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Is Regional Innovative Activity Path-dependent? An Empirical Analysis for Germany

by

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Abstract:

Based on a standard idea-based model of endogenous growth we test the hypothesis that regional innovative activity is path-dependent, and investigate the geographical scope of knowledge spillovers. Using data for West-German regions, two alternative indicators of the stock of knowledge are specified. One is based on patent applications, the other on numbers of researchers. With patents as indicator the path-dependence hypothesis is rejected, and knowledge spillovers from neighboring regions appear to be irrelevant. With numbers of researchers as indicator, by contrast, there is evidence for both path-dependence, and the relevance of interregional knowledge spillovers. Several extensions and refinements are discussed which may help resolving these apparent contradictions.

Keywords: regional innovation, knowledge spillovers, path-dependence, endogenous growth, spatial econometrics, Germany

JEL classification: C21, O31, R11

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Contents

I. Introduction

Following Romer (1990), a rich body of so-called idea-based models of endogenous growth has been developed in which R&D is assumed to exhibit increasing returns to scale. More specifically, innovative output is assumed to exhibit constant returns with respect to the stock of knowledge alone – knowledge which was accumulated in the past in the course of commercial (profit-oriented) R&D, and which over time has become available as a public good to a broader community of researchers. According to theory, this positive dynamic (intertemporal) externality of R&D induces innovative activity to be path-dependent, which is a necessary precondition for endogenous income growth.

There is little dissent among economists as to the existence of dynamic externalities of R&D. In his survey Griliches concludes that "... R&D spillovers are present, their magnitude may be quite large, and social rates of return remain significantly above private rates" (Griliches 1992: 43). More controversial, however, is the question whether R&D spillovers are really strong enough to create path-dependence.

The present paper is an attempt to empirically test for path-dependence of innovative activity at the level of West-German regions, facilitated by the work of Greif (1998, 2000) who made publicly available statistics on patent applications by German regions for selected years. From a standard idea-based model of endogenous growth we develop an empirical regional innovation-production function, and hypotheses on parameter values necessary for innovative activity to be path-dependent.[1] Moreover, we relax the closed-economy assumption of the basic model to capture interregional knowledge spillovers by means of their positive effects on regional R&D productivity.

The paper complements the existing literature in several respects. First, it adds evidence from Germany to the literature investigating the relevance of knowledge spillovers at the regional level (e.g. Jaffe et al. 1993, Anselin et al. 1997; Varga 1998; Kelly and Hagemann 1999, Verspagen and Schoenmakers 2000). In addition, it directly addresses the question whether knowledge spillovers are strong enough to induce innovative activity to be path-dependent. Second, from the German perspective it complements the existing literature on the relevance of R&D and localized knowledge spillovers for aggregate economic activity (e.g.,

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1 Instead, we could have used the so-called knowledge-production function proposed by Griliches (1979) as a point of departure. However, since Griliches' approach is lacking a formal, well-developed theoretical background it would not allow for deriving hypotheses on parameter values consistent with path-dependence. Nonetheless, to emphasize the similarities between endogenous growth theory and Griliches' approach we will adopt Griliches' terminology to characterize the theoretical approach to modeling the generation of innovations.

Niebuhr 1999; Funke and Niebuhr 2000; Keilbach 2000; Bode 1998; 2001). While previous work was restricted to identifying spillovers by means of their impact on regional income and productivity growth, this paper tries to trace spillovers more directly by focusing on the innovation process itself. Finally, it complements analyses of international knowledge spillovers (e.g., Eaton and Kortum 1996; 1999; Keller 2000; 2001) by focusing on spillovers of *tacit* knowledge across short geographic distances rather than on spillovers of codified knowledge across longer distances. Tacit knowledge cannot easily be codified or digitized. Usually, it requires face-to-face contacts, disclosing itself to the "recipient" not without intense discussion and/or inspection.

Based on the growth-theoretic background outlined in Section II, Section III develops two alternative specifications of the empirical model and addresses some methodological issues, most of which are related to testing for the properties of residuals and parameters in the spatial dimension. In section IV the empirical results are presented, and the empirical model is extended to incorporate interregional knowledge spillovers in addition to intraregional spillovers. Section V, finally, discusses the results and develops some prospects for future empirical research.

II. Theoretical background

Assume an economy comprising R regions. Each regional economy r (r =1, ..., R) is described by an endogenous-growth model of the Romer/Jones type (Romer 1990; Jones 1995). There are three sectors: an innovative sector developing new ideas (or blueprints), an intermediate good sector producing a large variety of intermediate goods, and a final good sector producing a homogeneous consumption good. The blueprints developed in the innovative sector are protected against imitation by infinitely lived patents.[2] They are sold competitively to firms in the intermediate good sector. Holding a patent, a firm has the exclusive know-how to produce one variety of a capital good (at constant marginal costs). The final consumption good sector, finally, uses all available varieties of the capital good as an input.[3] It exhibits constant returns to scale in a static environment, i.e., when the number of available varieties is fixed, but increasing returns to scale in a dynamic environment, i.e., when the number of

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[2] Clearly, the assumption of patent protection to be infinite is very restrictive. However, results would not change fundamentally if the market power granted by patents eroded after some time, as has been assumed frequently in so-called Schumpeterian models of endogenous growth (see, e.g., Aghion and Howitt 1992; 1998; Barro and Sala-i-Martin 1995).

[3] The number of varieties available at any point in time equals the number of innovations developed in the economy ever before.

available varieties is increasing due to innovations. The equilibrium growth rate of income (output) in the economy depends crucially upon the dynamics of innovation. If the incentives for high-skilled workers (researchers) to develop new blueprints diminish over time, the rate of income growth diminishes as well. Economic development and the innovation process are not path-dependent: The steady-state income-growth rate will turn out to be zero unless it is driven continuously by exogenous impulses such as a steadily growing number of high-skilled workers. Models of this kind, such as Jones (1995), are called semi-endogenous growth models. If, by contrast, incentives to develop new blueprints do not diminish over time, the economy experiences an ongoing growth process fuelled by an increasing stream of innovations. Under these circumstances the growth and innovation processes are path-dependent. The steady-state growth rate of income will turn out to be positive, with its magnitude depending upon the absolute number of high-skilled workers in the economy. Models of this kind, such as Romer (1990), are called endogenous growth models.[4]

