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COMPLEXITY AND INNOVATION: SOCIAL INTERACTIONS AND FIRM LEVEL TOTAL FACTOR PRODUCTIVITY

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Complexity and Innovation: Social 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 the structure of the utility functions for households and of the production functions for producers. In this paper, we apply the general concept of social interactions to the area of the economics of innovation and technological change. In particular, we discuss how both the knowledge spillovers literature and the Schumpeterian notion of creative reaction can be reconciled within a general framework building on the concept of social interactions within complex dynamics. The paper presents an empirical analysis of firm level total factor productivity (TFP) for a sample of 7020 Italian manufacturing companies observed during years 1996-2005. We show that changes in firm level TFP are significantly affected by localised social interactions. Such evidence is robust to the introduction of appropriate regional and sectoral controls, as well as to econometric specifications accounting for potential endogeneity problems. Moreover, we find evidence suggesting that changes in competitive pressure, namely the creative reaction channel, significantly affect firm level TFP with and additive effect with respect to localised social interactions deriving from knowledge spillovers.

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1. Introduction

The study of social interactions is a growing field of economics and more specifically of the economics of complexity. According to an extensive literature, social interactions occur when the gains of undertaking an action to one agent are increasing with the number of other agents that undertake the same action. Social interactions are a fundamental ingredient of complex dynamics. According to Lane and Maxfield, complex economic dynamics takes place when the propensity to undertake specific actions of a set of heterogeneous agents change because of their interactions with one another within structured networks (Lane, Maxfield, 1997).

Social interactions contrast market interactions. Market interactions consist of standard price/quantity adjustments. In the market place interacting, adaptive agents change their behavior but do not change the structure of their utility and production functions. 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 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. Social interactions may have effects upon costs only if they have effects upon production and utility functions: behaviors may change because of changes in the costs without any changes in the utility and production functions (Hanusch and Pyka, 2007).

Hence 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.

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. The baseline assumption of their analysis is that social interactions affect the behaviour of firms, as distinct from their performances. 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.

While the modelling approach and the econometric methodology of Guiso and Schivardi (2007) is fertile, it is not clear to what extent the significant covariance in the changes in employment among co-localized firms that they identify is the result of actual social interactions, and hence of effects of interactions upon the technology of each firm, or rather the outcome of the positive effects of colocalization upon the costs of inputs for each firms. As it is well known, pecuniary externalities -the reduction in factor costs stemming from co-localization- are likely to have positive effects upon the growth in employment for the traditional effects upon the costs curve.

The application of social interaction models to the economics of innovation and new technology seems promising, as it provides the tool to make a clear distinction between traditional externalities and actual changes in the production function. The former consists of the effects of interaction upon factor costs. The latter consist of the endogenous mechanisms that shape the changing characteristics of the production function of firms. The methodology of social interaction seems appropriate to implement the large literature that has explored this field. Two well distinct bodies of theoretical and empirical research have emerged: A) knowledge spillovers; B) creative reactions. Let us consider them briefly.

A) Knowledge spillovers and diffusion. Knowledge spillovers are the other side of the well-known appropriability problem. According to Arrow and Nelson, knowledge can be easily imitated (Arrow, 1962; Nelson, 1959). Co-localization and proximity favor the access to external knowledge spilling from ‘inventors’ with positive effects upon the productivity of resources invested internally in research and development expenditures (Jaffe, 1986; Griliches, 1992; Audretsch and Feldman, 1996).

Following the analysis of Arrow (1969) however, a distinction can be made between generic technological knowledge, with high levels of fungibility, i.e. with a wide scope of applications and specific technological knowledge characterized by strong idiosyncratic features. Specific knowledge can be appropriated; generic knowledge instead retains the typical features of a public good. Innovators generate generic knowledge while are engaged in the introduction of new specific knowledge embodied in new products and new processes. The production of specific knowledge takes advantage of the collective availability of generic one. The spillover of generic knowledge helps the generation of new specific knowledge by third parties and yet does not reduce the incentives to the generation of new knowledge for the strong appropriability of the specific applications (Romer, 1994).

The Hayekian notion of distributed knowledge, dispersed and fragmented in a myriad of economic agents, provides the foundations to the understanding of knowledge complementarities (Hayek, 1945). Only when a complementary set of knowledge fragments is brought together within a context of consistent interactions, successful innovations can be introduced and adopted: technological knowledge is the product of a collective activity. The results of the empirical analyses of Lundvall (1988) and Von Hippel (1976, 1998) 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 relevance of vertical interactions among heterogeneous agents in the generation of knowledge. The identification of knowledge spillovers led to the retrieval of the Marshallian analysis of knowledge externalities (Calderini and Scellato, 2005).

