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Cultural Diversity, Knowledge Diversity and Innovation

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Cultural Diversity, Knowledge Diversity and Innovation

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Abstract

The aim of this paper is to explore the impact of cultural diversity on innovation. In doing so, the paper investigates the interaction effects between cultural diversity, knowledge diversity and knowledge regime in an organizational context, where actors interact and exchange knowledge through networks. The underlying premise of the paper is that, the impact of cultural diversity on innovation depends on both the technological opportunities prevalent in the industry, and also the diversity in the competencies among actors. An agent based simulation study is carried out. In the model, networks form and evolve through the interactions between agents, through which they learn. The model investigates both the structural characteristics of networks that evolve, and the knowledge growth in the population, corresponding to varying degrees of cultural diversity and knowledge diversity. The results reveal that the extent to which cultural diversity yields more learning depends on the characteristics of the knowledge regime, as well as the extent of knowledge diversity within the population. In particular, in intermediate degrees of technological opportunities, cultural diversity has a negative impact on innovation.

Key Words: cultural diversity, innovation, network

1 Introduction

The impact of cultural diversity on innovation and creativity has long been an issue of debate in management and economics. According to the results obtained in this research field, cultural diversity is a "double-edged sword" (Milliken et al., 2003) which can have a positive or negative impact on innovation. Positive effects are related with increased synergies and spillovers which arise from the association of different viewpoints, and increased opportunities for knowledge recombination. Negative effects are related mostly to communication problems and problems which arise in conflict resolution.

The aim of this paper to explore the impact of cultural diversity on innovation. In doing so, the paper investigates the interaction effects between cultural diversity, knowledge diversity and knowledge regime in an organizational context, where actors interact and exchange knowledge through networks. The underlying premise of the paper is that, the impact of cultural diversity on innovation depends on the knowledge commonality between actors. Knowledge commonality is important, since it determines the extent to which actors can learn from each other (Schoenmakers and Duysters, 2006). In addition, the knowledge regime is influential in shaping the technological opportunities that are available in an industrial system. Amid this background, an agent based simulation study is performed. In the model, agents interact with each other and their interaction patterns are shaped by their cultural attributes. Networks form and evolve through the interactions, and through which agents learn. Depending on the parameter space defined by the technological opportunities, cultural diversity and the knowledge diversity of the population, the model investigates the innovative performance of the system.

In the first section, the background of the paper is presented. The second section presents the model and simulations performed. Third section is composed of results and discussion. Some concluding remarks follow.

2 Background

2.1 Diversity and Innovation

Diversity is considered as one of the most important ingredients of innovation (Schumpeter, 1934; Nelson and Winter, 1982). In organization studies, one of the questions that have attracted significant attention is concerned with the effects of diversity on firm performance (Harrison and Klein, 2007; Williams and o'Reilly, 1998). It is found in some studies that technological diversity can increase the innovative potential (Fleming, 2002; Garcia-Vega, 2006; Quintana-Garcia and Benavides-Velasco, 2008) through maintaining the availability of a broader set of alternative recombination paths (Weitzman, 1998; Carnabuci and Bruggeman, 2009). Miller et al. (2007) find that, knowledge transfer among divisions in technologically diverse firms increase the impact of inventions on subsequent technologies developed by the firms.

Nevertheless, some studies find that the level of knowledge diversity is critical. While too little diversity can be beneficial for economies of scale, it creates no opportunities for recombination (Van den Bergh, 2008). Leten et al. (2007) detect a curvilinear relationship between technological diversity and innovative performance, in which the coherence of technological areas plays a significant role in reducing costs of variety coordination. Similar results have been obtained as far as learning is concerned. When individuals or firms are too similar in terms of their knowledge bases, they can add few to each others' knowledge. At the same time, when they are too far, transfer of knowledge is difficult, hence learning is limited (Schoenmakers and Duysters, 2006). These studies imply that there is an optimal intermediate level of knowledge overlap between actors, which maximizes the level of knowledge transfer. This intermediate level of overlap also depends on moderating factors (Nooteboom et al., 2006). For example, exploratory innovation is commonly associated with regimes in which breakthrough innovations can be made, with little common knowledge overlap, underlining the positive impact of diversity. On the other hand, exploitative learning is associated with incremental innovations, in which parties have a high degree of knowledge overlap, in which case refinements in existing competencies is more likely than novel recombinations (Nooteboom et al, 2006).

Another strand of research focuses on the impact of cultural diversity on innovation. This literature is concerned with the business performance effects of multicultural teams in organizational contexts (Milliken et al., 2003; Cox and Blake, 1991) as well as, and on a more global scale, the impact of cultural diversity on economic performance (Audretsch et al, 2009). According to the findings of this literature, cultural diversity can have two opposing effects, thus it is a "double edged sword" (Milliken et al., 2003). On one hand, it can increase innovative potential, due to the synergies formed by integration of different viewpoints and thus culturally diverse teams can make better use of information (Dahlins et al., 2005; McLeod et al., 1996). The positive impact of cultural diversity on innovation has been shown in regional contexts (Gossling and Rutten, 2007; Niebuhr, 2009) and on creativity in entrepreneurial teams (Bouncken, 2004). On the other hand, cultural diversity can also have negative effects on innovation and creativity, due to difficulties in conflict resolution and identifying with the group (Milliken et al., 2003, Bouncken 2004), as well as problems of communication (Niebuhr 2009). The importance of cultural diversity is also mentioned in the context of EU Framework programmes, in which one of the policy priorities has been strengthening collaboration level in national and international arena. For example, for nanotechnology networks in EU funded programs, Pandza et al. (2011) confirm the significant collaboration intensity among different countries. Based on these two opposing effects, some studies investigate the moderating factors that shape this relationship like team size, task complexity and gender diversity (Stahl et al., 2010), as well as communication patterns (Grimes and Richard, 2003).