The theoretical dispute on path-dependence vs. path-independence of innovation and income growth originates mainly from different assumptions on the conditions under which innovations are developed. It is, therefore, sufficient for the purpose of our paper to concentrate on the innovative sector, where high-skilled workers are assumed to develop $\dot{N}_r$ innovative blueprints per instance of time using as inputs their own human capital (H_r), and region-specific publicly available knowledge (Q_r) which determines their productivity:

$$\dot{N}_{rt} = dN_{rt} / dt = dH_{rt}^{a_1} Q_{rt}^{a_2} , \qquad r = 1, ..., R. \qquad [1]$$

d is a constant productivity factor, a_1 and a_2 (a_1, $a_2 \geq 0$) are output elasticities. The stock of knowledge, Q, accumulates over time, fuelled by non-excludable knowledge developed as some sort of a by-product of blueprints. It is assumed that part of new knowledge cannot be codified and patented. This knowledge spills over to other researchers in the respective region and improves their future research productivity. Moreover, it is assumed for simplicity that each innovation produces the same amount of non-excludable knowledge, and that the stock of knowledge is directly proportional[5] to the number of innovations developed in the past:

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[4] For a detailed description of the full model, including the steady-state properties, see Romer (1990), Jones (1995), or the various textbooks on economic growth such as Barro and Sala-i-Martin (1995), Jones (1998), or Aghion and Howitt (1998).

[5] Following the theoretical literature, we assume the (constant) factor of proportionality to be one for simplicity (Grossman and Helpman 1991: 58).

$$Q_{rt} = N_{rt} = \int_{1}^{\infty} \dot{N}_{rt-t}\, dt \ . \qquad [2]$$

The knowledge-production function [1] is sufficiently general to comprise both models of endogenous, and of semi-endogenous growth. While Romer (1990) assumes $a_2 = 1$ (and $a_1 < 1$), Jones (1995) assumes $a_2 = 1 - a_1$. If innovation is subject to constant returns to scale with respect to knowledge alone ($a_2 = 1$) the rate of innovation ($\dot{N}_r / N_r = dH_r^{a_1}$) is independent of the technological level already attained, which is consistent with path-dependence. If, however, the marginal productivity of knowledge diminishes ($a_2 < 1$) the rate of innovation ($\dot{N}_r / N_r = dH_r^{a_1} Q_r^{a_2 - 1}$) decreases as the technological level increases which is not consistent with path-dependence. The main purpose of the following empirical investigation, thus, is to test $a_2 = 1$ against $a_2 < 1$.

III. Specification of the empirical model

1. Regional disaggregation and variables

The definition of the regional units of analysis may seriously affect regression results. Therefore, it should be based upon economic criteria as far as possible to avoid spurious interdependences between observations in the spatial dimension. In general, there should be particular strong economic ties within a region, but comparatively weak ties between different regions. In Germany, none of the major statistical entities is useful from an economic point of view. The 10 West-German *Bundesländer* (states), on the one hand, differ considerably in size and economic density. While the city-states of Hamburg and Bremen cover only the cores of metropolitan areas but not their economic hinterlands, other *Länder* comprise several economic cores as well as peripheral regions with only weak economic ties to those cores. The 327 West-German *Landkreise* (counties), on the other hand, are connected with their respective neighbors too closely. Therefore, we prefer the concept of *Raumordnungsregionen* (planning regions) developed by the *Bundesanstalt für Landeskunde und Raumordnung* (BfLR). Each of the 74 West-German *Raumordnungsregionen* comprises several *Landkreise* which are interlinked by comparatively high commuting flows.[6]

To transform the knowledge-production function [1] into an empirical model we use its log-linearized form, add a disturbance term as well as a few control

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[6] East German regions, including West-Berlin, are excluded from the analysis mainly because some statistical data, especially from the early 1990s, is less reliable than for West-German regions.

variables which are needed to adjust for systematic differences between theory and real world, and between dependent and explanatory variables:

$$\ln \dot{N}_r = \ln d + a_1 \ln H_r + a_2 \ln Q_r + a_3 (\text{control variables}_r) + m_r . \qquad [3]$$

The dependent variable ($\dot{N}_r$) which is the number of innovations developed in region r represents output of the innovation process. An ideal indicator would be the number of new goods introduced successfully to the markets by firms located in r (see, e.g., Brouwer and Kleinknecht 1996; Anselin et al. 2000a; or Baptista and Swann 1998). Such an indicator is, however, not available for German regions. As a substitute patent applications have been used frequently in the literature (e.g. Jaffe 1986; 1989; Kelly and Hageman 1999) – despite of their well-known shortcomings.[7] We follow these authors describing innovations by the number of patent applications (*PAT*). Patent applications were disaggregated down to the level of German *Landkreise* by Greif for 1992–1994 and 1998 (Greif 1998; 2000). Since two observations in time are not sufficient for a pooled cross-section and time-series analysis we have to confine ourselves to a pure regional cross-section analysis, the dependent variables being patent applications in 1998 (*PAT*98).[8]

The first explanatory variable, the number of researchers (H_r), is approximated by R&D personnel employed by commercial firms.[9] To appropriately capture the causality between the R&D effort and the respective patent application we have to allow for some time lag. Time is necessary to develop and to codify an idea, to prepare the application of the patent, and to check its relevance and innovativeness. There is substantial uncertainty in the literature as to the (average) length of this time lag. For the 1970s, Hall et al. (1986) observe the relationship between a change in R&D expenditures and the related change in the number of patent applications to be "close to contemporaneous with some lag effects which are small and not well established" (Griliches 1990: 1674). Greif and Potkowik (1990), by contrast, observe a time-lag of 1–2 years in Germany. Based on this evidence, we assume the time-lag to be roughly one year. Accordingly, the preferred variable is R&D personnel in 1997 (*H*97).

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7 See, e.g., Mansfield (1984), Griliches (1990), or Greif (1993) for extensive discussions.

8 The 1998 data set is based on 27,361 patents granted to domestic commercial firms and published by the German or the European patent office in 1998 (without double-counting). For the present purpose, the patents are assigned to their innovators' rather than the innovating firms' region of residence to avoid the bias resulting from centralized patenting by multi-site companies.

9 The statistic was prepared by Legler (1999) based on data collected by the German *Stifterverband*.

The second explanatory variable, the stock of knowledge available at the regional level (Q_r), is assumed in growth-theoretic models like Romer (1990) to be the sum of blueprints developed since the beginning of time (see eq. [2]). Of course, this assumption is both unrealistic and impracticable for empirical purposes. It is unrealistic to assume knowledge not to be subject to depreciation. Insights gained a century or more ago are given the same value in terms of productivity as recent innovations. And it is impracticable since it requires an immense amount of statistical information on innovations in the past which is not available.

