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Entrepreneurship, Agglomeration and Technological Change

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ABSTRACT. A growing body of literature suggests that variations across countries, in entrepreneurial activity and the spatial structure of economies could potentially be the source of different efficiencies in knowledge spillovers, and ultimately in economic growth. We develop an empirical model that endogenizes both entrepreneurial activity and agglomeration effects on knowledge spillovers within a Romerian framework. The model is tested using the GEM cross-national data to measure the level of entrepreneurship in each particular economy. We find that after controlling for the stock of knowledge and research and development expenditures, both entrepreneurial activity and agglomeration have a positive and statistically significant effect on technological change in the European Union.

KEY WORDS: agglomeration, economic geography, economic growth; entrepreneurship, knowledge spillovers, technological change

JEL CLASSIFICATION: O3, R1, J24, M13

1. Introduction

The story of the entrepreneurial process is one of the entrepreneur recognizing and acting on unexploited opportunity. Opportunity frequently exists in a crowded space of knowledge creating institutions, networks and venture capitalists. This 'Silicon Valley' story has been told in the context of other high technology agglomerations including Seattle, WA, Austin, TX, Boston, MA, and Washington, D.C. It also has its international counter parts in Bangalore, India, London, UK and Baden-Würtenberg, Germany. While this suggests that entrepreneurship and agglomerations play an important role in economic growth this has not been worked out theoretically (Bresnahan, Gambardella and Saxenian, 2001).

The seminal contribution of Romer (1986, 1990) to the literature on economic growth was to endogenize technological change within an economy in a general equilibrium model with well-specified market forms, selfish agents, perfect foresight and clearing markets. This provided a more realistic explanation of economic growth than the neoclassical theory that focuses on the role of investment in physical capital, increases in the supply of labor, and an exogenous change in technology. According to Romer (1996, 204):

> New growth theory started on the technology-as-public good path and worried about where technology came from, but it soon backed up and reconsidered the initial split that economists make in the physical world. New growth theorists now start by dividing the world into two fundamentally different types of productive inputs that can be called "ideas" and "things". Ideas are nonrival goods that could be stored in a bit string. Things are rival goods with mass (or energy). With ideas and things, one can explain how economic growth works. Nonrival ideas can be used to rearrange things, for example, when one follows a recipe that transforms noxious olives into tasty and healthful olive oil. Economic growth arises from the discovery of new recipes and the transformation of things from low to high value configurations.

The above view leads to insights that do not follow from the neoclassical model. It emphasizes

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that ideas are goods that are produced and distributed just as other goods are. If economic growth arises from the creation of new recipes to rearrange things, might not entrepreneurship and geography play some role in this transformation? However, the theory offers no insight into what role, if any, entrepreneurship and agglomeration might play in economic growth. In other words, it does not answer the question, "What is the role of entrepreneurship and agglomeration in technological change?"

An answer to this question can be pursued through the lens of the new economic geography and the modern theory of entrepreneurship. The distinguishing characteristic of the new economic geography is that it studies the economy within a framework that integrates space into general equilibrium theory (Fujita, et al., 1999; Krugman, 1991). One aspect of economic geography is the agglomeration of knowledge. Over the past decade, the new economic geography literature has tried to explain the development, and the economic role of geographic structures, and one of the important questions is related to the role of agglomeration in technological change and ultimately in macroeconomic growth (Fujita and Thisse, 2002).

The recent literature on entrepreneurship has shifted the emphasis in entrepreneurship from cultural and psychological traits to the discovery and exploitation of new knowledge by profit-seeking agents (Shane and Venkataraman, 2000). If entrepreneurs play an important role in the exploitation of technological opportunity the impact of entrepreneurship on growth becomes an important research question (Carree and Thurik, 2003). This relationship is especially important at the spatial level (Acs and Armington, 2004).