The literature of the economic of knowledge confirms and generalizes, adding important elements, the positive role of social interactions and social multipliers that had been already identified, in a more circumscribed context, in the literature on the diffusion of existing technologies, as distinct from the transfer of and access to technological knowledge.

According to large empirical evidence, the rates of adoption of new technologies are in fact favored by herd behavior and epidemic contagion (Griliches, 1957). The cost of adoption of new technologies is sensitive to the stock of adoption: the larger is the number of adopters and the lower are the information costs about the functionality of the new products, their manufacturing costs because of learning by doing and other increasing returns in production, and their prices because of the entry of new competitors in upstream markets (Karshenas and Stoneman, 1995). Moreover because of network externalities the larger is the number of adopters and the better is, in many circumstances, the functionality of the new technologies (Katz and Shapiro, 1986).

In sum, the economics of knowledge and the economics of diffusion provide large evidence about the pervasive role of social interactions and social multipliers in the dissemination and repeated use of both new technologies and new technological knowledge.

Social interactions here consist in the effects upon the production function of each agent exerted by the production of technological knowledge by other agents. The working of knowledge spillovers and epidemic contagion can be fruitfully framed into the methodology of social interactions and their effects can be analyzed as forms of positive feedbacks and social multipliers. The generation of new technological knowledge and the introduction of new technologies by a neighbor in the regional space have a direct effect on the production function of other agents co-localized in terms of positive technological and pecuniary knowledge externalities. Proximity in geographical space favors the dissemination of knowledge spillovers and reduces absorption costs. Distance has strong negative effects upon the density, reliability, symmetry, recurrence and quality of personal interactions among learning agents (Boschma, 2005). The generation of new knowledge by each agent has positive effects on the capability of other agents to generate in turn new knowledge because of the intrinsic indivisibility of knowledge, its limited appropriability and its effects upon the learning capabilities of all the interacting agents. Hence each firm not only can take advantage of the external knowledge spilling in the atmosphere and use it as an input in their own research activities, but learns by means of interactions and in so doing changes its own technology because of interactions. Social multipliers here take the form of localized increasing returns by means of knowledge externalities within regional innovation systems (Malerba, 1992; Breschi and Lissoni, 2003).

Durlauf (1993) has explored the dynamics of local technological interactions and has shown the possibility of productivity traps in which low productivity techniques are used, because other producers are also using low productivity processes.

Cingano and Schiavardi (2004) have applied the methodology of social interaction to test the role of knowledge spillovers at the territorial level. They show how both intra-industrial (Marshallian) knowledge externalities and inter-industrial (Jacobian) knowledge externalities have a direct effect on total factor productivity levels of firms.

B) Quite a different category of social interactions leading to social multipliers is detected when we assume that firms do more than adjusting prices to quantities and vice versa. If firms are credited with the capability to innovate as a part of their business conduct, the notion of creative reaction becomes relevant. The first analysis of the role of creative reaction is found in Schumpeter (1947) who fully elaborates the view that firms and agents at large are induced to react to the changing conditions of both product and factor markets in a creative way, with the introduction of innovations, both in technologies and organizations and changing their products and processes[2]. Schumpeter makes a clear distinction between adaptive and creative responses. Adaptive responses consist in standard price/quantity adjustments that are comprised within the range of existing practices. Creative responses consist in innovative changes that can be rarely understood *ex ante*, shape the whole course of subsequent events and their 'long-run' outcome: their frequency, intensity and success is influenced by a variety of conditional factors that are both internal to each firm and external. For a given shock, firms can switch from an adaptive

