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Interactive knowledge exchanges under complex social relations: A simulation model

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INTERACTIVE KNOWLEDGE EXCHANGES UNDER COMPLEX SOCIAL RELATIONS
A SIMULATION MODEL[1]

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ABSTRACT

This is a model of knowledge exchange by means of informal interaction among agents in low technology clusters. What this study seeks to do is to colour these exchanges by placing them in an environment of complex social relations, test whether the small-world network structure is the most favourable for knowledge exchanges in these environments, and explore the influence of social relations and network distance. These enquiries are the contribution of this model to the existing series of studies on efficient network structures for knowledge diffusion. We find that the small-world network structure may not be the best network structure for highest and most equitable knowledge distribution, when knowledge exchanges are undertaken in environments of complex social relations. Also, we confirm that the highest and most equitable knowledge distribution is achieved when there is perfect affinity among the agents.

KEYWORDS: Knowledge Exchanges, Small-Worlds, Social Networks, Complex Social Relations
JEL CLASSIFICATION: O33, Z13

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1. Introduction

This is a model of knowledge exchange by means of informal interaction among agents in low technology clusters, these clusters constituting a vast majority in a developing country like India. These clusters survive primarily on informal information exchanges, without which agents would be trapped with obsolete knowledge, and would never be able to source the new knowledge required to progress towards the technology frontier at which their peers are operating. The appreciation of knowledge exchanges by means of informal interaction through social networks is not superficial any more in the knowledge diffusion literature, and hence this study does not seek to re-investigate simple barter-like knowledge exchanges. What this study seeks to do is to colour these exchanges by placing them in an environment of complex social relations, test whether the small-world network structure is the most favourable for knowledge exchanges, and explore the influence of social relations and network distance.

Studies in the past (such as those by Cowan and Jonard) on knowledge diffusion across networks deal with the importance of network structure for equity and efficiency of knowledge distribution – an enquiry that remains necessary when we deal with rural traditional-technology clusters whose only source of new knowledge is by informal interaction. But the analysis has to be extended by setting it in environments of complex social relations that are often inevitable in this category of clusters. On the one hand informal knowledge exchanges may be clean and untouched by any sort of social barriers among units that are relatively homogeneous in their economic and social attributes (as in an environment of perfect affinity between agents), while on the other hand, these exchanges may arise as emergent properties of the social differences in a more heterogeneous environment (as in a regime of complex social relations, or, at an extreme, of severe homophily). Even today, in traditional technology clusters, long existing social prejudices and affinities may still hold and may influence knowledge exchanges. It might pay for agents to cross these long existing social group demarcations to access new knowledge, but probably not always since reciprocity, value introjection and solidarity may take primacy over economic self-interest. It is in these environments that the often established supremacy of the small-world network structure is tested in this study.

Hence, this study has two objectives. First, we test the hypothesis that the small-world network structure is still the most efficient for information diffusion through informal knowledge exchange in a cluster even in a complex social relations environment. And second, we explore the effect of – (1) intensity of social relations in a cluster, and (2) influence of network distance as a concern among knowledge exchanging agents – on the performance of the cluster. These enquiries are the contribution of this model to the existing series of studies on efficient network

structures for knowledge diffusion. In the next section, we review the background to this study, by visiting studies on informal knowledge exchanges, network structure and efficient diffusion of knowledge.

2. Network Structure and Efficient Knowledge Diffusion

2.1 Informal Knowledge Exchange and Networks

Exchanging new knowledge on the latest and best production practices and technologies, on a continuous basis, free of monetary cost, even to rivals, has often been considered by economists as "an undesired 'leakage' that reduces the incentives to invent" (Allen, 1983:21). But this activity is neither undesired, nor a leakage, and certainly does not reduce the incentive to invent. It is, according to Allen, an oft invoked practice of pursuing free release and exchange of information, since it is almost impossible and often expensive to keep knowledge as a secret and may sometimes work to the knowledge-giver's professional advantage to actually release the information[4]. Most information flows through informal channels of word-of-mouth knowledge exchanges and through social circles (Allen et al., 1983). In this environment, low-tech producers do not perform R&D as a continuous activity with internal investment exclusively dedicated to it; rather, they *satisfice*, i.e., they undertake a conscious local search among their co-located and connected peers for improvements to their present technologies and production practices, especially when performance is below par compared to observable peers (Romijn, 1999).

According to Cowan (2004), social space matters for knowledge exchange and diffusion and can best be understood in the context of networks. Agents acquire new information and learn more through their networks than through codified sources; "whom you know" has a significant bearing on "what you know", this being one of the most consistent findings in social science literature (Cross et al., 2003:8). Especially for low-tech firms, networking becomes a lifeline for survival and endurance. This was recognized by Allen et al. (1983), who proposed that networks developed in many industries for the sole purpose of disseminating information. If broadcasting information to 'those you know', 'those you trust', and 'those who are guaranteed to reciprocate' is a vital process of a region's existence and growth, the structure of the networks that form this region become vital for performance (Cowan and Jonard, 2003). Bougrain and Haudeville (2002) describe how networks allow small units to decode and appropriate large flows of information since they provide for the observation of strategic choices made by peers. Personal networks, Bougrain and Haudeville say, assist in transfer of tacit knowledge, as knowing 'who holds the

[4] See also von Hippel (1987, 1988) who wrote extensively on 'informal cooperative R&D', involving routine and informal trading of information, between even direct rivals.

information' is decisive in tough situations. Also, whether these networks are formal or informal, they help small units reduce the uncertainties and costs of irreversible decisions and resource allocations, by having access to new knowledge and to more experienced actors in the arena.

While codified knowledge can be diffused impersonally, the diffusion of tacit knowledge, especially if broadcast over a small space and over a few selected recipients, is heavily dependent on the structure of and relations within localized, informal information networks (Cowan and Jonard, 2003; Cowan, 2004). Individuals may adopt new knowledge or accept new production practices by gathering information from those whom she interacts with frequently – often neighbours – which on an aggregate, shapes innovation and learning in a region (Bala and Goyal, 1998; Goyal, 2007). It can therefore be proposed that interactive learning is essentially an emergent property of network structure and relations, especially where agents prefer learning through networks than through codified sources.

The idea of social networks shaping business and production relations between economic agents is not new, and rich strands of literature in economic sociology and management research have been devoted to it. The nature of knowledge exchange is often contingent on the social identity of the economic agents exchanging it, as work by Brian Uzzi (1996, 1997, for instance), among others, have illustrated in detail. Hence, production and exchange relations cannot be disregarded as being peripheral to social relations, and they may even develop as its emergent properties. Rogers, in his *Diffusion of Innovations* (Rogers, 1995), had stated that the ability of an economic agent to learn or innovate has been found to be affected not only by individual character but also the nature of the social system in which the agent is a member. That is, economic activities are, in most cases, embedded in social relations. Hence, investigating the effect of community character emerges as important as investigating into individual agent behaviour (Akçomak, 2009).

Networks gain prominence here, serving as vehicles not only for learning but also for reinforcing social norms and values, defining the nature of the social capital of the region. Networks act in a dual role as vehicles for knowledge exchange as well as for reinforcing social norms and values. They become a cluster's principal component and the vehicle on which learning is facilitated. Consequently, investigation into social networks emerges as more than just an appealing metaphor or vocabulary by providing a precise way to test theories and propositions about social relationships (Wasserman and Faust, 1994).

