  
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28 Pavitt (1984) classifies instrument engineering firms into the category of specialised  
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30 suppliers. In such industries innovative impetus stems from a variety of firms outside  
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32 the principal sector while its innovations in turn are used in a number of other sectors.  
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34 This already illustrates the role played by other industries and, as a consequence, a large  
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36 local variety of sectors may be conducive to the industry’s innovative activities.  
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### 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. This panel dataset tracks a  
reasonably large number of regions over the period 1999-2005. The main focus of this  
study is on the observation of 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 patents, a vector  
autoregression model is applied.

The regression equation of interest is of the following form:

$$w_{rt} = c + \beta w_{r,t-1} + CTRL_{rt} + \varepsilon_{rt} \quad (1)$$

where  $w_{it}$  is an  $m \times 1$  vector of random variables for region  $r$  at time  $t$ .  $\beta$  corresponds to an  $m \times m$  matrix of slope coefficients that are to be estimated. In this particular case,  $m=3$  and corresponds to the vector (Employment growth (r,t), R&D growth (r,t), growth of patent applications (r,t)). CTRL refers to our control variables, which are the specialization index, the diversity variable, and the population density of a region.  $\varepsilon$  is an  $m \times 1$  vector of disturbances.

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

$$x_r(t) = \log(X_r(t)) - \frac{1}{N} \sum_{r=1}^R \log(X_r(t)) \quad (2)$$

where  $R$  is the number of regions. In what follows growth rates are defined as the first difference of normalized (log) values according to

$$g_r(t) = x_r(t) - x_r(t-1) \quad (3)$$

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

Equation (1) is estimated 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 this 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 2009, Chapter 3), industrial sectors (Castaldi and Sapio, 2008) as well as at the level of countries (Lee et al., 1998). Figure 1 shows that the unconditional growth rates distributions for the present regional data also exhibit heavy tails. In this case OLS may provide unreliable results, and as a result Least Absolute Deviation (LAD) estimation seems to be appropriate, as it is better suited to the case of non-Gaussian residuals.<sup>3</sup>

FIGURE 1 ABOUT HERE

Since the main variables are expressed in terms of growth rates (i.e. differences rather than levels), one is not concerned with the issue of unobserved heterogeneity in the form of time-invariant region-specific ‘fixed effects’ because these fixed effects have effectively been removed in the process of taking differences.

It is also worth emphasizing that issues of causality between growth of employment, R&D and patents are not claimed to be strictly resolved. Instead, the results shall be interpreted merely in terms of describing the regularities that may be observed during the processes of industrial and regional evolution.

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 (see, e.g., Combes, 2000).

The data on patent applications is published by the German Patent Office in Greif and Schmiedl (2002). The applications by public research institutes 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 statistics provided by the German Federal Employment Agency. It covers all employees subject to social insurance contribution. 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.). From the same source data on industries' total regional employment are obtained. For sound empirical estimations the number of R&D employees is subtracted.

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, 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). A concordance between these two classifications is applied that has been developed by Broekel (2007). It adapts the concordance by Schmoch et al. (2003) to the present data. Table 1 gives an overview of the industries and the included technological fields.

TABLE 1 ABOUT HERE

Following van der Panne and van Beers (2006) the presence of MAR-externalities is approximated by an industry's location coefficients (*SPEC*). 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).

$$SPEC_{s,r} = \frac{empl_{s,r} / empl_r}{empl_s / empl}$$

with  $empl_{s,r}$  and  $empl_s$  referring to the employment of sector  $s$  and  $empl_r$  and  $empl$  represent the total employment in region  $r$  and Germany respectively. As put forward by Laursen (1998) the index is made symmetric by estimating:

$$\frac{SPEC_{s,r} - 1}{SPEC_{s,r} + 1} + 1$$

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.

In a common fashion, urbanization advantages are approximated by population density (Fritsch and Slavtchev, 2008). It is estimated as the number of inhabitants per square kilometre (*POP\_DEN*). The data for this variable are obtained from the German Federal Institute for Research on Building (INKAR, 2005).

In the literature, Jacobs externalities are approximated by many different indices. Following Henderson et al. (1995) an inverted Hirschman-Herfindahl index based on industry employment is used in this paper. As suggested by Combes (2000) the index is normalized at the value it takes at the national level. The index is estimated the following.

$$DIV_{s,r} = \frac{1 / \sum_{s'=1, s' \neq s}^S (emp_{s',r} / (emp_r - emp_{s,r}))^2}{1 / \sum_{s'=1, s' \neq s}^S (emp_{s'} / (emp - emp_s))^2}$$

$S$  represents the total number of sectors, i.e. the number of two-digit manufacturing industries. The numerator is maximal in the case that all industries (except the one under investigation) are of identical size. The advantage of this diversification index is that it estimates the “sectoral diversity faced by sector  $s$  in this zone [region] and is therefore not necessarily negatively linked with the own local specialization of sector  $s$ ” (Combes, 2000, p. 337). Hence, it is an industry specific diversification index, which is not just reflecting ‘negative specialization’. It indicates the diversification in the manufacturing sector. The index shares the same non-symmetry as the location coefficient, which is why it is made symmetric in an identical manner.

Some basic summary statistics regarding the main variables are reproduced in Table 2. The sizes of the four industries vary considerably across the regions. There are also a few null values in some cases for each of the variables leading to the exclusion of some observations in the subsequent analysis based on growth rates. In addition, data constraints limit this study to no more than three lags because of a sharp decline in the number of observations if more lags are taken.

TABLE 2 ABOUT HERE

In order to check for spatial autocorrelation Moran’s  $I$  was estimated on the regions’ average growth rates (see Table 3). Average growth rates were used 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 the subsequent

estimations in any serious way. This is even more so as LAD estimation techniques are preferred over standard OLS.

TABLE 3 ABOUT HERE

Results

The exhaustive results of the ‘reduced-form’ vector autoregressions are reproduced in Table 4, which should be read as follows. In the first row, the dependent variable is employment growth, and the explanatory variables are the three VAR series (three lags are included) and also the control variables; at the end of the row the  $R^2$  and the number of observations are reported. The second row shows the regression with patent growth as the dependent variable, and the third row shows the regression with R&D growth as the dependent variable.