In the present investigation we try to cope with the lack of data demanded by theory by formulating and testing two alternative empirical specifications of the stock of knowledge. The first specification uses the sum of patent applications in previous years as an indicator, the second the numbers of researchers.

Following the theoretical model (eq. [2]) the stock of knowledge may be approximated by the sum of patents developed in the past. Taking into consideration that it takes some time for new knowledge to become known to a broader community of researchers even within regions, we should allow for a time-lag of, say, one year between the granting of a patent and the aggregate productivity-enhancing effects of the respective knowledge.[10] Hence, the stock of knowledge ideally should comprise all patents granted up to 1996. However, since data is available for the years 1992–1994 only (Greif 1998) we use the sum of patent applications in these three years (*PAT*9294):[11]

$$Q_{1r} = f_1(PAT9294_r).$$

Just because of the lack of data from previous periods, the function f_1 should be as general as possible to capture any correlation over time. Therefore we assume a quadratic function of the form

$$a_2 \ln Q_{1r} = a_{21} \ln PAT9294_r + a_{22}\left(\ln PAT9294_r\right)^2. \qquad [4]$$

The second indicator of the stock of knowledge, the number of researchers in previous periods, is derived by repeatedly substituting the knowledge-production function [1] into [2], assuming time to be discrete, the parameters to be constant over time, and the stock of knowledge in the initial year to be negligible. That is,

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10 As to the appropriate average time lag for knowledge spillovers there exists substantial uncertainty. Discussing several empirical investigations, Branstetter concludes "that the time required for new innovations to leak out is quite short" Branstetter (2001: 60). Quite short means something in-between one month and two years.

11 Greif (1998) documented patent applications as averages over the years 1992–1994. Multiplying these averages by three gives approximately the three-years' sum.

the additional knowledge added to the stock of knowledge year by year is described by the knowledge-production function that generated this knowledge.

Again, tribute has to be paid to data availability; data on the numbers of researchers is available for only two years, 1995 and 1987 (H95, H87).[12] Using available statistics we get

$$Q_{2r} = f_2(H95_r, H87_r) = d^{1+a_2} H95_r^{a_1} H87_r^{a_1 a_2} + dH87_r^{a_1} \qquad [5]$$

or

$$a_2 \ln Q_{2r} = a_2 \ln d + a_2 \ln\left(d^{a_2} H95_r^{a_1} H87_r^{a_1 a_2} + H87_r^{a_1}\right) \qquad [6]$$

in logarithmic form. Although the output elasticities a_1 and a_2 can be identified by estimating [6] by non-linear Generalized Least Squares (GLS), the non-linearity seriously reduces our opportunities to test, and to control for systematic interdependences between neighboring regions such as spatial autocorrelation.[13] In spite of considerable advances made since the late 1980s, spatial econometric methodology and software still are sort of deficient in cases where non-linearities in explanatory variables coincide with spatial dependence. As will be seen below, the latter plays an important role in the present case. Therefore we prefer simplifying matters somewhat by assuming the second term in brackets in eq. [6] ($H87_r^{a_1}$) to have no additional explanatory power,[14] such that

$$a_2 \ln Q_{2r} = a_2(1+a_2)\ln d + a_1 a_2 \ln H95_r + a_1 a_2^2 \ln H87_r\,. \qquad [7]$$

Since the term $a_2(1+a_2)\ln d$ adds to the constant, we may define $b_{21}=a_1a_2$, and $b_{22}=a_1a_2^2$ in order to obtain a log-linear regression model. Note that the output elasticity of knowledge (a_2) can still be identified as, e.g., $a_2=b_{22}/b_{21}$.

To test the path-dependence hypothesis we will compare the results of the empirical model including [7] to a restricted model under H0: $a_2=1$, where

$$1\cdot \ln Q_{2r} = 2\ln d + a_1 \ln\left(H95_r H87_r\right)$$

is the proxy of the knowledge stock, by a Likelihood-Ratio test.

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[12] In principle the data is available since the Stifterverband prepares statistics on R&D personnel on an annual basis. However, publicly available data for levels below the states is incomplete due to data confidentiality.

[13] For a brief description of statistical tests for spatial dependence see section III.2.

[14] In the appendix, a test of the additional explanatory power of the term in question is reported. The test is based on a model specification where spatial interdependence enters linearly, avoiding the conflict mentioned above. The result is that the additional explanatory power of the term in question is very low, indeed.

In addition to the variables of the theoretical model a few control variables have to be added to the empirical model. On the one hand, differences in the size of regions must be controlled for to avoid spurious correlation due to omitted variables. This can be done either by standardizing all variables defined in absolute terms by an indicator of the size of regions (e.g., population, employment, or area), or by specifying the respective indicator as an additional regressor. For the present purpose, we add regional employment in 1996 (E_r) as a control variable to the empirical model.

On the other hand, differences between firms in the propensity to patent have to be controlled for. Those differences may result from various characteristics. First, the propensity to patent usually is much higher in manufacturing than in service industries, according to the German patent office (Greif and Potkowik 1990).[15] As a result, the output elasticity of high-skilled labor may be biased downward in regions where many researchers have been employed in service industries. Thus, we add as an explanatory variable $(Ser/Manu)_r$ which is the ratio of service to manufacturing workers in the regional economy. Second, the propensity to patent may vary systematically between industries within the manufacturing sector itself. According to an investigation by Greif and Potkowik (1990) for 1983, e.g., the patent intensity was much higher in machinery, electrical equipment, or rubber industries than in transport equipment industries. Although data on patent applications by industries is lacking for the time period under consideration we try to control for differing patent propensities between industries by combining available data on patent intensities by industries at the national level with regional industry structures. More specifically, we use as a proxy an indicator 'regional patent intensity' ($PATINT_r$) defined as the sum of the industries' shares in manufacturing employment weighted by the industries' relative patent intensities at the national level:

$$PATINT_r = \sum_{i=1}^{I} \frac{PAT_i \big/ \sum_i PAT_i}{RDEXP_i \big/ \sum_i RDEXP_i} \cdot \frac{E_{ir}}{\sum_i E_{ir}} . \qquad [8]$$

PAT_i denotes the number of patents granted to industry i ($i = 1, ..., I$) at the national level in 1983, $RDEXP_i$ the respective R&D expenditures, and E_{ir} the number of employees in industry i and region r. The higher the employment share of industries with comparatively high patent intensities are in a region, the higher is $PATINT_r$.

