A spatial econometric model for productivity and innovation in the manufacturing industry: the role played by geographical and sectorial distances between firms°

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Abstract

The paper assesses spillovers from total factor productivity (TFP) in the Italian manufacturing industry and the existence of potential TFP premiums originating from innovation, properly accounting for spatial distances in place between firms. We resort to firm-level geo-referenced data to estimate geographical TFP spillovers and to input-output matrices of inter-sectorial trade to detect sectorial TFP spillovers (both demand and supply driven). A complete spatial autoregressive model with spatial autoregressive disturbances (SARAR) is estimated, with the purpose to analyze the spatial diffusion of productivity shocks as well. To the best of our knowledge the present work comes to represent one of the first attempts to estimate a model of this type based on a relatively large panel of micro-data and resorting to dense matrices of firms' distances: customized versions of the available R routines were developed. Results show how total factor productivity benefits from spillover effects originated within the neighborhood. The estimated effect is considerably higher when geographical interactions are accounted for. Spatial diffusion of productivity shocks might differ, depending on how spatial influences are modeled: shocks spread negatively within geographical-based neighborhoods (competition framework) and positively within sectorial-based neighborhoods (cooperation framework). Furthermore, firms located in patent-intensive areas are suitable to show local productivity premiums: the result emerges as well clearly in correspondence to the subsample of small firms, thus corroborating the findings of an active role played by innovation in enhancing productivity.

Keywords: panel data, spatial models, TFP, manufacturing, spillover, agglomeration economy, patents

Jel classification: C33, D24, L60, O33, O34, R12

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Introduction

The paper assesses geographical and sectorial spillovers of total factor productivity (TFP) in the Italian manufacturing industry and the existence of potential TFP premiums originating from innovation, properly accounting for spatial distances in place between firms. The role played by industrial clustering is completely reshaped through the lens of the most recent techniques of spatial econometrics.

As a first step TFP estimates are retrieved at the firm level, resorting to the Levinsohn and Petrin (2003) semi-parametric approach: labour and capital productivity coefficients are allowed to vary over branches of economic activity. Data are extracted from the *Intesa Sanpaolo Integrated Database* (ISID) on corporate customers; the reference period spans from 2004 to 2011.

TFP spillovers are then estimated based on a complete spatial autoregressive model with spatial autoregressive disturbances (SARAR). More precisely, geo-referenced data are exploited to detect the presence of geographical-based spillovers and inter-sectorial trade coefficients from input-output matrices are employed as a proxy to estimate sectorial-based spillovers (both demand-side and supply-side driven). The model structure allows for a complementary analysis on spatial diffusion of productivity shocks.

The estimation framework is inclusive of a proper set of controls to isolate TFP premiums: *in primis*, patent applications at the European Patent Office (EPO) are considered to design a comprehensive indicator of technological space, suitable to capture the presence of potential indirect knowledge spillovers enhancing productivity.

The recursive structure pertaining to spatial models introduces computational difficulties when the magnitude of the dataset increases, as it is in the case of micro panels. Moreover, computational issues are exacerbated by the choice to exploit dense matrices of pairwise distances while setting up a spatial scheme for reciprocal influences between firms in our dataset (a formal spatial weights matrix): positive spatial dependence is in fact detected between levels of TFP pertaining to pairs of firms located in a radius of 300 Km.

We solve for these problems resorting to a Feasible Spatial 2SLS (Two Stage Least Squares) approach to consistently estimate the parameters of the proposed SARAR model. A customized version of the available GM package in the R software was developed.

To the best of our knowledge, the present work comes to represent one of the first attempts to estimate a complete SARAR model based on dense weights matrices and a relevant dataset of micro-data (around 9,000 manufacturing firms) - covering as well a consistent temporal length (8 years). From an economic perspective, we move the first steps towards a proper quantification of spillover effects from total factor productivity.

Results show how, consistently to the previous literature, firms' total factor productivity benefits from spillovers originated by neighboring firms. The estimated effect is considerably higher when geographical-based reciprocal influences are accounted for but still positive and significant in the case of sectorial-based interactions. Most of the strength of the geographical spillover has to be attributed to interactions played by sectorially heterogeneous geographical neighbours.

The clustering phenomenon can be regarded as reflection of long-term common strategies to be implemented by neighboring firms. By contrast short run dynamics, represented by the diffusion mechanism of shocks, come to be strictly dependent on the selected neighborhood definition. Shocks are found to spread negatively within a geographical neighborhood and positively within a sectorial-based one, with a stronger effect when a demand-driven logic is considered.

Results prove to be robust to the adoption of different specifications of the spatial weights matrices.

Furthermore, econometric estimates show how firms located in patent-intensive areas are suitable to benefit of local TFP premiums, independently on dimensional size.

The paper is organized in six more sections. The first one is devoted to literature review. Subsequent sections correspond to the different research steps addressed to build our spatial model and to test it on Italian manufacturing data. Section 2 is devoted to productivity estimation at firm level, with a brief discussion over the relevant working hypotheses. The features of a matched dataset between firms' balance sheets and patent data are instead presented in Section 3. Section 4 introduces the baseline version of our model for productivity and innovation, without spatial approach. Sections 5, 6 and 7 are instead devoted to a spatial econometric approach to the productivity subject: they come to represent the core of the paper, as well as the most innovative contribution to the existing literature.

1. Productivity and innovation, the main starting points in the literature

The present paper is intended to directly contribute to the wide literature on Total factor productivity (TFP) spillovers from industrial clustering, as well as to the literature on localized knowledge spillovers from innovation, modeling a formal spatial panel framework based on both geographical and sectorial distances between Italian manufacturing firms.

Total factor productivity comes to represent a well debated subject of the last years. Several academic works made an effort to explain what lies behind the decreasing trend in productivity growth characterizing the Italian manufacturing industry[1]. Both cyclical and structural factors are called into question to fully address the roots of the problem. Reference is made *in primis* to a set of characteristics directly attributable to the Italian production process: i.e. differences in terms of firms' dimensional size - with a predominance of SMEs (small and medium-size enterprises), ownership structure or international placement, as well as in terms of the amount of investments undertaken by the Italian manufacturing sector[2].

Despite Italian firms being penalized in the international context, especially in comparison to the productivity growth pertaining to other main competitors in Europe, there still exists the interest to shed light on the role played by key factors, like agglomeration of firms and innovation, in generating important spillovers and productivity premiums.

The most traditional way to assess the presence of TFP premiums is to proxy for firms' clustering. The seminal work from Marshall (1980) started stressing the point of the advantages deriving from spatial concentration of firms. "Sharing, learning and matching" are, according to Duranton and Puga (2004), the three main mechanisms explaining the tendency to cluster in space[3], with particular reference to input sharing – even in the form of specialized workers – and to potential benefits deriving from knowledge spillovers. Interactions between firms and workers are suitable to generate agglomeration economies: reference is made to Marshallian externalities when firms and workers belong to the same industry and to Jacobian externalities when they belong to different sectors of industrial activity. In fact, according to the competing theory of Jacobs (1969) transfers of

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[1]. Aiello, Pupo and Ricotta (2008); Bassanetti *et al.* (2004); Brandolini and Cipollone (2001); Daveri and Jonia-lasinio (2005); Fachin and Gavosto (2007); ISAE (2005); Venturini, (2004).

[2]. Allegra *et al.* (2004); Bugamelli and Rosolia (2006); Casaburi *et al.* (2008); Ciocca (2004); Confindustria (2006); Daveri (2006); Faini and Sapir (2005); Milana and Zeli (2003); Nicoletti and Scarpetta (2003).

[3]. Sharing (i.e. the possibility to share local indivisible public goods that raise productivity), matching (i.e. thick labor markets facilitate the matching between firms and workers), and learning (i.e. the frequent face to face interactions between workers and firms in the agglomerated areas generate localized knowledge spillovers).

knowledge and faster growth take place only when diversity is accounted for.

As a matter of fact, empirical tests produced from time to time quite controversial results in terms of the prevailing effect. Italy played to be one of the preferred environments to test the before mentioned predictions, because of its fragmented production base: especially during the Nineties, a popular strand of the literature focused on the so called "district effect", trying to quantify the advantages (in terms of TFP premiums, growth performances or financial solidity) from the location of firms into industrial districts - the latter being associated to externalities of the Marshallian type[4]. By contrast, contributions referring to other countries put more emphasis on the presence of "urban effects"[5], or in other words, to the presence of premiums pertaining to firms located in urban areas – the latter being associated to externalities of the Jacobian type.

The debate arising from the binomial "Marshallian versus Jacobian externalities" is far from having encountered a saturation point. A lot of papers based on aggregate data tried to investigate their effects over local economic growth[6]. At the micro-level, the recent papers from Di Giacinto *et al.* (2011) and Buccellato and Santoni (2012) concentrate on detecting and comparing productivity advantages of Italian firms located within industrial districts and urban areas, with respect to firms located outside agglomeration economies. Di Giacinto *et al.* (2011) shed light on the presence of stable productivity advantages of firms located in urban areas[7] (the reference period spans from 1995 to 2006), while observing a weakening of the advantages traditionally associated to Italian industrial districts. According to the same analysis, the productivity premium of urban firms is not directly driven by a different composition of the labor force, that in those areas is suitable to be characterized by a major presence of white collars. The weakening of the local advantages associated to industrial districts instead, does not represent *per se* a novelty in the literature: a wide stream of research has in fact documented the same

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[4]. Becattini (1990) was the first one formalizing the concept of industrial district as a specific socio-territorial entity bounded in space. It is suitable to involve firms sharing a common specialization - from leader firms to suppliers - as well as proper institutions (both political and financial) whose mission is to contribute to the functioning of such an environment. Signorini (1994), Fabiani et al. (2000) and Cainelli and De Liso (2005) are reference papers in the literature on the "district effect". For a more complete survey of the empirical analysis on Italian industrial districts, refer to Iuzzolino and Micucci (2011). A useful summary is contained also in Di Giacinto et al (2011).

[5]. Urban areas are density populated areas, traditionally associated to the presence of interactions between firms belonging to different sectors of activity.

[6]. For the Italian case: Cingano and Schivardi (2004) and Paci and Usai (2006) conduct an analysis at the level of ISTAT Local labor systems.

[7]. The manufacturing space is divided into Local labor systems (LLS) according to the criterion provided by ISTAT, the Italian national statistical institute. The presence of agglomeration economies, like industrial districts or urban areas, within local labor systems, is accounted for in estimation by means of simple binary variables.

phenomenon during the most recent years[8]. Buccellato and Santoni (2012) corroborate, as a first step, the findings of Di Giacinto *et al.* in terms of detectable productivity advantages of urban firms (in the 2001-2010 surveyed period). At the same time, they move the first steps towards an in-depth discussion of TFP productivity externalities in the Italian manufacturing industry, both within and between sectors, exploiting gravity variables. The variables design consists in aggregating productivity levels of neighboring firms[9]. Once gravity variables are employed into a regression of firm level productivity over a set of control variables and territorial characteristics (it is worth mentioning a specific indicator for the degree of urbanization of the territory where the firm is located) the result is a totally absorption of the local productivity advantages previously associated to firms placed in urban areas: premiums arising from increased productivity at the neighboring firms are higher if compared to premiums originating from an increased degree of urbanization of the territory. Moreover, the paper from Accetturo *et al.* (2013) confirms that agglomeration effects still play the major role in explaining local productivity premiums of Italian firms located in urban areas, with respect to firms' selection effects[10].

From this specific points moves the interest to develop the spatial model presented in the paper. The idea is to shed light on determinants of productivity through the lens of the most recent techniques of spatial econometrics. More precisely, the spatial autoregressive model proposed into the paper allows for a complete restyling of the concept of industrial clustering, modeling the presence of TFP spillovers originating from neighboring firms (the productivity spatial lag) in a more formal way - both geographical or sectorial neighbors, depending on the spatial weighting matrix to be considered. Moreover, it goes without saying that failing to take into account spatial dependence in the productivity phenomenon, is suitable to produce biased coefficients in estimation, because of the presence of considerable indirect effects: total factor productivity comes to represent a variable sensible to changes in the surrounding operational context.

