Discussion Paper

Discussion Paper No. 95-11

Firm Formation and Regional Spillovers - Evidence from Germany

Dietmar Harhoff

ZEW

Zentrum für Europäische Wirtschaftsforschung GmbH

Industrial Economics and International Management Series

Discussion Paper No. 95-11

Firm Formation and Regional Spillovers - Evidence from Germany

Dietmar Harhoff

Firm Formation and Regional Spillovers - Evidence from Germany

by

Dietmar Harhoff

University of Mannheim (Germany) and
Zentrum für Europäische Wirtschaftsforschung (ZEW)

Abstract

This paper studies the effect of regional spillovers on the rate of firm formation in two major West German industries for the time period from 1989 to 1993. I exploit regional variations in firm formation at the county level to identify the effects of historically given industry structure and employment structure on the emergence of new firms. The results are consistent with the existence of localization and urbanization effects. The emergence of high technology firms seems to be contingent on a heterogeneous historical industry structure, the existence of service providers and in particular on a high share of scientists in universities and extra-university research laboratories.

JEL Classification: O30, O18, R30, R58

Acknowledgement

This paper has profited from comments by Georg Licht, Eric Nerlinger, and Konrad Stahl. Previous versions were presented in January 1995 at the Conference on Employment Dynamics and Industry Evolution in Mannheim and at the 1994 Economics Seminar Ottobeuren. I would like to thank seminar participants and in particular Johannes Bröcker, Gebhard Flaig, and Mark Roberts for helpful comments.

1 Introduction

Research on regionally differentiated externality effects has a long tradition.[1] Nonetheless, the issue has recently been given renewed attention both in the productivity literature as well as in regional economics. In the productivity literature, the term spillovers is usually used in association with technical or scientific knowledge. The cost of transferring such knowledge may be a function of geographic distance, thus giving rise to regional spillover effects. In recent contributions to the regional growth literature, spillovers denote more than just scientific information and may encompass, for example, learning and imitation effects at the workplace (Glaeser and Maré 1994). The relationship between human capital and individual productivity may also be affected by regional spillovers as a recent contribution by Rauch (1991) has indicated.

For both notions of spillover effects, empirical measurement has been a formidable problem, since the underlying processes causing spillover effects are rarely observed. Moreover, there is no lack of competing hypotheses to explain economic phenomena like the clustering of specific industrial activities. Besides knowledge spillovers, Marshall (1949) mentions two other important sources of agglomeration economies: the existence of a large pool of qualified workers and the geographic proximity to vertically linked industries, e.g. suppliers and customers. More recently, these hypotheses have been extended to more complex models. Many empirical contributions refer to dynamic externalities as a potential determinant of how strongly agglomerations grow or how quickly they shrink. Glaeser et al. (1992) distinguish between MAR-type (Marshall-Arrow-Romer) and Jacobs-type externalities. MAR-type externalities arise within industries, while Jacobs externalities are presumed to occur between industries. Jacobs (1954) has argued that externalities in the tradition of Marshall may have an agglomeration-inducing effect, but that growth in regions with high degrees of specialization will be lower than growth in more heterogeneous regions.[2]

From the perspective of a regional planner, the difference between these types of externalities matters a great deal. MAR externalities represent *economies of scale* - it is advantageous to specialize in one particular activity and pursue it in large scale dimensions. In the long run, MAR externalities can then be interpreted as the glue that helps to maintain a persistent industry structure. By contrast, Jacobs externalities are similar to *economies of scope* for the regional planner. It pays to combine a set of

[1] See for expample Alfred Marshall's comments on the causes of regional agglomeration (e.g. Marshall 1949, IV, x, 3).

[2] For a theoretical model of self-defeating concentration see Matsuyama and Takahashi (1993).

heterogeneous activities in one region. Clearly, this distinctioin is relevant since it implies competing policy objectives for the regional planner.[3]

The contribution of this paper to the growing literature on regional spillover effects is an empirical analysis of the relationship between historically given industry structure and the rate of firm formation. The above-mentioned types of externalities can be seen as one determinant of future rates of return and should thus affect the rate with which new firms emerge in a given economic environment. In particular, the paper addresses the question whether the emergence of high-technology firms requires structural conditions that differ from those promoting the emergence of less technology-oriented enterprises.[4] One important aspect is therefore the extent to which a given region can build on some form of scientific infrastructure, e.g in the form of universities or research institutions.

The results provide some support for the notion that regional spillover effects exist and that they affect new business formation. First, there is strong evidence in favor of a specialization effect. Industry structures tend to be persistent in the sense that regions with high specialization in one industry attract new businesses in precisely that industry. The emergence of technology-oriented firms, however, is characterized by a much weaker persistence effect. Moreover, for the emergence of technology-oriented firms a heterogeneous industry structure and the existence of suitable service providers is of much greater importance than for firms in industries with low R&D intensity. The statistically strongest results emerge with respect to the employment share of scientists and engineers in universities or extra-university research organisations. Moreover, these results are apparently not driven solely by the leading high-technology regions - the relationships describe the firm formation process in less mundane regions as well.

The remainder of the paper has four sections. In section 2 I briefly summarize empirical results from a number of recent contributions. In section 3 I describe the empirical model and the econometric framework. Section 4 contains the presentation and discussion of the empirical results, while section 5 concludes and indicates avenues for future research.

---

[3] Note that the central issue in this literature is the growth of regional economies as a function of industry structure. Thus, the focus is different from empirical investigations of convergence phenomena where growth, e.g. in employment or wealth, is modelled as a function of initial levels of employment or wealth (e.g. Barro and Sala-i-Martin 1992).

