Measuring Knowledge Spillovers in Manufacturing and Services: An Empirical Assessment of Alternative Approaches

by

Ulrich Kaiser*

Abstract: In this paper it is tested which of the various alternative approaches for constructing knowledge spillover pools suggested in existing literature measures the extent to which a firm can costlessly receive external knowledge best. Since knowledge spillovers are unmeasurable, a 'goodness of fit' measure is constructed using innovation survey data. It turns out that measures of the uncentered correlation of firm characteristics seem to fit actual knowledge spillovers best. Direct measures constructed from innovation survey data appear to work reasonably well while measures of the Euclidean technological distance and of the geographical distance lead to counterintuitive results. Empirical evidence is provided for both the German service sector and the manufacturing sector.

Keywords: knowledge spillovers, technological distance, geographical distance, CIS–II data, Kernel density estimation, ordered probit estimation

JEL classification: O31, C12, C35

*I wish to thank Georg Licht for stimulating discussions and very helpful comments on earlier drafts of this paper. Knowledge spillovers from Joachim Inkmann, Max Keilbach, François Laisney and Winfried Pohlmeier were also internalized. This paper also gained from comments I received from participants, especially those of my discussant Alfred Kleinknecht, of the international conference on "Innovation, Appropriation Strategies and Economic Policy" at Paris, Nov. 19, 1999. The work done by the ZEW's Mannheim Innovation Panel team, which prepared the data set, is invaluable and often underestimated. I therefore owe much to Thorsten Doherr, Günther Ebling, Sandra Gottschalk, Norbert Janz and Hiltrud Niggemann. Marleen Choc, Henrietta Haasz, Christine Kaiser and Jürgen Moka provided excellent research assistance. Lastly, I am indebted to Semka Thorwaldsen and Paul Townsend for proof–reading. This research was partially funded by the German Science Foundation (Deutsche Forschungsgemeinschaft, DFG) within the 'Industrial Economics and Input Markets' program.
Corresponding address: Ulrich Kaiser, Centre for European Economic Research, Dep. of Industrial Organization and International Management, P.O. Box 10 34 43, D–68034 Mannheim, phone: +49.621.1235–292, fax: +49.621.1235–333, eMail: kaiser@zew.de.

Non–technical Summary

Whenever firms conduct research, part of the newly acquired knowledge leaks out to competitors, suppliers or customers. The amount of knowledge a firm receives from other firms without paying for it is called 'knowledge spillover'. This phenomenon has been widely observed and discussed in the economics literature.

Knowledge spillovers have an immediate impact on firms' innovation efforts. If a firm expects that own research results cannot be protected and spill over to rivals, the firm may decrease research efforts. There is, however, an additional aspect of knowledge spillovers. When an interviewer stated that Siemens, Europe's fifth largest enterprise in terms of employees, conducts too few R&D, Siemens CEO Heinrich von Pierer answered "We have installed our listening posts around". This highlights that firms may free ride on other firm's research efforts at least if large spillovers are present. Spillovers have a positive effect on the competitiveness of the firm receiving knowledge spillovers. Even if firms individually decrease research efforts in the presence of spillovers, the aggregate stock of knowledge may increase since it constitutes of both own research efforts and the part of the other firms' research efforts spilling over to the firm in question.

From an individual firm's perspective, spillovers usually create a disincentive effect to own research efforts. At the same time, large spillovers increase the appropriation possibilities of other firms' knowledge. What is the total effect of knowledge spillovers on firms' research efforts? This question is difficult to answer since knowledge spillovers are unmeasurable. Therefore, researchers have to find proxy variable for actual research spillovers. In this study, the most frequently used methods to proxy knowledge spillovers are reviewed and tested against one another. It is shown that approaches based on observable firm characteristics such as investment intensity, skill mix and factors hampering innovation proxy knowledge spillovers best.

"We have installed our listening posts around."
Heinrich von Pierer, Siemens CEO

1 Introduction

Economists have demonstrated that the social returns to innovation exceed the private returns to innovation if the knowledge produced in an innovation process is not fully appropriable by the innovating firm. As a consequence, spillovers may lead to Pareto–inferior Nash equilibria of innovation efforts as demonstrated by, e.g., Kamien et al. (1992), Mowery and Rosenberg (1989) and Suzumura (1992). Arrow (1962) was among the first to notice that a firm's incentive to invest in innovation decreases if knowledge generated by its innovation efforts is involuntarily transmitted to competitors.[1] In another early contribution, Schmookler (1966) articulated that technological progress achieved by a firm may not solely be a result of its own research efforts but also from other firms' research results.

The impact of knowledge transmission between firms on the firm's propensity to invest in innovative activity has been reemphasized by Spence (1984), who shows that the appropriability problem leads to a reduction of firms' incentives to invest in R&D. This basic result is shared by other authors using different model setups such as d'Aspremont and Jacquemin (1988, 1990), De Bondt et al. (1992), Henriques (1990), Kamien et al. (1992), Leary and Neary (1997) as well as Suzumura (1992). Empirical evidence on firms' appropriation strategies has first been presented by Cohen and Levinthal (1989).[2]

The non–appropriable amount of knowledge that is produced by a firm's innovation efforts is called 'knowledge spillover'.[3] Knowledge spillovers arise due to failures in the protection mechanisms of knowledge generated in an innovating firm. A typical protection mechanism is patenting activity. Patents confer full appropriablility of a firm's research efforts for a limited time period. Other well–known protection mechanisms include trade marks and cooperative R&D, where the knowledge produced within the research joint venture is exchanged by the cooperation partners and hence becomes fully appropriable to both of the partners. Levin et al. (1987) and Levin (1988) study the effectiveness of a wide range of appropriablity methods using survey data on US manufacturing firms and find that patents are most effective followed by secrecy, lead time and learning curves advantages as well as sales or marketing efforts.

The extent to which knowledge is voluntarily or involuntarily transmitted between firms depends on the extent to which knowledge is codifiable. Knowledge which can be transformed to explicitly stated information, such as a patent grant, is called 'codified' knowledge. Though it may not pay for all firms and all products — especially for the service sector — to patent, implying that copying remains a severe problem in many cases, cod-

[1]Firms may find it profitable, however, to deliberately transfer knowledge to downstream users in special cases. See Geroski (1995a) and Harhoff (1996) for fuller treatments of this issue.

[2]Since this paper is a firm–level study, I shall not talk about spillovers and their effect on economic growth here. Readers may refer to Aghion and Howitt (1992), Grossman and Helpman (1991) or Romer (1986, 1990).

[3]Griliches (1992, pp. 104–105) made the distinction between such 'knowledge spillovers' and 'rent spillovers' which are not considered in this paper. Rent spillovers – or 'market' spillovers as Jaffe (1996) calls them – occur if goods brought by one sector from another sector are not priced at their user value due to quality improvements that are not considered in the pricing of the good.

ified knowledge can generally be protected to some extent. The inherent nature of its counterpart 'tacit' knowledge renders it much more difficult to avoid involuntary information disclosure. Tacit knowledge is a main source of research spillovers since this type of knowledge is embodied in the skills of the firm's employees. The concept of 'tacit' knowledge has been introduced by Polanyi (1967) and is discussed in the context of evolutionary economics by Nelson and Winter (1982) as well as by Dosi et al. (1998). A theoretical framework for the relationship between the degree of knowledge codification and appropriability is formalized by Saviotti (1998). Informal exchanges between researchers and job turnover between firms are thus channels through which tacit knowledge flows from one firm to another (von Hippel, 1994).
As an externality, research spillovers may lead to market failures justifying governmental intervention. In the context of research spillovers, state intervention includes research subsidization and the foundation of public research laboratories.[4] Research spillovers thus do not only play an important role in economics literature, but also in public policy.[5]

In economics literature, investigated topics include the effects of research spillovers on economic growth (Aghion and Howitt, 1992), agglomeration (Feldman, 1999), R&D spending, on R&D productivity and on the propensity to co–operate in R&D projects.[6] Most of the papers concerned with research spillovers differentiate between 'horizontal' and 'vertical' spillovers. If the knowledge–receiving firms are in a different business field as to the sending firms, knowledge flows are defined as 'intra–industry' or 'vertical', as opposed to 'inter–industry' or 'horizontal' spillovers where receiving and sending firms are in the same business field.
A major problem with the handling of spillovers in empirical investigations is that they cannot be measured exactly. As Krugman (1991, p. 53) notes: "Knowledge flows (...) are invisible; they leave no paper trail which may be measured and tracked, and there is nothing to prevent the theorist from assuming anything about that she likes". Researchers who analyze the effects of research spillovers have to rely on more or less crude proxy variables. Many of these proxy variables are based on measures of 'proximity' or 'technological distance' between firms, sectors, or regions. If, e.g., firms conduct research in similar research areas, have a comparable skill structure or patent in the same patent class, they are said to be close to one another in 'technology space'. The outcome of any study on research spillovers is likely to depend on the way research spillovers are proxied since there "obviously is more than one dimension to R&D spillovers," (Mohnen 1997, p. 7). Despite the contribution of Anselin et al. (1997) who compare alternative ways to construct measures of geographical distance between firms, I am, however, not aware of any study that even compares the variation of results under alternative approximations

[4] Jaffe (1996) gives a comprehensive discussion of research policies' options with regard to the research spillover problem. Beise and Stahl (1999) describe the structure of publicly–funded research institutions in Germany and study whether these institutions actually have a positive impact on the innovative activities of the private sector.