2.2 Network Structure and Knowledge Diffusion

To understand learning, diffusion and innovative performance especially where tacit knowledge is freely exchanged or bartered to a subset of potentially interested agents, network dynamics and the structure of the network have to be examined, for which network models of diffusion provide an ideal venue (Cowan and Jonard, 2003; Cowan, 2004). A series of papers by Cowan and Jonard (Cowan, 2004; Cowan and Jonard, 2003, 2004, 2007) on knowledge diffusion across networks provide the basis for the model and analysis in this paper. In these models, the network structure is the pivotal element that decides the nature of knowledge exchanges and long run performance (in terms of mean knowledge level in the system, and speed and equity of knowledge distribution). They demonstrate that while short paths (and therefore a random network) diffuse knowledge the fastest, and that cliquishness brings about advantages that provide the very basis for clusters, it is generally a small-world network structure – employing the advantages of both short path lengths and cliquishness – that reigns. A small-world network[5] is a type of network structure which enjoys the best of local cohesiveness with proximity (which provide for rapid initial growth agents) as well as distant links (to access knowledge beyond the immediate locale which provide for continued growth) (Cowan, 2004). This result rigorously demonstrates an old theme in the diffusion literature on the strength of weak ties (Granovetter, 1973) which deals with the fact that while strong ties (and therefore strong cliques in networks) provide obvious benefits, it is weak ties (and therefore short path lengths) that provide the basis for continued progress and to source new ideas and know-how. While framing policy for clusters too, this recognition is important (reflected also by Cowan and Jonard, 2004:1572 and 2007:109).

Cowan and Jonard (2003) study the importance of network architecture on collective invention and the rate of innovation, and find that the structure of the network plays a fundamental role. They demonstrate the qualities of the small-world network as an efficient architecture, especially when absorptive capacity is low[6]. Cowan and Jonard (2004) study diffusion, treating it as a process of barter and exchange, where the barter occurs when it is mutually profitable for the exchanging agents. Their results also demonstrate that the small-world network structure is the most efficient architecture where average knowledge reaches its highest

[5] While Watts and Strogatz (1998) and Watts (1999) are popular citations for the small-world network structure, Freeman (2004) points out that it was Ithiel de Sola Pool and Manfred Kochen who introduced the term small-world in the network context, through a 1958 manuscript, which was republished as De Sola Pool and Kochen (1978), twenty years later. A 1967 article by Stanley Milgram drew from the 1958 manuscript, and it was only subsequent to Milgram (and unaware of the de Sola Pool and Kochen study) that Watts and Strogatz based their popular 1998 work on the small-world structure (Freeman, 2004:164).

[6] The only situation where the small-world network structure does not rule in this model is when knowledge is easy to transmit and absorb. A random network is most efficient in this case.

steady state and coefficient of variation is lowest. Cowan, Jonard and Özman (2004) take one step ahead and allow for the receiver of the new knowledge to innovate and leap ahead of the broadcaster, a behaviour that is common among competing firms in an industry where becoming the innovation leader is a top priority. Cowan and Jonard (2007) also moves further by analysing the relationship between network structure, population structure and scarcity of knowledge. They find that at an individual level, agents that have a large number of links (i.e., networks with structural holes, characteristic of younger industries) do well when knowledge is scarce, while individuals with cliquish links (i.e., networks with strong social capital, characteristic of mature industries) do well when knowledge is abundant and knowledge trading happens fervently.

Hence, one of the most consistent findings in the series of papers by Cowan and Jonard is that network structure is pivotal for knowledge diffusion and, in the 2003 and 2004 studies, that the small-world network structure is generally the most effective in progress and diffusion of knowledge, barring exceptional circumstances. Of all the studies, Cowan and Jonard (2004) is the most influential for this paper. And like Cowan and Jonard (2004), there is no innovation in this model, only knowledge exchange and learning.

3. The Model

3.1 Introduction

A cluster is comprised of N economic agents, each agent i connected to n other agents. Locations are fixed, but all agents can observe everyone else's production at all times across the cluster. Each agent's operates by a production function where capital and labour are fixed, so output is determined by an agent's efficiency a_i. For each agent, therefore, Q_i takes the form:

$$Q_i = \boldsymbol{K} a_i \qquad [1]$$

...where there is a vector of efficiency of knowledge $\mathbf{A} = [a_i]$

Agents in the cluster are equally distributed into η social groups, which have differing affinities to each other, represented in the NxN affinity matrix **M**. The social network is fixed, and generates an NxN social distance matrix **D**, where

$$\mathbf{D} = [d_{ij}] \qquad [2]$$

Every agent in every period can observe each agent's productivity. An agent i is always on the lookout that she does not lag behind others in the cluster in terms of productivity, and the manner in which this is possible is to ensure that her productivity not too far behind that of the other $(N-1)$ agents in the cluster, which she does by gaining knowledge through interacting. An

agent's decision-making process on whether or not to interact is based on evaluation of her payoffs from interacting. Agent i becomes a 'learner' when she observes that her know-how a_i is less than a_j, the know-how of another agent j, who she views as a potential 'teacher'.

If i learns from j, the potential knowledge gain is Δa_{ij}

$$\Delta a_{ij} = \max(0, a_j - a_i) \qquad [3]$$

But only a part of the know-how difference between teacher and learner, i.e., $\Delta a_{ij} = a_j - a_i$ can actually be absorbed or learnt by i, this fraction denoted by an absorptive capacity parameter α (Cohen and Levinthal, 1990), set constant for all agents in the cluster. So while j may in principle be willing to share k_{ij} in its entirety, the learner i can hope to gain only $\alpha\Delta a_{ij}$. Network distance d_{ij} between i and her potential teacher j is of consequence, its importance manifested in this model as parameter e_L, the 'strength of network distance', which has a negative effect for the learner as d_{ij} increases. Hence, there are two elements that bound learning: absorptive capacity and network distance.

There are two opposing effects of teaching that influence the teacher j while deciding whether or not to teach i. First is a 'warm glow', a positive effect in the form of a 'reward' for teaching. Second is a 'teaching irritation' β, an negative effect on account of time lost in production due to effort put in to teaching, which increases with Δa_{ij} as the bigger the knowledge gap, the more the teacher must struggle to teach.

3.2 Inter-Agent Affinities and Rewards

Agents have varying affinities with one another in this cluster. Matrix **M** shows affinity between the agents. For a cluster with N agents,

$$\mathbf{M} = \begin{bmatrix} 1 & m_{12} & m_{13} & m_{14} & \dots & m_{1N} \\ m_{21} & 1 & m_{23} & m_{24} & \dots & m_{2N} \\ m_{31} & m_{32} & 1 & m_{34} & \dots & m_{3N} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ m_{N1} & m_{N2} & m_{N3} & m_{N4} & \dots & 1 \end{bmatrix} \qquad \begin{array}{l} 0 \le m_{ij} \le 1 \\ m_{ij} = m_{ji} \\ m_{ii} = 1 \end{array}$$

Here, m_{ij} is a measure of the affinity between two agents i and j. Values of m range from 0 (complete prejudice) to 1 (complete affinity). Main diagonal elements are 1, out of each agent having perfect affinity towards oneself. There are four kinds of affinity matrices in this model, one without complexity in social relations, and three with complex social relations.