TABLE 4 ABOUT HERE

*Autocorrelation Series*

With respect to the observed autocorrelation R&D growth does not appear to be persistent. The respective coefficients are sometimes positive and sometimes negative but almost always insignificant. Growth of total employment instead shows a certain positive persistence. In fact the coefficients are positive and significant for the first lag in the transport equipment industry (TRANS), for the first and second lag in the Electrics and Electronics industry (ELEC), as well as for the second lag in the Chemical industry (CHEM). Only for the manufacturers of medical, optical and precision instruments (INSTR) the coefficients remain insignificant.

By contrast what turns out to be consistent over all industries is a negative autocorrelation of the patent growth variable, with coefficients of decreasing magnitudes for longer lags. The coefficients are negative and highly significant for all lags and all industries. A first intuition that this regularity could be caused by regions with very small amounts of patents is not confirmed by an analysis of sub-samples (see tables A1 and A2 in the appendix). The effect is confirmed for high and low patenting regions as well as for regions with high and low industry employment. Hence, this result might be ascribed to erratic growth dynamics since the innovative process as measured by patenting activity has a large stochastic element. 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.

### *Innovation and Employment*

Turning to hypothesis 1, for TRANS there are no significant correlations between growth of patent applications and subsequent growth of total employment. This, however, is perfectly in line with previous expectations concerning the industry's low patent propensity rate. Moreover, this industry is the most agglomerated of all four industries considered here and the results very likely encompass market-stealing effects within the region. Such may hide as well the 'real' relationship between these variables.

Concerning CHEM the coefficient for the first lag of growth of patent applications is negative and significant at the 10 % level, although the effect vanishes once the sample is split into high and low employment regions. While a possible explanation for this might be market-stealing effects within the region, the correlation should not be overrated because of the low significance level, the industry's comparatively low



regional concentration and the long time-to-market. As in the transport equipment industry the insignificant coefficients are consistent with earlier arguments based on the industry's innovation characteristics.

For the remaining two industries expectations were different and so are the results. Hypothesis 1 appears to be valid for the industries ELEC and INSTR. In both cases growth of patents is associated with subsequent growth of total employment. Regarding ELEC the coefficients are positive and significant for all three lags. The relationship is strongest for the first two lags, which 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. Moreover, the effect is stronger in regions which are larger in terms of industry employment.

For INSTR the analysis reveals positive coefficients for the second and the third lag of growth of patents, both being highly significant. However, in regions with low industry employment this relationship is not observable. Only for larger regions one can note that growth of patents is followed by growth of total employment two and three years later. Compared to ELEC the coefficients are smaller confirming the findings by Coad and Rao (2007). As in their analysis the relationship between innovation and employment here seems to be more pronounced in an industry (ELEC) in which innovation is dominated by large firms (Malerba and Orsenigo, 1996).

As a robustness check, the possibility was investigated that patents and R&D are imperfect indicators of a region's underlying innovation activity, although they both shed light on different facets of the innovation process. Therefore Principal Components Analysis (PCA) was used to extract the common variance between R&D levels and patent counts,<sup>4</sup> and then growth of innovation was calculated in terms of growth of this

PCA-generated variable. The results from this robustness check (not shown here) are that innovation is positively associated with subsequent employment growth in the ELEC sector, but no significant results were found for the other sectors.

In sum, the findings that patent growth is followed by employment growth suggest that, (i) there are positive compensation effects of innovations, and (ii) the employment gains of innovative firms are higher than the losses of less innovative firms potentially located in the same region.

### *Agglomeration Economies*

Regarding hypothesis 2 it has been argued that, for the CHEM, ELEC, and TRANS sectors, Jacobs externalities would be less relevant than MAR externalities due to the industries' innovation characteristics as reported in Pavitt (1984). The empirical results seem to support this view.

Specialisation is positively related to employment growth in the industries CHEM and ELEC, while at the same time the coefficients for diversity remain insignificant. Put differently, specialised regions experience stronger growth of employment than less specialised regions. Dividing the dataset reveals that in both industries this effect is more pronounced in regions with less industry employment (see Tables A1 and A2 in the appendix). For CHEM the effect even vanishes for larger regions while in smaller regions specialisation is additionally associated with growth of patents. The result indicates the existence of a self-reinforcing process regarding smaller regions. Small specialised regions grow faster in terms of employment which *ceteris paribus* again increases the regions' degree of specialisation. This might as well indicate a process of regional reallocation of employment towards smaller, though already specialised, regions.

For TRANS the same mechanisms as for CHEM and ELEC were expected but the coefficients for specialisation are insignificant. Nevertheless, there is a significantly negative relationship between diversity and employment growth. This relationship especially holds for regions with low industry employment in which population density is furthermore negatively correlated with growth of R&D. Considering only high employment regions, though, reveals a positive relationship between the degree of specialisation and growth of R&D employees. This is to say that diversified urban regions with low industry employment seem to be disadvantaged against specialised regions with high industry employment.

The results also reveal that MAR externalities do not necessarily affect all employment groups equally. Instead there seems to be a regional reallocation of R&D employees towards large and specialised regions, which highlights the importance of intra-industry knowledge spillovers for this industry as argued earlier in this paper. As total employment does not appear to be affected by specialisation, the transport industry might benefit from a relatively specialised manufacturing structure which is related to, but not exclusively consisting of, firms from the transport equipment industry. Important suppliers, for example, could potentially be classified into the machinery industry (NACE 29).

Interestingly, neither specialisation nor diversity is related to growth in the INSTR industry. Only low industry employment regions somehow seem to benefit from specialisation. Although it has been argued that Jacobs externalities would be more conducive to growth in specialised supplier industries like instrument engineering (Pavitt, 1984), the results do not support this line of reasoning. One explanation could be the relatively broad industry classification. Beaudry and Schiffauerova (2009) indeed show that at such aggregated levels only a small percentage of studies find a positive

relationship between diversity and innovation. Moreover, it is possible that diversity influences the innovation level in a region but not so much its growth rates which in general seem to be harder to explain. The missing link between diversity and growth of employment, though, is less surprising as this relationship is likely to be an indirect one mediated through growth of innovation which, however, separately enters into the regression.

### *R&D Dynamics*

The assumption of a positive relationship between growth of employment and subsequent growth of R&D put forward in hypothesis 3 is based on a ‘success-breeds-success’ mechanism. The results confirm the findings by Coad and Rao (2007) for the industries CHEM and TRANS at the regional level. In both industries past growth of employment is associated with growth of R&D employees one year later. For TRANS this effect is also detectable at the third lag while there is no such effect in the ELEC and INSTR industry.

