Social networks and the process of "globalization"

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Abstract

We propose a stylised dynamic model to understand the role of social networks in the phenomenon we call "globalization." This term refers to the process by which even agents who are geographically far apart come to interact, thus overcoming what would otherwise be a fast saturation of local opportunities. A key feature of our model is that the social network is the main channel through which agents search and exploit new opportunities. Thus only if the social network becomes global (heuristically, "reaches far") can global interaction be steadily sustained. To shed light on the conditions under which such a transformation may, or may not, take place is the main objective of the paper.

One of our interesting insights is that in order for a local social network to turn global, the economy needs to display a degree of "geographical cohesion" that is neither too high (for then global opportunities simply do not arise) nor too low (in which case there is too little social structure for the process to take off). And if globalization does arise, we show that it often occurs abruptly and consolidates as a robust state of affairs. We also show how it is affected by improvements in the flow at which information travels in the network, or the range at which the social network helps to monitor behavior.

Keywords: Social networks, Globalization, Search, Cooperation, Social Cohesion, Innovation.

JEL classif. codes: D83, D85, C73, O17, O43.

1 Introduction

The idea that most economies are fast becoming more globalized has become a commonplace, a *mantra* repeated by the press and popular literature alike as one of the distinct characteristics of modern times. And the emphasis is not only on trade – the typical focus of international economics – but on many other routes of interaction such as investment, communication, or research collaboration. Recently, economists have also started to devote substantial effort to constructing measures of globalization that extend well beyond the traditional concern with trade openness. The main objective of this predominantly empirical literature has been to investigate whether such indices of globalization have a significant impact on economic performance (see Section 2 for a short summary). The phenomenon, however, has yet received relatively scant attention from a theoretical viewpoint.

Our theoretical approach is based on two simple premises.

(P1) The social network plays a key role in agents' search or/and exploitation of new economic opportunities – specifically, only those that do not lie too far *in the social network* can be found or/and supported.

(P2) The set of economic opportunities that can arise within any given "geographical region" is limited – thus if agent interaction remains local, possibilities will in the end be exhausted

The former two premises lead naturally to the following conclusion:

(C) If economic activity is to expand steadily, it must turn global and hence the social network which supports it must become global as well.

In a nutshell, the transition described in the above conclusion is what we shall refer to as *globalization*. A number of important questions arise in this respect. How does globalization come about, sharply or gradually? Is it a robust/persistent state of affairs, or requires a very narrow (and thus ephemeral) set of circumstances in order to materialize? What is the role played by geography in the phenomenon? In particular, is some geographical cohesion beneficial or detrimental? Is there any role for policy, perhaps even a temporary one? And what is the effect of institutions, or the speed/range at which information flows in the social network? The aim of our model is to shed light on these and other questions within a stylized theoretical framework.

As stressed, our approach highlights the role of social networks in the phenomenon. In fact, we shall see that globalization is intimately associated to a topological property of the underlying social network – i.e. the feature that, irrespectively of how far agents lie apart geographically, they tend to be relatively close in the social network. Such network proximity is important because it bears on the ability of agents to find and undertake new opportunities and thus form new links. And this, in the end, is what underlies the performance of the economy. For, eventually, all links formed in the past become obsolete and disappear, hence a steady creation of new links is required to maintain a dense pattern of economic interaction.

Two of the considerations that enjoy a prominent role in our analysis of the problem are the following:
(a) the *social range at which information flows* – i.e. the maximum distance in the social network within which information can be used effectively;
(b) *geographical cohesion*, identified with the extent to which agent search and exploitation of opportunities is affected by "geography" (i.e. some underlying notion of space).[1]

The interplay between the former two considerations leads to interesting insights. For example, we find that some degree of geographical cohesion is required if globalization is to be attained. The reason is that, as explained, a robust build-up of the social network is required, and such a process cannot succeed unless geography provides some structure to the pattern of agent interaction. But too much such cohesion is harmful, for it exacerbates the problem of local saturation by inducing search of new opportunities to be too geographically bound. In the end, at what point this trade-off is optimal depends on the effectiveness of the social network. If information and support can be extended quite far in the social network, then the required degree of social cohesion can be kept quite low. This, in turn, allows opportunities to be exploited more globally and thus more effectively as well. In the opposite case (i.e. a social network with limited potential), social cohesion must come at the rescue, with the "side-effect" of limit the range of interaction and exploitation of new economic opportunities.

The paper is organized as follows. Section 2 reviews some related literature and briefly outlines a companion paper where we test empirically some basic implications of our theory. Section 3 presents the

[1]As is common in economics, the notion of space may be attributed different interpretations, tailored to the specific application at hand. Thus, also in our case, the notion of space could be geographical in nature or concern other characteristics in terms of which agents occupy a fixed position, e.g. ethnic or language diversity.

model: in Subsection 3.1 we describe the interaction framework, while in Subsection 3.2 the dynamics. Section 4 carries out the analysis, decomposed in three parts. Firstly, Subsection 4.1 discusses numerical simulations that illustrate some of the main features of the model. Secondly, Subsection 4.2 undertakes the theoretical analysis in a simplified benchmark set-up. Thirdly, Subsection 4.3 extends the theory to a general context. Section 5 concludes the main body of the paper with a summary and an outline of future research. In the Appendix, we add some complementary material: first we describe in some detail a game-theoretic foundation of our model and an auxiliary result, then we provide a detailed description of the algorithm used in that part of our analysis that we undertake numerically.

2 Related literature

As advanced, the bulk of economic research on the phenomenon of globalization has been of an empirical nature, with only a few papers addressing the issue from a theoretical perspective. Two interesting theoretical papers that display a certain parallelism with our approach are Dixit (2003) and Tabellini (2008). In both of them, agents are distributed over some underlying space, a tension arising between the advantages of interacting with far-away agents and the limits to this interaction imposed by geographical distance. Next, we outline these papers and contrast our different approaches.

The model proposed by Dixit (2003) can be succinctly summarized as follows: (i) agents are arranged uniformly on a ring and are matched independently on each of two periods; (ii) the probability that two agents are matched decreases with their ring distance; (iii) gains from matching (say trade) grow with ring distance; (iv) agents' interaction is modelled as a Prisoner's Dilemma; (v) information on how any agent has behaved in the first period arrives at any other point in the ring with a probability that decays with distance.

In the context outlined, the intuitive conclusion obtains that trade materializes only between agents that do not lie too far apart. Trade, in other words, is limited by distance. To overcome this limitation, Dixit contemplates the operation of some "external enforcement." The role of it is to convey information on the misbehavior of any agent to *every* potential future trader, irrespective of distance. Then, assuming that such external enforcement is quite costly, it follows that its implementation is justified only if the economy is large. For, in this case, the available gains from trade are also large and thus offset the implementation cost.

The second paper, Tabellini (2008), relies on a spatial framework analogous that of Dixit (2003). In it, however, distance bears *solely* on agents' preferences: each matched pair again plays a modified Prisoner's Dilemma, but with a warm-glow component in payoffs associated to being a cooperator whose size falls with the distance to the partner. Each individual plays the game only *once*. This allows the analysis to dispense with the information-spreading assumption of Dixit's model that is tailored to the fact that agents are involved in repeated interaction. Instead, the distinguishing characteristic of Tabellini's model is that agents' preferences (associated to the rate at which the warm-glow term decreases with distance) are shaped by a process of intergenerational socialization à la Bisin and Verdier (2001).

In a certain sense, "altruism" and cooperation act as strategic complements in Tabellini's model. This, in turn, leads to interesting co-evolving dynamics of preferences and behavior. For example, even if both start at low levels, they can reinforce each other and eventually lead the economy to a state with a large fraction of cooperating altruists (i.e. agents who care for, and cooperate with, even relatively far-away partners).

Under reasonable assumptions, such steady state happens to be unique. There are, however, interesting variants of the set-up where the enforcement of cooperation (i.e. the detection and reversion of cheating) is the endogenous outcome of a political equilibrium, and this allows for multiple steady states that depend on initial conditions.

In resemblance with the two papers just summarized, our approach attributes to some exogenous notion of distance a key role in shaping trade/interaction. When its effect is very strong (and therefore effective meeting probabilities decay sharply with distance), the level of interaction is severely affected by local saturation. Thus, just as in those papers, only if the role of distance is not too acute can interaction rise at high levels. But, in our model, this is merely a necessary condition. The economy still needs to tackle – by *endogenously* impinging on its network architecture – a configuration where information spreads widely (or enforcement is implemented effectively).[2] In Dixit (2003) and Tabellini (2008), this problem is tackled by an *external* mechanism, possibly implemented through some political process. In our context, instead, it is a crucial endogenous component of the model, since it is a feature associated to the topology of the co-evolving social network.