[4] The terms "high-technology" and "technology-oriented" will be used synonymously in this paper. High-technology industries will be identified on the basis of their R&D intensity, defined as total industry R&D divided by total industry sales.

2 Regional Spillover Effects - A Brief Survey

2.1 Regional Spillovers in R&D and Innovation

There are a number of potential explanations why knowledge may be costly to obtain for those economic agents who are not located in the geographic proximity of the knowledge source. First, the cost may not arise in the transfer itself, but can be related to the process of transforming "tacit" knowledge into encoded and transferable information (Polanyi 1958). While it may be possible to learn certain skills by imitation, it may be extremely costly to imitate without close observation (i.e. the benefit of proximity). Another important reason for the existence of regional spillover effects is related to the actual information transfer decision. Many communication processes appear to involve barter (cf. Schrader 1991 and von Hippel 1988), and regional proximity may simply allow the exchange partners to observe each other's behavior to avoid moral hazard problems. Moreover, proximity may facilitate the creation of random networks (Rapoport 1976) and may thus lead to informal information-sharing. Regional spillover effects may be particularly important for high-technology startup firms. Some case studies have revealed that the founders maintain or build contacts to local research organizations and universities (cf. Kulicke 1987). If the ensuing information transfer is valuable to the entrepreneur, then we should indeed expect a positive effect from regional "knowledge infrastructure" to new firm formation rates.

A number of econometric studies have focused on regional spillovers.[5] Jaffe (1989) uses data at the level of U.S. states. In his estimates university research is positively correlated with the number of private patent applications in the respective state. These effects appear to be particularly strong for medical technology, electronics, optical products and nuclear technology. Jaffe also argues that proximity to universities has an indirect effect on innovation by enhancing the private firms' R&D incentives. The elasticity of private R&D expenditures with respect to university R&D is about 0.70 in Jaffe's estimation, while the elasticity of patents is on the order of 0.60.[6]

While virtually all studies cannot point to direct evidence of "paper trails" left by spillover effects,[7] Jaffe, Trajtenberg and Henderson (1993) try to muster more direct evidence of spillover effects. They make use of patent citation data and link patents to regions (SMSAs) via the address information referring to the inventor. The results of

[5] For a more complete survey, see Griliches (1994).

[6] See also the work by Acs, Audretsch and Feldman (1992 and 1994).

[7] Krugman (1991a) has been particularly sceptical: "knowledge flows (...) are invisible; they leave no paper trail by which they may be measured and tracked (...)."

this study can be seen as the strongest evidence for regional spillovers to date. Patents which emerge within a given SMSA cite patents from the same SMSA with a frequency that is higher than the expected citation frequency which is computed to account for the ex ante localization of an industry. When U.S. states are used as units of analysis, the evidence is even stronger. Localization effects deteriorate over time, but after 10 years they have barely dropped to 50 per cent of the initial level.[8] Completely surprising is the result that patents with greater generality (presumably relatively close to basic R&D and the underlying sciences) are not characterized by weaker localization effects.

A recent study by Zucker, Darby and Brewer (1994) suggests that the evolution of the biotechnology sector was effectively shaped by scientists as owners of the necessary intellectual capital. New enterprises emerged in the home locations of the most productive scientists. Even venture capital firms followed this trend, they did not lead it. Apparently, the industry has also been characterized by abundant regional spillover effects. Joint publications are in this industry the paper trail that demonstrates extensive cooperation between scientists in universities and scientists in private companies.

2.2 Regional Spillovers as Dynamic Externalities

A second body of literature in which spillovers play a major role has developed in response to studies by Krugman (1991a/b/c) and Henderson (1988). As mentioned before, this literature takes a broader definition of spillovers. Glaeser et al. (1992) distinguish information spillover with respect to their orign. MAR (Marshall-Arrow-Romer) externalities work within industries. Concentrated industry structures, it is argued, are advantageous due to the internalization of spillovers. Local concentration within an industry is therefore supportive of growth (Romer 1990). Contrary to this point of view, Porter (1990) argues that local competition promotes regional growth, since spillover effects will enhance incentives for investment and innovation. A very different position has been attributed to Jacobs (1954). Jacobs perceives information spillovers from other industries to be more important for firms than within-industry information flows. Not specialization, but heterogeneity is seen as the most important regional growth factor. Moreover, competition is seen to improve incentives for innovation.

Glaeser et al. (1992) analyze the six largest industries in each of 170 U.S. cities. Their results are consistent with the presence of Jacobs-type externalities. First, the authors note that industries will grow sluggishly in cities with high degrees of specialization. Moreover, industries grow faster if there is sufficient heterogeneiy

[8] For U.S. states the localization probability is 9.7 per cent in the first year after patent publication, and 5.3 per cent after 10 years.

across the remaining industries in the same city. The effects of specialization on the one hand and heterogeneity on the other are also addressed in papers by Henderson, Kuncoro and Turner (1992) and by Henderson (1993, 1994). The results in these papers differ considerably from those obtained by Glaeser et al. Henderson, Kuncoro and Turner use data on three industries (mechanical engineering, electrical engineering and metal production). Their employment regressions include 207 SMSAs and cover the period from 1970 to 1987. Employment growth is positively affected by specialization, which contradicts the Glaeser et al. study. It is not clear how these deviations between these studies come about. Henderson, Kuncoro and Turner interpret their results as evidence for dynamic externalities. The positive specialization effect is explained as a consequence of communication networks *within* an industry. The authors also find evidence that high-technology industries thrive in economic environments with relatively heterogeneous industry structures.