Dividing the sample reduces the number of observations causing the disappearance of this effect in the CHEM industry. For TRANS instead the positive relationship can be observed at all three lags in small regions but only at the third lag in high employment regions. Remarkably, growth of employment is also associated with growth of R&D employees three years later in high industry employment regions in the INSTR industry. The same holds for ELEC when only low employment regions are considered. The somewhat longer lag structure may indicate that this effect is mediated through an increase in sales which succeeds growth of employment as reported by Coad (2010). Hence there is evidence for the validity of hypothesis 3 and thus for a regional ‘success-

breeds-success' mechanism in all industries which is, however, dependent on the size of the region.

As to hypothesis 4 regarding the relationship between patent growth and subsequent growth of R&D employees there are no significant correlations in the INSTR industry. But, surprisingly, the coefficient for the second lag of growth of patents is negative and significant for high and low employment regions in the TRANS industry as well as for regions with high industry employment in the CHEM industry.

There are several possible explanations for this relationship related to, e.g., the restructuring of R&D capacities. Most likely, however, the results indicate an innovation cycle in which a period of high innovative activities is followed by a period in which innovation activities are reduced. Due to the different reaction times of the two variables the above patterns may emerge. These cycles may relate to an industry's business cycle (see, e.g, Giedeman et al. 2006). However, such explanations remain speculative. Moreover, as patents are a very weak innovation indicator in the TRANS industry and considering the long time-to-market in the CHEM industry such relationship should not be overrated.

The expected positive correlations though are found for ELEC, which provides support for hypothesis 4 in this industry. The coefficients for the second and the third lag are positive and significant at the 5% level. Hence growth of patent applications is associated with growth of R&D employees two and three years later. This either suggests a 'success-breeds-success' mechanism and/or increased chances for opportunity spinoffs in this industry. Dividing the sample reveals that the relationship is driven by regions with high industry employment for which the effect is also detectable at the first lag. In low employment regions, though more numerous, the effect vanishes.

This is in line with the employment effects of innovation which are found to be stronger in high employment regions as well. Hence larger regions in general seem to benefit more from innovation in this industry.

## Conclusions

The paper aimed at investigating the co-evolutionary dynamics, i.e. the lead-lag relationship between growth of patent applications, R&D, and employment for German labour market regions over a period of seven years. Different types of agglomeration economies were additionally controlled for. The unique panel dataset employed comprises the Chemicals industry, manufacturers of transport equipment, manufacturers of medical, optical, and precision instruments, as well as the Electrics and Electronics industry. Because of the complex and endogenous nature of the respective growth rates, ‘reduced form’ vector autoregressions were applied. In introducing this methodology into the regional innovation literature the analysis provided deeper insights into the development of regions over time. To know about these processes is a prerequisite for designing appropriate regional innovation policies.

For the manufacturers of medical, optical, and precision instruments as well as for Electrics and Electronics past growth of patents is associated with subsequent growth of employment. For the latter industry there is also a positive relationship between growth of patents and later growth of R&D. Disaggregating by size of industry employment reveals that in both industries high employment regions benefit more from an increase in patents. Prima facie this finding might perhaps be interpreted as in line with a ‘picking the winner’ approach as applied in recent contest based innovation policies (see, e.g., Eickelpasch and Fritsch, 2005). However, the results still do not strongly

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4 suggest that this was a more effective way to achieve economic growth than a  
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7 'levelling-out' strategy.  
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11 turned out to exert different effects not only in different industries but also in different  
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13 regions and for different employment groups. In the Chemicals as well as in the  
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This is underlined by the results regarding agglomeration economies. Specialisation  
turned out to exert different effects not only in different industries but also in different  
regions and for different employment groups. In the Chemicals as well as in the  
Electrics and Electronics industry specialisation is associated with growth of  
employment. In both cases low employment regions seem to benefit more from a  
specialised industry structure. For manufacturer of transport equipment the opposite  
holds. In this industry specialisation is not related to growth of total employment but  
only to growth of R&D in regions with high industry employment. Hence if at all the  
results suggest that the adequacy of a 'picking the winner' approach crucially depends  
on the respective industry's characteristics and the employment groups addressed.

Moreover, the results show that in the Chemical and for the manufacturers of transport  
equipment growth of employment is associated with subsequent growth of R&D. This  
finding closely matches the firm-level results reported by Coad and Rao (2010).

A few limitations of this analysis should be mentioned at this point as well. First of all  
this study does not claim to resolve any issues of causality. The results should rather be  
interpreted as a description of the interrelated processes concerning the growth rates of  
the variables as may be observed during industrial and regional evolution. Since we  
cannot be certain about the causal nature of the relationships, we cannot guarantee that  
an exogenous policy stimulus to one variable will have the expected effects on the other  
variables. Nevertheless previous expectations based on the theoretical and empirical  
literature and the results obtained from this study match rather well.

Regarding the data one has to admit that patent data is not equally suited as an innovation indicator for all industries. In the case of the transport equipment industry the results support the previous concern that patent applications would not depict the industry's innovative activity properly. With respect to the Chemical industry this concern does not hold. However, the panel dataset employed seems to be too short in order to detect any long-term co-evolutionary dynamics related to innovation in the Chemical industry.



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Appendix

TABLE A1 ABOUT HERE

TABLE A2 ABOUT HERE

For Peer Review Only

## References

- Acs Z. J., Audretsch D. B. and Feldman M. P. (1992) Real Effects of Academic Research: Comment, *The American Economic Review* 82(1), 363-367.
- Antonucci T. and Pianta M. (2002) Employment Effects of Product and Process Innovation in Europe, *International Review of Applied Economics* 16, 295-308.
- Archibugi D. (2001) Pavitt's taxonomy 16 years on: A review article, *Economics of Innovation and New Technology* 10(5), 415-425.
- Arndt O. (2000) Innovative Netzwerke als Determinante betrieblicher Innovationstätigkeit: Das Beispiel Süd-Wales/UK., Selbstverlag im Wirtschafts- und Sozialgeographischen Institut der Universität zu Köln, Köln.
- Arrow K. J. (1962) The Economic Implications of Learning by Doing, *Review of Economic Studies* 29, 155-173.
- Arundel A. and Kabla I. (1998) What Percentage of Innovations are Patented? Empirical Estimates for European Firms, *Research Policy* 27, 127-141.
- Audretsch D. B. (1998) Agglomeration and the Location of Innovative Activity, *Oxford Review of Economic Policy* 14, 18-29.
- Audretsch D. B. and Feldman M. P. (1996) R&D Spillovers and the Geography of Innovation and Production, *The American Economic Review* 86, 630-640.
- Bade F.-J. (1987) Regionale Beschäftigungsentwicklung und produktionsorientierte Dienstleistungen, Sonderheft 143, Deutsches Institut für Wirtschaftsforschung, Berlin.
- Beaudry C. and Schiffauerova A. (2009) Who's right, Marshall or Jacobs? The localization versus urbanization debate, *Research Policy* 38, 318-337.