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[8]. Reference is made, for example, to the contributions of Brandolini and Bugamelli (2009), Corò and Grandinetti (1999), Foresti, Guelpa and Trenti (2009), Iuzzolino (2008), Iuzzolino and Menon (2010), Iuzzolino and Micucci (2011), Murat and Paba (2005).

[9]. Those firms located within a range of 20 kilometers of distance from each firm in the analyzed panel, belonging respectively to the same sector of industrial activity (within sector externalities) or to different sectors (between sectors externalities).

[10]. They expand the model of Combes *et al.* (2012) trying to disentangle the effects of the different drivers of local productivity advantages of urban firms: the two main explanations for the existing premiums are firm's clustering and selection. Their empirical findings confirm the prevailing effect of clustering, while showing a minor role played by selection effects in driving productivity - especially when asymmetric trade costs at the local market level are taken into account.

The reference dataset is a balanced panel of around 9,000 Italian manufacturing firms surveyed over the 2004-11 period. Data are extracted from the *Intesa Sanpaolo Integrated Database* on corporate customers (ISID)[11].

Last but not least, the present work contributes to another important strand of the literature, the one on localized knowledge spillovers, exploiting the features of a rich dataset on patent data – patent applications at the European Patent Office (EPO), referenced at the firm level - matched to the information on firms' balance sheets that is present in ISID[12].

The existence of a link between productivity and innovation is well established in the literature. One of the main determinants of firms' total factor productivity is innovative capacity or, in other words, the stock of accumulated knowledge. Since the pioneering paper from Jaffe (1989) - mainly focusing on the real effects of academic research – a strand of the literature on innovation, the so called "geography of innovation", concentrated indeed on measuring localized spillovers from R&D spending. Reference is made to all the contributions based on the "knowledge production function" approach proposed by Griliches (1979), relating innovative outputs (patent data, at the level of states, regions or cities) with measures of innovative inputs (R&D expenditure)[13]. With the purpose of detecting cross-border effects of the academic research, Anselin *et al.* (1997) revisited Jaffe's work applying for the first time spatial econometrics techniques to innovation models. It is worth stressing how the knowledge production function approach inspired also a lot of works based on Italian (and European) data[14]: the papers from Moreno, Paci and Usai

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[11]. The dataset, belonging to the Intesa Sanpaolo Research Department, is a large and representative proprietary database of firms where information on corporate customers' balance sheets (certified by Centrale dei Bilanci - CEBI, the main collector of balance sheets in Italy) is matched with qualitative variables, referring to several firms strategies (patents, brands, international certifications, foreign direct investments etc). Refer to next sections for further details.

[12]. See section 4 for a more detailed description of the data. The patent data come from the proprietary database Thomson Innovation, managed by Thomson Reuters. The matching with data on balance sheets was performed – and is revised on an annual basis – by the Intesa Sanpaolo Research Department.

[13]. In addition to the paper from Jaffe (1989), it is worth mentioning the contributions of Acs, Audretsch and Feldman (1994) and Audretsch and Feldman (1996, 1999), that are considered among the most representative and influential studies in this field.

[14]. Like the papers from, Breschi and Lissoni (2001), Breschi and Malerba (2001), Paci and Usai (2005), Marrocu, Paci and Usai (2011). It is worth recalling the contribution from Bronzini and Piselli (2006) that makes use of infrastructures of the public sector while determinants of productivity, exploiting an approach equivalent to the knowledge production function. The contribution from Dettori, Maroccu and Paci (2008) estimates instead a spatial Cobb-Douglas production function over a sample of European regions, considering the impact on productivity of different intangible assets (human capital, social capital and technological capital). The paper from Marrocu, Paci and Usai (2010) investigates instead the effects of local agglomeration externalities In Europe (specialization and diversity externalities) on total factor productivity. Last but not least, the paper from Carboni (2012), despite estimating a more general empirical model for R&D spending,

(2005) and Marrocu, Paci and Usai (2011) make specific use of spatial econometrics techniques to model innovation spillovers more precisely, at the regional level.

The drawbacks of the geography of innovation approach come to represent a well debated subject as well, mainly because of the lack of opportunities to disentangle in empirical works the presence of pure knowledge spillovers[15] from more complex knowledge transfers, mediated by market exchanges, the so called pecuniary or rent spillovers[16]. Such a debate – well summarized in Breschi, Lissoni and Montobbio (2004) – represented as well a new starting point for subsequent lines of research on innovation. Some authors started looking for alternative methods to directly measure knowledge flows and to identify their transfer mechanisms, retreating towards patent citations[17] - as a sort of "paper trails" left by knowledge transfers. At the same time, interest was growing towards a better understanding of international spillovers. A popular strand of the literature focused on detecting spillovers from the presence of multinational corporations (foreign direct investments), mostly exploiting a production function approach: the presence of horizontal spillovers can be inferred indirectly, though the estimation of their effects on firms' total factor productivity[18].

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applies spatial techniques to data at the micro-level, trying to model both geographical and sectorial (or vertical) spillovers from innovation.

[15]. Pure knowledge spillovers occur when firms benefit from the R&D activities undertaken by other firms (becoming so far a publicly available stock of knowledge), without directly compensating them. The concept mainly refers to the process of endogenous knowledge creation and growth introduced by Romer (1990).

[16]. The first theoretical distinction between the two types of spillovers is due to Griliches (1992): pecuniary or rent spillovers are market-mediated knowledge flows. They occur when "new or improved input is sold, but the producer cannot fully appropriate the increased quality of the product. In this case, some of the surplus is appropriated by the downstream producers but this mechanism *per se* does not create further innovations and endogenous growth" (Breschi, Lissoni and Montobbio (2004)). It is hard distinguish between the two types of spillovers in empirical works, especially when the main mechanisms of transmission of accumulated knowledge are called into question: social networks and labor mobility, in the case of local spillovers, trade and foreign direct investments from multinational enterprises, in the case of international spillovers.

[17]. The first contribution making the attempt to use patent citations to measure knowledge spillovers and to analyze their geographical distribution was the one from Jaffe, Trajtenberg and Henderson (1993). This pioneering work was subsequently taken up and extended by other works, like the ones from Mowery and Ziedonis (2001), Agrawal et al. (2003), Breschi and Lissoni (2005), Thompson and Fox-Kean (2005). Patent citations came to be considered also a powerful tool to detect international knowledge spillovers: reference is made to the contributions of Branstetter (2001a), Malerba and Montobbio (2003), Malerba, Mancusi and Montobbio (2003), Peri (2003).

[18]. Influential works are the ones from Aitken and Harrison (1999), Haskel et al. (2002) Javorick (2004). But again, such an approach renders it hard to distinguish between different types of the originated spillovers: interpretation of results mainly propended, in those cases, towards the detection of market-based spillovers.

We employ a similar approach to embed an indirect measure of knowledge spillover into our spatial model for productivity. Interpretation of results mainly propend – like in the case of a production function approach - towards the detection of market-based spillovers from innovation. Nevertheless, it is worth stressing how a precise quantification of a pure innovation spillover goes beyond the scope of our paper, where the effects of knowledge spillovers are jointly considered, together with spatial spillovers from total factor productivity.

More precisely, patent data allow the construction of specific indexes of innovative activity, both at the territorial level (the technological space where a firm is located) and at the firm level (applicant firm) - whose structure will be detailed in the next chapters. In particular, the employment of patent data that are precisely localized on the territory plays to be a valid alternative to the availability of a comprehensive list of localized public and private research centers in Italy[19] (and of a plausible and updated ranking of the quality of the produced research), that would have represented the ideal framework to be combined with spatial econometrics techniques, in order to detect the direct benefits originating from firms' proximity to such research units[20]. Up till now, in fact, technological transfers from research centers to firms have been detected - and sometimes quantified - with reference to the academic or public research only[21].

2. Estimating Total Factor Productivity (TFP) at the firm level: the underlying hypotheses

The process of estimating total factor productivity at firm level requires several issues to be preliminarily addressed. From a strictly qualitative point of view, it is sometimes hard to deal with missing data on the number of workers and/or on the amount of capital accumulated within firms, especially with reference to the smallest ones in the Italian industrial framework. Moreover it is necessary to select appropriate hypotheses to estimate the production function from an econometric point of view.

A choice was made to adopt a standard Cobb-Douglas specification for the production function, of the type:

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[19]. The matching between patent data and single research centers is sometimes possible but complex and subject to heavy measurement errors, because of the lack of an univocal identifier for those research units, like a fiscal code (as in the case of firms).

[20]. It is worth stressing how Confindustria, the Italian Confederation of Industries, started a few years ago a mapping process of the main public and private research centers in Italy ("Mappa delle competenze delle imprese in ricerca e innovazione"), with the purpose of detecting a precise picture of the industrial research and of the produced innovation. The existing map is nevertheless still preliminary and incomplete.

[21]. Among the papers directly referring to Italian data it is worth mentioning Buganza, Bandoni and Verganti (2007), Colombo, D'Adda and Piva (2009), Fantino, Mori and Scalise (2012), Piergiovanni, Santarelli and Vivarelli (1997), Pietrabissa and Conti (2005).

$$Y_{it} = \Phi_{it} L_{it}^{\beta l\_sect} K_{it}^{\beta k\_sect} \qquad [1]$$

where Y represents output, value added and inputs are labour L (the number of firm workers) and capital K. The subscripts t and i refer to time (year) and to the firm identifier, respectively.

The *beta* coefficients β_l e β_k, representing labour productivity and capital productivity respectively, are allowed to vary over sectors of activity (subscript *sect*). At this purpose and to overcome the problem of limited number of observations available at the level of standard "2-digit sectors" of the Ateco 2007 classification for industrial activities[22], firms showing similar technologies were grouped into a more compact ranking: the result are 12 final sub-groups or "branches" of economic activity (see table A1 in the Appendix for details).

The econometric version of equation *[1]*, that implies a logarithmic transformation, is a model of the form (logarithms in small letters):

$$y_{it} = \beta_0 + \beta_{l\_sect}\, l_{it} + \beta_{k\_sect}\, k_{it} + \phi_{it} + \mu_{\text{it}} \qquad [2]$$

where $\phi_{it} + \mu_{it}$ is a composite error term. The latter embeds a productivity shock ϕ_{it} which is made observable only to the firm affected by its occurrence (unobserved productivity) and an idiosyncratic error term μ_{it}.

More specifically, the estimation framework relies on hypotheses of:

- a labor input free to vary, according to productivity shocks;
- a capital input predetermined: based on investment decisions undertaken in the previous period and correlated to past productivity shocks only.

In light of the above, a simultaneity problem arises in the estimation of model *[2]*, invalidating standard econometric techniques. The panel Pooled OLS (Ordinary Least Squares) approach ignores, as a matter of fact, the existing correlation between regressors and disturbances resulting into biased and inconsistent estimates of the *beta* coefficients we are interested in. The Fixed Effect approach (Within Estimator) is suitable to provide a solution to the endogeneity problem, nevertheless implying a key assumption of a constant unobserved productivity over time (only between variation is preserved in the data) - quite restrictive. Moreover, it is common knowledge in the literature on productivity that fixed effects estimates of capital coefficients are often implausibly low and estimated returns to scale severely decreasing.

To overcome these problems, the semi-parametric estimation method proposed by Levinsohn and Petrin (2003) has been considered. The routine makes use of intermediate inputs m_{it} (raw materials) as instruments to solve for the simultaneity critical issue. More specifically, the invertibility of the demand for intermediate inputs (depending on capital and productivity, and

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[22]. Ateco 2007 is the Italian version of the NACE Rev.2 classification for industrial activities, adopted by the European Community.

being a strictly monotonic function of unobserved productivity) allows to rewrite productivity as a function of observable inputs only, in the estimation procedure: $\phi_{it} = \phi_{it} (k_{it}, m_{it})$[23]. In practice, labour and capital coefficients are estimated by means of a two-step procedure that exploits several hypotheses, *in primis* the one of a first order Markov process for productivity[24] (refer to Levinsohn and Petrin (2003) for a more detailed discussion).