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[2] Schumpeter (1947) makes the point very clear: "What has not been adequately appreciated among theorists is the distinction between different kinds of reaction to changes in 'condition'. Whenever an economy or a sector of an economy adapts itself to a change in its data in the way that traditional theory describes, whenever, that is, an economy reacts to an increase in population by simply adding the new brains and hands to the working force in the existing employment, or an industry reacts to a protective duty by the expansion within its existing practice, we may speak of the development as an *adaptive response*. And whenever the economy or an industry or some firms in an industry do something else, something that is outside of the range of existing practice, we may speak of *creative response*. Creative response has at least three essential characteristics. First, from the standpoint of the observer who is in full possession of all relevant facts, it can always be understood *ex post*; but it can be practically never be understood *ex ante*; that is to say, it cannot be predicted by applying the ordinary rules of inference from the pre-existing facts. This is why the 'how' in what has been called the 'mechanisms' must be investigated in each case. Secondly, creative response shapes the whole course of subsequent events and their 'long-run' outcome. It is not true that both types of responses dominate only what the economist loves to call 'transitions', leaving the ultimate outcome to be determined by the initial data. Creative response changes social and economic situations for good, or, to put it differently, it creates situations from which there is no bridge to those situations that might have emerged in the absence. This is why creative response is an essential element in the historical process; no deterministic credo avails against this. Thirdly, creative response –the frequency of its occurrence in a group, its intensity and success or failure- has obviously something, be that much or little, to do (a) with quality of the personnel available in a society, (b) with relative quality of personnel, that is, with quality available to a particular field of activity relative to the quality available, at the same time, to others, and (c) with individual decisions, actions, and patterns of behavior." (Schumpeter, 1947:149-150).

response to a creative response according to the quality of their internal learning processes, and the context into which they are embedded

In the Schumpeterian approach firms innovate in order to face unexpected changes in the economic environment. The notion of social interaction makes it possible to specify this hypothesis. The social multiplier in fact now consists in the inducement mechanism that leads firms confronted with the dynamics of their economic environment to try and change their technologies and their organizations (Antonelli, 1999 and 2007).

The rivalry among firms able to introduce –purposely- new technologies is a major factor in fostering the rate of technological change (Scherer, 1967). Here social interactions take a different form of strategic complementarities: the extent to which firms innovate depends upon the change in behavior, namely the introduction of innovations, by neighbors in the product and output markets.

The distinction of the two forms of innovative social interactions seems important and deserves careful examination. The distinction in fact makes it possible to discriminate between the factors that can affect the rates of introduction of technological innovations. The two forms of social interaction among innovative and learning agents are well distinct and their effects add on.

Knowledge spillovers, when available, provide firms with the access to external knowledge. Hence, the stronger the amount of knowledge spillovers within local innovation systems, and the higher the opportunity for co-localised firms to introduce new technologies. Knowledge social interactions display their effects within a local innovation system as they provide firms with the access to knowledge generate by each other firms, respectively: i) within the same industry (Marshallian externalities) and ii) across industries (Jacobian externalities).

Creative social interactions trigger the actual introduction of new successful innovations when firms are induced to change their technology by competitive pressure within the same industry. Hence, we argue that the stronger is the intensity of rivalry in product markets and the higher is the inducement to introduce new technologies (Dasgupta and Stiglitz, 1980). More specifically consider the hypothesis that firms are induced to innovate when their competitive advantage declines (Antonelli, 1989).

Adaptive responses, as opposed to creative ones, are likely to occur when firms have not access to knowledge social interactions and the generation of knowledge should rely only upon internal sources. On the other hand, knowledge spillovers and epidemic contagion are more likely to trigger the introduction of innovations when firms are induced to change their technologies by the increasing pressure of market rivalry.

When knowledge social interactions are missing and the competitive threat to established market position is weak and hence creative social reactions are not solicited, inferior technologies are likely to be resilient.

In this paper we investigate the presence and extent of localised complex interactions through the empirical observation of the effects of social interactions affecting the knowledge spillovers both within industry and across industries, as distinct from the effects of social interactions affecting the creative response of firms, with an in depth analysis of total factor productivity at the company level.

The paper is organized as follows. In section two we introduce our empirical methodology to identify the extent of localized social interactions. Section three contains a description of the dataset and the approach adopted to evaluate firm level total factor productivity. In section four we present our econometric results and robustness checks. Finally, in section five we discuss our evidence.

2. *Empirical methodology*

In this paper we investigate the presence and extent of localised complex interactions through the analysis of firm level total factor productivity measures. Total factor productivity seems a much more reliable indicator of the actual extent to which firms are able to command technological innovations (Scellato, 2007).