Both the relationship between geography and technological change, and between entrepreneurship and technological change, is interesting because these lines of research may prove fruitful in better explaining economic growth through knowledge spillovers. However, both approaches have severe limitations. For example, while there have been several attempts to model new growth theory with endogenously generated spatial structures this work is still in its infancy, until the very recent attempts by Fujita and Thisse (2002) and Baldwin et al. (2003). The purpose of this paper is to develop an empirical framework that endogenizes both entrepreneurial activity and agglomeration effects on knowledge spillovers. We present the first empirical test of the impact of entrepreneurial activity and agglomeration effects on the spillover of new knowledge, based on the Romerian (1990) model of endogenous technological change, as modified by Jones (1995). The model allows us to directly test the relationship between technological change and knowledge creation, conditioned by entrepreneurship and agglomeration effects, while controlling for knowledge spillovers.

We use a new and novel data set from the Global Entrepreneurship Monitor (GEM) project to test the effects of entrepreneurship on knowledge spillovers, and an index is created to measure the effect of agglomeration on knowledge spillovers in the European Union. Section 2 examines the relationship between agglomeration, knowledge spillovers and economic growth and the relationship between entrepreneurship, knowledge spillovers and economic growth. Section 3 extends the basic Romer framework, develops the empirical specification and presents the data, Section 4 has the results and the final section presents the conclusions. We find significant empirical support for the Romer model, where the coefficient on the stock of knowledge is significant but less then one. We also find support for the hypothesis that both agglomeration effects and entrepreneurship facilitate the knowledge spillover mechanism of new knowledge in economic growth.

2. Entrepreneurship and agglomeration

Technological change is the most important factor in long-run macroeconomic growth (Solow 1957). In new growth theory the technological element of the growth process is directly modeled within the economic system as a result of profit motivated choices of economic agents. Recently published findings in entrepreneurship, the geography of innovation and the new economic geography suggest that the extent to which a country is 'entrepreneurial' and its economic system is 'agglomerated' could be a factor that explains technological change. In this section we outline these literatures from an economic growth perspective.

2.1. *Entrepreneurship and technological change*

The origins of the discussion about the existence of opportunity can be traced to Joseph Schumpeter (1934). Schumpeter believed that the existence of opportunity required the introduction of new knowledge not just differentiated access to existing knowledge (Kirzner, 1973). One source of new knowledge came from changes in technology. These technological opportunities are innovative and break away from existing knowledge.

Opportunity therefore comes in part from the research and development (R&D) process that takes place in society. Technological change is an important source of entrepreneurial opportunity because it makes it possible for people to allocate resources in different and potentially more productive ways (Casson, 1995).

However, as was pointed out by Arrow (1974) the link between knowledge and economic knowledge is not well understood. The central problem is a gap in our understanding between technological change and the market that come into existence based on that innovation – this gap in our understanding is filled by the concept of entrepreneurial opportunity. An entrepreneurial opportunity consists of a set of ideas, beliefs and actions that enable the creation of future goods and services in the absence of current markets for them.

If technological opportunity is in part created by the production of new knowledge how is this opportunity discovered? One way in which people discover technological opportunity is through knowledge spillovers. Entrepreneurial discovery is in fact a process of knowledge spillover where knowledge is a non-rival good. Once entrepreneurs discover new opportunities, which are only partially excludable, they have the chance to exploit the opportunity. While most R&D is carried out in large firms and universities it does not mean that the same individuals that discover the opportunity will carry out the exploitation. In fact, because knowledge spills over, one person may discover an opportunity and another may exploit it.

The uncertainty inherent in new economic knowledge, combined with asymmetries between the agent possessing that knowledge and the decision making of the incumbent organization with respect to its expected value potentially leads to a gap between the valuations of the knowledge. This initial condition of not just uncertainty but greater degree of uncertainty vis-à-vis incumbent enterprises in the industry is captured in the theory of firm selection and industry evolution proposed by Jovanovic (1982). An implication of the theory of firm selection is that new firms may begin at a small scale of output, and then if merited by subsequent performance expand. What emerges from the new evolutionary theories and empirical evidence on the role of new firms is that markets are in motion, with a lot of new firms entering the industry and lots of firms leaving (Audretsch, 1995). The empirical evidence supports such an evolutionary view of entrepreneurship (Caves, 1998; Sutton, 1997).