Next, let me turn to the empirical literature concerned with the phenomenon of globalization. Typically, it has focused on a single dimension of the problem, such as trade (Dollar and Kraay (2001)), direct investment (Borensztein *et al.* (1998)) or portfolio holdings (Lane and Milesi-Ferretti (2001)). A good discussion of the conceptual and methodological issues to be faced in developing coherent measures along different such dimensions are systematically summarized in a handbook prepared by the OECD (2005 *a*,*b*). But, given the manifold richness of the phenomenon, substantial effort has also been devoted to developing composite indices that reflect not only economic considerations, but also social, cultural, or political. Good examples of this endeavour are illustrated by the interesting work of Dreher (2006) –see also Dreher *et al.* (2008) – or the elaborate globalization indices periodically constructed by A.T. Kearney/Foreign Policy (2006) and the Centre for the Study of Globalization and Regionalization (2004) at Warwick.

These empirical pursuits, however, stand in contrast with our approach in that they are not designed as truly systemic. That is, the postulated measures of globalization are based on the individual characteristics of the different "agents" rather than on their interplay with the overall structure of interaction. Our model, instead, calls for systemic, network-like, measures of globalization. A few papers in the recent empirical literature that move in this direction are Kali and Reyes (2007), Arribas *et al.* (2009), and Fagiolo *et al.* (2010). They all focus on international trade flows and report some of the features of the induced network that, heuristically, would seem appealing, e.g. clustering, node centrality, multi-step indirect flows, or internode correlations. Their objective is mostly descriptive, although Kali and Reyes show that some of those network measures have a significant positive effect on growth rates when added to the customary growth regressions. These papers represent an interesting first attempt to bring genuinely global (network) considerations into the discussion of globalization. To make the exercise truly fruitful, however, we need some explicitly formulated theory that guides both the questions to be asked as well as the measures to be judged relevant

[2] For the sake of focus, the leading motivation of our model emphasizes the informational implications of the social network in furthering economic interaction. But, complementary to this, in Appendix A we discuss an alternative interpretation where the social network fulfils instead an enforcement or monitoring role. This is in line with the influential work of Coleman (1988, 1990), who stressed that the cohesiveness (or, as he called it, "closure") of the social network is often key in deterring opportunistic behavior. This is a theme that has been revisited extensively by recent literature, generally casting the problem in game-theoretic terms – see e.g. Greif (1993), Haag and Lagunoff (2006), Lippert and Spagnolo (2006), Vega-Redondo (2006), Karlan *et al.* (2009) and Jackson *et al.* (2010).

In a companion empirical paper, Duernecker, Meyer, and Vega-Redondo (2011) have built on the theory presented here to undertaken a step in this direction. First, that paper introduces an operational counterpart of the measure of integration following from our present theoretical model. Then, it checks whether that measure is a significant variable in explaining intercountry differences in growth performance. In this exercise we again rely on the usual control variables that are considered in the growth literature but, most crucially, address the key endogeneity problem that lies at the core of the empirical issue. We find that our measure of integration is a robust and very significant explanatory variable, which supersedes traditional measures of openness (e.g. the ratio of exports and imports to GDP), rendering them statistically insignificant. This suggests that the network-based approach to integration that is proposed here adds (when compared with the usual "local" approach) a systemic perspective that is rich and novel. We refer the interested reader to the aforementioned companion paper for details.

3 The model

Our approach to modelling the process of globalization is very stylized. It can hardly accommodate, therefore, the manifold considerations that, even from a strict economic viewpoint, are involved in the phenomenon. As advanced, our perspective stresses the role of social networks as the mechanism through which globalization is attained. It also identifies the phenomenon itself with certain key properties displayed by the social network – in particular, with short network distances among the agents, even if they are very distant geographically.

In what follows, we describe the model formally, dividing the presentation in two parts. First, we describe the underlying spatial set-up and the social network that is superimposed on it. Second, we specify the dynamics through which the social network changes over time.

3.1 Interaction framework

Let N be a fixed (large) population of n agents, evenly spread along a one-dimensional ring of fixed length. To fix ideas, we shall speak of this ring as reflecting physical space but, as is standard, it could also embody any other relevant characteristic. The location of each individual in the ring is assumed fixed throughout. For any two agents i and j, the "geographical" distance between them is denoted by $d(i, j)$. By normalizing the distance between two adjacent agents to one, we may simply identify $d(i, j)$ with the minimum number of agents that lie between i and j along the ring, including one of the endpoints.

Time is modelled continuously. At each point in time $t \geq 0$, there is social network in place, $g(t) \subset \{ij \equiv ji : i, j \in N\}$, which consists of all the links ij currently established between every pair of interacting agents i and j. This introduces an alternative notion of social (network) distance, given by the length of the shortest network path connecting any two nodes. (If no such path exists, their social distance is taken to be infinite.) In general, of course, the prevailing social distance $\delta_{g(t)}(i, j)$ between any two nodes i and j can be higher or shorter than their geographical distance $d(i, j)$ – see Figure 1 for an illustration.

3.2 Dynamics

We conceive any link directly connecting two agents as an ongoing economic project that generates a certain flow of return for each of them as long as the project remains alive. In our leading interpretation of the model, links have no strategic considerations associated to them, and the primary role of the social network is to act

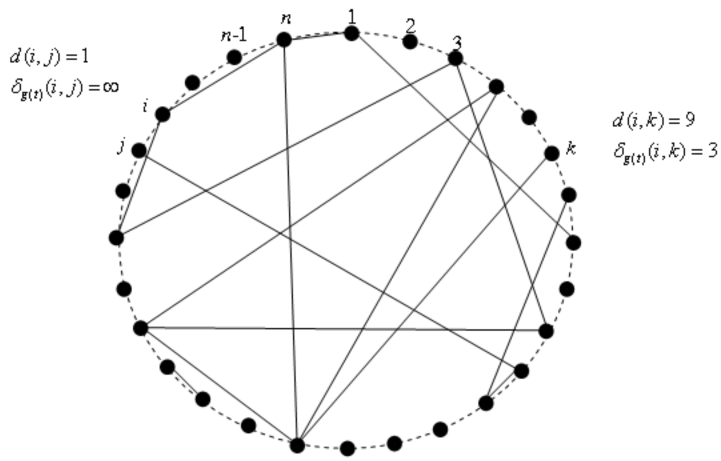


Figure 1: Snapshot of a situation at some t

as a channel for information on new economic opportunities. As advanced, however, one could also consider alternative (complementary) interpretations of the model in which the interaction between connected agents is strategic and thus link formation displays a game-theoretic dimension as well – see Appendix A for an illustration.

The law of motion of the model has the network $g(t)$ as the state of the system. It changes due to two forces alone: innovation and volatility. The first one fuels the creation of new links, while the second one leads to the destruction of existing ones. We describe each of them in turn.

3.2.1 Innovation

At every t, each agent i gets at a fixed rate $\eta > 0$ an idea for a new project. But this project requires the complementary skills of some other agent. From an *ex ante* viewpoint, the probability $p_i(j)$ that the agent required is some particular j is taken to satisfy:

$$p_i(j) \propto 1/\left[d(i,j)\right]^{\alpha}, \tag{1}$$

i.e. it decays with the geographical distance (geodistance, for short) between i and j, where the exponent $\alpha > 0$ modulates the effect of geography on the probability of finding the suitable match. In general, the suitability of a partner should be conceived as the net effect of how complementarity are the skills of the two agents involved as well as how compatible are their norms, behavior, or expectations. In this sense, one may think of α as a certain measure of "geographical cohesion," which is the convenient phrase that we shall often use for concision.

Consider now an agent i who has received an idea for a project that needs the concourse of another agent j. When will this idea indeed materialize into an actually running project? We posit that this will happen if, and only if, two conditions are jointly met:

(a) The agents i and j are not already involved in an ongoing project together.

(b) If i can learn of, or contact, j. This is assumed happens if at least one of the following situations arise:

(b.1) they are immediate geographical neighbors,

(b.2) they are at a social distance less than μ, a parameter of the model.

Condition (a) captures in a very simple and stark way one of the key ideas of our set-up – namely, that there is a limit to (or saturation of) the fruitful opportunities that can be carried out by repeatedly relying on a small set of partners. Thus, in order to expand such opportunities, the agents need to explore the "extensive margin" and expand the set of possible partners.

The additional Condition (b) also reflects an important feature of our approach. It specifies the crucial role of the social network in the search (or exploitation) of new opportunities. The requirement is that at least one of the following conditions apply. One possibility is that the two agents involved, i and j, are immediate geographical neighbors. Then the implicit assumption is that they know of each other's characteristics and can easily contact each other, hence they can readily exploit any bilateral opportunity that comes about. But if they are not geographic neighbors, they must rely on the social network for that. And, in this case, the requirement is that the social distance between them along the network not be too large. The implicit assumption is that information (or access potential) decays with social distance. Thus, in order for it to be effectively used, the social distance between the two agents in question cannot exceed μ. For conciseness, we shall briefly refer to this parameter as *institutions* since, intuitively, it reflects the extent to which agents are willing to act as social intermediaries in facilitating information or access to others, even when they are socially distant.[3]

3.2.2 Volatility

As advanced, volatility is the second force governing the process, inducing project decay. We posit that every existing project is discontinued (say, because it becomes "obsolete") at a constant rate λ, which will be normalized to unity ($\lambda = 1$) without loss of generality. Thus, for the sake of focus, we choose to model link destruction as an exogenous process, letting the interplay between the social network and the overall dynamics be channelled through the mechanism of link formation alone.