(1) **M1, Perfect Affinity:** an identity matrix, i.e., where all elements m_{ij} in **M** are 1 signifying complete affinity between agents, and in some sense, 'simple' social relations.

(2) **M2, Group Level Complex Relations:** where **M** becomes a block matrix. Each block G is a group of agents in one of the η social groups in the cluster. G_{ab} shows affinity between two social groups a and b, where $0 \leq G_{ab} \leq 1$. All agents in one group have equal affinity or prejudice towards all agents of another group, and all agents in a group have, naturally, the same affinity to one another. That is:

$$\mathbf{M} = \begin{bmatrix} 1 & G_{12} & G_{13} & G_{14} & \dots & G_{1\eta} \\ G_{21} & 1 & G_{23} & G_{24} & \dots & G_{2\eta} \\ G_{31} & G_{32} & 1 & G_{34} & \dots & G_{3\eta} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ G_{\eta 1} & G_{\eta 2} & G_{\eta 3} & G_{\eta 4} & \dots & 1 \end{bmatrix} \qquad \begin{array}{l} 0 \leq G_{ab} \leq 1 \\ G_{ab} = G_{ba} \\ G_{aa} = 1 \end{array}$$

(3) **M3, Perfect Homophily:** here, **M** becomes a block diagonal matrix where diagonal elements of **M** are 1 and all other G_{ab} are 0, showing severe homophily between social groups.

(4) **M4, Individual Level Complex Relations:** where **M** is composed of entirely heterogeneous m_{ij} , i.e., affinities and prejudices at an individual level. Only m_{ii} are 1.

Agents receive social rewards and penalties upon interacting, these based on the relations, i.e., affinities G_{ab}, between their social groups. The influence of these rewards and penalties are understood as a 'strength of affinity' effect γ, a parameter that manifests in their payoffs.

A learner is not rewarded at all for interacting with teachers from her own group, and increasingly rewarded for interacting with teachers from groups increasing in prejudice for the effort she has made in crossing a social barrier and accessing a more well-informed sub-network in the cluster. A teacher on the other hand is not rewarded at all for teaching an agent from a strongly prejudiced group, increasingly rewarded when she teaches agents in groups with increasing affinities and highly rewarded for teaching learners from the same social group, for helping reinforce group position. The reward for teaching within the same group is the highest. This is summarized in Table 1.

Table 1 Rewards for Learners and Teachers, based on Affinities

Affinities	Learner	Teacher
1 (highest)	Reward is lowest	Reward is highest
Decreasing from 0.99	Reward increases	Reward decreases
0.01 (lowest)	Reward is highest	Reward is lowest

3.3 Mechanics

Know-how a_i is randomly assigned to all N agents, and elements m_{ij} and G_{ab} also are randomly assigned. We randomly pick an agent i in the cluster and calculate Δa_{ij} with other (N-i) agents in the cluster, to look for potential teachers. For agent i for all agents in the cluster with whom $\Delta a_{ij}>0$, the decision to pick teacher j is contingent on the payoff $\boldsymbol{\Pi^L_{ij}}$ known as the 'learner's payoff' in this model. To recall, there are three elements that feature for the learner: an absorptive capacity parameter α, a strength of network distance parameter e_L, and the strength of affinity parameter γ.

$$\boldsymbol{\Pi^L_{ij}} = (\boldsymbol{\alpha}\Delta \boldsymbol{a_{ij}}) - (\boldsymbol{e_L}.\boldsymbol{d_{ij}}) - \boldsymbol{\gamma}(\boldsymbol{m_{ij}}) \qquad [4]$$

The objective of learner i is to find out which potential teacher j in the cluster maximizes [5]. L_i is a vector of payoffs from learning from agents $1...N$ in the cluster**.**

$$L_i = [\Pi^L_{ij} \ldots\ldots\ldots \Pi^L_{iN)}] \qquad [5]$$

For teacher j to decide whether or not to teach agent i we construct a teaching payoff $\boldsymbol{\Pi^T_{ji}}$. To recall, there are two elements influencing teaching: an irritation element β, and the strength of affinity parameter γ that is variable in affinities. The latter is a warm glow with a high reward when m_{ji} is high. Hence, the teacher's payoff is:

$$\boldsymbol{\Pi^T_{ji}} = \boldsymbol{\gamma}(\boldsymbol{m_{ji}}) - \boldsymbol{\beta} \qquad [6], \text{ where } \beta \text{ increases with } \Delta a_{ij}$$

The teacher j calculates [6] and teaches only if it is positive.

The direction of decision making is learner→teacher, i.e., first a random learner i is picked, her $\boldsymbol{\Pi^L_{ij}}$ and L_i is computed, and then corresponded with $\boldsymbol{\Pi^T_{ji}}$ of the teacher j.

Only when both learner and teacher agree do interaction and knowledge exchange proceed. If there is an agreement, at $t+1$, the learner i's know-how increases by $\alpha\Delta a_{ij}$, hence

$$a_{it+1} = a_i + \alpha\Delta a_{ij} \qquad [7]$$

In case $\Pi^T_{ij} \leq 0$ for all j, there is no interaction and know-how remains the same for the learner, i.e.,

$$a_{it+1} = a_i$$

4. Network Analysis and Settings

Having constructed the decision-making rules of the model, we now proceed to enquire, for each of the social relations regimes **M1**, **M2**, **M3** and **M4,** the network structure fostering the highest and most equitable knowledge diffusion in the cluster. We simulate interactions for knowledge exchange in the cluster across a three kinds of network structure (linear-, small-world- and random network structures), for four kinds of relations between the social groups in the cluster, represented by four affinity matrices listed above. Many studies of know-how exchange and diffusion, reviewed in section 2, have convincingly shown that the small-world network structure appears as the most efficient and equitable for knowledge diffusion among clustered agents engaging in barter and free broadcast of know-how when links are randomly generated. We follow an enquiry on network structure quite similar to the Cowan and Jonard series of studies, testing for various network structures on a simple diffusion process between boundedly rational agents, only that our model is coloured with social relations and their ramifications. For simulation, we introduce a cluster with N=1000 agents, divided into η=10 social groups, each agent possessing n=4 connections and an absorptive capacity α=0.80. In each of the four social relations regimes we rewire the cluster's network in three arrangements corresponding to log p values p=0.001 (ordered linear network), p=0.10 (small-world network) and p=1 (random network). Hence, we have twelve sets of results: for three network structures in each of the four social relations regimes.

Upon allowing the agents in the cluster to perform for 10,000 iterative periods (each 'period' being the entire mechanics of interaction that occurs over section 3 from surveying potential teachers to actually absorbing the new knowledge), we calculate a number of measures over each network structure for each social relations regime (i.e., for each p value across each **M** regime). For each p value, we calculate average knowledge *AvgK* of the cluster (i.e, the average of all agents' a_i) and coefficient of variation[7] *CoeffVar* (of the entire cluster's a_i) in know-how in the cluster.

The hypotheses we test in our analysis, that stem out of the two objectives of this study as listed at the end of section 1, are as follows:

Hypothesis 1: The small-world network structure is still the most efficient network structure for knowledge diffusion, in terms of performance (*AvgK* and *CoeffVar*), in an environment coloured with complex social relations.