Amid these research streams, an important question remains: how do cultural diversity and knowledge diversity interact with each other in influencing innovative performance? In addition, does this interaction effect depend on the knowledge regime? To what extent the positive and negative impacts of different diversity constructs interact with each other in learning? These are some of the questions that this paper investigates. In doing so, we assume that networks are the main mechanisms through which diversity is leveraged. This is because actors interact and learn during their interactions, and diversity will impact learning only in a collaborative context. Networks, in return, are seen as representations of this collaborative context, which are themselves shaped by the actors. Therefore the next section explores the network research paradigm in relation to culture and knowledge.

2.2 Networks, Culture and Knowledge

In this section, we first explore the relation between culture and networks, and secondly the relation between knowledge and networks. In this paper, a network view is adopted to investigate the relation between cultural diversity and innovative performance. In sociology, the relation between culture and social networks has long been an area of debate, and several ways of looking at the relationship exist (Mische, 2011). One of these emphasize a causality between networks and culture. A largely established literature, for example, takes networks as shaping a cultural context, through social influence, and diffusing values, and identity formation (Bearman, 1993; Gould, 1995, Granovetter, 1985). The structuralist network paradigm focuses on the impact of network on any measure of performance, and underlying this approach is a structuralist perception of social systems (Granovetter, 1985). More recently, studies look at the cases when the causality is reversed; examining the impact of culture on networks (Lizardo, 2006; Pachucki and Breiger, 2010; Srivastava and Banaji, 2011). According to this literature, cultural tastes and values which are embedded cognitively shape the structure of networks in different contexts (Srivastava and Banaji, 2011). As different from the sociological studies, in the management literature, culture is taken in a more tangible and measurable way, by referring to different nationalities in organizational contexts. In this literature, cultural diversity usually refers to, as we have covered above, diverse nationalities and ethnic groups.

Given this background, in this paper, cultural attributes are taken as drivers of networks. In return, these *emergent* networks shape learning and innovation in the system. We believe that such an approach is particularly suitable for cultural diversity, since the relation between networks and cultural context requires a bottom-up approach in which the formation of networks, and the cultural context is intermingled, and in which they coevolve.

While culture can be taken as one of the drivers of networks, in management and organization theory, knowledge of actors is also seen to shape the structure of networks, through learning (Ozman, 2010). In particular, organizational learning theories posit that, during the phases of exploratory and exploitation learning (March, 1991), networks are a means through which firms, or inventors access each others knowledge, through which they explore and exploit different knowledge bases, and through which they learn new competencies or strengthen existing ones (the leading study in this field is by Powell et al., 1996). In accordance with this research tradition, this paper also addresses questions about networks. What kinds of networks emerge and evolve, depending on the knowledge and cultural diversity in a population, under different technological regimes? How do these networks relate to overall learning?

Figure 1 shows the theoretical framework of the study. In this framework, the relation between diversity and innovation is analysed through networks since they form the main means through which diversity of the population shows its impact on innovation. In this sense, people communicate, share and build new knowledge through their networks, and their diversity is manifested during these interactions.

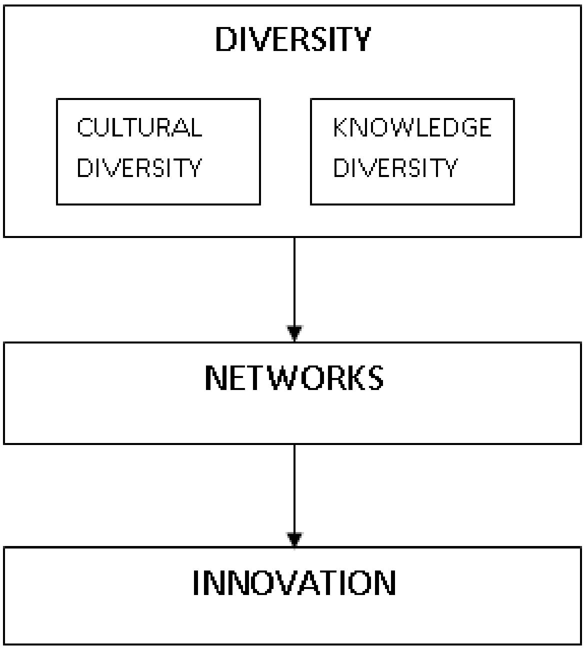

Figure 1: Conceptual framework of the model

As different from other studies on diversity, this paper considers the interaction effects between two different diversity constructs, as cultural diversity and knowledge diversity.

3 The Model

The aim of this model is to address the following questions, through an agent based simulation study.

1. How does cultural diversity and knowledge diversity interact with each other as far as they effect learning?
2. How does this interaction depend on the knowledge regime?
3. In a parameter space defined by knowledge regime, cultural and knowledge diversity, what are the structural characteristics of the networks that form and evolve, when agents select partners according to their self interest, and cultural attributes?

There are two stages in the model. In the first stage, agents select partners, and networks form. In the second stage, agents learn from their partners and knowledge diffuses. Below, each sage of the simulation model is explained.

3.1 A Brief Overview of the Model

There are N agents, and K knowledge fields. In a single simulation run, each agent i has different levels of knowledge in different fields, and the initial knowledge levels in each field is determined in a random way in the beginning of each simulation. Each agent assigns a value to his/her partnership with each of the other agents. This value is a function of the agent's cultural attributes, and his common knowledge level with the potential partner. Cultural attributes are taken as uncertainty avoidance and individualism (Hofstede,2001) . Agents send invitations for collaboration to each other, and the probability that a partnership will form depends on the values they assign to each other. From these collaborations, agents learn and their knowledge levels are updated. In the next simulation period, they allocate new values to each other agent. In this way, one simulation run consists of approximately 100 periods. The simulation model investigates the impact of the following parameters in the resulting knowledge levels: 1. The diversity in the cultural attributes of the population 2. The technological opportunities in the knowledge regime and 3. the distribution of knowledge among agents.

3.2 Partner Preferences

An agent i assigns the value v_{ij} to his/her partnership with j. This value depends on his general attitudes towards knowledge partnerships (which is assumed to be shaped by cultural variables), and the similarities in their knowledge base. Two cultural variables are taken into account (Hofstede, 2001). The first one is related with uncertainty avoidance. The second one is related with individualism.