Third, the intensity of patenting may vary systematically with firm size. While some authors (e.g., Licht and Zoz 1998) find patent elasticities to increase

15 In 1983, e.g., no less than 96.8 percent of all patents were granted to manufacturing industries (Greif and Potkowik 1990: 25).

monotonically with firm size, others argue that elasticities are higher for both small and large firms than for medium-sized firms (Giese and von Stoutz 1997). To control for firm-size effects in a fairly general way we add two explanatory variables, namely the employment share of big firms with 500 or more employees ($SH500_r$), and the employment share of small firms with less than 20 employees ($SH19_r$).[16] The benchmark, thus, are medium-sized firms with 20–499 employees.

Assuming a log-linear functional form for the additional (control) variables just discussed, the following alternative empirical models to estimate the knowledge-production function emerge. With the region-specific stock of knowledge ($\ln Q_r$) being approximated by patent applications in the period 1992–94 as defined in [4], it reads

$$\begin{aligned} \ln PAT98_r = \text{constant} &+ a_1 \ln H97_r \\ &+ a_{21} \ln PAT9294_r + a_{22} (\ln PAT9294_r)^2 \\ &+ a_3 \ln E_r + a_4 \ln SH19_r + a_5 \ln SH500_r \\ &+ a_6 \ln(Ser/Manu)_r + a_7 \ln PATINT_r + m_r, \end{aligned} \qquad [9a]$$

while we have

$$\begin{aligned} \ln PAT98_r = \text{constant} &+ a_1 \ln H97_r + b_{21} \ln H95_r + b_{22} \ln H87_r \\ &+ a_3 \ln E_r + a_4 \ln SH19_r + a_5 \ln SH500_r \\ &+ a_6 \ln(Ser/Manu)_r + a_7 \ln PATINT_r + m_r, \end{aligned} \qquad [9b]$$

if the stock of knowledge is approximated by the numbers of researchers in 1995 and 1987, as defined in [7].

2. Spatial econometrics methodology

The accuracy and reliability of regression results heavily depend upon a set of assumptions imposed upon the empirical model by econometric theory. Most prominently, the residuals m_r in [9] are assumed to be not autocorrelated and have the same variance across all observations, and the parameters a and b are assumed to be constant across all observations. While statistical tests for these assumptions have been standard in time-series analysis since long ago, they have been largely ignored in cross-section analysis, although appropriate test statistics have been developed in the course of the so-called spatial econometrics literature (see, e.g., Anselin 1988). In the present paper, considerable effort has been devoted to assessing the properties of residuals and parameters, and, if necessary,

[16] Data are from the latest general census in 1987.

applying appropriate regression techniques to ensure the theoretical assumptions to be met.

First, we test for the two possible forms of residual correlation across regions: spatial autocorrelation and spatial lag dependence. Spatial autocorrelation[17] is tested for by Moran's I[18] and two Lagrange Multiplier (LM_{ERR}, robust LM_{ERR}[19]) tests. Spatial lag dependence[20] is tested for by LM_{LAG} and robust LM_{LAG} tests. One feature of all these tests is that they require the structure of spatial dependence to be known. They are based upon a given spatial weight matrix (**W**) which defines the geographic scope and (relative) intensity of dependences among any two regions. In practice, however, the spatial structure of dependences is a priori unknown. Therefore, we perform several tests using 16 different spatial weight matrices each of which reflects a priori plausible patterns of spatial dependence. The spatial weight matrices include a first-order binary contiguity matrix, testing for dependence among immediate neighbors, and 7 inverse-distance weight matrices, testing for gravity-type dependences that decrease in intensity with increasing distance.[21] The weight matrices are specified in ordinary as well as in row-standardized form.

Whenever significant spatial dependence is detected, the empirical model is modified and re-estimated in order to ensure the residuals to be white noise. Since in cross-section regressions the OLS estimator of the autocorrelation parameter (r) is inconsistent, and that of the parameter of the spatially lagged dependent (l) is biased a Maximum Likelihood (ML) approach has to be applied (see Anselin 1988: 57 ff.).

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[17] Autocorrelation is assumed to take the general form $m = r\mathbf{W}m + \boldsymbol{v}$. r denotes the autocorrelation parameter, **W** the (RxR) spatial weight matrix defining the spatial structure of dependence, and $\boldsymbol{v}$ an i.i.d. disturbance term.

[18] Taken literally, Moran's I tests for spatial dependence in general, without being able to discriminate between spatial autocorrelation and spatial lag dependence.

[19] For methodological details see Anselin (1988; 1995), Anselin et al. (1996).

[20] Spatial lag dependence is assumed to take the general form $\boldsymbol{y} = l\mathbf{W}\boldsymbol{y} + \mathbf{X}b + e$ where l denotes the parameter of the spatially lagged dependent variable $\mathbf{W}\boldsymbol{y}$, and e a white-noise disturbance term.

[21] As to the inverse-distance weight matrices, the following functional forms and distance-decay parameters are specified: $\exp(-JD_{tr})$ with D_{tr} denoting the great circle distance between the economic centers of regions t and r, and the distance-decay parameter J taking values of J=0.01, 0.05, or 0.1; and D_{tr}^{-J}, with ϑ=1, 2, 3, or 4. It should be noted that the power of tests for spatial dependence depends on several aspects, including the complexity of the spatial weight matrix, the sign and the strength of dependence, and the presence of heteroscedasticity (Anselin and Rey 1991; Anselin and Florax 1995). In the present case, the tests based upon inverse-distance weights with low distance-decay parameters may have limited power since the number of non-zero matrix elements is quite high.

Second, homoscedasticity is tested for by F-tests (OLS), or Breusch-Pagan tests (ML) comparing residual variances of pairs of regional sub-samples. In contrast to time-series analysis the potential sources of heteroscedasticity have to be specified explicitly in cross-section analysis. In the present investigation four potential sources of spatial heteroscedasticity are specified.[22]

Finally, parameter stability is tested for by F (OLS), or Likelihood-Ratio tests (ML) using the same four pairs of regional sub-samples as described in the context of homoscedasticity tests. To assess parameter stability in the presence of a spatially lagged endogenous variable we use a dummy approach: Given the spatial lag model $\boldsymbol{y}=g\mathbf{W}\boldsymbol{y}+\mathbf{X}b+e$, e.g., we test for joint (in)significance of the parameters $b°$ from an extended model $\boldsymbol{y}=g\mathbf{W}\boldsymbol{y}+\mathbf{X}b+D\mathbf{X}b°+e$, where D represents one of the above-mentioned dummies.

IV. Regression results[23]

1. Knowledge stock approximated by past patent applications

Column (1.1) of Table 1 reports the OLS-regression results for eq. [9a] where the region-specific stock of knowledge is approximated by past patent applications.[24] The fit is quite well, according to the adjusted R^2 of more than 98 per cent.[25] However, LM tests indicate significant spatial lag dependence for 3 spatial weight matrices, the lowest error probability (prob=0.008)[26] being reported for a not row-standardized matrix with exp(-0.05D_{tr}) as spatial weight.

