(2013) 43, 191–212

The Review of Regional Studies

The Official Journal of the Southern Regional Science Association

Investment in Information and Communication Technologies (ICT): The Role of Geographic Distance and Industry Proximity*

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Abstract: Employing data from Italian manufacturing firms, this paper attempts to check the existence of geographic and industry distance effects on the investment in information and communication technology (ICT). Geographic distance is defined by the Euclidean distance between each possible pair of locations (municipalities) according to their geographical coordinates. Industry proximity is measured by the firms' industry distance according to the trade intensity between sectors. The model specified here refers to the combined spatial autoregressive model with autoregressive disturbances (SARAR), which are modelled simultaneously. The results show that both geographical and industry proximity have positive effects on the amount of ICT investment by firms. Furthermore, an econometric analysis shows that productivity, R&D activity, subsidies, reorganization, and labor composition are jointly correlated to ICT investment.

Keywords: ICT; spatial weights; spatial dependence; spatial models

JEL Codes: L86, C31, R15, O10, O31

1. INTRODUCTION

Theoretical and empirical literature on firms and the new economy have mainly focused on two areas: the impact of information and communication technology (ICT) on firms' productivity and on the main organizational changes of firms needed to maximize the gains in productivity offered by new technologies. While theories of knowledge spillovers were traditionally formulated to explain the concentration of industries in general, geographic distance might not be the only relevant factor for technological spillovers as the economic distance between two firms might also be important. The idea is that the amount of technology in one sector might be correlated to that in closely related sectors. From this perspective, firms may benefit from spillovers originating from their own or from neighboring industries. Such benefits may depend on the extent to which a sector trades with the other sectors. In such a view spillovers might be particularly important for explaining the clustering of technological expenditure in specific industries.

In principle the economic effects of ICT would appear far larger than it would by simply considering the amount of investment realized in a particular location, industry or firm. ICT generates a flow of "free" benefits substantially larger than their own direct returns. Its

*I am indebted to Juan de Dios Tena-Horrillo, Giuseppe Medda, and Claudio Detotto for valuable comments on matrix construction. I am also grateful to two anonymous referees whose comments greatly improved the quality of the paper. I also thank the Fondazione Banco di Sardegna for financial support. All the usual disclaimers apply.

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ISSN 1553-0892, 0048-749X (online)

www.srsa.org/rrs

contribution to economic growth spreads across industries and space, potentially stimulating further amounts of complementary investments and innovations. The interplay and feedbacks that strongly characterize the technological path gives rise to various kinds of spillovers. These may affect the use of a new capital-to-labor resource reallocation across firms, organization, and practices within the context of firm interaction. They also may concern additional infrastructure investment in proximal locations. ICT strongly depends on new knowledge, and the spatial and industry concentration of technological activity is likely to favor the exchange of information among firms about new products or production methods. Observing and distinguishing all this in a traditional regression is certainly not straightforward. From this perspective, spatial spillover analysis may be useful to investigate the mechanism by which ICT expenditure is distributed over industries.

This work investigates the ICT adoption in Italy in terms of its spatial dimension. The analysis is carried out on a sample of 1,941 manufacturing firms over the 2001–2003 period. Italy is a developed country that lags somewhat in terms of technology production and absorption. This is because its economy is characterized by a relative lack of competitiveness vis-à-vis other industrialized economies. Hence from this perspective, Italy represents an interesting case for ICT-related issues. In particular, two strong peculiarities of Italy (in the period considered here) are its marked digital divide between the north and the south of the country and its lack of an efficient network system among firms that could encourage a rapid flow of information and thereby generate positive externalities benefitting the whole system. This is of particular interest for the case of ICT investment and for the important role this kind of technology represents for firms' growth.

In more detail, this paper tries to examine whether the amount of a firm's investment in new technologies depend on the ICT investment made by other firms belonging to the same location or sector, as well as to related locations or sectors. Spatial proximity might be very important as spillovers flow across locations. However, since benefits from spillovers tend to decline with distance, it is expected that relative isolation leads to less ICT diffusion. Moreover if the spatial correlation is due to the direct influence of neighboring sectors, resulting ordinary least squares (OLS) estimates are necessarily biased and inefficient (Anselin, 1988).

Furthermore, while the literature on the diffusion of technology through trade is dominated by cross-country studies, very similar arguments apply at a more local level. In fact, most trade tends occur within a country. Hence intra-national interregional spillovers may be even stronger than their international equivalents. Together with the spatial analysis this reinforces the need for intra-national analyses like that attempted in the present paper.

The analysis contributes to the empirical research on ICT by constructing two distinct matrices to test the importance of physical and industry closeness and to investigate the determining factors that influence ICT investment. Physical proximity is defined by the Euclidean distance between each possible pair of location centroids (physical median locations within municipalities) using their geographical coordinates. The spatial influence on firm i will be related to the weighted sum of the ICT expenditure in each location j, where the weights are given by the inverse distance between unit i and unit j. Industry proximity is measured by the firms' industry distance according to the trade intensity among sectors. The spatial influence on firm i will be related to the weighted sum of the ICT expenditure in each industry j, where the weights are given by the share of sales (over total sales) of industry i to industry j.

The results of the spatial analysis suggest that in firms' ICT investment decisions are affected by spillovers originating from both neighboring firms and neighboring industries. Exogenous shocks (represented by the autoregressive disturbances) do not affect ICT spending in either a geographic or industry dimension. Although some caution is necessary, given that the explanatory variables have been used largely as control variables whose main purpose is to prevent the parameter of the lagged dependent variable from being biased, the econometric results suggest that productivity, R&D, labor composition, reorganization, and subsidies are good predictors of ICT investment. This is in line with previous studies.

The article is organized as follows. Section 2 contains a discussion of the related literature. Section 3 provides a description of the data set and the variables used. Section 4 describes the theory underlying the spatial regression models. Section 5 explains the construction of the two spatial weight matrices. Section 6 presents the results, followed by the conclusions in Section 7.