In particular, v_{ij} is constructed according to the following assumptions:

1. The more individualist the agent is, the lower value he assigns to a partnership

2. The more the agent is inclined to avoid uncertainty, the less is the marginal value of a one unit of increase in the number of past collaborations with the same partner.

3. The more similar is the knowledge bases of the agent with the potential partner, the more value he assigns to the partnership. In other words, agents are homophilic in their preferences, and they wish to form partnerships with agents who are similar in terms of knowledge endowments. v_{ij} is given by:

$$v_{ij} = f_i(c_i, u_i, h_i)m_{ij} \tag{1}$$

here, $f_i()$ refers to agent i's attitude towards collaboration, and m_{ij} refers to the similarity in the knowledge endowments of agents i and j. More on the function $f_i()$ in the next section.

3.2.1 Cultural attitude towards collaboration: collectivism and uncertainty avoidance

In particular, $f_i()$ measures two dimensions of agent i's attitude towards collaboration. The first dimension is related with collectivism (c_i), which increases the agent's openness to collaboration. The second dimension is related with uncertainty avoidance (u_i). It is assumed that, uncertainty avoidance is reflected in the extent to which the agent develops trust as a function of past meetings. Agents with a high value of the uncertainty parameter (u_i) are assumed to require a larger number of past meetings to allocate a certain value to a potential partner. These two dimensions are included in $f_i()$ in the following way:

$$f_i(c_i, u_i, h_i) = \frac{c_i}{1 + e^{u_i h_{ij} - m}} \tag{2}$$

In particular, in Equation 2, c_i measures the extent to which agent i is "open" to collaboration with agent j, and u_i measures his sensitivity to the number of past meetings, and h_{ij} refers to the number of times i and j have collaborated in the past. In particular, the more collective is the agent, and the more the two agents have met in the past, the higher is the value that agent i assigns to the partnership. In addition, the sensitivity of openness to the number of past meetings is determined by the uncertainty avoidance parameter of agent i, as given by u_i. Figure 1 shows function $f_i()$ with respect to past meetings, and for different values of c_i and u_i.

In Figure 2, as the number of past collaborations increase, the value that agent i assigns to his collaboration with j increases ($\frac{\partial f()}{\partial h} > 0$). Higher values of c_i indicate increased willingness of agent $i$to form a collaboration with agent j, for a given number of past collaborations. At the same time, the parameter u_i determines the importance that agent i assigns to past meetings. For a given c_i value, higher absolute values of u_i reflects that the marginal increase in the number of past meetings increases the value assigned to the partnership significantly, compared to lower values of u_i,

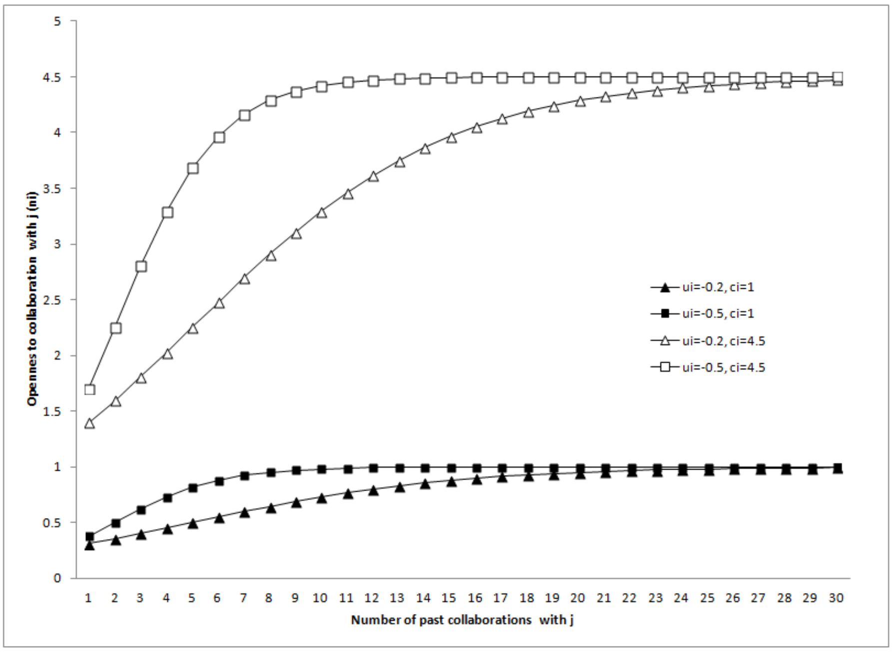

Figure 2: Openness to collaboration and number of past collaborations

where many additional meetings are necessary to achieve the same increase in value of partnership. In other words, people with low u_i parameters are uncertainty avoiders in their attitudes to collaboration. This is given by the exponential function, for which the second derivative of f with respect to h,

$$\begin{aligned} \frac{\partial^2 f()}{\partial h^2} &> 0 \quad \text{for } h < m/u \\ \frac{\partial^2 f()}{\partial h^2} &< 0 \quad \text{for } h > m/u \end{aligned}$$

After sufficient meetings, the marginal value of an additional partnership falls, for all values of u.

3.2.2 Knowledge similarity

While cultural parameters c_i and u_i measure the agent i's attitude towards collaboration, m_i measures the value he/she assigns to the partnership based on their knowledge similarities. It is assumed in the model that agents attribute a higher value of collaboration to other agents with similar knowledge endowments. The second term in the RHS of Equation 1, m_i indicates the similarity in the knowledge bases of agents i and j. In the model agents are endowed with a knowledge vector $\overrightarrow{\mathbf{k}}$, of size K, initially drawn from a uniform distribution, and where k_{ik} shows the level of expertise of agent i in field k. The commonality in the knowledge bases of two agents i and j is given by the *cosine index*:

$$\cos_{ij} = \frac{\sum_{k=1}^{K} k_{ik} k_{jk}}{\sqrt{\sum_{k=1}^{K} k_{ik}^2} \sqrt{\sum_{k=1}^{K} k_{jk}^2}} \tag{3}$$

Cos_{ij} ranges between the value of 0 and 1. As the commonality in the knowledge base of two agents fall, Cos_{ij} approaches zero.