[5] See Geroski (1992, 1993) for for a thorough discussion of public policy option in the context of R&D, R&D cooperation and antitrust policy.

[6] A survey of the theoretical literature on spillovers R&D spending is presented in DeBondt (1996) while Geroski (1995b) reviews the empirical evidence. An extensive survey of the relationship between spillovers and productivity is prepared by Mairesse and Mohnen (1994). A summary of both the empirical and the theoretical evidence on the impact of spillovers on the propensity to cooperate is given in Kaiser (1999).

of research spillovers. This paper adds to the existing literature in exactly that respect: four main approaches to construct knowledge spillover pools are presented and 'tested' against one another using innovation survey data.

The non–measurability of research spillovers implies that testing in a strict sense is impossible. However, the growing availability of innovation survey data and especially the founding of the Community Innovation Survey (CIS) not only enables researchers to obtain new measures of knowledge spillovers, but also provides proxy variables for the accurateness of spillover measures.[7] The Mannheim Innovation Panel (MIP), which is part of the CIS programme and is used as the main data source in this study, contains information on the quality of a spillover measures in that respect. The MIP contains information on sources of external expertise a firm gathers during an innovation process. These sources can be summarized as 'vertical' and 'horizontal' ones. I argue that the larger vertical spillovers are, the higher a firm's propensity to gather expertise from vertically related firms is — i.e., from customers and suppliers. Likewise, the larger horizontal spillovers are, the more likely it is that firms will use external knowledge from horizontally related firms — i.e., from competitors.

An alternative to this procedure is to capture research spillovers in a completely parameterized production function along the lines of Bernstein and Nadiri (1988), Mohnen and Lépine (1991) and Mamuneas (1999). Since (i) the MIP does not provide input price data and (ii) output measurement in services is problematic,[8] this approach is not pursued here.

Another novel feature of this contribution is that it considers both the service sector and manufacturing industries, as the MIP consists of two related, but with respect to their subject of investigation, two different data sets: one is concerned with the service sector (Mannheim Innovation Panel in the Service Sector, MIP–S), the other is concerned with manufacturing industries (MIP–M). Due to restricted data availability, existing studies related to innovation and R&D focus on manufacturing industries alone and thus not only disregard the impact of the service sector on innovative activity of the manufacturing sector (Licht et al., 1997), but also the growing overall economic importance of the service sector.[9]

The main findings of this paper are that measures of the uncentered correlation of firm characteristics represent knowledge spillover best while measures of of the Euclidean distances between firm characteristics may even lead to counterintuitive results. Approaches based on the geographical distance between firms and on 'direct' measures constructed from innovation survey data appear to work reasonably well.

[7] The CIS programme is intended to provide policy with data on innovative activities in member countries of the European Union. See Grünewald and Smith (1994) for an overview.

[8] See the special isssue of the Journal of Productivity Analysis (1993, vol. 4) on "Productivity Issues in Services at the Micro Level" for a detailed discussion of this issue.

[9] There are, however, a few studies which are concerned with the innovative activity in the service sector: König et al. (1996) study service firms' propensity to engage in co–operative R&D. Kleinknecht (1998) summarizes main findings of a Dutch innovation survey which also comprises the service sector. Kleinknecht and Reijnen (1992) use a related data set to study R&D cooperations in services and manufacturing industries. Gallouj and Weinstein (1997) characterize innovative activity in the services sector. Sirilli and Evangelista (1998) provide empirical evidence on innovative behaviour of Italian service firms. Finally, Amable and Palombarini (1998) conduct a comparison of R&D intensities across agriculture, manufacturing and services for eight OECD countries.

2 Proxying research spillovers

In this section, existing suggestions to proxy knowledge spillovers are reviewed. These approaches are tested in section 4 for their empirical validity. The majority of the methods listed here can easily be extended to international research spillovers or to spillovers at industry level.[10]

A broad variety of ideas concerned with the way in which research spillovers can be proxied exists in the economics literature. Extensive surveys are provided by Griliches (1979 and 1992) and Mohnen (1989). This section forms the basis of the empirical investigation of section 4, so that only those approaches which can be applied using the MIP data are reviewed. Since, however, the MIP is a versatile data set, of the frequently used methods applied in earlier empirical work, only the approach by Terleckyj (1974 and 1980) has to be skipped. Terleckyi and, more recently, Goto and Suzuki (1989) use firms' proximity in *sales/demand* space as a measure of distances between firms.[11] The baseline assumption is that the more firm i buys from firm j, the more knowledge is transmitted between both firms.

In the earliest and simplest formulation, the aggregate stock of knowledge S of a firm i is given by:

$$S_i = \sum_{j \neq i}^{N} K_j, \tag{1}$$

where N denotes the number of firms inside or outside firm i's sector. The variable K_j is firm j's stock of knowledge. A firm's own stock of knowledge has been proxied in many alternative ways, mostly depending on the variables the researcher has at hand. Candidates are the number of patents a firm possesses, innovativion expenditures, R&D investment, R&D capital stock — usually constructed from lagged R&D investment — and R&D personnel. In order to find out which proxy variable fits best into the current context, the various methods of proxying K have to be linked to the discussion of codified and tacit knowledge. Patents can only be good proxies for K if the knowledge generated by firm j is codifiable. Since codification is a difficult task especially for innovations in the service sector (Licht et al., 1997), patents do not appear to be an appropriate proxy for knowledge here. R&D investment and R&D capital cannot be taken into account here simply because the MIP–S lacks data on R&D expenditures. Hence, the best way to proxy K seems to be to consider the number of R&D employees and innovation expenditures. R&D personnel may also represent tacit knowledge best since tacit knowledge is embedded in the capabilities of a firm's workforce. The problem with R&D personnel, however, is that 80 percent of the service sector firms and 46 percent of the manufacturing sector firms do not employ any R&D workers with the unweighted average shares of R&D employees in total workforce being 2.1 percent in the service sector and 3.7 percent in manufacturing. Therefore, it appears to be more appropriate to consider innovation expenditures instead.

[10] For recent contributions on international research spillovers, see the surveys by Branstetter (1998). Case–study evidence on research spillovers is provided by Breshnahan (1986), Katz and Ordover (1990), Mansfield et al. (1977) and Trajtenberg (1990). Studies at the sectoral level can be found in the special issue of Economic Systems Research vol. 9 (1997) and, for Germany, in Meyer–Krahmer and Wessels (1989).

[11] Also see the special issue on "Input–Output Analysis of Interindustry R&D Spillovers" of Economic Systems Research (1997, vol. 9 (1)) for applications of this approach at the industry level.

A quarter of the service firms do not invest in innovation at all. The average innovation intensity (innovation expenditures over sales) in services is 4.9 percent. The related figures for manufacturing are 32 and 5.4 percent respectively.
Intra–industry and inter–industry spillover pools can be differentiated by summing either over all firms within firm i's own sector or by summing over all firms outside firm i's own sector. Bernstein (1988) construct for seven Canadian industries as in equation (1). It is, however, implausible that every firm can gain equally from the aggregate knowledge stock. In order to account for the different abilities of firms to internalize other firms' knowledge, equation (1) is extended by attaching weights, ω_{ij}, which represent firm i's ability to internalize pieces of firm j's knowledge stock. The larger these weights are, the more firm i can gain from firm j's knowledge stock and vice versa:

$$S_i \;=\; \sum_{j \neq i}^{N} \omega_{ij} \; K_j. \tag{2}$$

Three main suggestions for the calculation of ω_{ij} can be found in literature: (i) distance in 'technology space', (ii) geographical distance and (iii) 'direct' measures based on innovation survey data. The idea behind the first two methods is the assumption that the closer firms are with respect to geographical distance or in the type of technology they use, the more they can gain from each other's research efforts. Measures of the geographical distance between firms are closely related to tacit knowledge since the exchange of scientists is facilitated if firms are situated close to one another. Methods relying on distances in technology space include the approaches introduced by Jaffe (1986 and 1988), henceforth denoted by 'spillover pool A', by Adams (1990, spillover pool B) as well as by Inkmann and Pohlmeier (1995, spillover pool C). Measures of geographical distance (spillover pool D) are used by Anselin et al. (1997) and Beise and Stahl (1999). 'Direct measures' of knowledge appropriability, abbreviated by spillover pool E, are considered by Levin and Reiss (1988), by Inkmann (1998) as well as by Kaiser and Licht (1998).