4 Analysis

In a nutshell, the network formation process modelled in the preceding section can be succinctly described as the *struggle of innovation against volatility.* The primary objective of our analysis is to understand the conditions under which such a struggle allows, in the long run, for the maintenance of a high level of economic interaction (i.e. connectivity). More concretely, our focus will be on how the long-run performance of the system is affected by the (sole) three parameters of the model: η (the rate of innovation), α (geographical cohesion) and μ (institutions).

[3] An interpretation of the parameter μ as "institutions" is probably more intuitive in the strategic framework described in Appendix A. There, the social network acts as social collateral, with agents punishing a deviation from a cooperative social norm involving interactions they do not directly participate in (or, rather, threatening to do so). Such third-party enforcement of the social norm presumes that are agents feel concerned by what occurs in distant parts of the social network, the maximum distance at which this happens being a measure of institutional quality. See the aforementioned Appendix for further elaboration on this idea and a discussion of related literature.

The discussion is organized in three parts. First, we present numerical simulations that highlight a set of interesting observations that arise in our set-up. Second, we propose a theory that, even though directly applicable only to a extreme limiting case, sheds light on the key mechanisms that underlie the aforementioned observations. Third, we devise a general approach to solving the model numerically that allows us to generate a full array of comparative-statics results for all parameter configurations and thus provides an exhaustive understanding of the model.

4.1 Numerical simulations: some interesting observations

We have conducted numerical simulations by discretizing in a natural way the continuous-time theoretical model. (See the Appendix B for a detailed description of the algorithm used.) These simulations have given rise to a number of leading observations, which in turn have guided the subsequent theoretical analysis presented in Subsections 4.2 and 4.3. In what follows, we single out three observations. For each of them, we first summarize it in a concise statement, then report simulation evidence that supports it, and finally discuss its relevance.

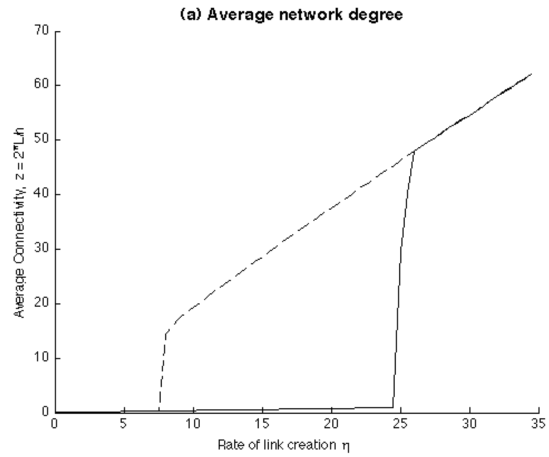
Our first observation can be formulated as follows.

Observation 1: *For suitably small values of μ and α, a dense social network (a high level of economic activity) only materializes if the innovation rate η is high enough. As η grows, the transition to a high-connectivity state occurs abruptly (discontinuously) at a well-defined threshold. This transition is associated to a phenomenon of fast* globalization*, i.e. the average geographical distance of links grows sharply and the average network falls sharply as well. Within an intermediate range for η, the model displays multiplicity and hysteresis. That is, both a high- and low-connectivity state are stable, and which one obtains depends on initial conditions.*

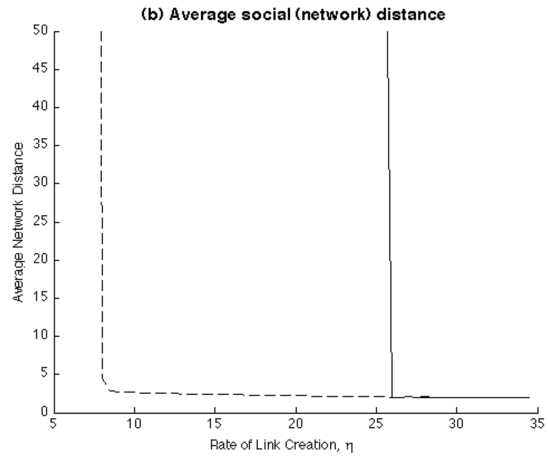
This observation is illustrated in Figure 2, where we trace the long-run values of four different variables, recorded at steady states of the process, as the parameter η changes. In conjunction, the four panels provide a good account of the main characteristics displayed by the *steady states* on which the system settles down in the long run. In Panel (a), we consider the average network degree (i.e. number of links per node) given by $\frac{2L}{n}$, where L stands for the number of links and n is the size of the population. In Panel (b), we focus on the average geodistance among connected nodes, $\frac{1}{L}\sum_{ij\in g} d(i,j)$. In Panel (c), we have the average social (network) distance between the nodes in the network, $\frac{1}{N}\sum_{i,j\in N} \delta_g(i,j)$. And, finally, in Panel (d) we depict the effective probability of link creation, which is defined as the conditional probability that, whenever any two agents meet, they actually form a new link.[4]

The results depicted in Figure 2 are obtained for $\alpha = 0.5$, $\mu = 3$, and $\eta \in [0, 35]$, with λ normalized to unity and a population size $n = 1000$. Any of the diagrams has to be read as follows: Each point located on either the solid or the dashed line represents the equilibrium value of the respective endogenous variable obtained for the given (α, μ, η). What distinguishes the outcomes on the solid and dashed lines is the approach used to computing the equilibrium in each case: the solid line traces the steady states obtained as one *increases* η very gradually, while the dashed line corresponds to very gradual *decreases* in η. More

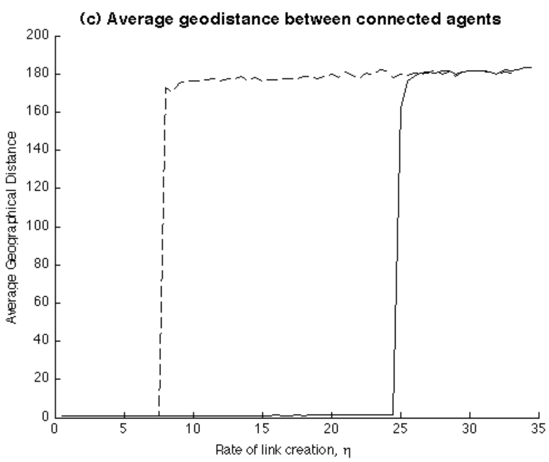
[4] Note that, typically, links are not formed for two different reasons: either because the agents in question are too socially apart or because the link is already in place. As we shall see, both reasons yield interesting considerations in our analysis.



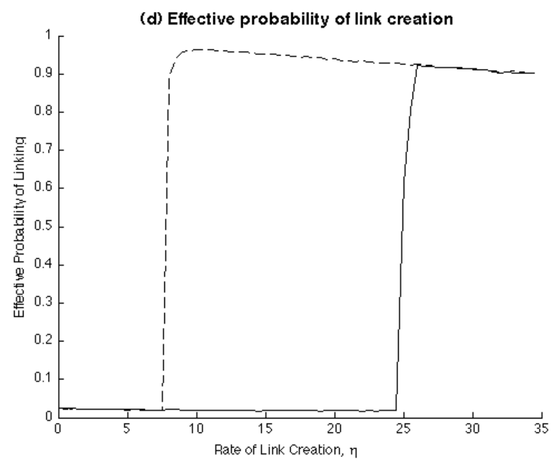
(a) Average network degree



(b) Average social distance



(c) Average geodistance



(d) Effective linking probability

Figure 2: Discontinuous transition in network connectivity, and hysteresis, as the innovation rate η changes for given (low) $\alpha = 0.5$ and $\mu = 3$ (with $\lambda = 1$, $n = 1000$).

precisely, for any given η, the corresponding point on the *solid line* is obtained by starting from initial conditions given by the steady state formerly computed at a very close value $\eta' < \eta$. From there, the system is simulated until a steady state is reached, which in turn acts as the initial conditions for a slightly higher $\eta'' > \eta$. Instead, the point associated to η on the dashed line is obtained from initial conditions given by the steady state formerly obtained for a slightly higher value. As we shall discuss shortly, these two procedures induce marked and interesting path-dependencies within a suitable parameter range.

The solid line in Panel (a) delivers the key message of our first observation: if α and μ are relatively low, economic activity (as measured by the average connectivity) is hardly affected by improvements in the innovation rate η up to a certain threshold. But, at this threshold, a new regime suddenly arises at which (i) the connectivity is drastically higher, and (ii) further increases in η translate into almost proportional increases in connectivity.

