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COMPLEXITY AND TECHNOLOGICAL CHANGE: KNOWLEDGE INTERACTIONS AND FIRM LEVEL TOTAL FACTOR PRODUCTIVITY

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Complexity and Technological Change:
Knowledge Interactions and Firm Level Total Factor Productivity[1]

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Abstract

The analysis of social interactions as drivers of economic dynamics represents a growing field of the economics of complexity. Social interactions are a specific form of interdependence whereby the changes in the behavior of other agents affect utility functions for households and production functions for producers. In this paper, we apply the general concept of social interactions to the area of the economics of innovation and we articulate the view that knowledge interactions play a central role in the generation of new technological knowledge so that innovation becomes the emergent property of a system, rather then the product of individual actions. In particular, we articulate and test the hypothesis that different layers of knowledge interactions play a crucial role in determining the rate of technological change that each firm is able to introduce. The paper presents an empirical analysis of firm level total factor productivity (TFP) for a sample of 7020 Italian manufacturing companies observed during the years 1996-2005 that is able identify the distinctive role of regional, inter-industrial and localized intra-industrial knowledge interactions as distinctive and significant determinants, together with internal research and innovation efforts, of changes in firm level TFP.

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1. Introduction

The aim of this paper is to contribute to articulating the view that innovation is an emergent property of system dynamics based upon positive feedbacks that take place by means of knowledge interactions and to derive a set of testable hypotheses that can be validated by means of empirical analysis, on the central role of knowledge interactions in the recombinant generation of new technological knowledge and in the eventual introduction of technological innovations.

This approach elaborates the hypothesis that innovation is indeed endogenous to economic activity but contrasts the view that is exclusively based upon the individual action of each innovating firm: only the organized complexity of an economic system structured as a nest of communication channels and interaction links can support individual efforts so as to make the reaction of firms to the changing conditions of product and market factors actually creative. This approach is based upon the hypothesis of a strong and necessary complementarity between individual action and collective endeavour (Antonelli, 2011).

Our approach to grasping the economic complexity of technological change is based upon two assumptions. First, agents are myopic but creative. They are not able to foresee all the possible events: so far their rationality is bounded. Yet firms can learn, accumulate competence and they can try and react to unexpected changes in product ad factor markets not only by means of adaptive traditional price/quantity adjustments in a given technical space. All changes in product and factor markets may induce firms to react creatively by means of the generation of new technological knowledge and the introduction of innovations (Schumpeter, 1947). Second, the reaction of firms can become actually creative and engender the introduction of productivity enhancing innovations only when social interactions make available the amount of external knowledge that is necessary to actually generate new technological knowledge. Hence innovation takes place when two complementary and indispensable conditions are fulfilled: a) agents are embedded with competence and are stirred to react to unexpected events, b) the system into which they are embedded provides sufficient access to the inputs of external knowledge that are necessary to actually proceed successfully in the recombinant generation of new technological knowledge.

The rest of the paper is devoted to explore and articulate the role of external knowledge, as the product of social interactions that complement and integrate transactions in knowledge markets, in the generation of new technological knowledge ad hence in making the creative reactions of firms, as opposed to adaptive ones. It is structured as it follows. Section 2 discusses the notion of social interactions and applies it to elaborating the notion of knowledge interactions. Section 3 presents the research hypotheses and the empirical methodology. Section 4 presents the data set, the econometric models and the results.

2. Social interactions and the economics of innovation

2.1 Social interactions

The study of social interactions is a growing field of economics and more specifically of the economics of complexity. Social interactions are a fundamental ingredient of complex dynamics. According to David Lane, complex economic dynamics takes place when the propensity to undertake specific actions of a set of heterogeneous agents changes because of their interactions with one another within structured networks (Lane, Maxfield, 1997; Lane et al. 2009).

As it is well known, in standard Walrasian economics all changes in utility and production functions are exogenous, as they do not stem from economic decision-making. According to the changing conditions of product and factor markets agents may change their behavior, but they do not change their preferences and their technologies. As soon as we abandon the hypothesis that technologies and preferences are exogenous, the role of social interactions becomes central. Social interactions differ and complement market interactions (Hanusch and Pyka, 2007).

Social interactions qualify the endogenous formation of preferences and technologies: ”Each person’s actions change not only because of the direct change in fundamentals, but also because of the change in behavior of their neighbors” (Glaeser and Scheinkman, 2000). Social interactions are a specific form of interdependence whereby the changes in the behavior of other agents affect the structure of the utility functions for households and of the production functions for producers (Durlauf, 2005). Hence it is important to stress that social interactions consist in the direct effect of interaction upon the structure of preferences both in production and consumption (Frenken, 2006).

When social interactions are at work, and the structure of the preferences of each household and each producer is affected by the changes in the behavior of other agents, both on the demand and the supply side, a social multiplier can be identified. The correlated actions among interacting agents induce amplified responses to shocks. Social multipliers are the result of positive feedbacks.

Models of social interactions have been used to analyze a variety of empirical contexts ranging from the analysis of the demand for restaurants (Becker, 1991) to crime (Glaeser, Sacerdote and Scheinkman, 1996). Guiso and Schivardi (2007) have provided an interesting test of the role of social interaction in the determination of employment levels. Specifically they test the hypothesis that the changes in employment of firms that are co-localized within industrial districts are shaped by significant social multipliers.

The methodology of social interaction fits nicely into the field of investigation of the economics of innovation and new technology. As a matter of fact this literature had anticipated the understanding of the key role of social interactions in at least two important areas of investigation: a) the adoption of new technologies and the diffusion of existing technologies, as distinct from the transfer of and access to technological knowledge. According to Griliches (1957) the appreciation of new technologies takes place, like an epidemic contagion, by means of interactions among experienced lead users and new perspective ones. The latter learn about the characteristics of the new technology by means of physical interactions with the former; b) the attributes of new products. The notion of network externalities throws new light upon the active role of users on the attributes of new technologies: the larger is the number of adopters and the better is, in many circumstances, the functionality of the new technologies (Katz and Shapiro, 1986).

