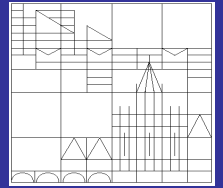University of Konstanz
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Evidence of Competition in Research Activity among Economic Departments using Spatial Econometric Techniques

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Abstract

Despite the prevalence of both competitive forces and patterns of collaboration within academic communities, studies on research productivity generally treat universities as independent entities. By exploring the research productivity of all academic economists employed at 81 universities and 17 economic research institutes in Austria, Germany, and German-speaking Switzerland, this study determines whether a research unit's productivity depends on that of neighboring research units. The significant negative relationship that is found implies competition for priority of discovery among individual researchers, as well as the universities and research institutes that employ them. In addition, the empirical results support the hypotheses that collaboration and the existence of economies of scale increase research productivity.

Keywords Research productivity, Competition, Collaboration, Negative spatial autocorrelation, Geo-referenced point data

JEL classifications C21, D85, I23, J24, R12

1. Introduction

In a series of articles beginning in the late 1950s, the sociologist Robert K. Merton convincingly delineated the behavior of scientists. According to Merton (e.g., 1973), scientists compete to establish the priority of their discovery by being first to communicate an advance in knowledge in a scientific journal. The basic goal of such behavior is to acquire scientific recognition from the scientific community at large, as also detailed by Collins (1998) from a historical perspective and Stephan (1996) from an economic perspective. Thus since Merton's pioneering work, considerable advances have been made to our understanding of the behavior of scientists and scientific institutions.

Economic inquiries in this growing research area often address the research productivity of individual scientists and the universities and research institutes that employ them. This literature has followed three main directions, which we summarize at greater length in the next section but describe briefly here. First, economic researchers have tried to rank universities and individual researchers on the basis of quality-adjusted measures of their publication activities. This stream reveals that research productivity is highly skewed, such that most articles are written by a limited number of scientists at major universities in just a few countries. Second, other researchers have tried to identify the drivers of research productivity at the individual, university, and even country level. Variables that emerge as important include lifecycle variables, such as gender, age, experience, and academic position, as well as institutional and locational variables, such as size and agglomeration effects. Third, literature has tried to identify the mechanisms for scholarly collaboration. The probability that two researchers work together on a project depends on the costs, which increase as function of geographical distance, and the benefits, which increase if both researchers are employed at an elite university (Frenken et al., 2009; Hoekman et al., 2009). Despite their contributions though, all three lines of research overlook Merton's (1973) basic notion that the primary goal of scientists is to establish priority of discovery, because there is little value in being second or third. If they cannot achieve this goal by publishing journal articles individually, scholarly cooperation may be beneficial, even if scientists remain competitors who strive to produce objective knowledge first to acquire esteem benefits.

With this study, we aim to verify empirically Merton's basic notion that universities and scientists are competitors. For this purpose, we apply spatial econometric techniques with geo-referenced research output data for universities. Although empirical literature on research productivity is growing, this article presents one of the first studies to test for competition and apply these advanced techniques.

Specifically, spatial econometrics refers to a subfield in econometrics that analyzes cross-sectional data in which the interaction among units relates to location and distance variables (Anselin, 1988; LeSage and Pace, 2009). According to Anselin (2010), this field has reached a stage of maturity through general acceptance of spatial econometrics as a mainstream methodology; the number of applied empirical researchers who use econometric techniques in their work also indicates nearly exponential growth. We make two key contributions. That is, positive spatial autocorrelation in empirical data appears far more frequent than negative spatial autocorrelation, and researchers tend to consider negative autocorrelation less relevant. If a particular variable increases (decreases) in one area, it also tends to increase (decrease) in neighboring areas. However, Griffith and Arbia (2010) offer three examples of negatively spatially autocorrelated phenomena, all based on the notion of competitive locational processes. If the manifestation of a certain phenomenon in one area occurs at the expense of its neighboring areas, then negative spatial autocorrelation is likely. We investigate whether universities compete and thereby contribute to the less explored area related to negative spatial autocorrelation.

Furthermore, spatial econometric techniques mainly have been used to explain lattice or areal data (e.g., rectangles, zip codes, municipalities, regions, states, jurisdictions, countries), as in Griffith and Arbia (2010) and the few other studies that provide empirical evidence of negative spatial autocorrelation. Because we use data observed at the individual level of universities though, this study is among the first to apply spatial econometric techniques to geo-referenced point data rather than lattice or areal data.

In the remainder of this article, we begin by offering some theoretical background from both sociology and economics to understand competition and collaboration among scientists and the institutions in which they are employed. In Section 3, we introduce spatial econometric models to operationalize the spatial interaction effects empirically.

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We then outline our database of research publications and academic career details for academic economists employed at universities or top research institutes in Austria, Germany, and German-speaking Switzerland in Section 4. In addition, we define our measure of research productivity and present its spatial distribution across our study area in Section 5. After surveying the potential determinants of research productivity, in Section 6 we review and discuss the results of our empirical analysis, focusing on the sign and significance of the spatial interaction parameter as our main evidence of research competition. In addition, we provide several robustness checks in Section 7. This article concludes with a summary and discussion of the main results in Section 8.

2. Research productivity: Competition and collaboration

In Merton's (1973) view, scientists compete to produce objective knowledge and thus acquire scientific recognition. Subsequent studies have questioned the hypothesis that scientific recognition is their sole motivation and have tried to give more meaning to the reward system provided by scientific fields. According to Hagstrom (1975), researchers not only produce knowledge to gain esteem but also aim to speed up their own personal advancement. Researchers offer their output as a gift (i.e., free of charge) to the entire community, with the purpose of attracting counter gifts. Bourdieu (1975) instead proposes that scientists behave as capitalists who work to place their scientific output at the right time in the right place in the scientific field, by investing in the most profitable subjects and methods in relation to demand. For this purpose, they must be familiar with the state of the field and the interest that other researchers have in advances, as well as what they are willing to give in exchange. Only then can they successfully exchange the scientific value of their research for social values.

Overviews published by Merton (1973), Stephan (1996), and Vinck (2010) indicate that the reward system—be it based on recognition, counter gifts, or social values—can take multiple forms. For example, it may grant access to employment, in the form of appointments as researcher, lecturer, or professor or requests to take charge of responsibilities for academic institutions, intellectual societies, or journals. Financial remuneration is another component of the reward system, generally imagined to consist of two parts. The fixed payment relates to the type of academic position, whereas the

priority-based part reflects successful contributions to science in the form of prize money, speaking and consulting fees, or income from a successful patent. Rewards can also take the form of eponymy, such as when the scientist's name is attached to a discovery or scientific prizes (e.g., the Nobel Prize). Other non-pecuniary rewards are the number of citations received on an article, invitations to speak at conferences, or easier acceptance of new work for publication, especially in prestigious journals. Finally, the reward system might feature money (e.g., research subsidies, grants), capital goods (equipment, software, data), and social recognition (prestige, renown, credit, authority, visibility).

Despite the differences in their emphasis, all these overview studies assume scientists are competitors and that the key to more or higher rewards is the production of more articles in higher-quality journals. Maske et al. (2003) go so far as to presume that a researcher's utility function depends on only one argument: total number of articles in refereed journals. A similar principle applies to universities or research institutes where the scientists hold academic positions (Stephan, 1996; Vinck, 2010). However, whereas researchers struggle to prove the scientific value of their work, universities must earn their budgets by showing governments and the public that they engage in worthwhile actions with the money they receive. To obtain funds, they must demonstrate their societal relevance to backers, such as by showing that they published a lot of research. For these reasons, the research productivity of individual scientists and that of the universities and research institutes in which they are employed have become primary topics of economic inquiry, across three main directions.

First, efforts focused on ranking research institutions, which eventually have expanded to rankings of individual researchers. One of the most comprehensive European studies is by Combes and Linnemer (2003), who rank approximately 600 economic research centers using quality-adjusted measures of publication activities. Their U.S. counterparts are Dusansky and Vernon (1998), who review and compare several rankings of top economic departments. The primary purpose of these studies is to provide "near-objective" information about the comparative quality of research in a world in which academic publications have reached a great deal of variety. These studies consistently find that research productivity is highly skewed, such that most articles are written by a

limited number of scientists, employed by major universities located in a few countries (for detailed figures, see Frenken et al., 2009; Vinck, 2010).

