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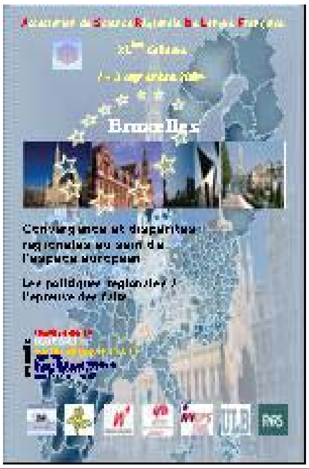

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INDUSTRIAL COMPOSITION AND INNOVATION

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Résumé :
Whether diversity or specialisation of economic activity better promotes economic growth has received a great deal of attention in the economics literature. The purpose of this paper is to assess the effect of the composition of a regions' underlying industrial structure on innovation. The analysis is based on a model that integrates different kinds of diversity measures aiming at capturing potential Jacobs externalities, a production specialisation measure aiming at capturing Marshall (1890)-Arrow (1962)-Romer (1986) (MAR) externalities and region as well as sector specific variables. Tested onto an extended sample of 153 European regions and 16 manufacturing sectors the estimates of the model suggest that both kinds of externalities positively and significantly influence innovation of European regions although the influence of Jacobs externalities is more important in the context of "high density" regions as well as for high tech sectors.

Mots clés : externalities, knowledge spillovers, specialisation, diversity, innovation

Classification : R00, O18, O31

INDUSTRIAL COMPOSITION AND INNOVATION

INTRODUCTION

According to the endogenous growth literature (Romer 1986, 1990; Lucas 1988; Krugman 1991), knowledge spillovers and externalities are important sources of innovation. These externalities induce increasing returns to scale within a geographically bounded region and thus higher rates of growth.

The empirical research regarding locally bounded knowledge spillovers and externalities can be roughly classified into two broad streams. A first stream investigates knowledge spillovers arising from R&D activities and seeks to understand whether and to what extent feedback and looping relations among the institutional sectors involved along the innovation process influence local knowledge creation. Jaffe (1989), Jaffe et al. (1993), Feldman (1994), Feldman and Florida (1994), Anselin et al. (1997), Varga (1998) and Greunz (2002, 2003) among others, find evidence for dynamic externalities between geographically close university and business R&D activities and highlight the importance of geographical proximity for the emergence of knowledge spillovers. A second stream of empirical literature which was "initiated" by the seminal contribution of Glaeser et al. (1992) examines whether dynamic externalities are shaped by the composition of economic activity within a given particular geographical area. A distinction between localisation and urbanisation economies is traditionally adopted (Lösch, 1954) in order to assess their respective influence on local development. A the moment the role of localisation economies associated to externalities arising from specialisation and urbanisation economies associated to externalities arising from diversity is not yet resolved as revealed by a relatively abundant literature with contrasting outcomes.

This paper aims at casting some modest light into the controversy between the importance of specialisation and diversity. A major motivation for adding yet another paper to this debate is the observation that apart from some few exceptions, a common shortcoming of the empirical literature in this field is the lack of a specific variable to measure innovative activity which makes the assessment of the role of technological externalities rather indirect (Usai and Paci, 1999, 2000). It can even be claimed that given the lack of innovative activity measures, these approaches are inappropriate to conclude on the role of specialisation or diversity (Massard and Riou, 2002). The model that we wish to test addresses the above mentioned shortcoming in assessing the extent to which externalities arising from specialisation and / or diversity influence the innovation of a given industrial sector in a given European region. Such an investigation has never been undertaken at the European regional level and should permit to answer three main questions. First, do localisation and / or urbanisation economies influence the knowledge creation of European NUTS II regions? Second, do externalities arising from specialisation and / or diversity differ in the context of "metropolitan" areas for which an increased speed of knowledge and idea flows is assumed given the spatial concentration of individuals? Third, does the influence of these externalities on knowledge creation differ for manufacturing sectors with different technological intensities? The answers to these questions have undeniably important implications with regard to science and technology (S&T) policy making.

The rest of the paper is organised as follows. Section one gives an overview of the related empirical literature and highlights some major shortcomings. After the definition of the different measures used in this study aimed at characterising the industrial structure of European regions, section two explains the model that we wish to investigate. Section three presents and explains the econometric estimates and highlights some striking observations. Finally, the conclusion summarises the most important findings, deduces policy implications and suggests future research topics.

I. THE IMPACT OF SPECIALISATION AND DIVERSITY EXTERNALITIES ON INNOVATION AND GROWTH

The now standard classification of agglomeration economies go back to Hoover (1937) who suggests a distinction between localisation economies associated to specialisation and urbanisation economies associated to diversity. While early studies focused on static externalities, Glaeser et al. (1992) was the first to go a step further in analysing the broader implications of dynamic externalities in terms of industrial development over time. In essence, Glaeser et al. (1992) consider two different types of externalities: Marshall (1890)-Arrow (1962)-Romer (1986) (MAR) externalities and Jacobs (1969) externalities[1].

MAR externalities associated to industrial specialisation suggest that an increased concentration of a particular industry within a specific geographic region facilitates knowledge spillovers across firms. Marshall (1890) observes that industries cluster geographically for three main reasons: (1) a thick market for specialised skills, (2) pecuniary externalities through forward and backward linkages and (3) technological or knowledge spillovers among firms. Arrow (1962) presents an early formulation of the economic implications of learning-by-doing which, in a more rigorous manner, is refined and extended in the contribution of Romer (1986). Given their complementary vision that spatial polarisation of firms active in similar industries induces externalities that can only be internalised by the firms belonging to the cluster, Glaeser et al. (1992) have grouped them together under the heading MAR externalities.

In opposite to MAR, Jacobs (1969) regards inter-industry spillovers as the most important source of new knowledge creation. She argues that the agglomeration of different industries within an urban region fosters innovation due to the diversity of available local knowledge sources. Only in a context of industrial diversity rather than industrial specialisation, does the exchange of complementary knowledge lead to cross fertilisation of ideas and new knowledge combinations which in turn favour innovation and economic growth[2].

In their contribution, Glaeser et al. (1992) investigate the six largest industries in 170 US cities between 1956 and 1987 and find evidence that diversity fosters industry employment growth but not specialisation. They conclude that important knowledge spillovers might occur between rather than within industries and thus accredit Jacobs externalities as driving force of growth. However, as briefly mentioned by the authors themselves and highlight more

[1] Glaeser et al. (1992) also refer to Porter (1990) (P) externalities which, like MAR externalities, are assumed to emerge when firms active in a same industry cluster geographically. The difference between MAR and P externalities concerns the role of competition. While for the former, the appropriability problem of returns associated to R&D efforts justifies monopoly, the latter argues that only competition can provide the necessary incitements for sustained innovation.

[2] In the debate between local monopoly and competition, Jacobs believes as Porter that local monopoly harms innovation. This debate is not addressed in this paper given the inadequacy of the usually used measure of local competition and the unavailability of data at the European regional level enabling to construct a better alternative.

explicitly by Duranton and Puga (2000), this finding could in part be a reflection of the recent relative decline in traditional manufacturing employment in the US pointing to the necessity to distinguish amongst sectors and account for the product-life-cycle.

Henderson et al. (1995) address the issue of the product-life-cycle in their contribution studying the growth of industrial employment of 242 US cities. They distinguish between traditional, mature industries (machinery, electrical machinery, primary metals, transportation and instruments) and new high-tech industries (electronic components, medical equipment and computers) and control, in contrast to Glaeser et al. (1992), for persistence of own industry employment and conditions on the output and labour market. While for their sample of mature industries the authors find strong evidence of MAR externalities but little evidence of Jacobs externalities, for new high-tech industries, both, Jacobs and MAR externalities matter. The authors argue that Jacobs externalities are important for attracting new industries, MAR externalities are important for retaining them. In a more recent contribution, Henderson (1997) shows that larger cities tend to be more diversified, a stylised fact which is also put forward by Duranton and Puga (2000). More precisely, in distinguishing between medium-sized cities (50,000 – 500,000 inhabitants) and large cities (over 500,000 inhabitants) Henderson (1997) shows that large cities are not only more diversified but also more specialised in new industries such as electronic components and instruments compared to medium-size cities.

Combes (2000) in his study of employment growth of 341 French local areas extends the analysis to service sectors. He finds evidence that the impact of the local economic structure differs in industry and services. While industry employment is negatively influenced by both industrial specialisation and diversity, service employment significantly benefits form diversity.