The notion of social interactions seems useful to implement a clear distinction between technological spillovers and external knowledge (Griliches, 1992; Breschi and Lissoni, 2003). The former engender 'technological' externalities, are available in the atmosphere and help increasing the output: they have no cost and are accessible without efforts (Scitovski, 1954). The latter is crucial in the generation of new technological knowledge and in the eventual introduction of innovations that change the production function. It is not free and can be accessed but at a cost. Pecuniary knowledge externalities can emerge when social interactions make the access to external knowledge cheaper than in equilibrium conditions.

2.2 From technological spillovers to knowledge interactions

The appreciation of the role of social interaction in the access to external knowledge can be considered the result of a long standing tradition of analysis upon the limitations of knowledge as an economic good. Let us recall briefly the key steps. According to Arrow and Nelson, knowledge can be 'too' easily imitated (Arrow, 1962; Nelson, 1959). Limitations to knowledge appropriability may lead to its undersupply but benefit the possible recipients: technological spillovers are the other side of the non-appropriability coin. Technological knowledge spilling from 'inventors' has positive effects upon the productivity of resources invested internally in research and development activities by passive recipients (Jaffe, 1986; Griliches, 1992; Jaffe, Trajtenberg, Henderson, 1993; Audretsch and Feldman, 1996).

The identification of relevant absorption costs makes it clear that technological knowledge does not spill freely in the atmosphere, nor are perspective recipients, passive. Dedicated resources are necessary to search, screen, identify, understand, acquire and absorb the technological knowledge generated and not fully appropriated by third parties (Cohen and Levithal, 1990). The grasping of the distinction between tacit and codified knowledge and the appreciation of the limitations of pure market transactions for knowledge has marked a second step in this direction. The results of the empirical analyses of Lundvall (1988), Von Hippel (1976, 1998) and Fransman (2010) on the key role of user-producers interactions, both upstream and downstream, as basic engines for the accumulation of new technological knowledge and the eventual introduction of new technologies, confirm the role of external knowledge, accessed by means of social interactions associated to market transactions within vertical filieres, in the generation of knowledge. Potential customers of knowledge need to establish qualified interactions with the sellers to actually command the knowledge that has been purchased (Mansfield Schwartz and Wagner, 1981). Knowledge interactions are necessary to complement and actually make possible knowledge transactions.

These notions mark a major shift in the literature, away from the notion of technological spillover, where knowledge spilling freely in the atmosphere from third parties exerts a supplementary role enhancing the productivity of internal resources invested by passive recipients, towards the notion of external knowledge viewed as a necessary and non disposable input, complementary to internal knowledge actively used into the intentional generation of new technological knowledge (Antonelli, 2008a).

This approach impinges again on the analysis of the limitations of knowledge as an economic good. Technological knowledge is characterized not only by limited appropriability, but also by substantial indivisibility -both synchronic across agents and disciplines at a given time and diachronic, through time- durability and non-exhaustibility: repeated use does not reduce its functionality as an input into the generation of new technological knowledge.

Yet all the existing knowledge cannot be comprised within a single organization. The Hayekian notion of distributed knowledge, dispersed and fragmented by its partial and limited possession by a myriad of economic agents, provides the foundations to the understanding the role of external knowledge (Hayek, 1945). Only when a complementary set of knowledge fragments is brought together with the support of consistent interactions, new technological knowledge can be generated and successful innovations can be introduced. Technological knowledge cannot be generated in isolation because of its intrinsic indivisibility and no agent can command all the knowledge available: technological knowledge is the product of a collective activity.

The identification of the knowledge generation function as an activity, where knowledge is at the same time an input and an output marks the crucial step in the appreciation of the key role of knowledge interactions (David, 1993). This new approach makes it possible to appreciate the role of external knowledge as a necessary and indispensable input viewed as the result of a distinctive and intentional activity into the generation of technological knowledge. New knowledge is in fact the product of the continual recombination of the different and yet complementary items that constitute, at each point in time, the body of existing knowledge (Weitzman, 1996 and 1998; Fleming and Sorensen, 2001; Arthur, 2009).

Knowledge interactions implemented by intentional firms that try and react to un-expected events by means of the introduction of technological innovations play a crucial role in making their reaction creative as opposed to adaptive. Knowledge interactions contribute to activate generative relations among learning agents and make available external knowledge that is now viewed as a necessary and indispensable input into the recombinant generation of new technological knowledge and the eventual introduction of technological innovations (Lane 2009; Lane and Maxfield, 1997).

The generation of new knowledge by each agent can take place only where and when knowledge interactions qualify and complement knowledge transactions and provide effective access to external knowledge, as a crucial input in the recombinant generation of new technological knowledge, at costs that are below equilibrium levels. The access to external knowledge as costs that are below equilibrium levels, in fact, leads to the introduction of total factor productivity enhancing innovations (Antonelli, 2007 and 2008b).

Knowledge multipliers here take the form of localized pecuniary externalities that make possible increasing returns within innovation systems. The access to external knowledge, by means of qualified knowledge interactions, in fact takes place at costs, including a range of items from purchasing prices to, search, screening, identification, transfer and absorption costs, that are below equilibrium levels. This enables the generation of additional technological knowledge that further increases it localized availability for third parties with positive effects on the capability of other agents to recombine and generate in turn new knowledge. At the same time the increasing availability of external technological knowledge enables the creative reaction of firms that can introduce technological innovations so as to increase the out-of-equilibrium conditions of the system with further increase in the amount of surprise and mismatch between expectations and actual product and factor market conditions. The conditions for a self-sustained out-of-equilibrium dynamics based upon the crucial role of knowledge interaction, external knowledge, pecuniary externalities and individual reaction are set (Antonelli, 2011).