It is worth stressing how levels of firms' total factor productivity (in logs) are obtained, after a few steps, as residuals of the production function. This implies - starting from the before mentioned labor and capital coefficients estimated by "branch" of industrial activity ($\beta_{l\_sect\_LEV}$ *e* $\beta_{k\_sect\_LEV}$):

$$Log(tfp)_{it} = y_{it} - \beta_{l\_sect\_LEV}\, l_{it} - \beta_{k\_sect\_LEV}\, k_{it} \qquad [3]$$

where again, l_{it} and k_{it} are the levels of labor and capital of firm i at time t, in logs and y_{it} is the corresponding value added.

3. The reference dataset for productivity estimates

The reference dataset exploited to obtain reliable estimates of total factor productivity, at the firm level, is a large unbalanced panel of approximately 16,000 Italian manufacturing firms, surveyed over the 2004-11 period.

Data are drawn from the *Intesa Sanpaolo Integrated Database* on corporate customers (ISID), belonging to the Intesa Sanpaolo Research Department. It is a proprietary and confidential dataset combining information on firms' balance sheets[25] with additional information on firms' strategies (patents, brands, foreign direct investments, international certifications etc.) and riskiness indicators (ratings and other indicators constructed from reporting to the Italian Credit Register of the Bank of Italy).

Choice was made to consider only those firms whose sales, at current prices, were higher than the threshold of 1 million euros in the first year of

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23. Alternatively, the methodology proposed by Olley and Pakes (1996) makes use of investments as a proxy to overcome simultaneity. Nevertheless, it is difficult to recover reliable data on investments for small and medium size firms in the Italian balance sheets. Moreover, the estimation method requires investment to be a strictly monotonic function of unobserved productivity. The presence of a lots of zero investments in the data, like in the Italian case, would strongly indicate that this is not the case: we are forced to assume that all firms presenting zero investment have the same level of unobserved productivity, that comes to represent an unrealistic hypothesis.

24. Past levels of productivity (with the only exception of the first lag) do not provide information about future productivity.

25. Certified by the CEBI (Centrale dei Bilanci), the main collector of balance sheets in Italy.

observation, to exclude micro firms[26]. Moreover, a continuity of four years in the data belonging to each surveyed firm was a strict prerequisite to enter the panel, in order to add stability to the analysis.

Dealing with missing data on both the accumulated capital stock and the labor force represents an obliged passage to obtain productivity estimates. According to the Italian accounting rules no specific obligations are in place to deposit detailed balance sheets pertaining to small firms. A simplified version is in fact required, not necessarily inclusive of the items needed to estimate a production function: namely the number of workers (labor input)[27] and the total capital accumulated within the firm (gross capital input). As far as the latter is concerned, obligation is made to declare the amount of tangible fixed assets pertaining to the same fiscal year of the balance sheet.

In light of the above, it is necessary to proceed by steps, estimating missing data. Following a common practice in the literature[28], the recursive procedure adopted to estimate missing data on the labor force at firm level (approximately the 20% in the dataset), embeds information on labor costs (drawn from balance sheets, at constant prices[29]). Missing data on the accumulated capital stock (the 36% in the sample), if absent for multiple years for a single firm, were instead inferred directly from ISTAT data on gross and net capital, at the maximum detailed sectorial breakdown, properly deflated[30].

On average, the number of workers recruited by firms in the sample is 82, while the median value is 33, indicating the presence of a substantial

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[26]. Micro firms are in fact suitable to bias the results. However, sales are allowed to freely vary in the subsequent years up to a threshold of 150 thousands Euros (imposed to exclude bankrupt firms from the sample). This trick is desirable to reduce the risk of overestimating firms performances, especially in the 2009 recessionary year.

[27]. This information is optional also for the most detailed financial statements.

[28]. A similar approach to the estimation of the number of workers, at the firm level, can be found in Di Giacinto *et al.* (2011).

[29]. The recursive procedure adopted to estimate missing data on the labor force embeds different steps depending on the available information at the firm level. As a first step, when information on labor costs (deflated according to ISTAT production price indexes, at 3 digit level - Ateco 2007/Nace Rev.2 classification for industrial activities) was made available for at least two years in the data referring to a single firm in the panel, estimated workers were obtained running a simple interpolation OLS framework controlling for firm size if available. For those firms not presenting such a detailed information, as well as for all the cases were negative values of estimated workers resulted from the first estimation step, a second step was implemented based on a Weighted Least Squares (WLS) procedure, where weights were calculated as the reciprocal of the labour costs, including industry and province dummies. All the cases where estimated number of workers was still negative were discarded from the sample. Last but not least, as a final step all the estimated values for workers were augmented for a stochastic error, distributed according to a Normal with zero mean and variance equal to the variance of the labour force available in the sample.

[30] Reference is made to ISTAT deflators for gross and net capital, by branch of activity (Ateco 2007/Nace Rev.2): tables “Gross fixed capital formation, stocks of fixed assets, consumption of fixed capital by branches” June 2012 and subsequent available editions.

proportion of small and medium-size firms. Data are in line with the central role played by SMEs within the Italian manufacturing base[31].

As a second step, a screening test was performed, involving the other variables entering the estimation of the production function. As already mentioned in the previous paragraph, the "value added" item was selected as the reference proxy for the output variable while the "net purchases" item to proxy directly for intermediate inputs - the ones entering the routine proposed by Levinsohn and Petrin[32]. The latter embeds all the proper costs pertaining to the purchase of raw materials and commodities entering the production process[33]. Firms presenting missing values on valued added and net purchases were deleted from the sample.

After these multiple steps were completed, total factor productivity was estimated, at the firm level, based on an unbalanced panel of 16,181 manufacturing firms (115,859 observations) observed over the 2004-11 period. As far as the sectorial composition of the dataset is concerned, it is worth observing the prevalence of the "Mechanic sector, electronic equipment, medical equipment" branch (showing an incidence of 21.3% over the total number of observations in the sample), followed by the "Metallurgical sector and fabricated metal products" branch (20,3%), the "Food and beverage" branch (11,7%) and the "Textiles and textile products" one (7,9%). They all account to represent key sectors of specialization within the Italian manufacturing industry.

Coefficients on capital and labor productivity, estimated by branch of activity, are suitable to identify a prevalent regime of decreasing returns to scale (DRS). The same DRS regime is recurrent in literature based on Italian data (Tab.1).

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[31]. According to standard size categories, firms are classified as "small" if presenting less than 50 workers, "medium-size" if the number of workers spans from 50 to 249 and "large" if workers are greater or equal to 250.

[32]. The routine Levpet available in STATA 12 has been exploited to estimate total factor productivity.

[33]. Both the items were deflated according ISTAT production price indexes, at 3 digit level of the Ateco 2007/Nace Rev.2 classification for industrial activities.

Tab.1 – Estimated labor and capital coefficients and returns to scale, for branch of activity: unbalanced panel 2004-11

Branch of economic activity	*Numb. Observ.*	*Levinsohn and Petrin*			*Pooled OLS (upward benchmark)*		
		Labour Coeff.	*Capital Coeff.*	*Returns to scale*	*Labour Coeff.*	*Capital Coeff.*	*Returns to scale*
Food and beverage	13,538	0.570 (0.025)	0.152 (0.014)	0.722	0.688 (0.027)	0.311 (0.016)	0.999
Textiles and textile products	9,160	0.643 (0.019)	0.086 (0.016)	0.729	0.813 (0.019)	0.124 (0.012)	0.937
Leather and footwear	3,838	0.639 (0.019)	0.068 (0.016)	0.707	0.786 (0.023)	0.187 (0.013)	0.973
Wood-made products (except furniture)	3,989	0.647 (0.017)	0.075 (0.020)	0.722	0.759 (0.022)	0.192 (0.015)	0.951
Paper, print and publishing sector	5,966	0.678 (0.025)	0.166 (0.059)	0.844	0.766 (0.036)	0.217 (0.027)	0.983
Chemical and pharmaceutical sector	6,139	0.725 (0.024)	0.094 (0.022)	0.819	0.908 (0.027)	0.160 (0.020)	1.068
Rubber and plastic products	8,338	0.685 (0.015)	0.079 (0.016)	0.764	0.798 (0.160)	0.193 (0.012)	0.991
Other non-metallic mineral products	7,751	0.638 (0.019)	0.106 (0.017)	0.744	0.798 (0.017)	0.207 (0.012)	1.005
Metallurgical sector and fabricated metal products	23,577	0.681 (0.012)	0.107 (0.012)	0.788	0.768 (0.012)	0.206 (0.007)	0.974
Mechanic sector, electronic equipment, medical equipment	24,677	0.706 (0.013)	0.073 (0.009)	0.779	0.898 (0.010)	0.113 (0.007)	1.011
Transport equipment	3,347	0.636 (0.024)	0.157 (0.028)	0.793	0.788 (0.023)	0.182 (0.017)	0.970
Furniture sector	5,539	0.664 (0.027)	0.104 (0.018)	0.768	0.887 (0.020)	0.113 (0.013)	1.000

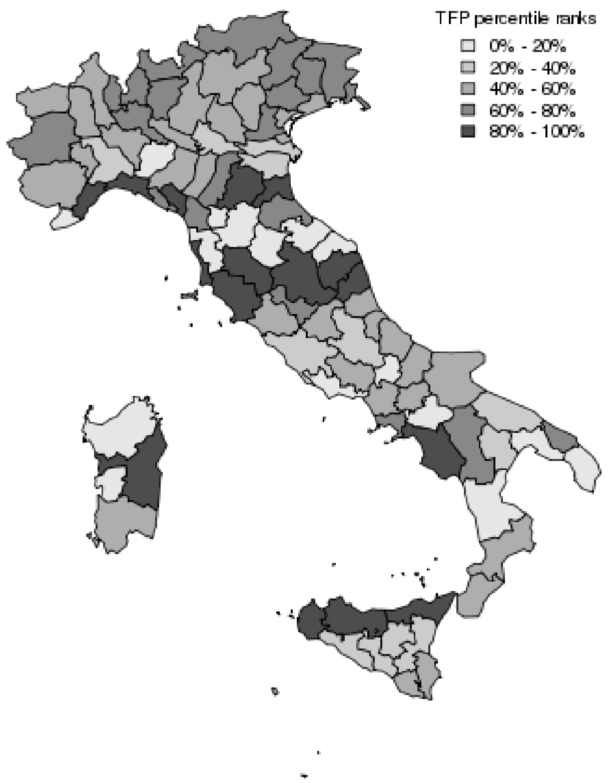
Note: Standard errors are in parenthesis. The sample size for productivity estimates is of 16,181 manufacturing firms, observed over the 2004-11 period. At this stage the panel is unbalanced (115,859 observations).

Table 1 reports as well the coefficients estimated by standard Pooled OLS approach[34]. As mentioned before, they do not account for the simultaneity in place between productivity shocks and the choice of inputs in the production function (i.e. labor input) but represent useful upward benchmarks for the Levinsohn an Petrin estimates[35].

[34]. Pooled OLS applied to regression equation [2], controlling for cyclical effects (time dummies). The option *robust* has been selected to take into account potential heteroskedasticity. Estimates are clustered by fiscal code firms' identifier, to control for the potential time correlation between observations belonging to the same firm.

[35]. By contrast, the estimates obtained applying the Fixed effect approach are not directly comparable to the Pooled OLS estimates and the Levinsohn and Petrin estimates, because of the different assumption made over the unobserved productivity shocks (supposed constant over time).

Fig.1 – Total Factor Productivity (TFP) in the Italian manufacturing industry: mean values 2004-11



4. The baseline model for productivity and innovation: exploiting the features of a matched dataset between patent data and balance sheets

The estimated levels of firms' total factor productivity were subsequently applied as the reference dependent variable (in logarithms) into a baseline model – without a spatial approach. The purpose was to shed light on potential productivity advantages originating from a set of characteristics of the operational context where firms are located.

At this purpose, the reference unbalanced panel for productivity estimates was reduced into a balanced one of 8,803 geo-referenced manufacturing firms, surveyed over the 2004-11 period as well. The balancing of the original dataset, suitable to produce a considerable drop in the number of available observations (70,424 observations were left, out of the 115,859 observations in the unbalanced dataset for productivity estimates), was desirable to prepare the ground for a further extension to a spatial panel data approach.