Interestingly, all of the aforementioned studies, which represent only an extract from the vast empirical research in this field[3], clearly rely on knowledge-based theories of endogenous growth assuming that the density of economic activity in cities facilitates face-to-face contacts and thus knowledge and idea flows either within (MAR) or between (Jacobs) industries. However, the adopted approach considering employment growth as the dependent variable addresses the issue of knowledge spillovers and the creation of new variety rather indirectly. It can therefore be put forward that the intermediary key link between knowledge spillovers and growth, namely innovation is somewhat neglected. A more direct approach consists to test the impact of the spatial environment on new variety, on the capacity of regions to develop new innovations or to adjust to new technology (Nelson, 1995). These considerations clearly link up with evolutionary thinking (Boschma, Lambooy, 1999).

To the best of our knowledge, there are currently only three studies addressing this issue. Feldman and Audretsch (1999) are the first to investigate a model where new product innovations within a given industry and a given US metropolitan area are a function of production specialisation, science based specialisation, localised competition and technological opportunity. In order to assess science base specialisation the authors classify four - digit standard industrial classification (SIC) sectors into six industrial groups which share a common science base (cf. Levin et al. 1987). Science base specialisation is then measured by the ratio of "science base – city" employment over "total city" employment relative to the average ratio at the national level. The authors interpret a positive sign on the

[3] An excellent overview of the state of the art is provided by Rosenthal and Strange (2004).

coefficient of science base specialisation as evidence of diversity externalities coming from complementary industries[4] given that, according to their argument, such externalities can not arise outside the common science base. Like Glaeser et al. (1992), Feldman and Audretsch (1999) consider the ratio of the number of local firms over local employment relative to the average ratio at the national level as a measure of local competition[5]. The authors conclude that specialisation of economic activity does not promote innovative output. Their results indicate that diversity across complementary economic activities sharing a common science base is more conducive to innovation than specialisation.

Based on a considerably improved "Feldman-Audretsch (1999)" approach, Paci and Usai (1999) investigate the Italian labour systems and find evidence for both, externalities arising from production specialisation as well as externalities arising from production and innovation diversity. With respect to the analysis of Feldman and Audretsch (1999) they introduce two kinds of diversity indexes based on the reciprocal of the Gini coefficient among their explanatory variables. The first uses employment data and proxies production diversity while the second is computed using patent application data to the European Patent Office (EPO) indicating innovation diversity within a given district.

Finally, the analysis of Massard and Riou (2002) concentrates on French departments. A distinctive feature of their approach with respect to the existing literature on this topic is the construction of a specialisation index based on R&D investment by industrial sector rather than employment data. As Henderson et al. (1995), they measure diversity by the inverse normalised Herfindahl index. Moreover, their model includes business R&D expenditures, public scientific publications, a measure that aims at capturing potential inter-regional externalities as well as the firm size. While private business and public R&D heavily influence the patenting activity within a given industry and department, according to their analysis, specialisation has a negative impact and diversity is not significant[6].

The purpose of this paper is to contribute to penetrate the black box of geographical space by identifying the extent to which the organisation of economic activity in European regions influences innovative output. The analysis should enable us to highlight first whether MAR and / or Jacobs externality matter for the creation of new knowledge of European regions. Second, since an increased speed of knowledge and idea flows is assumed to characterise densely populated places due to the spatial concentration of individuals, it is tested whether the impact of MAR and / or Jacobs externalities on innovation differs for industries located in metropolitan areas. Third, we assess whether the impact of these externalities differs for sectors with different technological intensities.

At this stage it should be noted that compared to the size of spatial entities investigated in the above-mentioned studies, the average size of European NUTS II regions analysed in this paper is sensibly larger. Glaeser at al. (1992, p. 1127) argue: *"If geographical proximity facilitates transmission of ideas, then we should expect knowledge spillovers to be*

[4] However, this argumentation is not convincing. If one considers the extreme case of a city where employment is concentrated in one single industrial sector then both, the production specialisation index and the science base specialisation index should be high. Since the entire employment is concentrated within one single industry, it is relatively ambiguous to interpret a positive sign of the science base specialisation for evidence of diversity externalities.

[5] This measure is not free of criticism as well. Consider a city with a single firm that hires 10 workers. Consider another city with 1000 firms that together hire 10000 workers. For both cities, the competition indicator will indicate the same degree of competition despite the fact that the first city is characterised by perfect monopoly.

[6] For their selected sample of departments, the authors find evidence for a significant negative impact of specialisation as well as a significant negative impact of diversity on the patenting activity of French departments.

particularly important in cities. After all, intellectual breakthroughs must cross hallways and streets more easily than oceans and continents." While we do not contest this reasoning, it is worth investigating whether such dynamic externalities can be observed and measured at an intermediate geographical scale. Such an investigation has never been undertaken and is precisely the aim of this paper which focuses on the European regional NUTS II level.

II. DATA, VARIABLES AND MODEL

In order to assess the impacts of diversity and specialisation externalities on regional industrial sector innovations which is the dependent variable of the model, different kinds of indexes have been constructed that reflect first, the region's production specialisation, second the region's degree of production and innovation diversity and third, industrial sector as well as regional specific characteristics.

II. 1. Production specialisation measure

Production specialisation aims at capturing MAR externalities and is measured as follows:

$$S_{ij}^{P} = \frac{E_{ij}}{\sum_{j=1}^{n} E_{ij}} \Bigg/ \frac{\sum_{i=1}^{m} E_{ij}}{\sum_{j=1}^{n}\sum_{i=1}^{m} E_{ij}} \tag{1}$$

where

i indexes the region (i = 1…m), m=153;

j indexes the industrial sector (j = 1…n), n=16;

E stands for the average employment over the period 1995-1997 (Source of data: Eurostat – REGIO).

If the degree of industrial specialisation of a given region equals the European average, the value of the indicator is one, while a higher / lower value points to a higher / lower degree of specialisation. The lower bound of the index is 0. In the regression analysis of the next section, a positive and significant coefficient on the specialisation measure would indicate that increased specialisation within a region is conductive to greater innovative output and would give support to the existence of MAR externalities. According to MAR, innovations mainly arise within those industrial sectors in which the region is specialised.

II. 2. Production diversity measure

The degree of production diversity of a region is measured by two different kinds of indexes namely, the reciprocal of the Gini coefficient and the Theil index. Both aim at capturing Jacobs externalities.

The reciprocal of the Gini coefficient is defined as follows:

$$GD_i^P = \frac{2}{(n-1)\sum_{j=1}^{n} E_{ij}} \sum_{j=1}^{n-1} CE_{ij} \tag{2}$$

where the definition of i, j and E are the same as in (1) and where CE_{ij} is the cumulative sum of employees up to industrial sector j when sector employment is listed in increasing order. The reciprocal of the Gini coefficient varies inside the interval of [0, 1] and increases together with production diversity.

The Theil index which is used in our model as an alternative measure of the degree of diversity of the region's productive system is defined as:

$$T_i = \frac{1}{n} \sum_{j=1}^{n} \frac{E_{ij}}{\mu_{Ei}} \ln\left[\frac{E_{ij}}{\mu_{Ei}}\right] \tag{3}$$

where the definition of i, j and E are the same as in (1) and (2) and where μ_{Ei} stands for the average employment over n sectors in region i. Since, under this formulation, the extreme values of the Theil index depend on the number of industrial sectors n, the index is divided by $\ln(n)$ in order to bring it within the interval [0, 1]. Given that the index increases together with concentration the adopted measure for diversity is as follows:

$$TD_i^P = \left[1 - \frac{T_i}{\ln(n)}\right] \tag{4}$$

An interesting feature of the Theil index is that the overall value of inequality can be completely and perfectly decomposed into a "between" and a "within" component:

$$T_i = T_i^B + T_i^W \tag{5}$$

To see this, it is useful to express the Theil index in the following less familiar form:

$$T_i = \sum_{j=1}^{n} \frac{E_{ij}}{\sum_{j=1}^{n} E_{ij}} \ln\left[\frac{E_{ij}}{\sum_{j=1}^{n} E_{ij}} \Bigg/ \frac{1}{n}\right] \tag{6}$$

which highlights the Theil's self-similar nature for any grouping structure chosen to aggregate sector employment into k generic groups. The degree of inequality between technological groups can be defined as follows:

$$T_i^B = \sum_{k=1}^{r} \frac{\sum_{j=1}^{r_k} E_{ijk}}{\sum_{j=1}^{n} E_{ijk}} \ln\left[\frac{\sum_{j=1}^{r_k} E_{ijk}}{\sum_{j=1}^{n} E_{ijk}} \Bigg/ \frac{n_k}{n}\right] \tag{7}$$

where the definition of i, j and E are the same as in (1), (2) and (3) and where

k indexes technological groups (k=1…r), r=4;

For each k, j goes from 1 to r_k with number of observations $n_k = \sum_{j=1}^{r_k} n_{jk}$.