The empirical evidence also supports the argument that technological change is a source of entrepreneurial opportunity. The evidence is indirect since we cannot measure the existence of opportunity. Acs and Audretsch (1989) found that young entrepreneurial firms play a key role in generating technological innovations, at least in some industries. Blau (1987) examined self-employment rates in the United States over a two-decade period and found that an increase in the rate of technological change led to an increase in the self-employment rate, Shane (1996) looked at the number of organizations per capita from 1899 to 1988 found that the rate of technological change, measured as the annual number of new patents issued, had a positive effect on the number of organizations per capita in the economy in the subsequent year.

While the relationship between technological change and opportunity cannot be measured directly, several authors have tried to measure the relationship between entrepreneurship and employment growth. Acs and Armington (2004) found that differences in the level of entrepreneurial activity, and the extent of human capital are positively associated with variation in growth rates. Holtz-Eakin and Kao (2003) using a rich panel of state-level data to quantify the relationship between productivity growth and entrepreneurship found that the effect of new firm formation on productivity is quite persistent.

These results are consistent with Audretsch and Keilbach (2004) who estimate a production function model for German regions based on start-up data from the 1990s. The empirical evidence suggests that entrepreneurship plays an important role in the discovery and exploitation of technological opportunity through knowledge spillovers, lead to higher economic growth.

Theories of entrepreneurship and economic growth are still relatively new even though the entrepreneurship literature does recognize that R&D is an important source of technological opportunity. The process by which knowledge spills over from the firm producing it for use by a third-party firm is exogenous in the model proposed by Romer (1990). The emphasis was on the influence of knowledge spillovers on technological change without specifying *why* and *how* new knowledge spills over. Yet, the critical issue in modeling knowledge-based growth rests on the spillover of knowledge. This was to some extent remedied by the neo-Schumpeterian models of endogenous growth (Aghion and Howitt, 1992, Cheng and Dinopoulos, 1992, Schmitz, 1989, Segerstrom,1991, Segerstrom, et al.,1990). However, these neo-Schumpeterian models design entrepreneurship as an R&D race where a fraction of R&D will turn into successful innovations.

While this implies a step forward, the essence of the Schumpeterian entrepreneur is missed. The innovation process stretches far beyond R&D races that predominantly involve large incumbent firms and concern quality improvements of existing goods. As pointed out by Schumpeter (1947) "the inventor produces ideas, the entrepreneur 'gets things done' ... an idea or scientific principle is not, by itself, of any importance for economic practice." Indeed, the Schumpeterian entrepreneur, by and large, remains absent in those models (Acs et al., 2004).

2.2. *Agglomeration and technological change*

As long as the knowledge necessary for technological change is codified (i.e., it can be studied in written forms either in professional journals and books or in patent documentations) the access to it is essentially not constrained by spatial distance: among other means libraries or the Internet can facilitate the flow of that knowledge to the interested user no matter where the user actually locates.

However, in case knowledge is not codified, because it is not yet completely developed, or it is so practical that it can only be transmitted while knowledge is actually being applied, the flow of knowledge can only be facilitated by personal interactions. Thus, for the transmission of tacit knowledge spatial proximity of knowledge owners and potential users appears to be critical (Polanyi, 1967). For example, several firms move their research facilities to geographic areas where significant amounts of related knowledge has already been accumulated in order to get easier access to that knowledge. Knowledge from other (industrial or academic) research facilities can be channeled via different means, such as, a web of social connections, the local labor market for scientists and engineers or by different types of consultancy relations between universities and private firms.

A large body of literature exists on the spatial extent of knowledge spillovers. At different levels of spatial aggregation (such as states, metropolitan areas, countries) in different countries (e.g. the US, France, Germany, Italy, Austria) and with the application of different econometric methodologies (e.g., various spatial or a-spatial methods) many of these studies conclude that geographical proximity to the knowledge source significantly amplifies spillovers between research and innovating firms. Strong evidence is provided both for the US (Acs et al., 2002; Jaffe et al., 1993; Varga 1998) and for Europe (e.g., Autant-Bernard, 2001, Fischer and Varga, 2003) that knowledge flows are bounded within a relatively narrow geographical range. Although certain industrial differences exists (such as for innovation in the microelectronics, instruments or biotechnology sectors proximity is more significant than for new technology development in the chemicals or the machinery industries) the hypothesis that spatial proximity is an important factor in innovation is strongly supported in the literature.