From a dimensional point of view, a predominance of small firms is detectable in the data: firms with less than 50 workers account for the 66,3% of the analyzed aggregate. Medium-size firms, with a number of employees spanning from 50 to 249, present instead an incidence of 29,5% and large firms, being those ones hiring more than 250 workers, account for the remaining 4% of the panel dataset[36].

Following the strand of the literature on local productivity advantages, we considered a panel data model of the form[37]:

$$
\begin{aligned}
Log(tfp)_{it} = {} & \beta_1 medium_{it} + \beta_2 large_{it} + \beta_3 innov\_lls_{\ell t} * small_{it} + \\
& + \beta_4 innov\_lls_{\ell t} * medium_{it} + \beta_5 innov\_lls_{\ell t} * large_{it} + \\
& + \beta_6 innov\_firm_{it} + \beta_7 distr_{it} + \beta_8 tec_{it} + infra_r + \\
& + m_t + m_\ell + m_v + \varepsilon_{it} \qquad [4]
\end{aligned}
$$

Medium and *large* are binary variables describing the belonging of a generic firm *i* in the specific year *t* to the subset of medium or large firms described before (depending on the number of workers). They capture, as a matter of fact, additional TFP premiums associated to medium and large firms in the comparison to the baseline group, small firms in the sample.

The variables $distr_{it}$ and tec_{it} capture instead the belonging to clusters of firms with common specialization, identified here in the more traditional sense: both the variables are dummy variables assuming value 1 if firms belong to industrial districts (the 22% in the dataset) and technological clusters (the 2% in the dataset) respectively. We exploit, at this purpose, the definitions of the 144 industrial districts and the 22 technological clusters monitored periodically by the Research Department of Intesa Sanpaolo: industrial districts refer to firms' agglomerations specialized in typical "Made in Italy" productions (i.e. mechanical, textiles, food and beverage, leather and footwear etc.) while technological clusters embed firms specialized in the most "technological-based" activities (aerospace and

[36]. The subsample of deleted firms is made up of 7,377 subjects, with a composition in terms of dimensional clusters similar to the one described so far for our balanced panel: small firms account to represent the 67% of the sample, followed by medium and large firms, with an incidence of 29% and around 3% respectively. This ensures that an almost random drop of firms from the original dataset was performed. The only slightly higher percentage of large firms remaining into our balanced panel (4%) is due to the higher probability of large firms (with respect to the smallest ones) to remain in the Intesa Sanpaolo Integrated Database for long time spans (i.e. to maintain a long banking relationship, such that their balance sheets are present for recursive years in the dataset). By contrast, the percentage of small firms removed from the original dataset (67%) is slightly higher with respect to the one characterizing the balanced panel (around 66%).

[37]. A choice was made to exclude the constant from the model. We assume indeed that when all the covariates of the model simultaneously assume a zero value, the dependent variable (TFP) is zero as well.

aeronautical sectors, pharmaceutical sector, Ict)[38]. It is worth stressing how the definitions we account for in the present paper might encompass the strategic proximity to urban areas, being also suitable to totally overlap to them, in a few cases[39].

In order to (indirectly) identify the presence of potential knowledge spillovers instead, suitable to generate important TFP premiums, we constructed an index of the innovative activity attributable to the operational space of firms in the panel. As already outlined in the previous section, the presence of knowledge spillovers can be inferred indirectly, through their impact on total factor productivity. Spillovers of these type are mainly to be considered mixed spillovers, originating from market-based exchanges. We exploited at this stage the features of a rich dataset on patent data – patent applications registered at the European Patent Office (EPO), referenced at the level of the applicant firm[40] – matched to the information on balance sheets that is present in the *Intesa Sanpaolo Integrated Database*[41]. To the best of our knowledge, the availability of massive matched data on patents at the firm level is quite rare (in Italy a similar dataset has been exploited so far only by the Bank of Italy[42]).

Patent data represent, as a matter of fact, a high-quality proxy of certified innovative output, the one subject to the lowest measurement errors: they are directly attributable to realized and certified product innovation at the firm level.

More precisely, we made use of patent data precisely localized on the territory to build-up a sort of technological space for industrial activities. We proceeded summing up demands for patents undersigned by manufacturing firms[43] at the level of broad territorial units, the ISTAT Local labor systems (LLS)[44], for each sector of activity ℓ (3 digit, or 2 digit

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[38]. For further details refer to the periodical reports “Industrial Districts Monitor” (quarterly) and “Economics and Finance of Industrial Districts” (yearly) edited by Intesa Sanpaolo SpA, Research Department.

[39]. There are no reason to retain “a priori” that industrial districts, being an agglomeration of firms with a common specialization, are necessarily located far apart with respect to urban centers and that those agglomeration economies are not in a position to benefit from the advantages that being part of a urbanized area might offer.

[40]. In the (residual) cases of multiple applicant firms, decision was taken to consider a multiple assignment of the same demand for patent.

[41]. The patent data come from the proprietary database Thomson Innovation, managed by Thomson Reuters. The matching with data on balance sheets was performed – and is revised on an annual basis according to new releases and/or revisions to the firm level data in the Thomson Innovation dataset – by the Intesa Sanpaolo Research Department.

[42]. The dataset was exploited to estimate a model of innovation and trade that does not take into account spatial features of firm productivity. Reference is made to the contribution of Accetturo et al. (2014).

[43]. All the manufacturing firms associated to patent innovations available in the Intesa Sanpaolo Integrated Database (around 4,800 firms) are considered.

[44]. Local labor systems are 784 territorial units identified by ISTAT (the Italian national statistics institute) based on socio-economic relations. More precisely, they are a broad

sector from the Ateco 2007 classification for industrial activities, depending on the available degree of detail in the matching process with patents' IPC codes – International patent classification codes[45]). As outlined before, LLS already proved to be a valid instrument to analyze the socio-economic structure of the country. At this stage of the matching process all the manufacturing firms associated to patent innovations available in ISID were considered (around 4,800 firms) - and not merely the geo-referenced firms present in our balanced panel (around 800 out of the 4,800). The summation process of demands for patents, by sector ℓ and LLS pair, was computed identical for each year *t* covered by our analysis – that spans from 2004 to 2011. Moreover, in order to take into account the potential time-lag occurring between a patent application at the EPO and the moment of formal assignment of a patent to an applicant firm, we proceeded summing up patent demands pertaining to a reference year (pivotal year) *t* in the panel and to the previous four years - obtaining so far a sort of rolling composite sum of patent applications. The variable $innov\_lls_{\ell t,}$ being an index for *relative patent intensity at the territorial (LLS) level* in the model (bounded between 0 and 100), was derived dividing such a rolling composite sum - available at the sector ℓ /LLS pair – for the same composite sum attributable to the ℓ*-th* specific manufacturing sector at the national level[46]:

$$innov_{(\ell,\,t,lls)} = \frac{\sum_{L=1}^{4} patents_{(\ell,t-L,lls)}}{\sum_{L=1}^{4}\sum_{lls} patents_{(\ell,t-L,lls)}} * 100$$

The variable was further assigned to firms in our balanced panel according to their sector of activity ℓ, to the reference year *t* and to the LLS they belong to. The mean value of the index is 2.7, suitable to identify a codified innovative activity that is well spread across sectors and local labour systems. As far as patent attitude of sectors is specifically concerned, a traditional predominance of the electronic sector (with a mean value of 19 demands for patents in the surveyed 2004-11 period), of the pharmaceutical one (mean value of 15 demands), of the chemical sector (mean value of 8 demands) and of the food sector (mean value of 5 demands) is detected.

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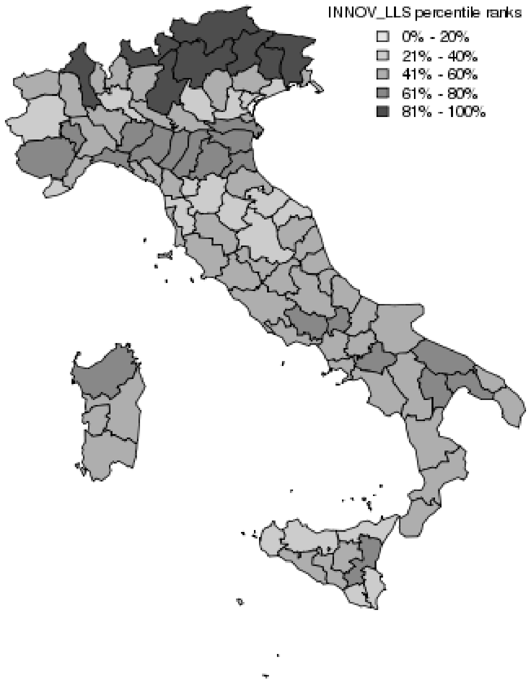
aggregate of municipalities identified compacting information (drawn from the population census survey) on daily trips of the resident population, for business purposes. The scope of such a classification is to link municipalities showing consistent interdependence relationships.

45. The matching process between IPC codes of patents and Ateco codes for industrial activities, at the level of applicant firms, has been executed at the maximum degree of the available breakdown (3 digits or 2 digits). The correspondence table between IPC codes and Ateco is based on an updated version of the one present in Schmoch et al. (2003).

46. It is the aggregation of the demands for patents localized into all the Italian Local labor systems, for a specific manufacturing sector (at 3 digit or 2 digit, depending on the maximum degree of the available breakdown).

Fig.2 – Patent intensity (Innov_lls) in the Italian manufacturing industry: mean values 2004-11



One might have the concern that in certain technological areas (before identified) innovative capacity or patent intensity is the result of investments undertaken by single driving firm - and that the estimated elasticity of total factor productivity to changes in the *innov_lls*$_{\ell t}$ variable might indeed capture this phenomenon. At this purpose, we proceeded interacting the index of innovative activity at the territorial level (LLS) with dimensional dummies in estimation (the same entering the model separately, to control for dimensional determinants of TFP), in order to check if the (expected positive) effect of territorial innovation over TFP survives in correspondence to the clusters of small and medium-sized firms.

Moreover, the construction of a control variable, being an *index of relative patent intensity at the firm level* was considered: the variable *innov_firm*$_{it}$ is the ratio between the number of patent applications associated to that specific firm *i* in the pivotal year *t* and in the previous four years (following the same logic as in the *innov_lls*$_{\ell t}$ case) and the corresponding composite sum of patent demands associated to the LLS of the firm; the latter is restricted to the specific firm's sector of activity ℓ:

$$innov_{(\ell,\,t,i)} = \frac{\sum_{L=1}^{4} patents_{(\ell,t-L,i)}}{\sum_{L=1}^{4}\sum_{i} patents_{(\ell,t-L,i)}} * 100$$

The mean value of the index is 4.4 and the median is 0, because of the still limited number of Italian manufacturing firms (the 9% in our panel - the 800 firms mentioned before) who gain access to a precise and codified innovative activity (i.e. patenting).

In particular, the 3% of firms is associated one patent application and the 2% two applications, corresponding indeed to the median value of patent demands in the sample - while the mean value is around six demands. In particular, the mean value of patent applications is two for the cluster of small firms (that account to represent the 30% of the sample of innovative firms), three for the cluster of medium firms (with an incidence of around 49%) and 15 for the one of large firms (accounting for the remaining 21%). Again, these evidences can be interpreted in favor of an innovative activity that is well spread across firms belonging to a specific LLS/sector pair and, in general, across the three broad dimensional clusters in our dataset[47].

The error term in model *[4]* is a composite one; it is made up of four components:

- a time-specific component m_t accounting for business cycle effects;
- an industry-specific component m_ℓ capturing sectorial peculiarities of the TFP behavior;
- a territorial specific component m_v accounting for territorial peculiarities of the TFP phenomenon;
- an idiosyncratic error term ε_{it}.