The 16 manufacturing sectors covered by the analysis are classified according to their global technological intensity estimated by the OECD (1997) into four groups: 1) high technology, 2) medium-high technology, 3) medium-low technology and 4) low technology[7].

It is worth noting that the structure of the Theil index that measures inequality between sector employment (6) is similar to the structure of the Theil index that measures inequality between technological groups (7). The within component of the overall inequality is given by a weighted average of the Theil index for each group, the weights being each group's employment share:

$$T_i^W = \sum_{k=1}^{r} \frac{\sum_{j=1}^{r_k} E_{ijk}}{\sum_{j=1}^{n} E_{ijk}} \sum_{j=1}^{r_k} \frac{E_{ijk}}{\sum_{j=1}^{r_k} E_{ijk}} \ln\left[\frac{E_{ijk}}{\sum_{j=1}^{r_k} E_{ijk}} \Big/ \frac{1}{n_k} \right] \tag{8}$$

where the definition of i, j, k and E are the same as in (7). As previously, in order to bring the indexes within the interval [0, 1], they have been divided by ln(n) and the adopted measures of the diversity between and within technological groups are respectively given by:

$$TDBTG_i^P = 1 - \frac{T_i^B}{\ln(n)} = TD_i^P + T_i^W \tag{9}$$

$$TDWTG_i^P = 1 - \frac{T_i^W}{\ln(n)} = TD_i^P + T_i^B \tag{10}$$

The regression analysis of the next section tests for the impact of these different kinds of diversification measures. A positive and significant coefficient on these measures is interpreted as evidence for Jacobs externalities. According to her hypothesis, innovation emerges mainly within an environment characterised by a high degree of diversity.

II. 3. Innovation diversity measure

Complementarily to production diversity, we test for the impact of innovation diversity. The applied measure is the same as the reciprocal Gini coefficient (2) except that instead of employment, patent data are used. Innovation diversity is therefore defined as follows:

$$GD_i^K = \frac{2}{(n-1)\sum_{j=1}^{n} P_{ij}} \sum_{j=1}^{n-1} CP_{ij} \tag{11}$$

[7] See Table A.1 of the appendix for more details.

where the definition of i and j are the same as previously and where P refers to the average number of patent application over the period (1995-1997) to the EPO attributed to the living place of the inventor[8]. CP_{ij} is the cumulative sum of patents up to industrial sector j when sector patents are listed in increasing order. Similar to the effect of production diversification, a positive and significant sign on the coefficient of innovation diversification is interpreted as evidence for Jacobs externalities.

II. 4. Sector specific variables

In order to control for sector specific characteristics two different kinds of indicators are constructed. The first one aims at capturing the technological opportunity while the second one measures the degree of overall spatial dispersion among European regions of a given industrial sector.

The technological opportunity indicator is introduced to take into account sector differences in terms of patenting activity and is defined as follows:

$$O_j^K = \sum_{i=1}^{m} P_{ij} \qquad (12)$$

where the definition of i, j and P is as previously.

The rationale behind the introduction of the technological opportunity indicator relies on the observation that the intensity of patenting activity is not equally distributed among sectors. Industrial sectors for which patenting activity is high, generally offer higher technological opportunities compared to sectors with low patenting activity. For the former, the availability of already existing specific knowledge is assumed to make new knowledge creation easier. Therefore a positive sign is expected for this measure.

The overall spatial dispersion of a given industrial activity among European regions is calculated using the Theil index in the following way:

$$T_j = \frac{1}{m} \sum_{i=1}^{m} \frac{E_{ij}}{\mu_{Ej}} \ln\left[\frac{E_{ij}}{\mu_{Ej}}\right] \qquad (13)$$

where the definition of i, j and E are the same as previously and where μ_{Ej} stands for the average employment over m regions in sector j. The final adopted measure of sector dispersion among the European landscape which is defined within the interval [0, 1] is given by:

$$TD_j^P = \left[1 - \frac{T_j}{\ln(m)}\right] \qquad (14)$$

[8] Patent data were originally classified according to the International Patent Classification (IPC) and have been converted to the International Standard Industrial Classification (ISIC rev. 2) thanks to the MERIT concordance table (Verspagen et al. 1994).

If a given industrial activity is highly spread among European regions none of them may reach the critical mass in terms of expertise, know-how and specific resources which are necessary for successful knowledge creation. Therefore, increased spatial dispersion of a given activity is assumed to negatively influence patenting activity.

II. 5. The model

By means of the previously explained measures we wish to assess the extent to which the innovation of a given industry in a given region is influenced by the degree of production specialisation in the same industry (MAR) and the degrees of production and innovation diversity (Jacobs) of the region's productive system in estimating the following basic model[9]:

$$P_{ij} = a_1 + a_2 S^P_{ij} + a_3 D^P_i + a_4\, GD^K_i + a_5 O^K_j + a_6 TD^P_j + a_7 HTS_i + a_8\, POP_i + \varepsilon_{ij} \tag{15}$$

$$\overbrace{GD^P_i \qquad TD^P_i}$$

$$\overbrace{TDBTG^P_i \qquad TDWTG^P_i}$$

where

- P_{ij} stands for the average number of patent applications over the period 1997–1998 of region *i* and sector *j* to the EPO and proxies innovation output[10]. Patents are attributed to the living place of the inventor;
- S^P_{ij} represents the production specialisation measure such as defined by (1) which aims at capturing MAR externalities;
- D^P_i stands for alternative measures aiming at capturing Jacobs externalities associated to production diversity. In models 1, 3 and 5 tested in the next section, production diversity is respectively proxied by the reciprocal of the Gini coefficient (GD^P_i) defined by (2), the global Theil index (TD^P_i) defied by (4) and the Theil index decomposed into its "between" and "within" technological group components ($TDBTG^P_i$ and $TDWTG^P_i$) defined by (9) and (10). All of them are based on sector employment data;
- GD^K_i aims at capturing Jacobs externalities related to innovation diversity which is proxied by the reciprocal of the Gini coefficient specified by (11) and based on patent application data;
- O^K_j stands for technological opportunity of innovation inherent to a given industrial activity and is given by (12);
- TD^P_j proxies the dispersion of a given industrial activity among the European regional landscape and is based on the global Theil index specified by (14);
- HTS_i proxies the availability of knowledge intensive services within a region and is measured by the average ratio of employment in knowledge intensive services over the period 1996–1997 [(NACE Rev.1 64 (telecommunication and postal services[11]), 72 (computer and related activities) and 73 (research and development)] over total employment;

[9] Tables A.2 and A.3 of the appendix report respectively the correlation matrix and the most important descriptive statistics of the variables taken into account in the model.

[10] Even if patent data do not perfectly reflect innovations (Griliches, 1979) there is a strong link between patents and innovations (Acs et al., 2002). Furthermore, at the European regional level, a better alternative to patent data is simply not available.

[11] Postal services clearly do not belong to knowledge intensive services but could not be excluded since more desaggregated data are not available at the European regional level.

POP_i stands for the average over the period 1995–1997 of total population and is introduced as a size control variable;

ε_{ij} is a random error term.

In summary, the model that we wish to test aims at investigating the extent to which MAR externalities and Jacobs externalities influence the patenting activity of a given industrial sector in a given European region. A positive and significant coefficient on the specialisation index ($S^P{}_{ij}$) is interpreted as evidence for MAR externalities while a positive and significant coefficient on the different production diversity measures ($GD^P{}_i$, $TD^P{}_i$, $TDBTG^P{}_i$ and $TDWTG^P{}_i$) and the innovation diversity measure ($GD^K{}_i$) supports the Jacobs hypothesis. The model accounts for sector specific characteristics such as the technological opportunity ($O^K{}_j$) and the overall dispersion among European regions ($TD^P{}_j$) as well as for region specific characteristics such as the size (POP_i) and the endowment of knowledge intensive services (HTS_i). The latter is assumed to positively influence the patenting activity of a region. The availability of knowledge intensive services opens up the possibility for the region's innovative firms to outsource specialised expert knowledge and thus to concentrate on their core activities. Furthermore, knowledge intensive services such as consultancy are important channels of knowledge transmission between firms carrying ideas from one location or context to another (Bessant et Rush, 1995; Gadray et al., 1995). Finally it is worth noting that the model does not account for local competition given that the commonly used measure based on the firm – employment ratio is inappropriate, as previously stated[12].