Varga (2000, 2001) provides empirical evidence that the spillover impact in knowledge production is positively related to the size of the region. Different types of agglomeration effects are at work to explain this phenomenon. Larger regions inhabit more firms connected by richer network linkages and as such the same knowledge generated by research in the area spills over to potentially more applications. Larger regions also offer a wider selection of producer services essential in technological innovation (e.g., information technology, legal, marketing services) contributing to a larger number of new technologies developed from the same knowledge base generated by (public and private) research in the area.

The new economic geography literature provides a general equilibrium framework where spatial economic structure is endogenously determined simultaneously with equilibrium in goods and factor markets (Fujita et al., 1999; Krugman,1991). This is a real breakthrough in economics given that before the appearance of the new economic geography no any school of economics since von Thünen' *Der Isolirte Staat* in the early nineteenth century had been able to build an economic model where the development of spatial structure is treated endogenously within a general equilibrium framework (Samuelson, 1983). The most recent models in the new economic geography incorporate the effects of knowledge spillovers on the formation of spatial economic structure as well as provide the first attempts to explicitly integrate the two 'new' schools of economics: the new growth theory and the new economic geography (Baldwin et al., 2003 Fujita and Thisse 2002). The need for the integration of the two schools is clear if one takes into account that agglomeration facilitates knowledge spillovers (according to the new economic geography) and knowledge spillovers determine per-capita GDP growth (according to the new growth theory) then it is not an unrealistic assumption that spatial economic structure affects macroeconomic growth.

Unfortunately, empirical investigations in the area of agglomeration and technological change are still relatively uncommon in the literature. The very few exceptions include Ciccone and Hall (1996), Ciccone (2002) and Varga and Schalk (2004). The following section presents the empirical modeling framework to integrate entrepreneurship and agglomeration into the explanation of technological change (and implicitly into the explanation of macroeconomic growth).

3.The empirical modeling framework

Our framework for empirical investigation is based on the Romer (1990) model of aggregate knowledge production as extended by Jones (1995). One of the most original contributions of Romer (1990) is the separation of economically useful scientific technological knowledge into two parts. The total set of knowledge consists of the subsets of non-rival, partially excludable knowledge elements that can practically be considered as public goods and the rival, excludable elements of knowledge. Codified knowledge published in books, scientific papers or in patent documentations belongs to the first group. This knowledge is non-rival since eventually it can be used by several actors at the same time and many times historically. On the other hand it is only partially excludable since only the right of applying a technology for the production of a particular good can be guaranteed by patenting while the same technology can spill over to further potential economic applications as others can study the patent documentation. Rival, excludable knowledge elements include the personalized (tacit) knowledge including particular experiences, insights developed and owned by the researchers themselves.

Equation (1) presents the manner the two types of knowledge interact in the production of economically useful new technological knowledge.

$$\mathring{A} = \delta H_{A} \lambda A^{\varphi} \tag{1}$$

where H_A stands for the number of researchers working on knowledge production in the business sector, A is the total stock of technological knowledge available at a certain point in time whereas $\mathring{A}$ is the change in technological knowledge resulting from private efforts to invest in research and development: δ, λ and φ are parameters. Equation (1) plays a central role in economic growth explanation since on the steady state growth path the rate of per capita GDP growth equals the rate of technological change ($\mathring{A}/A$).

Technological change is generated by research and it depends on the number of researchers involved in knowledge creation (H_A). However, their efficiency is directly related to the total stock of already available knowledge (A). Knowledge spillovers are central to the growth process: the higher A, the larger the change in technology produced by the same number of researchers. The same number of researchers with a similar value of A can raise the level of already existing technological knowledge with significant differences depending on the size of the parameters. Consider $\delta > 0$, which is the research productivity parameter. The larger is δ, the more efficient is H_A in producing economically useful new knowledge.

The size of φ reflects the extent to which the total stock of already established knowledge impacts knowledge production. Given that A stands for the level of codified knowledge (available in the academic literature or patent documentation), φ is called the parameter of codified knowledge spillovers. The size of φ reflects the portion of A that spills over and as such its value largely influences the effectiveness of research in generating new technologies. Hence the value of the aggregate codified knowledge spillovers parameter φ should be between 0 and 1.