Building upon these foundations a new crucial area of investigations opens up. It becomes in fact more and more relevant to enter into the new black box of external knowledge so as to try and identify different kinds of external knowledge and layers of knowledge interactions and investigate how each contributes the generation of new technological knowledge.

3. Research hypotheses and empirical methodology

The foregone discussion upon the role of knowledge interactions provides the underpinnings to substantiate the view that the introduction of technological innovations is an emergent system property because it is the endogenous result of specific forms of social interactions that affect the access to existing knowledge among learning agents within an economic system. Knowledge interactions provide the crucial access to the complementary inputs of external knowledge that together with internal competence and research activities make the recombinant generation of new knowledge possible. This argument has important implications as it becomes immediately clear that the rate and direction of technological change introduced by each firm does not depend exclusively upon its own internal efforts of research but also and mainly upon the characteristics of the system into which it is embedded with respect to the intensity and typology of knowledge interactions to which it has access.

In this paper we investigate empirically the role of knowledge interactions in the introduction of innovations through the analysis of firm level total factor productivity measures. Total factor productivity measures are sensitive to the strong underlying analytical assumptions about perfect competition in both input and output markets. At the firm level it is clear that they may be influenced by all imperfections in product and factor markets (Duguet, 2007). As a matter of fact, in our interpretative frame, total factor productivity is a reliable indicator of the actual extent to which firms are able to generate and exploit technological knowledge and to command technological innovations exactly because it stems from the crucial imperfections of the knowledge factor markets determined by the pecuniary knowledge externalities that consist in the access to external knowledge made possible by knowledge interactions at costs that are below equilibrium levels.

The baseline assumption of the analysis is that the internal efforts made by each firm to generate new technological knowledge are not sufficient to grasp the actual amount of technological knowledge that each firm can generate because the key role of external knowledge is missing. We contend that the access to external knowledge -gained by means of knowledge interactions at costs below equilibrium levels- exerts a crucial role in the generation of new technological knowledge and hence in the eventual introduction of technological innovations that enhance the levels of total factor productivity. Moreover we contend that the access to external knowledge by means of knowledge interactions takes place at different levels and in different layers according to the different levels of cognitive, industrial and geographical proximity.

The empirical identification of such interactions is a rather complex task for a number of reasons. First, there might be a problem related to self-selection of firms. In fact, it might be the case that firms sharing common unobserved features tend to co-locate in the same geographical area, leading to common observed behaviours which are not the results of interactions among them. Second, the analysis might be affected by a problem related to the separation of dynamic processes defined at the industry and geographical level, which are likely to generate common behaviours of companies, without actual interactions. As Charles Manski notes, it is difficult to distinguish between peer-group and contextual effects (Manski, 2000 and 2003). Our research strategy impinges upon the analysis of the stratification of the peer-group effects. Their stratification should enable to identify the distinctive role of each of the social interactions that act as carriers of external knowledge. Their simultaneous inclusion should be able to test the actual relevance of peer group effects, as distinct from contextual ones.

To handle the problem, we implement the approach presented by Guiso and Schivardi (2007) who test for the presence of social interactions assuming that, for a given decision $\Omega_{i,t}$ taken by company i at time t (in their case, a choice on employment levels), it is possible to identify the role of social multipliers, if, after accounting for firm-specific effects that are likely to influence such decision, one can still observe a significant relationship between $\Omega_{i,t}$ and the decision taken by the relevant reference groups of firm' peers ($\Omega_{-i,t}$).

The following equation (1) frames our approach. Here the observed action $\Omega_{i,t}$ for individual i is the level of total factor productivity and is explained by a set of firm-specific time varying factors Xit, and a set of time varying variables $\Omega_{-i,t}$ that measure the average total factor productivity of the firms belonging to each of the three relevant reference groups of firm i and account for the effects exerted by the knowledge interactions that take place within each of the three relevant reference groups:

$$\Omega_{i,t} = \alpha + \beta X_{it} + \gamma \Omega_{-i,t} + \varepsilon_{it} \quad (1)$$

The positive and significant value of the parameters γ that represent each of the reference groups and enter simultaneously the econometric model would highlight the presence of knowledge interaction among the firms belonging to each specific reference group.

In our approach, next to the variables that qualify the individual characteristics of the firm, such as the size and the intensity of efforts to generate new technological knowledge, we take into consideration the simultaneous effects of three distinct and yet overlapping peer groups that identify three reference groups: a) the Jacobian external knowledge that can be accessed by means of knowledge interactions among firms that belong to different industries but are located in the same region (Jacobs, 1969); (b) the Marshall-Arrow-Romer (MAR) external knowledge that can be accessed by means of knowledge interactions among firms that belong to the same industry, nationwide, irrespective of their location (Henderson, 1997); c) the localized external knowledge externalities that can be accessed by means of knowledge interactions qualified by the cognitive and geographic proximity among firms that are active within the same region and the same industry (Boschma, 2005). The simultaneous econometric significance of each of these should be able to account for their actual peer-group effect on the dependent variable.

At each of these levels, knowledge interactions, in fact, are expected to contribute the emergence of pecuniary knowledge externalities that make possible to each firm the use of technological knowledge generated by the other firms that belong to the same sub-system, and favour its performance in the generation of technological knowledge and in the eventual introduction of technological innovations that can effectively increase total factor productivity. When total factor productivity is associated to the access to external knowledge it is in fact clear that knowledge interactions gave access to an essential input at costs that were below equilibrium levels.