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[22] The pairs of sub-samples are: (i) 28 agglomerations and 46 peripheral regions, reflecting agglomeration effects; (ii) 38 north and 36 south German regions, reflecting the German south-north divide (Soltwedel 1986); (iii) 37 regions with below and 37 with above-average per-capita income, reflecting income effects; and 37 regions with below-average and 37 with above-average numbers of patent applications per employee, checking for positive correlation between patent intensity and residual variance. In Breusch-Pagan tests the pairs of sub-samples are represented by dummies (e.g. 1 for agglomerations, 0 for peripheral regions).

[23] The regressions and tests are done with SpaceStat and SAS.

[24] One outlying region, Regensburg, is neutralized by a dummy.

[25] Of course, the R^2 is somewhat inflated by the dummy, and by the preferred indirect method of controlling for regional differences in absolute size by adding ln$E$ as a regressor rather than dividing all variables by ln$E$.

[26] Throughout the paper the significance of parameter estimates is indicated by probability (prob-) values rather than standard deviations or t-statistics. A prob-value may be characterized as the probability that would barely allow to reject H0. The lower the prob-value the less credible is H0 (Wonnacott and Wonnacott 1979: 91 f.).

Table 1 — Regression results for equation [9a] with past patents as indicator of the region-specific stock of knowledge[a]

Regression		(1.1)		(1.2)	
Description		Basic model		Spatially lagged endog.	
Method		OLS		ML	
Variable		coeff	prob	coeff	prob
Constant		-1.29	0.12	-1.61	0.00
Researchers 1997	ln*H*97	0.09	0.01	0.07	0.02
Patents 1992–94	ln*PAT9294*	0.64	0.00	0.73	0.00
Patents 1992–94 squared	$(\ln PAT9294)^2$	0.01	0.34	0.01	0.40
Regional size	ln*E*	0.18	0.01	0.15	0.01
Employment share small firms	ln*SH19*	0.49	0.05	0.12	0.59
Employment share big firms	ln*SH*500	0.08	0.24	0.01	0.83
Service/Manufacturing empl.	ln(Ser/Manu)	-0.17	0.00	-0.12	0.02
Patent intensity	ln*PATINT*	-0.04	0.79	-0.08	0.56
Spatially lagged dep. variable[b]	**W**(ln*PAT98*)	–		-0.03	0.00
No of dummies		1		2	
R^2-adj.		0.98		.	
Log likelihood		52.92		59.50	
AIC[c]		-85.84		-95.00	
Autocorrelation (lowest prob)[d]		0.09[g]		0.23	
Lag dependence (lowest prob)[d]		0.01[h]		.	
Homoscedasticity (lowest prob)[e]		0.14		0.11	
Parameter stability (lowest prob)[f]		0.14		0.11	

[a] Cross-section regressions for 74 West-German planning regions; dependent variable: log number of patents granted to commercial firms, published in 1998 (ln*PAT*98). — [b] Spatial weight: $\exp(-0.05D_{tr})$, not row-standardized. — [c] Akaike information criterion. — [d] Several tests with different spatial weights; Table only reports test with lowest error probability (prob). — [e] F or Breusch-Pagan tests on homoscedasticity across 4 different sub-samples of regions (for definition see the text); table only reports test with lowest error probability. — [f] F, or LR-test on parameter stability across 4 different sub-samples of regions (for definition see the text); table only reports test with lowest error probability.— [g] Robust LM_{ERR}, spatial weight: $\exp(-0.1D_{tr})$, row-standardized. — [h] LM_{LAG}, spatial weight: $\exp(-0.05D_{tr})$, not row-standardized.

Source: Own estimations.

To control for spatial-lag dependence eq. [9a] is re-estimated as an auto-regressive model, adding a spatially lagged dependent variable **W**(ln*PAT*98) (column 1.2 of Table 1). As to the spatial weight matrix **W** inverse exponential distance weights with a decay parameter of ϑ=0.05 produce the best fit, as the tests for spatial-lag dependence in regression (1.1) have suggested. According to the test statistics at the bottom of Table 1 the spatial-lag model passes all autocorrelation, homoscedasticity and parameter-stability tests at conventional significance levels.[27] The parameter of the lagged dependent which is negative indicates that a region's intensity of innovation tends to be the lower the higher the patent intensity is in its neighborhood, and vice versa. Although the parameter turns out to be highly significant, the correlation may be spurious since and economic or statistical explanation is not at hand.[28]

Turning to the parameters of the knowledge-production function in regression (1.2), the elasticity of patents with respect to high-skilled labor (a_1) is estimated to be significantly different from zero but quite low. The point estimate is less than 0.1. The elasticity of the knowledge stock (a_{21}),[29] by contrast, is much higher (about 0.73) but significantly smaller than one. Hence, the hypothesis of path-dependence of regional innovative activities requiring the elasticity of the stock of knowledge to be at least one is rejected. Among the control variables, only the size of regions (ln*E*), and the service-manufacturing ratio (ln*Ser*/*Manu*) controlling for lower patent intensity in service industries show a significant impact with plausible signs on patent applications. The firm size (ln*SH*19, ln*SH*500), and the (average) patent intensity of manufacturing industries (ln*PATINT*), by contrast, seem to have no impact on the frequency of patent applications, neither individually nor jointly.

Summing up, when approximating the region-specific knowledge stock by past patent applications we find knowledge spillovers to have an important impact on regional innovativeness. Their productivity effects, however, seem to be too weak for regional innovation in Germany to be path-dependent.

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27 One additional region (Oberfranken-Ost), however, has to be neutralized by a dummy.

28 One explanation could be commuting of researchers across regional borders which has been controlled for as far as possible by the definition of regions but not ruled out completely. Recall that patent applications are assigned to the place of residence of the innovator while the number of researchers is assigned to the place of work. If this was true, there should be a corresponding positive correlation between patent applications in one and the numbers of researchers in the respective neighboring regions. That correlation, however, is negative as well. Detailed results are available from the author upon request.