III. ESTIMATES

The model explained in the previous section is tested on an extended sample of 153 European regions[13] mainly composed of NUTS II regions that covers the entire European Union except the new Länder of Germany and Luxembourg for witch the necessary data are not available. For each region, 16 manufacturing sectors[14] are considered.

Since the dependent variable of the model has a discrete nature with an important proportion of zeros[15], the use of conventional linear regression models may by inappropriate. Generally, in order to deal with the discrete and non-negative nature of the patent dependent variable, the simple Poisson regression model is considered as in the study of Feldman and Audretsch (1999). However, an important shortcoming of the Poisson model is its implicit assumption of equality between the first two conditional moments. The Cameron and Trivedi (1990) test for overdispersion strongly rejects equality between conditional mean and conditional variance of the dependent patent variable of our model suggesting overdispersion in the data. Therefore the use of the simple Poisson model in our case is inappropriate and we have to account for overdispersion. Given the evidence of overdispersion and the rejection of the Poisson restriction, the model is estimated by allowing for mean-variance inequality. The adopted approach consists in applying the quasi-generalised pseudo-maximum estimator developed by Gourieroux, Monfort and Trognon (1984)[16].

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[12] Local competition should be measured by variables reflecting the size and the number of local firms for which data at the European regional level are not available.

[13] For more details see Table A.4 of the appendix.

[14] For more details see Table A.1 of the appendix.

[15] For 23 % of observations there is no patent application during the considered period.

[16] Since we enter the explanatory variables of the models logarithmically, the coefficients can be interpreted as elasticities.

III. 1. Some base models

Table 1 reports the estimation results for different base models using alternative measures of diversity. A first look at Table 1 indicates the following. First, the positive and significant signs on the production specialisation and diversity measures suggest that the knowledge creation of European regions depends on MAR as well as on Jacobs externalities. This result contradicts the findings of Feldman and Audretsch (1999) and Massard and Riou (2002) but confirms the result of Paci and Usai (1999, 2000). Second, whatever the investigated model, the coefficients on production specialisation (as defined by 1) and technological opportunity (as defined by 12) remain considerably stable. To a sensibly lesser extent, this is also the case for innovation diversity (as defined by 11), the availability of knowledge intensive services and regional population. The stability of the coefficients suggests a satisfactory degree of stability of the model as a whole. Third, the impact of production diversity on innovation is relatively sensitive regarding the proxy used.

Table 1: Estimates of some base models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
dependent variable: P_{ij}						
c	-10.06 (-19.48)	-10.11 (-19.46)	-11.04 (-25.34)	-11.09 (-25.45)	-9.82 (-18.20)	-9.87 (-18.19)
$ln(S^P_{ij})$	0.41 (13.33)	0.42 (13.03)	0.40 (15.25)	0.41 (15.05)	0.41 (13.33)	0.42 (13.04)
$ln(TD^P_i)$	2.68 (4.98)	2.62 (4.85)				
$ln(TDBTG^P_i)$			12.85 (16.62)	12.78 (16.54)		
$ln(TDWTG^P_i)$			-8.06 (-10.34)	-8.13 (-10.43)		
$ln(GD^P_i)$					0.90 (4.31)	0.87 (4.16)
$ln(GD^K_i)$	0.77 (5.10)	0.77 (5.11)	0.92 (6.81)	0.92 (6.84)	0.78 (5.13)	0.78 (5.14)
$ln(O^K_j)$	0.96 (29.00)	0.95 (28.60)	0.96 (35.90)	0.95 (35.61)	0.96 (28.83)	0.95 (28.43)
$ln(TD^P_j)$		-0.62^c (-1.23)		-0.63^c (-1.58)		-0.63^c (-1.25)
$ln(HTS_i)$	0.88 (9.69)	0.87 (9.64)	0.63 (9.12)	0.63 (9.11)	0.89 (9.88)	0.89 (9.83)
$ln(POP_i)$	0.72 (15.17)	0.72 (15.08)	0.85 (21.60)	0.85 (21.60)	0.72 (14.92)	0.71 (14.83)
Log Lik.	-6903	-6900	-6638	-6634	-6915	-6912
LR stat.	22831	22726	33261	33469	22417	22327
Pseudo R^2	0.37	0.37	0.47	0.47	0.37	0.37

Note: Number of observations: 2448, Estimation method: Quasi-generalised pseudo-maximum likelihood, GLM robust z-statistics in brackets. The subscripts "a" indicates that [0.01 ≤ p-value < 0.05], "b" indicates that [0.05 ≤ p-value < 0.10] and "c" stands for a p-value ≥ 0.1. No subscript indicates that p-value < 0.01.

Models 1 and 2 of Table 1 test for MAR and Jacobs externalities when manufacturing diversity is measured by the global Theil index (defined by 4). The results indicate that a one percentage increase of production diversity in region *i* generates a 2.62 percentage increase of the patenting activity of region *i* in industry *j*. The alternative measure of production diversity, namely the reciprocal of the Gini coefficient (defined by 2) investigated in models 5 and 6, yields a significantly low elasticity which emphasises that the estimates should not be taken too literally but rather considered as indications. When the global Theil index of production diversity (defined by 4) is decomposed into its "between" and "within" technological group components (respectively defined by 9 and 10), one can observe from models 3 and 4 of Table 1 that only the "between" component positively influences the patenting activity of a given industry while the "within" component has a negative influence. The overall impact of production diversity however remains strongly positive. Ceteris paribus, this result suggests that a region should increase the diversity of its industrial structure but within a given technological group the efforts should be concentrated on a given industrial activity. In other words, on average, within a technological group specialisation rather than diversity fosters innovation. While this result needs further refinements on which we will come later on, it confirms, to a certain extent, Marshall's reflections, who despite his conviction that specialisation is the "engine" of growth, draws the attention on the danger underlying a *too* high degree of specialisation (Marshall, 1920, p. 273): "*A district which is dependent chiefly on one industry is liable to extreme depression, in case of a falling-off in the demand for its produce, or of a failure in the supply of the raw material which it uses. This evil again is in a great measure avoided by those large towns or large industrial districts in which several distinct industries are strongly developed*". Putting it differently, our findings reflect Marshall's concerns regarding local productive systems characterised by a mono industrial structure which generally lead to inertia and negative look-in due to the lack of ability of such regions to adopt and to generate new basic technology (Boschma, Lambooy,1999) [17].

Complementarily to production diversity, innovation diversity as well significantly influences the European region's knowledge creation. However, in all specified models its impact is lower compared to the one of production diversity. As previously stated, the coefficients on production specialisation (as defined by 1) estimated by the different base models of Table 1 are statistically equivalent. Increasing industry *j*'s specialisation in a given region by one percent leads, on average, to an augmentation of the sector's patenting activity by about 0.41 percent.

Regarding the first sector specific variable, namely technological opportunity, it has a positive and significant impact on innovation, suggesting, as anticipated, that higher technological opportunities are offered by industrial sectors with already high patenting activities. For the second sector specific variable, the spatial dispersion of a given industry (as defined by 14), a negative impact was expected. Despite the fact that the sign of the estimated coefficient in model 2, 4 and 6 of Table 1 is actually negative, it is not statistically significant at the 10 percent level[18] indicating that the spatial dispersion of a given industry does not really hamper innovation. Finally, and not surprisingly, the availability of knowledge intensive services within a region significantly and positively influences industrial knowledge creation.

III. 2. MAR and Jacobs externalities in the context of "high density" regions

MAR as well as Jacobs externalities are considered to be most compelling in the context of cities. It is argued that the spatial concentration of individuals, capacities, information and knowledge within a limited geographic area provides an environment in which ideas flow quickly from person to person. In other words, since dynamic externalities arise from communication between economic agents their effects should be more readily observable within an environment where communications are focused, which eases face-to-face contacts

[17] According to Grabher (1993), such a negative look-in caused the Ruhr area in Germany to fall into the so-called trap of rigid specialisation. Capron (2002a, 2002b) observes a similar situation for the Belgian Walloon region.
[18] For this reason models 2, 4 and 6 are no longer investigated in what follows.

and thus the spill over of (tacit) knowledge and ideas (Lucas, 1988). For MAR, knowledge spillovers mainly occur within the core industry. On the opposite, for Jacobs, most important knowledge transfers come from other industries. Given that our analysis is based on European NUTS II regions, the effect of MAR and Jacobs externalities in the context of cities can not be directly investigated. The adopted approach therefore consists in introducing into models 1, 3 and 5 dummy variables for "high density" regions defined as regions for which the density of population exceeds 500 inhabitants per squared kilometre[19].