4. Data and econometric models

4.1. The data set

Our dataset is based on financial accounting data for a large sample of Italian manufacturing companies, observed along years 1996-2005. The original data have been extracted form the AIDA database provided by Bureaux Van Dick which reports complete financial accounting data for public and private Italian firms with a turnover larger than 0.5 millions of Euros. The companies included in the analysis have been founded before year 1995, they are registered in a manufacturing sector according to the Italian ATECO classification, and they are still active by the end of year 2005[2].

[2] We acknowledge that entry can exert a relevant impact on innovation and technological change at industry level. As witnessed by Aghion et al. (2004) a non-negligible share of productivity growth of incumbents can be attributed to an enhancing effect exerted by (foreign) entrants. This is true under the assumption that entrants immediately locate at the technological frontier. This amounts to emphasize the role of incumbents with respect to entrants: this seems consistent with the basic intuition that the decision to innovate is made according to the expectations about the behavior of competitors. However, the core research question in this paper addresses the role of regional and cognitive proximity in shaping

Given the definition of our concept of social interactions the actual physical location of companies represents a crucial parameter. For this reason we have opted for using unconsolidated annual report data. Italian companies are often characterized by groups of smaller firms whose annual reports are then consolidated by a financial or operative holding which might be located in regions different that the ones of the smaller controlled firms. Hence, information provided by unconsolidated annual reports represents the thinnest available unit of analysis in order to geographically disaggregate our sample without missing the relevant data on capital, employees, investments and value added.

With respect to firm size, we have included all the companies with at least 15 employees at the end of fiscal year 1995. After collecting annual report data we proceeded by dropping all the companies with missing values. In order to drop outliers due to possible errors in the data source, we computed a number of financial ratios and yearly growth rates of employees, sales, tangible and intangible capital stock. We ended up with a balanced panel of 7020 companies. All financial data have been deflated according to sectoral deflators using year 2000 basic prices. In the two following tables we show the sectoral and geographical distribution of the companies across Italian regions (European Union NUTS2 level).

[TABLE 1]
[TABLE 2]

4.2. Computation of firm level total factor productivity

Firm level TFP has been calculated using Cobb-Douglas production functions with constant return to scale for each three-digit industry included in the sample[3].

$$TFP_{i,t} = \frac{Q_{i,t}}{L_{i,t}^{\beta} K_{i,t}^{1-\beta}} \qquad (2)$$

Where:
$Q_{i,t}$: deflated value added
$L_{i,t}$: average number of employees
$K_{i,t}$: fixed capital stock.

knowledge interactions that affect the generation of new technological knowledge. Nevertheless, we recognize that the inclusion of market entry will be a relevant future extension of our analysis tacking an even broader set of research questions.

[3] Industries are defined according to the Italian classification system ATECO. We have adopted a three-digit level. In some circumstances we had to aggregate data at two-digit level in order to have a sufficient number of firms for a statistically significant identification of the parameters of production functions. Previous studies have implemented the same approach based on two digit Ateco codes (Benfratello and Sembenelli, 2006).

In order to compute capital stock through time we applied a perpetual inventory technique according to which the first year accounting data i.e. year 1996, in our case, are used as actual replacement values. The subsequent yearly values of fixed capital are computed using a depreciation parameter δ, assumed equal to 6.5%, and adding deflated yearly investments.[4] The investment parameter ($I_{i,t,}$) has been computed as the yearly variation in net fixed capital in companies' annual reports plus yearly amortizations. Hence, the time series of fixed capital is defined as follows:

$$K_{i,t} = (1-\delta)K_{i,t-1} + I_{i,t} / p_t \tag{3}$$

In order to identify the parameter β at industry level to compute equation (2), we have estimated for each three-digit industry the following equation:

$$Log\left(\frac{Q_{i,t}}{K_{i,t}}\right) = \beta \times Log\,\frac{L_{i,t}}{K_{i,t}} + \alpha_i + \alpha_t + \varepsilon_{i,t} \tag{4}$$

We have used a fixed effect estimator (Blundell and Bond, 2000; Olley and Pakes, 1996), where α_i is a firm specific effect and α_t is a time specific effect. Additional variables used in the econometric analysis include size and intangible intensity, as a proxy of the efforts to generate technological knowledge, computed as the yearly incidence of intangible to tangible assets[5].

5. *Models and results*

[4] The level of yearly depreciation of physical capital has been chosen following the approach applied in previous studies that have applied perpetual inventory techniques to estimate yearly fixed capital levels adopting depreciation parameters in the range 5%-10% for physical capital. On this issue see Olley and Pakes (1996) and Parisi et al. (2006) for the Italian economy. Since the adopted depreciation parameter is constant across industries we should not expected changes in the significance of estimate coefficients for slight changes in δ.

[5] R&D expenditures are the traditional indicator used to measure the amount of efforts to generate new technological knowledge. Actually R&D statistics measure only a partial amount of the overall effort that firms make to introduce new technologies. Internal learning activities are not accounted for, neither is the cost to access external knowledge. Moreover the actual efficiency of the research activities is not considered as, of course, R&D activities only measure, partially, some inputs into the process. Additional issues that are specific to the Italian institutional and empirical evidence need to be considered. The Italian manufacturing industry is characterized by the geographical clustering of many small firms in specialized industrial districts. There are only a few large firms that represent a minority by all viewpoints. Reliable statistical evidence on R&D expenditures is missing. Official R&D statistics are based upon data collected from only 2200 agents (be firms or research organizations). As a consequence official R&D statistics provide a picture of the research activities conducted by a minor portion of the economic activity carried out in the country. Small firms do not reply to the detailed and time-consuming questionnaires that are used as the indispensable tool for the collection of R&D data that are not requested for the compilation of annual reports. Accountancy rules coupled with fiscal allowances however provide excellent and reliable evidence upon stocks of intangible capital that include capitalised research expenditures as well as purchasing costs for patents and licences and the costs incurred to build and implement brand and know how. It seems appropriate to rely upon the figures publicly available in all annual reports to get a reliable measure of the efforts to generate new technological knowledge.