- 1  
2  
3  
4 Brenner T. (2004) Local Industrial Clusters: Existence, Emergence, and Evolution,  
5  
6 Routledge, London.  
7  
8  
9 Brenner T. (2006) An Identification of Local Industrial Clusters in Germany, *Regional*  
10  
11 *Studies* 40, 991-1004.  
12  
13  
14 Brenner T. and Broekel T. (2009) Methodological Issues in Measuring Innovation  
15  
16 Performance of Spatial Units, *Papers in Evolutionary Economic Geography* No.  
17  
18 2009-04, Urban & Regional Research Centre Utrecht, Utrecht University.  
19  
20  
21 Brenner T. and Gildner A. (2006) The Long-term Implications of Local Industrial  
22  
23 Clusters, *European Planning Studies* 14, 1315-1328.  
24  
25  
26  
27 Broekel T. (2007) A Concordance between Industries and Technologies - Matching the  
28  
29 technological fields of the Patentatlas to the German Industry Classification, *Jena*  
30  
31 *Economic Research Papers* No. 2007-013, Friedrich Schiller University and Max  
32  
33 Planck Institute of Economics, Jena.  
34  
35  
36  
37 Broekel T. and Binder M. (2007) The Regional Dimension of Knowledge Transfers - A  
38  
39 Behavioral Approach, *Industry and Innovation* 14, 151-175.  
40  
41  
42 Castaldi C. and Sapio S. (2008) Growing like mushrooms? Sectoral evidence from four  
43  
44 large European economies. *Journal of Evolutionary Economics* 18 (3), 509-527.  
45  
46  
47  
48 Coad A. (2009) The growth of firms: A survey of theories and empirical evidence,  
49  
50 Edward Elgar, Cheltenham.  
51  
52  
53 Coad A. (2010) Exploring the processes of firm growth: evidence from a vector auto-  
54  
55 regression, *Industrial and Corporate Change*, 1-27, doi:10.1093/icc/dtq018.  
56  
57  
58  
59  
60

- Coad A. and Rao R. (2007) The Employment Effects of Innovations in High-Tech Industries, *Papers on Economics and Evolution* No. 0705, Max Planck Institute of Economics, Jena.
- Coad A. and Rao R. (2010) Firm growth and R&D expenditure, *Economics of Innovation and New Technology* 19(2), 127-145.
- Cohen W. M., Nelson R. R. and Walsh J. P. (2000) Protecting their Intellectual Assets: Appropriability Conditions and why U.S. Manufacturing Firms Patent (or not), *NBER Working Paper* No. 7552, National Bureau of Economic Research, Cambridge, MA.
- Combes P.-P. (2000) Economic Structure and Local Growth: France, 1984-1993, *Journal of Urban Economics* 47, 329-355.
- Cooke P. (1992) Regional innovation systems: Competitive regulation in the new Europe, *Geo-forum* 23, 365-382.
- Cooke P. (2001) Regional Innovation Systems, Clusters, and the Knowledge Economy, *Industrial and Corporate Change* 10, 945-974.
- de Jong J. P. J., Marsili O. (2006) The fruit flies of innovations: A taxonomy of innovative small firms, *Research Policy* 35, 213-229.
- de Lucio J. J., Herce J. A. and Goicolea A. (2002) The Effects of Externalities on Productivity Growth in Spanish Industries, *Regional Science and Urban Economics* 32, 241-258.
- DESTATIS (2002) Klassifikation der Wirtschaftszweige, Ausgabe 2003 (WZ2003), Statistisches Bundesamt, Wiesbaden.

- Doloreux D. (2002) What we should know about regional systems of innovation, *Technology in Society* 24, 243-263.
- Doms M., Dunne T. and Roberts M. J. (1995) The role of technology use in the survival and growth of manufacturing plants, *International Journal of Industrial Organization* 13, 523-542.
- Dranove D. and Meltzer D. (1994) Do important drugs reach the market sooner?, *The RAND Journal of Economics* 25, 402-423.
- Eickelpasch A. and Fritsch M. (2005) Contests for cooperation – A new approach in German innovation policy, *Research Policy* 34, 1269-1282.
- Ernst H. (1998) Industrial research as a source of important patents, *Research Policy* 27, 1-15.
- Evangelista R. and Savona M. (2003) Innovation, employment and skills in services. Firm and sectoral evidence, *Structural Change and Economic Dynamics* 14, 449-474.
- Feldman M. P. (1994) *The Geography of Innovation*, Kluwer, Boston.
- Feldman M. P. and Audretsch D. B. (1999) Innovation in Cities: Science-based Diversity, Specialization and Localized Competition, *European Economic Review* 43, 409-429.
- Feldman M. P. and Florida R. (1994) The geographic sources of innovation: technological infrastructure and product innovation in the United States. *Annals of the Association of American Geographers* 84, 210-229.
- Frenken K., van Oort F. and Verburg T. (2007) Related Variety, Unrelated Variety and Regional Economic Growth, *Regional Studies* 41, 685-697.