The presence of time specific effects is accounted for introducing time dummies (year dummies) in estimation, while sectorial dummies - at the level of the branches of industrial activity exploited to estimate total factor productivity - control for the presence of industry-specific effects. In order to control for the presence of territorial peculiarities in measuring TFP advantages, four categorical variables have been exploited, identifying the belonging to broad macro-areas (North-East, North-West, South and Islands, Center). Moreover, in addition to macro-geographical dummies, the inclusion of an index proxying for the regional infrastructural endowment was considered. At this purpose, we resorted to the indicators of infrastructural development constructed by the Association of Italian Chambers of Commerce (Unioncamere) in collaboration with the “Guglielmo Tagliacarne” research institute[48]. The index $infra_r$ (where the subscript r stays for regions) allows to directly control for the effect of

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47. The same checks have been executed over the subsample of firms drop from the original unbalanced dataset for productivity estimates, in order to uncover the presence of potential differences with respect to the balance dataset we have described so far. It is worth stressing a mean value of 2.5 for the territorial index of innovative activity and a mean value of 4.2 for the index capturing the degree of innovative activity at the firm level.

48. The indicators were successfully employed in other works based on Italian data. See for example the contribution from Minetti and Zhu (2011).

infrastructural development on firms' total factor productivity and to absorb (indirectly) potential spatial dependence in the data – the one attributable to common features in the way to exploit territorial infrastructures and institutions, that might differ considerably from one region to the other.

Given the reduced time variability of the variables in our baseline model (most of the regressors are time invariant), a panel estimation approach with fixed effects does not represent an available option. By contrast, to control for heterogeneity at the firm level (in addition to the before mentioned sectorial and geographical dummies) we propose an estimation framework based on random effects (RE). The representativeness of our sample allows to reasonably consider the selected firms as randomly drawn from a bigger population (random specific unobserved heterogeneity).

Preliminary estimates – that do not assume any spatial structure in the data (column 1 in Tab.2)[49] - highlight the presence of a strong link between productivity, at the firm level and the patent intensity of the local labor system where the firm is located, for what concerns its specific sector of industrial specialization – captured by the variable $innov\_lls_{\ell t}$. Even if firms are not patenting directly, they might benefit from being located into a patent intensive area. The result is suitable to support, at least indirectly, the central role of innovation in enhancing total factor productivity. The phenomenon is detectable in correspondence to all firms' dimensional clusters in the sample: it is worth stressing how a positive and strongly significant elasticity of TFP to territorial innovation is uncovered with reference to small firms (*innov_lls*small).* As mentioned before, the inclusion of an index for relative patent intensity at the firm level within the estimation framework ($innov\_firm_{it}$) ensures that the before results are not merely driven by erroneous attribution to areas of spillover effects pertaining to the innovative capacity of single larger firms.

Moreover, the inclusion in the model of a separate block of dimensional dummies controls for the relevant effects of dimensions on total factor productivity. Larger firms are traditionally associated "a priori" higher levels of TFP.

Last but not least, consistently to the literature, a positive link is established between total factor productivity and the belonging to clusters of industrial subjects sharing a common specialization: positive elasticities are in fact estimated in correspondence to dummies proxying for industrial districts and technological clusters.

As already outlined in the introductive section, standard econometric techniques are unable to account for important feedback loops arising from the multidirectional nature of spatial dependence in the productivity phenomenon: this is suitable to result into biased and inconsistent estimates (endogeneity bias), as well as into spatially dependent residuals - like the

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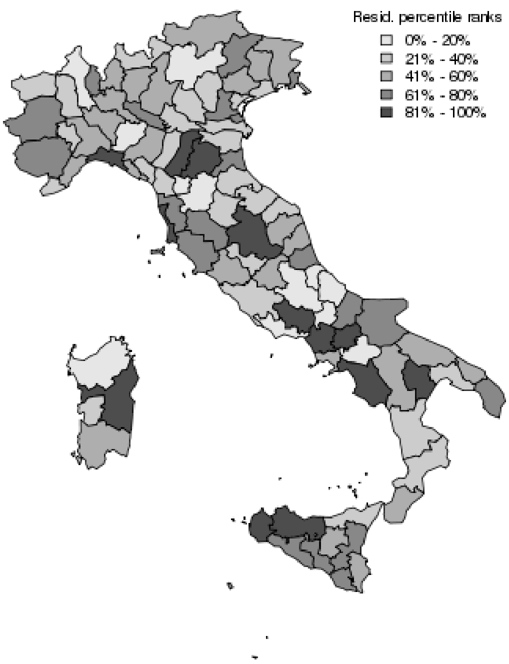
49. Estimates were performed through the R software (http://www.r-project.org/), *plm* package (Linear models for panel data, Croissant and Millo).

ones plotted in Fig.3 – and a poorly predicted dependent variable (a combined mix of underestimated and overestimated values of the variable in space (Anselin and Le Gallo, 2006). In order to allow for a proper estimation of the coefficient parameters, as well as for a proper quantification of the spatial content of the productivity spillover, we move to a formal spatial econometric framework.

Fig.3 – The plot of the residuals of the basic model, after non spatial estimation (Panel Random Effect estimator)



5. A spatial approach to productivity: the role played by geographical and sectorial distances between firms

Spatial econometrics comes to represent the econometric branch devoted to formalize and measure spatial relationships in place between objects (i.e. countries, regions or provinces at the macro level or firms at the micro level)[50]. In analyzing data pertaining to geographical entities, it is in fact important to deal with spatial dependence, in addition to simple spatial heterogeneity. The latter arises when diversified spatial units are employed

[50]. The contributions from Paelink and Klaasen (1979), Anselin (1988) and most recent ones from Anselin and Le Gallo (2008), Le Sage and Pace (2009) are considered milestones in the spatial econometrics field.

into the analysis and can be handled easily, resorting to standard econometric techniques. Spatial dependence instead, or spatial autocorrelation when the dependence is of the linear type, emerges when realizations of the same variable are ordered according to a spatial scheme[51]. More precisely, it is hard detecting a unique causal direction for connections established within a spatial context – differently from the time series processes, where the causal direction goes from "past to future" realizations of a variable: this renders standard econometric techniques improper to quantify the importance of spatial relationships.

Spatial econometrics' techniques are exactly designed to cope with this "multi-directional feature" of spatial phenomena. Our attention will move in particular towards the estimation of a spatial panel data model, with random effects, exploiting at best the features of our data.

As a preliminary step, a global index of spatial autocorrelation of the Moran's I type was applied to our productivity data, to highlight the importance of switching from a standard econometric approach to a spatial one. The index is intended to detect the presence of correlation of the spatial type: the more spatial objects (firms, in our case) are similar with respect to the values undertaken by a certain variable under scrutiny (productivity, our dependent variable in the model), the higher the value of the index[52]. It is nevertheless worth stressing that the Moran's I index is based on some restrictive assumptions[53]: it is desirable to limit the interpretation of results coming from the test to the detection of spatial correlation in the data, leaving the assessment of its strength to a more complex spatial econometric framework.

More precisely, we proceeded computing the Moran's I index with reference to our estimated (mean) TFP levels[54], the ones pertaining to the

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[51]. Spatial autocorrelation can be defined as the relationship in place between pairs of observations drawn from the same variable under scrutiny. The concept is implicit in the broader one of spatial concentration of objects, i.e. the attitude of empirical phenomena to assume similar values when close in space. More formally, spatial dependence means a covariance different from zero between the values assumed by a variable in different locations.

[52]. The values can vary between -1 (perfect dispersion) and +1 (perfect spatial correlation). When dealing with micro-data it is reasonable to accept values of the index that fall in a interval around zero: in the case of values of the index greater than zero, positive spatial dependence is detected.

[53]. A simplifying assumption is the one of equality of variances between the value assumed by a variable in one location i and the spatial lag of the same variable (based on the values assumed in locations j). The test can in fact be considered an extension to the spatial case of the Durbin Watson test applied to detect serial correlation in time series processes.

[54]. Choice was made to perform the test over mean TFP values (averaging over time) - instead of switching to a pooled Moran's I test option – to avoid computational issues and to reduce the memory footprint. Indeed, due to the magnitude of the W matrix (8.803 x 8.803) a pooled Moran I test would involve the construction of a pooled dense matrix of size $(n*t)^2$ = 7.75e9. Considering a double value storage, this would imply a memory footprint of approx. 58 GB, introducing heavy computational issues.

8,803 manufacturing firms of the balanced panel presented in Section 4. To identify spatial relationships in place between testable objects, a basic W matrix of reciprocal influences was constructed (whose role in the estimation procedure will be detailed further and whose structure will be subject to refinement in subsequent steps), based on their geographical distance. At this purpose, firms were geo-referenced according to latitude and longitude coordinates (Fig.4). The starting point was the location of the municipality pertaining to the main operational headquarter of each firm in the panel[55]: geographical distances in kilometers d_{ij} (between a firms i and a generic neighbor firm j) were computed accordingly, based on the great circle method[56].

Fig.4 - The 8,803 geo-referenced Italian manufacturing firms present in our balanced panel 2004-11

[55]. Choice was made to consider pluri-localized firms as uni-localized ones, based on the coordinates attributed to the main operative headquarter of the firm. In light of the above, it is possible to associate to each firm in the panel a univocally identified position and to build up a unique matrix of distances W, of the order $n \times n$, where n is the number of firms considered in the analysis.

[56]. According to the great circle method, distances are measured in kilometers taking into account the Earth curvature.

Based on the before mentioned “raw” W matrix, the performed Moran’s I test for spatial correlation (under both normal approximation and randomization assumptions) shows the presence of positive spatial correlation in the data, with a highly robust significance (p-value < 2.2e-16): the empirical value of the Moran's I statistic is 0.0520 (expected value E[I] = -1/(N-1) = -0.0011 and variance V[I]=7.9685e-07).

These preliminary results encourage the adoption of a spatial approach to properly estimate our productivity framework. If firm productivity levels at location *i* depend on the levels observed in location *j* and vice-versa, the data generating process becomes simultaneous: firms that are close in space tend to display similar values of productivity, because of spillover effects. Such a phenomenon is referred to as “clustering”[57].

More precisely the presence of a productivity spillover can be modeled, as a first step, resorting to a spatial (random effect) panel model of the type (in stacked form):

$$Log(tfp)_t = \lambda Wlog(tfp)_t + X_t\beta + \varepsilon_t \qquad [5]$$

where the $Log(tfp)_t$ object contains levels of total factor productivity (of a generic firm *i* at time *t*, in logs) estimated in Section 1, λ is the spatial autoregressive parameter associated to the spatial lag of productivity $Wlog(tfp)_t$ (the one accounting for weighted contributions of the productivity levels pertaining to neighboring firms *j*), X_t is a vector of exogenous covariates and ε_t is a pure idiosyncratic component. A spatial model of this type, where a spatially lagged dependent variable is present, is called Spatial autoregressive (SAR) of order one. Relationships in place between spatial objects can be better visualized rewriting the linear model in equation *[5]* as (substituting in X_t all the exogenous variables and control variables already described in Section 3):

$$\begin{aligned} Log(tfp)_{it} = {} & \lambda \textstyle\sum_{j=1}^{n} w_{ij} log(tfp)_{jt} + \beta_1 medium_{it} + \beta_2 large_{it} + \\ & + \beta_3 innov\_lls_{\ell t} * small_{it} + \beta_4 innov\_lls_{\ell t} * medium_{it} + \\ & + \beta_5 innov\_lls_{\ell t} * large_{it} + \beta_6 innov\_firm_{it} + \beta_7 distr_{it} + \\ & + \beta_8 tec_{it} + infra_r + m_t + m_j + m_v + \varepsilon_{it} \qquad [6] \end{aligned}$$

When the autoregressive parameter is greater than zero, the variable under scrutiny (productivity) is positively autocorrelated in space and a spillover effect is detected[58].

[57]. *Clustering* can be present in two different forms. In a true contagion framework leader firms are assumed to locate randomly in the space while “followers” or subcontractors display a positive probability to locate closeby. When instead exogenous conditions impose the location of firms in certain areas (or certain areas display a higher probability to host firms) a phenomenon of apparent contagion is in place. We will come back to this point when discussing spatial dependence in the error term of our selected model.

[58]. When instead the autoregressive parameter is negative (λ<0) the variable under scrutiny (productivity) is negatively autocorrelated in space: firms located closeby tend to display different values (*segregation*).