Building on the general model of social interactions presented in section two and on the empirical methodology articulated in section three, our modelling framework is based on the following baseline specification:

$$TFP_{it} = \alpha + \beta_1\ SIZE_{it} + \beta_2\ INTANG_{it} + \gamma_1\ REGTFP_{it} + \gamma_2\ SECTFP_{it} + \gamma_3\ LREFTFP_{it} + \varepsilon_{it} \qquad (5)$$

The dependent variable TFP_{it} is the total factor productivity for company i in year t. The variable $SIZE_{it}$ is measured by the log of total assets of company i in year t. $INTANG_{it}$ is the ratio of intangible assets to tangible assets of company i in year t [6]. $REGTFP_{it}$ is the yearly average TFP of all companies located in the same region of company i (excluding company i) in year t. This variable is expected to capture Jacobian pecuniary –inter-industrial - knowledge externalities. The variable $SECTFP_{it}$ is the yearly average TFP of all companies in the same sector of company i (excluding company i) in year t. This regressor is expected to capture the MAR pecuniary knowledge externalities that are available for all firms in the industry irrespectively of location. Finally, the variable $LREFTFP_{it}$ is average TFP of all companies co-localized in the same sector and region of company i in year t (excluding company i), namely the third reference group for company i. The latter regressor is expected to capture firm level TFP dynamics stemming from localized pecuniary knowledge externalities accessible within the local pools of technological knowledge with high levels of cognitive and regional proximity[7].

In the following table 3 we report results for the specification reported in equation 5, which also includes a set of year dummies. The model is estimated with fixed effect. As a robustness control selected model specifications have been estimated also using heteroskedasticity robust standard errors clustered both at the industry and at the regional level. Results are reported in Table 5 in annex A.

[TABLE 3]

The data highlight a positive and significant effect of the average TFP of all the three reference groups. This can be interpreted as evidence of the role of each specific form of external knowledge that each firm can access within the specific industrial pools of technological knowledge at the national level, the inter-industrial pools of technological knowledge within a region and the localized pools of knowledge qualified by proximity in both cognitive and geographical space. It is also worth noting, as expected, the presence of a significant correlation between TFP levels and intensity of intangible

[6] In the econometric analysis we have used different definition for the indicator of intangible intensity, using both book values and perpetual inventory approaches with depreciation rates for intangible assets equal to 15% and 20%. Results are not significantly affected. In the paper we present the results based on the yearly ratio of intangible to tangible assets based on book values.

[7] Following a consistent tradition in the applied econometrics of technological spillovers we rely on data at the firm level taking into account the main location of each firm (Mairesse and Cuneo, 1985; Cincera, 1997). This procedure is consistent with the empirical evidence considered: the dataset is based on information extracted from the annual reports of single companies. The average size is small. Multi-plant companies usually operate the different units by means of different legal identities. Hence each unit of information can be considered mono-plant.

assets. Results seem to provide a preliminary support of the existence of a social multiplier deriving from each of the three layers of knowledge interactions.

In section three we have stressed how inferring the presence of knowledge interactions looking for correlation among individual actions and average actions taken by a reference group is potentially exposed to selection problems. In particular, contextual effects in the initial sample of homogeneous firms within specific reference groups might affect the evidence presented (Manski, 2000 and 2003). In order to address this point and better identify actual peer-group effects we test a set of additional models in which we use the new following variables:

TFP REG OTHER $SECT_{i,t}$: the yearly average TFP of all the companies in the same region of firm i, but operating in other sectors. This variable should capture the effects of pure Jacobian externalities.

TFP SECT OTHER $REG_{,it}$: the yearly average TFP of all companies in the same sector of firm i but located in other regions. This variable should capture the working of cognitive MAR intra-industrial externalities that are independent of locational effects.

The new specifications should limit potential spurious correlations. The new set of regressions reported in the following Table 4 seems to provide evidence in support of our previous findings. As could be expected, the estimated elasticity of firm level TFP to average TFP of companies located in the same region but in other sectors (TFP REG OTHER SECT) is still significant but lower than the one previously estimated (TFP REG, in Table 3). This on the one hand confirms the presence of a relevant correlation among firm level TFP and the general conditions of the regional economic system. On the other hand, we obtain for this second set of estimates a significantly higher elasticity of firm level TFP to the average TFP of the co-localised reference group (LREFTFP). An analogous pattern can be appreciated for the sectoral dimension. The estimated coefficient for the industry level TFP decreases when considering only those companies not geographically co-localised (see models IV in Tables 3 and 4).

[TABLE 4]

The strong significance and robustness of the variable that measures the internal efforts of firms to generate new technological knowledge confirms that technological change, as proxied by TFP, is the result of an intentional action at the firm level, as proxied by the intensity of intangible to tangible capital stocks. The negative coefficient for the size of firms suggests that the specific distributed model of accessing and using technological knowledge in the Italian industry favours small firms.

When we include these results into the general picture provided by the empirical model we can appreciate how important is the contribution of three distinctive and specific sources of external knowledge, as a necessary and indispensable input into the generation of technological knowledge and the eventual introduction of technological innovations, as articulated in: a) regional external knowledge available in the region across industries, b) industrial external knowledge available in the industry at the national level, and c) localized external knowledge available in the cognitive and regional proximity provided by co-localization in the same region and industry.

Innovation is actually the emergent property of the organized complexity of an economic system that is able to socialize the generation of technological knowledge. The characteristics of the system and the intentional efforts of the individual agents are the two complementary and indispensable forces strictly intertwined that shape the dynamic of the process.