Second, researchers have tried to identify the drivers of research productivity. Research productivity can be measured and explained at the individual level, university level, or even the level of a particular area, such as nations. To explain research productivity at the individual level, most studies apply human capital models, in which lifecycle variables such as gender, age, experience, and academic position are significant. Thus the publishing activity of a researcher initially increases, then declines later in his or her career. According to Stephan (1996), the explanatory power of these lifecycle models remains rather low though, because they cannot explain why research productivity among scientists is so skewed. Two recent studies investigating publication data related to German economic and business economic researchers confirm this claim (Fabel et al., 2008; Rauber and Ursprung, 2008a) and indicate R-square values not greater than 0.18. Research conducted at the university level has surfaced additional explanatory variables. For example, Fabel et al. (2008) examine the impact of institutional characteristics, such as department size, the number of non-publishing professors, teaching loads, and the share of post-doctoral students. The first variable appears positive and significant, which implies economies of scale; the second variable is negative and significant; and the latter two are insignificant.

Other studies also concentrate on the relationship between research output and location characteristics. Bonaccorsi and Daraio (2005) investigate the impact of size and agglomeration effects on institutional productivity, using data about non-university research institutions that belong to the Italian National Research Council and France's INSERM (Institut national de la santé et de la recherche médicale). They find weak evidence in favor of agglomeration effects in France only and no evidence of economies of scale. However, their analysis is based on partial correlation coefficients rather than a multiple regression framework. Carvalho and Batty (2006) instead compute a power law decay function to test whether physical location matters to research output in the U.S. computer science field. They conclude that advantages stem from "good" locations, when they control for population and research funding. Kim et al. (2009) investigate research productivity for economics and finance faculty at the top 25 U.S. universities for the

period 1970–2001. Those top universities actually appear to have lost their ability to boost the productivity of their researchers during this period. Yet they nevertheless enjoy the highest average productivity, because they are still able to attract and retain the most productive researchers; top researchers thus agglomerate in institutions with prestigious undergraduate programs and strong research reputations. Such agglomeration could also be due to the utility of co-location with other creative minds or other non-market factors.

Third, prior literature has tried to explain why scientists seek coauthors and form networks of scientific cooperation. Through collaboration, perhaps with different coauthors, a scientist can diversify his or her research portfolio, which minimizes the risk that time invested in research and writing goes to waste if the papers are not accepted for publication. Another factor is quality. Scientists who collaborate may be more productive than individual investigators, because they tend to produce better science if they share knowledge and learn from one another (Ursprung and Zimmer, 2007). In addition, unknown, young researchers may find it difficult to get their contributions published, so they seek recognized scientists to work with them and coauthor their articles. These settled scientists in turn may be willing to advise and assist the young scientists due to of the so-called Matthew effect: When two researchers coauthor an article, readers tend to notice only the most eminent author and gradually forget the other, regardless of their actual levels of contribution to the work. In other cases, colleagues receive coauthorship status as a reward for sharing access to data, software, or equipment. Laband and Tollison (2000), in their examination of the increase of coauthorship incidence, cite the capital intensity of research as the main rationale for biology and the higher probability of publication as the reason in economic fields. They also investigate various types of collaboration and their impact on output quantity and quality in these two research areas.

Frenken et al. (2009) find that most collaborations are local or domestic rather than international. One explanation posed for such cooperation at the local level refers to agglomeration effects, such as economies of scale. According to Bonaccorsi and Daraio (2005), economies of scale are synonymous with critical mass. There exists a minimum efficient scale for the administrative costs of universities. Moreover, meaningful output requires the combination and coordination of many scientists from different fields who can provide competencies in both the substantive field and complementary areas, such as

measurement techniques, statistical analysis, scientific computing, software development, data processing and analysis, and so on. Size also may have benefits in terms of organizational support, including direct resources employed in scientific production such as assistants or equipment, shared resources such as libraries and facilities, and indirect resources such as competent colleagues.

Research examining the impact of agglomeration economies also has tried to explain agglomeration processes as results of intrinsic limits to the geographic mobility of technological and scientific knowledge. Such studies stress the importance of proximity for communication and the need for personal interactions to exchange tacit or barely formalized technological know-how. Yet other studies question the importance of agglomeration effects or its causality. For example, Kim et al. (2009) argue that the Internet and the concomitant decline in communication costs have given faculty even in remote places access to the latest developments, whereas Bonaccorsi and Daraio (2005) believe that scientific excellence creates its own agglomeration effects rather than that agglomeration effects make researchers more productive. When a researcher or university in a given location opens promising lines of research, doctoral and post-doctoral students may choose to follow, visiting professors are eager to deliver seminars, and suppliers of scientific instrumentation visit more frequently.

In summary, there are many good reasons for scientists to work together. However, whether the determinants of collaboration are strong enough to disrupt the basic notion that scientists and the institutions for which they work are competitors remains to be seen.

3. Spatial econometric modeling of competition

Spatial econometrics literature has produced three basic models to describe interaction effects: the spatial lag model, the spatial error model, and the spatial Durbin model. The first extends standard linear regressions to include a spatially lagged dependent variable, the second model incorporates a spatial autoregressive process in the error term, and the last model contains spatially lagged dependent and independent variables.

Most empirical research starts with a standard (i.e., non-spatial) linear regression model and then tests whether the model needs to be extended with spatial interaction

effects. The spatial lag model posits that the dependent variable depends on the dependent variable observed in neighboring units and on a set of observed local characteristics,

$$y_i = \delta \sum_{j=1}^{N} w_{ij} y_j + \alpha + x_i \beta + \varepsilon_{it} \,, \tag{1}$$

where y_i is the dependent variable (e.g., research productivity in our study) for unit i (i = 1, ..., N), α is the constant term parameter, x_i is a 1×K vector of exogenous variables, and β is a matching K×1 vector of fixed but unknown parameters. Furthermore, ε_{it} is an error term with mean 0 and variance σ^2. The variable $\sum_j w_{ij} y_j$ denotes the interaction effect of the dependent variable y_i with the dependent variables y_j in neighboring units, where w_{ij} is the i,j-th element of a prespecified nonnegative N×N spatial weights matrix W that describes the spatial arrangement of the units in the sample. By convention, the diagonal elements of W are set to 0, because no unit can be viewed as its own neighbor. For ease of interpretation, a common practice normalizes W, such that the elements of each row sum to 1. Because W must be non-negative, all weights can be interpreted as the average of neighboring values. Finally, δ is the spatial autoregressive coefficient. If W is row-normalized, δ is defined on the interval $(1/r_{min}, 1)$, where r_{min} equals the most negative purely real characteristic root of W (LeSage and Pace, 2009). If a relevant explanatory variable is omitted from the regression equation, the ordinary least squares (OLS) estimator of the coefficients for the remaining variables will be biased and inconsistent (Greene 2005); the spatially lagged dependent variable is one such variable that creates a bias if erroneously omitted.

According to Anselin (2006), the spatial lag model is typically considered a formal specification of the equilibrium outcome of a spatial or social interaction process, in which the value of the dependent variable for one agent is determined jointly with that of neighboring agents. In our study context, a negative value of the coefficient δ of the spatially lagged dependent variable $\sum_j w_{ij} y_j$ serves as an argument for competition among universities. That is, if a researcher working at a particular university publishes a journal paper, then δ, together with the spatial weights matrix W, determines the number of (quality-adjusted) journal papers that researchers working at other universities can no

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longer realize, because the publication eliminates their potential primacy. A positive value of δ instead would imply that the hypothesis that universities compete should be rejected, in favor of some productivity reinforcement.

In the spatial error model, the error term of unit i depends on the error term of neighboring units, according to the spatial weights matrix W and an idiosyncratic component ξ; formally:

$$y_i = \alpha + x_i\beta + \xi_{it}, \text{ and } \xi_i = \lambda\sum_{j=1}^{N} w_{ij}\xi_j + \varepsilon_{it}, \qquad (2)$$

where λ is the spatial autocorrelation parameter. This model is consistent with a situation in which the determinants of research productivity omitted from the model are spatially autocorrelated, as well as with a situation in which unobserved shocks follow a spatial pattern. In contrast, ignoring spatial error correlation, when present, leads to inefficient parameter estimates.

