CESIS
Electronic Working Paper Series

Paper No. 37

Accessibility to R&D and Patent Production [1]

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(JIBS)

August 2005

The Royal Institute of technology
Centre of Excellence for Science and Innovation Studies
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[1] Status of the paper:

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Abstract

The main purpose in this paper is to study to what extent accessibility to R&D can explain patent production. Therefore a knowledge production function is estimated both on aggregated level and for different industrial sectors. The output of the knowledge production is the number patent applications in Swedish municipalities from 1994 to 1999. In order to account for the importance of proximity, the explanatory variables are expressed as accessibilities to university and company R&D. The total accessibility is then decomposed into local, intra-regional and inter-regional accessibility to R&D. As often is the case with R&D outputs, the regional distribution of patents is highly skewed with influential outliers. The estimations are therefore conducted with quantile regressions. The main results on aggregated level indicate that high accessibility (local) to company R&D has the greatest positive effects on patent production. The effects are statistically significant for municipalities with a patent production corresponding to the median and to quantiles above the median. Local accessibility to university R&D is only of importance for certain industrial sectors and not on aggregated level. There is also evidence that intra-regional accessibility to company R&D affects patent production positively. A conclusion is that concentrated R&D investments in companies situated in municipalities with a high patenting activity would not only gain the municipalities themselves, but also the patent production in other municipalities in the functional region.

Keywords: innovations, patents, R&D, knowledge production functions

JEL-codes: C 30 O31, O33, O34

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1. INTRODUCTION

The five largest municipalities in Sweden account for 20 % of Sweden's population also account for 44 % of Sweden's patent applications. Can this be explained by the high concentration of university and company R&D to these municipalities, or is it because of other factors? In order to get satisfactory explanations of questions like this, the paper starts with a discussion of the importance of proximity on knowledge flows and innovation systems.

Knowledge flows is a concept that covers different types of flows where knowledge is involved. In Johansson (2004) knowledge flows are divided into two main groups:

i) Transaction-based flows, i.e. the parties involved agree on a transaction of knowledge

ii) Knowledge spillovers, i.e. knowledge is an unintended side effect of ordinary activities

Knowledge spillovers can in turn be mediated by market mechanisms or be a pure externality. A pure externality in this context is for example when companies observe and copy techniques from each other. Some models of knowledge diffusion assume that geography plays no role in the cost of adoption (Spence, 1984; Cohen and Levinthal, 1990). Other models based on theories of localisation suggest that just because knowledge spills over does not mean that it transmits without costs across geographic space. In particular, these theories argue that geographic proximity reduces the cost of accessing and absorbing knowledge spillovers. Fundamental to the theories of localised spillovers is the distinction between codified and tacit knowledge.

The importance of geographical proximity on knowledge diffusion has been revealed in several studies. Jaffe (1989), Jaffe et al. (1993), Feldman (1994) and Audretsch & Feldman (1996) stress that R&D and other knowledge spillovers tend to be geographically bounded within the region where the new economic knowledge was created. Closeness between agents and other members in the regional innovation system is more likely to offer greater opportunities to interact face to face, which will develop the potential of the innovation system. The theoretical explanation is that a great deal of new economic knowledge relevant in different innovation processes is hard to codify and is therefore not perfectly available. Any new knowledge of that kind will consist of a vast amount of skills, intuitions, and best practices, whose transmission will require face to face contacts and extensive explanations. As a result, only local actors will manage to access that tacit body of knowledge through frequent interaction with its sources. Especially the possibility to learn certain skills by imitation is rather costly without close observation (Harhoff, 1999). Bottazzi & Peri (2003) think of the imperfectly codified part of the knowledge as a "local public good" as it benefits scientists within the region or its neighbourhoods but it diminish as contacts and interactions decrease. Breschi & Lissoni (2001a,b) are on the other hand critical to the view that tacit knowledge are freely available locally. They argue that sharing of tacit knowledge not only require spatial proximity but also "social" proximity, i.e. elements like mutual trust. Audretsch & Feldman (1996) make a distinction between information and knowledge. They argue that even though the cost of transmitting information may not change with distance, most likely the cost of transmitting knowledge rises with distance. While information is easy to codify, the transmission of knowledge requires frequent contacts and the interaction of agents.

There are several possible ways to measure and account for geographical proximity. Jaffe (1989) introduces a geographical coincidence index between public and private sector research. Autant-Bernard (2001), Acs et al. (2002) and Bottazzi & Peri (2003) compare different geographical levels, by introducing external research stock occurring on the periphery of a particular area. A geographical area's innovation capacity is therefore related to internal R&D effort but also to spillovers flowing from research activities in neighbouring areas. Botazzi & Peri (2003) also use distance (in kilometres) between different regions when investigating the importance of geographical proximity on knowledge spillovers. Karlsson & Manduchi (2001) have proposed an accessibility concept in order to incorporate geographical proximity. The accessibility measure is based on Weibull (1976) and is constructed according to two main principles. Firstly, the size of attractiveness in a destination has a positive effect on the propensity to travel. Secondly, the time distance to a destination affects the propensity to travel negatively. Many years of research has shown that the functional form derived by Weibull (1976) is superior other measures explaining peoples' travel in space. One of the most appealing features of the accessibility concept is that it contains actual time distances between regions/municipalities. Beckman (2000) is also of the opinion that travel time is the most appropriate measure of distance when dealing with knowledge networks. Beside simulation of changes in the R&D stock, it is also possible to study effects of simulated improvements in the infrastructure of the transportation system. Andersson & Karlsson (2003) demonstrates how the accessibility concept can be used as a measure of proximity in studies of knowledge spillovers and innovations. In Andersson et al. (2003) the accessibility concept is applied as a measure of proximity in regional innovation systems.

There has been a discussion in the literature about relevant measures of the output of innovation systems. Jaffe et al. (1993) have used a "paper trail" of patent citations to track the direction and intensity of spillovers. Peri (2002) argues that this approach only can identify intensity and direction of knowledge flows and not R&D externalities. Moreover, citations do not capture non-codified knowledge flows and embodied knowledge flows, which could be important sources of localized spillovers, as Saxenian (1991) and Audretsch & Feldman (1996) argue. The two most common and frequently used innovation indicators are R&D efforts (measured by expenditures on R&D or persons carrying out R&D) and the number of patented inventions. According to Kleinknecht et al. (2002) these two measures have more weaknesses than it is often assumed. One obvious disadvantage is that R&D is an input of the innovation process and says very little about the output. Patents may be good indicators of the technology creation, even if not all new innovations are patented, but they do not measure the economic value of the technologies (Hall et al. 2001). In contrast to proxies of innovation activities such as R&D efforts or patents, literature-based innovation output measures provide a direct indicator of innovation (Acs et al. 2002; Kleinknecht et al. 2002). Screening the new product announcements in trade and technical journals generates literature-based innovation output indicators. The advantage of these indicators is that they document the actual commercialisation of technical ideas.

The final output of an innovation system is not patent applications or granted patents. Together with R&D efforts they are costs in the innovation process. Benefits from the process are measured when patents are commercialised and contributes to economic growth, but this is beyond the scope of this paper. Nevertheless, Acs et al. (2002) show in a comparison, between patents and the literature-based output measure that patents provide a fairly good measure of innovative activity in a knowledge production context. The purpose with this study is to explore the importance of accessibility to R&D, on the Swedish regional innovation systems. By estimating knowledge production functions for the innovation systems, both on aggregated level and for different industrial sectors, it is possible to answer questions like:

• To what extent can accessibility to university R&D and company R&D explain patent production in Swedish municipalities?

• To what extent does the surrounding economic activity affect the municipalities' patent production? Are there structural differences between different types of municipalities (small, big etc.)?