Table 2: Estimates with dummy variables for "high density" regions

	Model 1 with "high density" region dummy		Model 3 with "high density" region dummy		Model 5 with "high density" region dummy	
	(1)	(2)	(3)	(4)	(5)	(6)
dependent variable: P_{ij}						
c	-10.15 (-18.96)	-10.17 (-19.51)	-11.19 (-24.81)	-11.16 (-25.43)	-9.97 (-17.94)	-9.95 (-18.23)
$ln(S^{P}_{ij})$	0.43 (12.88)	0.43 (12.88)	0.42 (14.71)	0.41 (14.71)	0.43 (12.90)	0.43 (12.90)
$ln(TD^{P}_{i})$	2.42 (4.28)	2.59 (4.78)				
$ln(TDBTG^{P}_{i})$			12.82 (15.76)	12.87 (16.52)		
$ln(TDWTG^{P}_{i})$			-8.75 (-10.59)	-8.37 (-10.54)		
$ln(GD^{P}_{i})$					0.79 (3.52)	0.87 (4.13)
$ln(GD^{K}_{i})$	0.81 (5.19)	0.79 (5.16)	1.00 (6.99)	0.96 (6.90)	0.83 (5.18)	0.79 (5.16)
$ln(O^{K}_{j})$	0.96 (28.77)	0.96 (28.81)	0.96 (35.74)	0.96 (35.73)	0.96 (28.62)	0.96 (28.64)
$ln(HTS_{i})$	0.93 (9.78)	0.92 (9.74)	0.68 (9.40)	0.68 (9.37)	0.95 (9.91)	0.94 (9.85)
$ln(POP_{i})$	0.73 (14.54)	0.73 (15.33)	0.87 (20.78)	0.87 (21.88)	0.73 (14.42)	0.73 (15.07)
m	-0.43^{c} (-0.42)		-1.06^{c} (-1.36)		-0.48^{c} (-0.42)	
$ln(S^{P}_{ij})_{m}$	-0.18^{b} (-1.81)	-0.17^{b} (-1.77)	-0.17^{a} (-2.19)	-0.17^{a} (-2.19)	-0.18^{b} (-1.81)	-0.17^{b} (-1.81)
$ln(TD^{P}_{i})_{m}$	3.04^{c} (1.27)	1.88 (2.63)				
$ln(TDBTG^{P}_{i})_{m}$			-1.50^{c} (-0.51)			
$ln(TDWTG^{P}_{i})_{m}$			5.34^{b} (1.89)	3.45 (3.61)		
$ln(GD^{P}_{i})_{m}$					0.73^{c} (1.00)	0.35^{a} (2.34)
$ln(GD^{K}_{i})_{m}$	-0.77^{c} (-0.69)		-1.47^{b} (-1.74)		-0.94^{c} (-0.83)	
Log Lik.	-6896	-6886	-6627	-6626	-6913	-6902
LR stat.	22497	22940	32788	33033	22014	22471
Pseudo R^2	0.38	0.34	0.48	0.48	0.38	0.37

Note: Number of observations: 2448, Estimation method: Quasi-generalised pseudo-maximum likelihood, GLM robust z-statistics in brackets. The subscripts "a" indicates that [0.01 ≤ p-value < 0.05], "b" indicates that [0.05 ≤ p-value < 0.10] and "c" stands for a p-value ≥ 0.1. No subscript indicates that p-value < 0.01.

[19] According to this measure, about 10 percent of European regions are "high density" regions. The latter are clearly identified in Table A.4 of the appendix.

Table 2 reports the results for models 1 (columns 1 and 2), 3 (columns 3 and 4) and 5 (columns 5 and 6) when allowing for both, a different intercept and different slopes for production specialisation, production diversity as well as innovation diversity. It is worth noting that "non significance" in the context of dummy variable estimates simply indicates that the behaviour or impact of a given variable does not statistically differ from the one obtained for the entire sample. Therefore our comments mainly concentrate on the final results reported in columns (2), (4) and (6) where insignificant variables have been successively eliminated.

Table 2 suggests several striking observations. First, the elasticity of production specialisation in "high density" regions is significantly lower than the one obtained for the overall sample. While according to model 1, a one percentage increase of production specialisation of an average European region increases innovation by about 0.43 percent, in "high density" regions this increase is limited to about 0.26 percent. Second, regarding the role of production diversity it turns out to be much more important for "high density" regions than for the overall sample[20]. Indeed, the estimates reported in column (2) of Table 2 indicate that a one percentage increase of production specialisation induces a 4.47 percentage increase in "high density" regions and "only" a 2.59 percentage increase in an average European region. Taken together, these results suggest that in European "metropolitan" regions characterised by a high population density, Jacobs externalities have a considerably higher impact on knowledge creation than MAR externalities although both kinds of externalities are at work.

Column (4) of Table 2 reports the estimation results for model 3 when the global Theil index of production diversity is decomposed into its "between" and "within" technological group components. For the global sample the results remain almost the same as the ones obtained without the introduction of "high density" region dummies. Production diversity "between" technological groups importantly contributes to the region's knowledge creation while production diversity "within" a technological group has a negative impact although the global diversity effect remains positive. Previously, we stated that this result needs further refinements, result which suggests that a region should increase the diversity of its industrial structure but concentrate its efforts within a given technological group. One refinement is now provided by the introduction of dummy variables for "high density" regions. It appears that the negative impact of production diversity "within" technological groups is far less important for "high density" regions than for the overall sample. While for an average European region a one percentage increase of production diversity within a technological group decreases the rate of innovation by about 8.37 percent, the negative impact is about half as important in the case of "high density" regions. As far as the strongly positive impact of production diversity between technological groups is concerned, no significant difference can be observed between "high density" and "average" European regions. Considering the results of model 1 and model 3 simultaneously, one observes that the increased importance of production diversity in the context of "high density" regions is the result of a limited negative impact of the "within" technological group diversity. Further refinements of the seemingly surprising impact of the "within" technological group component of production diversity will be considered later on.

The results of model 5 in terms of production specialisation are similar to the ones of models 1 and 3. As previously, the impact of production diversity for the overall sample is lower but rises in the context of "high density" regions.

[20] Paci and Usai (1999, 2000) come to a similar conclusion.

III. 3. MAR and Jacobs externalities in the context of high tech sectors

Complementarily to the investigation of MAR and Jacobs externalities in the context of "high density" regions, it is useful to study whether these externalities differ according to the technological intensities of manufacturing sectors. Table 3 reports the estimation results for models 1, 3 and 5 when introducing a dummy variable for high tech sectors. As far as the results for medium-high, medium-low and low tech sectors are concerned, they are not reported since no significant differences emerged with respect to the overall sample.

Table 3: Estimates with dummy variables for sectors with high technological intensity

	Model 1 with dummy for tg1		Model 3 with dummy for tg1		Model 5 with dummy for tg1	
	(1)	(2)	(3)	(4)	(5)	(6)
dependent variable: P_{ij}						
c	-9.99 (-19.88)	-10.04 (-19.77)	-11.10 (-25.71)	-11.05 (-25.72)	-9.80 (-18.71)	-9.80 (-18.53)
$ln(S^P_{ij})$	0.37 (9.04)	0.40 (12.93)	0.38 (10.92)	0.38 (14.43)	0.37 (9.10)	0.40 (12.94)
$ln(TD^P_i)$	2.17 (3.87)	2.07 (3.68)				
$ln(TDBTG^P_i)$			11.93 (14.77)	11.99 (14.90)		
$ln(TDWTG^P_i)$			-8.84 (-10.54)	-8.76 (-10.49)		
$ln(GD^P_i)$					0.69 (3.17)	0.69 (3.21)
$ln(GD^K_i)$	0.96 (5.75)	0.91 (5.77)	1.06 (7.06)	1.09 (7.63)	0.98 (5.83)	1.00 (5.92)
$ln(O^K_j)$	0.96 (29.76)	0.96 (29.33)	0.96 (36.19)	0.96 (36.27)	0.96 (29.64)	0.96 (29.17)
$ln(HTS_i)$	0.86 (9.88)	0.87 (9.91)	0.64 (9.37)	0.63 (9.35)	0.88 (10.09)	0.89 (10.07)
$ln(POP_i)$	0.72 (15.79)	0.72 (15.57)	0.86 (22.16)	0.85 (22.11)	0.71 (15.55)	0.72 (15.33)
tg1	-0.24^c (-0.82)		0.17^c (0.62)		0.12^c (0.33)	
$ln(S^P_{ij})_{tg1}$	0.06^c (1.04)		-0.02^c (-0.32)		0.06^c (0.98)	
$ln(TD^P_i)_{tg1}$	3.03^a (2.25)	3.73 (2.97)				
$ln(TDBTG^P_i)_{tg1}$			6.35 (2.96)	5.73 (2.96)		
$ln(TDWTG^P_i)_{tg1}$			4.36^a (2.33)	4.14^a (2.24)		
$ln(GD^P_i)_{tg1}$					1.26^a (2.43)	1.24 (3.25)
$ln(GD^K_i)_{tg1}$	-0.80^a (-2.51)	-0.64 (-2.84)	-0.60^a (-1.96)	-0.73 (-3.58)	-0.86 (-2.67)	-0.94 (-3.19)
Log Lik.	-6901	-6891	-6639	-6627	-6911	-6901
LR stat.	24633	24194	26177	34607	24289	23791
Pseudo R^2	0.38	0.37	0.49	0.48	0.38	0.38