- 1  
2  
3  
4 Fritsch, M. and Slavtchev, V. (2008) Determinants of the Efficiency of Regional  
5  
6 Innovation Systems. *Regional Studies*, DOI:10.1080/00343400802251494.  
7  
8  
9 Giedeman D., Isely P. and G. Simons (2006) Innovation and the Business Cycle: A  
10  
11 Comparison of the U.S. Semiconductor and Automobile Industries, *International*  
12  
13 *Advances in Economic Research* 12(2), 277-286.  
14  
15  
16 Glaeser E. L., Kallal H., Scheinkman J. and Shleifer A. (1992) Growth in Cities, *Journal*  
17  
18 *of Political Economy* 100, 1126-1152.  
19  
20  
21  
22 Gomory R. (1992) The technology-product relationship: Early and late stages, in  
23  
24 Rosenberg N., Landau R. and Mowery D. (Eds) *Technology and the wealth of*  
25  
26 *nations*, pp. 383-394. Stanford University Press, Palo Alto, CA.  
27  
28  
29  
30 Greenan N. and Guellec D. (2000) Technological innovation and employment  
31  
32 reallocation, *Labour* 14, 547-590.  
33  
34  
35 Greif S. and Schmiedl D. (2002) Patentatlas 2002 Dynamik und Strukturen der  
36  
37 Erfindungstätigkeit, Deutsches Patent- und Markenamt, München.  
38  
39  
40 Greunz L. (2004) Industrial Structure and Innovation - Evidence from European  
41  
42 Regions, *Journal of Evolutionary Economics* 14, 563-592.  
43  
44  
45 Griliches Z. (1990) Patent statistics as economic indicators: A survey, *Journal of*  
46  
47 *Economic Literature* 28, 1661-1707.  
48  
49  
50  
51 Hall B. H. (1987) The Relationship Between Firm Size and Firm Growth in the US  
52  
53 Manufacturing Sector, *The Journal of Industrial Economics* 35, 583-606.  
54  
55  
56 Harrison R., Jaumandreu J., Mairesse J. and Peters B. (2005) Does innovation stimulate  
57  
58 employment? A firm-level analysis using comparable micro data from four  
59  
60 European countries, *MPRA Papers*, 1245, Universität München, Munich.

- Henderson V. (1997) Externalities and Industrial Development, *Journal of Urban Economics* 42, 449-470.
- Henderson V., Kuncoro A. and Turner M. (1995) Industrial Development in Cities, *The Journal of Political Economy* 103, 1067-1090.
- INKAR (2005). Aktuelle Daten zur Entwicklung der Städte, Kreise und Gemeinden, CD-Rom, Berichte 8, Volume 14. Bundesministerium für Bauwesen und Raumplanung, Berlin.
- Jacobs J. (1970) *The Economy of Cities*, Vintage Books, New York.
- Jaffe A. B. (1989) Real Effects of Academic Research, *The American Economic Review* 79, 957-970.
- Jaffe A. B., Trajtenberg M. and Henderson R. (1993) Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations, *Quarterly Journal of Economics* 108, 577-598.
- Klepper S. and Thompson P. (2005) Spinoff Entry in High-tech Industries: Motives and Consequences, *Working Papers* No. 0503, Department of Economics, Florida International University, Miami, FL.
- Klepper S. and Sleeper S. (2005) Entry by Spinoffs, *Management Science* 51, 1291-1306.
- Krugman P. (1991) *Geography and Trade*, MIT Press, Cambridge.
- Lachenmaier S. and Rottmann H. (2007) Effects of innovation on employment: A dynamic panel analysis, *CESIFO Working Papers* No. 2015, Ifo Institute for Economic Research, Munich.

- Laursen K. (1998) Revealed Comparative Advantage and the Alternatives as Measures of International Specialisation, *DRUID Working Papers* No. 98-30, Department of Industrial Economics and Strategy, Copenhagen Business School and Department of Business Studies, Aalborg University.
- Lee Y., Amaral L. A. N., Canning D., Meyer M. and Stanley H. E. (1998) Universal features in the growth dynamics of complex organizations, *Physical Review Letters* 1, 3275-3278.
- Mairesse J. and Mohnen P. (2005) The Importance of R&D for Innovation: A Reassessment Using French Survey Data, *Journal of Technology Transfer* 30, 183-197.
- Malerba F. and Orsenigo L. (1995) Schumpeterian patterns of innovation, *Cambridge Journal of Economics* 19, 47-65.
- Malerba F. and Orsenigo L. (1996) Schumpeterian patterns of innovation are technology-specific, *Research Policy* 25, 451-478.
- Marshall A. (1890) *Principles of Economics*, Macmillan, London.
- Neffke F., Svensson Henning M., Boschma R., Lundquist K.-J. and Olander L.-O. (2008) Who Needs Agglomeration? Varying Agglomeration Externalities and the Industry Life Cycle, *Papers in Evolutionary Economic Geography* No. 08.08, Urban & Regional Research Centre Utrecht, Utrecht University.
- Paci R. and Usai S. (1999) The Role of Specialization and Diversity Externalities in the Agglomeration of Innovative Activity, *Working Paper CRENoS* No. 199915, University of Cagliari.



- Pavitt K. (1984) Sectoral patterns of technical change: Towards a taxonomy and a theory, *Research Policy* 13, 343-373.
- Peters B. (2004) Employment Effects of Different Innovation Activities: Microeconometric Evidence, *ZEW Discussion Paper* No. 04-73, Centre for European Economic Research, Mannheim.
- Pianta M. (2005) Innovation and Employment, in Fagerberg J., Mowery D. C. and Nelson R. R. (Eds) *The Oxford Handbook of Innovation*, pp. 568-598, Oxford University Press, Oxford, New York.
- Porter M. E. (1990) *The Competitive Advantage of Nations*, Free Press, New York.
- Romer P. M. (1986) Increasing Returns and Long-Run Growth, *The Journal of Political Economy* 94, 1002-1037.
- Rosenthal S. S. and Strange W. C. (2001) The Determinants of Agglomeration, *Journal of Urban Economics* 50, 191-229.
- Schmoch U., Laville F., Patel P. and Frietsch R. (2003) Linking Technology Areas to Industrial Sectors, *Final Report to the European Commission*, DG Research, Karlsruhe, Paris, Brighton.
- Smolny W. (1998) Innovation, prices and employment – a theoretical model and an empirical application for West German manufacturing firms, *The Journal of Industrial Economics* XLVI, 359-381.
- Smolny W. (2002) Employment adjustment at the firm level. A theoretical model and empirical investigation for West-German manufacturing firms, *Labour* 16, 65-88.