29 The explanatory power of the squared term, by contrast, is negligible.

2. Knowledge stock approximated by past numbers of researchers

As an alternative to serially lagged patent applications we test a second specification where the region-specific stock of knowledge is approximated by past numbers of researchers. Column (2.1) of Table 2 reports the regression results for eq. [9b]. A view at the test statistics at the bottom of the table shows that the model violates almost all assumptions of econometric theory. The test statistics indicate significant lag dependence, spatial autocorrelation, and heteroscedasticity. The spatial dependence is best captured by a spatial-lag model (column 2.2), the best fit (highest Likelihood) being obtained for **W** being a binary first-order contiguity matrix. Obviously, the lagged dependent variable also removes autocorrelation and heteroscedasticity from the residuals simultaneously.[30] Turning to the parameter estimates we observe that – in contrast to the model using serially lagged patents as indicators of the knowledge stock – the parameter of the lagged dependent variable is positive (rather than negative, as in Table 1). We will discuss possible economic interpretations in the following section.

With respect to the parameters of the theoretical model, the estimated output elasticity of human capital (0.12) is slightly higher than the corresponding estimate in Table 1 (0.07) where patents have been used as indicator of the stock of knowledge. Quite interestingly, the estimated parameters of researchers in previous years (*H*95 and *H*87) which serve as indicators of the knowledge stock are of about the same magnitude (0.13 and 0.10).[31] Indeed, the Likelihood ratio test on path-dependence, as described in section III.1, does not reject the hypothesis H0: a_2=1, the error probability being quite comfortable (prob = 0.63). Thus, in contrast to the model using the patents-based indicator of the region-specific knowledge stock (Table 1) the model using researchers-based indicators suggest regional innovative activity in Germany to be path-dependent.

As to the control variables, all but one parameters are highly significant and show plausible signs. The results suggest that the absolute size of a region (ln*E*) should be controlled for, that the industry structure of the regional economy has an impact on aggregate innovative performance, be it the size of the manufacturing relative to the service sector (ln*Ser*/*Manu*), or be it the composition of the manufacturing sector itself (ln*PATINT*). Furthermore, the results suggest that small firms tend to have a higher patent propensity than medium-sized firms (ln*SH*19). Quite surprisingly they do not indicate the patent propensity of big

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[30] This may be due to strong interdependences between the test statistics, as noted earlier.

[31] Due to multicollinearity between the numbers of researchers from different years the standard errors are inflated. Jointly, however, the variables show a highly significant impact on patent applications.

Table 2 — Regression results for equation [9b] with past numbers of researchers as indicator of the region-specific stock of knowledge [a]

Regression		(2.1)		(2.2)	
Description		Basic model		Spatially lagged endog.	
Method		OLS		ML	
Variable		coeff	prob	coeff	prob
Constant		-5.19	0.00	-4.72	0.00
Researchers 1997	ln*H*97	0.20	0.16	0.17	0.18
Researchers 1995	ln*H*95	0.10	0.57	0.13	0.40
Researchers 1987	ln*H*87	0.13	0.20	0.10	0.27
Regional size	ln*E*	0.80	0.00	0.75	0.00
Employment share small firms	ln*SH19*	1.91	0.00	1.83	0.00
Employment share big firms	ln*SH*500	0.21	0.14	0.26	0.04
Service/Manufacturing empl.	ln(Ser/Manu)	-0.64	0.00	-0.54	0.00
Patent intensity	ln*PATINT*	1.26	0.00	1.17	0.00
Spatially lagged dep. Variable [b]	**W**(ln*PAT98*)	–		0.01	0.01
No of dummies		0		0	
R^2-adj.		0.93		.	
Log likelihood		-3.38		0.13	
AIC [c]		24.75		19.75	
Autocorrelation (lowest prob) [d]			0.01[g]		0.12
Lag dependence (lowest prob) [d]			0.00[h]		.
Homoscedasticity (lowest prob) [e]		H-L	0.04		0.11
Parameter stability (lowest prob) [f]			0.12		0.06

[a] Cross-section regressions for 74 West-German planning regions; dependent variable: log number of patents granted to commercial firms, published in 1998 (ln*PAT*98). — [b] Binary first-order contiguity matrix; not row-standardized. — [c] Akaike information criterion. — [d] Several tests with different spatial weight; Table only reports test with lowest error probability (prob). — [e] F or Breusch-Pagan tests on homoscedasticity across 4 different sub-samples of regions (for definition see the text); table only reports test with lowest error probability. — [f] F, or LR-test on parameter stability across 4 different sub-samples of regions (for definition see the text); table only reports test with lowest error probability. — [g] Robust LM_{ERR}, spatial weight: D_{tr}^{-4}, not row-standardized. — [h] Robust LM_{LAG}, spatial weight: D_{tr}^{-4}, row-standardized.

Source*: Own estimations.*

firms (ln*SH*500) to be higher as well. This, however, may be due to multicollinearity among the two firm-size indicators which inflates their standard deviations.[32]

3. Interregional knowledge spillovers

Up to this point the regional economies under consideration have been assumed to be closed. Any economic interdependences between neighboring regions have just been eliminated from the residuals by spatially lagged endogenous variables. However, even in the present investigation which focuses on the diffusion of tacit knowledge during a comparatively short time period it is hardly sensible to assume knowledge diffusion to abruptly stop at regional borders. Although spillovers of tacit knowledge usually require frequent face-to-face contacts and, thus, may be limited in geographic scope because of transaction costs, there is no reason to assume these costs to become prohibitively high at borders, in particular within a country. Indeed, several empirical studies find considerable evidence for income growth and innovative activity at the regional level being affected positively by research done beyond regional borders. Verspagen et al., e.g., have identified a positive impact of spatial proximity on the frequency of patent citations in Europe in several studies (see, e.g., Verspagen and Schoenmakers 2000).[33] These proximity effects usually are said to reflect knowledge spillovers.

In the present investigation, we have identified a significantly positive impact of spatially lagged patent applications on regional innovative activity in one of the two alternative specifications, namely the model using researchers in the past as proxies for the knowledge stock.[34] At first sight this may serve as a hint as to the relevance of interregional spillovers. A spatially lagged dependent variable, however, may not be the most appropriate indicator of such spillovers for two reasons. First, it does not allow for a time-lag between the creation and the (R&D-) productivity-enhancing effects of new knowledge, and second, it is defined as the sum of logged patent applications in neighboring regions,

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[32] In fact, the estimated parameters of ln*SH*19 and ln*SH*500 are jointly significant at the 99 percent level (prob<0.01).

[33] Similar results have been obtained by Jaffe et al. (1993) in their pioneering work on patent citations in the US. See also Niebuhr (1999), and Keilbach (2000) for German regions, and Jaffe (1986; 1989), Rauch (1993), and Anselin et al. (1997; 2000a; 2000b) for US regions.