Alternative indicators can be questioned on many counts. Research and development expenditures measure a partial amount of the overall effort that firms make to introduce new technologies. Internal learning activities are not accounted for, neither is the access to external knowledge. Moreover the actual efficiency of the research activities is not considered as, of course, research and development activities only measure, partially, some inputs into the process. On the opposite side patent statistics measure the output of research activities when it consists of knowledge with low levels of 'natural appropriability'. As it is well known, firms rely much more on patents for product innovations than for process innovations. In sum, patent statistics reflect asymmetrically the actual amount of technological knowledge as the propensity of firms to protect their knowledge by means of the intellectual property right regime is heavily influenced by a number of sectoral, technological and market conditions. Finally, patent statistics cannot appreciate the effects of the creative adoption of new technologies introduced by third parties (Griliches, 1990).

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 a number of spurious factors ranging from the quality of human capital that is not appreciated by wages and the effects of imperfect competition, especially in product markets (Duguet, 2007).

Following an extensive literature on spillover and localised technological change, the baseline assumption of the analysis is that social interactions eventually affecting the innovative conduct of firms as measured by total factor productivity take place between firms industrially and geographically similar. In this context it seems important to try and identify the two forms of social interactions that have been identified, namely the knowledge social interactions and the creative social interactions.

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 shocks defined at the industry and geographical level, which are likely to generate common behaviours of companies.

As previously stated, a model of social interactions assumes that the utility that an agent draws from an action is linked to the choices made by all the other agents within its group.

Specifically, the analysis builds on the approach presented in Guiso and Schivardi (2007), which define the following general model to test for the presence of social interactions. Assume that $\Omega_i(t)$ is a decision taken by company i at time t, $\Omega_{-i}(t)$ is the average decision taken by all other companies belonging to the same group of company i, $\delta_i(t)$ represents firm specific idiosyncratic shocks potentially influencing the decision and $\varphi(t)$ include a set of common shocks. Then, in the following equation a positive and significant value of the parameter β_1 would highlight the presence of some form of interaction among firms belonging to a specific group:

$$\Omega_i(t) = \alpha_i + \beta_1\Omega_{-i}(t) + \beta_2\delta_i(t) + \beta_3\varphi(t) + \varepsilon_i(t) \qquad (1)$$

Where $\varepsilon_i(t)$ is an error term uncorrelated to both $\delta_i(t)$ and $\varphi(t)$. Given this modelling structure, in order to detect actual localised social interactions within the group, it is crucial to properly define the set of shocks $\varphi(t)$ which are common to companies not included in the same group. In particular, we will use $\Omega_i(t)$ as the total factor productivity of firm i, while $\Omega_{-i}(t)$ is the average total factor productivity of firms belonging to the same group of firm i. In our model, common shocks are represented by all those economic events which are reflected in: A) the average total factor productivity of firms operating in the same sector of firm i; B) the average total factor productivity of firms operating in the same region of firm i. The first type of shock is expected to capture general industry-level dynamics in productivity, accounting for changes in innovation opportunities which can be achieved independently of the specific geographical environment surrounding the company. The second type of shock is expected to capture general regional conditions potentially affecting productivity levels through time, such as the local availability of knowledge intensive infrastructure.

The introduction of the two controls allows us to estimate the additional sensitivity of TFP among firms in the same group, which is not related to region-specific factors or industry-specific dynamics. In our analytical framework, for each company the reference group is represented by all the other companies located within the same region and operating in the same sector.

This kind of model aims at the identification of a knowledge social multiplier, deriving from knowledge spillover and technological diffusion effects.

In order to investigate the impact of creative social interactions we will add a set of variables which account for the changes in the competitive pressure at industry level as well as within a specific reference group. If adjustments in firm level TFP are driven by the competitive pressure we expect that reductions in average margins will positively affect subsequent levels of TFP. However the latter effect should not harm the positive and significant sign of the parameter accounting for knowledge social interactions.

3. The Dataset

Our dataset is based on complete 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. The introduction of the latter condition implies that we do not consider market exit/entry. However, this is not expected to generate relevant biases for our specific line of enquiry. 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 balance sheet 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 and fixed capital stock. After a manual checking we eventually dropped 45 companies which showed unreasonable data. Given the characteristics of the empirical analysis, we have been forced to drop the companies located in regions with less than 10 companies included in the sample. This criterion leaded to the exclusion of 28 companies. We ended up with a balanced panel of 7020 companies. All financial data have been deflated according to a sectoral two-digit deflator using year 2000 basic prices. For the whole sample of analysed companies we have also computed the variable price-cost-margin (PCM).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]

Computation of firm level total factor productivity

In order to compute firm level TFP we have estimated a set of Cobb-Douglas production functions with constant return to scale for each industry included in the sample. It is possible to compute TFP for company *i* in year *t* according to the following expression:

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

Where:

$Q_{i,t}$:deflated value added

$L_{i,t}$:average number of employees

$K_{i,t}$:fixed capital stock.