Some of these results may simply be due to unobserved region-specific effects. Henderson (1994) tries to account for this possibility by using a panel data set for 742 cities in the U.S. covering the period from 1977 to 1988. Henderson estimates dynamic panel regressions for four different industries. Effects of historically given industry and employment structure are included in Almon lags. The statistical results of Henderson's panel data analysis are mixed and only tentative, due to the short time series used so far. Henderson estimates lag models for an industry's own employment share and for the Herfindahl index of employment shares. The latter variable is interpreted as a measure of heterogeneity of industrial activity. Time lags for own employment shares are effective for about five or six years, while the heterogeneity measure shows even longer lag effects. Both effects are positive and point to a tradeoff for regional planners. Some specialization is advantageous for growth, but heterogeneity is also necessary in the long run. Henderson argues that these persistent lag effects can be interpreted as evidence in favor of spillover effects, since adjustments to demand conditions or scale advantages should occur faster.

An interesting methodological alternative to some of the approaches described so far entails the use of individual-level data. Rauch (1991) and Glaeser and Maré (1994) relate the city wage effect to regional spillover effects. Rauch shows that the productivity of an individual does not only depend on his or her own human capital, but also on the human capital of other individuals in the same city. In the Glaeser and Maré model, search and accumulation processes play a prominent role and leave their traces in the workers' age-earnings profiles. According to the latter study, cities allow for faster accumulation of human capital than do other regions.

Due to its relevance for economic policy, the emergence of new high-technology enterprises has been studied in a number of recent papers. Bania, Eberts and Fogarty (1994) analyze the frequency of high-technology start-ups and find a surprisingly small effect of university research funding on the start-up rate in the electrical and electronic equipment (SIC36) sector. No discernable effect can be found in the instruments and related products (SIC38) sector. Phillips, Kirchoff and Brown (1991) show that high-technology sectors in the U.S. displayed strong employment growth, but there was no sign that agglomerations fared much better in terms of start-up frequency than rural areas.

While a number of researchers have studied regional variations in start-up activity in Germany[9], this paper is (to the best of my knowledge) the first study that has undertaken such an analysis of the role of spillover effects on firm formation and of their impact on high-technology startups in particular. The next section describes the underlying model used in this empirical exercise.

3 An Empirical Model of Regional Spillovers and New Firm Formation

The results summarized in section 2 may demonstrate how difficult the empirical treatment of regional spillovers is, but they also show that there is some evidence supporting the notion that these externalities play a potentially important role. In this section I will describe a simple empirical model in which some of the ideas central to the regional spillover literature can be incorporated. The empirical studies summarized above suggest that regional industry and employment structure will be important determinants of regional employment growth. If entrepreneurs are aware of some of these regionally differentiated externalities, then their incentives to form a new enterprise should be affected accordingly. Moreover, in the case of technology-oriented firms the regional availability of "knowledge infrastructure" in the form of universities and research laboratories should matter and can be measured more easily than - for example - the potential for learning by imitation. Note also that the null hypothesis can be extended to provide a somewhat sharper test: for firms that do not belong to the group of technology-oriented enterprises "knowledge infrastructure" should play no or a considerably minor role. Analyzing new firm formation thus offers an avenue to combine the above-mentioned heterogeneous perspectives on regional spillovers.

New firm formation can be analyzed in a number of ways, but there are probably two particularly prominent frameworks which can be called the production function approach and the discrete choice approach. Data constraints often force researchers to analyze the number of new firms that have been founded in a particular region. It is by and large not known whether the founder has undertaken a comprehensive search for the optimal region or whether mobility is associated with costs so that there is no choice between regions. In the first case, a discrete-choice approach appears to be the most appealing option (e.g. Carlton 1983). Oster (1979) suggests that even in the case of subsidiaries, firms may not always go through an extensive search before choosing a new location.

---

[9] See for example Gerlach and Wagner (1994), Koller (1994) and Fritsch (1992).

If we presume that firms are founded by individuals (and not by existing firms), the assumption of imperfect mobility seems to be reasonably realistic, in particular for Germany. Much of the case study evidence does not support the notion that entrepreneurs in Germany or the U.S. are perfectly mobile individuals (cf. Kulicke 1987). Conversely, for subsidiary enterprises this assumption seems less satisfactory. In the dataset used later, subsidiary firms represent less than 10 per cent of all new firms. Thus this group may be an interesting sample for the application of a discrete-choice model, but for the vast majority of observations the production function approach appears more promising.

The Model

The empirical model is supposed to address the following questions:

1) Will regional specialization on specific industries have a positive or negative effect on the regional rate of firm formation in that particular industry?

2) How will heterogeneity of economic activities in a given region affect the local rate of new firm formation?

3) Does regional "knowledge infrastructure" have a significant effect on the incidence of new firm formation?

The discussion of the literature has shown that these questions have been answered differently for technology-oriented or other firms. To provide at least partial answers we need an econometric model that relates historically given industry and employment structures to the incidence of new firm formation. I follow suggestions by Papke (1991), Carlton (1979), and Bania et al. (1993). The derivation of the model can briefly be described as follows:

In a given region i there are N_{im} potential entrepreneurs who are immobile, but can decide whether to enter self-employment by openening a new business in industry m. Let the probability of entering self-employment by the representative potential entrepreneur be given as p_{im}. The conditional expectation of the number of new enterprises in region i and industry m can then be written as

$$E\left[Y_{im}|X\right] = N_{im}p_{im}(X)$$

$$\text{or } \ln E\left[Y_{im}|X\right] = \ln N_{im} + \ln p_{im}(X),$$

where X is a matrix of independent variables. I will assume that the pool of potential entrepreneurs is given by the number of employees in region i.[10]

The logarithm of the average (or representative) likelihood of entering self-employment $\ln p_{im}$ will be approximated as a linear function of employment shares, of regional price and cost data, and of measures of other regional characteristics which are likely to affect the typical self-employment decision.[11] The prime reason for choosing a linear probability approximation is simplicity of interpretation. Formal specification tests are presented below.