The following text starts with a model description, arguing for the proper model to be used. Then some descriptive statistics of the data is presented. Section 4 begins with a discussion regarding the choice of model and estimation method and ends with estimation results and result interpretations. The analysis is conducted on aggregated level and for different industrial sectors. The paper is ended with concluding remarks.

2. MODEL

The conceptual framework for analyzing geographic spillovers is based on the knowledge production function of Griliches (1979). In order to examine the influence of knowledge flows on the output of regional innovation systems, it is possible to use the number of patents in each region as an endogenous variable, regressed against the R&D effort from companies and universities (see Jaffe 1989, Feldman & Florida 1994, Fischer & Varga 2003, among others). In this paper, the accessibility to R&D is used instead of R&D effort. The accessibility concept is shown in detail in Andersson et al. (2003) and the concept's major features are for expository purposes repeated here. In this paper, however, the research unit is municipalities instead of regions. Then the number of observations increases and enables a more developed model. It is also possible to estimate effects that are very local. A downside is that many observations get zero values.

The accessibility of municipality *i* to it self and to *n-1* surrounding municipalities is defined as the sum of its internal accessibility to a given opportunity *D* and its accessibility to the same opportunity in other municipalities,

$$A_i^D = D_1 f(c_{i1}) + ... + D_i f(c_{ii}) + ... + D_n f(c_{in}) \qquad (2.1)$$

where A_i^D is the total accessibility of municipality *i*. D_i is a measure of an opportunity (face-to-face contact), which can be an opportunity such as universities, R&D institutes, suppliers, customers etc. *f(c)* is the distance decay function that determines how the accessibility value is related to the cost of reaching the opportunity. A common approximation of *f(c)* is to apply an exponential function, and then it takes the following form,

$$f(c_{ij}) = \exp\{-\lambda t_{ij}\} \tag{2.2}$$

where t_{ij} is the time distance between municipality *i* and *j,* and λ is a time sensitivity parameter. The value of λ depends on if the interaction is intra-municipal, inter-municipal within the region, or inter-municipal outside the region. Equation (2.1) and (2.2) together generate

$$A_i^D = \sum_{j=1}^{n} D_j \exp\{-\lambda t_{ij}\} \tag{2.3}$$

It is apparent that the accessibility value may improve in two ways, either by an increase in the size of the opportunity, D_j, or by a reduction in the time distance between municipality *i* and *j*. If the total accessibility to a specific opportunity is decomposed into intra-municipal, inter-municipal within the region, and inter-municipal outside the region, then (2.3) becomes

$$A_i^D = A_{iL}^D + A_{iR}^D + A_{iXR}^D \tag{2.4}$$

where $A_{iL}^D = D_i \exp\{-\lambda_1 t_{ii}\}$, intra-municipal (local) accessibility

$A_{iR}^D = \sum_{r \in I,\ r \neq i} D_r \exp\{-\lambda_2 t_{ir}\}$, inter-municipal accessibility within the region

$A_{iXR}^D = \sum_{k \notin 1} D_k \exp\{-\lambda_3 t_{ik}\}$, inter-municipal accessibility outside the region

r defines municipalities within the own region *I*, and *k* defines municipalities in other regions. λ_1 is set to 0.02, λ_2 to 0.1 and λ_3 to 0.05. Johansson, Klaesson & Olsson (2003) estimated these values by using data on commuting flows within and between Swedish municipalities in

1990 and 1998.[2] They showed that there is a clear distinction between local, intra-regional and inter-regional commuting and that the difference between theses categories of commuting cannot be described correctly by one single exponential function. There is a need for a separate representation of time sensitivity for each of the three geographical levels. It could perhaps look strange that the intra-regional accessibilities have the highest parameter value (λ_2 = 0.1). But according to Johanson, Klaesson & Olsson (2003) the intra-regional commuting trips, which are in the time span from approximately 15 to 50 minutes, are the ones that are most time sensitive. That is, increased commuting time in this time span will hamper the propensity to travel the most.

An advantage of the decomposition besides the obvious inferential aspects is that the model gets more sensitive to capture spatial interdependencies. It is well known that economic activities often tend to agglomerate in space. This tendency is particularly strong with respect to innovation indicators (e.g. Audretsch & Feldman, 1996). Using the accessibility concept on the three geographical levels may reduce problems with spatial autocorrelation in the estimation procedures. When the accessibility variables are calculated they can be entered in a Cobb-Douglas type of knowledge production function

$$\ln K_i = \alpha + \sum_{D=1}^{k} \beta_D \ln A_i^D + \varepsilon_i \tag{2.5}$$

where K_i is the knowledge output in municipality *i*. β_D is the elasticity for accessibility A_i^D, where D denotes the specific opportunities. ε_i is a normally distributed error term. However, if data consists of a large number of zeroes, then equation (2.5) is not applicable. This is the case with local accessibility to R&D and therefore (2.5) is replaced by a straight forward additive linear model.

$$K_i = a + \sum_{D=1}^{k} b_D A_i^D + \varepsilon_i \tag{2.6}$$

In this paper the number of patent applications is used as output measure (K_i). Local, intra-regional and inter-regional accessibility to university and company R&D are the explanatory

[2] Johansson, Klaesson & Olsson (2003) use a preference function for an individual commuter. The preference function is assumed to have a random-choice form of the logit type. The parameters of the function are estimated by means of a multiple-constraint optimisation model.

variables. It could also be questioned if the Cobb-Douglas production function really is the best choice when university R&D and company R&D are the input factors. One can argue that these two factors are more like perfect substitutes to each other and therefore a more proper model is the linear one. Thus, to check if accessibility to university R&D and company R&D explain patent production in Swedish municipalities, the following model is estimated:

$$Pat_i = a + b_1 A_{iL}^{uR\&D} + b_2 A_{iR}^{uR\&D} + b_3 A_{iXR}^{uR\&D} + b_4 A_{iL}^{cR\&D} + b_5 A_{iR}^{cR\&D} + b_6 A_{iXR}^{cR\&D} + b_7 D_1 + b_8 D_2 + \varepsilon_i \tag{2.7}$$

In addition, two dummy variables, measuring the size of the population in the municipalities, are included in the model. These variables enable a comparison between municipalities with a large (D_1), medium sized (D_2) and a small population. The hypothesis is that municipalities with large populations have an economic activity that exceeds smaller municipalities' and this ought to affect patent production. In order to test for increasing or diminishing returns, quadratic terms of local accessibility to R&D are also used in the regressions. It could also be the case that co-variation between university and company R&D matters and therefore the term ($A_{iL}^{uRR\&D} \cdot A_{iL}^{cR\&D}$) is also included and tested for. The quadratic and the co-variation variables are also useful to identify potential scale effects, implying benefits with concentrated investments in R&D. This hypothesis of scale effects and concentrated investments is supported by Varga (1998a, 1998b & 2000). Varga (1998a, 1998b) studies the effect of agglomeration on regional academic technology transfers for US Metropolitan Areas. At the aggregate level of high technology industry, these studies demonstrate diverse regional impact of the same amount of research depending on the level of concentration of economic activities in the geographic area. In Varga (2001) a similar study is conducted on disaggregated level for different industries. The findings once again indicate that the same amount of university research results in differences in knowledge production depending on the concentration of economic activities in the metropolitan area.

3. DATA AND DESCRIPTIVE STATISTICS

The data concerning the number of patent applications are taken from The European Patent Office. Statistics Sweden collects data on performed R&D in universities and companies and National Road Administration in Sweden is the data source when it comes to commuting time between and within Swedish municipalities.