A spatial Durbin model extends the spatial lag model with spatially lagged independent variables,

$$y_i = \delta\sum_{j=1}^{N} w_{ij}y_j + \alpha + x_i\beta + \sum_{j=1}^{N} w_{ij}x_j\theta + \varepsilon_{it}, \qquad (3)$$

where θ, similar to β, is a $K \times 1$ vector of parameters. LeSage and Pace (2009) offer a motivation based on omitted variables for including spatially lagged independent variables. If unobserved or unknown, but relevant, variables that follow a first-order spatial autoregressive process are omitted from the model, and these variables are correlated with independent variables included in the model, the spatial lag model with spatially lagged independent variables will produce unbiased coefficient estimates, but a spatial lag model will not. Furthermore, the spatial Durbin model will also produce unbiased coefficient estimates if the true data generation process would be a spatial error model.

The null hypothesis, $H_0: \theta = 0$, can test whether it is possible to simplify the spatial Durbin model to the spatial lag model; another null hypothesis, $H_0: \theta + \delta\beta = 0$, tests whether it can be simplified to the spatial error model (for mathematical details, see Burridge, 1981). Finally, the hypothesis $H_0: [\delta\ \theta']' = 0$ serves to test whether the spatial Durbin model can be simplified to a standard, non-spatial, linear regression model. The

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first two tests follow a chi-square distribution with K degrees of freedom; the last test uses K + 1 degrees of freedom.

LeSage and Pace (2009) and Elhorst (2010) demonstrate that a change in a single explanatory variable in unit i has a direct effect on the dependent variable of unit i, as well as an indirect effect on the dependent variable of other units $j \neq i$ in a spatial Durbin model. The matrix of partial derivatives of dependent variable in the different units with respect to the kth explanatory variable in the different units (say, x_{ik} for i = 1, …, N) is

$$
\begin{bmatrix}
\dfrac{\partial y_1}{\partial x_{1k}} & . & \dfrac{\partial y_1}{\partial x_{Nk}} \\
. & . & . \\
\dfrac{\partial y_N}{\partial x_{1k}} & . & \dfrac{\partial y_N}{\partial x_{Nk}}
\end{bmatrix}
= (I - \delta W)^{-1}
\begin{bmatrix}
\beta_k & w_{12}\theta_k & . & w_{1N}\theta_k \\
w_{21}\theta_k & \beta_k & . & w_{2N}\theta_k \\
. & . & . & . \\
w_{N1}\theta_k & w_{N2}\theta_k & . & \beta_k
\end{bmatrix}
= (I - \delta W)^{-1}(\beta_k I + \theta_k W) , \quad (4)
$$

for which we use the property that states the diagonal elements of W are 0. Following LeSage and Pace (2009), we can approximate the direct effect of the kth explanatory variable by the average of the diagonal elements of the matrix $[(I - \delta W)^{-1}(\beta_k I + \theta_k W)]$ and the indirect effect by the average of the row (or column) sums of the non-diagonal elements of that matrix. The indirect effect measures the impact of changing an exogenous variable in a particular university on the research productivity of all other universities.

Of particular interest for this study are the direct and indirect effects of size. If the direct effect of the size of economic departments is positive and significant, we can conclude that research output is subject to economies of scale. If the indirect effect of the size of economic departments also is positive and significant, cross-fertilization with nearby universities takes place. Both outcomes would imply the existence of agglomeration economies. Equation (4) indicates that whether the direct and indirect effects of size are positive and significant depends on the signs, magnitudes, and significance levels of the underlying coefficients δ, β_k, and θ_k, as well as on the magnitude of the elements of the spatial weights matrix W. Agglomeration economies thus may emerge even if universities are competitors, that is, if δ is negative.

Three methods can estimate models that include spatial interaction effects, based on maximum likelihood (ML), instrumental variables and the generalized method of moments (IV/GMM), or the Bayesian Markov chain Monte Carlo (MCMC) approach. A

disadvantage of IV/GMM estimators is the possibility of ending up with a coefficient estimate for δ that falls outside its parameter space (Pace et al., 2010). Whereas this coefficient is restricted to the interval $(1/r_{min}, 1)$ by the Jacobian term in the log-likelihood function of ML estimators or the conditional distribution of the spatial parameter of Bayesian estimators, it is unrestricted using IV/GMM, which ignores the Jacobian term.

One advantage of Bayesian over ML estimators is that they offer a criterion, the Bayesian posterior model probability, for selecting the spatial weights matrix that best describes the data. A comprehensive selection process for various spatial weight matrices overcomes the major weakness of spatial econometric models, that is, that the spatial weights matrix W cannot be estimated but must be specified in advance, even though the economic theory underlying spatial econometric applications often has little to say about the specification of W (Leenders, 2002). For this reason, common practice now investigates whether the results are robust to alternative specifications of W. However, empirical literature has proposed many more alternative specifications of W that could be tested (please see the discussion of our W choices in Section 7). If a spatial econometric model is estimated by ML based on S different spatial weight matrices, with the log-likelihood function value of every model estimated, the researcher can select the spatial weight matrix that exhibits the highest log-likelihood function value. Formally though, tests for significant differences between log-likelihood function values, such as the likelihood ratio (LR) test, do not apply if the models are not nested (i.e., based on different spatial weight matrices). In contrast, Bayesian posterior model probabilities do not require nested models for these comparisons. Rather, they set prior probabilities equal to 1/S, such that the different models are equally likely a priori; estimate each model with Bayesian methods; then compute posterior probabilities using the data and the estimation results of the S models. Matlab routines applying Bayesian methods to the spatial lag, spatial error and spatial Durbin models can be downloaded for free (www.spatial-econometrics.com[1]), which makes it relatively easy to conduct such comparisons.

The advantage of ML estimators over IV/GMM and Bayesian estimators is that they are more accurate (Pace et al., 2010). Many test statistics are also based on the

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[1] This Web Site has been developed and is still maintained by James P. LeSage.

likelihood function of different spatial econometric models. Therefore, we use ML to estimate the spatial econometrics models in Equations (1), (2), and (3) and the Bayesian MCMC approach to select the spatial weight matrix that best describes the data.

4. Economic research across German-speaking countries: Quantity and quality

Our primary data source for the empirical analysis is a database of all individual researchers in economics, finance, and business administration currently affiliated with an Austrian, German, or German-speaking Swiss university or economic research institute. This "research monitoring" *(Forschungsmonitoring[2])* database falls under the auspices of the German Economic Association[3] and provides, for each researcher, all of his or her journal articles indexed in EconLit,[4] as well as additional personal information, such as affiliation, current position, career length, and gender. Furthermore, it provides information about all coauthors (regardless of affiliation). The research monitoring database is updated annually, self-validated, and inclusive of new researchers. We use the December 2009 version.

For our analysis, we selected only researchers in economics who received their doctoral degrees no later than in 2008. Altogether we gather data about 1373 researchers affiliated with 81 universities and 17 research institutes: 80 are German (68 universities, 12 institutes), 12 Austrian (8 universities, 4 institutes), and 6 Swiss (5 universities, 1 institute). The institutes include the research departments of the three national central banks and the European Central Bank in Frankfurt. Economists affiliated with universities or research institutes with very small economic departments are excluded.[5]

To measure research productivity for the 98 research units in our sample, we calculate the number of articles published in academic journals, weighted by quality. Following most bibliometric literature, we do not include research published in other

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[2] See www.forschungsmonitoring.org.
[3] The German Economic Association (Verein für Socialpolitik) is the professional association for German-speaking economists (www.socialpolitik.org).
[4] EconLit is the American Economic Association's electronic bibliography of economic literature (www.econlit.org).
[5] This criterion excludes 41 researchers working in 33 different organizations that included no more than 3 economists each.

outlets, such as monographs or collected volumes, because the quality of these results generally has not been evaluated through a peer review process.

Our benchmark measure of research productivity at the university level uses the following formula:

$$y_i = \frac{1}{N_i} \sum_{r_i=1}^{N_i} \left[\frac{1}{l_{r_i}} \sum_{p_{r_i}=1}^{P_{r_i}} \frac{q_{p_{r_i}}}{a_{p_{r_i}}} \right], \tag{5}$$

where y_i denotes the ith unit's average research productivity over a particular period of time. We use the ten-year period, 2000–2009. The expression in square brackets is the average annual research productivity of researcher r_i, where r_i runs from 1 to N_i, which refers to the total number or researchers employed in research unit i. Researcher r_i contributes to P_{r_i} research results (published journal articles) in the observation period, with a maximum length of 10 years (l_{r_i} = 10). If a researcher r_i's academic career is shorter than 10 years, we adjust l_{r_i} accordingly. Each publication p_{r_i} of researcher r_i is weighted with a journal quality index $q_{p_{r_i}}$ and divided by the number of authors $a_{p_{r_i}}$ of that publication. We use the journal quality index developed by Ritzberger (2008), who ranked 261 ISI[6] journals in economics and related fields on a scale from 1 (*Econometrica*) to 0 (19 journals got a score of 0). In Section 5, we test whether our results are robust to alternative measures, including an alternative journal quality index, another measure of the importance of the publication, and a longer time period.