The conditional expectation of the number of new enterprises in region i is modelled as

$$\ln E[Y_{im}|.] = \alpha \ln N_i + \beta_1 \frac{N_{im}}{N_i} + \beta_2 \left(\frac{N_{im}}{N_i}\right)^2 + \sum_{k=1}^{K} \gamma_k \frac{N_{ik}}{N_i} + \delta H_{im} + \sum_{t=1}^{T} \lambda_t r_{it}$$

where N_i is the total number of employees in region i. N_{im} is the number of employees in industry m in region i. The employment share N_{im}/N_i will be interpreted as the degree of specialization of region i with respect to industry m. The quadratic term captures possible nonlinearities in specialization. *With specialization acting according to the MAR-hypothesis we would expect a positive marginal effect of these specialization terms.* The employment shares of other industries which are likely to have an impact on new firms formation are represented by the variables N_{ik}/N_i. The variable H_{im} is a measure of heterogeneity within manufacturing (excluding manufacturing industry m). As in Henderson et al. (1992) a Herfindahl index is used to compute this measure, thus an increasing Herfindahl index indicates greater concentration or lack of heterogeneity. *In the presence of urbanization effects and Jacobs-type externalities we would expect a negative coefficient for this variable.* The variables r_{it} capture the effect of up to T inputs, since they will affect the expected rate of return of the new enterprise and thus have a bearing on the firm formation rate. Thus we should expect a negative coefficient for these variables. More specifically, prices for land, municipal tax rates and average regional manufacturing wages will be used as price indicators. Note that wages may also pick

---

[10] Including the number of unemployed in the pool of potential entrepreneurs did not affect the results reported below in any significant way.

[11] For example the pool of potential entrerpeneurs can be specified as $N(1+\delta K/N)$ where N is the total number of employees and K is a subgroup. The coefficient δ measures the excess contribution of group K individuals to the pool of potential founders. Taking logarithms yields $\ln(N(1+\delta k/N)) = \ln N + \ln(1+\delta K/N) \approx \ln N + \delta K/N$ for small $\delta K/N$.

up human capital effects. Therefore the interpretation of the respective coefficient can be ambiguous.

In addition to the variables mentioned here I include the county-specific employment shares of R&D personnel for scientific personnel (engineers and scientists) in universities, and for scientific personnel in extra-university research laboratories and institutes. For these variables we would expect positive coefficient estimates in the case of technology-oriented firms, but little or no effect on the firm formation rate of other types of enterprises. The firm formation rate should also be affected by the share of employees with high human capital, hence I include a suitable control. Finally, demographic shifts are taken into account by including a variable that measures regional population growth for the period between 1985 and 1989.

As regional units I use the 328 counties of pre-1989 Germany. The choice of a particular regional unit of analysis may have advantages and disadvantages. County boundaries may not always coincide with the economic demarcation of labor markets. Nonetheless, counties appear to offer a reasonable compromise between a detailed representation of regional disparities on the one hand and data availability on the other hand.[12] The county-specific variables and the data sources for these variables are listed in Table 1.

In addition to the variables listed here, the regressions include two dummy variables for city counties and for urban fringe counties.[13] These indicator variables are included to capture unobserved congestion and suburbanization effects which would otherwise - via an omitted variables problem - be attributed to other variables. Rural counties are the reference group for these dummy variables.

[12] Using larger regional units (*Raumordnungsregionen*) of analysis yielded very similar results for most coefficients, but these estimates were not estimated with great precision. That is not surprising given that these larger units encompass counties with very different underlying economic conditions.

[13] Out of 328 counties in West Germany (including West Berlin) 92 were classified as city counties, 122 as urban fringe counties, and 114 as rural counties.

Table 1
County-specific Variables and Data Sources

Variable	Data Source
ln(total number of employees) (1987)	Census of Establishments 1987
employment share of own industry (*specialization*) (1987)	Census of Establishments 1987
employment share of other manufacturing industries (1987)	Census of Establishments 1987
employment share of providers of business services (1987)	Census of Establishments 1987
heterogeneity of industry structure within manufacturing (1987)	Census of Establishments 1987
employment share of R&D personnel (1989)	Legler (1994)
employment share of scientific personnel in universities (1989)	German Science Council (*Wissenschaftsrat*)
employment share of scientific personel in extra-university research laboratories and institutions (1989)	Federal Statistical Agency *(Statistisches Bundesamt)*
employment share of highly qualified personnel (beyond the share accounted for by R&D personnel and scientific personnel) (1989)	BfLR (1992)
average manufacturing wage (1989)	BfLR (1992)
land prices (1989)	BfLR (1992)
municipal tax rate (1989)	Statistisches Bundesamt

Data on Firm Formation

The data on new firm formation originate from Germany's largest credit rating agency, *Verband der Vereine Creditreform* (*VVC*). They cover the period from January 1, 1989 to December 31, 1993 and will be analyzed as a pooled cross-section.[14] The data encompass all new firms which are compelled to file information with the commercial registrar (*Handelsregister*). Such a registration is necessary for virtually all firms except for small single proprietorships and professionals in the service sector. During the period from beginning of 1989 to end of 1993, a total of 220517 new firms with computer-readable industry classifications were registered in the Creditreform database. 27857 of these (12.6 per cent) were manufacturing firms. For the empirical analysis, all entries of firms in two specific two-digit industries will be used. In order to abstract from dependencies of industries on natural resources or transportation systems, the electrical machinery sector and the mechanical engineering sector were chosen.