However, not only codified but also non-codified, tacit knowledge can spill over as detailed in the previous section. The value of λ, in (1) reflects the extent to which tacit knowledge spills over within the research sector. The larger is λ in equation (1), the stronger the impact the same number of researchers plays in technological change. In contrast to φ and δ, which are determined primarily in the research sector and as such their values are exogenous to the economy, λ is endogenous because its value depends on the spatial pattern of economic activities and the level of entrepreneurial activity in the country. The size of λ in equation (1) relates to spatial economic structure in two ways. First, the higher the spatial concentration of research, the higher λ because spatial proximity promotes spillovers to a large extent. Second, as recent empirical studies suggest, the magnitude of localized knowledge spillovers from research is also influenced by agglomeration.

The value to λ is also influenced by the amount of entrepreneurial activity because the value of new economic knowledge is uncertain. While most R&D is carried out in knowledge creating institutions (large firms and universities) it does not mean that the same individuals that discover the opportunity will carry out the exploitation. An implication of the theory of firm selection is that new firms may enter an industry in large numbers to exploit knowledge spillovers. The higher the rate of new firm entry the greater should be the value of λ because of knowledge spillovers.

Based on the literature we assume that these spillovers are influenced largely by agglomeration as well as by the level of entrepreneurial activity in the country.To empirically investigate the extent to which entrepreneurship and agglomeration affect knowledge spillovers we develop an empirical model in which we endogenize the parameter λ in equation (1).

$$\log(\mathrm{NK}) = \delta + \lambda \log(H) + \varphi \log(A) + \varepsilon \qquad (2)$$

$$\lambda = (\beta_1 + \beta_2 \log(\mathrm{ENTR}) + \beta_3 \log(\mathrm{AGGL})) \qquad (3)$$

where NK. stands for new knowledge (i.e., the change in A), ENTR is entrepreneurship, AGGL is agglomeration, A is the set of publicly available scientific-technological knowledge and ε is stochastic error term, Implementation of (3) into (2) results in the following estimated equation:

$$\begin{aligned}\log(\mathrm{NK}) = \delta &+ \beta_1 \log(\mathrm{H}) \\ &+ \beta_2 \log(\mathrm{ENTR}) \log(H) \\ &+ \beta_3 \log(\mathrm{AGGL}) \log(H) \\ &+ \varphi \log(A) + \varepsilon \qquad (4)\end{aligned}$$

In (4) the estimated values of the parameters β_2 and β_3 measure the extent to which research interacted with entrepreneurship and agglomeration contributes to knowledge creation.

In the estimation of (4) the units of observation are selected industrial sectors in European countries for the year 2001.[1] The selection of countries and sectors is determined by data availability. The number of patent applications operationalizes NK. Although patents are good indicators of new technology creation, they do not measure the economic value of these technologies (Hall et al., 2001). According to Griliches (1979) and Pakes and Griliches (1980, 378) "patents are a flawed measure (of innovative output) particularly since not all new innovations are patented and since patents differ greatly in their economic impact." However, a recent comparative study of direct innovation measures and patent applications evidence that patent applications are good proxy for innovation in econometric models (Acs et al, 2002).

R&D expenditures in Euro measure H. Data accessibility explains this choice to measure H in (1). An earlier comparison of R&D expenditures and employment data conclude that the two measures are highly correlated with each other and the results of regression analyses are not significantly different (Varga, 1998). This makes us confident to apply R&D expenditures in our study.

A is operationalized by the total number of available patents in all the sectors in the country (i.e., the total number of patents granted by inventors of the country in the last 20 years). The source of patent data is the OECD patent database. International patent classification (IPC) classes are assigned to industrial classes (ISIC Rev. 2) by the application of the MERIT concordance table developed by Verspagen, Moergastel and Slabbers (1994), Eurostat provides R&D expenditures data.

AGGL is measured by the agglomeration index that is calculated as the share of employment of city regions where the number of employees exceeds 500,000 in country total employment.[2] Eurostat provides regional employment data. ENTR is empirically measured by the total entrepreneurial activity (TEA) index developed within the framework of the GEM project.