[7] We use coefficient of variation instead of a simple measure of variance since as, advised by Cowan and Jonard (2003:10), results shown by a measure of variance can be misleading when the mean increases through scaling effects.

Hypothesis 2a: A regime with perfect affinity and no complexity in social relations, namely **M1**, is the regime that achieves highest performance in terms of both *AvgK* and *CoeffVar*.

Hypothesis 2b: A regime with perfect homophily, namely **M3**, is the regime that performs best among the complex social relations regimes **M2, M3,** and **M4**.

Hypothesis 3a: Strong affinity effects (captured by the 'strength of affinity' parameter γ) and network distance effects (captured by the 'strength of network distance' parameter e_L) generally decrease *AvgK* in the cluster as a whole.

Hypothesis 3b: Strong affinity effects (captured by γ) and network distance effects (captured by e_L) generally worsen equity, i.e., increase *CoeffVar* in the cluster as a whole.

5. Results

The first part of this section looks at results compared across network structures for each social relations regime, while the second part looks at individual effects of γ and e_L. More often than not, **M2** (affinities and prejudices between social groups) and **M4** (affinities and prejudices between individuals, without social groups) share rather similar results, which is also the case with **M1** (perfect affinity) and **M3** (severe homophily). Hence, most results discussed for **M2** are applicable to **M4**, similarly most **M1** results are applicable to **M3**. In this study, **M2** takes focus over the other three regimes, as this is the regime where interactions occur in complex social relations environments across social groups.

5.1 Performance across Social Relations Regimes and across Network Structures

In this section, we compare results across the three network structures and across the affinity regimes. We know from the literature that small-world networks by far allow for the most efficient and equitable knowledge distribution among network structures as they capture the benefits of both high cliquishness and short path lengths. In an ordered network, cliquishness is very high but path length is low, permitting quick transfer of knowledge among proximate nodes but slow diffusion to far-off nodes, which also means that they are inefficient in quickly tapping valuable information from distant nodes. Random networks on the other hand may surmount the network distance issue, but problems arise due to low cliquishness. Hence, small-world networks, which provide for the benefits both short path length and high cliquishness, provide the most efficient and equitable knowledge diffusion and distribution. In our model, we test this result for networks where interactions and knowledge diffusion are coloured with complex social relations,

with affinities and prejudices among agents. We see here that small-world networks are not particularly efficient either in knowledge diffusion or in equitable knowledge distribution. Let us see the results for each type of network structure.

We compare the magnitudes of *AvgK* and *CoeffVar* between network structures and across social relations regimes. First, we ask at which network structure each social relations regime scores its respective highest *AvgK* and lowest *CoeffVar*. Second, we find out which social relations regime scores the highest *AvgK* and the lowest *CoeffVar* for each network structure. After this, we study the underlying dynamics of knowledge exchange in each network structure, for each social relations regime.

5.1.1 Performance of network structure across social relations regimes

For our study, which wishes to contribute to the existing series of studies on the superiority of the small-world network structure, the results discussed in this section are of prime importance. We ask here at which network structure each social relations regime performs the best. For this, we refer to the results in Table 2 and Table 3. These tables display, in simple terms, at what network structure each **M** regime has its respective highest *AvgK* (Table 2) or lowest *CoeffVar* (Table 3).

Table 2 Network Structure at which each Regime scores Highest AvgK

M1 Perfect Affinity		**M2** Group Level Complex Relations		**M3** Perfect Homophily		**M4** Individual Level Complex Relations	
Network Structure	Highest *AvgK*	Network Structure	Highest *AvgK*	Network Structure	Highest *AvgK*	Network Structure	Highest *AvgK*
Random	0.835	Ordered	0.816	Ordered	0.801	Random	0.813
Small-World	0.834	Small-World	0.811	Small-World	0.762	Small-World	0.794
Ordered	0.833	Random	0.805	Random	0.678	Ordered	0.780

Table 3 Network Structure at which each Regime scores Lowest *CoeffVar*

M1 Perfect Affinity		**M2** Group Level Complex Relations		**M3** Perfect Homophily		**M4** Individual Level Complex Relations	
Network Structure	Lowest *CoeffVar*	Network Structure	Lowest *CoeffVar*	Network Structure	Lowest *CoeffVar*	Network Structure	Lowest *CoeffVar*
Ordered	0.209	Ordered	0.215	Ordered	0.218	Random	0.256
Random	0.210	Random	0.264	Random	0.304	Ordered	0.270
Small-World	0.347	Small-World	0.341	Small-World	0.330	Small-World	0.345

We see that a small-world network structure is only, and consistently, the second best network structure at which the regimes reach their highest *AvgK*. Though in the case of **M1** the difference between the highest *AvgK* is scored at small-world network structure and highest *AvgK* scored at a random network structure is very small. But in the other complex social relations regimes, the margin is significantly high. And when we see equity in knowledge distribution, it is clear that the regimes score a rather high *CoeffVar* (lower equity) in a small-world network structure compared to ordered or random; and with a very high margin too. Table 4 summarizes in a nutshell the results of Table 2 and Table 3. We see that most regimes score their best not with small-world network structures but generally with ordered and/or random network structures.

Table 4 Summary of Results in Tables 2 and 3

Regime	Network structure at which highest *AvgK* is attained	Network structure at which lowest *CoeffVar* is attained
Perfect Affinity (**M1**)	Random	Ordered
Group Level Complex Relations (**M2**)	Ordered	Ordered
Perfect Homophily (**M3**)	Ordered	Ordered
Individual Level Complex Relations (**M4**)	Random	Random

One hypothesis to test in this study was whether the small-world network structure is the most favourable to interaction, learning, and equity; i.e., whether generally highest *AvgK* and lowest *CoeffVar* are achieved in small-world than ordered and random networks in clusters with complex social relations. The results here seem to indicate that this is not the case. Ordered networks give quick access to teachers in one's own social group who are only willing to teach you, while random networks give quick access to teachers of distant groups with whom you are rewarded if you learn from. This is a reason why ordered and random network structures are better for complex social relations, as compared to small-world network structure. This implies that the superiority of the small-world network structure does not hold for interactions in environments with complex social relations (just as it may not hold, according to Cowan and Jonard (2003), for very high absorptive capacity values). This emerges as an important proposition, addressing Hypothesis 1, which we can reject.

Proposition 1: *The small-world network structure may not be the best network structure for highest and most equitable knowledge distribution, when knowledge exchanges are undertaken in environments of complex social relations among networked agents in a cluster.*

5.1.2 Performance of social relations regimes across network structures

We now address the second hypothesis of this study. This hypothesis has two parts, first, that **M1** is the regime that, compared to the other regimes, and in any network structure, achieves highest performance in terms of both *AvgK* and *CoeffVar* (Hypothesis 2a). Second, that **M3** is the regime that performs best among the complex social relations regimes **M2, M3,** and **M4** (Hypothesis 2b). Hypothesis 2a is very simple to understand, as, knowledge exchanges are easiest where there are no complications in terms of affinities and prejudices between groups, or rewards and penalties for learners and teachers, and hence knowledge exchange is pretty smooth. Due to this, knowledge is most equitably distributed too. Hypothesis 2b may appear strange at first, considering that a regime with perfect homophily will perform the worst at any network structure as it has the highest prejudices between social groups. However, the reason we hypothesize that **M3** is the best performing regime among the other regimes with complex social relations is that **M3** is nothing but a set of 10x10 unit matrices, which allows for a large majority of interactions within these blocks; these therefore being ten versions of what happens with **M1**.[8]

To address these hypotheses, we look at Table 5.