Spillover pool A: Uncentered correlation of firm characteristics
The uncentered correlation approach suggested by Jaffe (1986 and 1988) extends the idea of Scherer (1982 and 1984), who uses patent citation data to approximate knowledge flows between industries. His assumption is that knowledge flows between industries a and b are proportional to the share of patents of industry b in the area of industry a. Jaffe (1986 and 1988) applies this basic idea to firm–level data. He defines k–dimensional patent distribution vectors, $\boldsymbol{f}$, whose elements are the fractions of firm j's research efforts devoted to its k most important field of patent activity. His measure of technological distance between firm i and firm j is the uncentered correlation between $\boldsymbol{f_i}$ and $\boldsymbol{f_j}$:

$$\omega_{ij} \;=\; \frac{\boldsymbol{f_i}\boldsymbol{f_j}'}{\Big((\boldsymbol{f_i}\boldsymbol{f_i}')(\boldsymbol{f_j}\boldsymbol{f_j}')\Big)^{\frac{1}{2}}}. \tag{3}$$

If firm i's and firm j's patent activity perfectly coincide, ω_{ij} takes on the value 1. If they do not overlap at all, it takes on the value 0. Jaffe's measure of technological distance suffers from the same drawback as the approaches by Scherer (1982 and 1984) since, as Griliches (1990, p. 1669) points out: "Not all inventions are patentable, not all inventions are patented, and the inventions that are patented differ greatly in 'quality' (...)."[12] Although Griliches' remark only matters if the ratio of patented to unpatented inventions varies across the economic units under consideration, the shortcoming that "not all inventions are patented" is especially binding in the services sector where innovation is often tied to tacit knowledge which cannot be patented. Instead of filling the $\boldsymbol{f}$–vector with patent citation data, I fill it with the following a priori chosen variables which I think represent technological proximity between firms best: the shares of high (university and technical college graduates), medium (workers with completed vocational training) and unskilled labor in total workforce, expenditures for continuing education and vocational training of the employees (per employee), labor cost per employee, investment (scaled by sales) and five variables summarizing five main factors hampering innovative activity.[13] For the construction of the latter three variables I applied a factor analysis on the 13 possible answers to the following question asked in the MIP questionnaires: "Please indicate the importance of the following factors hampering your innovative activity on a scale from 1 (very important) to 5 (not important)." The possible answers include (1) high risk with respect to the feasibility of the innovation project, (2) high risk with respect to market chances of the innovation, (3) unforseenable innovation cost, (4) high cost of the innovation project, (5) lasting amortization duration of the innovation project, (6) lack of equity, (7) lack of debt, (8) lack of qualified personnel, (9) lack of technical equipment, (10) non–matured innovative technologies, (11) internal resistance against innovations, (12) lasting administrative/authorization processes and (13) legislation. From the factor analysis of the questions five main factors can be identified which I call 'risk' (consisting of questions (1), (2) and (3)), 'cost' (questions (4)—(5)), 'capital' (questions (6)—(7)), 'intern' (questions (9)—(11)) and 'law' (questions (12)—(13)). I use total factor scores scaled by the maximum total score for each of the three variables. E.g., if firm i indicates that lack of equity is of high importance (score=5) and indicates that lack of debt is of no importance (score=1), the total score for factor 'capital' is $5 + 1 = 6$ and the variable eventually used takes on the value $0.6 = 6/(5 + 5)$.

Spillover pool B: Uncentered correlation of firms' skill mix

An approach closely related to spillover pool A has been suggested by Adams (1990), who replaces the patent citation data with the firms' shares of scientists in each of its k "fields of science" (Adams, 1990, p. 679). The reasoning of Adams is that an industry's knowledge stock is generated by scientific personnel who are aware of the advances in science. If firms i and firms j employ large shares of scientific staff, they are assumed to gain to similar extents from technological progress achieved in an economy (and vice versa). This relates to Nightingale's (1998, p. 689) observation of knowledge "as a capacity that is embodied in the brain" and hence to the discussion of tacit and codified knowledge. Scientific personnel find it easier to decode codified knowledge while at the same time possibly gaining from the tacit expertise of scientific colleagues of other firms. I extend Adams' idea by including the skill mix, e.g. the shares of high, medium and low skilled labor, as elements of the $\boldsymbol{f}$–vectors since not only the share of R&D personnel but

[12]Pavitt (1985 and 1988) comments on the usefulness of patent statistics as indicators for economic activity. See Arundel and Kabla (1998) and Brouwer and Kleinknecht (1999) for estimates of patent propensities for innovations.

[13]These are, however, measures of distances in firm characteristics rather than measures of technological distance in a strict sense.

also the share of low skilled labor is informative with respect to measuring the kind of technology a firm uses.

Spillover pool C: Euclidean distance of firm characteristics
Inkmann and Pohlmeier (1995) extend Jaffe's idea by introducing a measure of technological distance which does not rely on patent data and which allows technologically distant firms to be both leading and lagging since both type of firms, as Inkmann and Pohlmeier (1995, p. 9) argue: "(...) can reveal high absorptive capacity." They argue technologically lagging firms may gain from the knowledge pool more than the average since the quality of the aggregate knowledge stock is higher for them relative to the quality of their own knowledge stock. In analogy to Jaffe's $\boldsymbol{f}$–vectors, Inkmann and Pohlmeier consider vectors of firm characteristics. Examples for the P elements of their vector are e.g. firm size, demand expectations and sectoral affiliation. Inkmann and Pohlmeier's measure of technological distance is based on the Euclidean distance between the P elements of the vector of firm characteristics $\boldsymbol{x_i}$:[14]

$$\omega_{ij} = \sqrt{\sum_{p=1}^{P} \Big(\frac{x_{ip} - x_{jp}}{sd(\boldsymbol{x_p})}\Big)^2}, \tag{4}$$

where $sd(\boldsymbol{x_p})$ denotes the standard deviation of characteristic p across all firms. In the case of identical firms $\omega_{ij} = 0$ and in the case of very different firms, ω_{ij} goes to infinity. In analogy to the construction of spillover pool A, the $\boldsymbol{x_i}$–vectors consist of the same elements as the $\boldsymbol{f}$–vectors.

Spillover pool D: Geographical distance between firms
For the construction of spillover pool D, the geographical coordinates of each firm are merged to the MIP data.[15] The firms' coordinates are measured as geographical distance to Germanys' geographical midpoint according to their position within their postal area.[16] As in Beise and Stahl (1999), the weights ω_{ij} are calculated as the inverse of the geographical distance between firms i and j, which is measured using Pythagoras' rule.

Spillover pool E: Measures of imitation hazard
More direct measures of knowledge flows have become available with the growing accessability of innovation survey data. Levin and Reiss (1988, p. 546) try to measure "interindustry differences in technological opportunity" by analyzing innovation survey data with respect to what extent materials and equipment suppliers as well as customers contribute to innovative activity. Inkmann (1998), who also uses the MIP–M data, considers information on firms' apprehension that their innovative ideas may be involuntarily transferred to other firms. His weighting scheme is based on the MIP question on factors hampering innovative activity as already described above. Using this information,

[14]Inkmann and Pohlmeier (1995) call this 'Euclidean' distance but it is in fact a Mahalanobis distance since the squared distances are scaled by the standard errors. See Janz (1997, ch. 4.2.6) for a discussion of statistical distance measures.

[15]I am indebted to Henrietta Haasz and Jürgen Moka for doing this task for me.

[16]There are 41,268 postal code areas in Germany. If two firms are situated in the same postal code area, their distance is assumed to be one kilometer.