Note: Number of observations: 2448, Estimation method: Quasi-generalised pseudo-maximum likelihood, GLM robust z-statistics in brackets. *tg1* stands for the dummy variable relative to high tech sectors. The subscripts "a" indicates that [$0.01 \leq$ p-value < 0.05], "b" indicates that [$0.05 \leq$ p-value < 0.10] and "c" stands for a p-value ≥ 0.1. No subscript indicates that p-value < 0.01.

Table 3 highlights some interesting results. Production diversity turns out to be a particularly important input for new knowledge creation in high tech sectors. For the latter, models 1 and 5 suggest that with respect to the overall sample, the impact of production diversity on patenting activity is about three times higher. From model 3 it can be deduced that both, "between" and "within" technological group diversity are increasingly at work. The estimation results clearly reflect that variety is the source of new variety creation, the main driving force of growth in evolutionary models (Nelson and Winter, 1982). Pointing to the fact that spatial dynamics occur largely within the limits of the spatial productive matrix laid down in the past, Henderson at al. (1995) for the US case raised the question what historical environments have an advantage in the ongoing race to attract new industries and come to a similar conclusion. New high tech industries are more likely to take root in cities with a history of industrial diversity, suggesting that Jacobs externalities are important for these industries. Thus, Jacobs externalities are not only increasingly at work in "high density" regions as previously shown but also in high tech sectors. [21].

The outcome is somewhat different for innovation diversity. While for the overall sample, this variable positively influences the region's patenting activity, in the special case of high tech sectors the positive influence is much lower. In other words, while a more equal distribution of patents among sectors fosters the patenting activity of a given "average" sector, this positive impact almost vanishes for high tech sectors. What is the rationale behind this finding? High tech innovations are generally spreading or diffusing technologies enhancing the knowledge creation of other sectors. Under some qualification it can even be considered that high tech innovations constitute an input for knowledge creation in sectors with lower technological orders. The opposite is less likely since low tech innovations hardly fuel high tech innovations. Given that high tech sectors source much less from sectors with lower technological orders, it is quite logical that the impact of innovation diversity on high tech knowledge creation is smaller. Finally, Table 3 indicates that the impact of production specialisation on patent applications is not significantly different in high tech sectors compared to the overall sample.

III. 4. MAR and Jacobs externalities in the context of high tech sectors in "high density" regions

Having separately investigated the influence of MAR and Jacobs externalities in the case of "high density" regions as well as in the case of high tech sectors, it is worth simultaneously considering the two cases. Table 4 reports the estimation results for models 1 and 3 when investigating the impact of MAR and Jacobs externalities on the innovative activity of high tech, medium-high tech and medium-low tech manufacturing sectors located in "high density" regions.

While the impact of production specialisation on high tech innovations was comparable to the one obtained for an "average" manufacturing sector when no distinction between regions was operated (Table 3), in the context of "high density" regions, the estimates reported in columns

[21] When investigating models 1, 3 and 5 separately for each technological group, it appears that the impact of production diversity on innovation declines with diminishing technological intensity. In other words the higher the technological intensity of a sector, the higher is the impact of diversity on innovation. However one should be aware of the fact that new emerging industries / technologies are only unsatisfactorily or not at all taken into account by industrial classifications such as ISIC since the latter are generally based on the past. Thus, statistics only imperfectly reflect the current borders of industries which of course might influence the estimation results regarding the predominance of Jacobs externalities for the innovation of industries with high technological intensities.

Table 4: Estimates of models 1 and 3 with dummy variables for "high density" regions and technological groups

	Model 1 with dummies for "high density" regions and						Model 3 with dummies for "high density" regions and					
	tg1 high tech		tg2 medium-high tech		tg3 medium-low tech		tg1 high tech		tg2 medium-high tech		tg3 medium-low tech	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
dependent variable: P_{ij}												
c	-10.07 (-19.20)	-10.07 (-19.22)	-10.16 (-19.32)	-10.19 (-19.63)	-10.04 (-19.44)	-10.06 (-19.55)	-11.07 (-25.36)	-11.08 (-25.47)	-11.18 (-25.18)	-11.17 (-25.51)	-11.03 (-25.31)	-11.04 (-25.41)
$ln(S^{P}_{ij})$	0.43 (13.44)	0.43 (13.44)	0.41 (13.12)	0.41 (13.36)	0.40 (13.06)	0.40 (13.06)	0.42 (15.72)	0.42 (15.71)	0.40 (14.94)	0.40 (15.30)	0.39 (14.89)	0.39 (14.90)
$ln(TD^{P}_{i})$	2.49 (4.55)	2.49 (4.56)	2.56 (4.70)	2.65 (4.93)	2.68 (4.96)	2.68 (5.01)						
$ln(TDBTG^{P}_{i})$							12.67 (16.33)	12.82 (16.64)	12.81 (16.28)	12.91 (16.70)	12.89 (16.56)	12.86 (16.67)
$ln(TDWTG^{P}_{i})$							-8.38 (-10.72)	-8.38 (-10.74)	-8.32 (-10.46)	-8.21 (-10.47)	-8.06 (-10.30)	-8.04 (-10.35)
$ln(GD^{K}_{i})$	0.78 (5.13)	0.78 (5.13)	0.79 (5.19)	0.78 (5.17)	0.76 (5.09)	0.76 (5.12)	0.94 (6.92)	0.94 (6.89)	0.97 (6.95)	0.95 (6.92)	0.93 (6.77)	0.93 (6.82)
$ln(O^{K}_{j})$	0.96 (28.68)	0.96 (28.69)	0.97 (28.93)	0.97 (28.99)	0.95 (28.85)	0.96 (29.01)	0.96 (36.01)	0.96 (36.03)	0.97 (35.84)	0.97 (35.89)	0.96 (35.69)	0.96 (35.90)
$ln(HTS_{i})$	0.89 (9.73)	0.89 (9.73)	0.90 (9.89)	0.90 (9.85)	0.90 (9.84)	0.90 (9.85)	0.65 (9.33)	0.64 (9.28)	0.66 (9.41)	0.65 (9.36)	0.65 (9.31)	0.65 (9.31)
$ln(POP_{i})$	0.72 (14.89)	0.72 (14.92)	0.72 (14.98)	0.73 (15.33)	0.72 (15.00)	0.72 (15.23)	0.86 (21.57)	0.86 (21.72)	0.86 (21.36)	0.86 (21.81)	0.85 (21.42)	0.85 (21.69)
$mtgk$	0.81^{c} (0.36)	1.11^{b} (1.76)	0.16^{c} (0.10)		1.69^{c} (0.80)		0.45^{c} (0.27)	0.81^{b} (1.81)	-0.61^{c} (-0.53)		0.94^{c} (0.56)	
$ln(S^{P}_{ij})_{mtgk}$	-0.53 (-3.40)	-0.53 (-3.52)	0.03^{c} (0.15)		0.47^{b} (1.80)	0.49^{a} (2.02)	-0.58 (-4.44)	-0.51 (-4.50)	0.05^{c} (0.38)		0.42^{a} (2.02)	0.46^{a} (2.41)
$ln(TD^{P}_{i})_{mtgk}$	9.49^{b} (1.77)	9.83^{a} (2.09)	4.46^{c} (1.25)	2.33^{a} (2.30)	2.34^{c} (0.49)							
$ln(TDBTG^{P}_{i})_{mtgk}$							9.92^{c} (1.35)		1.67^{c} (0.38)		-1.08^{c} (-0.18)	
$ln(TDWTG^{P}_{i})_{mtgk}$							10.24^{b} (1.75)	12.73^{a} (2.28)	5.02^{c} (1.20)	4.16 (3.09)	2.76^{c} (0.48)	
$ln(GD^{K}_{i})_{mtgk}$	-0.32^{c} (-0.13)		-0.19^{c} (-0.11)		1.89^{c} (0.79)		-0.81^{c} (-0.47)		-0.99^{c} (-0.79)		1.16^{c} (0.61)	
Log Lik.	-6895	-6895	-6907	-6897	-6898	-6899	-6633	-6631	-6635	-6627	-6633	-6634
LR stat.	22395	22397	22556	22918	22971	22985	32893	33020	32960	33464	33370	33416
Pseudo R^2	0.38	0.38	0.38	0.37	0.38	0.38	0.49	0.49	0.48	0.47	0.47	0.47