The intent of GEM is to systematically assess two things: the level of start-up activity or the prevalence of nascent firms and the prevalence of new or young firms that have survived the start-up phase. First, start-up activity is measured by the proportion of the adult population (18–64 years of age) in each country that is currently engaged in the process of creating a nascent business. Second the proportion of adults in each country who are involved in operating a business that is less than 42 months old measures the presence of new firms. The distinction between nascent and new firms is made in order to determine the relationship of each to national economic growth. For both measures, the research focus is on entrepreneurial activity in which the individual involved have a direct but not necessarily full, ownership interest in the business. There are numerous ways to measure entrepreneurial activity. One important distinction is between opportunity-based entrepreneurial activity and necessity-based entrepreneurial activity. Opportunity entrepreneurship represents the voluntary nature of participation and necessity reflecting the individual's perception that such actions presented the best option available for employment but not necessarily the preferred option. Opportunity entrepreneurship differs from necessity by sector of industry and with respect to growth aspirations. Opportunity entrepreneurs expect their ventures to produce more high growth firms and provide more new jobs. The 16 European Union countries in 2001 had an average prevalence rate of about 8 percent (Reynolds et al., 2001).

To further explore this question of high potential entrepreneurs the 2002 GEM researchers added several new questions to the GEM protocol in order to isolate those ventures widely believed to have the greatest possibility for having a substantial impact on the economy. These new items were utilized to locate those ventures with potential to create new markets. Two additional criteria were added to further distinguish those new ventures with the potential to make a major contribution to the national economy: (1) the expectation of 20 or more jobs created within five years and (2) the intention to export goods or services. Of the 9615 star-ups and new firms identified in the 37 countries, only 926 met all of these criteria, about 9.6 percent (Reynolds et al., 2002).

4. Empirical results

In empirically estimating equation (4) two issues should get particular attention: multicollinearity (because H appears three times in the equation) and heteroskedasticity (since the expected heterogeneity of the country-industry dataset).

Table I presents empirical estimation results for equation (4). The equation is estimated by OLS. Standard errors are based on the White heteroskedasticity consistent covariance matrix estimator that provides correct estimates of the coefficient covariances in the presence of heteroskedasticity of unknown form (White 1980).

In Model 1 the estimated parameter of log(H) is highly significant. The logarithm of R&D expenditures explains 75 percent of the variations in the logarithm of patent applications at the country-industry level. The additional effect of log(A) where A is measured by the aggregate stock of available patents is considerable: it improves regression fit by 24 percent. Both coefficients are highly significant indicating that the original Romer (1990) equation captures well the main factors in technological change.

In Model 2 ENTR is measured by the high potential index. Extending Model 1 by the interaction terms Log(H)*Log(AGGL) and Log(H)*-Log(ENTR) improves regression fit only slightly.[3] The estimated parameter for Log(H)*log(ENTR) is significant at ($p < 0.05$) while the agglomeration effect is not significant in Model 2. This latter result might be the outcome of a shortcoming of the measurement applied (i.e., the agglomeration index is not sensitive to differences in the relative geographical positions of city regions within a country). Technical constraints could not make it possible for us to improve on this agglomeration measure. However, we also assumed that perhaps the United Kingdom as an outlier observation of AGGL might cause the unexpected result.[4]

To account for this effect in agglomeration a dummy variable (DUMUK) is included in Model 2a. The parameter of DUMUK is marginally significant ($p < 0.10$) whereas the interaction term's parameter becomes significant ($p < 0.05$). This supports the hypothesis that in Model 2a the high potential index enters the estimated equation with a highly significant parameter value ($p < 0.01$). Regression fit increases only slightly as compared to the original Romer equation in

TABLE I
Ols regression results for Log(Patent applications) for selected industries in selected European countries ($N = 63$, 2001)