Inkmann (1998) calculates his weighting scheme as:

$$\omega_{ij} = \frac{\Pi_i + \Pi_j - 1}{10}, \tag{5}$$

where Π_i denotes the firm i's judgement of the imitation hazard.
Kaiser and Licht (1998), who use the MIP–M data as well, additionally include sales expansion factors to firms' R&D expenditures to actually capture the *total* knowledge stock instead of the *sample* knowledge stock. This is an important distinction since equation (2) implies that the summation is over all N firms in (i) the sector if horizontal spillovers are considered or (ii) over all firms which are *not* in the sector if vertical spillovers are considered.
In the following, I proceed along the lines of Kaiser and Licht (1998) and expansion factors are attached to each firms' innovation expenditures, the knowledge proxy variable chosen in this paper.[17]

3 Data

In order to capture both intra–industry and inter–industry knowledge spillovers, the Mannheim Innovation Panel in manufacturing industries (MIP–M) and its counterpart for the service sector (Mannheim Innovation Panel in the service sector, MIP–S) is used. The MIP–M and the MIP–S are closely related not only by their names but also with respect to their contents. Both surveys are collected by the Centre for European Economic Research (ZEW) and are part of the European Commission's Community Innovation Surveys (CIS II) program. The concept, the design and main empirical findings of the MIP–M are thoroughly described in Harhoff, Licht et al. (1996). Related information on the MIP–S is provided by Licht et al. (1997). I use the first wave of 1995 of the MIP–S and the corresponding third wave of the MIP–M.[18]
The innovation panels are mail surveys and are commissioned by the German Federal Ministry of Education and Research. The population of the surveys consists of all firms with more than four employees. The MIP–M and the MIP–S are both stratified random samples, stratified with respect to sectoral and regional affiliation (East/West Germany) and with respect to firm size classes. Four main issues lie in the center of the questionnaires: (i) development and dispersion of innovative activity, (ii) development and measurement of innovative success, (iii) importance and structure of factors hampering innovation and (iv) dispersion and results of public innovation promotion activities. The MIP–M and the MIP–S contain some questions which are repeated annually, such as questions concerning process and product innovation, economic effects of innovation, R&D expenditures, investment, skill structure, labor cost, sales, and export share. On a biennial basis, additional topics such as questions on technology transfer, information sources for innovative activity and co–operations are covered.
The MIP–S is restricted to marketed services only and therefore comprises wholesale and

[17] The spillover pools were generated using my own GAUSS procedure which can be downloaded from the internet at ftp://ftp.zew.de/pub/zew-docs/div/spillo.prg. The estimation results presented in section 4 were obtained using the software package STATA6.0.

[18] Public use files are available for both data sets used in this paper. Write to Norbert Janz at the Centre for European Economic Research (`janz@zew.de`).

retail trade, transport, traffic, banking, insurance, software, technical consultancy, marketing, and 'other' business–related services. The survey design of the MIP–S extends the traditional concept of innovation survey in manufacturing industries, as summarized in the OECD Oslo–Manual (OECD, 1997), to the service sector. The experience made with the MIP–S shows that the innovation survey concept originally developed for manufacturing industries is also, with some slight modifications, applicable to the service sector (Gault, 1996).

4 Empirical investigation

Since the weighting schemes of the spillover pools are bounded within different ranges, the descriptive statistics of the alternative spillover pools show sharp differences between the different weighting schemes. For the uncentered correlation approaches (A and B) and for the geographical distance method (D), $\omega_{ij} \in [0,1]$.[19] for the Euclidean distance approach (C), $\omega_{ij} \in [0,\infty]$ and for the "direct" measure (F), $\omega_{ij} \in [0.1, 0.9]$. Table 1 displays descriptive statistics of the variables used for the construction of the spillover pools. It is differentiated between horizontal and vertical spillovers. The calculation of the spillover pools captures 115 different sectors, 66 for manufacturing and 49 for services. I aimed at yielding narrow definitions of sectors in order to avoid mixing up horizontal and vertical spillovers. At least 10 firms are situated in each of the 115 sectors.
Table 1 shows that according to the uncentered correlation approach — spillover pool A —, the mean service firm receives knowledge spillovers from competitors worth 1.65 billion German Marks (DM). The related standard error is 2.06 billion DM. Knowledge spillovers from vertically related firms are much larger simply because there are more vertically related than horizontally related firms. The mean service firm receives knowledge worth 113.92 billion DM from vertically related firms.
While the mean spillovers a firm receives are quite similar in magnitude for spillover pools A, B and E, there are striking differences regarding spillover pools C and D. The difference of spillover pool C to the other pools is a consequence of the fact that the measure of the Euclidean distance is unbounded from above. Spillover pool D deviates from the other spillover pools mainly due to the way in which geographical distance is measured. In the present case, it is measured in kilometers. If meters or 1,000 kilometers were considered instead, means and standard errors would change accordingly.
As a general comparison, roughly 88 billion DM were invested in innovation by manufacturing firms, 62 billion DM were invested in innovation by service sector firms in 1994. These numbers are, just as in the construction of the spillover pools, weighted by sales expansion factors.

Insert Table 1 about here!

In order to shed some light on what spillovers may look like, Figure 1 shows, in clockwise direction, Kernel density estimates of the spillover pools constructed by the uncentered

[19] If the distance between firm i and firm j was less than one kilometer, the distance was replaced by one kilometer in order to avoid the economically senseless effect that firm i internalizes more of firm js knowledge than firm j possesses, and vice versa, since for the geographical distance d between firms i and j approaching zero, $\omega_{ij} = 1/d$ goes to infinity.

correlation approach, by the Euclidean distance idea, the geographical distance method and by the direct measure of imitation hazard. Figure 1 clearly shows that the four measures of spillovers have entirely different empirical distributions. The uncentered correlation approach is skewed to the left and is similar to a log–normal distribution while the geographical and the Euclidean distance measures are left–skewed and have a mirrored log–normal shape. As has already become apparent from equations (3) and (4), the uncentered correlation approach generates weights which get larger the more similar firms are while the Euclidean distance measure generates weights which get larger the more different firms are. Consequently, the Kernel density estimate of spillover pool A looks like a mirror of spillover pool C. The Kernel density estimates of the geographical spillover pool suggest that the firms are geographically quite distant from one another. It has to be stressed here, however, that the MIP data are not stratified with respect to regions.
The peculiar shape of the Kernel density estimate is due to the ordinal nature of the variable reflecting imitation hazard. The five–modality of the empirical distribution of the spillover pool constructed using the measure of imitation hazard implies that using this spillover pool approach may lead to an error–in–variables problem.

Insert Figure 1 about here!

To give some additional descriptive evidence, Table 2 displays the correlation coefficients for the five spillover pools. By keeping in mind the fact that all spillover pools essentially measure the same, namely the weighted sum of the other firms' innovation expenditures, the correlation across the pool is modest. Spillover pools A and B are highly correlated since they are based on the same method of measuring firm distances. Spillover pool E shows quite a high correlation with spillover pool A, which might reflect that technologically similar firms give similar assessments of imitation hazard. These patterns are present for both services and manufacturing in the case of horizontal spillovers. The correlation across the vertical spillover pool variables is considerably lower than across the horizontal ones by construction since vertical spillovers do not take into account the similarity across sectors.

Insert Table 2 about here!

Due to the non–measurability of knowledge spillovers, there is no natural way of testing which spillover pool construction is superior to the others. The MIP data, however, contain a question which indirectly reflects the extent to which knowledge is available in a sector and in an economy: "In order to realize innovations, external know–how is often needed. Please assess on a scale ranging from 1 (no importance at all) to 5 (very important) the importance of the following external information sources for innovation." In the MIP–S, a list of the following sources follows the initial question: (1) customers from the manufacturing sector, (2) customers from the service sector, (3) suppliers and (4) competitors. The first three sources are related to vertical relationships between firms while the last is related to horizontal relationships between firms. Note that the question on information sources is only answered by firms which actually conduct innovations.
I argue that the more vertical spillovers are present, the larger the probability is that

firms use vertically related firms as an information source. The same reasoning applies for the case of horizontal spillovers. In some sense, I compare the 'artificial' world of the knowledge spillover proxy variables with the 'real' world judgments of firms' information sources.

I claim that a spillover pool 'correctly' measures actual spillovers if its impact on the choice of the information sources is significantly positive. E.g., the sign of the horizontal spillover pool variable on the choice of competitors as an information source should be positive and the coefficient should be significantly different from zero.

The estimations are run separately for manufacturing and services in order to take into account the inherent differences between both sectors. Since the MIP–M of 1995 does not contain a question on the information sources, I merge the lacking variables from the data of the MIP–M of 1996.[20] By proceeding this way, I assume that the knowledge information sources remained constant between 1995 and 1996. The questions on information sources were asked in an almost identical way in the 1996 MIP–M and the 1995 MIP–S.

Since the variables depicting knowledge information source take on natural numbers and follow a natural ordering — a large number indicates great importance of the related information sources —, I use ordered probit models (i) to estimate the relationship between horizontal knowledge spillovers and a firm's propensity to use horizontally related firms as an information source and (ii) to estimate the relationship between vertical knowledge spillovers and vertically related firms as an information source.[21]

It is important to note that comparisons of the estimated vector of coefficients in ordered probit models across different ordered probit models are impossible to make due to well known problem of identification in qualitative dependent variable models. In these models, the estimated coefficients are all scaled by the standard error of the disturbance term.