Table 5 For each network structure, which social relations regime performs best

Ordered Network (p=0.001)				**Small-World Network** (p=0.10)				**Random Network** (p=1)			
Regime	Max *AvgK*	Regime	Min *CoeffVar*	Regime	Max *AvgK*	Regime	Min *CoeffVar*	Regime	Max *AvgK*	Regime	Min *CoeffVar*
M1	0.833	**M1**	0.209	**M1**	0.834	**M1**	0.204	**M1**	0.835	**M1**	0.210
M2	0.816	**M2**	0.215	**M2**	0.811	**M2**	0.229	**M4**	0.813	**M4**	0.256
M3	0.801	**M3**	0.218	**M4**	0.794	**M3**	0.245	**M2**	0.805	**M2**	0.264
M4	0.780	**M4**	0.270	**M3**	0.762	**M4**	0.269	**M3**	0.678	**M3**	0.304

From Table 5 we see that **M1** clearly scores the highest *AvgK* and the lowest *CoeffVar* most consistently across all network structures. Hence, as hypothesized, a cluster with agents among whom there is perfect affinity is the one that performs the best. We therefore accept Hypothesis 2a, and state Proposition 2.

Proposition 2: *The highest and most equitable knowledge distribution, with informal knowledge exchanges among networked agents in a cluster, is achieved when there is perfect affinity among the agents.*

[8] Following this, we can also assume that in **M3**, cross-group interactions may only be occasional. This is not a hypothesis to be tested out in this study, but we explore below extent of cross-group interactions between regimes across network structures in the discussion.

But Hypothesis 2b can be rejected immediately. We see here that among the three complex social relations regimes **M2**, **M3** and **M4**, it is **M2** and **M4** that generally perform better than **M3**. In fact, **M2** takes the lead with a better performance than the other two in an ordered and small-world network. And, **M3** performs relatively better than **M4** only in an ordered network. Hence, we can reject Hypothesis 2b.

We also observe the extent of cross-group interactions in each social relations regime across network structure. And very interestingly, the regime that hosts the highest cross-group interactions is the one where inter-group prejudices are the *highest*, i.e., in a perfect homophily regime **M3**. As observed in Table 6, the difference between cross-group interactions in **M3** as compared to even the regime in second position in this table is very high (*double*, in an ordered and small-world network structures). A perfect affinity regime **M1** seems to have lowest inter-group interaction in two out of three network structures.

Table 6 Proportion of cross-group interactions (as a per cent of all learner-teacher interactions) across regimes, for each network structure

Ordered Network (p=0.001)		**Small-World Network** (p=0.10)		**Random Network** (p=1)	
Regime	Per cent	Regime	Per cent	Regime	Per cent
M3	10.50	**M3**	37.25	**M3**	71.50
M2	5.50	**M1**	19.00	**M2**	54.00
M1	3.25	**M2**	16.75	**M1**	49.25

This may be because, in this model, learners are given the highest rewards when prejudices are highest, and hence in a perfect homophily regime they strive to tap knowledge from teachers out-of-group as much as possible. But it could be argued, as a converse, that teachers are given the highest penalties when prejudices are highest and must hence refuse to teach. The reason why cross-group interactions are the highest in **M3** may simply be because the difference in knowledge Δa_{ij} between teachers and learners may be low enough to allow the teachers' payoff [6] to remain positive, for teachers to actually agree to impart knowledge learners who come from highly prejudiced social groups. The limitation of this, and the reason why we do not frame a generalizable proposition here, is that this result may have stemmed out of the way the rewards and penalties in this model have been constructed.[9]

[9] Not to suggest that this model has been engineered to give this result – in fact, given the rewards/penalties structure, we had assumed in the contrary that **M3** would most likely have the *lowest* cross-group interactions.

5.2 Individual effects of γ and e_L on Performance

For the discussion that follows in this section, we refer the contour plots and the graphs in Figures 1 to 5. While results for the complex social relations regimes **M2**, **M3** and **M4** are represented by contour plots, results for the regime **M1** are represented by simple line graphs, as γ has no effect in the **M1**.

5.2.1 Individual effects of γ and e_L on AvgK

There are clear differences in the results across social relations regimes for each network structure, and across network structures for each social relations regime. What is interesting, however, is that the results for **M3** (at ordered and random network structures) are quite in contrast to the other results, in that high *AvgK* in **M3** is achieved at high-γ- medium/high-e_L levels, whereas for the other regimes, a high *AvgK* is achieved at high-γ-low-e_L levels. In all cases, however, high γ levels seem to be always necessary for achieving high *AvgK*. This is corroborated by the line graphs in Figures 3 and 4, which show that in all cases, *AvgK* is increased with increase in γ. Some of these results, though unexpected, are not surprising if we go a step deeper and look at the mechanisms involved in their formulation.

The results for **M3** are worthy of comment. Recall from Table 6 that cross-group interactions were highest in the perfect homophily regime **M3**. This regime is special, in that learners are offered very high rewards for any cross-group interactions (due to the fact that affinity between groups is the lowest in this regime). From the learners' point of view, γ delivers such strong effects that it overpowers e_L at low levels of e_L. Learners are willing to contact well-endowed teachers located even at far network distances. But, in an ordered network, this overpowering effect of γ over e_L lasts only up to a point (as clearly seen in the contour plot for **M3** at ordered network p=0.001) after which the effect of e_L also exerts its influence on learners in the same manner as seen in the other regimes. For teachers, in a perfect homophily regime, who comes to them for learning is irrelevant (unless the learners are of the same social group – when they get high rewards), and they have little disincentive to teach. In a small-world network, however, the overpowering effect of γ over e_L lasts longer.[10] The reason is that in an ordered network teachers of other groups are on average very distant in the network, but in a small-world network they can be close. Consequently, the cost of approaching good teachers of other social groups, in terms of network distance, are lower in small-world networks due to the presence of long distance links in the network. Hence, learners enjoy the strong positive effects of γ for longer in a small-world network, as clearly seen in the contour plot.

[10] Due to the scaling of the *AvgK* axis in the **M3** contour plot at p=0.10, the point after which e_L delivers its effects is not clearly visible, and appears at around e_L = 0.75.

The conjectural result while framing Hypotheses 3a (that strong affinity effects, captured by the 'strength of affinity' parameter γ, and that strong network distance effects, captured by the 'strength of network distance' parameter e_L, generally decrease *AvgK*) was expected to be so since it was logical that with higher γ and higher e_L, agents would end up learning only from proximate teachers and those in one's own social group. This would, logically, lead to low levels of *AvgK* in the cluster as a whole, once the interactions were over. As far as the effect of e_L goes, this conjectural result has turned out correct (except in the case of **M3** at ordered and small-world network structure). Hence, the part of the Hypothesis 3a that states that strong network distance effects would decrease *AvgK*, can be accepted.