The weighting scheme, the one suitable to model reciprocal influences within the neighborhood, is contained into the W matrix. Therefore, it is worth discussing in detail the construction of such an object, that is crucial to correctly identify productivity spillovers: spatial econometrics estimates are in fact particularly sensitive to the choice of W. The latter is a quadratic matrix *n x n* (where *n* is again the number of firms in the sample, 8,803), with zero diagonal elements[59]. The generic elements w_{ij} are referred to as "spatial weights", measuring the strength of the relationship between a firm *i* and a neighbor firm *j*.

$$W = \begin{bmatrix} 0 & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & 0 \end{bmatrix}$$

Different approaches can be accounted for to retrieve those coefficients. The reference matrix in our analytical framework relies on geographical influences exerted by first order neighboring firms[60]. Influences are in turn calculated relying on the d_{ij} distances mentioned before: more precisely, spatial weights come to represent the reciprocal of the d_{ij} pairwise distances in kilometers between firms in the dataset: $w_{ij}=1/d_{ij}$.

This way of modeling influences is not free from drawbacks. When distances between firms are small, in fact, the elements w_{ij} of the matrix tend to assume large values: $\lim_{d\to 0} w=\infty$. In light of the above, it is desirable to introduce some corrections. *In primis*, firms displaying pairwise distances lower than 1 kilometer were assigned a unitary distance (maximal reciprocal influence $w_{ij}= 1$).

Moreover, the structure of the W matrix was additionally refined, exploiting results from the analysis of the Moran's I index as a function of pairwise distances. Upon construction of a correlogram (Fig.5) it is possible to shed light on a clear pattern of decay in spatial correlation between levels of TFP of Italian firms, as long as geographical distance increases: correlation becomes close to zero when pairwise distances fall within the range [300,400] Km.

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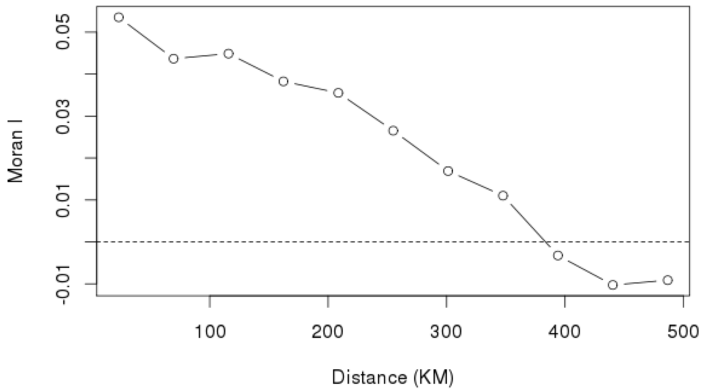
59. The diagonal elements correspond to the influence exerted by a firm on itself.

60. It could be possible to define weights based on the interactions between neighbours of the second order as well (neighbours of neighbours). But second order neighbours are, in their turn, the first order neighbours of other spatial objects: this introduces simultaneous interactions into the model, where each observation depends on the influence exerted by both second order and first order neighbours. The influences λ of order greater than the first one tend to decrease exponentially.

Fig.5 – Correlogram showing spatial correlation (Moran's I) as a function of firms' pairwise distances (KM)



In light of the above, our main assumption was to set a cut-off at 300 Km to clean-up the raw W matrix introduced so far: only valuable reciprocal influences are accounted for. The selected spatial weights matrix remains nevertheless quite dense despite corrections (with a considerable share of non-zero elements), introducing computational issues in the estimation of a former spatial econometric model.

Furthermore, a row-standardization approach was adopted - such that spatial weights sum to 1 in each row of the W matrix ($\Sigma_j w_{ij} =1$) - in order to coerce the spatial autoregressive parameter to assume a value in the range [-1, 1] and to preserve its economic interpretation. A spatial model can in fact be assimilated to an equilibrium system and the selected parameter space is suitable to rule out situations of unstable equilibria.

As a further step different definitions of the W weights matrix were considered, in order to prepare the ground for robustness checks. Different cut-off distances (other than the 300 km selected before) were employed to truncate the influence exerted by pairwise firms in the spatial weighting scheme: the main alternative is represented by a matrix with a cut-off set at 400 km[61]. Results from the adoption of these alternative matrices are qualitative comparable to the reference ones and available upon request.

Furthermore, one should note that spatial dependence might follow different paths other than a merely geographical one. It is in fact possible to model distances between firms from a sectorial point of view: firms belonging to a generic manufacturing sector *i* can potentially benefit from externalities coming from industry *j* and the magnitude of the externality depends on the intensity of trade flows between interconnected firms.

[61]. In this case pairwise firms located more than 400 km far apart are assigned a null spatial weight in the W matrix.

Balance sheets do not report information concerning intra-firm trade but it is reasonable to rely on sectorial proxies (Medda and Piga, 2007). ISTAT input output matrices offer the right framework to disentangle the intensity of trade connections in place between main sectors in the economy[62]. In order to model the effects of productivity spillovers from other industries two additional matrices were constructed *Wd* (for demand-driven spillovers) and *Ws* (for supply-driven spillovers). In the specific case of the demand driven spillover matrix *Wd,* spatial weights wd_{ij} correspond to the sales' share of industry *i* to industry *j* or intermediate sales (how much of the production of industry *i* is allocated to industry *j*[63]), at 2 digit level (Ateco 2007/Nace Rev.2 classification for industrial activities), standardized by the total amount of sales assigned to the sector *i* in the economy (the sum of intermediate sales and final sales), to control for its relative importance. By contrast, spatial weights wd_{ij} in the supply driven matrix *Ws* correspond to the purchases' share of industry *i* from industry *j,* properly standardized as well. Moreover, in order to preserve the same economic interpretation for the spatial autoregressive parameter λ in the model, sectorial-based spatial weights were further row-standardized.

From the point of view of an econometric estimation of model *[6]*, it is worth stressing the inconsistency and inefficiency of standard panel data estimators (i.e. the random effect panel estimator adopted in section 4), not accounting for the correlation in place between errors and the spatially lagged dependent variable (endogeneity issue).

The maximum likelihood approach (Anselin, 1988) comes to represent the "most popular"[64] routine to consistently estimate the parameters of a spatial model but results in turn to be hardly implementable on large samples, like the one we are considering in the present paper (where the spatial recursive system is based on a dense W weights matrix of order 8,803 x 8,803 and is extended to encompass a panel structure with a temporal length of 8 years). In fact, when spatial dependence is detected in the data and a spatially lagged dependent variable is considered to model it directly (SAR model), the log-likelihood function is augmented for an additional term depending on the autoregressive parameter λ (the Jacobian or the log determinant of the $(I-\lambda W)$ matrix). That latter is going to introduce computational difficulties in estimation: different from the time series case, the Jacobian is not supposed to tend to zero as the sample size increases. As a matter of fact, it constrains the autoregressive parameter

[62]. Specific reference is made to the ISTAT symmetric input output matrix of the "sector by sector"[62] type (release 2013 – the one corresponding to the release 2010 of the Italian national accounts).

[63]. They represent, as a matter of fact, the inter-industrial intermediate flows between the different sectors in the economy before the final product is made available on the consumption or investment market. Sales from a generic sector i to sectors j can be red in rows within the symmetric matrix.

[64]. The preferred choice in dealing with small finite samples.

values to their feasible range between the inverses of the smallest and largest eigenvalues of the spatial weights matrix W [65].

Moreover, computational issues are going to be exacerbated by a further refinement of the spatial framework considered in our paper. With the purpose to allow explicitly for spatial diffusion of disturbances in the model, the error term in *[5]* was assigned an additional autoregressive structure $\rho W u_t$, where u is a composite error term (the sum of the AR(1) term and the idiosyncratic term ε).

Once the new error equation is embedded into the SAR model, an evolution of the basic model is achieved, the SARAR model (in stacked form):

$$log(tfp)_t = \lambda W log(tfp)_t + X_t\beta + u_t$$
$$u_t = \rho W u_t + \varepsilon_t \qquad [7]$$

The W matrix in the error equation is assumed identical to the one in the main equation.

The SARAR approach is justified by the presence of potential latent variables correlated in space, not properly accounted for in the previous specification of the model. While the spatial lag $Wlog(tfp)_t$ is suitable to model direct spatial dependence in the data, the introduction of additional structure into the error term can be indeed viewed as a way to model indirect spatial dependence or, in other words, to model a dependence coming from an external source. In particular, once an autoregressive structure is considered (of order one, in our case), dependence in the error term is potentially allowed to propagate without restrictions[66].

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[65]. The simple SAR model $y= \lambda Wy + X\beta + \varepsilon$ can be rewritten as $(I-\lambda W)y= X\beta + \varepsilon$ exploiting matrix properties, with $\varepsilon \sim N(0, I\sigma^2)$. The parameter vector is $\Theta= (\lambda, \beta, \sigma^2)$. For $\lambda \neq 0$ the log likelihood becomes:

$$\ell(\Theta) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(\sigma^2) - \frac{(y-\lambda Wy - X\beta)'(y-\lambda Wy - X\beta)}{2\sigma^2} + \ln|I - \lambda W|$$

The inclusion of the $\ln|I - \lambda W|$ term, that is referred to as the Jacobian, is suitable to introduce computational problems in estimating spatial models with a consistent amount of data (a spatial panel of 8,800 manufacturing firms surveyed over 8 years, in our specific context), even when "saving time" or approximation procedures are adopted. The most recurrent one is the "eigenvalues method" proposed to approximate the Jacobian. In fact, unlike the time series case, the logarithm of the determinant of the $(n \times n)$ asymmetric matrix $(I - \lambda W)$ does not tend to zero with increasing sample size: it constrains the autoregressive parameter values to their feasible range between the inverses of the smallest and largest eigenvalues of W – corresponding exactly to the range [-1,1] when the matrix is row-standardized.

[66]. In fact, the error term AR(1) equation can be rewritten as:
$\varepsilon= (I + \rho W)^{-1}u = u + \rho Wu + \rho^2 W^2 u + \ldots$
This expanded formula is suitable to show how spatial dependence is allowed to go far away with respect to a Moving Average (MA) specification of the type $u= \rho W\varepsilon + \varepsilon$, where instead dependence is much more restricted.

A battery of LM (Lagrange Multiplier) tests is reported here to justify the adoption of the SARAR specification. In particular, a Conditional LM test for λ (the autoregressive parameter of the spatially lagged dependent variable) and a Conditional LM test for ρ (the autoregressive parameter of the error term) were selected to properly evaluate the fit of the model. While testing for the presence of a single type of spatial dependence in the data (direct or indirect), these tests - extended by Baltagi et al. (2003) to the case of spatial panel data models - prove to be robust to the simultaneous presence of the other effect[67].

More precisely, a variant of the tests proposed by Baltagi et al. was implemented in the paper, based on the residuals coming from a GM/IV estimation of our spatial model (further details on the GM/IV routine will follow)[68].

The conditional LM test for λ (assuming $\rho \geq 0$) reports a statistic of 4.6823, showing a highly significant spatial autocorrelation (p-value = 2.837e-06). The conditional LM test for ρ (assuming $\lambda \geq 0$) reports instead a statistic of 192.9238, showing strong random spatial dependence (p-value<2.2e-16). These results corroborate the previous choice for the model structure.

To estimate a complete SARAR model, based on dense matrices and on a large panel - like to one we introduced before, a switching to the Spatial 2SLS (Two Stage Least Squares) estimator proposed by Kapoor et al. (2007) was considered, based on an ideal set of instruments for the endogenous spatial lag variable[69]. The Spatial 2SLS resorts in turn to a GM approach to consistently estimate the autoregressive parameter ρ in the error equation. From now on we will refer to this procedure as the GM/IV routine. More precisely, the ideal estimation framework for ρ encompasses the use of a complete list of optimally weighted[70] sample moments, to construct an expression for the "quadratic form in sample moments", the

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[67]. The variance of the statistic is properly adjusted to take into account the presence of the other effect (the one that is not the object of testing), resulting therefore in a more correct inference.