6. Conclusions

This paper has shown that the application of the methodology of social interactions to the economics of innovation is fertile. Social interactions are relevant for the economics of innovation because they make it possible to identify the specific mechanisms by means of which external knowledge contributes the effort of each firm to generate new technological knowledge and change endogenously their production functions. Because of the central role of knowledge interactions to access external knowledge and its key role in the generation of new technological knowledge, innovation is endogenous to the system, rather than to each individual firm. Innovation is an emergent property of the organized complexity of an economic system structured as a stratified nexus of networks that enable and qualify relevant knowledge interactions that take place at different and specific levels. Our results have shown, in fact, that firms benefit of three distinct and specific layers of knowledge interactions: the MAR intra-industrial nationwide knowledge interactions, the Jacobian intra-industrial -within region- knowledge interactions, and the localized intra-industrial knowledge interactions that take place within geographical clusters.

These results are most important from a theoretical perspective. They show that different layers of social interactions play the crucial role of carriers of the external knowledge that it is necessary for each agent to succeed in the recombinant generation of new technological knowledge. When knowledge interactions take place swiftly, the internal research efforts of each firm can complement the larger amount of external knowledge that becomes available at below-equilibrium costs. The provision of external knowledge at such below-equilibrium costs enables them to react creatively to un-expected out-of-equilibrium conditions with the introduction of technological innovations, rather than adaptively with sheer technical price/quantity adjustments. The access to below-equilibrium cost external knowledge is the ultimate source of total factor productivity that is –of course- calculated assuming that all factor (and product) markets are in perfect equilibrium conditions. Within organized complex systems, endowed with efficient communication infrastructures, close and frequent knowledge interactions among learning agents, can trigger cascades of positive feedbacks in terms of self-sustained rates of introduction of new technologies. Within such a multilayer organized complexity, each firm contributes the spreading and strengthening of out-of-equilibrium conditions at different levels.

These results have implications from a policy and strategy perspective as well. The design of governance mechanisms that enable the creation and implementation of knowledge interactions becomes a central concern for action both at the government and the corporate level. Creation of appropriate networks of interaction matters as well as proximity in multilayer space, including the geographical, industrial and technological dimensions, in order to favor the density, reliability, symmetry, recurrence and quality of knowledge interactions among learning agents and hence reduce external knowledge searching, screening, access and absorption costs. The ultimate objective is to create a system of knowledge interactions that make it possible to access external knowledge at costs that are below equilibrium levels, i.e. to take advantage of significant pecuniary knowledge externalities and hence to feed the continual introduction of technological innovations that can engender the growth of total factor productivity.

7. References

Aghion, P., Blundell, R., Griffith, R., Howitt, P., Prantl, S. (2004), Entry and productivity growth: Evidence from microlevel panel data, *Journal of the European Economic Association* 2, 265-276.

Antonelli, C. (2007), The system dynamics of collective knowledge: From gradualism and saltationism to punctuated change, *Journal of Economic Behavior and Organization* 62, 215-236.

Antonelli, C. (2008a), *Localized technological change. Towards the economics of complexity*, Routledge, London.

Antonelli, C. (2008b), Pecuniary knowledge externalities: The convergence of directed technological change and the emergence of innovation systems, *Industrial and Corporate Change* 17, 1049-1070.

Antonelli, C. (ed.) (2011), *Handbook on the economic complexity of technological change*, Edward Elgar, Cheltenham.

Arrow, K. J. (1962), Economic welfare and the allocation of resources for invention, in Nelson, R. R. (ed.) *The rate and direction of inventive activity: Economic and social factors*, Princeton University Press for N.B.E.R., Princeton, pp. 609-625.

Arrow, K. J. (1969), Classificatory notes on the production and transmission of technical knowledge, *American Economic Review* 59, 29-35.

Arthur, W.B. (2009), *The nature of technology*, The Free Press, New York.

Arthur, W.B., Durlauf, S.N., Lane, D.A. (1997), Introduction, in Arthur, W.B., Durlauf, S.N., Lane, D.A. (eds.), *The economy as an evolving complex system II*, Addison-Wesley, Reading, (pp.-14).

Audretsch, D. B., Feldman, M. (1996), Spillovers and the geography of innovation and production, *American Economic Review* 86, 630-640.

Becker, G. (1991), A note on restaurant pricing and other examples of social influences on price, *Journal of Political Economy* 99, 1109-116.

Benfratello, L., Sembenelli, A. (2006), Foreign ownership and productivity: Is the direction of causality so obvious?, *International Journal of Industrial Organization* 24, 733-751.

Blundell, R., Bond, S. (2000), GMM estimation with persistent panel data: An application to production functions, *Econometric Reviews* 19, 321-340

Boschma, R. A. (2005), Proximity and innovation: A critical assessment, *Regional Studies* 39, 61-74.

Breschi, S., Lissoni, F. (2003), Knowledge spillovers and local innovation systems: A critical survey, *Industrial and Corporate Change* 10, 975-1005.

Cincera, M. (1997), Patents R&D and technological spillovers at the firm level: Some evidence from econometric count models for panel data, *Journal of Applied Econometrics* 12, 265-280.

Cohen, W.M. and Levinthal, D.A. (1990), Absorptive capacity: A new perspective on learning and innovation, *Administrative Science Quarterly* 35, 128-152.

David, P.A. (1993), Knowledge property and the system dynamics of technological change, *Proceedings of the World Bank Annual Conference on Development Economics*, The World Bank, Washington.

Duguet, E. (2007), Innovation height spillovers and TFP growth at the firm level: Evidence from French manufacturing, *Economics of Innovation and New Technology* 15, 415-442.