- 1  
2  
3  
4 Spiezia V. and Vivarelli M. (2000) The Analysis of Technological Change and  
5  
6 Employment, in Vivarelli M. and Pianta M. (Eds) The Employment Impact of  
7  
8 Innovation – Evidence and Policy, pp. 12-25, Routledge, London, New York.  
9  
10  
11 Stock J. H. and Watson M. W. (2001) Vector autoregressions, *Journal of Economic*  
12  
13 *Perspectives* 15, 101-115.  
14  
15  
16 van der Panne G. and van Beers C. (2006) On the Marshall-Jacobs Controversy: It  
17  
18 Takes Two to Tango, *Industrial and Corporate Change* 15, 877-890.  
19  
20  
21 van Reenen J. (1997) Employment and Technological Innovation: Evidence from U.K.  
22  
23 Manufacturing Firms, *Journal of Labor Economics* 15, 255-284.  
24  
25  
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Tables and Figures

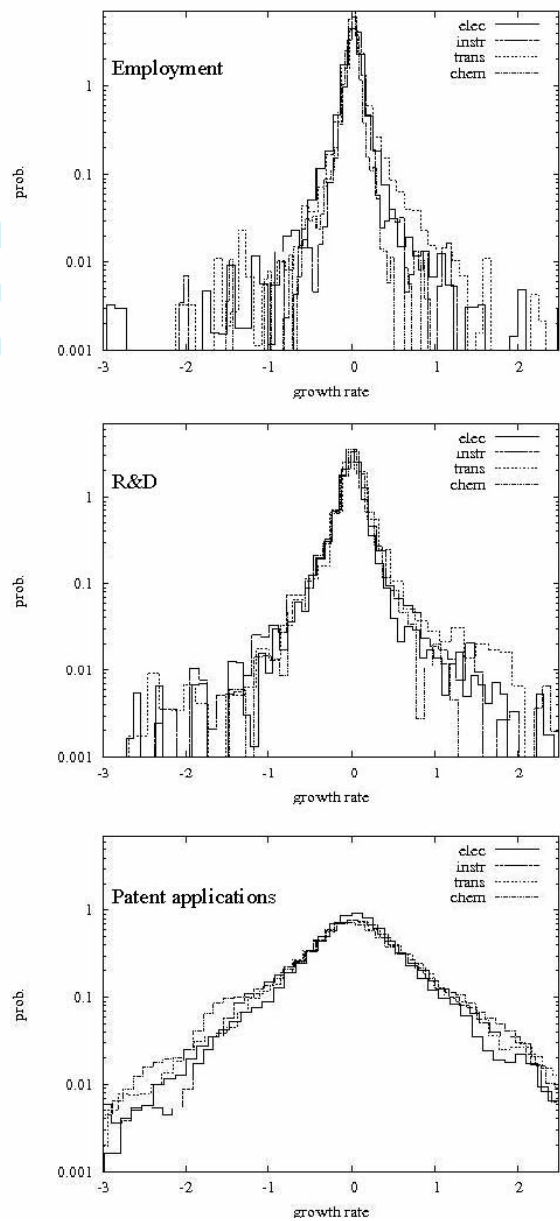


Figure 1: Annual growth rate distributions for regional employment, R&D and patent applications. Growth rates are normalized around zero for each year, and then the years are pooled together. Kernel densities computed using an Epanenchnikov kernel.

Sector	Technological fields*	Industries**
CHEM	TF5, TF12, TF13, TF14, TF15	DG24, DI26
ELEC	TF27, TF28, TF29, TF30, TF31	DL30, DL31, DL32
INSTR	TF4, TF16, TF26	DL33, DF23
TRANS	TF10, TF22	DM34, DM35
* As defined in Greif & Schmiedel (2002); ** According to the GIC DESTATIS (2002)		

Table 1: Overview technological fields.

	Mean	Std Dev	10%	25%	median	75%	90%	Min	Max	Obs
Chem										
Empl	2793.189	4875.299	323	644	1319	2658	6069	38	49218	270
R&D	146.930	402.685	5.5	14	40.5	112	304.5	0	4408	270
Patents	12.371	38.869	0	0.6	1.9	6.2	27.75	0	382	270
ELEC										
Empl	2421.804	5024.096	107	275	836	2476	5623.5	1	55861	270
R&D	610.819	1405.686	7	42	165	591	1555.5	0	16548	270
Patents	22.240	73.180	0	1.8	6.15	16.8	42.15	0	956.2	270
INSTR										
Empl	1544.874	2729.405	123.5	244	614.5	1593	3517	11	18124	270
R&D	254.207	541.826	2	11	64	193	703.5	0	3731	270
Patents	11.500	28.149	0	1	3.3	11.1	26.25	0	272.3	270
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	16.632	64.966	0	1.3	4.5	12	32.5	0	951.1	270

Table 2: Summary statistics for the four industries in 1999. The statistics refer to the absolute numbers of total employment, R&D employees and patent applications.

Moran's I	CHEM	ELEC	INSTR	TRANS
R&D	-0.0178	-0.0018	0.0.03*	0.0621***
Pat	0.058**	0.0114**	0.103***	0.0313*
Empl	-0.002	0.0065	0.005	0.085***
*p-value based on Monto-Carlo simulation.				

Table 3: Check for spatial autocorrelation.