3.3 Network Formation

Each agent i assigns a value of collaboration to all other agents, $j = 1.....N$ $(i \neq j)$, as explained in the previous section. In the model, networks form by agents sending invitations to each other to form a partnership. The probability that agent i sends an invitation to agent j is proportional to the value he assigns to their partnership, which was determined in the previous section, in Equation 1. The probability that the invited agent will accept the invitation is also proportional to the value he assigns to their partnership with i. Although the number of past meetings and knowledge similarity is symmetric for the two agents, because their attitudes to collaboration may be different, their corresponding values that they assign to each other are asymmetric. Therefore, if the invited agent assigns a low value to the partnership, he/she is likely to reject the invitation. In this way networks form. It is important to note that, in a single simulation period, an agent can have many partnerships, or none at all. After partnerships, agents learn from each other.

3.4 Learning in Networks

In the first stage of the model, partnerships form. In the second stage, agents learn from their partners, by augmenting their knowledge endowments. In the following simulation period, they form partnerships with their updated knowledge levels. Here it is assumed that when agents are making their decisions about partners, they have an estimation of the similarity in knowledge levels, but they are not farsighted enough to estimate what they can learn from their partners, given the combination of their own knowledge and the partner's knowledge. At the end of one period, agent i learns from the collaboration with firm j according to[1]

$$k_{i,kt+1} = k_{ikt}\left[1 + \mathbf{y}\left(k_{ikt}, k_{jkt}\right)\right] \tag{4}$$

where, $k_{ik,t}$ refers to agent i's knowledge in field k, in period t .In this function, $\mathbf{y}\left(k_{ikt}, k_{jkt}\right)$ is specified as,

$$g\left(k_{ikt}, k_{jkt}\right) = \max\left\{0; r_{ik,j}^{\gamma}\left(1 - r_{ikj}\right)^{\gamma}\right\}$$

with

$$r_{i,j} = \frac{k_{i,t}}{k_{j,t}} \tag{5}$$

According to Equation 4 the extent of learning depends on two factors. Firstly, the relative knowledge levels between i and j in field k, and second, technological opportunities which is a knowledge regime parameter given by γ (Cowan et al., 2004 and Ozman, 2008). According to this specification, if agent i knows more than agent j in knowledge k, his/her final knowledge does not change. The increment to the knowledge of agent i decreases the less is his/her relative knowledge level compared to j. Depending on the knowledge regime parameter γ, an agent i can also leapfrog an agent j, in which case his final knowledge will be higher than the previous knowledge of j. This is modeled as the creation of new knowledge.

Parameter γ measures two aspects of learning: diffusion and innovation (Cowan et al., 2004; Ozman, 2008). Figure 3 shows the relative knowledge levels before and after collaboration according to this function. In particular, for higher values of γ new knowledge, aver and above that of existing partner is created. On the other hand, for low levels of relative knowledge, learning is in the form of diffusion.

Once diffusion occurs, knowledge levels of agents are updated, and in the next period, process of partner selection is repeated. We look into the types of networks that emerge and the distribution of knowledge among firms, in the parameter space defined by technological opportunities, the characteristics of the population in terms of heterogeneity in cultural attitudes in terms of collectivism and uncertainty avoidance.

[1] Here, we use the time subscript (t+1) because this updated knowledge level will be used in the partner selection process of the next period (t+1).

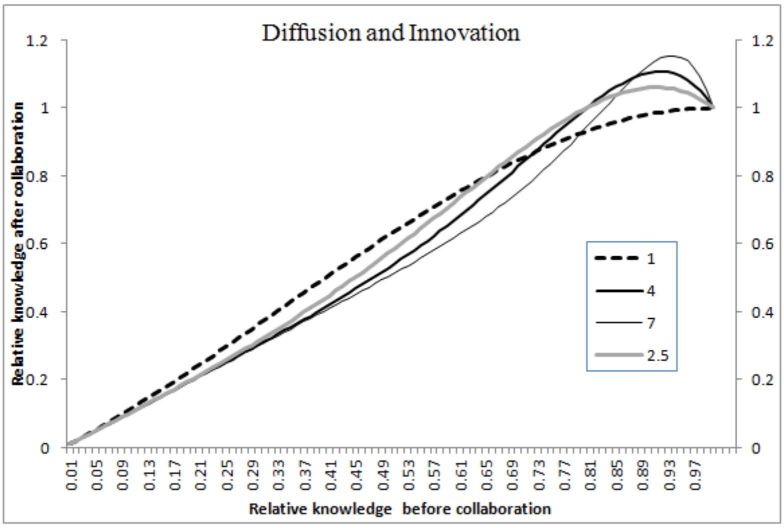

Figure 3: Technological opportunities: diffusion and new knowledge creation

3.5 A Summary of the Simulation Model

There are N agents, each of which is endowed with a knowledge vector $\overrightarrow{k}$, assigned randomly in $t = 0$. The size of the knowledge vector is $K = 100$; in other words, agents can be knowledgeable in 100 different knowledge areas. One simulation run lasts 100±10 periods. A total of 5 simulations are run, for each point in the parameter space. Each simulation is a different combination of three parameters. These are:

1. The technological opportunities parameter $\gamma \in [1, 7]$ which determines knowledge regime.

2. The knowledge diversity parameter $\beta \in [0.1, 0.8]$, which measures the average number of knowledge fields for each agent which is greater than zero. In particular, this parameter is used in assigning the initial values of knowledge fields. Each knowledge field of each agent, is assigned according to the following probability

$$P(k_{ik} > 0) = \beta$$

Therefore, a regime with high diversification includes agents who are knowledgeable in a diverse range of fields, thereby it is more likely that two agents will be more similar to each other (i.e. having a high value of $\cos_{ij}$).In this sense, low values of β indicate a population with high knowledge diversity.