The average annual research productivity of the analyzed research units, according to our benchmark index, ranges from 0.000 to 0.167. The mean, calculated for all 98 research units, equals 0.028, and the standard deviation is 0.034. These results imply that an economist employed at a top institution produces the equivalent of one single-authored *Econometrica* article every six years or the equivalent of one single-authored article in a good journal such as the *Journal of Public Economics* (quality index 0.171) annually. To produce the equivalent of one single-authored article in a good journal, the average economist employed at an ordinary university needs approximately six years.

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[6] Institute for Scientific Information.

Figure 1 features a map of staff size of the research units and their research productivity at the units' various geographical locations. The left panel shows that the number of economists employed at the various locations corresponds to the regions' populations, which likely reflects local demand for education. The right panel indicates that large universities do not necessarily produce more efficiently; some smaller units are highly productive (e.g., University of Basel), whereas some larger units' productivity is well below average (e.g., University of Hamburg). Yet remote universities tend to be less productive than institutions in central cities. The financial centers of Germany and Austria, Frankfurt and Vienna, host each country's most productive universities (Frankfurt University and University of Vienna) and institutes (European Central Bank and Institute for Advanced Studies). In Germany, other productive universities are mostly located in large cities in the west (e.g., Mannheim, Bonn, Cologne). Universities located in the east of that country exhibit lower levels of research productivity. The capital Berlin is an anomaly, mainly due to the Berlin Free University. In Austria, other than the University of Vienna, only the University of Innsbruck exhibits above-average research productivity. In German-speaking Switzerland, all universities and the Swiss National Bank have highly productive economics departments.

<< Figure 1 about here >>

Other than Switzerland and the Frankfurt area though, we observe no obvious clustering, nor are the highly productive institutions distributed in any strikingly uniform manner across the three countries. A visual analysis thus cannot reveal whether the location of a research institution in relation to its neighbors affects the productivity of the researchers it employs. A formal test is needed to disentangle the potential effect of location; therefore, we estimate the spatial econometric models discussed in the previous section.

5. Data and functional form

On the basis of previous research, we assess the non-spatial explanatory variables of research productivity. First, we control for lifecycle effects by including career age, which measures the number of years since the researcher received his or her doctoral degree. Several studies have found that the relationship between career age and research

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productivity is nonlinear, such that productivity tends to be high and increasing in the early years of a scientist's career but then declines, eventually at a decelerating rate. The identification of the nonlinear relationship usually relies on the square of career age as a regressor (Maske et al., 2003), though some studies use higher-order polynomials (Kim et al., 2009; Rauber and Ursprung, 2008b). We therefore consider career age and its square.

Second, many studies include a gender variable (Fabel et al., 2008; Maske et al., 2003; Rauber and Ursprung, 2008b; Taylor et al., 2006); depending on the surrounding conditions, it appears that female economists publish less than male economists. Fabel et al. (2008) attribute this lower level of productivity to career interruptions (e.g., maternity leaves). Because significant gender effects emerge in previous studies with German data, we control for the share of female staff.

Third, we control for institutional characteristics. The size of the institution, measured as the number of researchers, provides a test for economies of scale. Fabel et al. (2008) find some evidence of positive but decreasing economies of scale, so we also include the square of this size measure. Research institutes differ from university departments, because their staff is not required to teach, and unsurprisingly, some studies reveal that teaching has a negative effect on research productivity (Fox, 1992; Taylor et al., 2006). However, research institutes also rely heavily on consulting, which may not transform easily into publications suitable for first-rate scientific journals. To control for these institutional differences, we include a dummy variable that assumes the value of 1 if the institution is a research institute.

Fourth, some studies control for the composition of the staff, which strongly influences the prevailing organizational culture (Cainelli et al., 2006; Fabel et al., 2008; Kim et al., 2009). Research activity by colleagues can generate positive spillovers through exchanges of expertise, ideas, and feedback on ongoing projects. According to Taylor et al. (2006), the presence of active peers should increase productivity, because it enhances both formal and informal collaboration and may produce a competitive environment that encourages "keeping up" with colleagues. In contrast, in an academic environment in which nobody has published in (top) journals, a researcher may redirect his or her activities toward tasks that do not contribute to research production, according to our definition (Kim et al., 2009). Because research productivity generally is lower in

institutions with a larger share of non-publishing members, we control for the share of researchers in each department who have never published an article in a journal indexed by Ritzberger (2008). Fabel et al. (2008) similarly capture this peer effect by including the share of junior members (assistant and associate professors) as an explanatory variable of average research productivity and find a significant negative effect.

Fifth, to determine whether the integration of a research unit into the science system affects research productivity, we include a variable that measures the number of scholars who have collaborated with coauthors outside their own research unit, as a fraction of all staff members who have published in journals indexed by Ritzberger (2008). Maske et al. (2003) and Taylor et al. (2006) find that the percentage of coauthored articles and average number of coauthors have positive and significant effects on research productivity.

Sixth, following Fabel et al. (2008), we allow for different intercepts in Germany, Austria, and Switzerland. We use Germany as a benchmark and add country dummies for Austria and Switzerland. These country fixed effects control for all country-specific, time-invariant variables whose omission could bias the parameter estimates, such as differences in the remuneration of university professors. Table 1 lists all these potential drivers of research productivity.

<< Table 1 about here >>

We now turn to the functional form of the relationship between research productivity and the chosen non-spatial explanatory variables, relying on our discussion of the different approaches to estimating spatial interaction effects in Section 3. Whereas most studies adopt a linear relationship, Fox (1992) starts with a log-linear functional form to normalize the skewed distribution of productivity—that is, that a few researchers produce many articles and many publish few or none. To test the linear and log-linear functional forms, we first estimated the Box-Cox nonlinear regression model by ML with a common parameter γ for the research productivity dependent variable and the right-hand side variables of career age and size. Dummies or variables measuring shares were not transformed, and we left spatial interaction effects aside at this stage of the empirical analysis. If γ is not significantly different from 0, we may conclude that the log-linear functional form is more appropriate. Conversely, if γ is not significantly different from 1,

we conclude that the linear functional form is more appropriate. We find that $\gamma = 0.182$, with standard error of 0.142, so we settled for the log-linear specification.[7]

6. Results

Table 2 reports our estimates of the determinants of research productivity, based on the period 2000–2009 and 98 observations of university economics departments and institutes that conduct economic research. The first column shows the OLS estimator results applied to the log-linear functional form, without any spatial interaction effects. This model provides a benchmark for models that allow for spatial interdependence. The spatial models are based on a row-normalized inverse distance matrix, in which the spatial weights represent the Euclidian distances between each pair of research organizations. We derived these distances from GPS data reported by Google Earth and consider alternative specifications subsequently.

To determine if the spatial lag or spatial error model is more appropriate to describe the data, we use classic Lagrange multiplier (LM) tests proposed by Anselin (1988) and the robust LM tests (LM_δ^r and LM_λ^r) proposed by Anselin et al. (1996), which test for the existence of one type of spatial dependence conditional on the other. Both the classic and the robust tests rely on the residuals of the OLS model and follow a chi-squared distribution with one degree of freedom.