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. The investment parameter ($I_{i,t,}$) has been computed as the yearly variation in net fixed capital in companies' balance sheets plus yearly amortizations. Hence, the time series of fixed capital is defined as follows:

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

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

$$Log\left(\frac{Q_{i,t}}{K_{i,t}}\right) = \beta \times Log\frac{L_{i,t}}{K_{i,t}} + \alpha_i + \alpha_t + \varepsilon_{i,t} \qquad (3)$$

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.

4. Econometric models and results

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

$$TFP_{i,t} = \alpha_i + \beta_1 REGTFP_{i,t} + \beta_2 SECTFP_{i,t} + \beta_3 REFTFP_{i,t} + \delta_t + u_{i,t} \qquad (4)$$

The dependent variable is total factor productivity for company i in year t. The variable REGTFP is the yearly average TFP of all companies located in the same region of company i (excluding company i). This regressor is expected to capture general regional conditions potentially affecting productivity levels through time, such as the presence of knowledge intensive infrastructure, the local development of financial institutions or specific characteristics in the input markets.

The variable SECTFP is the yearly average TFP of all companies in the same sector of company i (excluding company i). This regressor is expected to capture general industry-level dynamics in productivity. Hence, it should account for any change in innovation opportunities which can be achieved independently of the specific geographical environment surrounding the company.

Finally, the variable REFTP is average TFP of all companies in the same sector and region of company i, namely the reference group for company (excluding company i). The latter regressor is expected to capture firm level dynamics in TFP which might be linked to localised knowledge social interactions. In the following table 3 we report the first results for this specification, which also includes a full set of year dummies. The model is estimated with fixed effect.

[Table 3]

The previous set of models might pose problems caused by the potential endogeneity of the regressors. To allow for the endogeneity, we adopted the procedure developed by Arellano and Bond (1991), re-estimating the equations in first-differences and then using the entire set of lagged values of the dependent and the other covariates as instruments in a GMM procedure. The Arellano and Bond method assumes that the error term has a moving average structure of order 1 in the equations in differences. To check the validity of this assumption, we performed tests on both first and second order serial correlations on the residuals (M1 and M2 in the Tables) along with the Sargan test of over-identifying restrictions for the models. Given the new model structure in table 4 we report among regressors the one year lagged value of companies' total factor productivity.

[Table 4]

The data reported in both table 3 and table 4 highlight a positive and significant effect of average TFP of the reference group (REFTFP), even after controlling for general industrial and geographical dimensions. This can be interpreted as evidence of a specific and additional form of interaction along time among firms sharing both technological specialisation and geographical location. It is also worth noting the presence of a strong and significant persistence in the level of total factor productivity as witnessed by the estimated coefficients for the variable TFP_{t-1}. Our results provide a preliminary support of the existence of a social multiplier deriving from localised complex interactions.

As previously discussed, however one might argue that the significant correlation between firm specific TFP and average TFP of the reference group defined at the regional level is indeed the outcome of creative social interactions. More specifically, we consider the hypothesis that firms are induced to innovate when directly facing a decline in their competitive advantage.

In order to empirically address this point, we introduce a new model specification in which we add measures of competitive pressure by means of a price-cost-margin index (PCM). Also in this case we have computed firm level PCM and then averaged this index at industry level (SECPCM) and for the reference group (REFPCM). Under the hypothesis that the introduction of innovations which affect productivity is driven by previous changes in price-cost margins, we expect a negative relationship between TFP and lagged values of PCM. In the following model we test this hypothesis by introducing the two variables SECPCM and REFPCM, lagged one year. The model is estimated with fixed effect.

[Table 5]

The results highlight that industry-level changes in price-cost-margins significantly affect firm level TFP. Such evidence supports the hypothesis of a creative reaction mechanism governing TFP levels through time. Note that the introduction of the variable SECPCM in model I of table 5 does not influence the estimated coefficient of REFTFP, which is still positive and significant, suggesting an additive effect of knowledge social interactions and creative reactions. When testing the impact of average price cost margins within the reference group (REFPCM in model II of table 5) we obtain a negative but not significant correlation. This is consistent with the hypothesis of creative reactions being based on changes in competitive pressure in product markets which are not geographically bounded.