[68]. The tests presented in Baltagi et al. (2003) and implemented within the *splm* R package are instead based on the residuals from a maximum likelihood estimation of a spatial model.

[69]. The endogeneity of the spatially lagged dependent variable in a spatial model requires an IV approach to be implemented. The ideal instrument for the spatial lag, in a generic spatial SAC/SARAR model of the type $y= X\beta +\lambda Wy +u$, with $u= \rho Wu +\varepsilon$, is represented by its expected value (conditional to the exogenous covariates of the model): $E(Wy|X)$. The expression can be rewritten as a linear combination of the type: $E(Wy|X) = W\,E(y|X) = W\,(I-\lambda W)^{-1}X\beta = W(I + \lambda W + \lambda^2W^2 + \ldots)X\beta = WX\beta + W^2X(\lambda\beta) + W^3X(\lambda^2\beta) +\ldots$
The ideal set of instruments H must contain at least the linearly independent columns of (X, WX) such that $H = [\ X, WX, W^2X, \ldots]$. The proposed 2SLS estimator is based on the crucial assumption $E(H'u)=0$. See Kapoor et al. (2007) for further details.

[70]. In the GM theory the optimal weighting matrix, to be exploited within the expression for the "quadratic form in sample moments", is represented by the inverse of the variance covariance matrix of the sample moments, at the true parameters values. Emphasis is given to the sample moments estimated more precisely (the ones with the smallest variance).

core of the minimization problem in the GM theory[71]. Nevertheless, to account for situations where computational difficulties arise[72], a simplified weighting scheme is considered in Kapoor et al. This is exactly the case of our model. Moreover, it is worth stressing how the GM/IV multistep procedure is suitable to bypass the problem of calculating the Jacobian in the log-likelihood function (the most critical point in the maximum likelihood estimation) and to relax as well the normal distributional assumption on the disturbances (that is implicit in a maximum likelihood framework[73]).

The before mentioned procedure, with simplified weighting scheme, has been implemented to consistently estimate the parameters of the SARAR model proposed in equation *[7]*[74], exploiting different definitions of spatial neighborhood – the ones implicitly contained in W (geographical-based or sectorial-based neighborhood). We resort to a customized version of the available GM/IV package in R software (spgm), rearranged to solve for specific computational issues pertaining to the adoption of dense spatial weights matrices[75].

6. Commenting on empirical estimates

Results from the GM/IV estimation of a Spatial Autoregressive model of order one (SAR) and a complete SARAR model with additional AR(1) spatially autoregressive disturbances - based on our balanced panel of 8,803 Italian manufacturing firms, surveyed over the 2004-11 period -

[71]. The GM estimator is exactly the minimizer of that expression and the one exploiting the optimal weighting scheme described before is also the efficient one.

[72]. In fact, the asymptotic variance covariance matrix of the sample moments involve a computational count of up to $O(n^3)$ and the computation of the matrix becomes difficult when a huge amount of data is taken into account.

[73]. An hypothesis of independent and identically distributed innovations ε is instead maintained, allowed to be heteroskedastic, and is crucial to derive the set of moment conditions exploited in the GM framework.

[74]. To account for the simplified weighting scheme within the estimation procedure implemented with R code, the option "*weights*" has been selected in the *spgm* function (GM estimation of spatial panel data models) of the *splm* package (Spatial panel data models in R, Millo and Piras).

[75]. The R package "splm" (Millo and Piras, 2012) was modified accordingly in order to deal with dense matrices of distances, using the class "dgeMatrix" and the Lapack routine of the package "Matrix" (Bates and Maechler, 2014). The routine allows for optimization of linear algebra calculations and matrix operations in presence of dense numeric matrices. Moreover, all the kronecker products involving the use of big dense spatial matrices W were decomposed accordingly, thus reducing allocated memory. In some extreme cases (as the one of a matrix exceeding 80 GB) matrices were stored as memory-mapped files, using the infrastructure of the R packages "bigmemory" and "bigalgebra" (Kane, Emerson and Weston, 2013).

prove to be highly comparable, as far as the impacts of exogenous covariates are concerned (the ones contained in the X matrix of equations *[5]* and *[7]*). Indeed, what spatial models return as coefficient estimates are the direct impacts of covariates on the dependent variable[76].

As a matter of fact, the complete SARAR model has to be considered the preferred choice when both types of spatial dependence are detected in the data, direct and indirect - as already outlined in the comment to the conditional LM tests. The SARAR model allows to quantify both the strength of the spillover coming from neighboring firms and the propagating mechanism of shocks within the neighborhood[77].

In light of the above, from now on we will concentrate on commenting the estimates coming from the complete SARAR model only (Tab.2), focusing in particular on the autoregressive parameters and on their economic interpretation.

The result which, amongst all, deserves the greatest attention is the different sign assumed by the ρ autoregressive parameter in the error equation of our model once different specifications of the spatial context are taken into account. By contrast, the coefficient λ associated to the spatial lag variable is always positive, independently on the selected specification for the spatial neighborhood.

To assign an economic interpretation to results it is worth thinking again to a spatial model as an equilibrium system, where interactions between firms might reflect the adoption of different market rules. Positive direct spatial dependence is suitable to capture the presence of positive externalities (positive spillover effects) while negative direct spatial dependence, even if rare in empirical applications – is conventionally associated to negative externalities.

Total factor productivity, our dependent variable, is traditionally assigned to the former case: externalities might arise from productivity of interconnected firms. The strength of the TFP spillover coming from the neighborhood is well captured by the magnitude and the significance of the autoregressive parameter λ. The estimated effect is stronger (equal to 0.914) once spatial interactions are considered from a geographical point of view (firms clustering in the geographical space). Influences between

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76. The recursive structure of the model, the one arising from spatial interconnection of firms, can instead be accounted for computing more complex impact measures, or total effects. They represent the sum of the direct impacts described before - i.e. the effect of a unitary change of a covariate x_i, pertaining to a generic firm *i*, over the dependent variable of the same firm - and of indirect impacts. The latter are defined as the effect of a unitary change of covariates x_j, pertaining to neighboring firms *j*, over the dependent variable of the firm *i*. As a matter of fact, total effects exploit the multi-directionality of the connections in place within firms, modeled through the weights matrix W or matrix of influences. In the case of total impacts, the SAR model and the SARAR one would return completely different estimates.

77. The estimation of a simple SAR model based on data characterized by both direct and indirect spatial dependence might result into overestimated autoregressive parameters. Refer to the Appendix for SAR estimates of the model presented in the paper.

sectorially-connected firms reveal instead the presence of a weaker sectorial clustering phenomenon (the estimated parameter λ is 0.365 in the case of demand-driven reciprocal influences and 0.257 in the case of supply-driven reciprocal interactions). Nevertheless, it is worth recalling that sectorial spatial weights matrices make use of proxies for real trade connections in place between firms in the dataset. In light of the above, sectorial spillover effects might suffer from a bias with respect to the real spillover strength.

The analysis can be complemented by commenting on the autoregressive parameter of the error term ρ, the one mirroring the strength and the direction of spatial diffusion of shocks or indirect spatial dependence. As a general argument, positive (indirect) spatial dependence has to be interpreted as an evidence in favor of a cooperation framework in place between spatial objects while negative (indirect) spatial dependence has to be reconducted to a competition framework.

Results show how productivity shocks occurring to firms propagate negatively within geographical space or, in other words, produce immediate negative effects over geographical-based neighboring firms: for example, the adoption of a new technology, pertaining to a specific firm, generates immediate negative effects over neighboring actors. The estimated effect is -0.917. The propagating direction of shocks is instead reversed in the sectorial-based context: firms located within interconnected sectors benefit immediately from shocks occurring to neighboring firms. The demand driven estimated effect (0.663) seems stronger than the supply-driven one (0.540): a shock occurring to customers' productivity propagates to suppliers in a stronger way (the latter might be obliged to fill their productivity gap to remain aligned to their customers in the market).

Independently on how shocks spread within a selected neighborhood, what emerges clearly from the estimated SARAR model is the importance to account for positive TFP spillover effects in place between Italian firms. In fact, if it is true that competing firms negatively discount shocks occurred to neighboring firms, it is also true that repeated interactions between firms, as well as the adoption of goal-seeking strategies - aiming to emulate performances of neighboring competitors or to protect market shares - represent the right incentive to align levels of total factor productivity within a certain neighborhood.

The clustering effect can be regarded, in other words, as a phenomenon induced by long-term common strategies while spatial diffusion of shocks is assumed to follow short-term dynamics.

Results are robust to the inclusion of a proper set of controls in the estimation framework (i.e. macro-geographical dummies, sectorial dummies and the index for infrastructural endowment at the regional level), suitable to partially absorb spatial heterogeneity.

We are left to comment on potential TFP premiums originating from exogenous covariates in the model (the ones included in the X matrix). The main variable of interest is again the index measuring relative patent intensity at the territorial level (LLSs) *innov_lls,* the one constructed based on patent applications at the European Patent Office. Despite the index being univocally assigned to each firm in the panel based on sector of specialization and territorial location (LLS), it does not represent *per sè* a firm-specific variable. In light of the above, we will comment on direct impacts produced over total factor productivity only (the computation of total effects would result, as a matter of fact, into overestimated effects of the variable over TFP)[78].

Results corroborate qualitative findings underlined in section 4. A positive linkage is again detected between productivity and the belonging of a firm to a patent intensive local labour system (indirect effect of innovation over TFP), independently on firms' dimensional size: even small firms (with less than 50 workers) might benefit from the location within a patent intensive area. The estimated coefficient is of 0.131 in the case of a geographical-based spatial model and only slightly higher in the case of sectorial-based models (refer to Table 2).

The former effect survives to the inclusion of the *innov_firm* index as a control variable in estimation, being the relative patent intensity at the firm level. As mentioned before, the variable account for potential confounding effects - in other words, for a situation of erroneous assignment of the innovative capacity of single large firms to the whole surrounding areas (LLSs).

Last but not least, the relevance of dimensions in conditioning the level of total factor productivity emerges again clearly, once augmenting the model with a proper set of dimensional controls. The latter accounts for the a-priori capacity of large firms to accumulate a considerable stock of knowledge (embedded into the human capital and within the production processes), that in turn is suitable to exert a positive stimulus for innovation and productivity.

7. Robustness checks

To provide a robustness check for the magnitude and the significance of the autoregressive parameters of the SARAR model with geographical distances - very close to the bound - we performed a Maximum Likelihood (ML) estimation of the same model, based on a reduced sample (random draw)[79]. Despite the two estimators (GM/IV and ML) being not directly comparable, results show how both direct spatial dependence (the one

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[78]. In addition to the index for relative patent intensity, the model is augmented for a set of dummies variables and control variables whose features allow for a comment on direct impacts only.

[79]. The choice is motivated by computational issues. A customized version of the available spatial ML routine in R (spml) was developed.

captured by λ) and indirect spatial dependence (captured by ρ) remain considerably high in magnitude.

One might have the concern that geographical spillover effects are in turn the result of crossing inter-sectorial interactions, implicitly embedded within the process of clustering in space. In light of the above, it might be interesting to analyze whether and in what direction sectorial logics are suitable to influence the overall estimated geographical effect.

More precisely, the presence of "double clustering" phenomena could in principle act as a driving force. Reference is made to positive TFP externalities coming from firms who cluster at geographical and sectorial level simultaneously - the broader definition of Marshallian externalities. The latters still represent a significant attitude in the Italian manufacturing sector; two broad types of industrial agglomerations have to be acknowledged: industrial districts and technological clusters. By contrast, according to a complementary view, geographical spillover effects could be driven by sectorial heterogeneity (Jacobian externalities).

The regression framework presented so far does not allow for a precise quantification of total factor productivity spillovers originated from these peculiar clusters of firms. In fact, what the model specification encompasses is an active role played by *distr* and *tech* dummies in capturing potential TFP premiums - pertaining to firms within industrial districts and technological clusters respectively (both the variables are assigned a positive estimated coefficient in Table 2).