2. LITERATURE BACKGROUND

It is a common accepted that ICT reduces the economic importance of geographic distance. ICT has the potential to disseminate information over space and to overcome geographical barriers. According to this idea, the New Economy implies that transport costs would be dramatically reduced, distance would be less important, and peripheral regions would benefit from new technology (Kelly, 1998; Quah, 2000). Consequently, the geographical concentration of income opportunities and wealth should dissipate over time (Compaine, 2001).

Nevertheless, although ICT represents an extraordinary tool to sustain economic growth (among many others, see Schreyer, 2000; Oliner and Sichel, 2000) and to disseminate information and deliver services over space, its potential to promote growth and bring about the new age of "the death of distance" (Cairncross, 2001; Quah, 2000) apparently has not yet arrived. Contrary to most expectations, overall empirical studies indicate huge disparities in the intensity of ICT adoption across and within countries. For example, using data from Irish manufacturing firms Haller and Siedschlag (2011) analyze the factors driving inter- and intra-firm diffusion of ICT. They find that the path of ICT diffusion has been uneven across firms, industries and space.

Forman, Goldfarb, and Greenstein (2005a) supply evidence that both industry and location are important in explaining the geographic variance in technology adoption. They also find that industries are different in their sensitivity to location and provide evidence for an industrial digital divide. Forman, Goldfarb, and Greenstein (2005b) study how new technology investment shaped geographic differences in economic outcomes. They show that participation in the Internet is more likely in rural areas than in urban areas, particularly for technologies that involve communication across establishments. Nevertheless, frontier Internet technologies for communication within an establishment are more often observed in urban areas. Forman, Goldfarb, and Greenstein (2005c) investigate the sources of geographic variance in commercial Internet use and supply a view ("industry composition theory" in their words) that asserts the demand for the Internet is increasing in location size because of the concentration of information-intensive firms in urban areas. They show evidence on factors influencing the dispersion of Internet technology to business. They further demonstrate that business use of the Internet is shaped significantly by the prior geographic distribution of industry. With respect to Italy, Bonaccorsi, Piscitello, and Rossi (2005) find that the diffusion of Internet use has much higher geographic concentration than population or income. Through their empirical evidence from the Italian case, they conclude that more-isolated areas suffer from severe difficulties in adjusting to the new technology.

Mack and Grubesic (2009) find that the provision of broadband telecommunication services in the United States is spatially heterogeneous. Parajuli and Haynes (2012) explore the spatial heterogeneity associated with broadband Internet and new firm formation. Employing Geographically Weighted Regression they find that the association between single-unit firm births and the provision of broadband varies across counties in Florida and Ohio. Differences in the spatial distribution of ICT have been explained in terms of differences in technological levels, infrastructural endowments (Marrocu, Raffaele, and Pala, 2000; Iammarino, Jona-Lasinio, and Mantegazza, 2004) and local spillover effects (Audretsch and Feldman, 1996; Galliano and Roux, 2006).

The geography of innovation literature stresses that space matters in the innovation process because of better and easier interpersonal relationships and contacts. It is assumed that the benefit a firm can receive from other firms' technological efforts is inversely related to its distance from the firm generating the externality (Wolff and Nadiri, 1993; Keller, 2002). Several important contributions model the spatial dependence that might be inherent to ICT adoption and telecommunications policy. Gaspar and Glaesar (1998) explore the substitutability or complementarity between IT and the face-to-face contacts made possible by cities. Galliano, Roux, and Filippi (2001) focus on the effects of the organizational and spatial structures and behaviors of firms on ICT adoption in a sample of French manufacturing firms. Their results support the importance of spatial factors—such as the type of areas where firms are located—and show that ICTs not only enable the firm to manage problems related to distance but also help it to overcome spatial hurdles that can be associated with new organizational modes.

Sohn, Kim, and Hewings (2002, 2003) investigate the spatial linkages between ICTs and urban form for Chicago and Seoul. Forman, Goldfarb, and Greenstein (2003) distinguish between the *use* of the Internet, since it is now basically necessary for businesses' promotional purposes, and the *adoption* of Internet technology to enhance computing processes for competitive advantage. They find that participation and enhancement display contrasting patterns of dispersion and that there are substantial differences across industries. Forman (2005) investigates Internet adoption decisions in a large sample of organizations in the finance and services sector. By observing the adoption patterns of geographically concentrated and dispersed firms, the author finds that Internet technology helps to reduce coordination costs related to geographic distance.

Grubesic (2006) finds support for spillover effects of broadband competition to smaller communities that are close to the largest urban areas. Mack and Grubesic (2009) employ a combination of basic spatial statistical analytical tools and geographic information systems to evaluate the relationship between firm location and broadband provision trends in the state of Ohio. They suggest that changes in broadband provision have no relationship with changes in firm location. Only at a disaggregated firm-level analysis do their results provide statistically significant results for a subset of industrial sectors. Mack, Anselin, and Grubesic (2011) use spatial econometric models to investigate the importance of broadband provision to knowledge-intensive firms in U.S. metropolitan statistical areas. They show the need for both a spatial econometric and a metropolitan-area-specific evaluation of this relationship. Their results also suggest potential spillover effects to knowledge-intensive firm locations. Mack (2012) studies the relationship between the spatial distribution of broadband providers and the presence of knowledge-intensive firm clusters in U.S. counties. This may explain why some regional economies are relatively more successful at stimulating firm growth in this sector.

3. DATA DESCRIPTION

The empirical analysis relies on two main data sources: sectorial-level data, provided by the Italian National Institute of Statistics (ISTAT) and firm-level data taken from the Survey of Manufacturing Firms (SMF) that was carried out by the Research Department of Capitalia Bank (Capitalia, 2003). The SMF contains questionnaire responses from firms about their structure and behavior, and 15 years (1989–2003) of data from their balance sheets. The SMF surveyed sample of Italian firms with 11 to 500 employees. The survey sample frame was stratified according to the number of employees in the firm, the sector to which the firm belongs, and its location. The sample was pulled from respondents to *The Census of Italian Firms*, which included all manufacturing firms with more than 500 employees. Unfortunately, access to longitudinal data is limited. Since just a small fraction of the observations overlap, only the 2001–2003 survey is used in the empirical application. This clearly prevents the analysis from addressing long-term considerations. The survey supplies information about the total amount of ICT investment over the triennium. After data cleaning, the final sample contains 1,941 observations.