3. The cultural diversity parameter α. It determines the characteristic of the

whole population, in terms of the homogeneity of cultural variables collectivism and uncertainty avoidance (c_i and u_i). In particular α is determined in the following way:

$$\alpha = (c_{\max} - c_{\min}) + (u_{\max} - u_{\min})$$

where, $[c_{\min,} c_{\max}]$ indicate the bounds of the collectivism parameter in the simulation run, and $[u_{\min,} u_{\max}]$ indicate the bounds of the uncertainty avoidance parameter. The higher is the range between the maximum and minimum values of these parameters, the more heterogeneous the population is, in terms of cultural parameters. In other words, the max and min values set the limits of the collectivism and uncertainty parameters any agent can have in the population. These values are assigned randomly in the beginning of the simulation run, where, for agent i, $c_i \in [c_{\min,} c_{\max}]$ and $u_i \in [u_{\min,} u_{\max}]$.At the same time, a smaller range implies similarity in terms of cultural attributes. In the simulations, the following ranges are used. For a population with minimum cultural diversity: $[c_{\min,}\ c_{\max}] = [2.9, 3.1]$ and $[u_{\min,} u_{\max}] = [-0.4, -0.5]$.For a population with maximum cultural diversity: $[c_{\min,}$ $c_{\max}] = [1.5, 4.5]$ and $[u_{\min,} u_{\max}] = [-0.05, -0.85]$.Corresponding to these limits, the cultural diversity parameter $\alpha \in [0.3, 3.8]$[2].

4 Results

The results of the simulations are presented in three parts. In the first part, results are given in the parameter space cultural diversity and technological opportunities; in the second part, results are analysed with respect to knowledge diversity and technological opportunities. The third part analyzes the interaction effect between knowledge diversity and cultural diversity. In these spaces, three variables are analysed. The first one is the average knowledge growth, which measures the growth of knowledge per period in a simulation run, averaged over all agents. The second variable is network density; which measures the intensity of interactions between different agents. It is measured by taking into account the final networks at the end of simulation runs. It is given by,

$$D = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} x_{ij}}{N(N-1)}$$

[2]Limits found by in the following way: (3.1-2.9+0.5-0.4=0.3) and (4.5-1.5+0.85-0.05=3.8).

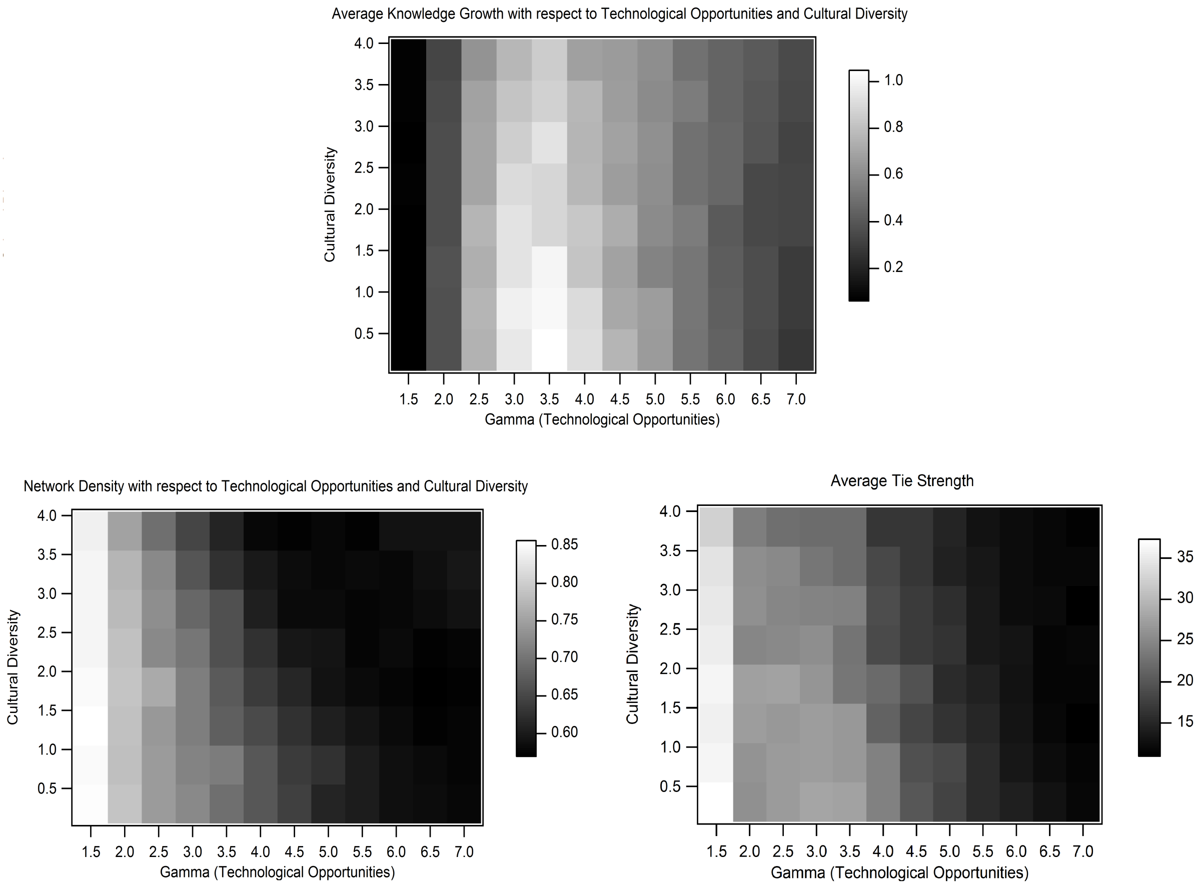

Figure 4: Cultural Diversity and Technological Opportunities

where $x_{ij} = 1$ if there is an edge between i and j and 0 otherwise and N is the total number of nodes. The third variable is tie strength. It measures the average number of times two agents interact with each other; measuring the extent to which ties are repeated between the same agents.

4.1 Cultural Diversity and Technological Opportunities

Figure 4 shows average knowledge growth, network density and strength of connections in the parameter space defined by cultural diversity and technological opportunities.