The results of the (robust) LM tests show that neither the hypothesis of no spatially lagged dependent variable nor the hypothesis of no spatially autocorrelated error term can be rejected at the 5% significance level.[8] Elhorst (2010) argues that in such circumstances, it still might be useful to estimate the spatial lag and spatial error models: If the spatial autoregressive coefficient δ and/or the spatial autocorrelation coefficient λ turns out to be significant, we may still conclude that the OLS model must be rejected in

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[7] One university produced no positive output, so log(y) could not be defined. Fox (1992) suggests using log(y + 1) in such circumstances, but because log(y + 1) ≈ y if y approaches 0, and the average annual research productivity of the research units is rather small, this logarithmic transformation actually would approximate the rejected linear functional form. We therefore decided to use a method proposed by Griffith et al. (1989) to find the log(y) of this particular university. We set y to equal the smallest non-zero observation in the sample, estimated the model, predicted y, and replaced the starting value of y with this predicted value. We repeated the procedure until it reached convergence.
[8] A similar result occurs for the linear functional form.

favor of the spatial lag model, the spatial error model, or both. The results in the second and third columns of Table 2 suggest this scenario is exactly what we face here. Whereas the hypothesis of uncorrelated spatial error terms again appears acceptable (λ is not significantly different from 0), the hypothesis of no influence of the spatially lagged dependent variable cannot be rejected: The coefficient of spatial autoregression is negative and significant at 5% and 1% significance levels. Therefore, the spatial lag model is more appropriate than the spatial error model or the OLS model. Perhaps the reason the (robust) LM tests do not reject the OLS model, even though spatial autoregression appears to be present, is that the performance of these tests has been investigated only for positive values of δ, ranging from 0.1 to 0.9 at increments of 0.1 (see Anselin et al., 1996).

<< Table 2 about here >>

The fourth column of Table 2 contains the results of the spatial Durbin model. The coefficients of the spatially lagged independent variables appear insignificant. To test the hypothesis pertaining to whether the spatially lagged independent variables are not jointly significant, $H_0: \theta = 0$, we also performed a likelihood ratio (LR) test, whose results (2.42, with 8 degrees of freedom [df], $p = 0.97$) indicate that we cannot reject this hypothesis. Consequently, there is no reason to reject the spatial lag model in favor of the spatial Durbin model.[9] The spatial autoregressive coefficient in the spatial lag model equals -0.451 and is highly significant (t-value = -2.91). Therefore, if a researcher working at a particular organization publishes one additional journal article, the productivity of researchers working at other organizations falls on average by 0.34 journal articles.[10] To be more precise: One article in *Econometrica* (quality weight = 1) might displace another article in *Journal of Economic Theory* (weight = 0.346), but a paper published in the latter journal might displace a paper in *Journal of Business Venturing* (weight = 0.115, or approximately 0.346 × 0.34).

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[9] Similarly, we cannot reject the hypothesis that the spatial Durbin model can be simplified to the spatial error model, $H_0: \theta + \delta\beta = 0$ (4.32, 8 df, $p = 0.83$).

[10] This coefficient is the average row (or column) sum of the non-diagonal elements of the matrix $(I-\delta W)^{-1}$, with $\delta = -0.451$ and W equal to the inverse distance matrix, based on Euclidian distances among research institutes. Also see the explanation we offer after Equation (4).

In line with previous studies, the coefficients of the non-spatial explanatory variables in both the OLS and the spatial lag model have the expected signs. In addition, column 3(d) of Table 2 reports the results when research productivity depends on all our explanatory variables. Not every coefficient in this extended regression equation appears significant, so we dropped some variables from the model. We discuss these non-significant variables in detail subsequently.

The coefficient of the size of economic departments is positive and highly significant. This result corroborates the hypothesis that larger economic departments make their faculty more productive; peer pressure appears to generate economies of scale. Because research productivity and size are both measured as logs, the coefficient of the size variable represents an elasticity. The estimated coefficient of 0.46 can be interpreted as follows: Assume two research organizations at the same location, one of which is twice as large as the other. Economists working for the larger organization should be 46% more productive than peers employed by the smaller organization.

The square of the size variable has a negative coefficient, which indicates decreasing returns to scale. However, because the coefficient is insignificant, we drop this variable. To test for the agglomeration effect of nearby universities, we also estimated the model with the spatially lagged independent variable W × log size. The coefficient estimate of this variable is negative and insignificant (-0.124, t-value = -0.27); therefore, the size of neighboring research institutes, similar to the spatially lagged dependent variable of research productivity, reflects the competitive forces among scientists employed at different organizations. Because the coefficient was not positive and significant, we find no empirical evidence in favor of cross-fertilization effects across nearby universities. This result corroborates Bonaccorsi and Daraio's (2005) view that scientific excellence creates its own agglomeration effects rather than that agglomeration effects make researchers more productive, except for economies of scale.

The coefficient of the log of career age is negative and significant, consistent with the observation that productivity tends to be high in the first years of a career and declines thereafter, such that younger departments are more productive. The coefficient of its square is positive; toward the very end of a person's career productivity slightly increases again. However, this coefficient is insignificant, so we drop this variable.

Collaboration has a positive and highly significant effect on research productivity. This result reveals that collaboration is beneficial and that collaboration and competition generally coexist. According to the coefficient estimate and the average degree of collaboration in our sample, the decision to cooperate with coauthors employed by other organizations increases productivity by approximately 18%.[11]

The coefficient of the variable that measures the share of the researchers who do not publish is negative and significant. The presence of many inactive peers thus may induce colleagues to be less active as well. Alternatively, perhaps inactive colleagues create an academic environment that provides insufficient feedback, formal or informal collaboration, and/or exchanges of expertise and new ideas, which is not conducive to high research productivity. We also included a variable measuring the organizations' share of junior staff and find a negative estimated coefficient, just as in Fabel et al. (2008), though it was not significant at conventional levels. We therefore exclude it.

The coefficient of the research institute dummy is negative and weakly significant (10% level), likely because the publication of articles in scientific (top) journals is not a primary task for research institutes, unlike for universities. The lower statistical significance might be explained by the high teaching loads of many university professors, which has a dampening effect on research productivity and results in rather small productivity differences in relation to research institutes. The coefficient of the gender dummy is negative but not significant (t-value = -0.72). The frequently identified negative impact of characteristic career patterns by female scientists is not apparent in our result, which may reflect the aggregate nature of our data.

Finally, the coefficient of the intercept dummy for Switzerland is positive and significant. Economists working at Swiss research organizations are slightly more productive than their colleagues in Austria and Germany. Whether this outcome is a consequence of higher Swiss salaries and ensuing selection effects or of different institutional arrangements is unclear and deserves further inquiry.

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[11] The average university has 14.01 staff members, of whom 7.53 have published journal articles with coauthors outside their own university. If the latter number rises by 1 staff member, the collaboration variable increases from 0.54 to 0.61. Because its direct effect is 2.538, the log of research productivity increases by approximately $(0.61 - 0.54) \times 2.538 = 0.178$, or 18%.

Because we find that the spatial lag model is more appropriate than the OLS model, we identify the estimated coefficients of the explanatory variables in the OLS model and the corresponding direct and indirect effects as biased. In the OLS model, the direct effect of an explanatory variable equals the coefficient of that variable, whereas its indirect effect is set to 0 by construction. In contrast, in the spatial lag model, the direct effect is measured by the average of the diagonal elements of the matrix $(I - \rho W)^{-1}$ times the coefficient β of the corresponding variable, and the indirect effect is the average of the row sums of the non-diagonal elements of the matrix $(I - \rho W)^{-1}$ times the coefficient β of the corresponding variable. This description follows from Equation (4) when the coefficient θ_k is set to 0.

Comparing the estimated direct effects of the OLS model with their counterparts in the spatial lag model, we observe noteworthy differences. In the spatial lag model, the direct effect of the dummy for Switzerland is 0.816; in the OLS model, it is 0.530. Therefore, the latter effect is underestimated by 35.0%. Similarly, the direct effect of career age is underestimated by 10.1%, that of size by 1.0%, and that of collaboration by 6.3%. Conversely, the direct effect of the dummy variable for research institutes is overestimated by 33.3% and that of the share of non-publishing staff by 6.3%.

The difference between the direct effects estimated by the spatial lag model and the estimates of the response parameters in the spatial lag model reflects the feedback effects that arise as a result of impacts passing through neighboring research organizations and then back to the original organization. However, such feedback effects appear relatively small. For example, the direct effect and the coefficient estimate of the size of economic departments are 0.481 and 0.463, respectively, so the feedback effect is only 3.9%. Other feedback effects range from 0.6% to 12.1% and average 3.6%. Although small, this positive value indicates that every publication slightly reinforces the productivity of the researcher's own economic department.