Robustness of results

In section two we have stressed how inferring the presence of knowledge social interactions looking for correlation among individual actions and average actions taken by a reference group is potentially exposed to selection problems. In particular, the evidence presented above, might be driven by agglomeration effects in the initial sample of homogeneous firms within specific references groups.

In order to address this point we test a set of additional models in which we use the new following variables:

$OTHER\_SECTFP_{i,t}$: the variable is 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 Jacobian externalities.

$OTHER\_REGTFP_{i,t}$: the average is the yearly average TFP of all companies in the same sector of the specific firm but located in other regions. This variable should capture the effects of Marshallian externalities.

The new specification should limit potential spurious correlation. We have implemented the new specification also to test for creative reactions (see table 5), including among regressors both the sectoral and the reference group level average price-cost-margins. The new model is estimated with both fixed effects and with the Arellano Bond GMM method. Result are reported in the following tables 6 and 7.

[Table 6]
[Table 7]

The new set of regressions supports 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 (OTHER_SECTFP) is still significant but lower than the one previously estimated (REGTFP, in table 3 and 4). This confirms the non negligible correlation among firm level TFP and general conditions of the regional economic system. An analogous pattern can be appreciated for the sectoral dimension, comparing model I in table 7 and model III in table 4. Furthermore, the last set of models (models II and III in tables 6 and 7) seems to suggest a specific sensitivity within the reference groups, as it is still robust to the inclusion of covariates accounting for changes in competition patterns.

5. 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 mechanisms by means of which firms change endogenously their production function as a consequence of the interaction with other agents. So far the methodology of social interactions make it possible to go beyond the analysis of externalities upon the cost of firms. Social interactions in fact do not consist of the effects of interactions upon the cost equations of firms, but of the effects of interactions upon the production function of firms. Two well distinct forms of social interactions take place: creative social interaction and knowledge social interactions.

Creative social interactions define the inducement mechanisms that push firms to react to the decline of their competitive advantage in a product market by means of the generation of new technological knowledge and the introduction of new technologies. In this case social interactions induce firms to change their production function so that the productivity of each firm appears as the result of the creative reaction that firms implement in order to face the threat raised by the dynamics of market forces. Creative social interactions take place within industrial sectors defined by the contiguity of product markets. The introduction of innovations is endogenous to the structure of social interactions within the group of firms that belong to the same industrial sector and operate in the same product markets. Social multipliers here take the form of the positive feedbacks that are ultimately measured by the levels of total factor productivity.

Knowledge social interactions consist in the knowledge spillovers and more generally in the knowledge technological and pecuniary externalities that each firm can take advantage of, especially within circumscribed geographical contexts, because of the imperfect appropriability of knowledge. Social multipliers here take the form of knowledge externalities: firms can use existing knowledge generated by third parties and that cannot be fully appropriated by inventors, as an input into their own generation of new knowledge. Knowledge social interactions take place within local innovation systems: the regional space and geographical distance are relevant in this case.

The two forms of social multipliers are additive. Firms would be less able to react creatively to the decline of their performances if external knowledge could not be accessed and used in order to introduce technological innovations. On the other hand it seems clear firms would be less able to take advantage of the access to knowledge generated by other firms if an inducement mechanism were not in place.

Our analysis has confirmed the intertwined causal relations between the continual adaptation of heterogeneous agents that interact locally by means of the perpetual introduction of novelty. Within complex systems close and frequent interactions of innovative agents that are co-localized within geographical clusters can trigger cascades of positive feedbacks in terms of self-sustained rates of introduction of new technologies, especially when they are exposed to the increasing pressure of a competitive rivalry that threatens their profitability.

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LIST OF TABLES

Table 1- Sectoral distribution of companies included in the sample

Industry – ATECO Classification	**Number of companies**	**Percentage**
Food and beverages	561	8.0%
Textile	607	8.6%
Textile product industry	212	3.0%
Leather and leather products manufacturing	249	3.5%
Wood and wood products manufacturing	155	2.2%
Pulp, paper and paper products manufacturing	174	2.5%
Printing	193	2.7%
Chemical industry	401	5.7%
Plastics and rubber manufacturing	421	6.0%
Non-metallic mineral product manufacturing	390	5.6%
Metallurgy	275	3.9%
Metal products manufacturing	983	14.0%
Mechanical machinery and equipment manufacturing	1,078	15.4%
Computer and electronic manufacturing	24	0.3%
Electrical machinery and equipment manufacturing	287	4.1%
Telecommunication machinery and equipment	91	1.3%
Medical, optical and precision equipment	143	2.0%
Transportation equipment manufacturing	122	1.7%
Other transport equipment manufacturing	61	0.9%
Furniture	487	6.9%
Software	106	1.5%
Total	7,020	100.0%

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 – Testing the knowledge social interaction model. Dependent variable: firm level total factor productivity. Model estimated with fixed effects.