	Model 1 Romer	Model 2 Extended Romer with TEA high potential	Model 2a Extended Romer with TEA high potential	Model 3 Extended Romer with TEA Opportunity	Model 4 Extended Romer with TEA Necessity	Model 5 Extended Romer with TEA
Constant	−3.175[a]	−2.843[a]	−2.966[a]	−3.711[a]	−3.506[a]	−3.513[a]
	(0.346)	(0.360)	(0.368)	(0.467)	(0.468)	(0.482)
Log (H)	0.298[a]	0.355[a]	0.442[a]	0.204[c]	0.396[a]	0.257[c]
	(0.061)	(0.074)	(0.080)	(0.102)	(0.079)	(0.134)
Log(H) *Log(AGGL)		0.024	0.086[b]	0.112[b]	0.100[c]	0.089[c]
		(0.032)	(0.042)	(0.046)	(0.054)	(0.047)
Log(H)*Log(ENTR)		0.069[b]	0.079[a]	0.143[b]	0.038	0.073
		(0.028)	(0.030)	(0.056)	(0.048)	(0.062)
Log(A)	0.723[a]	0.679[a]	0.698[a]	0.794[a]	0.775[a]	0.773[a]
	(0.063)	(0.055)	(0.056)	(0.072)	(0.077)	(0.075)
DUMUK			−0.740[c]	−0.852[b]	−0.716[c]	−0.711[c]
			(0.378)	(0.327)	(0.407)	(0.407)
R^2-adj	0.92	0.93	0.93	0.93	0.93	0.93
F-statistic	357[a]	189[a]	160[a]	162[a]	145[a]	147[a]

Note: TEA high potential index is available only for year 2002; White heteroscedasticity–consistent estimated standard errors are in parentheses.
[a] Denotes significance at least at 0.01.
[b] Denotes significance at least at 0.05.
[c] Denotes significance at least 0.10; variables are introduced in the main text.

Model 1. Estimated parameters of the Romer equation as well as their significance patterns are stable across models 1 to 2 These observations suggest that multicollinearity is not a serious issue in the model.

Table I also shows estimates for the different additional measures of entrepreneurship provided by the GEM project. Model 3 shows results for opportunity entrepreneurship, Model 4 gives the results for necessity entrepreneurship and Model 5 is the output with TEA. While in Model 3 the coefficient for opportunity entrepreneurship is positive and statistically significant, for both Model 4 and Model 5, the interaction term for entrepreneurial activity is not significant. This result is consistent with the fact that necessity entrepreneurship, having to become an entrepreneur because you have no better option, will not lead to technological change, although it may lead to employment growth. The same is true of entrepreneurial activity in general.

The estimated elasticity of technological change with respect to available codified knowledge is less than 1 (0.7) that corresponds to what is suggested by Jones (1995). The estimated research spillover effect in Model 2a is related to high potential entrepreneurship and agglomeration according to the following equation:

$$\lambda = 0.44 + 0.086^{*}\mathrm{Log(AGGL)} + 0.079^{*}\mathrm{Log(ENTR)} \qquad (5)$$

What do these results suggest for entrepreneurship and agglomeration? Table II shows the coefficients for knowledge spillovers for the nine countries with and without the effect of entrepreneurship and agglomeration. As shown in column two agglomeration varies considerably from country to country with a high of 0.59 in the UK to a low of 0.14 in Poland. The TEA high potential index also varies from a low of 0.19 percent in Belgium to a high of 1.52 in Ireland. The elasticity of R&D spillovers with respect to new knowledge is 0.30 (Model 1 in Table I), This number is relatively small with respect to the 0.70 elasticity found for the total stock of knowledge.

One would suspect that entrepreneurship and agglomeration would be able to significantly raise the effect of R&D spillovers from new knowledge. This would especially be true if entrepreneurs played an important role in knowledge spillovers as suggested by the entrepreneurship literature. In Table II, column four shows the value of the coefficient of λ extended by entrepreneurship and agglomeration effects. The coefficient varies between 0.31 and 0.42 and is greater than 0.30 in all the countries in the sample. How should we interpret these results? Compared to what? The only other study we know of that measures the interaction between entrepreneurship and research and development is Michelacci (2003) who found that the value of λ for the United States varied between 0.24 and 0.48 for the post-war period. These findings are broadly consistent with those results. The last column shows the ratio of the extended coefficient divided by the non-extended coefficient. The ratio varies from 1.04 to 1.41.