- The number of patents is a yearly average during the period of 1994-1999 in the municipalities of Sweden.
- Accessibility to university R&D is computed using the stock of university R&D measured in man years during the period 1993/94-1999 for Swedish municipalities.
- Accessibility to company R&D is computed using the stock of company R&D measured in man years during the period 1993-1999 for Swedish municipalities.

Data of the commuting time between and within municipalities in 1990 and 1998 is used for calculating the accessibility variables. The descriptive statistics of the variables in equation 2.7 are presented in table 3.1. The variable “Large population” equals one if population is greater than 100 000 and “Medium population” equals one if population is between 50 and 100 000.

Table 3.1: Descriptive statistics

Variable	# municip	# zeroes	Minimum	Maximum	Median	Mean	Std. Dev.
No of patents	288	22	0	838.67	1.83	10.38	53.83
Access to univ R&D, municip	288	194	0	3012.26	0	52.53	320.82
Access to univ R&D, intra-reg	288	86	0	1990.38	1.73	114.91	300.98
Access to univ R&D, inter-reg	288	0	0.0005	1022.65	22.64	96.49	164.15
Access to comp R&D, municip	288	144	0	643.80	0	8.34	46.34
Access to comp R&D, intra-reg	288	61	0	383.32	0.641	19.47	50.91
Access to comp R&D, inter-reg	288	0	0.0001	168.15	7.39	13.89	19.34
Large population (>100 000)	288	277	0	1	0	0.038	0.192
Medium popul. (50 to 100 000)	288	252	0	1	0	0.125	0.331

Note especially the large number of zeroes for some variables, which made a Cobb-Douglas production function inappropriate to use. Note also the deviation between the mean and the median for the dependent variable, which may affect the choice of estimation method. Table 3.2 shows the ten municipalities in Sweden with the highest patent production. Note that the concentration of patents, university and company R&D to the largest municipalities is higher than it is for population. University R&D and/or company R&D within a municipality seems to explain the patent production for most of these municipalities.

Table 3.2: Share of Sweden's patent production, population and R&D (rank)								
Municipality	Patents (1994-99)		Population (1999)		University R&D (man-year, 1993-99)		Company R&D (man-year 1993-99)	
Stockholm	28.1%	1	8.3%	1	19.1%	1	26.0%	1
Göteborg	9.1%	2	5.2%	2	17.1%	3	8.3%	3
Västerås	4.6%	3	1.4%	6	0.2%	24	4.6%	7
Södertälje	3.8%	4	0.9%	20	0.03%	48	7.7%	4
Lund	3.4%	5	1.1%	12	13.3%	4	7.3%	5
Uppsala	3.4%	6	2.1%	4	18.5%	2	4.8%	6
Sandviken	2.7%	7	0.4%	55	0.0%	63	0.9%	16
Solna	2.0%	8	0.6%	37	5.3%	7	0.8%	17
Järfälla	1.9%	9	0.7%	30	0.0%	92	0.7%	18
Malmö	1.8%	10	2.9%	3	1.7%	10	2.9%	8

4. ESTIMATION RESULTS

4.1 Model considerations and estimation methods

Before starting to interpret the regression results, an investigation must be conducted to check whether the OLS estimator is the most appropriate estimator of the parameters. The results of this investigation indicate that the data is collinear and also that the disturbances is heteroscedastic. The most obvious problem with multicollinearity is the large standard errors of the estimates. By using a ridge regression estimator the standard errors are reduced, but instead you get a biased estimator.[3] Another way of reducing the multicollinearity problem is of course to skip variables that are causing the problem. The positive side of this is that the remaining parameter estimates are unbiased if the deleted variables in the model are of no

[3] A difficulty with ridge regression is to choose a proper value of k in the ridge regression estimator,

$$b_r = [X'X + kD]^{-1} X'y ,$$

where D is a diagonal matrix containing the diagonal elements of $X'X$ (Greene, 1993).

significance. When the disturbances are heteroscedastic the OLS estimators are no longer efficient but the estimators retain their properties of unbiasedness and consistency. One way of dealing with heteroscedasticity is therefore to retain the OLS approach but make use of the appropriate expression for the variance-covariance matrix of the estimators.[4] White (1980) suggests that the diagonal elements in the variance-covariance matrix of the disturbances should be estimated by the square of the corresponding OLS residual, that is $Var(\varepsilon_i) = \sigma_i^2$ by e_i^2 for all *i*. A nice feature of White's correction is that the values will be correct whether or not you have heteroscedasticity.[5]

Another problem with the data is the rather skewed distribution of the dependent variable, with a few very large observations. This could affect both the model specification and the choice of estimation method. In table 4.1 the estimation results of five model specifications are listed. All regressions are done with the approach suggested by White (1980). I have also chosen to omit variables instead of using ridge regression.

The first regression (R1) is on the model specification according to equation 2.7. Unfortunately there is a serious multicollinearity problem, especially between the intra-regional (VIF = 11.3) and also to some extent between the inter-regional variables (VIF = 3.3), which could explain the negative signs of the parameter estimates for "Access to univ R&D, intra-reg" and "Access to comp R&D, inter-reg".[6] One feature of multicollinearity is that some variables may be overestimated (here "Access to comp R&D, intra-reg" and "Access to univ R&D, inter-reg") and others underestimated (here "Access to univ R&D, intra-reg" and "Access to comp R&D, inter-reg").

In R2 both "Access to univ R&D, intra-reg" and "Access to comp R&D, inter-reg" are deleted from the model. Any other combination of intra- and inter-regional variables would also accomplish a low degree of multicollinearity. I have chosen to keep the pair that has the

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[4] This gives
$Var(b) = (X'X)^{-1} X'VX(X'X)^{-1}$
where V is the variance-covariance matrix of the disturbances (Greene, 1993).

[5] The OLS estimator of the regression coefficients is unbiased even when the errors are heteroscedastic and then it follows that R is no more or less biased than usual as a result of heteroscedasticity. Thus, R^2 is not affected by the use of a heteroscedasticity-consistent standard error estimator (such as White's) (Greene, 1993).

[6] VIF = $1/(1-R^2)$, where R^2 is the goodness of fit measure for the auxillary regressions. For instance "Access to univ R&D, municip" on LHS and the other explanatory variables on RHS (Greene, 1993).

highest correlation with patent production, which also is resulting in the highest coefficient of determination.

Table 4.1 Estimation results of equation 2.7 and modifications of 2.7 (OLS with White's correction to avoid heteroscedasticity) (n=288, period 1994-1998)

	R1	R2	R3	R4	R5
(Constant)	**2.677** **(2.96)**	0.808 (1.40)	**1.179** **(2.24)**	**0.931** **(2.09)**	**0.876** **(2.34)**
Access to univ R&D, municip	0.011 (0.56)	0.026 (0.89)	-0.033 (-1.03)	-0.034 (-1.19)	-0.011 (-0.77)
Access to univ R&D, intra-reg	-0.075 (-1.77)	-	-	-	-
Access to univ R&D, inter-reg	0.029 (1.69)	0.011 (1.05)	0.005 (1.22)	-0.002 (-0.49)	0.0001 (0.03)
Access to comp R&D, municip	**1.030** **(4.56)**	**0.928** **(3.24)**	**0.549** **(2.49)**	**1.172** **(4.46)**	**1.432** **(7.13)**
Access to comp R&D, intra-reg	**0.420** **(1.97)**	0.016 (0.38)	**0.065** **(2.58)**	**0.075** **(2.73)**	**0.045** **(2.48)**
Access to comp R&D, inter-reg	-0.205 (-1.85)	-	-	-	-
(Access to univ R&D, municip)^2	-	-	-0.011 (-0.80)	-0.002 (-0.14)	0.007 (1.64)
(Access to comp R&D, municip)^2	-	-	-1.400 (-1.67)	**-3.928** **(-4.03)**	**-4.775** **(-6.40)**
(Access to univ R&D, municip)* (Access to comp R&D, municip)	-	-	**0.628** **(3.80)**	**0.420** **(2.00)**	-0.056 (-0.94)
Large population (>100 000)	5.037 (0.48)	5.360 (0.43)	**30.04** **(2.14)**	15.82 (1.37)	-0.774 (-0.14)
Medium population (50 to 100 000)	-9.432 (-1.59)	-9.070 (-1.45)	**5.122** **(2.37)**	2.287 (1.03)	2.331 (1.08)
Adjusted R^2	0.878	0.854	0.964	0.840	0.824