The indirect effects in the OLS model are set to 0, but those in the spatial lag model amount to approximately -31% of the direct effects. The t-statistics calculated with

a set of 1,000 simulated parameter values[12] indicate that the indirect effects of the size, career age, no top publishers, and collaboration variables differ significantly from 0. In other words, if one of the variables driving research productivity at the organization level changes, the result is a change in not only the research productivity of the economists employed by that organization but also the research productivity of neighboring organizations. The change at neighboring organizations moves in the opposite direction and is on an order of magnitude of approximately 31% of the original change. The total effect on all organizations is thus only around 73% of the direct effect on the organization that instigated the change.[13]

7. Robustness tests

We now turn to whether our conclusions are sensitive to the choice of the spatial weights matrix and the method used to measure research productivity. Table 3 contains the log-likelihood function values, Bayesian posterior model probabilities, and the parameter estimate of the residual variance (σ^2) for five alternative specifications (1–5) of the spatial weights matrix (plus the inverse distance matrix based on Euclidian distances used thus far). The alternative specifications cover a wide range of spatial weights matrices from empirical research: p-order binary contiguity matrices (if p = 1, only first-order neighbors are included; if p = 2, the first- and second-order neighbors are considered; and so on), distance matrices (linear or exponential distance decay functions, with or without a cut-off point), q-nearest neighbor matrices (where q is a positive integer), and block diagonal matrices in which each block represents a group of units that interact with one another but not with the units in other groups.

To obtain the log-likelihood values and residual variances, we estimate the spatial lag models by ML, and for the Bayesian posterior model probabilities (which sum to 1), we estimate the spatial lag models with the help of the Bayesian MCMC method (see Section 3).

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[12] To draw inferences about the statistical significance of these effects, we used the variation of 1,000 simulated parameters combinations drawn from the multivariate normal distribution implied by the maximum likelihood estimates (for mathematical details, see LeSage and Pace, 2009; Elhorst, 2010; for the software, see the Matlab routine "sar" posted on LeSage's web site, www.spatial-econometrics.com).

[13] Equal to 100% + 4% (feedback effect) – 31% (indirect effect) = 73%.

The first spatial weights matrix, labeled W-region, combines a binary contiguity matrix with a group interactions matrix. Its elements are 1 if two German organizations are located in the same state (Bundesland), and 0 otherwise.[14] The W-4 is a four-nearest neighbor matrix, measured in terms of driving distances; it is the only matrix that is not symmetric. The W-distances ≤ 165 km combines an inverse distance matrix with a cut-off point and a group interactions matrix, because every organization within 165 kilometers is considered a neighbor. This matrix assumes no interaction effects between research organizations beyond the cut-off point, which we chose to prevent any organizations from lacking any interaction partner. In the next distance matrix, we include an exponential distance decay function (exp[-d]). All the matrices have been row-normalized, so the entries of each row add to 1. Finally, a last matrix assumes that all universities are neighbors and that the impact of each university is the same; all non-diagonal elements equal 1 before row-normalizing and $1/(N - 1)$ afterwards. The idea underlying this equally weighted, single group interaction matrix is as follows: If researchers truly compete with one another, every researcher, regardless of his or her employer, is a competitor.

Formally though, this spatial weight matrix should be rejected for reasons of consistency. Lee (2004) proves that any spatial weight matrix must satisfy one of the following two conditions: (1) the row and column sums of the matrix W before W is row normalized should be uniformly bounded by the absolute value as N approaches infinity, or (2) the row and column sums of W before row normalization should not approach infinity at a rate equal to or faster than the rate for the sample size N. Elhorst (2010) shows that the row and columns of the single group interactions matrix, before it is row normalized, are $N - 1$ and that the rate at which these row and column sums approach infinity is the same as the rate at which the sample size N does. Therefore, this matrix satisfies neither condition, but by considering it, we test whether this matrix should be rejected empirically as well.

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[14] Four city-states or small states merged with their immediate neighbors: Berlin with Brandenburg, Bremen with Lower Saxony, Hamburg with Schleswig-Holstein, and Saarland with Rhineland-Palatinate. Austria comprised two groups, Vienna and rest of the country. Switzerland and its six German-speaking research organizations represented one group.

The results in Table 3 show that the inverse distance matrix based on Euclidian distances has the highest log-likelihood function value, the highest Bayesian posterior model probability, and the lowest parameter estimate for residual variance. The probability that this matrix is the most appropriate is approximately 1.9 times greater than the respective probabilities for its counterpart based on an exponential distance decay function, 2.1 times greater than that for the equally weighted group interaction matrix, 3.5 times as large as that for the four-nearest neighbor matrix, 9.4 times as large as for the W-region matrix, and more than 10 times greater than the W-distances $\leq$ 165 km matrix. In summary, spatial weights matrices with many zero non-diagonal elements underperform compared with spatial weights matrices with no zero non-diagonal elements, and the inverse distance matrix based on Euclidian distances is the best approximation of this latter group of matrices. This finding may reflect the labor market for scientists: Reputable universities always want to hire good researchers away from other universities to add their publications to their publication records. But just as the tendency to collaborate with other researchers decreases with distance, so does the willingness to relocate. That is, researchers appear willing to accept job offers from other universities if the remuneration exceeds their current salary plus the costs of relocation. Migration literature provides abundant evidence that these costs increase with distance. If instead of the inverse distance matrix, we were to adopt one of the other matrices, the competition parameter remains negative, though in most cases, the significance level declines from 5% to 10% (see the last two columns of Table 3).

In a second battery of tests, we checked whether our results in Table 2 are robust to alternative measures of research productivity (Table 4). As we mentioned in Section 4, there are many alternatives to our benchmark measure of research productivity, as provided in Equation (5). Several studies include the number of pages of each article as an indicator of research significance, including Combes and Linnemer's (2003) ranking of European economics departments, Rauber and Ursprung's (2008a) ranking of economics departments in Germany, and Kim et al.'s (2009) investigation of research productivity in economics and finance departments at 25 top U.S. universities. If we extend the productivity measure in Equation (5) to account for the length of journal articles, we obtain:

$$y_i = \frac{1}{N_i} \sum_{r_i=1}^{N_i} \left[\frac{1}{l_{r_i}} \sum_{p_{r_i}=1}^{P_{r_i}} \frac{q_{p_{r_i}} s_{p_{r_i}}}{a_{p_{r_i}}} \right], \tag{6}$$

where s denotes the number of pages of the article. Instead of using Ritzberger's (2008) journal quality weights, we can use the quality weights that inform the popular research ranking of Austrian, German, and Swiss economics departments published by the business newspaper *Handelsblatt*. This journal list includes more than 1,200 journals, compared with the 261 journals rated by Ritzberger (2008).[15] Furthermore, *Handelsblatt* considers only seven different quality levels: 1, 0.6, 0.3, 0.2, 0.1, 0.15, and 0.05. Thus the Handelsblatt weights are more evenly distributed than the quality weights proposed by Ritzberger. Although the use of quality weights is perhaps the most controversial item in productivity measures, Krapf (2011) shows that the ranking of economic research departments across different weighting schemes (including Ritzberger's and the Handelsblatt version) are very robust.

As a third robustness check, we considered the length of the sample period. To provide perspective on the ten-year period (2000–2009) for our benchmark regressions, we investigated a sample covering 40 years (1970–2009). The Ritzberger (2008) and Handelsblatt journal quality weights refer to the more recent past, so we used weights proposed by Laband and Piette (1994) for the first two decades (1970–1989) and those proposed by Kalaitzidakis et al. (2003) for the 1990–1999 period.[16]

In the fourth robustness check, we limited the analysis to university departments to investigate whether the competitive pressure between university departments extends to research institutes.

<< Table 4 about here >>

The results in columns 2–5 of Table 4 show that the size of the spatial autoregressive coefficient and its significance level remain largely unchanged when we include the number of journal pages as an indicator of productivity, carry out the analysis

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[15] See http://www.handelsblatt.com/singleclip.aspx?_t=dgtool&id=15&obj=1.