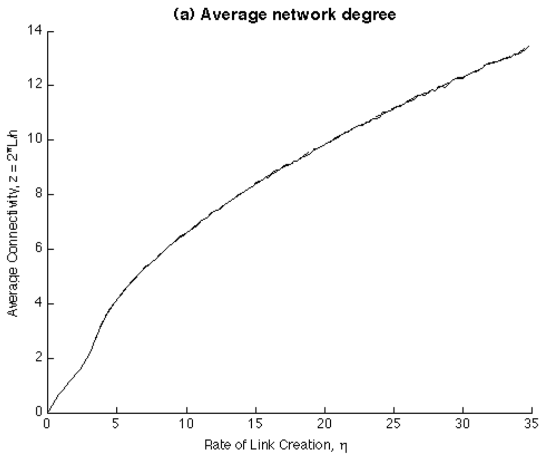
The intuition for this behavior is as follows. Under a low value of α, agents' effective meetings occur at a global scale – i.e. a high fraction of the partners who are needed for profitable collaborations lie geographically quite apart. Thus, if institutions μ are weak and the original network is quite sparse, social distances between those agents tend to be too long. Collaboration opportunities, therefore, tend to be "wasted" and links are not formed, which perpetuates a low-connectivity state. The same state of affairs continues to hold up to the point where the network reaches a critical size for which further increases in η start to have some nonnegligible effect. This, in turn, feeds on itself by reducing the social distance between agents and thus allowing more links to be formed. In the end, the process can settle only at a steady state with much larger connectivity, which is the sharp increase seen in Figure 2. When such a transition takes place, the social distance among even geographically distant agents is much reduced, so further increases in η are translated into a sustained (almost proportional) increase in connectivity. Thus a new regime sets in, which is what we called *globalization.* In fact, within a some intermediate region for η (the interval $(7, 25)$ in our illustration) whether such a regime materializes or not depends on whether the initial conditions embody a globalized state or not. This reflects the phenomenon that is often described as hysteresis. Conceptually, it amounts to saying that transitions are robust, i.e. not reversed by small changes in the the parameter η in either direction. It also leads to strong path-dependencies, with "history" playing a key role in explaining why the economy is at its current state.

Indeed, the preceding understanding of the phenomenon at an intuitive level is strongly supported by the remaining Panels (b)-(d) in Figure 2. There we find that the upward shift in connectivity is accompanied, as a mirror image, by the following changes: a corresponding sharp decrease in the average social distance, an acute increase in the average geodistance of prevailing links, and a steep rise in the effective linking probability. Therefore, the basic insight one obtains is that, in effect, *globalization* (characterized, as two sides of the same coin, by both short social distances and links of long geodistance) is a necessary and sufficient condition for high economic activity. Under a low value of α (weak geographical cohesion), effective meetings take place at a global scale and thus there is the *potential* for the benefits of global interaction as well. But this potential materializes only if the social network manages to attain enough structure and becomes itself global. Under these conditions, even if institutions are poor (in our case, $\mu = 3$), links can continue to be formed at a good rate (from Panel (d), at least 80% of the time) because a the average social distance is low (as seen in Panel (b), somewhat below 3).

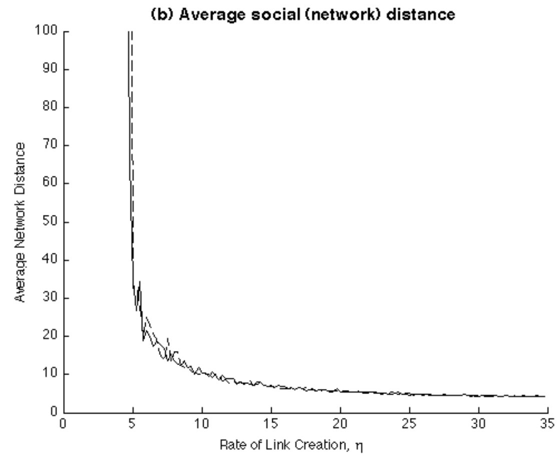
Observation 2: *If geographical cohesion is high* (α *large*)*, the effect of the innovation rate* η *on network connectivity is gradual and no multiplicity arises. Globalization is no longer a crucial issue but local saturation does become important. Thus, as* η *grows, even if the effect on connectivity stays sizably positive, the effective linking probability* (*i.e. the fraction of meetings that give rise to new projects*) *remains low and eventually decreases significantly.*

This observation is illustrated in Figure 3. Panels (a)-(d) depict, as before, the equilibrium outcomes of, respectively, the average connectivity in the network, the average geographical and social distances, and the effective probability of link creation. The results visualized in Figure 3 are obtained for $(\alpha = 2, \mu = 5)$ and $\eta \in [0, 35]$. Comparing them to Figure 2 we observe the following marked differences.

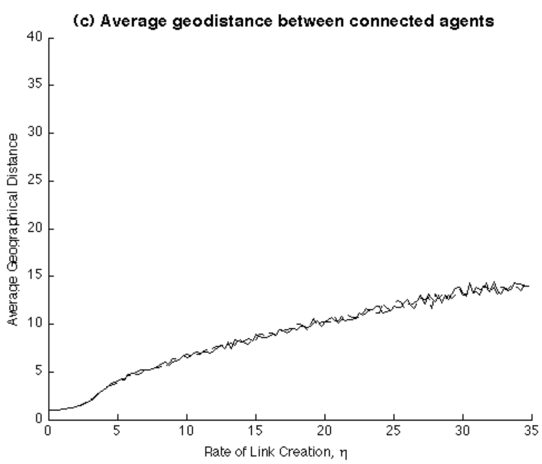
First and foremost, we find in Panel (a) that the effect of the innovation rate η on economic activity is gradual and there is no hysteresis. The key to explaining this observation is that, for $\alpha = 2$, geographical



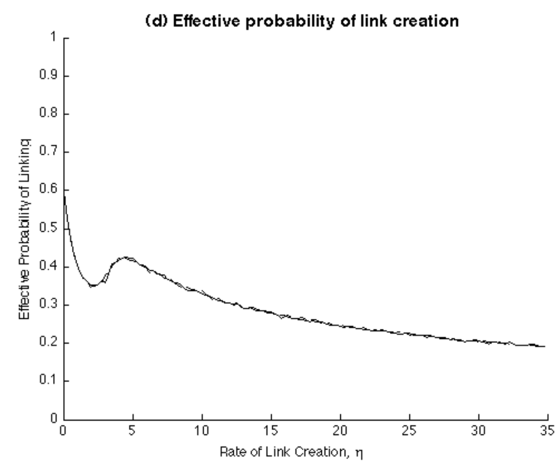
(a) Average network degree



(b) Average social distance



(c) Average geodistance



(d) Effective linking probability

Figure 3: Continuous change in network connectivity, without hysteresis, as the innovation η rate changes when $\alpha = 1$ and $\mu = 5$ are relatively high ($\lambda = 1$, $n = 1000$).

cohesion is very high and, therefore, there is not even a genuine *potential* for globalized interaction. Thus the bulk of the process unfolds locally and most of the meetings occur between nearby agents, who are generally able to form a link if they are not already connected. Therefore, as η grows, the rise in the average connectivity occurs continuously, and is largely unaffected by the network considerations (e.g. there is no need for the sharp reconfiguration of the network topology that underlay the transition to globalization in the former case).

Again this intuitive understanding of the situation is well supported by Panels (b)-(d) in Figure 3. In Panel (c) we see that links are mostly local – the average geodistance is low and it grows gradually with η. Naturally, as η rises, the corresponding increase in connectivity induces a falling social distance. But, as visualized in Panel (b), such a decrease is much more gradual than in the former scenario.

Probably the most interesting feature is found in Panel (d). There we see that the effective linking probability falls significantly with η as this parameter grows high. This is the consequence of a saturation effect that is essentially absent in a globalized state. As η grows and more of the local links have already been formed, meeting opportunities tend to be wasted because the agents involved are already linked. This leads to an overall fall in the effective linking probability, which is only shortly offset in a narrow intermediate range due to positive – but ephemeral – network effects. In a sense, the short rise observed can be interpreted as a frustrated attempt to move towards globalization. In the end, the curse of local saturation dries up the flow of fresh opportunities that arise when η increases, thus underscoring why, in our model, globalization is an indispensable basis for *sustained* economic growth.