However, it has turned out that at higher γ levels, learners might have actually preferred accessing teachers out-of-group since, as observed also at the end of section *5.1.2*, learners are given high rewards as prejudices between groups increase, and their rewards are only compounded if the effect of social group (through the strength of affinity parameter γ) is strengthened furthermore. And as long as Δa_{ij} offsets the teacher's penalty for teaching an out-of-group learner, interaction commences and learning occurs, which may have very well been the case in our simulations. This is one reason why high *AvgK* is achieved at high γ levels. Thus, the part of the Hypothesis 3a that states that strong affinity effects would decrease *AvgK*, can be rejected.

5.2.2 Individual effects of γ and e_L on CoeffVar

Let us now turn to the individual effects of γ and e_L on equity of knowledge distribution, i.e., *CoeffVar*. We had hypothesized that strong affinity effects (through γ) and strong network distance effects (through e_L) would generally worsen equity (increase *CoeffVar*). We had expected that with higher e_L, those learners who were proximate in network distance to very knowledgeable teachers would learn more and those who were proximate to not-so-well-knowledgeable teachers would learn comparatively less, due to which knowledge distribution in the cluster would become more unequal. Also, we expected that at higher γ, agents would learn only from own-group teachers, which would result in knowledge progressing only in those groups with more knowledgeable teachers, with the cluster ultimately ending up in being unequally endowed with knowledge.

Very interestingly, both these conjectural results are refuted. Higher γ and higher e_L seem to lead to *higher* equity (lower *CoeffVar*). Observe the contour plots and line graphs in Figure . The darker green patches signifying lower *CoeffVar* are concentrated in the high-γ-high-e_L region of the **M2**, **M3** and **M4** plots. For the line graph in the **M1** column too, we see that *CoeffVar*

decreases with increase in e_L. The individual effects of γ and e_L in Figure 3 and Figure 4 also corroborate this. Hence the Hypothesis 3b that strong affinity effects (through γ) and network distance effects (through e_L) generally worsen equity (increase *CoeffVar*) can be rejected.

6. Summing Up Results, and Lessons

Two propositions have emerged out of this study:

(1) **Proposition 1:** The small-world network structure may not be the best network structure for highest and most equitable knowledge distribution, when knowledge exchanges are undertaken in environments of complex social relations among networked agents in a cluster.

(2) **Proposition 2:** The highest and most equitable knowledge distribution, with informal knowledge exchanges among networked agents in a cluster, is achieved when there is perfect affinity among the agents.

These are based on the results of this simulation, summed up, as follows, in Table 7.

Table 7 Summary of Results

Objective	Hypothesis	Result
Whether a small-world network structure is most efficient in a complex social relations environment	**Hypothesis 1**: The small-world network structure is still the most efficient network structure for knowledge diffusion, in terms of performance (*AvgK* and *CoeffVar*), in an environment coloured with complex social relations.	A small world network structure is not prominent in complex social relations environments. Hypothesis 1 is rejected.
Which social-relations regime generally performs the best	**Hypothesis 2a**: A regime with perfect affinity and no complexity in social relations, namely **M1**, is the regime that achieves highest performance in terms of both *AvgK* and *CoeffVar*.	**M1** (perfect affinity) does turn out to be the best performing regime in achieving both highest *AvgK* as well as lowest *CoeffVar*. Hypothesis 2a is accepted.
	Hypothesis 2b: A regime with perfect homophily, namely **M3**, is the regime that performs best among the complex social relations regimes **M2, M3,** and **M4**.	The next best, however, are **M2** and **M4** (in a random network). **M3** seems to perform relatively well only in an ordered network. Hypothesis 2b is rejected.

Individual effects of strength-of-affinity and strength-of-network distance on performance	**Hypothesis 3a:** Strong affinity effects (captured by the 'strength of affinity' parameter γ) and network distance effects (captured by the 'strength of network distance' parameter e_L) generally decrease *AvgK* in the cluster as a whole.	The expected result holds for the individual effect of e_L on *AvgK*, i.e., *AvgK* decreases with increases in e_L, especially after middle levels of γ. The only exception is for **M3** in a small-world network. But contrary to expectation, *AvgK* reaches its peak at higher γ levels. Hypothesis 3a can be rejected for γ, but accepted for e_L.
	Hypothesis 3b: Strong affinity effects (captured by γ) and network distance effects (captured by e_L) generally worsen equity, i.e. increase *CoeffVar* in the cluster as a whole.	*CoeffVar* seems to decrease (equity improves) with increase in e_L as well as γ, in all cases, contrary to expectation. Hypothesis 3b can be completely rejected.

And in addition, we have observed that the regime with the most cross-group interactions is **M3** (perfect homophily), with even **M1** (perfect affinity) generally having much less cross-group interaction.

As we have discussed in section 2.2, a stream of the literature in know-how diffusion across social networks in clusters deals with the importance of network architecture and the equity and efficiency of knowledge distribution. Vega-Redondo (2007:9), explains that network architecture is the key issue while studying diffusion across networks. When we deal with rural traditional-technology clusters inhabited by economic agents whose only source of new knowledge is informal interaction and defensive innovation, enquiring on efficient network structure is necessary, as Vega-Redondo explained, but the analysis has to also be coloured with the complex social relations that are inevitable in such clusters. This is the contribution of this model to the existing series of studies on efficient network structures for knowledge diffusion around a new technology. In recent times when production demands and technology upgradation takes the foremost priority among agents even in traditional technology clusters, long existing complex social relations may still hold sway in economic decision making; but they may not be able to grab complete control of agents' behaviour at an individual level while calculating interaction and knowledge exchange decisions. When agents are defensively innovating they might cross these social groups to exchange know-how. Even for knowledge givers ('teachers' in this model) who

provide their new know-how, old inclinations to retain group dominance may fall flat. We end the study on this positive note: demarcations erected by prejudices between social groups can be overcome, permitting knowledge exchanges and learning, and allowing for the aggregate progress of a low-tech cluster in an environment of complex social relations.

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Figure 1 Effect of e_L (strength of network distance) and γ (strength of social relations) on *AvgK*