In estimations for service sector firm's valuation of the two information sources, besides the horizontal spillover pool variables, the following control variables for observable firm heterogeneity are included: (1) a dummy variable for East Germany, (2) five size class dummy variables, (3) six sectoral affiliation dummy variables and (4) three variables intended to represent product market competition: export share, and three dummy variables for (i) presence of foreign competition in the home market, (ii) expected presence of foreign competition in the home market and (iii) own activity in a foreign country. Additionally, firms' innovation intensity I/L (innovation expenditures, I, over labor, L), is included in the estimating equation since the ability to appropriate other firms' knowledge depends positively on own innovation effort (Cohen and Levinthal, 1989).[22]

For the manufacturing sector, the same set of variables is used with the exception of the market structure information since in the MIP–M there is no information on the presence of foreign competition, the expected presence of foreign competition and on own activity in a foreign country. The export share variable is included in the estimations for the manufacturing sector as well. The results of the ordered probit estimations for the choice of horizontal information sources are displayed in Tables 3—6 for services and manufacturing respectively.

For the sake of brevity, all tables display coefficients as well as standard errors for the spillover pool variables, own innovation intensity (I/L) and the interaction variable

[20]For organizational reasons, the MIP–S was not collected in 1996.

[21]See Greene (1997, ch. 19.8) for a detailed discussion of the ordered probit model.

[22]Recall that firms' *own* innovation expenditures are *not* included in the spillover pools.

alone.[23]

Table 3: Horizontal spillovers and horizontal information sources (service sector)

Table 3 shows the estimation results for the relationship between the choice of horizontal information sources and the amount of horizontal spillovers for the service sector. None of the coefficients related to the spillover pools considered here are significantly different from zero at the usual significance levels. All of them carry, however, the expected positive sign: the larger horizontal spillovers are, the higher — though insignificantly — is the probability that firms choose horizontally related firms as information source.

The impact of own innovative activity exhibits the same patterns as the horizontal spillover pools. It is insignificant and positive. This indicates that the ability to appropriate knowledge is not mainly determined by own innovative activity.

The two goodness–of–fit–measures, the pseudo R^2 suggested by McFadden (1974, abbreviated by R^2_{MF}) and the measure suggested by McKelvey and Zavoina (1975, abbreviated by R^2_{MZ})[24] indicate that firm's decision to use horizontally related firms as information source is not very accurately measured.

Insert Table 3 about here!

Table 4: Horizontal spillovers and horizontal information sources (manufacturing industries)

Just as in Table 3 for the service sector, horizontal spillovers do not carry the expected positive sign for manufacturing, too. Their effect is, though insignificantly, positive.

Own innovative activity has a significantly positive impact on the choice to use horizontally related firms as information sources. This indicates that own innovation effort is needed in order to appropriate other firm's knowledge.

The goodness–fit–measures indicate that the decision to choose horizontally related firm is much better described by the variables I used in manufacturing than in services. This, though to a lesser degree, also holds for the choice of vertically related firms as information source.

Insert Table 4 about here!

With respect to the other variables taken into account in the estimation for the choice of vertically related firms as information source, further differences between services and manufacturing become apparent. While firm size explains much of the decision to use horizontally related firms as an information source for services — with firm size having a nonlinear impact on firms' choice of information sources —, it does not significantly matter in manufacturing.

The market structure variables are usually significantly different from zero for services and

[23]The entire set of estimates can be downloaded from the internet at `ftp://ftp.zew.de/pub/zew-docs/div/spillres.pdf`.

[24]Veall and Zimmermann (1992) demonstrate that the McKelvey and Zavoina (1975) pseudo R^2 is superior to other goodness–of–fit measures that as the ones proposed by Aldrich and Nelson (normalized and not normalized), McFadden and Cragg and Uhler (see Veall and Zimmermann, 1992, for references).

insignificant for manufacturing. In this context, presence or expected presence of foreign competition is usually insignificant and own activity in a foreign country has a significantly negative impact on the choice of horizontal information sources. Export activity turns out not to significantly explain the use of competitors as an information source.
Own innovative activity is insignificant in the choice of horizontal information sources for service sector firms while larger own innovative activity leads to an extended use of horizontal information sources. This highlights marked differences between manufacturing and services. Manufacturing sectors firms' absorptive capacity increases their use of external knowledge, while for service sector firms such an relationship cannot be found. For service sector firms, the use of external knowledge seems to be unrelated to own absorptive capacity.

Table 5: Vertical spillovers and vertical information sources (services)
The estimation results displayed in Table 5 can be briefly summarized as follows: the coefficients related to the uncentered correlation approach A in the estimations carries the expected positive sign in the choice of vertically related firms as an information source. The effects are, however, not significantly different from zero for the choice of customers from the service sector as information source.
The coefficients related to the measures of the Euclidean distance and of the geographical distance do not carry the expected sign and are insignificant. The uncentered correlation approach based on the skill mix information alone and the 'direct' measure usually carry the expected signs but are insignificant.
Own innovative activity is, as in the determination of choosing horizontal information sources, insignificant.
Sectoral affiliation and the competitive environment a firms has to face appear to be important determinants for the choice of vertically related firms as information source.

Insert Table 5 about here!

Table 6: Vertical spillovers and vertical information sources (manufacturing industries)
For manufacturing industries and the choice of vertically related firms, Table 6 suggests that the 'direct' measure (pool E) seems to measures spillovers best. The related coefficients are significantly positive both for the choice of customers and for the choice of suppliers. The coefficients related to the uncentered correlation approaches are positive but insignificant. The use of the geographical distance approach as well as the Euclidean distance measure may lead to counterintuitive results.
As in the case of horizontal information sources, sectoral affiliation and firm size are important determinants of the decision to choose vertically related firms as information sources.
Innovation intensity has a highly significant and positive impact on the decision to choose vertically related firms as an information source.

Insert Table 6 about here!

Summing up the results displayed in Tables 3—6 implies that the uncentered correlation approaches serve well for both services and manufacturing. For manufacturing, the imitation hazard method also appears to be a good proxy variable for vertical spillovers. As a general conclusion, horizontal spillovers are not proxied well for both manufacturing and services. This result is not attributable to too narrowly–defined sectors as it turned out from estimations based on more narrowly defined sector definitions.
The use of spillover pools constructed by Euclidean distance may lead to counterintuitive results indicating that the hypothesis, both technologically leading and lagging firms may gain from other firm's expertise equally, underlying this approach is not true.
A striking result is that the determinants of information choice differ markedly between manufacturing and services. This is indicated by the considerably lower goodness–of–fit measures between the specifications for manufacturing and for services and by the insignificant impact of own innovation effort on information source choice for services. In manufacturing, own innovative activity has a significant and positive impact on the choice of information sources. In order to further explore the differences between the two main sectors, I have run Minimum Distance Estimations (Kodde et al., 1990) to test whether the estimated parameter vectors are significantly different from one another. Including only those variables available for both services and manufacturing, it turned out that equality of the parameter vector cannot be accepted at the usual significance level.
Though geographical spillovers are usually insignificant, they at least carry the expected positive sign in the choice of information sources. Geographical spillovers may, however loose their importance as a spillover measure due to the fact that modern information and communication technologies (ICT) rapidly gain in importance. Face–to–face relationships between employees of different firms then loose their significance in firms' innovation processes since "ICTs (...) move the border between tacit and codified knowledge" as noted by Freeman and Soete (1997, p. 405).
Lastly, using R&D personnel instead of innovation efforts as proxy variable for knowledge stock K did not to qualitatively different result. One exception, however, is that the 'direct' approach to measure technological distances between firms turned out to be more often consistent with my predictions with R&D as proxy variable than with innovation efforts as proxy variable.

5 Conclusion

This paper reviews existing approaches to proxy knowledge spillovers and studies the quality of the alternative ways to construct knowledge spillover variables. Four main approaches to calculate knowledge spillover pools are reviewed and empirically implemented for the German services and the German manufacturing sector. The Mannheim Innovation Panel in the service sector (MIP–S) and in manufacturing industries (MIP–M) are used in the empirical investigation. It is differentiated between horizontal and vertical knowledge spillovers.
Due to the unmeasurability of knowledge spillovers, it is difficult to assess the quality of a knowledge spillover pool variable empirically. However, the MIP–M and the MIP–S contain a question on sources of external knowledge in an innovation process. I argue that the larger horizontal (vertical) knowledge spillovers are, the more likely it is that a

firm gathers information from horizontally (vertically) related firms.
The spillover pools constructed using the uncentered correlation approach proposed by Jaffe (1986 and 1988) generally fit this prediction best. Spillover pools based on the Euclidean distance between firms in technology space and of the geographical distance between firms prove to be poor measures of knowledge spillovers while approaches based on direct measures taken from innovation survey data are consistent with my predictions. For both manufacturing and services, horizontal knowledge spillovers are not proxied well. As a byproduct, it became apparent that there are striking differences in the importance of horizontal and vertical information sources in the innovation process. This is indicated by signs and significancies of the involved variables, by the goodness–of–fit measures and by a formal test based on a Minimum Distance Estimation. A more thorough exploration of this issue is left for further research.
A straightforward extension of this paper is to allow knowledge stocks to accumulate over the course of time. This will be pursued as soon as further waves of the MIP data become available.