Different from other advanced countries (particularly the U.S.) where DSL and cable compete for market share with a consequence of a dramatic impact on pricing and ICT adoption, Italy lagged particularly in terms of ICT infrastructures and ICT diffusion at the start of the decade 21st century. In 2001 only about 10 percent of firms used broadband compared to the 88 percent at the end of 2011. This share is even more peculiar if seen from a regional perspective. In the period 2001–2003 firms in south Italy were 30 percent behind their north Italy counterparts, giving rise to a marked intra-national digital divide. However, it is worth underlining that such divide progressively reduced so that the gap is now down close to about 7 percent (ISTAT, 2012).

Table 1 shows the descriptive statistics for the firms in the sample. The total amount of ICT expenditure per worker for the whole sample is 2,152€. Value added per employee is 53,000€, and the average firm size is 119 workers. Fixed capital per worker is 152,000€, and the ratio of bank credit over value added is 68 percent. Half of the firms in the sample have R&D expenditures, 17 percent of the firms received public support for investment in technology, about 80 percent exported, and 42 percent reorganized over the study period. The average firm age was 29 years, and the white/blue collar ratio is 0.58.

Considering the geographic distribution, 87 percent of the companies in the sample were located in the most economically advanced part of the country (north) and 26 percent were settled in cities with more than 250,000 inhabitants. Since not all industries contain a sufficient sample observation count to allow statistically viable estimations, some sectors were merged based on technological similarities. Thus 15 useable industries were derived according to the industry ATECO two-digit classification.

From Table 2 it emerges that the sample under investigation is dominated by firms in metals and metallic products, and industrial machinery. Then there follow the textiles and clothing and the food and tobacco industries. On the other hand, petroleum oil and coal industries are represented by only few firms.

Table 1: Descriptive statistics

Variable	obs: 1,941 Mean	(Std. Dev.)
Continuous:		
ICT per employee (€, total for the triennium)	2151.68	4603.73
Added value per employee (€, triennium average)	52700	27460
Employees (2001)	118.50	362.54
Fixed capital per worker (€, 2001)	152150	171290
Bank credit over value added (€, triennium average)	.68	.72
AGE: firm age	29.43	19.6
WCBC: white collar blue collar ratio	.58	.55
Dummies:		
RESEARCH=1 if firm has R&S expenditures	.50	.50
GRANT=1 if firm received public support for investment in technology	.17	.37
EXPORT=1 if firm has exported	.79	.40
INNORGA=1 if firm carried out a process of reorganization	.42	.49
NORTH=1 if firm is located in the North of Italy	.87	.33
CITY=1 if firm belongs to a city >250'000 inhabitants	.26	.43
TECH=1 if firm belongs to the "science-based" industry pavitt classification ($pavitt_4$)	.04	.20

Source: own elaborations from Capitalia (2003).

Table 2: ICT Intensity: Industry Distribution

Manufacturing sector (Nace two-digit)	Number of firms	ICT intensity (€, industry mean)	s.d.
15, 16: Food, tobacco	200	1986.62	3576.26
17, 18: Textiles, Clothing	229	1806.72	2855.82
19: Shoes, leather	75	1910.65	6868.45
20: Wood and wood products (no furniture)	46	1572.20	1396.60
21, 22: Paper, printing and publishing	93	2036.21	3095.93
23: Petroleum, coal	10	1913.28	2556.77
24: Chemicals	104	2684.25	4612.95
25: Rubber, plastics	99	1731.06	3404.26
26: Non-metallic minerals	104	1253.77	2011.60
27, 28: Metals, metallic products	343	2211.34	5285.31
29: Industrial machinery	300	2120.24	3178.33
30, 31, 32, 33: Professional instruments, electric and electronic equipment, radio, TV and telecommunications, Optical, jewelry, measurement equipment	156	2813.48	4366.22
34, 35: Auto and motor vehicles, other transportation equipment	50	4150.12	12635.80
36: Misc.: furniture, musical instruments, toys	132	2419.03	5946.32
Total	1,941	2151.67	4603.72

Within each sector the differences in ICT intensity are substantial, as indicated by the fact that the standard deviation is larger than the mean in most of the 15 sectors. It is straightforward to observe that firms investing in ICT are not uniformly spread across industries. ICT expenditure per worker is the lowest for the nonmetallic and minerals sector (1,253€) and for the wood sector. It is highest in the auto, motor vehicles, and other transportation equipment (4,150€). The ratio of the largest to smallest sector is 3.3, thus confirming that the distribution of investment in new technologies is heterogeneous across the sample. This represents a starting point for this paper which attempts to ascertain if such heterogeneity has effects on the ICT intensity in individual sectors. Finally, the 15 sectors obtained are used to construct the sectoral links weight matrix employed for the spatial analysis described below.

4. THE VARIABLES EMPLOYED

This section highlights a range of firm-specific profiles that can help to explain the intensity of ICT investment at a certain time. The variable under investigation is the amount of ICT expenditure over the three-year period (2001–2003) on computer hardware, computer software, and telecommunications equipment. When divided by the number of workers, it yields a measure of ICT spending per employee (*LogICT*). Thus, unlike many other studies, this work considers a continuous dependent variable when exploring the relative importance of the different factors in ICT spending and the existence of spatial effects. A measure of firm efficiency, proxied by the added value per employee (*LogAVY*), is included in the analysis to control for possible effects on ICT investment decisions that derive from different productive performance among firms. In line with the existing literature, firm size is included as an explanatory variable. This variable is measured as the logarithm of the number of employees and refers to the initial year (*LogEMP*). Size may influence ICT spending through better organization, easier access to the financial markets, specialization of activities and routines, and investment in complementary activities to technology.

Capital intensity (*LogKAP*), is measured as physical assets per employee, to account for the fact that firms in more capital-intensive productions may have a higher demand for ICT investment, assuming complementarity between ICT and non-ICT capital. A binary variable indicating whether firms are engaged in research activity (*RESEARCH*) is included in the regression. The rationale is that R&D activities may help firms in absorbing new technologies, particularly those firms using ICT in production processes (Lal, 1999).