The firms in these industries were classified into technology-oriented and other firms, using a classification scheme originally suggested by Legler et al. (1992).[15] In essence the classification is based on the R&D intensity of four- and five-digit industries. Typically, the R&D intensity of the industries classified as technology-oriented is 8.5 per cent or higher, thus technical information should constitute an important input for these firms. The technology-oriented industries include (among other sectors) the manufacture of air- and spacecraft (WZ 2480), of electronic data processing equipment (WZ 2435), of telecommunications, electric control equipment and electromedical devices (WZ 2506), optical devices (WZ 2521) and medical technology (WZ 2527).

The number of technology-oriented new firms in the dataset is 1646 in the eletrical engineering (WZ 25) and 576 in the mechanical engineering, automotive and computer equipment sector (WZ 24). 4396 enterprises in the latter industry were classified as not technology-oriented. In the electrical enginerring sector, there were 2645 firms of this type. As should be expected, the share of technology-oriented firms is higher in the electrical engineering industry.

---

[14] The firm formation data are available for four years, and in priniciple panel estimation techniques could be applied. However, it has proved difficult so far to obtain data for the independent variables described in this section.

[15] The classification by Legler et al. (1992) constructs three groups of firms: those in four-digit industries with an R&D intensity of 8.5 per cent or more, those with an R&D intensity between 3.5 and 8.5 per cent, and finally a group of industries with R&D intensity below 3.5 per cent. In this paper, the first group constitutes the technology-oriented or high-technology category, while the latter two are combined in the residual group.

Econometric Specification

To reflect the integer nature of the dependent variable, I employ a simple pseudo maximum likelihood procedure based on a Poisson model (Gourieroux et al. 1984a/b).[16] This method has a number of advantages which look appealing in this context. The consistency of the parameter estimates will not depend on strict validity of the underlying distributional assumptions. In particular, as long as the conditional mean is specified correctly, the PML estimates will remain consistent if the distribution is not Poisson, but still within the linear exponential family of distributions. For the computation of the variance-covariance matrix the procedure suggested by White (1982) will be used.

4 Estimation Results

Table 2 summarizes the main results. Note that the underlying specification is log-linear so that the coefficient for ln(county employees) can be interpreted as an elasticity. Similarly, coefficients for employment shares have the usual semi-elasticity interpretation and indicate the relative (per cent) change of the number of new firms due to a change in the share variable by one percentage point.

The coefficient of the employment variable assumes values close to one, and the hypothesis of a unit value cannot be rejected in this model. This result can be interpreted as some support for the specification adopted in this paper. Large deviations from a unit coefficient would certainly hint towards some form of mis-specification. *Ceteris paribus*, city counties appear to have a somewhat lower new firm formation rate than rural counties, but this effect is barely significant for the high-technology firms in columns (1) and (2). It is more reasonable to interpret the dummy variables as proxies for unobserved congestion effects. For both groups of firms, the effect sizes are very similar. But while the coefficients of the CITY and URBAN FRINGE dummy variables are not estimated with great precision, they are highly significant for the residual group of firms. The results are consistent with the observation that - on average - urban fringe regions have recently gained in terms of employment, often at the cost of the cities in Germany (Koller 1994).

One of the central questions concerned the effect of regional specialization on new firm formation. The results in Table 2 indicate for both groups of firms that regional specialization has an initially increasing, positive effect on firm formation. For high degrees of specialization the effect is decreasing again. For high technology firms, the critical employment share which yields decreasing returns to specialization is 17 per cent (Table 2, column (1)), for the firms that are not technology-oriented the

[16] Estimates using a negative-binomial specification yield results that are very close to those described in Table 2. The neg-bin estimates also indicate that there is considerable over-dispersion in the data-generating process.

respective threshhold share is 24 per cent (Table 2, column (3)). Thus, highly specialized industry structures are less likely to attract high-technology firms. Nonetheless, this result indicates a strong persistence effect in that industry structures have a tendency to perpetuate themselves, since the observed degrees of specialization in this sample exceed the critical level only for 10 per cent of all West German counties.

Concentration of employment in the remaining manufacturing sectors (outside of the industry under consideration) has been interpreted by Glaeser et al. (1992) and Henderson et al. (1992) as a measure of heterogeneity (or the lack thereof). Again, the two groups of firms display considerable differences. High-technology firms are attracted by heterogeneous industry structures while there appears to be no effect of industry heterogeneity for the group of other firms. Note that the results obtained here cannot be compared easily to those of Glaeser et al. (1992), since they use employment as their dependent variable. However, the simultaneous existence of specialization effects and attraction of high-technology firms by heterogeneous industry structures is qualitatively close to results described by Henderson et al. (1992). Note also that this pattern is consistent with spillover effects as described by Jacobs (1954). Complementing the Jacobs interpretation, one could argue that heterogeneity in industry structure has some option value for high-technology firms if there is uncertainty with respect to the importance of future input and output markets and if some form of transportation costs or spillover effects are likely to be present.