TABLE II

Country coefficients with and without extension for entrepreneurship and agglomeration

	AGGL	TEA HIGH	Coefficient (Model 2a)	Coefficient (Model 1)	Coefficient ratio
Belgium	0.31	0.64	0.38	0.30	1.28
France	0.34	0.57	0.38	0.30	1.28
Germany	0.18	1.47	0.39	0.30	1.31
Hungary	0.24	0.76	0.38	0.30	1.27
Ireland	0.35	1.52	0.42	0.30	1.40
Italy	0.18	0.71	0.37	0.30	1.23
Poland	0.14	0.19	0.31	0.30	1.04
Spain	0.43	0.64	0.40	0.30	1.33
United Kingdom	0.59	0.99	0.42	0.30	1.41

These results suggest that increasing research and development expenditures, without increasing entrepreneurial activity, and or agglomeration effects, may not achieve the same result as if it was accompanied by entrepreneurial activity and agglomeration effects (Acs et al., 2004). After taking into account the effect of the stock of knowledge and research and development expenditures, both agglomeration and entrepreneurship have a weak positive effect on technological change. It is unlikely that a substantial high technological entrepreneurial sector will develop in the absence of broad national participation in entrepreneurship. If one wanted to increase technological change in the European Union more agglomeration of economic activity and more entrepreneurship may increase the amount of knowledge spillovers.

5. Conclusion

This paper developed an empirical model that endogenizes both entrepreneurial activity and agglomeration effects on knowledge spillovers within a Romerian framework. We tested a modified model of technological change to ascertain the impact of agglomeration effects and entrepreneurial activity on endogenous technological change. Specifically, we examine the impact of entrepreneurial activity and agglomeration effects on the spillover of new knowledge. The effect of agglomeration on technological change is positive and statistically significant. The effect of entrepreneurship on technological change is positive and highly significant. When the interactive terms are taken into account the regression fit increases only slightly. Consequently we found significant, but not too strong agglomeration and entrepreneurship effects on technological change for selected European countries. These results are broadly consistent with a growing body of literature suggesting that entrepreneurial activity and agglomeration play a positive role in knowledge spillovers and therefore in technological change and economic growth.

We also find that the endogenous growth model developed by Romer (1990) does a good job of modeling economic growth. We found support for Jones (1995) that the spillover effects from codified knowledge are less then one. There are several caveats that should be kept in mind. First, the GEM data might not be a good measure of either opportunity entrepreneurship in general or high technology entrepreneurship in particular. However, strong co-occurrence among these diverse measures indicated that the indices are reasonable measures of the overall level of different types of entrepreneurial activity. Second, we only have one year of data at the start of a recession. A longer time period may reveal different results. Finally, the inter relationship between agglomeration effects and entrepreneurial activity may be important. However, we did not model this in our paper and is an interesting topic for further research.

Notes

[1] Industrial sectors include Chemistry and Pharmaceuticals, Computers and Office Machines, Electrical Machinery, Electronics, Instruments, Other Machinery, Transportation Vehicles. The following European countries are included; Belgium, Germany, France, Hungary, Ireland, Italy, Poland, Spain and the United Kingdom.

[2] With the exception of Belgium and the UK where the highest level of data aggregation is NUTS 2 for the rest of the countries the agglomeration index is calculated using NUTS 3 level aggregated employment data.

[3] Equation (4) forms the basis of our empirical investigations. This explains why we do not account for the direct effect of either ENTR or AGGL on technological changer.

[4] A closer investigation of the agglomeration index suggests that economic activities exhibit an exceptionally high level of spatial concentration in the UK (relative to the rest of the countries in the sample). While the agglomeration index for the UK is 0.59 the corresponding average value for the rest of the sample countries is 0.27. According to this the UK economy appears to be more than two times concentrated geographically than the rest of Europe. This observation might well be the sign of aggregation bias as the lowest level of data aggregation for the UK is NUTS 2 while for the rest of the countries (with the exception of Belgium) data are aggregated at NUTS 3 level. While this does not seem to distort the value of the index for Belgium (i.e., the size of NUTS 2 regions are compatible with the average size of NUTS 3 regions in our sample) it might not be the case for the UK. Running separate regressions with and without the UK further supports the presence of regional data aggregation bias: with the exception of the 'agglomeration effect' the UK follow very similar patterns to the rest of Europe: parameter estimates and their significances are similar for $\log(H)$, $\log(A)$ and $\log(H)*\log$ (ENTR) This is not repeated for the geography effect: the number of patents in the UK exceeds the rest of the sample

average only slightly as it is 632 in the UK and 478 otherwise while AGGL is more than twice as high in the UK

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