Significant parameter estimates in bold (95% confidence level). T-values in parenthesis.
Note that the squared variables and the co-variation variable are divided by 1000.
R1 = model according to Eq. (2.7)
R2 = without "Access to comp R&D, inter-reg" and "Access to comp R&D, inter-reg"
R3 = with squared variables and the co-variation variable
R4 = with squared variables and the co-variation variable, the largest observation of the dependent variable deleted (Stockholm)
R5 = with squared variables and the co-variation variable, the two largest observations of the dependent variable deleted (Stockholm and Göteborg)

In R3, R4 and R5 the squared local accessibilities and the co-variation variable are included in the model. In R3 all observations are used in the regression, but in R4 the largest (Stockholm) and in R5 the two largest observations (Stockholm and Göteborg) of the dependent variable are deleted. The reason for this is to check the robustness of the model specification and OLS. From Table 4.1 it is obvious that the fit of the OLS regression surface is influenced substantially by a small number of particularly large observations in the data. Although these observations are regarded as being valid and useful information, the OLS assign them undue significance. As a consequence the squared variables and the co-variation variable could be questioned in the specification.

According to Table 4.1 accessibility to university R&D has by it self no statistically significant effect on patent production. It only affects the number of patent produced in a municipality when company R&D is conducted in the same municipality. A comparison of R3, R4 and R5 reveals that this result relies heavily on two observations (Stockholm and Göteborg) (see R3 and R4). Local accessibility to company R&D has on the other hand a strong effect on patent production.

One way of dealing with highly influential outliers is to use quantile regression as an alternative to OLS. The quantile regression method has the important property that it is robust to distributional assumptions. The quantile regression estimator gives less weight to outliers of the dependent variable than OLS, which weakens the impact outliers might have on the results. OLS regression estimates the conditional mean of the dependent variable as a function of the explanatory variables. In contrast, quantile regression enables the estimation of any conditional quantile of the dependent variable as a function of the explanatory variables. Furthermore, by estimating the marginal effects of the explanatory variables for different quantiles, the heteroscedasticity problem is dealt with and a more complete description of the relationship between dependent and explanatory variables is achieved as well.

Originally, quantile regressions were suggested by Koenker and Basset (1978) as a robust regression technique alternative to OLS for the case when the errors are not normally distributed. The quantile regression model specifies the conditional quantile as a linear function of covariates. For the θ^{th} quantile, a common way to write the model (see, e.g.

Buchinsky, 1998) is

$$y_i = x_i'\beta_\theta + \varepsilon_{\theta i}, \qquad (4.1)$$

where β_θ is an unknown vector of regression parameters associated with the θ^{th} quantile, x_i is a vector of independent variables, y_i is the dependent variable and $\varepsilon_{\theta i}$ is an unknown error term.

The θ^{th} conditional quantile of y given x is $Q_\theta(y_i|x_i) = x_i'\beta_\theta$ and denotes the quantile of y_i, conditional on the regressor vector x_i. The only necessary assumption concerning $\varepsilon_{\theta i}$ is $Q_\theta(\varepsilon_{\theta i}|x_i) = 0$. The θ^{th} regression quantile ($0 < \theta < 1$) of y is the solution to the minimization of the sum of absolute deviations residuals

$$\min_\beta \frac{1}{n}\left(\sum_{i:y_i \geq x_i'\beta} |y_i - x_i'\beta|\theta + \sum_{i:y < x_i'\beta} |y_i - x_i'\beta|(1-\theta) \right) \tag{4.2}$$

Different quantiles are estimated by weighting the residuals differently. For the median regression, all residuals receive equal weight. However, when estimating the 75th percentile, negative residuals are weighted by 0.25 and positive residuals by 0.75. The criterion is minimized, when 75 percent of the residuals are negative. In contrast to OLS, equation (4.2) cannot be solved explicitly since the objective function is not differentiable at the origin, but it can be solved with linear programming (see e.g. Buchinsky 1998).

A method of Koenker and Bassett (1982) and Rogers (1993) is generally used to estimate the variance–covariance matrix of the coefficients and generate estimates of regression coefficient standard errors. However, this method tends to underestimate standard errors for data sets with heteroscedastic error distributions (Rogers 1992). It is therefore important to use some other method for estimating standard errors, such as bootstrap re-sampling techniques. In this paper, standard errors will be obtained by bootstrapping the entire vector of observations (Gould 1992). When the bootstrap resampling procedure is used, only estimates of standard error and significance levels are affected, with estimates of quantile regression coefficients remaining unchanged.[7]

Note that quantile regression is not the same as applying OLS to subsets of the data produced by dividing the complete data set into different quantiles of the dependent variable. This way of handling the problem would initiate a truncation on the dependent variable and a sample selection bias and will result in a procedure where not all of the data are being used for each

[7] The procedure is called the design matrix bootstrap, where pairs (x_i,y_i), $i = 1,\dots, n$ are drawn at random from the original observations with replacement. For each of these samples drawn, an estimator of the parameters vector, β_θ is recomputed. Repeating this procedure Z times yields a sample of Z parameter vectors whose sample covariance matrix constitutes a valid estimator of the covariance matrix of the original estimator. This procedure is automated in the Stata statistical package.

estimate. In contrast, for each quantile regression estimate all of the data are being used, some observations, however, get more weight than others.

Another problem with the data is the large proportions of zeroes of the dependent variable. Thus, the number of patent applications is a censored variable. The remedy is ordinarily to use a tobit specification, but the censored dependent variable does not at all influence the results for conditional quantiles above the censoring threshold (zero). Of course, this is not true for the conditional mean used in OLS. Powell (1984, 1986) has proposed an estimator that enables the estimation of all conditional quantiles when the data is censored. Powell's method is not used in the present paper because the problem only occurs for some quantiles on sector level and not for aggregated data.

The number of patents is an example of count data and then the choice is often the Poisson regression model or the negative binomial. In the case of bounded counts, when the response can be viewed as the number of successes out of a fixed number of trials, the standard distribution for regression modelling is the binomial. In the case of unbounded counts, Poisson regression models are standard. The number of produced patents in a municipality is unbounded (at least in theory), so in that sense Poisson is a better choice. But a problem with the Poisson regression model is its restrictiveness for count data. The fundamental problem is that the distribution is parameterised in terms of a single scalar parameter (the mean, μ) so that all moments of y are a function of μ. In contrast, the normal distribution has separate parameters for location (μ) and scale (σ^2). Even though there are developments of the standard Poisson regression models (see e.g. Cameron & Trevedi, 2001) that are less restrictive I am going to stick to the quantile regression model in this study, because of the appealing opportunity to investigate the distribution at different quantiles.[8]

The quantile regression technique has been widely used in the past decade in many areas of applied econometrics. Applications include investigations of earnings mobility (Eide &