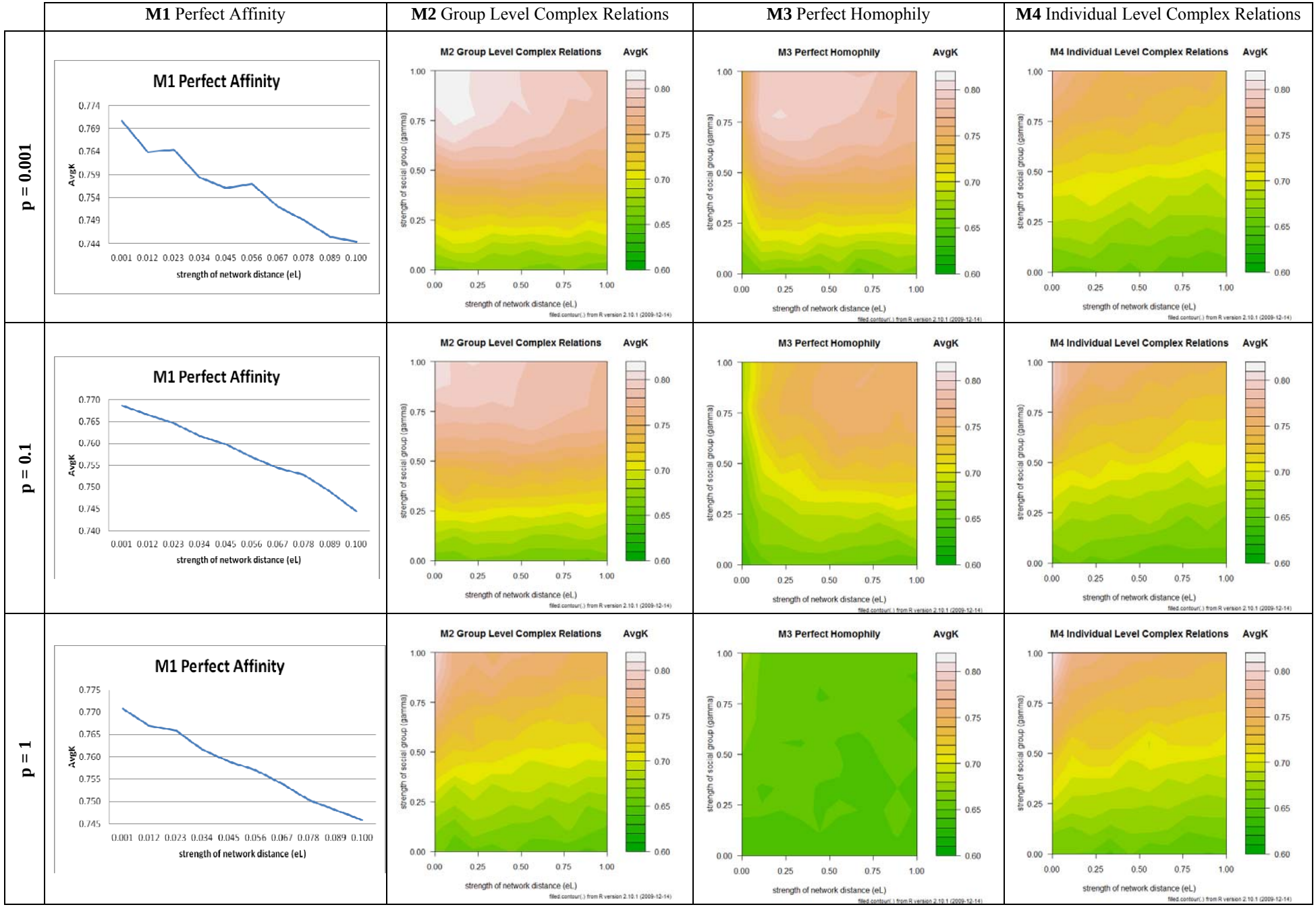


Figure 2 Effect of e_L (strength of network distance) and γ (strength of social relations) on *CoeffVar*