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$w_t$	$\beta_{t-1}$			$\beta_{t-2}$			$\beta_{t-3}$			spec	div	pop_den	$R^2$	Obs
	gr_empl	gr_pat	gr_rnd	gr_empl	gr_pat	gr_rnd	gr_empl	gr_pat	gr_rnd					
CHEM														
gr_empl	0.0376	-0.0059	0.0066	0.0883	-0.0013	-0.0179	0.0475	0.0008	-0.0399	0.0167	-0.0002	0.0000	0.0212	562
t-stat	1.48	-1.86	0.83	2.88	-0.40	-1.51	1.58	0.26	-3.35	3.07	-0.04	-0.44		
gr_pat	0.4086	-0.5780	0.0260	0.1264	-0.3237	0.1092	-0.1490	-0.1372	0.1148	0.1012	-0.0838	0.0000	0.1285	547
t-stat	1.08	-12.05	0.21	0.28	-6.48	0.63	-0.33	-3.04	0.65	1.25	-1.05	0.31		
gr_rnd	0.1271	-0.0083	-0.0286	0.0496	0.0026	-0.0321	0.1313	-0.0006	-0.1552	0.0068	0.0041	0.0000	0.0143	562
t-stat	2.22	-1.17	-1.35	0.74	0.35	-1.19	1.95	-0.08	-5.79	0.56	0.35	0.04		
ELEC														
gr_empl	0.0381	0.0237	0.0126	0.0512	0.0254	0.0234	0.0411	0.0117	0.0195	0.0138	-0.0067	0.0000	0.0413	665
t-stat	2.47	4.18	0.91	2.51	4.52	1.60	1.90	2.40	1.39	1.96	-0.86	-2.23		
gr_pat	-0.0635	-0.3727	0.0285	-0.1393	-0.2415	0.1232	0.0878	-0.1427	-0.1276	0.0417	0.0425	0.0000	0.0781	655
t-stat	-0.50	-8.77	0.29	-0.93	-5.76	1.10	0.56	-3.99	-1.22	0.80	0.73	-0.98		
gr_rnd	0.0190	0.0137	0.0338	-0.0046	0.0187	0.0097	0.0273	0.0184	-0.0089	0.0015	-0.0011	0.0000	0.0076	665
t-stat	0.73	1.62	1.70	-0.15	2.24	0.42	0.86	2.54	-0.44	0.14	-0.09	-0.58		
INSTR														
gr_empl	0.0215	0.0047	0.0180	0.0019	0.0111	-0.0093	0.0336	0.0105	0.0055	0.0065	0.0009	0.0000	0.0155	633
t-stat	0.97	1.20	1.68	0.10	2.71	-1.04	1.52	2.99	0.67	0.94	0.15	-1.35		
gr_pat	-0.0315	-0.6058	0.1169	-0.1700	-0.2670	0.0714	0.1078	-0.1490	-0.0677	0.0683	0.0558	0.0000	0.1714	629
t-stat	-0.15	-15.19	1.08	-0.77	-6.46	0.76	0.47	-4.23	-0.80	0.98	0.88	-1.35		
gr_rnd	0.0584	0.0010	0.0126	0.0148	0.0008	0.0206	0.0134	-0.0026	-0.0173	-0.0032	-0.0011	0.0000	0.0050	633
t-stat	1.94	0.18	0.88	0.49	0.14	1.59	0.43	-0.54	-1.47	-0.34	-0.12	-0.36		
TRANS														
gr_empl	0.0395	-0.0088	-0.0123	0.0176	-0.0060	-0.0101	0.0119	0.0022	-0.0051	0.0137	-0.0302	0.0000	0.0189	573
t-stat	3.26	-1.62	-1.07	1.29	-0.98	-1.01	0.98	0.41	-0.67	1.92	-3.18	-0.37		
gr_pat	-0.0612	-0.5605	-0.0308	-0.0484	-0.3715	0.1423	0.0451	-0.2719	-0.0157	-0.0433	0.1205	0.0000	0.1612	569
t-stat	-0.51	-11.24	-0.29	-0.45	-6.57	1.57	0.40	-5.63	-0.20	-0.67	1.39	-1.17		
gr_rnd	0.0541	-0.0074	-0.0055	0.0204	-0.0228	0.0007	0.0666	-0.0071	-0.0054	0.0184	-0.0071	0.0000	0.0115	573
t-stat	2.86	-0.96	-0.33	1.22	-2.64	0.05	3.10	-0.95	-0.45	1.83	-0.53	-1.12		

Table 4: LAD estimation of equation (1) where m=3 and corresponds to the vector (gr\_empl (r,t), gr\_pat (r,t), gr\_rnd (r,t)).

$w_t$	$\beta_{t-1}$			$\beta_{t-2}$			$\beta_{t-3}$			spec	div	pop_den	$R^2$	Obs
	gr_empl	gr_pat	gr_rnd	gr_empl	gr_pat	gr_rnd	gr_empl	gr_pat	gr_rnd					
CHEM														
gr_empl	0.0121	-0.0092	0.0064	0.0460	0.0018	-0.0436	0.0259	-0.0004	-0.0570	0.0431	-0.0088	0.0000	0.0525	214
t-stat	0.23	-1.37	0.35	0.75	0.24	-1.92	0.41	-0.07	-2.64	1.96	-0.66	1.27		
gr_pat	0.3067	-0.6667	0.0771	-0.3805	-0.4484	-0.0823	-0.3678	-0.1749	0.3219	0.6498	-0.2414	0.0000	0.1774	202
t-stat	0.52	-10.70	0.58	-0.78	-6.77	-0.40	-0.62	-2.99	1.53	3.15	-1.98	0.41		
gr_rnd	0.0712	-0.0261	-0.0213	0.0648	-0.0006	-0.0548	0.1125	-0.0040	-0.1174	0.0857	-0.0075	0.0000	0.0415	214
t-stat	0.51	-1.70	-0.51	0.47	-0.04	-0.97	0.79	-0.27	-2.28	1.68	-0.24	0.69		
ELEC														
gr_empl	0.0340	0.0176	0.0148	0.0590	0.0229	0.0084	0.0501	0.0077	0.0008	0.0357	0.0132	0.0000	0.0399	401
t-stat	1.49	2.08	0.76	1.87	2.72	0.38	1.39	1.07	0.03	2.14	1.01	-1.21		
gr_pat	-0.1209	-0.3997	0.0456	-0.3459	-0.2634	0.1438	0.0523	-0.1809	-0.3013	0.0725	0.0498	0.0000	0.0869	391
t-stat	-0.81	-7.45	0.39	-1.79	-5.00	1.00	0.24	-4.06	-2.16	0.70	0.62	0.25		
gr_rnd	0.0230	0.0069	-0.0208	0.0677	0.0166	-0.0171	0.1020	0.0185	-0.0333	0.0043	-0.0014	0.0000	0.0100	401
t-stat	0.69	0.60	-0.79	1.61	1.47	-0.55	2.21	1.93	-1.15	0.20	-0.08	0.70		
INSTR														
gr_empl	0.0367	-0.0002	0.0010	0.0145	0.0072	-0.0162	0.0239	0.0081	0.0047	0.0333	0.0065	0.0000	0.0164	424
t-stat	1.03	-0.04	0.07	0.46	1.16	-1.17	0.67	1.56	0.37	2.35	0.59	0.22		
gr_pat	-0.0082	-0.5799	0.0927	-0.3055	-0.2539	0.1461	0.3052	-0.1472	-0.1726	0.1117	0.1107	0.0000	0.1735	420
t-stat	-0.03	-12.60	0.80	-1.27	-5.37	1.42	1.06	-3.75	-1.75	1.03	1.33	-0.64		
gr_rnd	0.0527	0.0044	0.0008	0.0333	0.0013	0.0353	0.0370	-0.0032	-0.0311	0.0230	-0.0079	0.0000	0.0074	424
t-stat	1.31	0.63	0.05	0.92	0.18	2.20	0.88	-0.54	-2.05	1.42	-0.64	0.86		
TRANS														
gr_empl	0.0442	-0.0009	-0.0202	0.0194	0.0026	-0.0114	0.0208	0.0031	-0.0077	0.0237	-0.0414	0.0000	0.0250	362
t-stat	2.98	-0.12	-1.31	1.21	0.30	-0.90	1.11	0.42	-0.76	1.58	-2.84	-0.46		
gr_pat	-0.0363	-0.5876	-0.0507	-0.0604	-0.4157	0.1318	0.1124	-0.2478	-0.1319	0.0970	0.1558	0.0000	0.1777	358
t-stat	-0.41	-12.44	-0.56	-0.67	-7.86	1.70	1.24	-5.35	-1.80	1.05	1.67	0.21		
gr_rnd	0.0749	-0.0061	-0.0186	0.0328	-0.0247	-0.0085	0.0883	-0.0117	-0.0367	0.0152	-0.0019	0.0000	0.0142	362
t-stat	3.90	-0.69	-1.06	1.94	-2.40	-0.56	3.92	-1.31	-2.98	0.85	-0.11	-2.99		