References

Adams, J.D., 1990. Fundamental Stocks of Knowledge and Productivity Growth. Journal of Political Economy 98 (4), 673–702.

Aghion, P., Howitt, P., 1992. A Model of Growth through Creative Destruction, Econometrica 60 (2), 323–351.

Amable, B., Palombarini, S., 1998. Technical Change and Incorporated R&D in the Service Sector. Research Policy 27 (7), 655–675.

Anselin, L., Varga, A., Acs, Z., 1997. Local Geographic Spillovers between University Reesearch and High Technology Innovations. Journal of Urban Economics 42 (3), 422–448.

Arrow, J.K., 1962. Economic Welfare and the Allocation of Resources for Invention. In: Nelson, R.R. (Ed.), The Rate and Direction of Inventive Activity. Princeton University Press, 609–625.

Arundel, A., Kabla, I., 1998. What Percentage of Innovations are Patented? Empirical Estimates for European Firms. Research Policy 27 (2), 127–141.

Beise, M., Stahl, H., 1999. Public Research and Industrial Innovations in Germany. Research Policy 28 (4), 397–422.

Bernstein, J., 1988. Costs of Production, Intra– and Interindustry R&D Spillovers: Canadian Evidence. Canadian Journal of Economics 21 (2), 324–347.

Bernstein, J., Nadiri, M.I., 1988. Intraindustry R&D Spillovers, Rates of Returns, and Production in High–Tech Industries. The American Economic Review 78 (2), 429–434.

Branstetter, L.G., 1998. Looking for International Knowledge Spillovers: A Review of Literature with Suggestions for New Approaches. Annales D'Économie et de Statistique 49/50, 517–540.

Breshnahan, T.F., 1986. Measuring Spillovers from "Technical Advance". The American Economic Review 76 (4), 742–755.

Brouwer, E., Kleinknecht, A., 1999. Innovative Output, and a Firm's Propensity to Patent. An Exploration Using CIS Micro Data. Research Policy 28 (6), 615–624.

Cohen, W.M., Levinthal, D.A., 1989. Innovation and Learning: The Two Faces of R&D, The Economic Journal 99 (3), 569–596.

D'Aspremont, C., Jacquemin, A., 1988. Cooperative and Noncooperative R&D in Duopoly with Spillovers, The American Economic Review 78 (5), pp. 1133-1137.

D'Aspremont, C., Jacquemin, A., 1990. Cooperative and Noncooperative R&D in Duopoly with Spillovers: Erratum, The American Economic Review 80 (3), 641-642.

De Bondt, R., Slaets, P., Cassiman, B., 1992. The Degree of Spillovers and the Number of Rivals for Maximum Effective R&D, International Journal of Industrial Organization 10 (1), 297–313.

De Bondt, R., 1996. Spillovers and Innovative Activity. International Journal of Industrial Organization 15 (1), 1–28.

Dosi, G., Chytry, J., Teece, D.J., 1998. Technology, Organization and Corporate Change. Oxford University Press, Oxford.

Feldman, M.P., 1999. The New Economics of Innovation, Spillovers and Agglomeration: A Review of Empirical Studies. Economics of Innovation and New Technology 8 (1–2), 5-24.

Freeman, C., Soete, L., 1997. The Economics of Industrial Innovation. MIT Press, Cambridge.

Gallouj, F., Weinstein, O., 1997. Innovation in Services, Research Policy 26 (4–5), 537–556.

Gault, F., 1996. Service Industries in the Innovation Survey: Background Paper for the Revision of the OSLO–manual, OECD–document STI/EAS/STP/NESTI 96 (4), Paris.

Geroski, P., 1992. Vertical Relations between Firms and Industrial Policy. The Economic Journal 102 (1), 138–147.

Geroski, P., 1993. Antitrust Policy Towards Co–Operative R&D Ventures. Oxford Review of Economic Policy 9 (2), 58–71.

Geroski, P., 1995a. Markets for Technology: Knowledge, Innovation and Appropriablity. In: Stoneman, P. (Ed.), Handbook of Innovation and Technological Change. Blackwell Publishers, Oxford, 90–131.

Geroski, P., 1995b. Do Spillovers Undermine the Incentives to Innovate? In: Dowrick, S. (Ed.), Economic Approaches to Innovation. Ashgate, Brookfield, 76–97.

Goto, A., Suzuki, K., 1989. R&D Capital, Rate of Return on R&D Investment and Spillover of R&D in Japanese Manufacturing Industries. The Review of Economics and Statistics 71 (4), 555–564.

Greene, W.H., 1997. Econometric Analysis. Prentice–Hall, Upper Saddle River.

Griliches, Z., 1979. Issues in Assessing the Contribution of Research and Development to Productivity Growth. The Bell Journal of Economics 10 (1), 92–116.

Griliches, Z., 1990. Patent Statistics as Economic Indicators: A Survey. Journal of Economic Literature 28 (4), 1,661–1,707.

Griliches, Z., 1992. The Search for R&D Spillovers. Scandinavian Journal of Economics 94 (Suppl.), 29–47.

Grossman, G., Helpman, E., 1991. Innovation and Growth in the Global Economy. MIT Press, Cambridge.

Grünewald, W., Smith, K., 1994. The Community Innovation Survey: Status and Perspectives. Office for Official Publication of the European Communities, Luxemburg.

Harhoff, D., Licht, G. et al., 1996. Innovationsaktivitäten kleiner und mittlerer Unternehmen: Ergebnisse des Mannheimer Innovationspanels. Nomos–Verlag, Baden–Baden.

Harhoff, D., 1996. Strategic Spillovers and Incentives for Research and Development, Management Science 42(6), 907–925.

Henriques, I., 1990. Cooperative and Noncooperative in a Duopoly with Spillovers: Comment, American Economic Review 80 (3), 638–640.

Inkmann, J., 1998. Horizontal and Vertical R&D Cooperation. University of Konstanz discussion paper.

Inkmann, J., Pohlmeier, W., 1995. R&D Spillovers, Technological Distance and Innovation Success, University of Konstanz mimeo.

Jaffe, A.B., 1986. Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value. The American Economic Review 76 (5), 584–1001.

Jaffe, A.B., 1988. Demand and Supply Influences in R&D Intensity and Productivity Growth. The Review of Economics and Statistics 70 (3), 431–437.

Jaffe, A.B., 1996. Economic Analysis of Research Spillovers: Implications for the Advanced Technology Program. Advanced Technology Program research memorandum; downloaded from the internet at `http://www.atp.nist.gov/www/eao/gcr708.html`.

Janz, N., 1997. Ökonometrische Panelanalysen des Investitionsverhaltens deutscher Aktiengesellschaften. Nomos Verlag, Baden–Baden.

Kaiser, U., Licht, G., 1998. R&D Cooperation and R&D Intensity: Theory and Micro–Econometric Evidence for Germany. ZEW discussion paper 98–32.

Kaiser, U., 1999. R&D Cooperation and R&D Investment with endogenous spillovers: Theory and microeconometric evidence. ZEW mimeo.
downloadable at `ftp://ftp.zew.de/pub/zew-docs/div/endo.pdf`

Kamien, M. I., Muller, E., Zang, I., 1992. Research Joint Ventures and R&D Cartels, The American Economic Review 82, 1293-1306.

Katz, M.L., Ordover, J.A., 1990. R&D Cooperation and Competition. Brookings Papers on Economics Activity: Microeconomics, 137–203.

Kleinknecht, A., 1998. Measuring and Analysing Innovation in Services and Manufacturing: An Assessment of the Experience in the Netherlands. Rotterdam Institute for Business Studies discussion paper.

Kleinknecht, A., Reijnen, J.O.N., 1992. Why do firms cooperate on R&D? An Empirical Study. Research Policy 21, 347–360.

Kodde, D.A., Palm, F.C., Pfann, G., 1990. Asymptotic Least Squares Estimation, Efficiency Considerations and Applications. Journal of Applied Econometrics 5 (3), 229–243.

König, H., Kukuk, M., Licht, G., 1996. Kooperationsverhalten von Unternehmen des Dienstleistungssektors. In: Helmstädter, E., Poser, G., Ramser, H.J. (Eds.), Beiträge zur angewandten Wirtschaftsforschung: Festschrift für Karl Heinrich Oppenländer. Duncker & Humblodt, Berlin.

Krugman, P., 1991. Geography and Trade. MIT Press, Cambridge.

Leary, D., Neary, J.P., 1997. Public Policy Towards R&D in Oligopolistic Industries, The American Economic Review 87 (4), 641–662.

Levin, R.C., 1988. Appropriability, R&D Spending, and Technological Performance. The American Economic Review 78 (2), 424–428.

Levin, R.C., Klevorick, A.K., Nelson, R.R., Winter, S.G., 1987. Appropriating the Returns from Industrial Research and Development. Brookings Papers on Economic Activity 3 (0), 783–820.