Durlauf, S.N. (2005), Complexity and empirical economics, *Economic Journal* 115, 225-243.

Fransman, M. (2010), *The new ICT ecosystem. Implications for policy and regulation*, Cambridge University Press, Cambridge.

Fleming, L., Sorenson, O. (2001), Technology as a complex adaptive system: Evidence from patent data, *Research Policy* 30, 1019-1039.

Frenken K. (2006), Technological innovation and complexity theory, *Economics of Innovation and New Technology* 15, 137-155.

Glaeser, E., Scheinkman, J.A. (2000), Non-market interactions, NBER Working Paper Series 8053.

Glaeser, E., Sacerdote, B. and Scheinkman, J.A. (1996), Crime and social interactions, *Quarterly Journal of Economics* 109, 507-548.

Griliches, Z. (1957), Hybrid corn: An exploration in the economics of technological change, *Econometrica* 25, 501-522.

Griliches, Z. (1992), The search for R&D spillovers, *Scandinavian Journal of Economics* 94, 29-47.

Guiso, L., Schivardi, F. (2007), Spillovers in industrial districts, *Economic Journal* 117, 68-93.

Hanusch, H., Pyka, A. (2007), Principles of Neo-Schumpeterian economics, *Cambridge Journal of Economics* 31, 275-289.

Hayek, F.A. (1945), The use of knowledge in society, *American Economic Review* 35, 519-530.

Henderson, J.V. (1997), Externalities and industrial development, *Journal of Urban Economics* 42, 449-470.

Katz, M.L., Shapiro, C. (1986), Technology adoption in the presence of network externalities, *Journal of Political Economy* 94, 822-841.

Jacobs, J. (1969), *The economy of cities*, Jonathan Cape, London.

Jaffe, A.B. (1986), Technological opportunity and spillover of R&D: Evidence from firms' patents, profits and market value, *American Economic Review* 79, 985-1001.

Jaffe, A.B., Trajtenberg, M. and Henderson, R.M. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations, *Quarterly Journal of Economics* 108, 577–98.

Lane, D. A. et al. (2009), *Complexity perspectives in innovation and social change*, Springer, Berlin.

Lane, D.A., Maxfield, R. (1997), Foresight complexity and strategy, in Arthur, W.B., Durlauf, S.N., Lane, D.A. (eds.) *The economy as an evolving complex system II*, Westview Press, Santa Fe, pp.169-198.

Lundvall B. (1988), Innovation as an interactive process: From user-producer interaction to the national system of innovation, in Dosi, G. et al., (eds.), *Technical Change and Economic Theory*, Frances Pinter, London, pp. 349-69.

Mairesse, J., Cuneo, P. (1985), Recherche-development et performances des entreprises: Une etude econometrique sur donnees individuelles, *Recherches Economique* 36, 100-141.

Manski, C.F. (2000), Economic analysis of social interactions, *Journal of Economic Perspectives* 14, 115-136.

Manski, C.F. (2003), Identification problems in the social sciences and everyday life, *Southern Economic Journal* 70, 11-21.

Nelson, R.R. (1959), The simple economics of basic scientific research, *Journal of Political Economy* 67, 297-306.

Olley, S., Pakes, A. (1996), The dynamics of productivity in the telecommunications equipment industry, *Economerica* 64, 1263-1297.

Parisi, M.L., Schiantarelli, F., Sembenelli, A. (2006) Productivity, innovation and R&D: Microevidence for Italy, *European Economic Review* 50, 2037-2061.

Schumpeter, J. A. (1947), The creative response in economic history, *Journal of Economic History* 7,149-159.

Scitovsky, T. (1954), Two concepts of external economies, *Journal of Political Economy* 62, 143-151.

Von Hippel (1976), The dominant role of users in the scientific instrument innovation process, *Research Policy* 5, 212-239.

Von Hippel, E. (1998), Economies of product development by users: The impact of "sticky" local information, *Management Science* 44, 629-644.

Weitzman, M.L. (1996), Hybridizing growth theory. *American Economic Review* 86, 207-212.

Weitzman, M.L.(1998) Recombinant growth. *Quarterly Journal of Economics* 113, 331-360.

LIST OF TABLES

Table 1- Sectoral distribution of companies included in the sample

Industry	**Companies**	**%**
Food products	234	3,33%
Miscellaneous Food Preparations	190	2,71%
Grain mill products	137	1,95%
Textile: broadwoven	277	3,95%
Textile: Narrow frabic and knitting mills	330	4,70%
Textile: Dyeing and finishing textile, thread mills	212	3,02%
Leather: leather tannig and finisching, boot and shoe	135	1,92%
Leather: luggage and other leather products	114	1,62%
Wood and wood products manufacturing	155	2,21%
Pulp, paper mills	94	1,34%
Converted paper and paperboard products	80	1,14%
Printing	193	2,75%
Industrial inorganic and plastic materials	298	4,25%
Drugs	62	0,88%
Soap detergents and cleaning preparations	41	0,58%
Fabricated rubber products	303	4,32%
Miscellaneous plastic products	118	1,68%
Primary metal industry	390	5,56%
Non-metallic mineral product manufacturing	275	3,92%
Metal products manufacturing	267	3,80%
Fabricated Structural Metal Products	310	4,42%
Metal Forgings And Stampings	406	5,78%
Mechanical machinery and equipment manufacturing	381	5,43%
Metalworking Machinery And Equipment	205	2,92%
Engines And Turbines	111	1,58%
General Industrial Machinery And Equipment	381	5,43%
Computer and electronic manufacturing	24	0,34%
Electrical machinery and equipment manufacturing	287	4,09%
Telecommunication machinery and equipment	91	1,30%
Medical, optical and precision equipment	143	2,04%
Transportation equipment manufacturing	122	1,74%
Other transport equipment manufacturing	61	0,87%
Furniture	487	6,94%
Software	106	1,51%
Total	7020	100,00%

Table 2- Regional distribution of companies included in the sample

Region	Number of companies	Percentage
Abruzzo	97	1.38%
Campania	144	2.05%
Emilia-Romagna	833	11.87%
Friuli	281	4.00%
Lazio	168	2.39%
Liguria	58	0.83%
Lombardia	2,543	36.23%
Marche	173	2.46%
Piemonte	722	10.28%
Puglia	60	0.85%
Sardigna	28	0.40%
Sicilia	44	0.63%
Toscana	489	6.97%
Trentino	124	1.77%
Umbria	77	1.10%
Veneto	1,179	16.79%
Total	7,020	100.00%

Table 3 – Fixed effect panel model. Dependent Variable TFPit.