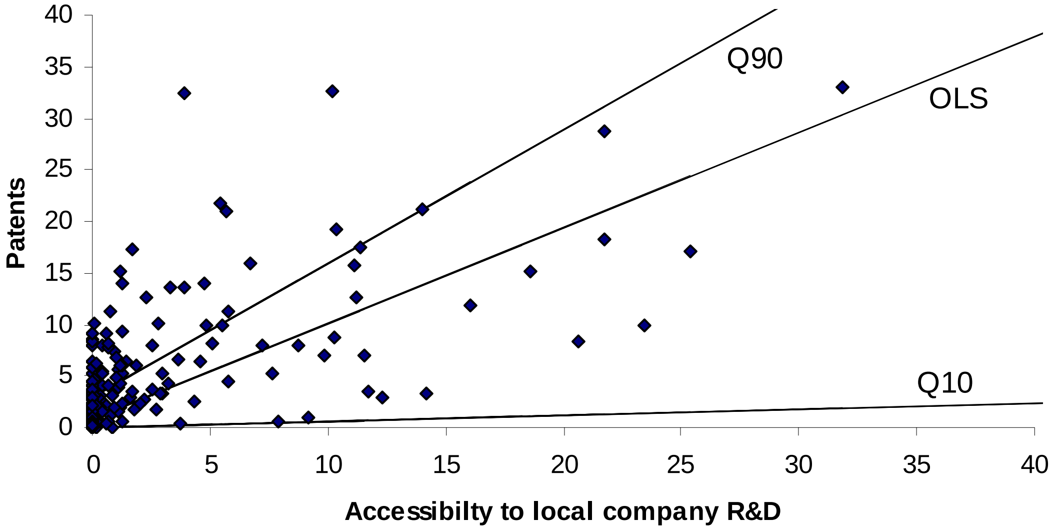
[8] According to Cameron & Trevedi (2001), the restrictiveness for count data manifests itself in many applications when a Poisson density predicts the probability of a zero count to be considerably less than is actually observed in the sample. This is termed the excess zeros problem, as there are more zeros in the data than the Poisson predicts. A second and more obvious way that the Poisson is deficient is that for count data the variance usually exceeds the mean (overdispersion), which will lead to deflated standard errors. The Poisson instead implies equality of variance and mean (equidispersion).

Showalter, 1999), educational attainment (Eide & Showalter 1998) and estimation of factors of high risk in finance (Chernozhukov & Umantsev, 2001). Appplications concerning regional innovation systems and knowledge production are not that easily found. One exception is Audretsch, Lehmann & Warning (2004) in their examination of locational choice as a firm strategy to access knowledge spillovers from universities, using a data set of young high-technology start-ups in Germany.

4.2 Aggregated results with quantile regression

To illustrate the heteroscedasticity problem and the advantage with quantile regression versus OLS, Figure 4.1 is presented. The figure pictures observations on aggregated level as dots, which clearly reveals the increasing conditional variance of y (patents) for increasing values of x (accessibility to local company R&D). The two estimated quantile regressions and the OLS regression perfectly mirror the heteroscedastic structure of the error term. With a non-heteroscedastic error structure the hyperplanes would be parallel.

Figure 4.1: Q10, Q90 and OLS illustrating the heteroscedasticity problem



In Table 4.2 the quantile regression results on aggregated level for Q10, Q25, Q50, Q75 and Q90 are presented. OLS results are also reported for comparison. The interpretation of the quantile regression model is analogous to the least square, now the coefficient answers the question of "how does the θ^{th} conditional quantile of y_i react to a (ceteris paribus) change of x_i".

In the interpretation and the discussion of the parameter estimates I am going to use increases of the accessibility by 10. The accessibility can be improved either by increasing the R&D effort or by reducing the commuting time. If the commuting time within a municipality is 15 minutes, then the accessibility increase by 10 can be accomplished if university or company R&D increases by 13.5 man-years. Under the assumption that university or company R&D in a municipality is 100 man-years and the commuting time is 15 minutes, the commuting time must be reduced to 8.7 minutes in order to get the required accessibility increase.

All quantile regressions in Table 4.2 are evaluated at quantiles above the censoring threshold (zero), thus the results are not affected by the zeroes. According to Table 4.2 accessibility to university R&D has no statistically significant effect on patent production. Accessibilty to company R&D plays, on the other hand, an important roll. The parameter estimates of "(Access to comp R&D, municip)" raises from 0.059 (not statistically significant) for Q10 to 1.297 for Q90. Thus, an accessibility increase in a municipality having a patent production corresponding to a low quantile (Q10) does not have a proved effect on patent production. For Q90 the parameter estimate is 1.297, indicating almost 13 more patents from a local accessibility increase of 10. The OLS estimate of "(Access to comp R&D, municip)" obviously misses these differentiated effects because it is only evaluated at a single point, the conditional mean.

Table 4.2 Quantile regression, with bootstrap to avoid heteroscedasticity (3000 replications) and OLS (White). (n=288, period 1994-1998)

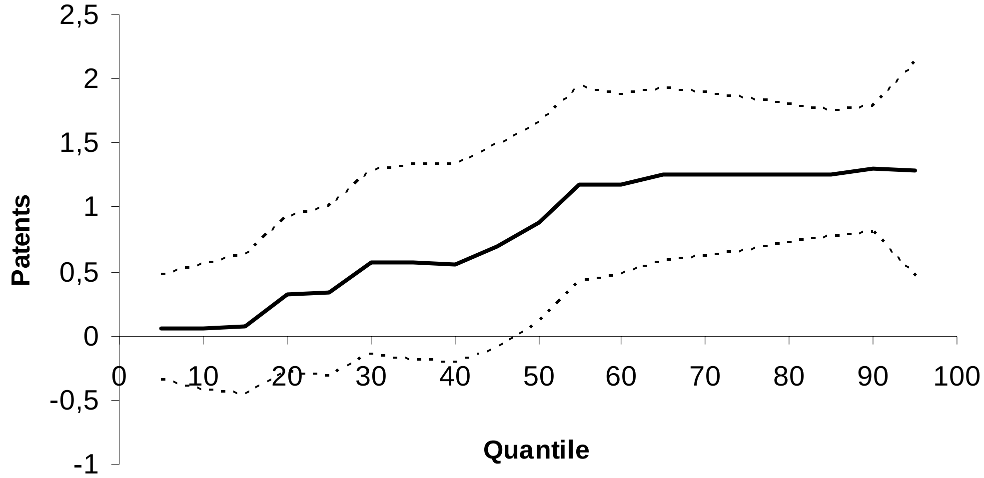
	Q10	Q25	Q50	Q75	Q90	OLS, W
Access to univ R&D, municip	0.032 (1.66)	0.020 (0.88)	-0.001 (-0.03)	0.008 (0.37)	-0.003 (-0.14)	0.026 (0.89)
Access to univ R&D, inter-reg	0.001 (0.38)	0.001 (0.48)	0.001 (0.68)	0.001 (0.51)	0.005 (0.77)	0.011 (1.05)
Access to comp R&D, municip	0.059 (0.24)	0.341 (1.01)	**0.881** **(2.24)**	**1.257** **(4.22)**	**1.297** **(4.69)**	**0.928** **(3.24)**
Access to comp R&D, intra-reg	**0.026** **(2.06)**	**0.029** **(3.54)**	**0.047** **(3.72)**	**0.059** **(2.35)**	**0.153** **(2.95)**	0.016 (0.38)
Large population (>100 000)	5.625 (0.32)	4.726 (0.39)	3.325 (0.25)	-0.397 (-0.02)	1.987 (0.13)	5.364 (0.43)
Medium population (50 to 100 000)	1.184 (0.93)	1.181 (1.12)	1.804 (1.08)	3.638 (1.34)	**10.56** **(2.08)**	-9.073 (-1.45)
Pseudo R^2, Adj R^2	0.169	0.293	0.466	0.704	0.826	0.857
Quantile value, mean value	0.167	0.5	1.833	5.917	15.167	10.381

Significant parameter estimates in bold (95% confidence level). T-values in parenthesis

Besides being the dominating variable on local level, company R&D has the advantage of being useful also for municipalities within the own functional region. According to Table 4.1 the parameter estimates of “Access to comp R&D, intra-reg” are between 0.026 and 0.153. Thus an accessibility increase of 10 yields a raise of 0.26 patents for municipalities close to Q10 and 1.53 patents for municipalities producing patents according to Q90. Note that the OLS regression does not at all pick up these effects. Compared to the local variable, the magnitudes of the marginal effects are smaller for the intra-regional variable. This is in line with theory, the importance decreases with (time-) distance. In evaluating the results, it is crucial to realize that the reported pseudo R^2 is not directly comparable to the traditional R^2. Unlike R^2 which is a global measure of goodness of fit, pseudo R^2 measures the relative success of the corresponding quantile regression model and can be interpreted as a local goodness of fit value for a particular quantile. Pseudo R^2 only approaches one when each observation is predicted as a conditional quantile.