Levin, R.C., Reiss, P.C., 1988. Cost–Reducing and Demand–Creating R&D with Spillovers. RAND Journal of Economics 19 (4), 538–556.

Licht, G., Hipp, C., Kukuk, M., Münt, G., 1997. Innovationen im Dienstleistungssektor: Empirischer Befund und wirtschaftspolitische Konsequenzen. Nomos–Verlag, Baden–Baden.

Mamuneas, T.P., 1999. Spillovers from Publicly Financed R&D Capital in High–Tech Industries. International Journal of Industrial Organization 17 (1), 215–239.

Mansfield, E., Rapoport, J., Romeo, A., Wagner, S., Beardsley, G., 1977. Industry–University R&D Linkages and Technological Innovation. The Quarterly Journal of Economics 91 (2), 221–40.

Mairesse, J., Mohnen, P., 1994. R&D and Productivity Growth: What have We Learned from Econometric Studies? paper presented at the EUNETIC conference, Strasbourg, Oct. 7–8, 1994.

McFadden, D., 1974, Analysis of qualitative choice behaviour, in: P. Zarembka, Frontiers in econometrics (Academic Press, New York).

McKelvey, R., Zavoina, W., 1975. A Statistical Model for the Analysis of Ordinal Level Dependent Variables. Sociological Methods and Research 8, 95–109.

Meyer–Krahmer, F., Wessels, H., 1989. Intersektorelle Verflechtung von Technologiegebern und Technologienehmern — Eine empirische Analyse für die Bundesrepublik Deutschland. Jahrbücher für Nationalökonomie und Statistik 206 (6), 563–82.

Mohnen, P., 1989. New Technologies and Interindustry Spillovers. STI Review, 131–147.

Mohnen, P., 1997. Introduction: Input–Output Analysis of Interindustry R&D Spillovers. Economic Systems Research 9 (1), 3–8.

Mohnen, P., Lépine, 1991. R&D, R&D Spillovers and Payments for Technology: Canadian Evidence. Structural Change and Economic Dynamics 2 (1), 213–228.

Mowery, D.C., Rosenberg, N.P., 1989. Technology and the Pursuit of Economic Growth. Cambridge University Press, Cambridge.

Nelson, R.R., Winter, S.G., 1982. An Evolutionary Theory of Economic Change. The Belknap Press of Harvard University Press, Cambridge.

Nightingale, P., 1998. A Cognitive Model of Innovation. Research Policy 27 (7), 689–709.

OECD, 1997. Guidelines for Collecting and Interpreting Innovation Survey Data — The Oslo manual, OECD, Paris.

Pavitt, K., 1985. Patent Statistics as Indicators of Innovative Activities: Possibilities and Problems. Scientometrics 7, 77–99.

Pavitt, K., 1988. Uses and Abuses of International Patent Statistics. In: Van Raen, A.F.J. (Ed.), Handbook of Quantitative Studies of Science and Technology, North Holland, Amsterdam.

Polanyi, M., 1967. The Tacit Dimension. Doubleday–Anchor, Garden City.

Nightingale, P.P., 1998. On the Dynamics of Appropriability, of Tacit and of Codified Knowledge. Research Policy 27 (7–8), 843–856.

Romer, P., 1986. Increasing Returns and Long Run Growth, Journal of Political Economy 94 (5), 1,002–1,037.

Romer, P., 1990. Endogeneous Technical Change, Journal of Political Economy 98 (5, part II), 71–102.

Saviotti, P.P., 1998, On the dynamics of appropriability, of tacit and of codified knowledge, Research Policy 26 (7–8), 843—856.

Scherer, F.M., 1982. Interindustry Technology Flows and Productivity Growth. The Review of Economics and Statistics 64 (4), 627–634.

Scherer, F.M., 1984. Using Linked Patent and R&D Data to Measure Interindustry Technology Flows. In: Griliches, Z. (Ed.), R&D, Patents and Productivity, University of Chicago Press, Chicago.

Schmookler, J., 1966. Invention and Economic Growth, Harvard University Press, Cambridge.

Sirilli, G., Evangelista, R, 1998. Technological Innovation in Services and Manufacturing: Results from Italian Surveys. Research Policy 27 (9), 881–899.

Spence, M., 1984. Cost Reduction, Competition, and Industry Performance. Econometrica 52 (1), 368–402.

Suzumura, K., 1992. Cooperative and Noncooperative R&D in an Oligopoly with Spillovers. American Economic Review 82 (5), 1307–1320.

Terleckyj, N., 1974. Effects of R&D on the Productivity Growth of Industries: An Exploratory Study. National Planning Association, Washington (D.C.).

Terleckyj, N., 1980. Direct and Indirect Effects of Industrial Research and Development on the Productivity of Industries, In: Kendrick, J.N., Vaccara, B.N. (Eds.), New Developments in Productivity Measurement and Analysis, University of Chicago Press, Chicago (Ill.).

Trajtenberg, M., 1990. Economic Analysis of Product Innovations. Harvard University Press, Cambridge (Mass.).

Veall, M., Zimmermann, K.F., 1992. Pseudo R^2's in the Ordinal Probit Model. Journal of Mathematical Sociology 16 (4), 333–342.

von Hippel, E., 1994. “Sticky Information” and the Locus of Problem Solving: Implications for Innovation. Management Science 40, 429–439.

Table 1
Descriptive statistics of the spillover pools

Services

	horizontal spillovers			vertical spillovers		
	# of obs.	Mean	Std. err.	# of obs.	Mean	Std.err.
A	2054	1.65	2.06	2054	113.92	9.42
B	2222	1.53	2.00	2222	100.51	21.46
C	2054	7.73	9.10	2054	5901.89	217954.60
D	2323	25.75	77.86	2323	37.02	216.87
E	2337	0.99	1.19	2337	63.21	19.76

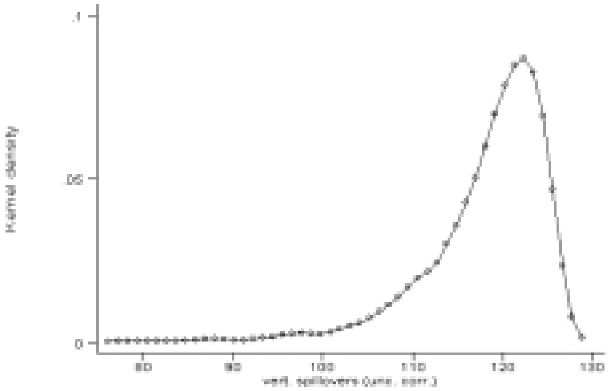
Manufacturing

	horizontal spillovers			vertical spillovers		
	# of obs.	Mean	Std. err.	# of obs.	Mean	Std.err.
A	2432	1.45	1.23	2432	118.30	6.59
B	2436	1.33	1.18	2436	106.43	16.49
C	2432	6.59	5.58	2432	874.06	235.37
D	2374	11.61	20.77	2374	37.68	251.57
E	2445	0.79	0.68	2445	66.81	17.55

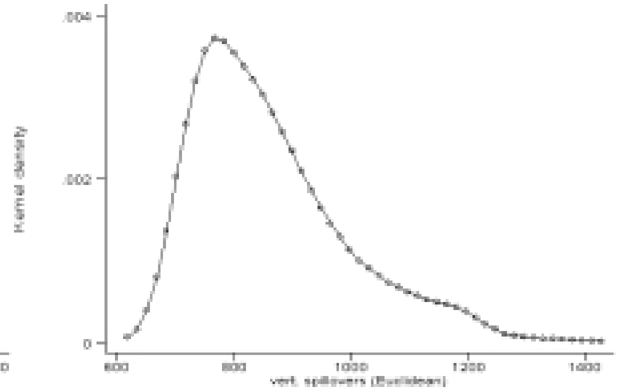
Table 1 shows means and standard errors of the spillover pool variables. Means and standard errors are in billion DM. The letters A—E denote the respective spillover pools. A: uncentered correlation (full set of variables), B uncentered correlation (skill mix information only), C: Euclidean distance, D: geographical distance, E: direct measure.