Observation 3: *Building up a highly connected social network from a sparse one requires some degree of geographical cohesion. In general, given η, the "optimal" value of α that maximizes long-run connectivity falls with μ, the quality of institutions. If these are poor, it is best that new linking opportunities arise at a relatively local level so that the structure provided by "geography" can offset such limitations. This, however, implies that the overall degree of connectivity that can be achieved is correspondingly low.*

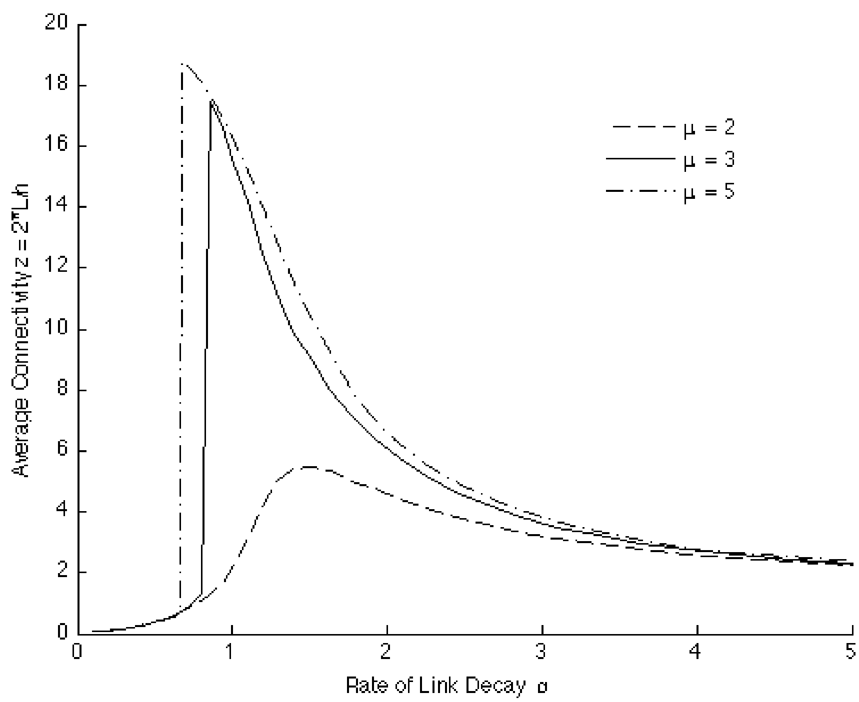


Figure 4: Network connectivity as geographical cohesion α grows, for a given value of $\eta = 10$ and different values of institutions μ ($\lambda = 1$, $n = 1000$).

This observation is illustrated in Figure 4, which depicts the average network connectivity as a function of the parameter α, for a fixed $\eta = 10$ and three different scenarios regarding the strength of institutions, i.e. $\mu \in \{2, 3, 5\}$. In every case, the simulation is started at an empty network. The range under consideration is $\alpha \in (0, 5]$. As will be recalled, high values of α entail that most opportunities arise locally and thus the typical geographical scale at which new links are formed is small, while low values imply that most opportunities unfold between geographically distant agents.

Let us refer to the value α^* at which economic/network activity is maximized as the "optimal geographic cohesion" (OGC) – graphically, it corresponds to the point in the horizontal axis where the functions depicted in Figure 4 attain their respective maxima. First we note that, for each value of μ, the OGC is reached at an intermediate value – i.e. it is neither extremely small nor extremely large. This is indeed quite intuitive. In principle, in the absence of network considerations (i.e. if link formation were independent of the prevailing network), the best situation would be one in which the meetings giving rise to new opportunities take place as globally as possible. For, clearly, this is the situation that minimizes the detrimental effects of local saturation. But if, as postulated in our model, the creation of a new link requires that the two agents involved are not too distant socially, such a large long geographical scale is suboptimal. The problem in this case is that the population is unable to develop enough social structure *from scratch* to sustain link formation when the network is sparse. By contrast, the problem can be partially remedied if those meetings take place at a shorter scale. Then, the population can rely upon the structure afforded by geographical cohesion to seed, and then fuel, the early stages of the network build-up.

In the end, the optimal compromise between the two previous considerations – geographical structure and local saturation – is reached at some intermediate level, the OGC α^*. And, naturally, the "price" to be paid in the form of local saturation of opportunities must be tailored to the importance of the linking-supporting structure, which in turn depends on the quality of institutions. Indeed, as Figure 4 shows, the OGC falls (i.e. opportunities should become more global) the stronger are institutions. Naturally, this is simply because the higher is μ, the less severe are the network-based limitations imposed on link formation and, therefore, the less detrimental it is to rely on a global mechanism.

4.2 Benchmark theory: low geographical decay

In this section, we consider a benchmark extreme case where the mechanism that underlies new linking opportunities is essentially unaffected by geographic distance – i.e. a context with a vanishingly small α and a very large population size. The insights gained from studying this case will help us understand the essential role that the spatial dimension plays in the general model. We shall see, in particular, that "geography" provides the crucial structure that allows the system to escape an initial configuration where the network is empty (i.e. has no links).

Our analysis will revolve around the following simple characterization of the stable steady states of the process. Let ϕ denote the effective (or conditional) linking probability prevailing at some steady state, i.e. the probability that an agent who receives an innovation draw effectively forms a link with the partner she happens to meet. Then, the induced (total) rate of project/link creation is $\eta\,\phi\,n$, where recall that η is the innovation rate and n is the population size. On the other hand, if we denote the average degree (number of links per node) by z, then the rate of project/link destruction is $\lambda(z/2)n = \frac{1}{2}zn$. (Note that the number of links is half the total degree because every link contributes to the degree of its two nodes.) Thus, finally, bringing the former two expressions together, the condition "rate of link creation = rate of link destruction" that characterizes a steady state can be written as follows:

$$\phi = \frac{1}{2\eta} z. \tag{2}$$

Naturally, the difficulty here lies in a proper determination of ϕ, which in general must be a function of the state of the system and the full array of parameter values. In this respect, it is useful to make the simplifying (approximately correct)[5] assumption that, at a steady state, the induced social network can be represented by the canonical construct of the random network literature: an Erdös-Rényi (binomial) network. For, in this case, the overall (statistical) properties of the network when the population is arbitrarily large are fully captured (asymptotically) by the average degree of the network z. And therefore, we may conceive $\phi = \phi(z)$ to be a function of z as well. Then, the equilibrium condition (2) becomes merely an equation in z and we can solve it to find the values of the average degree that define a steady state of the process. More precisely, our aim is to single out the solutions of the equation that are stable, since these are the only ones that are truly relevant as predictions of the model.

Let us now summarize some standard properties of an Erdös-Rényi (ER) network that will be of important use in our analysis. First, it is well known that if the expected degree is large enough, there is a unique component of the network that has a significant fractional size, i.e. encompasses a fraction of nodes that is bounded above zero when n is large – see, e.g., Bollobás (1985).[6] Indeed, it turns out that a necessary and sufficient condition for the existence of such a giant component is simply that $z > 1$. And, in that case, its fractional size $\chi > 0$ can be computed as the unique positive solution to the following equation (cf. Vega-Redondo (2007)):

$$\chi = 1 - e^{z\chi}, \tag{3}$$

inducing the function $\chi(z)$ that is depicted in Figure 5.

The function $\chi(z)$ can be used to define an upper bound of the function $\phi(z)$ that specifies the effective linking probability for the present benchmark model. Recall that the *conditional* probability ϕ that any agent i, upon receiving an idea, establishes a link to a particular agent j is equal to the probability that either they are geographical neighbors or/and their social distance is no higher than the prevailing (finite) value of institutions μ. Clearly, the first event may be ignored if α is infinitesimal and n infinitely large. And concerning the second event, note that its probability is bounded above by the probability that both i and j belong to the same component. For only if two agents are part of a common component may their distance be finite and thus not exceed the prevailing (finite) value of institutions μ. From an *ex-ante* viewpoint, the probability of such event is χ^2, where χ is the fractional size of the giant component derived from (3). This allows us to write:

$$\phi(z) \leq [\chi(z)]^2, \tag{4}$$

which defines the advanced upper bound for the effective linking probability.

For simplicity,[7] let us provisionally abstract from the dependence on institutions by assuming that, albeit

[5] As shown in Lemma 1 in Appendix A, the assumption that the degree distribution is Poisson (i.e. the limit of a binomial distribution for large n) is fully accurate when the network connectivity is high enough that all nodes belong to a single component. When network connectivity is relatively low and a significant fraction of nodes do not belong to the giant component, the Poisson assumption introduces some distortions (see Remark 1). These distortions, however, do not affect the qualitative behavior of the model for low α, as confirmed in Subsection 4.3.

[6] Naturally, all the statements made concerning an ER network must be probabilistic. Thus, when a property is said to apply, it is interpreted to be true with asymptotic probability converging to unity when the number of nodes grows large, i.e. as $n \to \infty$. Also note that by asserting that there is a unique giant component, it is implied that all other components must have a vanishing fractional size for large n.

[7] In general, however, for the present argument to apply, it is enough that μ is of order $\ln(n)$. This follows through standard arguments from our maintained assumption that the social network in the globalized state can be suitably conceived as a random network.