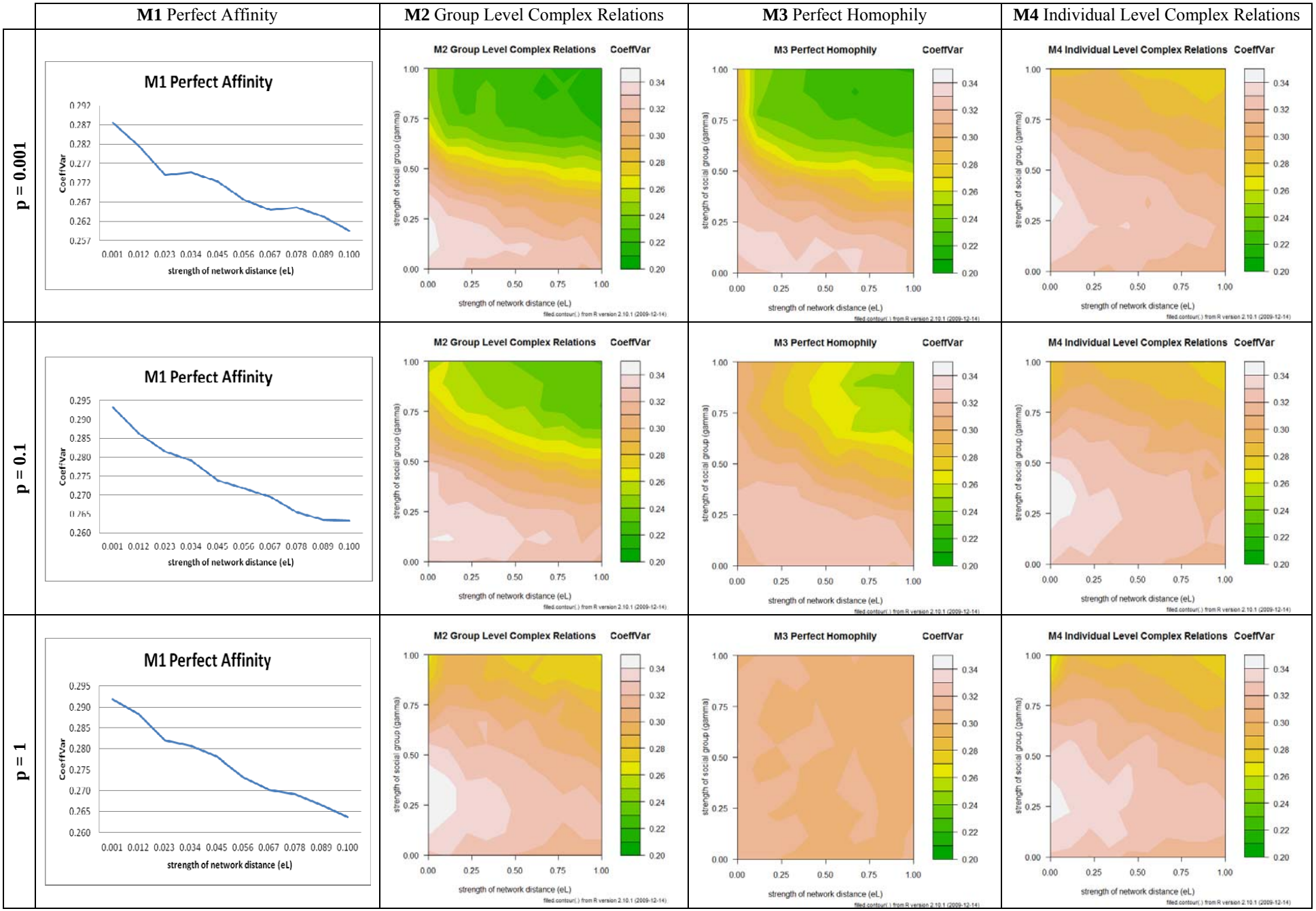


Figure 3 Individual effects of γ and e_L on AvgK

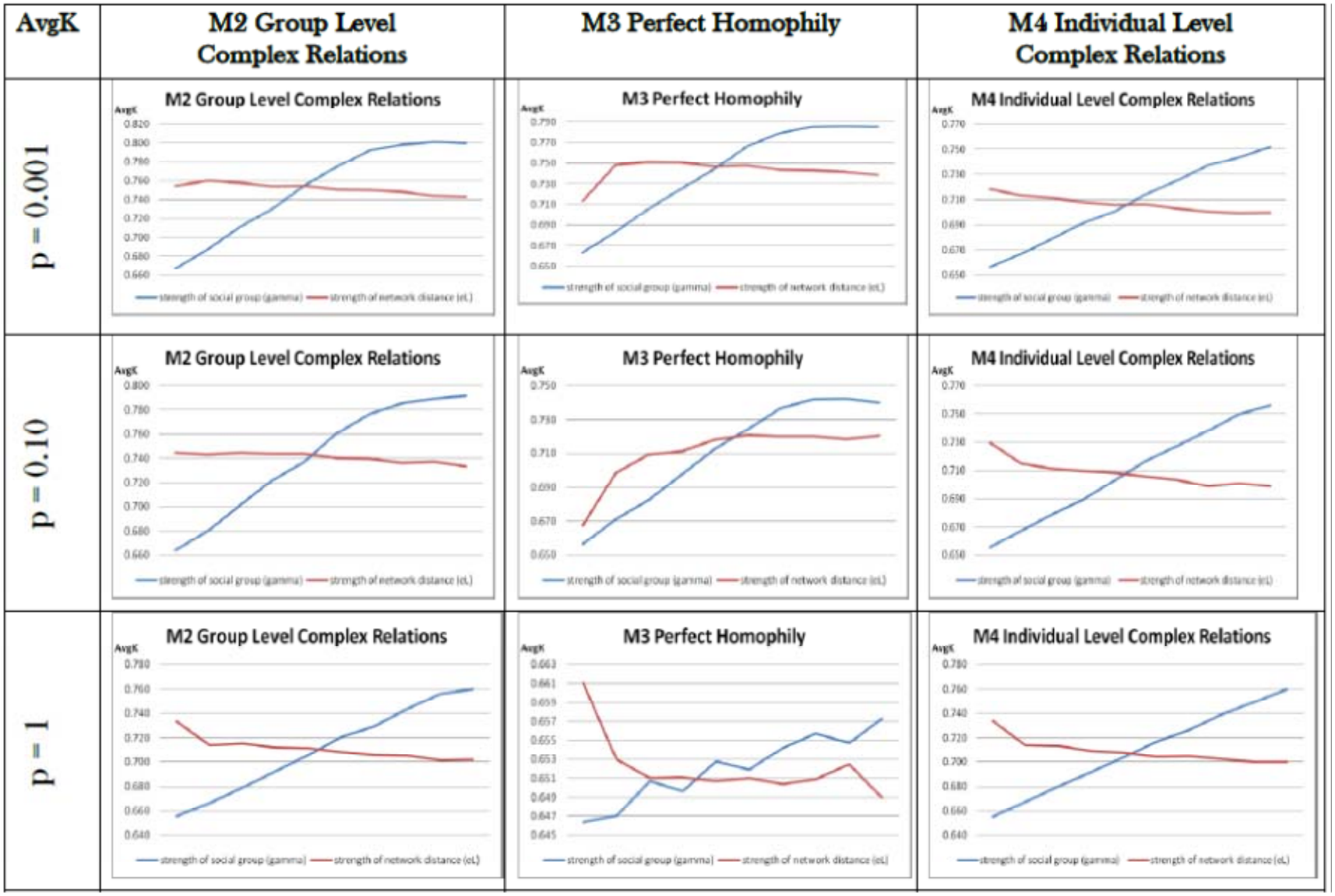
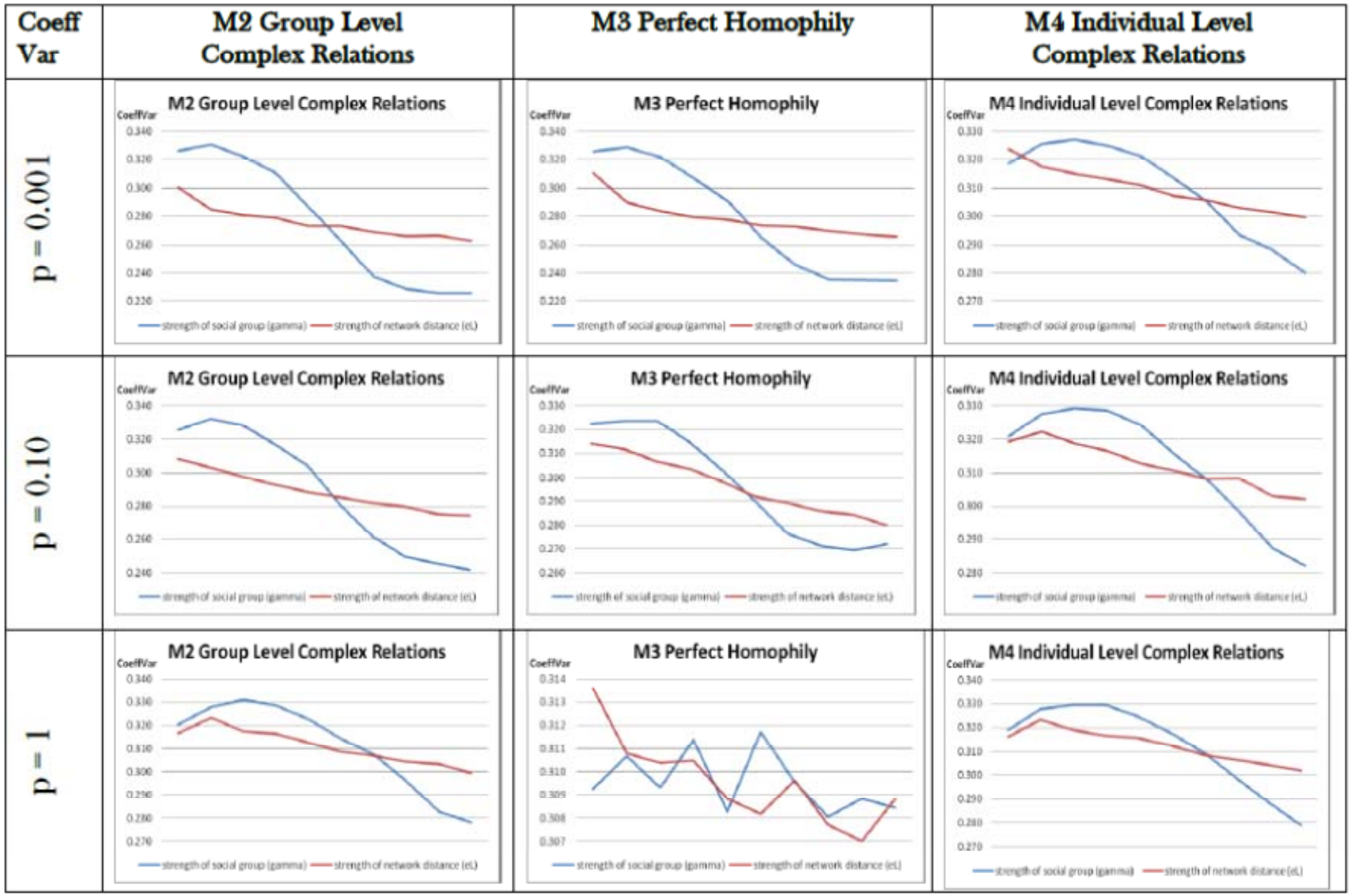


Figure 4 Individual effects of γ and e_L on *CoeffVar*



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