Nonetheless, these results may also be an effect of unobserved localisation or urbanization externalities. In order to account at least for some of these effects, the regressions also include the share of employees in manufacturing industries other than the own sector. If close proximity to suppliers and buyers of industrial products is important, then this variable should be expected to have a positive coefficient. However, the coefficient is only significant in column (3) and relatively small. The effect of the employment share of firms offering services for the private sector is highly significant and positive. Note that household services were excluded from this employment share variable. While services of this type have a positive effect on firm formation rates in all specifications, they appear to be particularly important for high technology firms where the point estimates are about 50 per cent higher than for the other firms.

Table 2
Poisson Model of Firm Formation Rates
(PML Estimates - Robust Standard Errors in Parentheses)

	Dependent Variable: Number of New Firms Within County			
	High Technology Firms		Other Firms	
Independent Variables	*(1)*	*(2)*	*(3)*	*(4)*
ln(County Employees)	0.943 (0.067)	0.897 (0.065)	0.950 (0.038)	0.957 (0.041)
City	-0.386 (0.232)	-0.434 (0.206)	-0.356 (0.115)	-0.328 (0.116)
Urban Fringe	0.167 (0.098)	0.183 (0.103)	0.146 (0.046)	0.141 (0.047)
Specialization	4.655 (1.580)	4.790 (1.569)	5.614 (1.047)	5.513 (1.960)
Specialization^2	-16.025 (5.421)	-13.643 (5.655)	-11.645 (2.931)	-11.584 (3.873)
Manufacturing Employees*	0.267 (0.500)	0.727 (0.624)	0.790 (0.345)	0.690 (1.028)
Service Employees*	4.444 (1.841)	5.845 (1.905)	3.307 (1.111)	2.980 (1.294)
Lack of Heterogeneity in Manufacturing	-1.622 (0.540)	-1.145 (0.523)	-0.357 (0.330)	-0.351 (0.526)
Scientific Personnel and R&D Employees*	15.929 (4.872)		-1.112 (2.618)	
R&D Employees*		7.020 (3.944)		-1.440 (6.498)
Scientific Personnel not in Universities*		24.570 (7.946)		3.649 (16.538)
Scientific Personnel in Universities*		28.587 (15.645)		-11.513 (17.371)
Highly Qualified Employees*	9.779 (6.134)	9.920 (6.176)	1.830 (2.932)	2.832 (3.985)
Land Price/1000	0.008 (0.129)	0.175 (0.132)	-0.113 (0.068)	-0.114 (0.072)
Manufacturing Wage/1000	-1.412 (0.876)	-1.403 (0.911)	-1.707 (0.494)	-1.708 (0.303)
Tax Rate	-0.281 (0.150)	-0.166 (0.092)	-0.122 (0.291)	-0.076 (0.251)
Population Growth 1985-1989	1.040 (1.063)	1.040 (1.063)	1.121 (0.586)	1.126 (0.345)
log Likelihood	-1392.0	-1381.2	-2535.6	-2527.7
Chi-Squared (df)	2586.0 (15)	2607.1 (17)	6705.7 (15)	6721.6 (17)
Pseudo-R^2	0.482	0.486	0.569	0.571
Robust Hausman Test	23.7	25.7	22.4	24.3

Note: N=656. Pooled county data for two industries (mechanical engineering and electrotechnical engineering products). Independent variables labelled with * are defined as shares of total county workforce. All regressions contain two dummy variables for industries. The critical values for the Hausman tests in columns (1) and (3) are 26.3 (23.5) at significance level p=0.05 (0.10) and 28.9 (26.0) in columns (2) and (4).

Even stronger differences between the two groups of firms become apparent with respect to the effect of regional "scientific infrastructure" on firm formation. As the results in column (1) show, the employment share of scientists and R&D employees has a strong and significant positive effect on formation rates for high-technology firms. Disaggreation of this variable into its three components is also instructive. Both scientific personnel in universities and in research institutions not within the university system display large and significant effects, but the latter coefficient is measured with much greater precision. This may not be surprising given that the measure of scientific personnel in universities includes departments that are not relevant for the mechanical engineering and electrotechnical engineering products industries. Conversely, most of the public non-university research laboratories (such as *Max-Planck* and *Fraunhofer* institutes) are engaged in R&D in precisely these fields. A similar caveat applies to the employment share of R&D personnel. This variable does not only capture scientists and engineers, but also technicians and other support staff. Typically, the share of scientists among R&D employees is on the order of 45 per cent in these industries. If we assume that only scientists have a positive effect on the formation rate of new enterprises, then the implied coefficient would be about 15.0 per cent (compared to 7.0 per cent in column (2)). However, this may be only a rough guideline since the share of scientists and engineers among R&D personnel is significantly higher in cities than in fringe or rural counties. Taking specification (1) as a benchmark, the empirical results indicate that increasing the regional share of scientists and R&D employees by 1 percentage point would lead to a 15 per cent increase in the number of newly founded high-technology firms.

Clearly, these results are fundamentally ambiguous because we do not observe in this dataset whether scientists and engineers in universities or other research laboratories become entrepreneurs themselves, or whether they simply enhance the average likelihood of other individuals becoming entrepreneurs in the given region. The case study literature in this field (see especially Kulicke (1987) and Picot et al. (1991)) produces a number of interesting results with respect to this question. In Kulicke's sample of technology-oriented firms, about 70 per cent of the entrepreneurs worked in other private firms prior to becoming self-employed. This figure favors the second interpretation of the regression results. But independent of the specific interpretation adopted here, the economic implications of the results may be quite similar in that publicly funded research activities appear to have a positive impact on new firm formation in the high-technology area.