Firstly, average knowledge growth is highest in the intermediate of technological opportunities. In other words, very high technological opportunities and very low technological opportunities yield less knowledge growth. As explained in the previous sections, technological opportunities have two dimensions, opportunities for diffusion, and new knowledge creation. Intermediate levels of technological opportunities correspond to regimes in which both knowledge diffusion and new knowledge creation exists. High technological opportunities on the other hand, correspond to regimes in which new knowledge creation is dominant. These results show that in regimes where both diffusion and new knowledge creation characterizes the knowledge regime, cultural diversity has a negative impact on knowledge growth. In the other regions, the impact of cultural diversity on knowledge growth is less pronounced.

When one looks at the results with respect to network density, it is possible to observe that, high technological opportunities tend to reduce the extent to which different agents interact, and also the strength of the existing interactions. In other words, collaboration is less. This also depends on cultural diversity. In general, cultural diversity reduces interactions, as evident by reduced network density and tie strength. However, there is an interaction effect between technological opportunities and cultural diversity. As technological opportunities increase, the negative impact of cultural diversity on network density is enhanced. In other words, cultural diversity of the population has more important impact on interactions. As technological opportunities reduce, increasing cultural diversity promotes interactions in the system, and network density increases (observe the diagonal line in Figure 4 showing network density). Cultural diversity promotes interactions for low degrees of technological opportunities. Yet, surprisingly, this increase in interactions is only partly reflected in average knowledge growth levels. While interactions are highest when technological opportunities are low, knowledge growth is very limited in this area.

Surprisingly, network dynamics and knowledge dynamics follow different patterns with respect to technological opportunities. In particular, the highest interactions occur in the system when technological opportunities are low, yet this does not imply highest knowledge growth (compare the left hand side of figures showing knowledge growth and network density in Figure 4). This can be explained by tie strength.

The strength of network connections show how many times on the average two agents interact. When strength is high, it connotes a network regime in which repeated interactions occur frequently. In Figure 4, it is possible to observe that, strength of connections are highest when technological opportunities are low. In other words, when there is solely knowledge diffusion in the system, with minimum opportunities for new knowledge creation, agents tend to repeat their interactions with the same partners. This is also one of the reasons why knowledge growth is limited.

The level of interactions in the system is also a function of knowledge diversity. This is why one also needs to look at the interaction effects between knowledge diversity and technological opportunities to be able to further interpret the results.

4.2 Knowledge Diversity and Technological Opportunities

Figure 5 shows the knowledge and network dynamics in the parameter space defined by technological opportunities and knowledge diversity. Here, the horizontal axis measures the knowledge homogeneity in the population, given by β. Figure 5 also confirms the results in the previous section. In particular, in mid-levels of technological opportunities, knowledge growth is highest. This is the region where there is both the diffusion of existing knowledge, and also creation of new knowledge. At the same time, Figure 5 highlights the role of knowledge diversity in this result. Highest knowledge homogeneity in the population, combined with mid levels of technological opportunities produce the highest knowledge growth Stated differently, high knowledge growth can be achieved when agents have many common knowledge fields, and in a regime in which this knowledge both diffuses, as well as there are rich opportunities for leapfrogging each others' knowledge.

Combined with the results in the previous section, these results show that, highest knowledge growth occurs when agents are similar both in terms of their knowledge, and in terms of their culture. Yet, these are not sufficient; both diffusion and new knowledge creation should characterise the knowledge regime.

One of the implications of these results are concerned with a widely established view in the learning literature, which is concerned with an inverted-u relation between learning and knowledge diversity in a population. According to this view (Mowery et al, 1998; Schoenmakers and Duysters, 2006, Nooteboom et al, 2007) when agents are too similar, there is limited learning, because they cannot add to each others'knowledge. Learning is also limited when agents are increasingly dissimilar, because then communication is limited. Our results reveal that this optimal degree of knowledge diversity depends on technological opportunities in the system. The results confirm the inverted- relationship only when technological opportunities are low (in Figure 5, note that until $\gamma = 3$, mid levels of knowledge diversity yield highest knowledge growth). In addition, as Nooteboom et al. (2007) find, exploitative innovation is associated with increased knowledge overlap between actors. Our results reveal that, as technological opportunities increase beyond a certain limit, the extent of exploitative innovation between parties having similar knowledge levels, also reduces (observe the upper right parts knowledge growth graph in Figure 5).

With respect to network density, it can be seen in Figure 5 that, knowledge commonality increases interactions. There is also a strong interaction effect between technological opportunities and knowledge commonality (as evidenced by the diagonal band in Figure 5, showing network density). When technological opportunities are low (where knowledge only diffuses, with few opportunities for new knowledge creation), mid levels of knowledge commonality yields densest interactions. As technological opportunities get richer, higher degrees of knowledge similarity is required to increase interactions in the networks. A similar result can be observed for network strength in Figure 5. It is interesting to note that, there is a region in which network density is very low, and network strength is relatively high (left parts of figures showing network density and tie strength). In this region, agents interact with the same partners throughout, which limits knowledge growth.

4.3 Cultural Diversity and Knowledge Diversity

Finally Figure 6 shows the knowledge and network dynamics in the parameter space defined by cultural diversity and knowledge diversity. Firstly, average knowledge growth is highest when both cultural diversity and knowledge diversity is low. In other words, homogeneity in terms of culture and knowledge yields the highest knowledge growth (note that, these results are obtained by taking the average values of technological opportunities in the parameter space). However, interestingly, tie strength and network density follow different patterns. The highest rate of tie repetition occur at mid levels of knowledge diversity, or when complementarities between agents are highest.