A measure of indebtedness is also considered in order to control for firms' potentials to find financial sources. It is expressed as the ratio of debt to banks over average value added (*DEBT*). The analysis also includes government subsidies to technological investment (*GRANT*). These are usually very influential in the general investment activities of firms and sectors.

An export dummy (*EXPORT*) is included because firms that compete in foreign markets tend to be more technological savvy than are others. Operating in more competitive environments, exporting firms are more inclined to adopt new technologies (Hollenstein, 2004; Lucchetti and Sterlacchini, 2004; Bayo-Moriones and Lera-Lopez, 2007; Giunta and Trivieri, 2007). There may also be an indirect effect, deriving from the richer network of customers, suppliers or competitors that exporting firms may have access to.

A variable indicating if the firm has introduced innovations in the organization (*INNORG*) is also included among the regressors. Several studies show the complementarity of the adoption of new models of workplace organization and the introduction of ICT (Bresnahan, Brynjolfsson and Hitt 2002; Brynjolfsson and Hitt, 2000). Organizational advances directly increase productivity. Nevertheless the relationships between ICT and organizational change are quite controversial. Using Italian manufacturing data, Piva and Vivarelli (2004) find that organizational change has a significant marginal effect on the demand for skills. Employing the same dataset, Piva, Santarelli, and Vivarelli (2005) also find support that organizational complementarity matters. On the other hand, Giuri, Torrisi, and Zinovyeva (2008) find no evidence of complementarity between ICT and skills in Italy.

The skill composition of employees, expressed as the ratio of white collar workers to blue collars workers (*WCBC*) is used as a proxy for human capital. This enables the capture of the absorptive capacity enabled by ICT. Since the knowledge required to master ICT is rapidly changing, a variable reflecting the level of skills within the firm may be an opportune indicator (Bresnahan, Brynjolfsson, and Hitt, 2002).

Firm's age (AGE) is employed as an explanatory variable in most studies of adoption behaviour (Karshenas and Stoneman, 1995). One reason for including age is that there might be a positive impact on adoption in the case of older firms as specific (technological) experience might be accumulated (learning dynamics). Nevertheless, it is worth noting that there might be a twofold effect. On the one hand, the firm age proxy for the accumulation of experience and, hence, reductions in the perceived risk of investments in new technologies. On the other hand younger firms may be formed because start-up entrepreneurs embrace unusually innovative developments and carry out reorganizations that facilitate related ICT investment.

A dummy variable indicating whether a firm is located in the north of Italy (*NORTH*) is also added among the regressors. The rationale for this derives from a marked and persistent regional divide between the two parts of the country. Southern regions lag behind in almost all economic, financial, and technology indicators compared to the Northern ones and this might have an influence on ICT expenditure.[1] A variable indicating whether firms belong to large municipalities (*CITY*) is considered in the regression in order to control for potential difference between central and peripheral locations.[2]

A dummy variable indicating whether a firm is a high-tech firm is also included in the analysis (*TECH*). Such variable is constructed according to the "science-based" industry Pavitt classification. The rationale is that there might be significant differences in technological opportunity, appropriability conditions that may affect behavior, competencies, and fixed costs of individual technological establishments. Finally, where useful, variables are divided by labour units so as to reduce collinearity with firm size and they are log-transformed in order to avoid dimensional effects. Variables are referred to the initial period in order to mitigate possible endogeneity.

[1] In this analysis the South comprises nine regions (Lazio, Abruzzo, Molise, Campania, Apulia, Basilicata, Calabria, Sicily, Sardinia. The North comprises ten regions (Lombardy, Pidmont, Liguria, Trentino, Friuli, Veneto, Emilia, Tuscany, Umbria, Marche).

[2] According to ISTAT, Italy has 13 big municipalities: Turin, Genoa, Milan, Verona, Venice, Bologna, Florence, Rome, Naples, Bari, Palermo, Messina, Catania.

5. THE SPATIAL REGRESSION MODEL

The analysis employs a combined spatial-autoregressive model with spatial-autoregressive disturbances (SARAR in the terminology of Anselin and Florax, 1995). In modeling the outcome for each observation as related to a weighted average of the outcomes of other units, this model determines the outcomes simultaneously (Drukker, Egger, and Prucha 2010):

$$(1) \qquad y_i = \lambda \sum_{j=1}^{n} w_{ij} y_j + \sum_{p=1}^{k} x_{ip} \beta_p + u_i$$

$$(2) \qquad u_i = \rho \sum_{j=1}^{n} m_{ij} u_j + \varepsilon_i$$

where **y** is an n dimensional vector of observations on the dependent variable, **X** is an n by k matrix of observations on k right-hand-side exogenous variables. $\boldsymbol{\beta}$ is the corresponding $k \times 1$ parameter vector. **W** and **M** are n by n spatial link matrix with zero diagonal elements. $\boldsymbol{\lambda}$ is the spatial dependence parameter and ρ is the spatial error parameter. $\boldsymbol{\varepsilon}$ are *i.i.d.* disturbances. The spatial weight matrix (**W**) measures the distance between any pair of units. The resulting spatial lag $w_{ij}y_j$ can be viewed as a spatially weighted average of the units at neighboring locations. Thus they represent the corresponding spatial-autoregressive scalar parameters. The spatial-weighting matrices **W** and **M** are known, nonstochastic, and part of the model definition. In this application **W** = **M**, which implies that the spatial lag and spatial error are modeled using the same weight matrix.

Nonzero off-diagonal elements of the spatial weights matrix express the degree of potential spatial interaction between each possible *i-j* location pair. Entry w_{ij} represents the extent to which y_i depends on y_j, and thus the extent to which actor j influences i. The spatial weights matrix allows collapsing the spatial interactions across locations into a single (weighted) variable. However, it is limited in that it does not directly test for either the set of regions with which each region interacts or the strength of those interactions (Harris, Moffat, and Kravtsova, 2011).

5.1 The weights matrix construction

Networks of interdependencies are typically modeled as a network autocorrelation model where parameter estimates and inferences are based upon the specification of a weights matrix. In some studies, proximity is defined on a geographical basis (among many others Orlando, 2004; Ponds, Van Oort, and Frenken, 2007) while other studies determine economic spaces within manufacturing sectors to explore intra-industry spillovers. Bertinelli and Nicolini (2005), for instance, test the existence of positive spatial autocorrelation for R&D investments that lead R&D expenditures to cluster. They find that the proximity to other firms investing in R&D may produce positive externalities.