Note: Number of observations: 2448, Estimation method: Quasi-generalised pseudo-maximum likelihood, asymptotic GLM robust z-statistics in brackets. *mtgk* stands for dummy variables for the k technological groups in "high density" regions, k=1, 2, 3. The subscripts "a" indicates that [$0.01 \leq$ p-value < 0.05], "b" indicates that [$0.05 \leq$ p-value < 0.10] and "c" stands for a p-value ≥ 0.1. No subscript indicates that p-value < 0.01.

(2) and (8) of Table 4 suggest that production specialisation has a global slightly negative impact on high tech innovations. On the other hand, production diversity turns out to be highly influential. When investigating model 1 where the production diversity is measured by the global Theil index, the impact of production diversity on high tech innovation located in "high density" regions is about five times as important as the one obtained for the overall sample. Perhaps the most appealing result of the simultaneous investigation of high tech sectors and "high density" regions is obtained when the Theil index of production diversity is decomposed into its "between" and "within" technological group components. The estimates of model 3 (column 8) clearly indicate that in the context of "high density" regions, high tech innovations are positively influenced by both kinds of production diversities. A one

percentage increase of production diversity "within" technological groups increases the innovative output of high tech industries in "metropolitan" areas by about 4.35 percent. Taken together, these considerations clearly indicate the superiority of Jacobs externalities for high tech industries located in "high density" regions.

For sectors with lower technological intensities such as medium-high tech and medium-low tech manufacturing sectors, one can observe from Table 4 that in the context of "high density" regions, MAR externalities remain important and their impact on innovation increases with decreasing technological intensity. While for manufacturing sectors with medium-high technological intensities (columns 4 and 10) the impact of specialisation on knowledge creation is statistically not different from the one obtained for an "average sector" it is more than twice as important for manufacturing sectors with medium-low technological intensities (columns 6 and 12). In opposite to MAR externalities, the impact of Jacobs externalities is highest for high tech sectors and decreases with decreasing technological intensity. While for medium-high tech sectors the impact of production diversity on innovation is significantly higher than the one obtained for the overall sample, for medium-low tech sectors, it is statistically the same. At this stage, it is interesting to link up with the notion of urban product cycles of Henderson et al. (1995). According to the authors, who consider employment growth in cities as the dependent variable, Jacobs externalities are crucial for *attracting* new industries but MAR externalities are important for retaining them. Based on a more "direct vision" of the mechanisms underlying endogenous growth in considering local innovation as to be the outcome of externalities, our study shows that Jacobs externalities are crucial for the *generation* of high tech innovation in "high density" regions while both MAR and Jacobs externalities matter for the development of new variety in sectors with lower technological intensities.

CONCLUSION

Since the seminal contribution of Glaeser et al. (1992), the impact of local industrial composition on the growth of industry employment has received a great deal of attention in recent economics literature. However, extremely few attempts have been undertaken so far to understand whether the organisation of economic activity shapes innovation – the intermediary link between externalities and growth. This paper aimed at contributing to a better understanding of the impact of MAR and Jacobs externalities on innovation and concentrates on the case of European regions for which such an analysis has never been performed.

Our investigation is based on a model where the dependent variable, namely innovation, is proxied by the number of patent applications to the EPO of region i and sector j. The main explanatory variables are a production specialisation index for region i and sector j and a production and innovation diversity index for region i. The model also accounts for sector specific characteristics such as the technological opportunity and for regional specific characteristics such as the endowment of knowledge intensive services. It is tested onto an extended sample of 153 European regions and 16 manufacturing sectors and leads to the following findings.

On average, lumping together sectors and regions, the European region's patenting activity is influenced by both, MAR externalities arising from industrial specialisation as well as Jacobs externalities associated with the diversity of the region's underlying industrial structure. However, whatever the investigated model, diversity influences innovation more than specialisation. This result is in line with the findings of Paci and Usai (1999, 2000) who studied this topic for the case of Italian districts but contrasts with the conclusions of Massard and Riou (2002) who concentrated their analysis on French departments.

Dynamic externalities are generally considered to be most compelling in cities given that the high degree of geographical concentration of individuals and the density of communication infrastructure ease intended and unintended communication among individuals leading to knowledge and idea spillovers. Thus, a question that naturally arises is what kind of externality is the driving force of innovation in European regions characterised by high population densities. The answer is provided by introducing dummy variables for “high density” regions into the investigated model. The results clearly indicate that in the context of “high density” regions Jacobs externalities are increasingly at work while MAR externalities are much less important. In other words, innovation in European metropolitan areas is mainly the outcome of externalities arising from diversity and to a much lesser extent from specialisation.

However, this result is only true on average. Indeed, when distinguishing between sectors with different technological intensities it turns out that high tech innovations in “high density” regions exclusively depend on Jacobs externalities and are even slightly negatively influenced by MAR externalities. The higher the technological intensity of an industrial activity the more innovation depends on diversity. On the opposite, for sectors with lower technological intensities such as medium-high tech and medium-low tech manufacturing sectors, MAR externalities remain important and their impact on innovation increases with decreasing technological intensity. Linking up with the findings of Henderson et al. (1995), our findings are consistent with their notion of urban product cycles.

In a nutshell, on average, both MAR and Jacobs externalities influence the innovation of European regions. With respect to this average result, high tech innovations source more extensively form diversity. A similar observation prevails for innovations realised in “high density” regions. For the special case of high tech innovations in “high density” regions only Jacobs externalities are at work but MAR externalities matter for innovation in sectors with lower technological intensities.

The investigation of MAR and Jacobs externalities in the context of knowledge creation has undeniably important implications for policy makers. Perhaps the most fundamental implication but also the most general one is that selection and positive discrimination in favour of a given industrial activity or a given technology by means of public intervention such as grants should be avoided if not based on prior extremely careful analysis of the underlying regional production system in terms of industrial organisation and composition.

However, in general, it is preferable that public policy stimulates diversity which, according to our results, has in all examined cases potentially higher impacts on innovation than industrial specialisation. Moreover, diversity opens up the possibility for increased flexibility and thus the capacity of the regional innovation and production system to adjust to exogenous changes. Therefore, regions with a diversified production matrix are much better equipped to prevent a process of negative lock-in. The key policy concern should therefore be to identify the commonalities of the regional productive system and the manner how to foster such diversity. Since each region is unique and characterised by its specificities, no general recipe can be given. Nevertheless, diversification efforts should not be restricted to industrial activity but also entail the service sector. The development of knowledge intensive services has been shown to positively influence the regions' capacity to create knowledge.

From our results it can also be deduced that public policy aimed at "creating" high tech activities in lagging regions with low industrial bases may fail to hit the target. High tech knowledge creation has been shown to importantly source from diversified knowledge externalities which probably can not be provided by regions with low industrial activities or regions with "mono-industrial" structures.

Finally, three main extensions are worth being investigated in the future. First, it would be fruitful to find an adequate measure for intra-regional competition. While MAR are in favour of local monopoly since it allows easy internalisation of externalities, Porter argues that only local competition can provide the necessary incitements for sustained innovation, an argumentation which is also shared by Jacobs. Despite the fact that there are clear policy implications of this debate, the commonly applied approach in the related literature to capture intra-regional competition is highly unsatisfactory. Second, it would be highly interesting to decompose the global Theil index according to the underlying common science and technology bases that are shared by different industries. This would enable to assess whether a diversified or, on the contrary, a specialised science and technology base is more conductive to innovation. Finally, the analysis could be improved by taking into account potential spatial autocorrelation. Given the discrete nature of our dependent variable, our estimates are performed by means of a negative binomial model which can not be estimated by traditional spatial econometrics estimation packages. These extensions of the model constitute a real challenge and should be investigated in the future.