	Model I	Model II	Model III
REFTFP	0.769**	0.246**	0.213**
	(0.006)	(0.012)	(0.012)
REGTFP			0.180**
			(0.013)
SECTFP		0.670**	0.576**
		(0.014)	(0.015)
Const.	90.653**	28.550**	59.798*
	(25.841)	(12.850)	(33.106)

*Robust standard errors in parentheses **: significant at the 95% level; *: significant at the 90% level.*

Table 4 – Testing the knowledge social interaction model. Dependent variable: firm level total factor productivity. Model estimated in first difference with the GMM Arellano-Bond method.

	Model I	Model II	Model III
TFP_{t-1}	0.475**	0.455**	0.453**
	(0.005)	(0.005)	(0.005)
REFTFP	0.637**	0.287**	0.240**
	(0.010)	(0.018)	(0.018)
REGTFP			0.221**
			(0.020)
SECTFP		0.451**	0.349**
		(0.021)	(0.022)
Const.	42.349**	51.744**	57.874**
	(2.486)	(2.470)	(2.500)
M1	-83.66*	-83.20*	-83.10**
M2	4.17	4.37	4.32
Sargan Test χ^2	4829.44**	4919.39**	4909.69**

*Robust standard errors in parentheses **: significant at the 95% level; *: significant at the 90% level.*

Table 5 – Testing the creative reaction model. Dependent variable: firm level total factor productivity. Model estimated with fixed effects.

	Model I	Model II
REFTFP	0.210**	0.211**
	(0.012)	(0.013)
REGTFP	0.200**	0.198**
	(0.015)	(0.015)
SECTFP	0.570**	0.571**
	(0.016)	(0.016)
$SECPCM_{t-1}$	-0.734**	
	(0.371)	
$REFPCM_{t-1}$		-0.378
		(0.242)
Const.	37.678	31.316
	(38.322)	(38.020)

*Robust standard errors in parentheses **: significant at the 95% level; *: significant at the 90% level.*

Table 6 – Robustness test. Models for knowledge social interactions and creative reactions. Dependent variable: firm level total factor productivity. Model estimated with fixed effects.

	Model I	Model II	Model III
REFTFP	0.366**	0.3621**	0.362**
	(0.011)	(0.011)	(0.011)
OTHER_SECTFP	0.171**	0.195**	0.193**
	(0.012)	(0.015)	(0.014)
OTHER_REGTFP	0.428**	0.416**	0.416**
	(0.013)	(0.015)	(0.015)
$SECPCM_{t-1}$		-0.698*	
		(0.373)	
$REFPCM_{t-1}$			-0.379
			(0.244)
Const.	99.521**	89.292**	83.510**
	(33.842)	(39.246)	(38.949)

*Robust standard errors in parentheses **: significant at the 95% level; *: significant at the 90% level.*

Table 7 – Robustness test. Models for knowledge social interactions and creative reactions. Dependent variable: firm level total factor productivity. Model estimated in first difference with the GMM Arellano-Bond method.

	Model I	Model II	Model III
LAGTFP	0.459**	0.457**	0.458**
	(0.005)	(0.005)	(0.005)
REFTFP	0.379**	0.377**	0.375**
	(0.016)	(0.016)	(0.016)
OTHER_SECTFP	0.184**	0.183**	0.187**
	(0.017)	(0.018)	(0.018)
OTHER_REGTFP	0.240**	0.241**	0.244**
	(0.019)	(0.019)	(0.019)
$SECPCM_{t-1}$		-0.701*	
		(0.407)	
$REFPCM_{t-1}$			-0.454
			(0.293)
Const.	56.882**	56.82**	56.934**
	(2.532)	2.525	2.530
M1	-83.27*	-83.25*	-83.27*
M2	4.24	4.21	4.23
Sargan Test χ^2	5004.75**	5013.61**	5049.05**

***: significant at the 95% level; *: significant at the 90% level.*