The incidence of new firm formation outside the high-technology area is apparently not affected by regional "knowledge infrastructure." This is true for specification (3) in Table 2 as well as for specification (4) where all three employee groups are separated. The result may seem trivial, but it adds credence to the positive result from analyzing firm formation in technology-oriented industries. Price and cost data have the right sign in most of the specifications, but most of the coeffients are not statistically significant. An exception to this rule is the wage variable which is negative and significant in the case of new firms without technology orientation. Including population growth is again significant for the same group, but does not help to explain the incidence of new firms in the technology-oriented industries. It is somewhat surprising that the share of employees with high human capital does not play a role in the regressions. The size of the coefficients appears quite plausible (about 9.7 for high-technology firmsand about 1.8 for the residual group), but the standard deviations are about as large as the coeffients themselves. Unfortunately, there were no other human capital indicators available for this analysis, but the point definitely requires more attention in future work.

Robustness and Specification Testing

The results displayed in Table 2 are quite robust with respect to changes in the specification. In particular, there were no indications that further nonlinearities played a major role. I also tested whether the strong results regarding the local "scientific infrastructure" were driven mostly by the high-technology counties Berlin, Munich and Aachen. Excluding these counties from the regressions yielded essentially the same results as shown in Table 2, but the coefficients for scientific personnel dropped by about 15 per cent. Hence, while these counties have a strong effect, they are not solely responsible for the results discussed before. The results are also supported by a number of formal specification tests. Following suggestions by Wooldridge, I tested the specification of the PMLE model using conditional moment tests (Wooldrige 1990). The test statistics and critical values are included in Table 2. The specification used here is not rejected by these tests ($p>0.05$).

5 Conclusions and Further Research

While the results described in this paper may still be vulnerable to a number of alternative explanations (and thus may share the fate of many other empirical studies in this field), there is nonetheless some suggestive evidence that points to the existence of regional spillover effects. The results demonstrate that regional availability of a well-developed "knowledge infrastructure" is correlated with relatively high firm formation rates in technology-oriented industries. While it is possible that this correlation can be driven by unobservables (e.g. region-specific fixed effects), I have argued that the spillover interpretation appears more plausible and that it is consistent with the available evidence from case studies. Moreover, the other two effects promoting the formation of high-technology industries, the existence of providers of business services and a heterogeneous industry structure, are consistent with tentative empirical results presented by Henderson et al. (1992). It is also interesting that these results are not driven by a small number of exceptionally active counties with high formation rates in high-technology sectors. Nonetheless, drawing policy conclusions from these results should be delayed until panel data allow a better evaluation of alternative explanations.

The statistically strong specialization and urbanization effects in these data may also have a spillover interpretation, in this case in the spirit of recent empirical papers focussing on dynamic externalities. To tighten these results, further industries should be analyzed, possibly at a less aggregated industry level. Again, it would be helpful to analyze firm formation with more comprehensive panel data. Nonetheless, the use of this cross-section has already provided some promising results towards evaluating the nexus between regional spillovers and the formation of new firms.

References

Acs, Z., D. Audretsch and M. P. Feldmann (1992). "Real Effects of Academic Research - Comment," American Economic Review, Vol. 82, pp. 363-367.

Acs, Z., D. Audretsch and M. P. Feldmann (1994). "R&D Spillovers and the Geography of Innovation and Production," Paper presented at the CEPR Conference on The Location of Economic Activity: New Theories and Evidence, Vigo, December 1993.

Bania, N., Eberts, R. W. and F. S. Fogarty (1994). "Universities and the Startup of New Companies: Can We Generalize From Route 128 and Silicon Valley?" Review of Economics and Statistics, Vol. LXXV, pp. 761-766.

Barro, R. J. and X. Sala-i-Martin (1992). "Convergence," Journal of Political Economy, Vol. 100, pp. 223-251.

BfLR (Bundesforschungsanstalt für Landeskunde und Raumordnung 1992). Materialien zur Raumentwicklung. Bonn.

Bröcker, J. (1989). Determinanten des regionalen Wachstums im sekundären und tertiären Sektor der Bundesrepublik Deutschland 1970 bis 1982. München.

Carlton, D. W. (1983). "The Location and Employment Choices of New Firms: An Econometric Model with Discrete and Continuous Endogenous Variables," Review of Economics and Statistics, Vol. 65, pp. 440-449.

Carlton, D. W. (1979). "Why New Firms Locate Where They Do: An Econometric Model," in W. Wheaton (ed.), Interregional Movements and Regional Growth, pp. 13-50. Washington, D.C.:The Urban Institute.

Fritsch, M. (1992). "Regional differences in new firm formation: evidence from West Germany, " Regional Studies, Vol. 26, pp. 233-241.

Gerlach, K. and J. Wagner (1994). "Regional differences in small firm entry in manufacturing industries: Lower Saxony, 1979-1991, " Entrepreneurship & Regional Development, Vol. 6, pp. 63-80.

Glaeser, E. L., H. D. K. Kallal, J. A. Scheinkman and A. Schleifer (1992). "Growth in Cities," Journal of Political Economy. Vol. 100, pp. 1126-1152.

Glaeser, E. L. and D. C. Maré (1994). "Cities and Skills," NBER Working Paper No. 4728, National Bureau of Economic Research, Cambridge, Mass.

Gourieroux, C., A. Monfort and A. Trognon (1984a). "Pseudo Maximum Likelihood Methods: Theory," Econometrica, Vol. 52, pp. 681-700.

Gourieroux, C., A. Monfort and A. Trognon (1984b). "Pseudo Maximum Likelihood Methods: Application to Poisson Models," Econometrica, Vol. 52, pp. 701-720.

Griliches, Z. (1994). "The Search for R&D Spillovers," Scandinavian Journal of Economics, Vol. 94 (Supplement), pp. 29-47.