Figure 1
Kernel density estimates

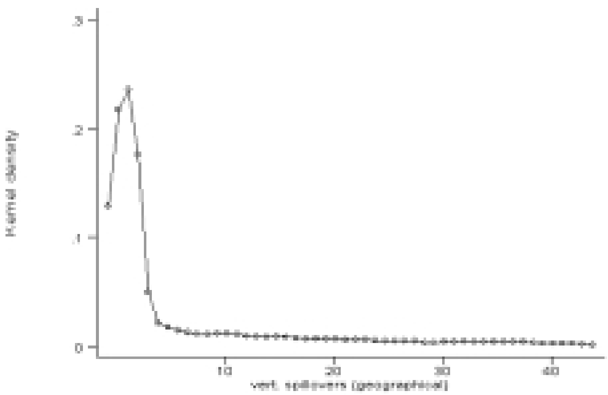
Spillover pool A.: uncentered correlation



Spillover pool C.: Euclidean distance



Spillover pool D.: geographical distance



Spillover pool E.: direct measure

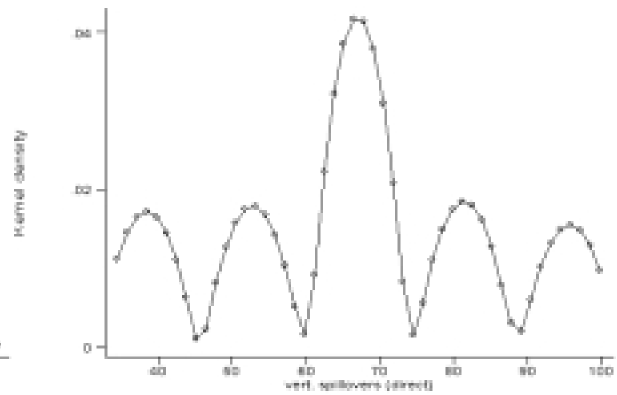


Figure 1 displays Kernel density estimates of the vertical spillover pools for manufacturing industries.

Table 2
Correlations of the spillover pools[a]

Services

	horizontal spillovers					vertical spillovers				
	A	B	C	D	E	A	B	C	D	E
A	1					1				
B	0.95	1				0.66	1			
C	0.90	0.80	1			-0.26	0.01	1		
D	0.34	0.32	0.33	1		-0.06	-0.08	0.00	1	
E	0.92	0.85	0.84	0.30	1	0.24	-0.02	0.02	0.02	1

Manufacturing

	horizontal spillovers					vertical spillovers				
	A	B	C	D	E	A	B	C	D	E
A	1					1				
B	0.98	1				0.74	1			
C	0.92	0.89	1			-0.39	-0.24	1		
D	0.41	0.40	0.38	1		0.00	-0.01	0.00	1	
E	0.90	0.88	0.86	0.36	1	0.12	-0.03	-0.04	0.05	1

[a] The letters A—E denote the respective spillover pools. A: uncentered correlation (full set of variables), B uncentered correlation (skill mix information only), C: Euclidean distance, D: geographical distance, E: direct measure.

Table 3
Ordered probit estimation results for the effects of horizontal spillovers on firms' probability to use horizontal relations as information source for the service sector[a b c]

	A	B	C	D	E
I/L	.0348	.0316	.0329	.0294	.0303
	(.0387)	(.0377)	(.0387)	(.0367)	(.0366)
horizontal	.01981	.01383	.0268	.0181	.0146
spillovers	(.0202)	(.0286)	(.0196)	(.0183)	(.0186)
R^2_{MF}/R^2_{MZ}	1.2/4.1	1.0/3.6	1.1/3.6	1.0/3.7	1.0/3.6
# of obs.	1,199	1,290	1,199	1,320	1,320

[a] The letters A—E denote the respective spillover pools. A: uncentered correlation (full set of variables), B uncentered correlation (skill mix information only), C: Euclidean distance, D: geographical distance, E: direct measure.
[b] Estimations include six firm size dummies, six sector dummies, four variables representing market structure and three variables representing the customer structure.
[c] R^2_{MF} denotes the pseudo R^2 measure suggested by McFadden (1974), R^2_{MZ} denotes the pseudo R^2 suggested by McKelvey and Zavoina (1975).

Table 4
Ordered probit estimation results for the effects of horizontal spillovers on firms' probability to use horizontal relations as information source for the manufacturing sector[a b c d]

	A	B	C	D	E
I/L	.1241***	.1237***	.1234***	.1226***	.1244***
	(.0105)	(.0105)	(.0106)	(.0107)	(.0105)
horizontal	.0188	.0239	.0173	.0106	0.0185
spillovers	(.0327)	(.0324)	(.0324)	(.0302)	(.0329)
R^2_{MF}/R^2_{MZ}	10.5/33.3	10.5/33.3	10.4/33.2	10.7/34.2	10.6/33.7
# of obs.	980	981	980	967	991

[a] The letters A—E denote the respective spillover pools. A: uncentered correlation (full set of variables), B uncentered correlation (skill mix information only), C: Euclidean distance, D: geographical distance, E: direct measure.

[b] The asterisks *** denote significancy at the 1 percent significance level.

[c] Estimations include six firm size dummies, six sector dummies and four variables representing market structure.

[d] R^2_{MF} denotes the pseudo R^2 measure suggested by McFadden (1974), R^2_{MZ} denotes the pseudo R^2 suggested by McKelvey and Zavoina (1975).

Table 5
Ordered probit estimation results for the effects of vertical spillovers on firms' probability to use vertical relations as information source for the service sector[a b c d]

	A	B	C	D	E
Customers producing sector					
I/L	.0262	.0548	.0199	.0570	.0596
	(.0424)	(.0410)	(.0422)	(.0398)	(.0399)
vertical	.0629*	.1974	-.3504**	-.0022	.2267
spillovers	(.0371)	(.2255)	(.1796)	(.0304)	(.8960)
R^2_{MF}/R^2_{MZ}	6.3/21.4	6.2/21.1	6.4/21.5	6.0/20.3	6.1/20.9
# of obs.	1,207	1,299	1,207	1,354	1,357
Customers service sector					
I/L	.0164	.0180	.0149	.0134	.0152
	(.0392)	(.0379)	(.0388)	(.0369)	(.0370)
vertical	.0372	-.0771	-.0778	.0106	-1.1111
spillovers	(.0336)	(.2003)	(.1619)	(.0274)	(.8158)
R^2_{MF}/R^2_{MZ}	2.0/9.2	1.7/6.4	1.9/8.8	1.6/5.8	1.6/6.0
# of obs.	1,221	1,310	1,221	1,350	1,371
Suppliers					
I/L	.0953**	.0796**	.0934**	.0681*	.0740**
	(.0403)	(.0391)	(.0400)	(.0379)	(.0380)
vertical	.0652*	.4458**	-.2640	-.0265	1.3277
spillovers	(.0345)	(.2052)	(.1665)	(.0287)	(.8396)
R^2_{MF}/R^2_{MZ}	4.5/16.3	4.3/16.6	4.4/15.8	3.9/14.3	4.1/14.9
# of obs.	1,212	1,302	1,212	1,358	1,362

[a] The letters A—E denote the respective spillover pools. A: uncentered correlation (full set of variables), B uncentered correlation (skill mix information only), C: Euclidean distance, D: geographical distance, E: direct measure.

[b] The asterisks **/* denote significancy at the 5/10 percent significance level, respectively.

[c] Estimations include six firm size dummies, six sector dummies, a dummy variable for East German firms and four variables representing market structure.

[d] R^2_{MF} denotes the pseudo R^2 measure suggested by McFadden (1974), R^2_{MZ} denotes the pseudo R^2 suggested by McKelvey and Zavoina (1975).

Table 6
Ordered probit estimation results for the effects of horizontal spillovers on firms' probability to use vertical relations as information source for the manufacturing sector[a b c d]

	A	B	C	D	E
Customers					
I/L	.1552***	.1525***	.1570***	.1529***	.1578***
	(.01186)	(.0119)	(.0118)	(.0118)	(.0118)
vertical	.0960	.9266***	.4061	.0084	2.9706**
spillovers	(.0634)	(.3106)	(.3585)	(.0239)	(1.2534)
R^2_{MF}/R^2_{MZ}	14.2/45.8	14.4/46.4	14.2/45.9	14.1/45.7	14.4/47.0
# of obs.	980	984	983	971	990
Suppliers					
I/L	.1061***	.1053***	.1082***	.1052***	.1063***
	(.0104)	(.0104)	(.0103)	(.0104)	(.0102)
vertical	.0652	.3767	-.1522	-.0012	1.9204*
spillovers	(.0619)	(.2972)	(.3468)	(.0229)	(1.1921)
R^2_{MF}/R^2_{MZ}	8.8/27.2	8.8/27.2	8.8/27.3	8.5/26.5	8.8/27.4
# of obs.	974	972	983	965	984

[a] The letters A—E denote the respective spillover pools. A: uncentered correlation (full set of variables), B uncentered correlation (skill mix information only), C: Euclidean distance, D: geographical distance, E: direct measure.
[b] The asterisks ***/**/* denote significancy at the 1/5/10 percent significance level, respectively.
[c] Estimations include six firm size dummies, six sector dummies, a dummy variable for East German firms and four variables representing market structure.
[d] R^2_{MF} denotes the pseudo R^2 measure suggested by McFadden (1974), R^2_{MZ} denotes the pseudo R^2 suggested by McKelvey and Zavoina (1975).