[34] By contrast, a negative influence of patent applications in neighboring regions obtains when the knowledge stock is proxied by past patent applications. This is obviously incompatible with knowledge spillovers. Actually, we doubt that the negative correlation reflects economic influences. Therefore, in what follows, we will concentrate on the second case.

implying that *each* region's knowledge enters the knowledge-production function [1] multiplicatively.

To allow for interregional knowledge spillovers at the theoretical level we follow Park (1998) who has analyzed the effect of spillovers from academics on innovative activity and economic growth within an idea-based endogenous growth model, assuming the knowledge-production function to take the form

$$\dot{N}_r = dH_r^{a_1} Q_r^{a_2} QN_r^{a_8}; \qquad QN_r = \sum_{t=1}^{R_r} w_{tr} Q_t \; . \qquad [10]$$

QN denotes knowledge that spilled over from neighboring regions t ($t = 1, \ldots, R_r,\ t \neq r$) in the past, R_r is the number of neighboring regions from which knowledge may spill over, and w_{tr} is a weighting factor.

For the empirical implementation we specify again two alternative indicators of the knowledge stock in neighboring regions: patent applications in 1992-94 and researchers in 1995 and 1987. Defining as a neighboring region t to r each region that shares a common border with r,[35] and following the same procedure as in section III.1, we get

$$a_8 \ln QN_{1r} = a_8 \ln\left(\sum_t PAT9294_t \right); \qquad [11]$$

$$a_8 \ln QN_{2r} = a_8 \ln d + a_8 \ln\left(\sum_t \left(d^{a_2} H95_t^{a_1} H87_t^{a_1 a_2} + H87_t^{a_1} \right) \right) \qquad [12]$$

as proxies for the effects of interregional knowledge spillovers. To simplify matters we assume again that the last term in [12] does not have any additional explanatory power, arriving at

$$a_8 \ln QN_{2r} = a_8 (1 + a_2) \ln d + a_8 \ln\left(\sum_t \left(H95_t^{a_1} H87_t^{a_1 a_2} \right) \right). \qquad [13]$$

[35] In test regressions, we used inverse exponential distances instead of binary contiguity weights. Although this approach comes closer to the idea that the intensity of knowledge spillovers decreases monotonously with rising distance due to increasing traveling costs for face-to-face contacts, its explanatory power is lower that that of the preferred weighting scheme based on a first-order contiguity. The results which are not reported here are available from the author upon request.

Adding [11], or [13] to the empirical model [9b] and estimating the resulting equations linearly by OLS, resp. non-linearly by GLS[36] we obtain the results given in columns 3.1 and 3.2 of Table 3. Both measures improve the explanatory power of the model vis-à-vis the spatial lag model (2.2), the results of which are repeated in the first column of Table 3 to allow for a direct comparison. Both have a higher Likelihood and, correspondingly, a lower AIC value, the highest Likelihood (lowest AIC value) being reported for the patents-based indicator.[37] Moreover, the output elasticity of interregional spillovers (0.17, or 0.27) is estimated to be much higher for spatially and serially lagged exogenous variables than for the spatially lagged dependent variable (0.01) which is due to the above-mentioned different definitions (sum of logs vs. log of sum). Taken together, there is fairly strong evidence of interregional knowledge spillovers to be significant and quantitatively important, if the regional stock of knowledge is approximated by researchers rather than by patent applications.

On this basis, we can test again the hypothesis of path-dependence of regional innovative activity. Applying essentially the same procedure as described above we find again that the H0: a_2=1 is not rejected in both cases, the error probabilities (prob>0.80) being even more comfortable than that obtained for the spatial lag model (2.2; see bottom row of Table 3).

V. Conclusions and prospects for future research

To address the question whether regional innovative activity in Germany is path-dependent we have estimated a knowledge-production function, as has been used frequently in idea-based models of endogenous growth such as Romer (1990) or Jones (1995). Allowing for time-lags for innovations to be developed, for ideas to be patented, and for knowledge to become available to a broader community of researchers within a region, we have approximated the region-specific stock of knowledge by two alternative indicators. The first is the sum of patent applications in previous years, the second the numbers of

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[36] In the second specification the exponents of $H95_t$ and $H87_t$ (a_1 and a_1a_2 in [13]) are restricted to be equal to the parameters of ln$H97_r$ and of $H95_r$ (a_1 and b_{21} in [9b]).

[37] A fairly low error probability of 0.054 for one robust LM_{ERR} statistic is due to an outlying observation. If a single region, Oberfranken-West, were neutralized by a dummy the respective error probability would increase to prob=0.14. However, we refrain from adding this dummy because we prefer the goodness-of-fit indicators (Likelihood, AIC) between the alternative specifications of interregional effects to be directly comparable. In fact, it can be shown that an additional dummy for Oberfranken-West does not affect the parameter estimates or standard deviations to a notable extent.

Table 3 — Regression results for equation [9b] extended by alternative indicators of interregional knowledge spillovers [a]

Regression		(2.2)		(3.1)		(3.2)	
Description		Spatially lagged endogenous variable		Spatially & serially lagged patents		Spatially & serially lagged researchers	
Method		ML		OLS		GLS	
Variable		coeff	prob	coeff	prob	coeff	prob
Constant		-4.72	0.00	-6.27	0.00	-5.49	0.00
Researchers 1997	ln*H*97	0.17	0.18	0.12	0.34	0.23	0.04
Researchers 1995	ln*H*95	0.13	0.40	0.15	0.34	0.08	0.60
Researchers 1987	ln*H*87	0.10	0.27	0.11	0.23	0.08	0.39
Regional size	ln*E*	0.75	0.00	0.77	0.00	0.74	0.00
Employment share small firms	ln*SH19*	1.83	0.00	1.58	0.00	1.60	0.00
Employment share big firms	ln*SH*500	0.26	0.04	0.18	0.15	0.24	0.07
Service/Manufacturing empl.	ln(*Ser*/*Manu*)	-0.54	0.00	-0.44	0.00	-0.46	0.00
Patent intensity	ln*PATINT*	1.17	0.00	1.07	0.00	1.03	0.00
Spatially lagged dependent	**W**(ln*PAT98*)[b]	0.01	0.01	–		–	
Knowledge neighbors (pat92-94)	lnQN_1[b]	–		0.17	0.00	–	
Knowledge neighbors (res95, 87)	lnQN_2[b]	–		–		0.27	0.00
R^2-adj.		.		0.94		0.94	
Log likelihood		0.13		4.70		3.32	
AIC [c]		19.75		10.60		13.36	
Autocorrelation (lowest prob) [d]			0.12		0.05		0.45[g]
Lag dependence (lowest prob) [d]			.		0.41		.
Homoscedasticity (lowest prob) [e]			0.11		0.12		0.07
Parameter stability (lowest prob) [f]			0.06		0.11		0.06
Test for path-dependence (H0: a_2=1)		0.23	0.63	0.04	0.84	0.002	0.97

[a] Cross-section regressions for 74 West-German planning regions; dependent variable: log number of patents granted to commercial firms, published in 1998 (ln*PAT*98). — [b] Binary first-order contiguity matrix; not row-standardized. — [c] Akaike information criterion. — [d] Several tests with different spatial weight; Table only reports test with lowest error probability (prob). — [e] F or Breusch-Pagan tests on homoscedasticity across 4 different sub-samples of regions (for definition see the text); table only reports test with lowest error probability. — [f] F, or LR-test on parameter stability across 4 different sub-samples of regions (for definition see the text); table only reports test with lowest error probability. — [g] Moran's I tests only.