Henderson, V., A. Kuncoro and M. Turner (1992). "Industrial Development in Cities," NBER Working Paper No. 4178, National Bureau of Economic Research, Cambridge, Mass.

Henderson, V. (1993). "Externalities and Industrial Development," Paper presented at the CEPR Conference on The Location of Economic Activity: New Theories and Evidence, Vigo, December 1993.

Henderson, V. (1994). "Where Does an Industry Locate?," Journal of Urban Economics, Vol. 35, pp. 83-104.

Jacobs, J. (1969). The Economy of Cities. New York: Vintage.

Jaffe, A., M. Trajtenberg and R. Henderson (1993). "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations," Quarterly Journal of Economics. Vol. 108, No. 3, pp. 577-598.

Jaffe, A. B. (1994). "Real Effects of Academic Research," American Economic Review, Vol. 79, pp. 957-970.

Koller, M. (1994). "Regionale Arbeitsmärkte im Umbruch: Welche Veränderungen zeigen sich und welche Auswirkungen ergeben sich für die räumlich Entwicklung und die Regionalpolitik?" Vortrag beim Symposium "Regionale Arbeitsmärkte im Umbruch" der IHK München.

Krugman, P. (1991a). Geography and Trade. Cambridge, Mass.: MIT Press.

Krugman, P. (1991b). "History versus Expectations," Quarterly Journal of Economics, Vol. 107, pp. 651-667.

Krugman, P. (1991c). "Increasing Returns and Economic Geography," Journal of Political Economy. Vol. 99, No. 3, pp. 483-499.

Kulicke, M. (1987). Technologieorientierte Unternehmen in der Bundesrepublik Deutschland: Eine empirische Untersuchung der Strukturbildungs- und Wachstumsphase von Neugründungen. Frankfurt: Peter Lang.

Legler, H., H. Grupp, B. Gehrke and U. Schasse (1992). Innovationspotential und Hochtechnologie - Technologische Position Deutschlands im internationalen Wettbewerb. Heidelberg: Physica.

Legler, H. (1994). "Die regionale Verteilung des FuE-Personals," mimeo, Niedersächsisches Institut für Wirtschaftsforschung (NIW).

Mahajan, V., E. Muller and F. M. Bass (1990). "New product diffusion models in marketing: A review and directions for research," Journal of Marketing, Vol. 54, pp. 1-26.

Marshall, A. (1920). Principles of Economics. London: Macmillan.

Matsuyama, K. and T. Takahashi (1993). "Self-Defeating Regional Concentration," NBER Working Paper No. 4484, National Bureau of Economic Research, Cambridge, Mass.

Oster, S. (1979). "Industrial Search for New Locations: An Empirical Analysis," Review of Economics and Statistics, Vol. 61, pp. 288-292.

Papke, L. E. (1992). "Interstate Business Tax Differentials and New Firm Location," Journal of Public Economics, Vol. 45, pp. 47-68.

Phillips B. D., B. A. Kirchoff and H. S. Brown (1991). "Formation, growth and mobility of technology-based firms in the US economy," Entrepreneurship & Regional Development, Vol. 3, pp. 129-144.

Picot, A., U.-D. Laub and D. Schneider (1989). Innovative Unternehmensgründungen: Eine Ökonomisch-Empirische Analyse. Berlin: Springer.

Polanyi, M. (1958). Personal Knowledge: Towards a Post-Critical Philosophy. Chicago: University of Chicago Press.

Porter, M. (1990). The Comparative Advantage of Nations. London: Macmillan.

Rapoport, A. (1979). "A Probabilistic Approach to Networks, " Social Networks, Vol. 2, pp. 1-18.

Rauch, E. J. (1991). "Productivity Gains from Geographic Concentration of Human Capital: Evidence from the Cities," NBER Working Paper No. 3905, National Bureau of Economic Research, Cambridge, Mass.

Romer, P. (1986). "Increasing Returns and Long-Run Growth," Journal of Political Economy. Vol. 64, pp. 1002-1037.

Romer, P. (1990). "Endogenous Technological Change," Journal of Political Economy. Vol. 94, pp. 71-102.

Saxenian, A. L. (1990). "Regional Networks and the Resurgence of Silicon Valley," California Management Review, Vol. 33, pp. 89-112.

Schrader, S. (1991). "Informal Technology Transfer Between Firms: Cooperation Through Information Trading," Research Policy, Vol. 20, No. 2, pp. 153-170.

Schulz, N. (1993). Unternehmensgründungen und Markteintritt. Habilitation Thesis, University of Mannheim.

von Hippel, E. (1988). The Sources of Innovation. New York: Oxford University Press.

Wolff, H., G. Becher, H. Delpho, St. Kuhlmann, U. Kuntze and J. Stock. FuE-Kooperaton von kleinen und mittleren Unternehmen. Heidelberg: Physica.

Wooldridge, J. M. (1990). "A unified approach to robust, regression-based specification tests," Econometric Theory, Vol. 6, pp. 17-43.

Wooldridge, J. M. (1991). "Specification Testing and Quasi-Maximum-Likelihood Estimation," Journal of Econometrics, Vol. 48, pp. 29-55.

Zucker, L. G., M. R. Darby and M. B. Brewer (1994). "Intellectual Capital and the Birth of U.S. Biotechnology Enterprises," NBER Discussion Paper No. 4653, National Bureau of Economic Research, Cambridge, Mass.

White, H. (1982). "Maximum Likelihood Estimation of Misspecified Models," Econometrica, Vol. 50, pp. 1-25.