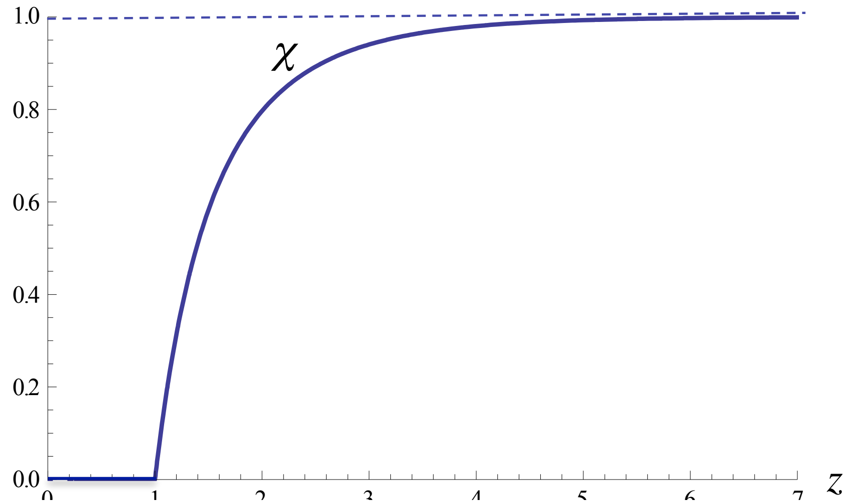


Figure 5: The fractional size $\chi = \chi(z)$ of a Poisson random network, as a function of the averagedegree z.

being finite, μ is arbitrarily large – in particular larger than the population size n. Then, we can invoke inequality (4) with equality and the steady state condition (2) can be formulated as follows:

$$[\chi(z)]^2 = \frac{1}{2\eta} z.$$

As explained, expression (3) determines $\chi(z)$ as depicted in Figure 5, in turn leading to the graphical representation of the steady-state condition that is illustrated in Figure 6.

Steady states are represented in Figure 6 by intersections of the sigmoidal-like function $[\chi(z)]^2$ and the ray of slope $1/(2\eta)$. If η is small enough (such as $\eta' = 1$), the induced ray is so steep that the only steady state involves a network displaying a zero average degree. Instead, for larger values of η (such as $\eta'' = 2$ or $\eta''' = 5$) there are two *additional* steady states with a positive average degree (z_2'' and z_3''' for η''). These two latter equilibria differ, however, in their stability properties. The one with a lower degree is unstable because, in its vicinity, the discrepancy between the rates of link creation and destruction moves the system away from it. Instead, the other one yields exactly the opposite local dynamics and hence is stable.

A key observation to highlight is that, for every value of η, the zero-degree equilibrium is *locally stable*, no matter how high is the value of η. This leads to the following important point. If the system starts with a very low average connectivity, it will never be able to escape such a state of affairs through a (gradual) dynamic adjustment of the situation, *even if the environment becomes arbitrarily good* in terms of the rate at which new ideas arrive. The economy, in other words, is stuck in a low-activity trap, from which it cannot free itself by relying on individual behavior alone. As we explain next, the root of the problem is that, because $\alpha \simeq 0$, the mechanism of network formation is not helped at all by (i.e. does not profit from) the underlying geographic structure. But, as we shall see, to rely on *some* such structure is indispensable for the process by which an originally low-interaction economy may become global and thus sustain a high level of interaction!

To shed light on the problem, let us see how the value of α affects the extent to which geography can afford the required structure. As it turns out, the specific value $\alpha = 1$ marks the threshold that separates

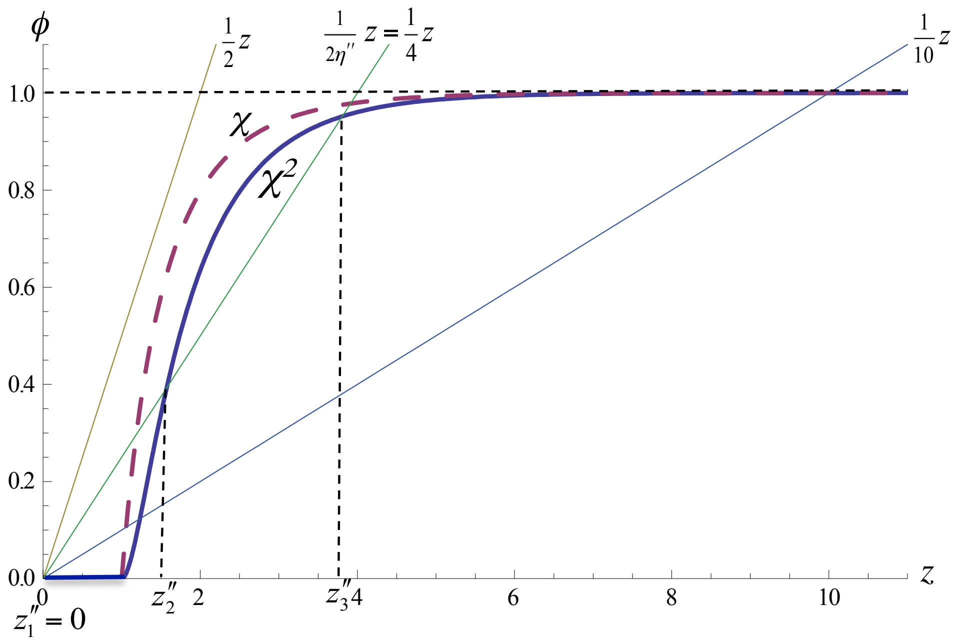


Figure 6: Illustration of the equilibrium condition for the benchmark model for three different values of the innovation rate: $\eta' = 1$, $\eta'' = 2$, $\eta''' = 5$. For the intermediate η'', there are three equilibria, whose corresponding average degrees are denoted by $z''_1(=0)$, z''_2, and z''_3. While the first and third are stable, the one associated to z''_2 is unstable.

two regions where the situation is qualitatively different. On the one hand, if $\alpha \leq 1$, the probability that any agent i meets an agent j within some pre-specified finite (but arbitrarily large) distance converges to zero as $n \to \infty$. This follows from the fact that, for any given $\tilde{d}$, the probability of selecting a partner within this distance as the population grows can be approximated by

$$p(\tilde{d}, n) = \left[\int_1^{n/2} x^{-\alpha} \mathrm{d}x\right]^{-1} \int_1^{\tilde{d}} x^{-\alpha} \mathrm{d}x$$

and therefore

$$\lim_{n \to \infty} p(\tilde{d}, n) = 0$$

because the function $x^{-\alpha}$ is not integrable (i.e. does not have a bounded integral) over the range $[1, \infty)$ when $\alpha \leq 1$. Under these conditions, therefore, if the network displays an average degree lower than one, the effective linking probability must be zero. For, on the one hand, the probability that two randomly selected nodes belong to the same (infinitesimal) component is zero. And, moreover, the same applies to the probability that two geographical neighbors meet. Thus, relying on the same argument as before, we may conclude that the empty network is locally stable for *any* finite value of η. In the end, we arrive at the conclusion that the case where $\alpha \leq 1$ is qualitatively the same as that where α is vanishingly small.

Matters, however, are quite different when $\alpha > 1$. In this case, the probability that any agent i has her close geographic neighbors selected for a possible partnership is positive – in particular, the probability that either of the two *immediate* ones is selected is given by (assuming n is odd) $\left[\sum_{d=1}^{(n-1)/2} d^{-\alpha}\right]^{-1}$, which is bounded above zero as $n \to \infty$. This induces an important qualitative contrast with the conclusions obtained for the case $\alpha \leq 1$. In particular, as we shall see, there is no longer a inescapable trap for low-activity states. The corresponding stability analysis is illustrated in Figure 7.

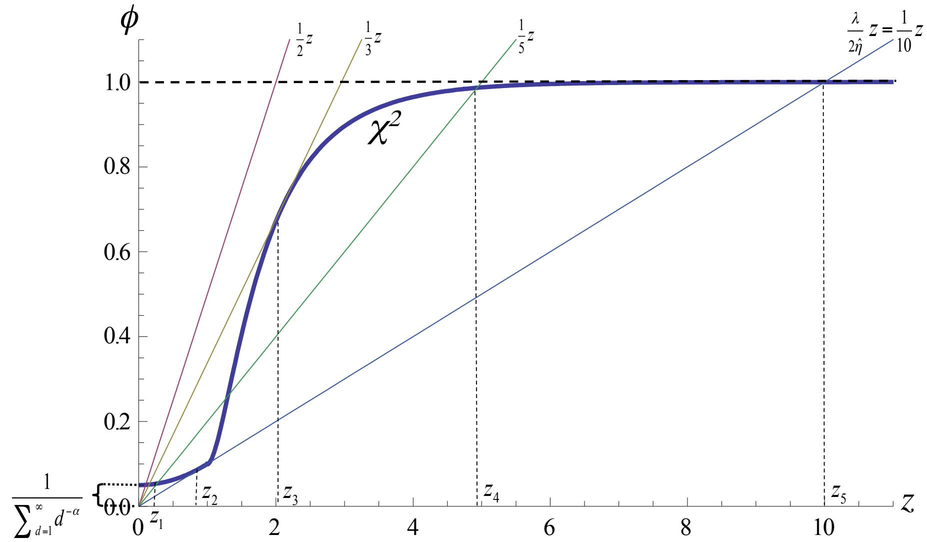


Figure 7: Destabilization of the low-activity equilibrium in the benchmark model for $\eta > \hat{\eta} = 0.1$.