Table A1: LAD estimation of equation (1) for regions with low industry employment.



w <sub>t</sub>	β <sub>t-1</sub>			β <sub>t-2</sub>			β <sub>t-3</sub>			spec	div	pop_den	R <sup>2</sup>	Obs
	gr_empl	gr_pat	gr_rnd	gr_empl	gr_pat	gr_rnd	gr_empl	gr_pat	gr_rnd					
CHEM														
gr_empl	0.0671	-0.0055	0.0024	0.1146	-0.0089	0.0020	-0.0359	-0.0027	0.0131	0.0016	-0.0028	0.0000	0.0305	348
t-stat	1.43	-0.92	0.10	1.84	-1.52	0.08	-0.58	-0.50	0.48	0.17	-0.33	-0.82		
gr_pat	0.4133	-0.4559	-0.2164	0.6949	-0.2297	0.2942	-0.2031	-0.0900	0.1444	-0.0807	-0.0682	0.0000	0.1255	345
t-stat	0.94	-8.47	-1.12	1.22	-4.15	1.25	-0.36	-1.82	0.58	-0.97	-0.88	-0.38		
gr_rnd	0.0163	-0.0022	0.0377	0.1304	-0.0189	0.0097	0.0798	-0.0047	-0.1030	-0.0084	-0.0111	0.0000	0.0137	348
t-stat	0.24	-0.26	1.12	1.43	-2.20	0.26	0.89	-0.60	-2.58	-0.67	-0.91	0.21		
ELEC														
gr_empl	0.0102	0.0233	0.0217	0.0805	0.0310	-0.0185	0.0362	0.0236	-0.0049	0.0285	-0.0275	0.0000	0.0937	264
t-stat	0.33	2.96	0.71	2.79	3.53	-0.90	1.41	2.94	-0.26	2.81	-2.95	0.10		
gr_pat	0.5194	-0.4181	-0.3119	-0.1156	-0.1991	0.2140	-0.1346	-0.0025	0.2408	0.1151	0.0426	0.0000	0.1093	264
t-stat	2.48	-7.34	-1.51	-0.58	-3.32	1.54	-0.79	-0.05	1.91	1.66	0.69	-0.83		
gr_rnd	-0.0910	0.0495	0.2474	-0.0297	0.0423	-0.0104	-0.0283	0.0359	-0.0072	0.0386	-0.0071	0.0000	0.0561	264
t-stat	-1.29	2.60	3.50	-0.43	2.31	-0.21	-0.50	2.04	-0.18	1.67	-0.35	0.48		
INSTR														
gr_empl	-0.0165	0.0039	0.0349	-0.0522	0.0186	0.0097	0.1434	0.0187	0.0128	0.0112	-0.0063	0.0000	0.0386	209
t-stat	-0.40	0.53	1.20	-1.64	2.15	0.46	3.64	2.22	0.79	0.99	-0.78	0.01		
gr_pat	-1.1539	-0.6993	0.6106	0.0738	-0.2667	0.0832	0.1616	-0.0721	0.0720	0.0430	-0.0590	0.0000	0.2128	209
t-stat	-2.21	-7.25	1.70	0.17	-2.24	0.31	0.30	-0.61	0.30	0.28	-0.52	-0.08		
gr_rnd	-0.0219	-0.0122	0.1500	-0.1051	0.0128	-0.0639	0.1797	0.0059	-0.0022	0.0070	-0.0025	0.0000	0.0313	209
t-stat	-0.47	-1.44	4.53	-2.90	1.26	-2.82	4.11	0.59	-0.12	0.54	-0.27	-0.06		
TRANS														
gr_empl	0.0025	-0.0175	0.0052	-0.0439	-0.0127	-0.0214	0.0473	-0.0033	0.0035	0.0214	-0.0105	0.0000	0.0297	211
t-stat	0.05	-1.73	0.18	-0.58	-1.30	-0.76	0.82	-0.42	0.18	1.59	-0.71	0.29		
gr_pat	0.0772	-0.4683	-0.0648	0.2811	-0.2964	-0.0034	0.4173	-0.1842	0.1959	-0.1269	0.1663	0.0000	0.1767	211
t-stat	0.31	-5.37	-0.31	0.43	-3.24	-0.01	0.83	-2.32	1.12	-1.10	1.31	-0.91		
gr_rnd	-0.0116	-0.0107	0.1120	0.0336	-0.0228	-0.0303	0.1390	-0.0056	0.0073	0.0299	-0.0051	0.0000	0.0316	211
t-stat	-0.35	-1.09	3.89	0.42	-2.20	-1.12	2.25	-0.68	0.34	2.24	-0.35	-1.23		

Table A2: LAD estimation of equation (1) for regions with high industry employment.

## Endnotes

<sup>1</sup> Note, however, that Cohen et al. (2000) find higher ratios for product innovations in the car/trucks and autoparts industry. But their results for the much more important process innovations in these industries again are comparable to those by Arundel and Kabla (1998).

<sup>2</sup> Note however that the industries in the present study are defined broader than the industries in Malerba and Orsenigo (1996).

<sup>3</sup> We also investigated the possibility of heterogeneous effects at different quantiles of the conditional distribution of the dependent variable, using quantile regression. This analysis did not yield any remarkable results, however.

<sup>4</sup> In each case, the generated innovation indicator extracts over 90% of the common variance in R&D and patent levels, and is very highly correlated with each of these two variables.