Scherer (1982) uses product R&D data to measure R&D spillovers and constructs an interindustry flow matrix. Coe and Helpman (1995) highlight international spillovers of technology through the trade of intermediate goods and show that productivity depends on domestic and on foreign R&D capital stocks. They use cumulative spending for R&D of a country to measure the domestic stock of knowledge, while the foreign stock of knowledge is calculated as import-weighted sum of cumulative R&D expenditures of the trade partners of the country. The OECD (1996) uses input-output matrices to calculate R&D flows among sectors. After comparing distributed R&D with own R&D, that study concluded that medium- and low-technology industries gain more than do high-technology industries from sectoral spillovers. As a corollary, the latter appear to enable a force that reduces technological differences, thereby enabling technological convergence among the three industry groups.

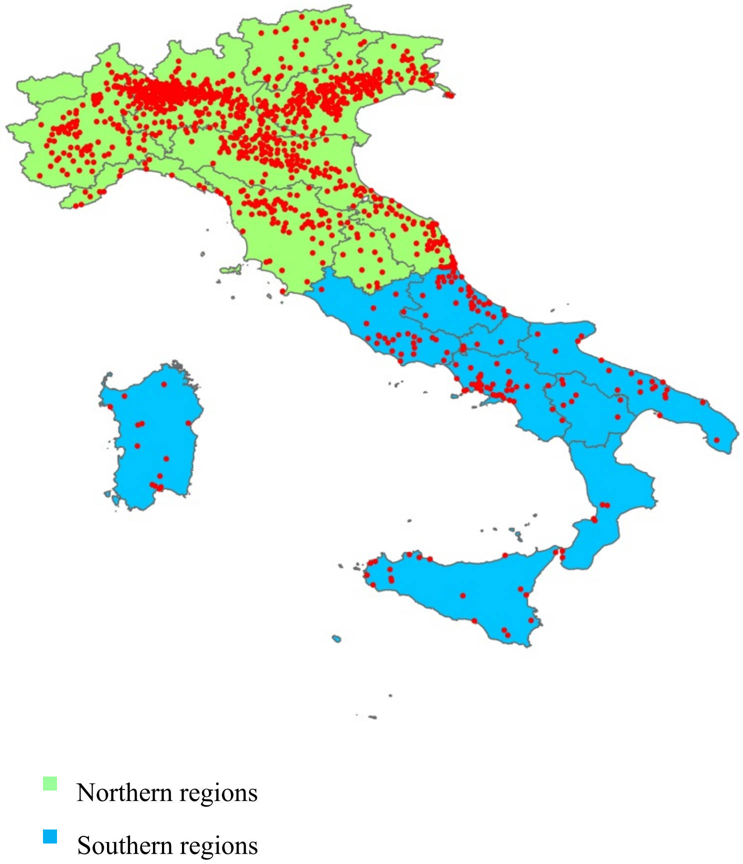
Some scholars measure distance between firms by considering inter-sectoral flows of intermediate goods. Other scholars employ patents of innovations to construct technology spaces. Negassi (2002) models the external technological spillover on the basis of firms' resources devoted to cooperation and capital flows. Aiello and Cardamone (2008) weigh the (external) R&D capital stock of all firms in the dataset by a variable that reflects firms' technological similarity and geographical proximity and show that geography is important in determining the role of the external technology. Marrocu, Rafaele, and Usai (2011) analyze the concept of proximity combining the geographical dimension with the institutional, technological, social and organizational proximity in 276 regions in Europe and find that geography is important but less so than are technological and cognitive proximity: social and organizational networks play a modest role. Cunningham and Werker (2012) investigate the effects of organizational, technological and geographical proximity on European nanotechnology collaborations and find that geographical closeness is most significant in statistical terms and technological closeness has the highest magnitude of effect.

This paper uses two different types of weights matrices, one based on geographical distance, the other on industry distance. These two dimensions of proximity are considered conditions for firms' potential interactions.

Geographical proximity is a standard and widely used indicator of closeness measured by the distance between location pairs. It considers all potential interactions among units so that spillovers are not limited to those locations that share a border (c.f., a contiguity matrix). In this analysis, the inverse of the geographic distance between locations is used to fill in the off-diagonal elements of the weights matrix. Locations are represented by Italy's 467 administrative municipalities in which firms in the sample are located. The $(i, j)^{th}$ element of the inverse-distance spatial-weighting matrix is $1/d_{ij}$, where d_{ij} is the Euclidean distance between the centroids of municipalities i and j. Interactions represent the weighted average of neighboring firms' ICT per worker. This captures the intensity of the potential influence that a firm in location i receives from the ICT expenditure in all the other j firms. Firms farther away yield proportionally less influence. For firms located in the same municipality (d_{ij}=0), the "zero" distance is replaced by the minimum distance observed in the sample, which corresponds to that of two small, border-sharing municipalities. This enables inclusion in the analysis of spatial interactions among municipally co-located firms. Figure 1 displays the distribution of the 1,941 ICT investing firms across the country.

Industry proximity may be important for ICT decisions, and this may be particularly the case in integrated economies. Though intersectoral relationships are aspatial, the assumption underlining the following analysis is that, mathematically speaking, sectors can be treated as regions by using an appropriate "spatial" contiguity matrix. To construct industry weights, previous studies have used sector-based trade flow statistics. Morrison and Siegel (1999) distinguish between potential spillovers as being either demand-driven or supply-driven. Their approach relies on the assumption that the more industry i acquires from and sells to industry j,

Figure. 1: Geographic Distribution of ICT-investing Firms in Italy



the more it can be influenced by industry j (Audretsch and Feldman,1996; Peri, 2005; Piga and Poyago-Theotoky, 2005).

In order to consider industry proximity effects, this work employs a matrix based on a measure of trade intensity between sectors derived from the input-output matrix for Italian manufacturing sectors (ISTAT, 2004; Medda and Piga, 2013). The hypothesis here is that the national bilateral input-shares between industries are valid also in the 1,941 firms in the sample. Given the representativeness of the firms in the survey, this is possibly not a compromising hypothesis.