The results reveal that, there is an interaction effect between knowledge diversity and cultural diversity. Firstly, knowledge growth is highest in populations characterised by cultural and knowledge homogeneity. At the same time, the interaction effect reflects that, when knowledge diversity is high, cultural diversity has no impact on knowledge growth. As agents become more and more similar in terms of

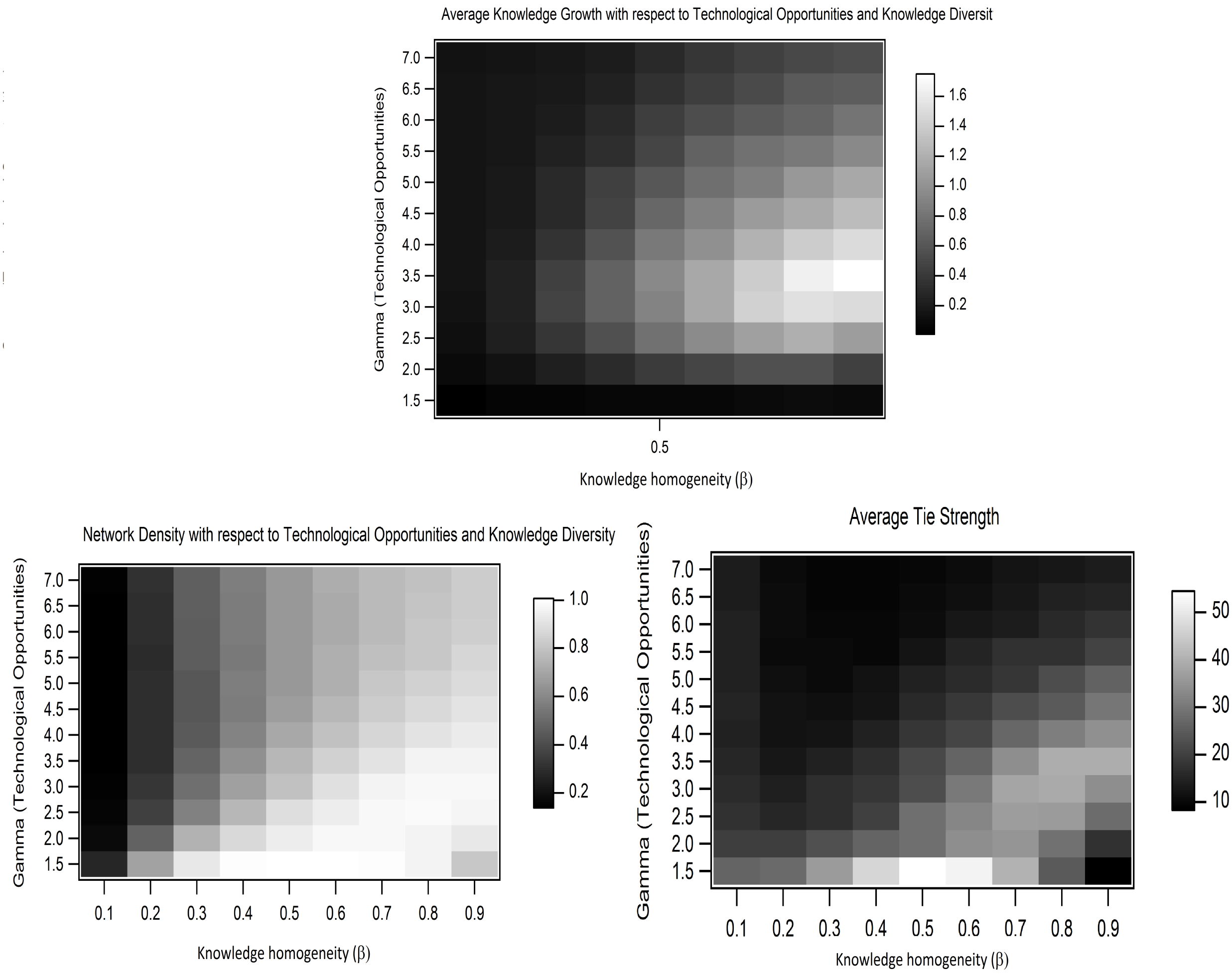

Figure 5: Knowledge Diversity and Technological Opportunities

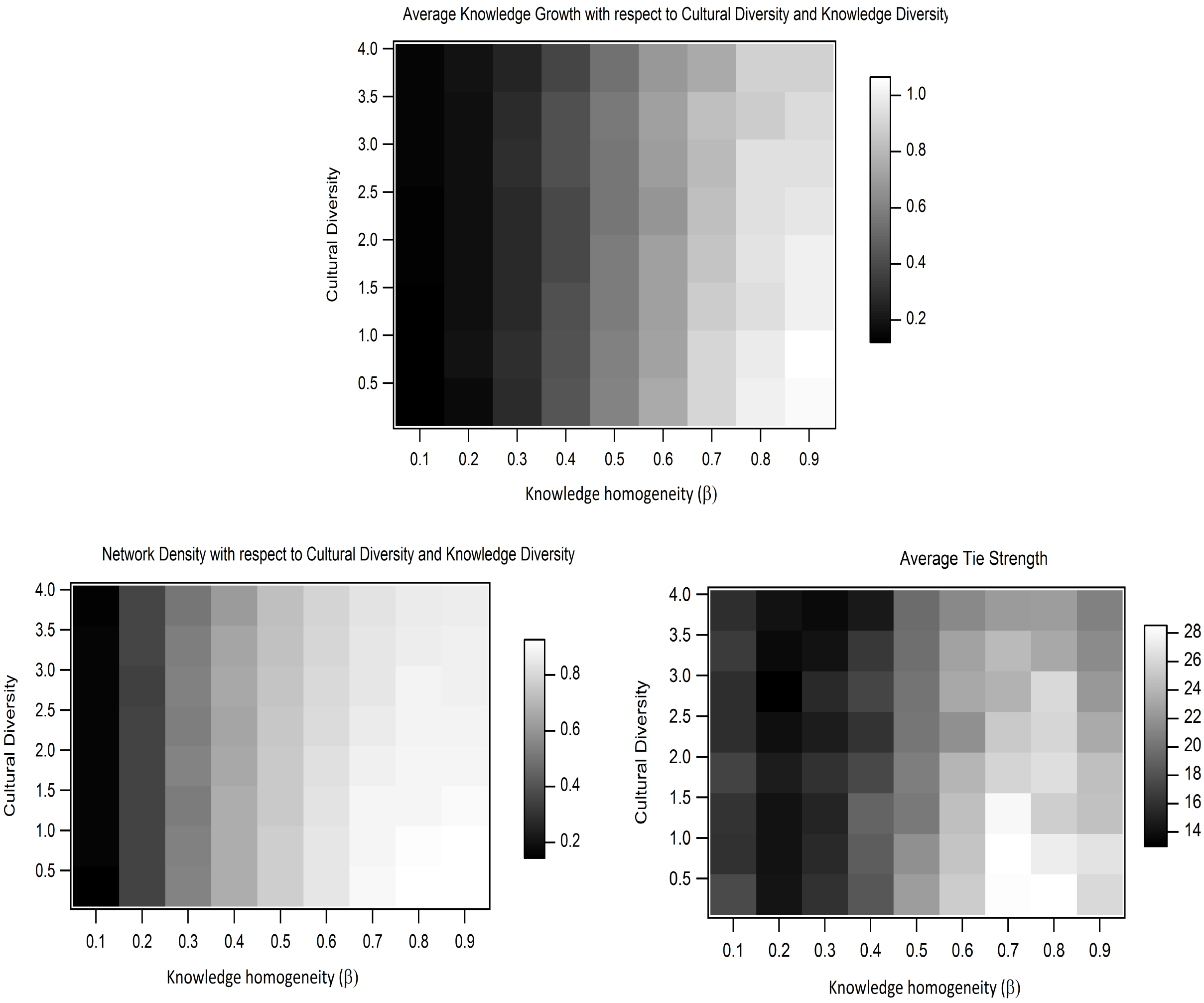

Figure 6: Cultural Diversity and Knowledge Diversity

their knowledge, the negative impact of cultural diversity on knowledge becomes more pronounced. In other words, if a population is characterised by high knowledge similarity (right sides of Figure 6 showing knowledge growth), cultural diversity has stronger negative impact on knowledge growth. To explain this, it is better to observe network density. A similar pattern is observed, whereby interactions get more dense as similarities in knowledge increases, yet, increasing cultural diversity has an effect of reducing the extent of interactions between different agents. As far as network strength is concerned, the interaction effect between cultural diversity and knowledge diversity is also pronounced. As a general rule, cultural diversity reduces ties strength. In other words, when cultural diversity is high, agents have less tendency to repeat interactions. At the same time, knowledge diversity also tends to reduce tie strength.

5 Conclusion

In this paper, the impact of three constructs on knowledge and networks is investigated. These constructs are, cultural diversity, knowledge diversity and technological opportunities in an industry. Although the impact of these factors on innovation has been studied in separate literature strands in previous literature, how they interact with each other in a dynamic setting, where networks form endogeneously, has not been studied before. In this sense, the results of the paper highlights some interesting interaction effects between cultural diversity, knowledge diversity and innovation. Overall, the results of the paper reveal that the impact of cultural diversity on innovation depends on the existing technological opportunities, and how the knowledge is distributed in a population of agents. The simulation exercise consists of a population of agents, who select partners for knowledge exchange and learning. Partner selection depends on the attitude of agents towards knowledge sharing, which we modeled as determined by the cultural attributes. In addition, partner selection depends on the knowledge complementarities between the agent and the potential partners. In the model, agents form partnerships, they learn from each other, their knowledge levels are updated, and with the updated knowledge levels they select new partners. In this way, networks form. The paper addressed three questions in such a regime. First question is concerned with the impact of the diversity in cultural attributes of the population on knowledge growth and networks. Second question is concerned with the impact of knowledge diversity of the population on knowledge and networks. Finally the third question is concerned with how these effects are shaped by the surrounding knowledge regime, which we characterised by technological opportunities.