[16] Laband and Piette (1994) rank 92 economic research journals according to impact-adjusted citations over the period 1975–79 and 130 journals over the period 1985–89. We used these rankings accordingly to weight the papers in our data set from 1970–79 and 1980–89, respectively. For 1990–99, we used Kalaitzidakis et al.'s (2003) ranking of 159 journals; they repeat Laband and Piette's (1994) analysis for 1994–98. For the last decade, we used the Ritzberger (2008) ranking again.

for the period 1970–2009, or estimate the model for university departments only. In contrast, we obtain an insignificant but still negative value when we use the Handelsblatt journal quality weights. The finding that competition is weaker according to the Handelsblatt weights indicates that scientific competition mainly motivates top performers; journeymen scientists appear motivated by other factors. To substantiate this hypothesis, we estimate a so-called biparametric spatial autoregressive model (Brandsma and Ketellapper, 1979),

$$y_i = \delta_1 \sum_{j=1}^{N} w_{ij} y_j + \delta_2 \sum_{j=1}^{N} v_{ij} y_j + \alpha + x_i \beta + \varepsilon_{it}, \qquad (7)$$

where w_{ij} is the i,j-th element of the inverse distance matrix based on Euclidian distances (i.e., the best choice), and v_{ij} is the i,j-th element of the same spatial weights matrix limited to m top research units. In this setup, δ_1 measures the competition effect among all research units, and δ_2 measure it among only the top units. If our hypothesis is true, δ_1 will equal 0 and δ_2 will be less than 0. To determine the number of top units, we estimate the model for different values of m (m = 5 to 93) and select that model for which the difference between δ_1 and δ_2 is significant and the log-likelihood function achieves its maximum. Column (6) in Table 4 contains the results with the Ritzberger weights, and column (7) features those for the Handelsblatt weights. These results confirm that the whole sample of research organizations can be subdivided into a group of top performers, who operate in strong competitive environments, and another group of weaker performers. The group of top performers includes 44 research units, with a spatial autoregressive coefficient of -0.617 (t-value = -4.10) with the Ritzberger weights; when we use the Handelsblatt weights, we include 20 research institutes with a spatial autoregressive coefficient of –0.334 (t-value = -2.85) in the top performers group. The latter finding corroborates the view that scientific competition exists even if we measure research productivity with Handelsblatt weights.

The impact of the intercept dummy for Switzerland appears most pronounced in the analysis for the longer period but smaller with the Handelsblatt weights. The coefficient of the dummy for research institutes, which was negative and weakly significant when we used Ritzberger's weights, appears negative and weakly significant when we include the number of journal pages. However, the coefficient becomes

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insignificant if we conduct the analysis for the 1970–2009 period. The impact of the dummy for research institutes almost completely disappears with the Handelsblatt weights—likely because top research traditionally has been written mainly at universities.

The coefficient of the size variable is positive and highly significant in all model specifications. Because the interval for this coefficient appears rather small (0.350 to 0.568), this finding reconfirms the existence of economies of scale. The negative coefficient of career age is significant in all model specifications. However, the age effect grows most pronounced when we include the number of journal pages and least when using the Handelsblatt weights.

The coefficient of the no top publishers variable is negative and significant in most model specifications. For the period 1970–2009 and considering only university departments, the impact of "sleepers" becomes more pronounced. This rather plausible result reflects that scientific competition was less global in the past, so local factors played a larger role. As for the research institutes, we posit that their staff is less susceptible to peer group effects because of the traditionally strong leadership by institute managers. The opposite result emerges for collaboration though. The estimated coefficient of this variable is substantially smaller for 1970–2009 than for the benchmark period, regardless of the model specification. This result indicates that networking and collaboration among researchers have become much more important in the recent past.

Finally, the coefficient of the gender dummy is sizable, negative, and significant for the 40-year period. This finding may offer evidence that modern female scientists are better able combine their family lives with their academic aspirations.

8. Conclusions

We provide strong empirical evidence in favor of Merton's (1973) basic notion that scientists are engaged in competition. If a researcher working at a particular university publishes a journal paper, the number of (quality-adjusted) journal papers that researchers working at other universities can realize decreases, as a result of that focal publication. The extent of the effect depends on the specification of the spatial weights matrix, the method of measuring research productivity, and the sample setup. Using Bayesian posterior model probabilities, maximum likelihood function values, and estimates of the

residual variance, we find that a spatial weights matrix without zero non-diagonal elements best describes the data; an inverse distance matrix based on Euclidian distances offers the best approximation of that spatial weights matrix.

With this matrix, we find that the negative and significant competition effect ranges from -0.334 to -0.451 when we (1) use Ritzberger weights, (2) consider journal page productivity rather than just articles, (3) investigate universities only rather than both universities and research institutes, (4) conduct the analysis over a period of four decades (1970–2009) rather than only the past decade (2000–2009), and (5) use Handelsblatt weights instead Ritzberger weights, though only in the biparametric spatial autoregressive model in this latter case.

The most important control variables for research productivity are the size of economic departments, career age, the share of non-publishing staff, and the degree of collaboration. Larger economic departments make their faculty more productive because they offer economies of scale. Research productivity tends to be higher for younger research units and declines for older units, in concordance with lifecycle theories of research productivity. The greater the share of staff that does not publish, the more journal-targeted research of active colleagues will be redirected to other activities too, which causes research productivity to fall disproportionally. Even when researchers are competitors, their collaboration with coauthors outside their own university pays off, on average by 18%.

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Table 1. Potential drivers of research productivity

Explanatory variable	Description	Mean	Min/Max
Career age	Number of full years since PhD (average over department researchers)	13.74	3.8/31.8
Female	Share of female staff members in department	0.15	0/0.5
Size	Number of department researchers	14.01	4/60
Institute	Equal to 1 if the department is not a university		
No top publishers	Share of members without publications in a journal with non-zero Ritzberger weight	0.45	0/1
Collaboration	Department researchers who have an outside coauthor, as a fraction of researchers who published any paper during 2000–2009	0.62	0/1
Austria, Switzerland	Country dummies (Germany is a benchmark)		

Table 2. Explaining log research productivity using different model specifications

Determinants	(1) OLS	(2) Spatial error model	(3) Spatial lag model (a) Coefficient	(3) (b) Direct effects	(3) (c) Indirect effects	(3) (d) More regressors	(4) Spatial Durbin X	(4) W×X
Constant	-3.010**	-3.009**	-4.896**			-3.852**	-4.306**	
	(-2.38)	(-2.56)	(-3.67)			(-1.08)	(-0.78)	
Austria	0.220	0.259	0.111	0.124	-0.037	0.383	0.052	0.022
	(0.74)	(1.13)	(0.40)	(0.43)	(-0.38)	(1.05)	(0.11)	(0.03)
Switzerland	0.530	0.492	0.795**	0.816**	-0.273	0.797	0.834	0.384
	(1.27)	(1.46)	(2.00)	(2.00)	(-1.58)	(1.99)	(1.43)	(0.35)
Institute	-0.724**	-0.660**	-0.540*	-0.544*	0.173	-0.718**	-0.438	0.665
	(-2.37)	(-2.25)	(-1.90)	(-1.91)	(1.62)	(-2.06)	(-1.28)	(0.70)
Log size	0.476**	0.445**	0.463**	0.481**	-0.155**	0.686	0.433**	-0.085
	(3.06)	(3.04)	(3.24)	(3.34)	(-2.41)	(0.69)	(2.82)	(-0.16)
Log² size						-0.051		
						(-0.26)		
W×Log size						-0.124		
						(-0.27)		
Log career age	-1.012**	-1.037**	-1.094**	-1.126**	0.364**	-1.732	-0.993**	-0.375
	(-3.14)	(-3.60)	(-3.70)	(-3.77)	(2.49)	(-0.81)	(-3.09)	(-0.43)
Log² career age						0.103		
						(0.24)		
Junior professor						-0.894		
						(-1.09)		
No top publishers	-2.184**	-1.994**	-1.912**	-1.971**	0.636**	-1.852**	-2.057**	0.474
	(-3.11)	(-3.07)	(-2.97)	(-3.02)	(2.28)	(-2.81)	(-3.11)	(0.16)
Female	-0.756	-0.920	-0.607	-0.610	0.183	-0.517	-0.474	-3.426
	(-0.82)	(-1.08)	(-0.72)	(-0.69)	(0.61)	(-0.57)	(-0.52)	(-0.94)
Collaboration	2.378**	2.500**	2.459**	2.538**	-0.813**	2.557**	2.331**	0.531
	(3.22)	(3.60)	(3.63)	(3.73)	(-2.58)	(3.73)	(3.32)	(0.17)
δ or λ		-0.376*	-0.451**			-0.450**	-0.528**	
		(-1.91)	(-2.91)			(-2.70)	(-2.96)	
(Pseudo) R^2	0.649	0.666	0.645			0.647	0.654	
Log Likelihood	-173.90	-123.30	-122.35			-121.66	-121.14	

Spatial Lag, OLS model:		Spatial Lag, spatial Durbin model:	
LM_δ	3.26	$LR_{\theta=0}$	3.33
Robust LM_δ	1.02		
Spatial Error, OLS model:		Spatial Error, spatial Durbin model:	
LM_λ	2.24	$LR_{\theta+\delta\beta=0}$	5.63
Robust LM_λ	0.00		

** Significant at 5%. * Significant at 10%.

Notes: The spatial weights matrix is an inverse distance matrix based on Euclidian distances. T-values are in parentheses; LM statistics are based on OLS residuals, and LR statistics are based on log-likelihood function values.