The industry spatial indicator captures the intensity of the potential influence that a firm in industry i receives from the amount of ICT expenditures in all the other j industries that supply industry i. Weights are proportional to the inter-industry trade flows (Wolff and Nadiri, 1993) and are reported in Table 3. Each element of the distance matrix (w_{ij}), is defined as the average of the bilateral input-shares between sectors i and j (Coe and Helpman, 1995; Anselin and Bera, 1998) and represents the intensity of the relation between these two industries. The elements of the symmetric spatial connectivity matrix are calculated as:

(3) $$w_{ij} = \frac{z_{ij} + z_{ji}}{2}$$

Table 3: Bilateral (Symmetric) Input Shares between Industry *i* and Industry *j*

Industry	**15, 16**	**17, 18**	**19**	**20**	**21, 22**	**23**	**24**	**25**	**26**	**27, 28**	**29**	**30, 31, 32, 33**	**34, 35**	**36**
15, 16	**40.8**													
17, 18	0.3	**83.9**												
19	3	5.55	**76.9**											
20	0.7	0.45	0.2	**34.7**										
21, 22	4.55	1.4	1.15	0.55	**71**									
23	1.35	0.5	0.15	0.15	0.15	**6.4**								
24	1.85	3.55	0.8	0.6	6.6	4.53	**28.9**							
25	2.8	1.85	0.75	0.75	2.5	0.25	9.45	**12.1**						
26	2.65	0.1	0	1.1	2.05	0.95	3.5	1.05	**18.1**					
27, 28	1.05	0.7	1.15	1.9	2.95	3.2	2.7	2.9	4.25	**63.2**				
29	1.05	0.85	0.45	0.65	2.8	0.45	1.45	5.55	1.3	24.6	**47.5**			
30, 31, 32, 33	0.85	1	0.5	0.65	2.45	0.45	1.95	5.1	2.35	10.8	16.8	**28**		
34, 35	0.6	0.55	0.4	0.8	1	0.25	0.7	5.45	1	11.1	5.7	11.65	**83.8**	
36	0.5	3.85	3.2	18.25	1.4	0.15	1.3	1.65	1.35	6.2	2.05	2.9	1.55	**34.9**

Source: own elaborations from ISTAT (2004)

where $i \neq j$, z_{ij} are the bilateral input-shares of sector i from sector j and $i=j$, z_{ij} are the bilateral input-shares within the same sector. The distance between two sectors represents the connectivity and it is used to produce a trade-intensity space.

Since not all sectors contain a sufficient number of observations to allow running the estimations, some sectors have been grouped according to their technological similarities and finally 15 sectors were obtained with the industry ATECO two-digit classification. It is worth noting from Table 3, that most of the trade takes place within the same sector. Nevertheless, each sector does show input exchange with the remaining industries.

The spatial weight matrices are standardized. This enables one to interpret the lag term as a mere spatially-weighted average of observed neighboring values (y_j). For instance, cohesion suggests that actors are influenced by adjacent actors, normalization then decreases the individual strength of influence with the number of influencers. The normalization method used in this work, is the row-normalization. In a row-normalized matrix, the (i, j) element of w becomes, $w_{ij} = w_{ij}/\Sigma r_i$, where Σr_i is the sum of the i row of w.

These two procedures yield to two 1,941 by 1,941 dimension matrices of weights which have been created with the *spmat* command in STATA (Drukker et al., 2011). From Table 4 it emerges that there are 3,755,216 and 3,749,712 total links respectively for the geographic and the industry matrix.

The reason why this work employs "continuous distance" to construct the weights matrices is linked to the advantage that this kind of procedure offers compared to others (binary neighbors distance) which is to consider all the potential interactions among units so that spillovers are not limited to those locations which share a border (e.g. contiguity matrix).

Table 4: Summary of Spatial-weights Matrices

Dimensions: 1,941x1,941		Geographic Distance	Industry distance
Links:			
	total	3,765,540	3,749,712
	min	1,940	1,836
	mean	1,940	1,931
	Max	1,940	1,940

However to corroborate the results the analysis has also been carried out using a contiguity distance matrix where a neighborhood of 25 kilometers has been generated.[3] Within such distance firms are considered neighbors (connectivity=1) and outside such distance (connectivity=0). The resulting matrix (Table A.1 in the Appendix) shows 95,704 total links ranging from 0 to 211.The econometric results based on this matrix confirm the general analysis, though the spatial coefficient is smaller than in the general analysis (λ=0.05; p=0.065, see Table A.2).

In the same way, based on the idea of neighborhood, an inter-industry weight matrix has been created. In order to include all industries, the minimum distance allowed in the analysis corresponds to the minimum bilateral input-shares between sectors (i.e. petroleum, coal). Above such distance firms are considered neighbors (connectivity=1) and below such distance connectivity equals zero. As Table A.1 depicts, there are 898,406 total links ranging from a minimum of 9 to a maximum of 848. Again the results confirm the general analysis (λ=0.365; p=0.000, see table A.2).

6. EMPIRICAL ANALYSIS AND RESULTS

This section performs a cross-sectional analysis based on a sample of 1,941 Italian manufacturing firms committed in ICT investment. The purpose is to check for potential spatial effects and to explore the determinants of ICT spending. The conjecture is that the amount of ICT in one location may be correlated with the amount of ICT in nearby locations. The analysis follows two steps. Firstly, the OLS model is run and tested for heteroskedasticity. Then, the combined spatial-autoregressive model with spatial-autoregressive disturbances is estimated employing the maximum likelihood procedure. The ICT model is:

$$(4)\quad LogICT_{INT} = \beta_0 + \beta_1 LogAVY + \beta_2 LogEMP + \beta_3 LogKAP + \beta_4 DEBT + \beta_5 AGE + \beta_6 WCBC + \\ +\beta_7 INNORG + \beta_8 RESEARCH + \beta_9 GRANT + \beta_{10} EXPORT + +\beta_{11} NORTH + \beta_{12} CITY + \beta_{13} TECH + u_i$$

Since ordinary least squares regression assumes homogeneity of variance, the Breusch–Pagan test is employed on the residuals of the linear model. The test indicates that heteroskedasticity is unlikely to be a problem in the study sample (χ^2= 0.03 with a p-value =0.85). The second step is to detect potential spatial dependence among observations. The most common global test of spatial autocorrelation is based on a statistic developed by Moran (1950).