There we see that the conditional linking probability ϕ is positive, even at $z = 0$. This implies that there has to be a high enough value of η (i.e. a ray with a sufficiently low slope $1/\eta$) that de-stabilizes the low-connectivity steady state. In fact, if α is sufficiently close to 1, a continuity argument with respect to the scenario with $\alpha \leq 1$ implies that, at some threshold value $\hat{\eta}$ (in the illustration displayed in Figure 7, $\hat{\eta} \simeq 0.1$) the low-degree state (which would be locally stable for $\eta < \hat{\eta}$) becomes unstable for $\eta > \hat{\eta}$ and only a high-degree state remains (globally) stable. In a dynamic set-up, this leads to the following conclusion. If the economy were to start at a low-degree equilibrium for an innovation rate η slightly below $\hat{\eta}$ and then this rate increased a little past $\hat{\eta}$, a large discontinuous jump in the average degree would be observed. Reciprocally, if once the aforementioned transition has taken place, the value of eta were to decrease gradually past $\hat{\eta}$ to a value lower than it, the relatively high degree of the network would be preserved. Thus we reproduce the sharp transitions cum hysteresis that, as will be recalled, was the pattern found in our numerical simulations for low values of α.

The usefulness of the benchmark theory is not limited to shedding light on the transition to globalization as the innovation rate η rises. It also helps one understand interesting properties of the globalized phase itself. By way of illustration, consider again Figure 2, and focus on panel (a) that shows how the average degree of the network changes with the innovation rate η, both below and above the globalization threshold. A clear-cut feature of the globalized phase is that the average degree is linear in η with a slope that is approximately equal to 2.

To see that the benchmark model predicts this conclusion, let us return to the simple condition (2) that characterizes the steady states of the system. In a globalized state, it can be suitably postulated that essentially all nodes are part of the (single) giant component of the network. Then, under our maintained simplifying assumption that μ is large enough (cf. Footnote 7), it follows that $\phi \simeq 1$ and thus equation (2) may be approximately rewritten as follows:

$$z = 2\eta \tag{5}$$

But even if we consider a wide range of different values for μ, some even quite small, the above relationship continues to hold once the transition to globalization has taken place. This is illustrated in Figure 8, where such a transition is depicted for different values of μ.[8]

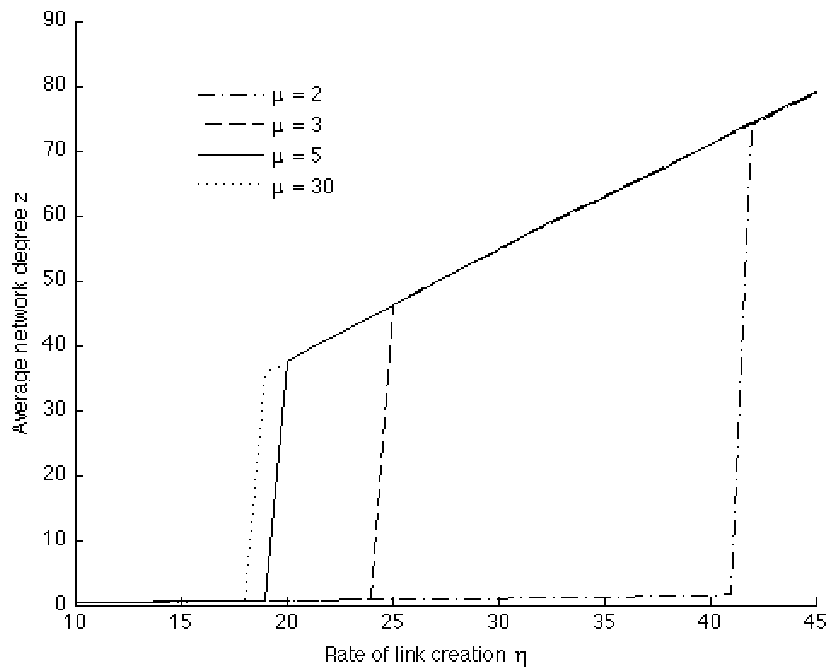


Figure 8: Network connectivity as the innovation rate η rises, for a given (low) value of $\alpha = 0.5$ and different values of institutions (with $\lambda = 1$, $n = 1000$).

The benchmark model considered in this subsection has been proposed as the stylized idealization of a context where the cohesion parameter α is small and thus geographical cohesion plays little role other than in the transition to globalization. Another limitation of the benchmark model is that it only works well asymptotically for very large populations and, short of that, can lead only to approximate predictions (see Footnote 8) or qualitative ones (e.g. the existence of sharp transitions and hysteresis if α is small). In general, of course, it is quite of some interest to expand on the analysis to remedy those problems: first, in order to study cases where the limiting assumptions underlying the benchmark model are not adequate; second, to obtain numerically accurate predictions. This is the objective of the following Subsection 4.3.

[8] The fact that the common slope displayed in Figure 8 is slightly below 2 must be viewed as a correction originated by finite-population effects of two sorts. First, not all nodes are indeed at distance lower than μ, since this can only be asserted asymptotically. Second, there is some positive probability that, in a finite population, two agents who are currently linked actually meet even if the meeting probabilities are uniform.

4.3 From the benchmark model to the general approach

The approach pursued here to undertake a general analysis of the model builds crucially upon the conceptual and methodological insights resulting from our analysis of the benchmark model in Subsection 4.2. In particular, we shall continue to rely on the steady-state condition (2) to determine the values of average connectivity around which the system gravitate over time. And, as before, this will allow us to single out the stable steady states, as well as the transitions between them induced by small changes in the parameters of the model. But, in order to proceed in this fashion, we must first develop a way of determining the function $\phi(z)$ that gives the effective linking probabilities associated to different values of z. In this case, we shall do it numerically rather than graphically or analytically. Thus, in contrast with our former approach, we shall rely on numerical methods to arrive at a good estimate of the function ϕ, and on the basis of it a theoretical analysis parallel to that conducted for the benchmark set-up will be subsequently conducted

Specifically, for any given any parameter configuration, the value $\phi(z)$ associated to any value of z is determined as follows. First we simulate the process starting from an empty network but putting the volatility component on hold – that is, avoiding the destruction of links. We continue with this initial volatility-free phase until the average degree z in question is reached. Thereafter, we move into a second phase where random link destruction is brought in so that, at each point in time, the average degree remains always equal to z. [9] Then, as the simulation proceeds in this fashion during the second phase of the procedure, we record the fraction of times that a link is created between selected partners. When this frequency stabilizes, the corresponding value is identified with $\phi(z)$.

Given the function ϕ computed in this fashion, the value $2\eta\phi(z)$ induced for each z acts, just as in the benchmark model, as a key theoretical reference. For, in effect, it specifies the "notional" rate of project creation that would ensue (normalized by population size) *if* such average degree z were stationary. When the overall (normalized) rate of project destruction $\lambda z = z$ equals $2\eta\phi(z)$, the former "if" applies and thus a steady state obtains. Thus, diagrammatically, the situation can be again depicted as a point of intersection between the function ϕ and a ray of slope equal to $1/(2\eta)$. Figure 9 includes different panels where such intersections are depicted for different values of α and μ and a fixed ratio $1/(2\eta)$, using the corresponding function ϕ obtained as explained.

As a quick and informal advance of the systematic analysis that is undertaken below, note that Figure 9 shows behavior that is fully in line with the benchmark model and how it has shaped our intuitive understanding of the phenomenon of globalization. First, we see that the transition towards a highly connected network is abrupt and large for low values of α, but gradual and significantly more limited overall for high values of this parameter. To focus ideas, consider specifically the panel for $\alpha = 0.5$ and the case with $\mu = 3$. There, at the value of η associated to the ray being drawn ($\eta \simeq 15$), the system is at a point of a discontinuous transition. This situation contrasts with that displayed in the panels for larger α – see e.g. the case $\alpha = 2$ where the differences are starkest – in which changes in η trace a continuous change in the equilibrium values. Finally, observe that if one fixes η at its given value and considers instead how changes in α affect the lowest-connectivity equilibrium, the effect is non-monotonic. First, the average degree increases with α, which reflects the positive impact of stronger geographic cohesion on the ability to form new links when the social network is sparse and local. Then, beyond a certain point, further increases in α

[9] In practice, this implies that at each instant in which a new link is created, another link is subsequently chosen *at random* to be eliminated (thus link deletion is done in an unbiased manner) so that the average degree of the network remains always equal to the desired value of z