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APPENDIX

Table A.1: Classification of manufacturing sectors according to their technological intensity

Technological intensity	ISIC code (rev. 2)	Denomination
high	3825	Manufacture of office machinery and computers
high	3832	Manufacture of radio, television and communication equipment and apparatus
high	3522	Pharmaceutical industry
medium-high	3820 without 3825	Manufacture of machinery and equipment n.e.c.
medium-high	3850	Manufacture of medical, precision and optical instruments, watches and clocks
medium-high	3843	Manufacture of motor vehicles, trailers and semi-trailers
medium-high	3830 without 3832	Manufacture of electrical machinery and apparatus n.e.c.
medium-high	3510+3520 without 3522	Manufacture of chemicals, chemical products
medium-high	3840 without 3843	Manufacture of other transport equipment
medium-low	3600	Manufacture of other non-metallic mineral products
medium-low	3550+3560	Manufacture of rubber and plastic products
medium-low	3810	Manufacture of fabricated metal products, except machinery and equipment
medium-low	3710+3720	Manufacture of basic metals
low	3100	Manufacture of food product, beverages and tobacco
low	3200	Manufacture of textiles and textile products, skin
low	3400	Manufacture of pulp, paper and paper products, publishing and printing

Source: OECD (1997)

Table A.2: Correlation matrix

	$ln(S^P_{ij})$	$ln(TD^P_i)$	$ln(TDBTG^P_i)$	$ln(TDWTG^P_i)$	$ln(GD^P_i)$	$ln(GD^K_i)$	$ln(O^K_j)$	$ln(HTS_i)$	$ln(POP_i)$	$ln(TD^P_j)$
$ln(S^P_{ij})$	1.00	0.39	0.39	0.24	0.40	0.32	-0.07	0.26	0.25	0.39
$ln(TD^P_i)$		1.00	0.93[(a)]	0.70[(a)]	0.99[(a)]	0.63	-5.4E-18	0.42	0.42	1.2E-17
$ln(TDBTG^P_i)$			1.00	0.39	0.91[(a)]	0.58	4.8E-18	0.41	0.28	-4.5E-18
$ln(TDWTG^P_i)$				1.00	0.72[(a)]	0.45	7.6E-20	0.30	0.53	5.3E-18
$ln(GD^P_i)$					1.00	0.64	3.8E-18	0.44	0.47	6.2E-18
$ln(GD^K_i)$						1.00	-4.2E-18	0.48	0.54	-1.3E-18
$ln(O^K_j)$							1.00	1.1E-17	6.9E-18	-0.14
$ln(HTS_i)$								1.00	0.38	-1.8E-17
$ln(POP_i)$									1.00	-1.2E-18
$ln(TD^P_j)$										1.00

Note: (a) The corresponding variables are not considered simultaneously within a given model.

Table A.3: Summary statistics

	mean	standard deviation	minimum	maximum
P_{ij}	17.96	41.05	0	428
$ln(S^P_{ij})$	-0.86	1.89	-9.12	2.19
$ln(TD^P_j)$	-0.19	0.11	-0.91	-0.05
$ln(TDBTG^P_i)$	-0.09	0.07	-0.54	-0.00
$ln(TDWTG^P_i)$	-0.09	0.04	-0.21	-0.02
$ln(GD^P_i)$	-0.79	0.28	-2.38	-0.35
$ln(GD^K_i)$	-1.03	0.51	-3.27	-0.47
$ln(O^K_j)$	7.61	0.93	5.12	8.75
$ln(HTS_i)$	0.78	0.69	-2.96	3.13
$ln(POP_i)$	7.39	0.87	4.77	9.80
$ln(TD^P_i)$	-0.18	0.07	-0.34	-0.09

Table A.4: Cross section sample of European regions
("high density" regions are underlined)

NUTS Code	Region	NUTS Code	Region
Austria			
AT11	Burgenland	AT31	Oberösterreich
AT12	Niederösterreich	AT32	Salzburg
<u>AT13</u>	<u>Wien</u>	AT33	Tirol
AT21	Kärnten	AT34	Vorarlberg
AT22	Steiermark		
Belgium			
<u>BE1</u>	<u>Région Bruxelles-capitale</u>	BE3	Région Wallonne
BE2	Vlaams Gewest		
Germany			
DE11	Stuttgart	DE73	Kassel
DE12	Karlsruhe	DE91	Braunschweig
DE13	Freiburg	DE92	Hannover
DE14	Tübingen	DE93	Lüneburg
DE21	Oberbayern	DE94	Weser-Ems
DE22	Niederbayern	<u>DEA1</u>	<u>Düsseldorf</u>
DE23	Oberpfalz	<u>DEA2</u>	<u>Köln</u>
DE24	Oberfranken	DEA3	Münster
DE25	Mittelfranken	DEA4	Detmold
DE26	Unterfranken	DEA5	Arnsberg
DE27	Schwaben	DEB1	Koblenz
<u>DE3</u>	<u>Berlin</u>	DEB2	Trier
<u>DE5</u>	<u>Bremen</u>	DEB3	Rheinhessen-Pfalz
<u>DE6</u>	<u>Hamburg</u>	DEC	Saarland
DE71	Darmstadt	DEF	Schleswig-Holstein
DE72	Gießen		
Denmark		DK	Denmark
Spain			
ES11	Galicia	ES42	Castilla-la Mancha
ES12	Principado de Asturias	ES43	Extremadura
ES13	Cantabria	ES51	Cataluña
ES21	Pais Vasco	ES52	Comunidad Valenciana
ES22	Comunidad Foral de Navarra	ES53	Baleares
ES23	La Rioja	ES61	Andalucia
ES24	Aragón	ES62	Murcia
<u>ES3</u>	<u>Comunidad de Madrid</u>	ES7	Canarias (ES)
ES41	Castilla y León		
Finland			
FI11	Uusimaa	FI14	Väli-Suomi
FI12	Etelä-Suomi	FI15	Pohjois-Suomi
FI13	Itä-Suomi		
France			
<u>FR1</u>	<u>Île de France</u>	FR51	Pays de la Loire
FR21	Champagne-Ardenne	FR52	Bretagne
FR22	Picardie	FR53	Poitou-Charentes
FR23	Haute-Normandie	FR61	Aquitaine
FR24	Centre	FR62	Midi-Pyrénées
FR25	Basse-Normandie	FR63	Limousin
FR26	Bourgogne	FR71	Rhône-Alpes
FR3	Nord-Pas-de-Calais	FR72	Auvergne
FR41	Lorraine	FR81	Languedoc-Roussillon
FR42	Alsace	FR82	Provence-Alpes-Côte d`Azur
FR43	Franche-Comté	FR83	Corse
Greece			
GR12	Kentriki Makedonia	GR24	Sterea Ellada
GR14	Thessalia	GR25	Peloponnisos
GR21	Ipeiros	<u>GR3</u>	<u>Attiki</u>
GR23	Dytiki Ellada	GR43	Kriti
Ireland		IE	Ireland
Italy			
IT11	Piemonte	IT53	Marche
IT12	Valle d`Aosta	IT6	Lazio
IT13	Liguria	IT71	Abruzzo

IT2	Lombardia	IT72	Molise
IT31	Trentino-Alto Adige	IT8	Campania
IT32	Veneto	IT91	Puglia
IT33	Friuli-Venezia Giulia	IT92	Basilicata
IT4	Emilia-Romagna	IT93	Calabria
IT51	Toscana	ITA	Sicilia
IT52	Umbria	ITB	Sardegna
The Netherlands			
NL11	Groningen	NL31	Utrecht
NL12	Friesland	NL32	Noord-Holland
NL13	Drenthe	NL33	Zuid-Holland
NL21	Overijssel	NL34	Zeeland
NL22	Gelderland	NL41	Noord-Brabant
NL23	Flevoland	NL42	Limburg (NL)
Portugal			
PT11	Norte	PT14	Alentejo
PT12	Centro (P)	PT15	Algarve
PT13	Lisboa e Vale do Tejo		
Sweden			
SE01	Stockholm	SE05	Västsverige
SE02	Östra Mellansverige	SE06	Norra Mellansverige
SE03	Smland med öarna	SE07	Mellersta Norrland
SE04	Sydsverige	SE08	Övre Norrland
United Kingdom			
UK1	North	UK7	West Midlands
UK2	Yorkshire and Humberside	UK8	North West
UK3	East Midlands	UK9	Wales
UK4	East Anglia	UKA	Scotland
UK5	South East	UKB	Northern Ireland
UK6	South West		