The results of the simulation study reveal that the impact of cultural diversity on innovation depends on knowledge diversity and technological opportunities. Distinguishing between three knowledge regimes, low technological opportunities characterise a system in which there is only knowledge diffusion, and weak opportunities for knowledge creation. In a high technological opportunity regime, the dominant form of innovation is continuous creation of new knowledge. In the intermediate technological opportunity regime, innovation landscape is characterised by both diffusion and new knowledge creation. Real world examples from such regimes would be on one side, traditional low tech industries, in which innovation intensity is lower than others. The case of industries with high technological opportunities correspond to cases like the software, in which a certain "software code" can be used in a variety of different contexts, which connote an industry with continuous new knowledge creation. Other industries can fall in between these two extremes.

The results reveal that, cultural diversity has a negative impact on the knowledge growth, in intermediate degrees of technological opportunities, where there is both diffusion and new knowledge creation. Knowledge diversity also has a similar effect on innovation. In such knowledge regimes, homogeneous populations yield highest knowledge growth. The underlying reason behind this result can be related to the networks of actors. In particular, in the model knowledge growth happens through networks. It is found that, high degrees of cultural diversity tends to reduce the extent of network density between a variety of agents. A similar result is obtained for the impact of knowledge diversity, which reduces the extent of partnerships between a different agents. According to the results of the simulation analysis, there is also an interaction effect between knowledge diversity and cultural diversity. In particular, the highest knowledge growth, and the highest level of interactions occur when both cultural diversity and knowledge diversity is minimum.

How can these results be interpreted in the context of existing literature? Two conclusions can be drawn. Firstly, the impact of cultural diversity on innovation is found in the literature to be a "double edged sword" (Milliken et al., 2003), emphasizing both potential advantages, and disadvantages of cultural diversity. In this paper, we showed that this largely depends on the other characteristics of the industrial system, like the knowledge diversity and technological opportunities. Even if cultural diversity has a negative impact on knowledge, this negative effect can be partially offset by a more homogeneous distribution of knowledge among actors. Secondly, the negative side of the double edged sword is especially valid in industrial regimes with intermediate degrees of technological opportunities. Finally, the paper also shows that, the impact of knowledge diversity on innovation depends on technological opportunities. The generally accepted idea of an inverted-u relation between knowledge similarity and learning (Schoenmakers and Duysters, 2006) is valid only in certain knowledge regimes, where technological opportunities are relatively low.

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