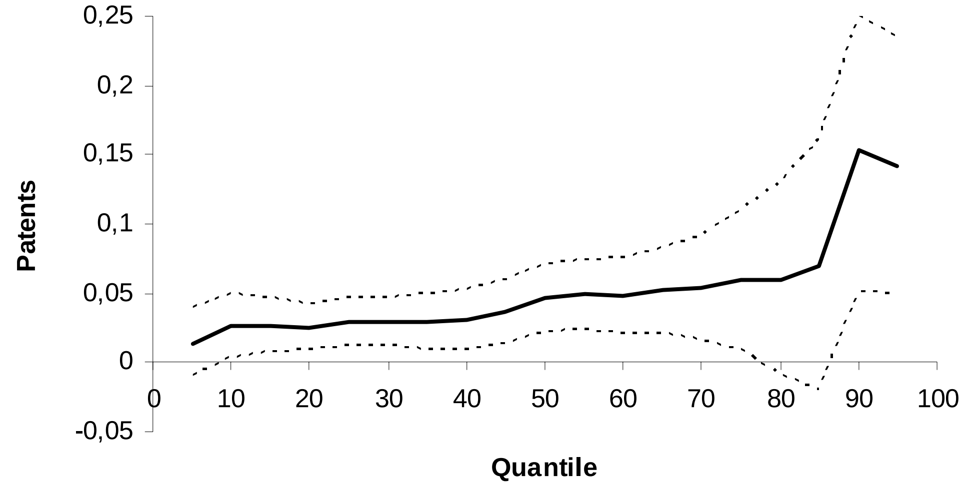
A more comprehensive way than Table 4.2 is to present the results graphically. Figure 4.2 displays the estimated marginal effects for 19 quantiles (Q5, Q10, … , Q95). The 95% confidence bands from bootstrapped estimation errors are also shown as dotted lines. Figure 4.3 shows the corresponding marginal effects of “(Access to comp R&D, intra-reg)”.

Figure 4.2: Marginal effects of "Accessibility to local company R&D", with confidence limits (95%)



From Figure 4.2 it is possible to see that accessibility to local company R&D has a statistically significant positive effect on patent production for municipalities corresponding to quantiles higher than the median. The marginal effects of accessibility to local company R&D is also slightly increasing for the upper tail of the conditional distribution, indicating municipalities being more productive having a high patent production.

Figure 4.3: Marginal effects of "Accesibilty to intra-regional company R&D", with confidence limits (95%)



According to Figure 4.3 accessibility to intra-regional company R&D has a positive and statistically significant effect on patents produced for almost all quantiles. The only ones where the estimates are not significant are Q5, Q80 and Q85. The insignificances for Q80 and Q85 could also explain why the OLS estimate of the variable is not significant (see Table 4.2). The patent mean is 10.381 and the patent quantile Q85 is 9.66. This also demonstrates the weakness of the OLS regression estimating the conditional mean of the dependent variable as a function of the explanatory variables. Municipalities having a patent production in the upper quantiles also experience a much larger positive effect from an increased accessibility within the own functional region.

Before continuing the analysis on aggregated level, a short sum up might be in order.

1. Accessibility to university R&D has no proved effect on patent production in a municipality.
2. Accessibility to R&D conducted in companies within the own municipality has a positive effect on patent production. The effects are increasing and statistically significant for municipalities with a patent production above the median.

3. Accessibility to R&D conducted in companies within the own functional region has a positive statistically significant effect for almost all quantiles. The largest impact is for municipalities in the upper region of the conditional distribution.
4. Accessibility on inter-regional level does not matter.

The consensus in the literature is that both university and company R&D have positive effects on patent production (see Anselin et al. 1997 and Acs et al 2002, among others). Acs et al (2002) use data based on 125 US Metropolitan Areas (MSAs) in a knowledge production framework with patents and new product innovations as dependent variables. Their empirical findings show a clear dominance of company R&D over university research. However, this dominance is not so accentuated for new product innovations. This pattern is also replicated for research spillovers from surrounding areas; university R&D being more important for new product innovations and company R&D being the dominant factor for patents. The empirical findings in this paper do not support the results in Acs et al (2002). While Acs et al. (2002) find statistically significant effects of local university research for the MSAs in US, local accessibility to university R&D for Swedish municipalities is of no importance. It could however matter in the largest municipalities. Remember what happened when Stockholm and Göteborg were deleted in the OLS regressions in Table 4.1. With these municipalities included, accessibility to local university R&D was of significance if company R&D was conducted in the municipalities. When Stockholm and Göteborg were excluded from the data set the co-variation variable was not statistically significant. Varga (1998a, 1998b, 2000 & 2001) is also of the opinion that a 'critical mass' of economic agglomeration, which mainly can be found in big municipalities, is needed in order to expect substantial effects of university research on regional innovation. He establishes the size of economic agglomeration by the size of company and university R&D, population and industry employment.

4.3 Elasticities on aggregated level

Where in Sweden does a percentage increase of the accessibility have the largest percentage effect on patent production? The 10 municipalities with the largest accessibility elasticities of "Access to comp R&D, municip" and "Access to comp R&D, intra-reg" (statistically significant variables) are listed in Table 4.3. The table also shows the predicted values and the residuals for the actual municipalities. The elasticities show the percentage increase in patent production if the municipalities perform according to their prerequisites, i.e. the predicted values are used in the elasticity calculations.[9,10]

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[9] Formula for the elasticity calculations: $\varepsilon = \frac{\partial(Pat_i)}{\partial A_i} \cdot \frac{A_i}{Pat_{i,pred}}$

[10] The sum of the residuals from a quantile regression is not zero. I have chosen to use the regression equation of the median (Q50), which gives a sum of the residuals closest to zero, in the elasticity calculations.