Table 3. Spatial weight model, comparison with spatial lag model

Spatial weights matrix (W)	Log-likelihood function value	Bayesian posterior model probability	Bayesian posterior model probability	$\hat{\sigma}^2$	δ	t-value δ
(1) W-region (0/1)	-123.52	0.043	0.053	0.746	-0.236	-1.66
(2) W-4 nearest neighbors (0/1)	-123.26	0.115	0.141	0.719	-0.240	-1.87
(3) W-driving distances < 165 km (0/1)	-123.87	0.038	0.047	0.759	-0.236	-1.64
(4) W- Euclidian distances (exp[-d])	-123.75	0.211	0.260	0.694	-0.528	-1.70
(5) W-single group interactions (1/(N-1))	-124.19	0.188	-*	0.723	-0.306	-0.65
(6) W- Euclidian distances (1/d)	-122.35	0.406	0.500	0.694	-0.451	-2.91

* Without the inconsistent single-group interactions matrix.

Table 4. Variants of the spatial lag model from Table 2

Determinants	(1) Spatial lag model Table 2§	(2) Journal page prod.	(3) Handelsblatt weights	(4) Period 1970-2009	(5) Universities only	(6) Top Ritzberger t	(7) Top Handelsblatt t
Constant	-4.896	-0.104	-1.772	-4.156	-5.234	-5.237	-1.900
	(-3.67)	(-0.08)	(-2.34)	(-2.80)	(-3.37)	(-4.35)	(-2.63)
Austria	0.111	0.104	0.147	0.203	0.134	0.331	0.283*
	(0.40)	(0.34)	(0.86)	(0.64)	(0.41)	(1.31)	(1.69)
Switzerland	0.795**	0.690	0.389	1.042**	0.848*	0.698*	0.312
	(2.00)	(1.59)	(1.57)	(2.26)	(1.80)	(1.92)	(1.30)
Institute	-0.540*	-0.588*	-0.166	-0.447	-	-0.398	-0.156
	(-1.90)	(-1.89)	(-0.93)	(-1.34)		(-1.51)	(-0.91)
Log size	0.463**	0.515**	0.350**	0.505**	0.568**	0.409**	0.342**
	(3.24)	(3.30)	(3.94)	(3.06)	(3.68)	(3.10)	(3.97)
Log career age	-1.094**	-1.377**	-0.635**	-0.803**	-0.991**	-0.999**	-0.550**
	(-3.70)	(-4.25)	(-3.37)	(-2.33)	(-2.77)	(-3.67)	(-3.02)
No top publishers	-1.912**	-1.940**	-2.125**	-2.875**	-2.391**	-1.369**	-2.191**
	(-2.97)	(-2.75)	(-4.62)	(-4.83)	(-3.24)	(-2.26)	(-4.94)
Female	-0.607	-0.751	-0.885*	-1.298**	0.333	-0.834	-0.735
	(-0.72)	(-0.81)	(-1.68)	(-2.31)	(0.38)	(-1.07)	(-1.45)
Collaboration	2.459**	2.683**	1.357**	1.251**	1.891**	2.104**	1.109**
	(3.63)	(3.62)	(2.95)	(2.01)	(2.53)	(3.36)	(2.46)
δ / δ_1	-0.451**	-0.403**	-0.132	-0.369**	-0.490**	0.037	0.056
	(-2.91)	(-2.59)	(-0.89)	(-2.16)	(-2.46)	(0.19)	(0.36)
δ_2						-0.617**	-0.334**
						(-4.10)	(-2.85)
(Pseudo) R^2	0.645	0.642	0.740	0.570	0.683	0.669	0.761
Observations	98	98	98	98	81	98 (m=44)	98 (m=20)

§ Results reported in Table 2: article productivity, Ritzberger weights, period 2000–2009, universities plus research institutes.

t Biparametric spatial lag model for top and other research units, based on Ritzberger or Handelsblatt weights.

** Significant at 5%. * Significant at 10%
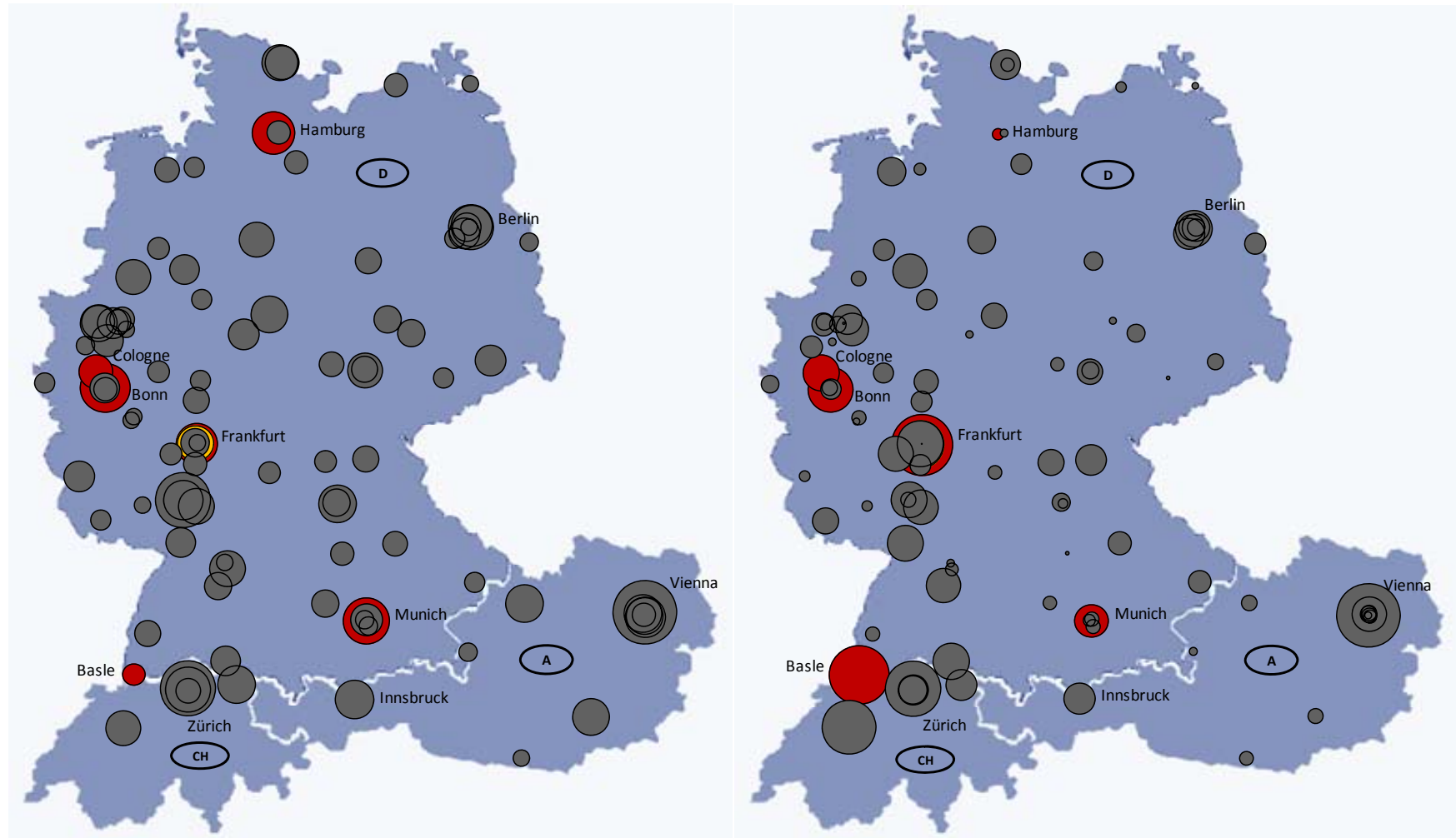
Notes: T-values are in parentheses.

Figure 1: Geographical distribution of research units in the study data sets
Each circle represents one of the 98 research units. The size of a circle indicate the relative size (left) or relative research productivity (right) of a unit. Productivity (right) is calculated according to 2000–2009 publications weighted by Ritzberger's (2008) journal weights.