Source*: Own estimations.*

researchers in previous years. Using the currently available statistical information for a cross section of 74 West-German planning regions, and controlling for regional differences in size and industry structure, we have obtained contradictory results for the two indicators: While the path-dependence hypothesis is not supported when the indicator of the stock of knowledge is based on past patent applications, there is evidence of path-dependence when the indicator is based on researchers. Investigating, furthermore, the spatial dimension of knowledge spillovers we have obtained contradictory results as well. There is no evidence for knowledge spillovers from neighboring regions to affect a region's innovative activity positively when the indicator is based on past patent applications. By contrast, there is fairly strong evidence for interregional knowledge spillovers when the indicator is based on researchers.

Based on the information currently available it is hardly possible to decide upon which indicator of the regional knowledge stock should be favored. According to goodness-of-fit indicators like adjusted R^2, Log-likelihood, or Akaike Information Criterion (AIC) the patents-based indicator fits the data better than the researchers-based. However, since the patents-based indicator essentially is a serially lagged endogenous variable its estimated parameter may be less reliable. It probably captures a great deal of the unobserved, time-invariant heterogeneity in patent applications across regions, in addition to the output elasticity of knowledge.[38]

To refine the analysis, future research should aim at making available longer time-series of innovative output and input indicators to derive better indicators of the stock of knowledge. Moreover, heterogeneity in regional innovative performance resulting from various sources should be controlled for more effectively. To control for differences in innovation intensities and patent propensities between industries, e.g., which appear to be non-trivial from empirical investigations for the USA (see e.g.. Anselin et al. 2000a; 2000b; Kelly and Hageman 1999), either sector-specific approaches, or the spatial-expansion method (Casetti 1972; 1997) seem to be appropriate. As a by-product, a sector-specific approach may allow for identifying those industries where (intra-industry) knowledge spillovers are of particular relevance, and those, that are important "suppliers" of knowledge spillovers to other industries.

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[38] This is probably the reason for some of the control variables being insignificant in the presence of the patents-based indicator but highly significant in the presence of the researchers-based indicator. The parameter of the patents-based indicator may, in addition, be biased downward because of regression to the mean which is well known from cross-section convergence regressions (see, e.g., Quah 1993; Bode 1998; Bliss 1999; Cannon and Duck 2000).

Finally, pooling of cross-section and time series information within a panel data approach will allow for distinguishing more carefully between variation in space and in time. As yet, mainstream spatial cross-section analysis has largely ignored time-specific effects, and mainstream panel data analysis has paid little attention to spatial dependence. Usually, the latter is disposed as trash into regional fixed effects although it may be highly informative as to the extent of interregional knowledge spillovers. Some initial, promising steps towards allowing for serial as well as spatial dependence in panel data analysis have been taken by Elhorst (2001a; 2001b). Several methodical problems, however, still remain to be resolved.

Appendix: Test of the simplifying assumption in equation [7]

In section III.1 we made a simplifying assumption, namely that the last term in equation [6] describing our second indicator of the region-specific stock of knowledge

$$a_2 \ln Q_{2r} = a_2 \ln d + a_2 \ln\left(d^{a_2} H95_r^{a_1} H87_r^{a_1 a_2} + H87_r^{a_1}\right) \qquad [6]$$

can be ignored. The reason was mainly to avoid non-linearities in our econometric model. To keep the test whether this assumption affects the estimates to a notable extent, as simple as possible, a model similar to that in regression (3.1) is used. The advantage of (3.1) vis-à-vis regression (2.2) is that it controls for interregional knowledge spillovers by a spatially lagged *exogenous* variable rather than a spatially lagged *endogenous* variable which introduces a non-linearity in itself. And the advantage of (3.1) vis-à-vis (3.2) is that the test may concentrate on the indicator of knowledge developed in the region *r* itself. If, as in (3.2), interregional knowledge spillovers would be proxied by a researchers-based indicator, the test had to be extended to include respective terms in the proxy of knowledge spillovers from neighboring regions *t* (see equation [13] in section IV.3).

In principle, we should test the hypothesis H0: c=0 in

$$\begin{aligned} \ln PAT98_r = \text{constant} &+ a_1 \ln H97_r \\ &+ a_2 \ln\left(d^{a_2} H95_r^{a_1} H87_r^{a_1 a_2} + cH87_r^{a_1}\right) \\ &+ a_3 \ln E_r + a_4 \ln SH19_r + a_5 \ln SH500_r \\ &+ a_6 \ln(Ser/Manu)_r + a_7 \ln PATINT_r \\ &+ a_8 \ln\left(\sum_t PAT9294_t\right) + m_r , \end{aligned} \qquad [A.1]$$

by means of a t or a Likelihood-ratio (LR) test. However, [A.1] is under-identified because there is one more parameter than regressors. One way of circumventing this problem would be to eliminate the constant productivity factor (d) from the term in brackets. This might be done by approximating [6] by

$$a_2 \ln Q_{2r} \approx a_2(1 + a_2)\ln d + \ln\left(H95_r^{a_1} H87_r^{a_1 a_2} + cH87_r^{a_1}\right). \qquad [6']$$

Table A.3 — Test of the simplifying assumption in equation [7] [a]

Test	Test statistic	prob
t-test	0.18	0.86
LR-test	0.26	0.61

[a] Cross-section regressions for 74 West-German planning regions; dependent variable: log number of patents granted to commercial firms, published in 1998 (ln*PAT*98). lnL=4.83.

Source*: Own estimations.*

The results shown in Table A.3 do clearly not reject the H0. The probability values (0.86, resp. 0.61) are very high, indicating that the additional explanatory power of the term in question is very low. Therefore, our assumption which, indeed, greatly simplifies the estimation, probably does not affect the results to a notable extent.

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