[3] As an anonymous referee points out, given its connectivity structure the interindustry weights matrix contains a considerable number of links. Hence, the analysis is also carried out using a smaller set of links within a binary framework.

Table 5: Tests for Spatial Autocorrelation

Moran's *I* Statistics (*): Lag spatial	Geographic Distance		Industry distance	
Tests	Normal Approximation	Randomization Assumptions	Normal Approximation	Randomization Assumptions
Moran's *I*	0.0035	0.0035	0.0074	0.0074
Mean	-0.0005	-0.0005	-0.0005	-0.0005
Std dev	0.0014	0.0014	0.0013	0.0013
p-value (Two-tailed test)	0.0039	0.0039	0.0000	0.0000

(*) The number of random permutations is 999

This statistic compares the value of the observed variable at a location with the value of the same variable at neighboring locations.

Moran's *I* is used here to analyze the spatial interaction of the ICT intensity at the level of the establishment. If Moran's *I* is larger than its expected value, then the overall distribution of the variable under observation can be seen as characterized by positive spatial autocorrelation, meaning that the value of ICT intensity at each location *i* tends to be similar to the values taken on by the same variable at spatially close locations. Table 5 depicts the results of the test. Concerning the geographical analysis, the value of this statistic is 0.0035 while its mean is -.0005. This suggests that spatial lag dependence is an issue in this specification (*p*-value=0.0039) with both normal approximation and randomization assumptions. Concerning the industry analysis, the value of this statistic is 0.0074 while its mean is -0.0005, so positive spatial autocorrelation is detected with a highly robust statistical significance (*p*-value=0.0000) with both normal approximation and randomization assumptions. It is worth emphasizing that these tests explicitly incorporate the weight distance matrices discussed.

The Moran's *I* test, however, is a global statistic, which means that it accounts for spatial autocorrelation for all the units but supplies no information about the contribution any single unit. Local indices of spatial correlation are more likely to account for this drawback. Since spatial autocorrelation is detected (though of small dimension) and given the absence of heteroskedasticity, the model is re-estimated to incorporate corrections simultaneously for both spatial error and spatial lag. For this purpose the *spreg-ml* routine available in STATA is used (Drukker, Peng, Prucha, and Raciborski, 2011). Table 6 reports the results for the OLS and the regressions that correct for spatial dependence either according to geographical or industry distance. For the two spatial models, the total external ICT expenditures per employee is measured by the weighted sum of ICT expenditures of other firms in the same or different locations (Griliches, 1979; Los and Verspagen, 2000; Aiello and Cardamone, 2008).

Although the estimated parameters (β_s) do not have the same interpretation as in a simple linear model, because including a spatial lag of the dependent variable implies that the outcomes are determined simultaneously (LeSage and Pace, 2009), the results of the geographical spatial estimation shows evidence of ICT spillovers. The null hypothesis of zero spatial lag error (λ=0) can be safely rejected. The spatial lag parameters are positive and strongly significant, indicating spatial-autoregressive dependence in ICT spending. This means that firm's investment in ICT is positively affected by the same type of investment of neighboring firms considering both the geo-spatial and the industry-spatial distance (λ=0.247; *p*=0.000 and λ=0.384; *p*=0.000 respectively). Although the dimension of these parameters does not allow a direct economic interpretation, the general results of the spatial analysis strongly support the hypothesis of

Table 6: Regression Results, *n*=1,941

Dependent variable: ICT intensity	OLS		Spatial autoregressive model: (Maximum likelihood estimates)			
			Geographic Distance		Industry Distance	
Variables	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
LogAVY	.512***	(.074)	.511***	(.096)	.502***	(.077)
LogEMP	.007	(.029)	.006	(.030)	.007	(.029)
LogK$_{INT}$	.040	(.032)	.038	(.040)	.036	(.032)
RESEARCH$^{(\S)}$	.198 ***	(.060)	.200***	(.059)	.194***	(.059)
DEBT	.093	(.039)	.097**	(.043)	.096**	(.039)
GRANT$^{(\S)}$	.148***	(.074)	.150**	.075)	.145**	(.074)
EXPORT$^{(\S)}$	.137**	(.071)	.138*	(.071)	.141**	(.072)
INNOV$^{(\S)}$	.318***	(.056)	.318***	(.057)	.321***	(.056)
WC-BC	.351***	(.053)	.347***	(.056)	.345***	(.053)
AGE	-.067*	(.041)	-.068	(.043)	-.067*	(.046)
NORTH$^{(\S)}$	-.005	(.085)	-.019	(.089)	-.001	(.084)
CITY$^{(\S)}$	-.013	(.062)	-.008	(.066)	-.015	(.062)
TECH$^{(\S)}$	.021	(.140)	.020	(.884)	-.005	(.138)
Cons	4.288***	(.280)	2.60	/	1.68	/
Lambda		/	.247***	(.044)	.384***	(.050)
Rho		/	.128	(.502)	-.261	(.604)

$^{(\S)}$*dummies*

*, **, ***, indicate significance at the 10%, 5% and 1%, respectively

interdependence among geographical locations and industries in this sample of 1,941 Italian firms. The parameter ρ is statistically non-significant in the two spatial models suggesting the absence of SAR dependence in the error term.

In order to further corroborate the results, the analysis also checks for possible relations between geographic and industry proximity. For this reason the two models above are estimated allowing for error industry interactions in the geographical model and allowing error geographical interactions in the industry model. The previous results appear to be confirmed (λ=0.30; p=0.000 and ρ =0.24; p=0.73 and λ=0.27; p=0.000 and ρ =0.30; p=0.70, respectively).