Table 4.3: Accessibility elasticities, predicted values and residuals. Top ten municipalities. (period 1994-1998)							
Local accessibility to company R&D				Intra-regional accessibility to company R&D			
Municipality	Elasticity	Predicted	Residual	Municipality	Elasticity	Predicted	Residual
Stockholm	0.995	570.4	268.2	Lomma	0.906	5.5	3.7
Lund	0.991	152.3	-52.0	Värmdö	0.896	8.2	0.3
Uppsala	0.983	102.5	0.0	Salem	0.890	7.4	-6.4
Södertälje	0.967	173.9	-61.7	Partille	0.876	10.0	-2.2
Mölndal	0.965	256.6	-232.6	Staffanstorp	0.872	5.1	3.2
Västerås	0.958	105.0	31.5	Ekerö	0.851	5.9	-2.4
Sandviken	0.955	18.2	62.3	Kungälv	0.843	5.2	0.9
Göteborg	0.943	177.7	94.8	Sundbyberg	0.829	11.9	-4.6
Karlskoga	0.937	10.7	6.8	Nacka	0.821	21.9	-7.9
Linköping	0.936	50.7	-12.3	Svedala	0.779	2.9	-0.3

Stockholm has the highest local elasticity. A 10% increase of the local accessibility to company R&D in Stockholm raises the number of patents with approximately 9.95 %. For Uppsala the residual is zero, which means that the predicted value of patents is equal to the actual value. For other municipalities, like Stockholm and Mölndal, the residuals have large positive or negative values. When this happens the interpretation of the elasticity must be especially careful. Table 4.3 shows, as mentioned above, the percentage increase in patent production if the municipalities perform according to their prerequisites. But if the municipalities continue to perform as in the period when data was collected the elasticities may over- or underestimate the impact on patent production.

The top ten elatsticities of the intra-regional accessibility to company R&D are all municipalities in functional regions where Stockholm, Göteborg and Malmö/Lund are situated. Lomma, a municipality in the Malmö/Lund region, has the largest elasticity. A 10% increase of the intra-regional accessibility to company R&D raises the number of patents by approximately 9%.

So where do R&D investments have the largest effects on patent production? According to the elasticities presented in Table 4.3, R&D investments would be preferred in companies situated in Stockholm, Göteborg and Lund. Because then the investments would not only gain the municipalities themselves, but also municipalities in their functional regions.

4.4 Population effects

Does the surrounding economic activity affect the municipalities' patent production? To check for this, the explanatory variables in Table 4.2 are supplemented with local accessibility to population. Population is used as a proxy for the economic activity in a municipality. Other variables could be number in employment or wage sum. To avoid problems with multicollinearity the variables intra-regional and inter-regional accessibility to population are not included. The dummy variables are deleted for the same reason. It could be argued that the size of the population in a municipality only has an indirect effect on patent production. It is of course the case that most of the R&D is conducted at universities and companies that most often are located in larger municipalities. But the size of a population is not an input in an innovation process. Thus, the population variable is only used as a control. The results are presented in table 4.4. A comparison with Table 4.2 reveals that the population variable crowds to some extent out the effects of the R&D variables. Local accessibility to company R&D is for instance no longer statistically significant for municipalities corresponding to the median. The pseudo R^2 and the adjusted R^2 are slightly increased.

Table 4.4: Quantile regression, with bootstrap to avoid heteroscedasticity (3000 replications) and OLS (White). (n=288, period 1994-1998)

	Q10	Q25	Q50	Q75	Q90	OLS, W
Access to univ R&D, municip	0.030 (1.85)	0.017 (0.86)	0.002 (0.09)	-0.007 (-0.32)	-0.016 -0.85	- 0.0005 (-0.04)
Access to univ R&D, inter-reg	0.0007 (0.29)	- .00009 (-0.04)	- 0.0006 (-0.40)	-0.001 (-0.69)	0.004 (0.50)	0.0009 (0.15)
Access to comp R&D, municip	0.061 (0.27)	0.342 (1.14)	0.686 (1.77)	**1.180 (3.99)**	**1.161 (4.80)**	**0.603 (2.30)**
Access to comp R&D, intra-reg	0.013 (1.26)	**0.021 (2.24)**	**0.031 (2.36)**	0.048 (1.76)	**0.133 (2.76)**	-0.036 (-0.78)
Access to population, municip	**0.063 (2.75)**	**0.094 (2.94)**	**0.113 (2.81)**	**0.154 (3.56)**	**0.205 (2.10)**	**0.532 (2.81)**
Pseudo R^2, Adjusted R^2	0.211	0.337	0.502	0.725	0.836	0.906
Quantile value, mean value	0.167	0.5	1.833	5.917	15.167	10.381

Significant parameter estimates in bold (95% confidence level). T-values in parenthesis
Note that the variable "Accessibility to population" is computed using population in thousands.

4.5 Spatial autocorrelation

Besides checking whether OLS is the best estimator or not it is also recommended to check for spatial autocorrelation. Spatial autocorrelation is a problem for regression models when the error terms show a spatial pattern in which municipalities close together are more similar than municipalities that are far apart. One way of measuring the correlation among the neighbouring municipalities is by using the spatial autocorrelation statistic Moran's *I*. Computation of Moran's I is achieved by division of the spatial co-variation by the total variation. Resultant values are in the range from -1 to 1. The general formula for computing Moran's *I* is:

$$I = \frac{N\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij} z_i z_j}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij} \sum_{i=1}^{N} z_i^2} \qquad (4.3)$$

Where z's are deviations, i.e. $z_i = y_i - y_{mean} = y_i - y_{i\,pred} = e_i$, N = number of municipalities. I have tested the spatial error dependence with two weight matrices, W1 and W2. In W1 the cells are $w_{ij} = 1$ if i and j are municipalities within the same functional region, 0 otherwise. The weight matrix is also row normalised. W2 is an inverse distance matrix with $w_{ij} = 1/d_{ij}$ if municiplity i and j are less than 30 minutes apart (travelling by car), i.e. $d_{ij} < 30$ minutes, 0 otherwise. In Table 4.5 the results from the calculations on OLS and quantile regression residuals (median, Q50) are presented.

Table 4.5: Moran's I results on OLS and Q50 residuals (n=288, period 1994-1998)

	OLS		Q50	
	W1	W2	W1	W2
Moran's I	0.0014	-0.0887	-0.0151	-0.5590
E(I)	-0.00348	-0.00348	-0.00348	-0.00348
SD(I)	0.0872	0.3298	0.0872	0.3298
Z(I)	0.0565	-0.2585	-0.1329	-1.6843

The Moran's *I* is significant and positive when the observed value of locations within a certain distance tend to be similar, negative when they tend to be dissimilar, and approximately zero when the observed values are arranged randomly and independently over space. The test statistic *Z(I)* < 1.96 for the 95% confidence level. Thus, there is no evidence for spatial autocorrelation.

4.6 Estimations for different industrial sectors

The analyses on sector level are conducted for the three sectors with the highest yearly average of patents in the period 1994-1999. The multicollinerarity problem is less severe on sector level, but when two variables are collinear I have chosen to keep the variable measuring the accessibility to company R&D. The number of patents in sector *j* is regressed against the accessibility measures for university R&D on aggregated level and the three accessibility measures for company R&D in sector *j*. The proportion of municipalities with no produced patents during the investigated period is of course increased on sector level. Thus the censoring problem is more pronounced and as a consequence the interpretations when the quantile value is zero must be taken with care.

Refined petroleum products and chemical products

A comparison between OLS and quantile regression parameter estimates in Table 4.6 shows that OLS misses the effect of local accessibility to company R&D for the upper quantiles. An accessibility increase of 10 yields approximately three more patents for municipalities with a patent production corresponding to Q75 and Q90. There are also beneficial knowledge flows between municipalities within a functional region. Company R&D spills to some extent over to other municipalities in the functional region. If the intra-regional accessibility to company R&D increases by 10, then a municipality will produce 0.25 to 0.91 more patents depending on which quantile is evaluated. The main difference between this sector and the aggregated level is that university R&D seems to matter. Municipalities having a patent production according to the median (and Q25) benefit from increased accessibility to local university R&D.