Models	I	II	III	IV
SECTFP	0.644**	0.771**	0.774**	0.687**
	(0.017)	(0.020)	(0.020)	(0.024)
REGTFP	0.320**	0.575**	0.588**	0.525**
	(0.017)	(0.026)	(0.026)	(0.029)
LREFTFP				0.108**
				(0.015)
INTANG			0.180**	0.200**
			(0.054)	(0.054)
SIZE			-0.096**	-0.096**
			(0.002)	(0.002)
CONST	0.171**	-2.993**	-1.865**	-1.500**
	(0.062)	(0.256)	(0.259)	(0.277)
YEAR DUMMIES	No	Yes	Yes	Yes
Observations	70200	70200	70200	70200
Overall-Rsq	0.783	0.787	0.771	0.775
Within Rsq	0.213	0.216	0.243	0.247
Between Rsq	0.860	0.859	0.837	0.841
Rho	0.691	0.625	0.636	0.627
F Test	8533.6**	1579.6**	1553.8**	1463.0**

*Significant at the: * 95%; ** 99% level*

Table 4 – Fixed effects panel model. Dependent Variable TFPit. Model specification controlling for spurious agglomeration effects.

MODELS	I	II	III	IV
TFP SECT OTHER REG	0.607**	0.586**	0.599**	0.412**
	(0.015)	(0.020)	(0.020)	(0.022)
TFP REG OTHER SECT	0.353**	0.346**	0.363**	0.266**
	(0.015)	(0.025)	(0.025)	(0.027)
LREFTFP				0.304**
				(0.013)
INTANG			0.172**	0.202**
			(0.054)	(0.054)
SIZE			-0.096**	-0.096**
			(0.002)	(0.002)
Constant	0.204**	0.420**	1.532**	1.380**
	(0.063)	(0.277)	(0.281)	(0.293)
YEAR DUMMIES	No	Yes	Yes	Yes
Observations	70200	70200	70200	70200
Overall-Rsq	0.771	0.769	0.739	0.765
Within Rsq	0.200	0.201	0.228	0.239
Between Rsq	0.852	0.852	0.809	0.833
Rho	0.721	0.732	0.728	0.669
F Test	7898.2**	1442.4**	1430.6**	1402.9**

*Significant at the: * 95%; ** 99% level*

ANNEX A

Table 5 – Robustness control. Selected model specifications estimated with heteroskedasticity robust standard errors clustered at the industry level (models I and II) and at the regional level (models III and IV).

VARIABLES	I	II	III	IV
TFP SECT	0.687**		0.687**	
	(0.051)		(0.050)	
TFP REG	0.525**		0.525**	
	(0.039)		(0.054)	
TFP LREF	0.108*	0.304*	0.108*	0.304**
	(0.044)	(0.052)	(0.040)	(0.078)
TFP SECT OTHER REG		0.412**		0.412**
		(0.062)		(0.055)
TFP REG OTHER SECT		0.266**		0.266**
		(0.056)		(0.060)
INTANG	0.200*	0.202*	0.200**	0.202**
	(0.073)	(0.076)	(0.057)	(0.056)
SIZE	-0.096**	-0.096**	-0.096**	-0.096**
	(0.008)	(0.008)	(0.003)	(0.003)
Constant	-1.500**	1.380*	-1.500*	1.380
	(0.490)	(0.541)	(0.585)	(0.679)
YEAR DUMMIES	Yes	Yes	Yes	Yes
Observations	70200	70200	70200	70200
Within Rsq	0.247	0.239	0.247	0.239
Overall Rsq	0.775	0.765	0.775	0.765
Between Rsq	0.841	0.833	0.841	0.833
Rho	0.627	0.669	0.627	0.669
Ftest	1958.2**	1052.8**	3137.0**	2652.7**

*Significant at the: * 95%; ** 99% level*

Table 6 – Description of variables and summary statistics

Variable	Description	Mean	St dev	1%	99%
TFPit	Log of the TFP of company i in year t	8.081	0.798	5.662	9.561
SECTFPit	Log of the average TFP of all companies operating in the same sector of company i (excluding company i)	8.146	0.712	5.764	9.240
REGTFPit	Log of the average TFP of all companies operating in the same region of company i (excluding company i)	8.327	0.162	8.057	8.623
LREFTFPit	Log of the average TFP of all companies operating in the same region and sector of company i (excluding company i)	8.137	0.720	5.790	9.279
TFP SECT OTHER REGit	Log of the average TFP of all companies operating in the same sector of company i (excluding company i) but not in same region of company i.	8.135	0.711	5.763	9.236
TFP REG OTHER SECTit	Log of the average TFP of all companies operating in the same region of company i (excluding company i) but not in the same sector of company i.	8.324	0.167	7.862	8.648
INTANGit	Ratio of intangible assets to tangible assets of company i in year t	0.158	0.194	0	0.858
SIZEit	Log of total assets of company i in year t	14.300	1.382	10.979	17.703