Some interesting indications arise from the resulting regressions. Some caution is necessary, however, given that the explanatory variables have been used mostly as mere corrections whose main purpose is to prevent the parameter of WY from being biased. The added value per employee is shown to be positive and strongly significant confirming that efficiency is important in decisions about ICT investment amounts. Indeed, ICT investments may require a higher level of efficiency compared to other types of capital, and skills of workers are particularly crucial. As expected, in fact, the R&D variable positively affects the level of ICT. In line with a priori expectations, the organization variable (*INNOV*) and the human capital variable

(*WCBC*) are positively and strongly related to the amount of ICT investment. This reflects the idea that ICT requires skills to be properly adopted and used in the productive process.

The analysis shows that capital intensity of the firm exerts no statistically significant influence on the amount of ICT. Obtaining a public R&D subsidy to technological investment and being indebted have a positive and statistically significant impact on ICT engagement. Also the export variable is found to have a positive impact on the dependent variable. Interestingly, being in the northern part of the country and being located in big municipalities does not affect the amount of ICT investment, in both the geographic and the industry spatial analysis. These two variables show highly insignificant coefficients and possibly suggest that macro geographic and peripheral locations are not an issue in ICT spending for the 1,941 manufacturing firms in the sample. Surprisingly, firms in the most technological sectors do not appear to be different from the rest of the sample.

7. CONCLUDING REMARKS

The relations between ICT and the location of economic activities have yet to be clearly understood. On the one hand, it is commonly argued that ICT produces effects that are similar to transport cost reduction, by improving market access for peripheral regions, and that this might potentially turn into new opportunities for remote areas. On the other hand, overall empirical studies indicate huge disparities in the intensity of ICT adoption across firms, industries, and space, suggesting that rather than reducing regional disparities, ICT may be reinforcing them.

ICT has the characteristics of technologies for which gains in productivity spread across all industries, hence it plays a special role in determining overall output growth. As new ICT equipment is introduced in many other sectors, they can boost the diffusion of knowledge, and ameliorate the system possibility frontier. This characteristic of pervasiveness makes the spatial aspects of ICT investment especially interesting to investigate.

Following the industry spillover literature, this work attempts to contribute towards understanding the links among ICT investment, spatial dimension, and firms' characteristics. Specifically, this paper tries to examine whether the firm's spending in new technologies may depend on ICT efforts made by other firms belonging to the same location or sector as well as to other related locations or sectors in a sample of Italian manufacturing firms. The rationale is that ICT spatial spillover effects are unobserved and may affect firms in a given location or industry. Technological spillovers have a potentially important role in shaping the incentives for development activities of private firms. Technological (or cognitive) proximity facilitates knowledge transfer. The closer two firms are in the technological or market space, the more they benefit from each other's research efforts.

Many empirical works do not consider spatial autocorrelation. However, if the spatial correlation is due to the direct influence of neighboring sectors, OLS estimation is biased and inefficient. The spatial econometric framework used in this work attempts to cope with this problem. Moreover, while studies on the diffusion of technology through trade are dominated by cross-country studies, the same arguments also apply at a more local level. Most trade tends to be inter-regional hence intra-nation spillovers may be even stronger than international spillovers. Together with the spatial analysis, this reinforces the need of intra-nation analysis such as done in this work.

This paper analyzes the effect of two proximity dimensions by using distinct matrices in order to test the relative importance of space in firms' ICT spending. Spatial proximity is defined either by a measure of geographical distance or by a measure of firms' industry distance based on the trade intensity between sectors. In both cases the spatial influence corresponds to the weighted sum of the ICT expenditures per employee of other firms in the same or different locations or industries. Weights are given by Euclidean distance and the share of sales (over total sales) among industries for the geographical and industry analysis respectively.

The results of the spatial estimation show that both geography and industry proximity favor ICT spending among the firms in the sample. This indicates geographical and sectoral ICT complementarities. Conversely, external shocks do not affect the amount of ICT either when the geographical distance or when the sectoral distance is considered. The econometric analysis shows that productivity, research engagement, technological subsidies, export labor composition and reorganization, are good predictors of ICT investment decisions. Finally, firms in the most industrial and technological part of the country (north) and firms in big municipalities do not show any difference from the sample in both spatial measures considered, possibly suggesting the absence of peripheral-core location issues in ICT investment decisions.

In terms of policy design, the results of this analysis provide interesting implications. The existence of positive ICT spillovers among locations and sectors suggests that ICT has the potentiality to be considered as one of the potential levers to reduce technological disparities. Although the analysis does not allow us to define the trajectory (this is an open issue that merits future investigation), given the trade relations among sectors, the cross-spread of spillovers is likely to favor the diffusion of technology over industries and space.

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APPENDIX

Table A.1: Summary of Binary Spatial Weights Matrices

Dimensions: 1941x1941			
		Geographic Distance	Industry distance
Links:			
	total	95,704	898,406
	min	0	9
	mean	49	462
	Max	211	848

Table A.2: Regression Results (binary neighbor matrices) *n*=1,941

Dependent variable: ICT intensity	Spatial autoregressive model: (Maximum likelihood estimates)			
	Geographic Distance		Industry Distance	
Variables	Coef.	(SE)	Coef.	(SE)
$LogAVY_{INT}$	.510***	(.073)	.500***	(.075)
LogEMP	.008	(.028)	.007	(.029)
$LogK_{INT}$	.038	(.032)	.036	(.032)
$RESEARCH^{(\S)}$	.199 ***	(.059)	.198***	(.059)
$DEBT_{AVY}$	.095**	(.039)	.096**	(.039)
$GRANT_{TECH}^{(\S)}$	.148***	(.074)	.138*	(.074)
$EXPORT^{(\S)}$	.133*	(.071)	.137*	(.072)
$INNOV_{ORG}^{(\S)}$	.317***	(.056)	.318***	(.056)
WC-BC	.352***	(.054)	.348***	(.053)
AGE	-.067	(.041)	-.065	(.041)
$NORTH^{(\S)}$	-.046	(.087)	-.001	(.084)
$CITY_{BIG}^{(\S)}$	-.022	(.062)	-.018	(.062)
$TECH^{(\S)}$	.021	(.140)	-.004	(.140)
Cons	4.00***	(.280)	1.83	/
Lambda	.049***	(.026)	.365***	(.043)
Rho	.006	(.070)	-.125	(.321)

*, **, ***, indicate significance at the 10%, 5% and 1%, respectively

$^{(\S)}$*dummies*