Table 4.6: Manufacture of refined petroleum products and chemical products (n=288, period 1994-1998)						
	Q10	Q25	Q50	Q75	Q90	OLS, W
Access to univ R&D, municip	ns	0.011 (2.52)	0.011 (2.73)	ns	ns	0.009 (2.64)
Access to comp R&D, municip	ns	ns	ns	0.342 (2.45)	0.337 (2.32)	ns
Access to comp R&D, intra-reg	ns	ns	0.025 (2.68)	0.061 (3.80)	0.091 (3.19)	0.037 (2.69)
Access to comp R&D, inter-reg	ns	ns	ns	ns	ns	ns
Large population (>100 000)	ns	ns	ns	ns	8.847 (2.10)	ns
Medium population (50 to 100 000)	ns	ns	ns	ns	0.629 (2.13)	ns
Pseudo R^2, Adjusted R^2	0.2105	0.3164	0.4725	0.6661	0.8092	0.7360
Quantile value, mean value	0	0	0.026	0.415	1.511	1.326

Only statistically significant parameter estimates presented (95% confidence level). T-values in parenthesis.
ns = Not statistically significant (95% confidence level).

Machinery and equipment

Increasing the R&D effort in companies has no positive local effect on the number of patents produced in a municipality. Other municipalities in the same functional region can, however, make use of this increase (see Table 4.7). The return from an intra-regional accessibility increase by 10 is approximately five patents for Q25, Q50 and Q75. Municipalities in other regions can also in some cases (Q75) benefit. The inter-regional effect of accessibility to company R&D is 0.346, indicating 3.5 more patents from an accessibility increase of 10. Increasing local accessibility to university is an effective strategy in municipalities corresponding to Q90. The OLS regression does not capture any effect in this sector.

Table 4.7: Manufacture of machinery and equipment (n=288, period 1994-1998)						
	Q10	Q25	Q50	Q75	Q90	OLS, W
Access to univ R&D, municip	ns	ns	ns	ns	0.067 (2.02)	ns
Access to comp R&D, municip	ns	ns	ns	ns	ns	ns
Access to comp R&D, intra-reg	ns	0.428 (2.88)	0.449 (4.71)	0.565 (3.33)	ns	ns
Access to comp R&D, inter-reg	ns	ns	ns	0.346 (2.02)	ns	ns
Large population (>100 000)	ns	ns	ns	ns	ns	ns
Medium population (50 to 100 000)	0.789 (2.40)	1.763 (3.27)	2.266 (3.20)	ns	ns	ns
Pseudo R^2, Adjusted R^2	0.1019	0.1375	0.2040	0.3076	0.7360	0.5173
Quantile value, mean value	0.02	0.198	0.717	1.969	4.925	3.209

Only statistically significant parameter estimates presented (95% confidence level). T-values in parenthesis.
ns = Not statistically significant (95% confidence level).

Office machinery, electrical machinery and communication equipment

The goodness of fit measures show higher values in this sector than on aggregated level (see Table 4.8 and 4.2).

Table 4.8: Manufacture of office machinery, electrical machinery and communication equipment (n=288, period 1994-1998)						
	Q10	Q25	Q50	Q75	Q90	OLS, W
Access to univ R&D, municip	ns	ns	ns	ns	ns	ns
Access to univ R&D, inter-reg	ns	ns	ns	ns	ns	ns
Access to comp R&D, municip	ns	ns	2.048 (3.13)	1.958 (3.09)	1.959 (3.19)	1.840 (9.49)
Access to comp R&D, intra-reg	ns	0.019 (2.02)	0.042 (3.22)	0.039 (2.65)	0.055 (2.72)	ns
Access to comp R&D, inter-reg	ns	ns	ns	ns	ns	ns
Large population (>100 000)	ns	ns	ns	ns	ns	ns
Medium population (50 to 100 000)	ns	ns	0.545 (1.96)	0.830 (2.69)	ns	ns
Pseudo R^2, Adjusted R^2	0.2853	0.4208	0.5589	0.7905	0.8999	0.9568
Quantile value, mean value	0	0.007	0.127	0.534	1.74	2.409

Only statistically significant parameter estimates presented (95% confidence level). T-values in parenthesis.

ns = Not statistically significant (95% confidence level).

The marginal effect of local accessibility to company R&D is significant and approximately constant for the median and quantiles above the median. An accessibility increase of 10 is resulting in approximately 20 more patents. The parameter estimates of intra-regional accessibility to R&D are positive and statistically significant for all quantiles except for Q10. Once again OLS overlooks the intra-regional effect.

5. CONCLUSIONS

My effort in this paper has been to investigate to what extent accessibility to university R&D and company R&D can explain patent production in Swedish municipalities. When dealing with innovation indicators on regional/municipal level there are often statistical problems with spatial autocorrelation and heteroscedasticity. The data also often contains a few very influential observations (outliers). I have used the test statistic Moran's *I* to check for spatial autocorrelation. If it is the use of the accessibility concept, the chosen model or lack of spatial dependence in the data that solve these problems in my study are left for a separate paper. The heteroscedasticity can be solved by using White's robust standard errors. Thus, regarding spatial autocorrelation and heteroscedasticity it is alright to use OLS. The remaining problem is the outliers, which requires another estimation method. I have used quantile regression with bootstrapped standard errors. Besides handling the outlier problem, there are several advantages with this method. A heteroescedastic error structure is not a problem when the distribution of the dependent variable is investigated at different conditional quantiles as long as the standard errors are bootstrapped. There are many examples and applications in the literature, where quantile regression has been used. Despite its appropriateness when dealing with regional innovation systems, there are only a few examples (to my knowledge) where quantile regression has been applied.

The results from the quantile regressions on aggregated level indicate that investments in company R&D have a positive impact on the patenting capacity in a municipality. There is no evidence that university R&D affects patent production. It could be the case that university R&D affects the innovative capacity indirectly through its impact on company R&D. The output of university R&D is often published articles and papers, books etc. and not patents directly. To clarify the relation between university and company R&D a simultaneous approach is required. Thus, a further extension of the analysis conducted here is necessary. For this reason it may be too early to form a policy that favour R&D investments in companies, although the results in this paper point in that direction.

Furthermore, I have shown in accordance with the literature that spatial proximity matters for establishing a productive link between R&D efforts and the number of patent applications. By using the accessibility concept on three geographical levels it is clear that local accessibility dominates the other two. The local effects are statistically significant on aggregated level for municipalities with a patent production above the median. The result also indicate that local accessibility to company R&D is most effective in the upper tail of the patent distribution for Swedish municipalities, i.e. investments in R&D have a greater impact on patent production when they are made in municipalities with high patenting activity. Knowledge flows within a functional region, i.e. intra-regional accessibility to R&D, are also of some importance. The sizes of these positive effects are smaller, but the effects are on the other hand statistically significant for almost all quantiles. The population size of a municipality plays also a roll explaining patent production. Big municipalities in Sweden with large populations produce, ceteris paribus, more patents than smaller ones. The quantile regression results show that patent production in many municipalities is rather insensitive to changes in accessibility to R&D, i.e. it requires a lot of R&D and/or infrastructural improvements to accomplish patent applications. Nevertheless, there are municipalities that perform better than others and concentrated efforts could be worth while. Even so, an interesting issue to stress is why certain municipalities perform better/worse compared to their prerequisites.

Regarding the three analysed industrial sectors the main concluding results are to some extent diverse. Accessibility to local university R&D seems to be more important in the sector "Manufacture of refined petroleum products and chemical products" than on aggregated level. Intra-regional accessibility to company R&D is the dominating variable for patent production in "Manufacture of machinery and equipment". For the industrial sector, "Manufacture of office machinery, electrical machinery and communication equipment" the link between company R&D efforts and patents produced is very strong. The final output of an innovation process is not patent applications. Together with R&D efforts they are costs in the innovation process. Benefits from the process are measured when patents are commercialised and contributes to economic growth. Thus, further investigations to what extent patent applications contribute to economic growth are required.

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