To explore these points in detail, the original geographical W matrix was split into two distinct matrices: a first matrix including geographical neighboring firms pertaining to the same sector of specialization and a second matrix including geographical neighboring firms belonging to heterogeneous sectors. The SARAR model was re-estimated considering the two additional matrices as alternative specifications for the geographical neighborhood, based on a GM/IV strategy.

Results highlight the presence of a spillover effect that is stronger in the case of sectorially-heterogeneous geographical neighbours: the estimated λ coefficient is 0.731, compared to a coefficient of 0.408 in the case of geographical neighbours sharing a common specialization (Appendix A2). Both the coefficients are considerably reduced in magnitude with respect to the overall geographical estimated effect and far from the bound. Consistently to previous literature, major emphasis is given to externalities coming from inter-sectorial interactions or externalities of the Jacobian type.

Moreover, we have to acknowledge a reduction in the estimated ρ coefficients as well, once the new W matrices are included in the model. A predominance of negative indirect spatial dependence is again detected - the one describing short-run dynamics (i.e. competitive framework) - that is stronger in the case of sectorially-heterogeneous geographical neighbours.

Despite a sectorial declination for the newly estimated autoregressive parameters, it is worth stressing how they are not directly comparable to the sectorial spillover effects estimated in the previous section. In the latter cases in fact, sectorial space (proxied by trade) is considered to construct pairwise interactions and modeled accordingly (input-output coefficients). In the former cases instead, sectorial affiliations are exploited to further refine the matrix of geographical interactions.

Table 2 – Coefficient estimates

	RE **Baseline model**	**SARAR (GM/IV)** **Geographical distances**	**SARAR (GM/IV)** **Demand-side Sectorial distances**	**SARAR (GM/IV)** **Supply-side Sectorial distances**
λ (spatial lag autor. parameter)		0.914 ***	0.365 ***	0.257 **
		(0.061)	(0.091)	(0.089)
ρ (error term spatial autor. parameter)		-0.917[(a)]	0.663[(a)]	0.504[(a)]
Medium	0.144 ***	0.142 ***	0.140 ***	0.140 ***
	(0.005)	(0.005)	(0.005)	(0.005)
Large	0.330 ***	0.326 ***	0.322 ***	0.321 ***
	(0.013)	(0.013)	(0.013)	(0.013)
*Innov_lls*small*	0.189 ***	0.131 **	0.184 ***	0.178 ***
	(0.047)	(0.045)	(0.046)	(0.046)
*Innov_lls*medium*	0.257 ***	0.202 ***	0.252 ***	0.248 ***
	(0.055)	(0.052)	(0.053)	(0.053)
*Innov_lls*large*	0.872 ***	0.822 ***	0.818 ***	0.831 ***
	(0.103)	(0.100)	(0.100)	(0.100)
Innov_firm	0.073 ***	0.073 ***	0.069 ***	0.070 ***
	(0.009)	(0.009)	(0.009)	(0.009)
Distr	0.017 *	0.016 *	0.018 **	0.018 *
	(0.007)	(0.007)	(0.007)	(0.007)
Tech	0.123 ***	0.118 ***	0.107 ***	0.107 ***
	(0.022)	(0.021)	(0.022)	(0.022)
Index for infrastructural endowment (regional)	0.001 ***	0.001 ***	0.001 ***	0.001 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Time dummies (m_t, yearly dummies)	added	added	added	added
Sectorial dummies (m_ℓ)	added	added	added	added
Macro-geographical dummies (m_v)	added	added	added	added
σ^2_ε *(var. of the idiosyncratic error)*	0.068	0.067	0.066	0.066
σ^2_μ *(var. of individual effects)*	0.096			
$\sigma^2_1 = \sigma^2_\varepsilon + T\sigma^2_\mu$		0.830	0.835	0.837
$\theta = 1 - \sigma^2_\varepsilon / \sigma^2_1$	0.715	0.715	0.718	0.718

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(a) The GMM routine does not report the significance of the coefficient *ρ*. The model structure is justified by conditional Lagrange Multiplier tests, the ones commented in Section 5. *Medium* and *large* are dummies representing the dimensional cluster of medium-size firms (workers from 50 up to 249) and large firms (more than 250 workers); *Innov_lls* is the index of relative patent intensity at the local labour system (LLS) level, interacted with dimensional dummies; *Innov_firm* is the index of relative patent intensity at the firm level; *Distr* is a dummy variable identifying the belonging to an industrial district; *Tech* is a dummy variable identifying the belonging to a technological cluster. *Sectorial dummies* are added at the level of the branches of industrial activity exploited to estimate total factor productivity.

Conclusions

The goal of the paper was to assess spillovers from total factor productivity (TFP) in the Italian manufacturing industry, based on both geographical and sectorial influences in place between firms and to disentangle the effects of some core determinants of TFP premiums, innovation *in primis*.

We have provided concrete evidence of the importance to adopt a spatial framework in dealing with series of data characterized by spatial dependence, like productivity ones.

The concept of spillover effects from industrial clustering, still playing a key role within the Italian industrial framework, can indeed be treated in a more formal way while resorting to spatial econometrics techniques. More precisely, exploiting a complete SARAR model we explicitly moved the first steps towards a proper quantification of spillover effects from TFP and tried to interpret propagation mechanisms of productivity shocks.

When geographical space is selected to define reciprocal interactions, evidence was found of productivity shocks propagating in a negative way within the neighborhood. By contrast, when attention is posed on sectorial space, a positive propagating direction of shocks was detected. As a general rule, positive indirect spatial dependence is suitable to identify the presence of a cooperation framework and negative indirect spatial dependence of a competition framework. Declining the argument towards our case, it is feasible to think at geographical-based neighboring firms as competing ones and to sectorial-based neighboring firms as cooperating ones. Furthermore, the demand-driven sectorial estimated effect is stronger than the supply-driven one: shocks occurring to customers' productivity propagates to suppliers in a stronger way.

The diffusion mechanism of shocks can indeed be assumed to mirror short-run dynamics within a more general equilibrium system, like a spatial econometric framework is. By contrast, the adoption of long-term common strategies reflects into positive spillover effects. Significant evidence was found of a positive spillover effect from total factor productivity of Italian manufacturing firms. The effect is large in magnitude in the geographical context (strong clustering phenomenon) while turning to be considerably lower in the sectorial framework (weaker clustering phenomenon). Once geographical spatial weights matrices are filtered according to sectorial affiliation (common specialization versus sectorial heterogeneity), a stronger geographical clustering effect is detected in correspondence to the latter case – thus corroborating the findings of a primary role played by Jacobian externalities.

The model presented in the paper contributed as well to the literature on localized knowledge spillovers. We exploited the power of a measure of relative innovative activity at the local labor systems' (LLS) level, to detect (at least indirectly) the presence of potential knowledge spillovers boosting productivity. Firms located in patent intensive areas benefit from local productivity premiums. The positive innovation effect is detectable in correspondence to all firms' dimensional clusters in the sample.

Appendix

A1. Branches of industrial activity

Branch	*Name*	*Ateco 2007/Nace Rev.2 corresponding codes*
1	Food and beverage	C.10, C.11
2	Textiles and textile products	C.13, C.14
3	Leather and footwear	C.15
4	Wood-made products (except furniture)	C.16
5	Paper, print and publishing sector	C.17, C.18
6	Chemical and pharmaceutical sector	C.20, C.21
7	Rubber and plastic products	C.22
8	Other non-metallic mineral products	C.23
9	Metallurgical sector and fabricated metal products	C.24, C.25
10	Mechanic sector, electronic equipment, medical equipment	C.26, C.27, C.28
11	Transport equipment	C.29, C.30
12	Furniture sector	C.31

A2. Robustness checks, SARAR model with geographical distances

	SARAR (ML) Geographical distances, reduced sample (random draw)	SARAR (GM/IV) Geographical distances, common sectorial specialization	SARAR (GM/IV) Geographical distances, heterogeneous sectorial specializations
λ (spatial lag autor. parameter)	0.905 ***	0.408 ***	0.731 ***
	(0.001)	(0.028)	(0.060)
ρ (error term spatial autor. parameter)	-0.704 ***	-0.580[(a)]	-0.824[(a)]
	(0.055)		
Medium	0.112 ***	0.136 ***	0.143 ***
	(0.008)	(0.005)	(0.005)
Large	0.328 ***	0.309 ***	0.328 ***
	(0.019)	(0.013)	(0.013)
*Innov_lls*small*	0.149 *	0.157 *	0.160 *
	(0.069)	(0.042)	(0.045)
*Innov_lls*medium*	0.296 ***	0.205 ***	0.231 ***
	(0.079)	(0.050)	(0.053)
*Innov_lls*large*	0.580 ***	0.855 ***	0.845 ***
	(0.148)	(0.098)	(0.100)
Innov_firm	0.066 ***	0.068 ***	0.073 ***
	(0.013)	(0.008)	(0.009)
Distr	0.019	0.019**	0.015
	(0.011)	(0.006)	(0.007)
Tech	0.122 ***	0.085 ***	0.119 ***
	(0.030)	(0.018)	(0.021)
Index for infrastructural endowment (regional)	0.001 ***	0.001 ***	0.001 ***
	(0.001)	(0.001)	(0.001)
Time dummies (m_t)	added	added	added
Sectorial dummies (m_ℓ)	added	added	added
Macro-geographical dummies (m_v)	added	added	added
$\phi = \sigma^2_\mu / \sigma^2_\varepsilon$	1.743 ***		
	(0.049)		
σ^2_ε *(var. of the idiosyncratic error)*		0.064	0.067
$\sigma^2_1 = \sigma^2_\varepsilon + T\sigma^2_\mu$		0.847	0.832
$\theta = 1 - \sigma^2_\varepsilon / \sigma^2_1$		0.724	0.715

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(a) The GMM routine does not report the significance of the coefficient ρ. The model structure is justified by conditional Lagrange Multiplier tests, the ones commented in Section 5.

A3. GM/IV estimates, SAR model

	SARAR (GM/IV) Geographical distances	SARAR (GM/IV) Demand-side Sectorial distances	SARAR (GM/IV) Supply-side Sectorial distances
λ (spatial lag autor. parameter)	0.928 ***	0.889***	0.893 **
	(0.006)	(0.006)	(0.006)
Medium	0.143 ***	0.139 ***	0.140 ***
	(0.005)	(0.005)	(0.005)
Large	0.326 ***	0.319 ***	0.321 ***
	(0.013)	(0.013)	(0.013)
*Innov_lls*small*	0.104 *	0.166 ***	0.184***
	(0.047)	(0.047)	(0.047)
*Innov_lls*medium*	0.183 ***	0.237 ***	0.253 ***
	(0.054)	(0.054)	(0.054)
*Innov_lls*large*	0.809 ***	0.829 ***	0.836 ***
	(0.103)	(0.103)	(0.103)
Innov_firm	0.074 ***	0.069 ***	0.069***
	(0.009)	(0.009)	(0.009)
Distr	0.019**	0.018 *	0.018 *
	(0.007)	(0.007)	(0.007)
Tech	0.115 ***	0.081 ***	0.110***
	(0.022)	(0.021)	(0.021)
Index for infrastructural endowment (regional)	0.001 ***	0.001 ***	0.001 ***
	(0.001)	(0.001)	(0.001)
Time dummies (m_t, yearly dummies)	added	added	added
Sectorial dummies (m_ℓ)	added	added	added
Macro-geographical dummies (m_v)	added	added	added
σ^2_ε *(var. of the idiosyncratic error)*	0.068	0.067	0.067
σ^2_μ *(var. of individual effects)*			
$\sigma^2_1 = \sigma^2_\varepsilon + T\sigma^2_\mu$	0.832	0.838	0.836

Notes: *Medium* and *large* are dummies representing the dimensional cluster of medium-size firms (workers from 50 up to 249) and large firms (more than 250 workers); *Innov_lls* is the index of relative patent intensity at the local labour system (LLS) level, interacted with dimensional dummies; *Innov_firm* is the index of relative patent intensity at the firm level; *Distr* is a dummy variable identifying the belonging to an industrial district; *Tech* is a dummy variable identifying the belonging to a technological cluster. *Sectorial dummies* are added at the level of the branches of industrial activity exploited to estimate total factor productivity.

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