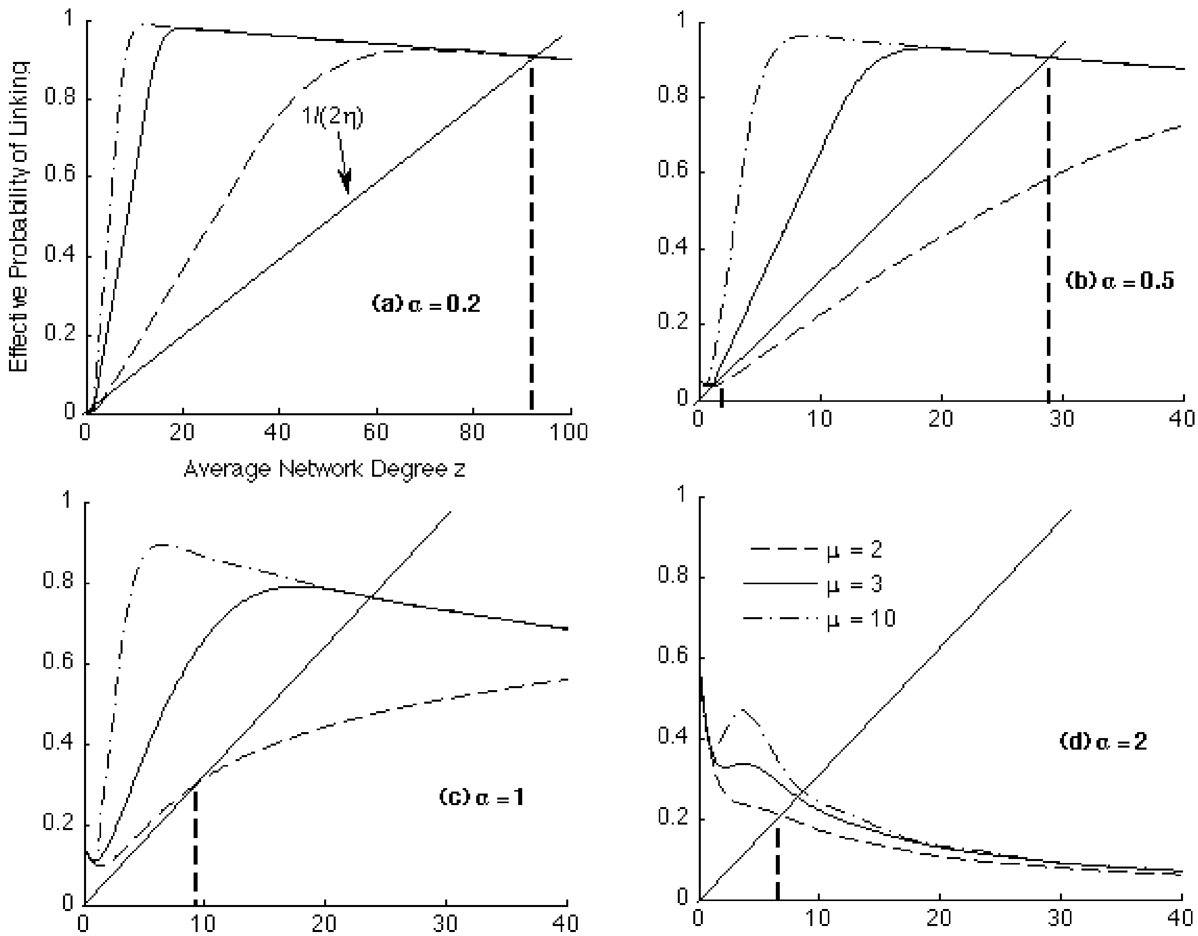


Figure 9: Graphical representation of the equilibrium condition (2) in the general framework. The diagrams trace the steady states as points of intersection between a fixed ray of slope $1/(2\eta)$ and the function $\phi(z)$ computed for different institutions μ (within each panel) and decay parameters α (across panels).

are detrimental on equilibrium connectivity, which is the familiar effect due to local saturation that arises as the opportunity-generation mechanism becomes too local.

Figure 10 shows that there is a precise correspondence – not just qualitative but also *quantitative* – between the theoretical predictions induced by our present approach and our earlier simulations. This is evinced by bringing together in the same diagrams the predictions induced by the equilibrium (steady-state) condition (2) applied to the numerically computed $\phi(\cdot)$ and the simulation results reported in Subsection 4.1 – recall Figures 2 -4

We can confidently regard, therefore, our present approach as a suitable way of analyzing theoretically the model, very much along the lines used for the benchmark set-up in Subsection 4.2. This is the objective of the remainder of the subsection, where we conduct a comparative analysis of the interplay between the different parameters. Since, as explained, the function ϕ is computed numerically, we need to discretize the continuous variables η and α (institutions μ is already defined to be discrete). For η we choose a grid of

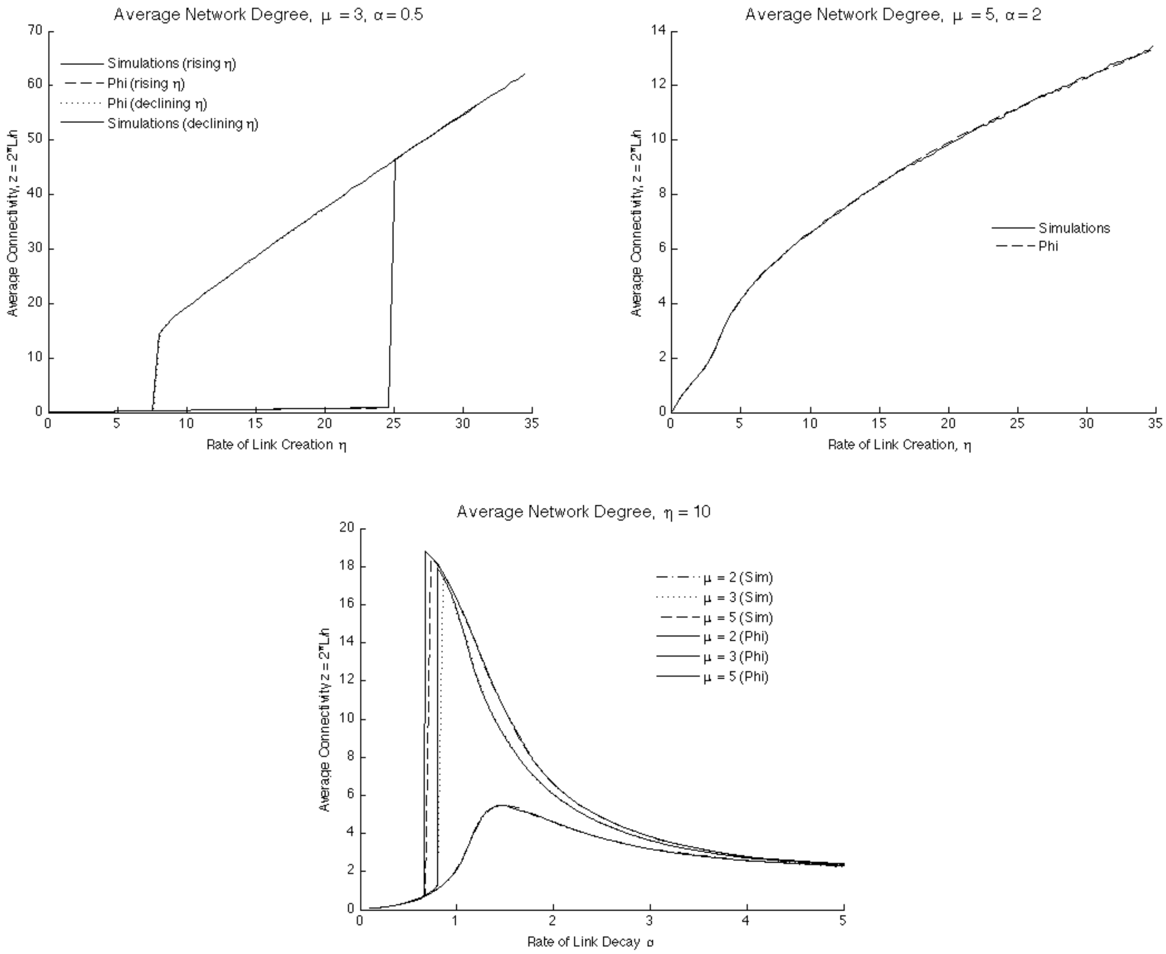


Figure 10: Comparison between the theoretical predictions and the numerical simulations for each of the parameter-dependence exercises conducted in Observations 1-3.

unit step, i.e. the set $\Psi_\eta = \{1, 2, 3, ...\}$ while for α the grid step is chosen equal to 0.05, thus the grid is $\Psi_\alpha = \{0.05, 0.1, 0.15, ...\}$. As population size, our results below are reported for $n = 1000$. All of our ensuing conclusions are obtained by an exhaustive exploration of the parameter space. We have also conducted robustness checks to confirm that they are unaffected by the use of even finer grids or larger population sizes.

4.3.1 Transition to globalization and the innovation rate

We start with the study of the issue that was first brought up in Subsection 4.1 when discussing Observation 1 – that is, to understand under what conditions (given α and μ) the transition to globalization induced by changes in η is abrupt and displays hysteresis. Let $\zeta_0(\eta; \alpha, \mu)$ be the function that specifies the *lowest average degree* at a *stable equilibrium* associated to the indicated parameter configuration. First, we need to put forward a precise criterion as to when the function $\zeta_0(\cdot; \alpha, \mu)$ is said to behave discontinuously when

η changes on the (discrete) grid Ψ_η. We shall declare any such function to be discontinuous at some $\tilde{\eta}$ (for given values of α and μ) when the change in ζ_0 induced by the increase $\tilde{\eta} \to \tilde{\eta}+1$ is at least one order of magnitude larger than those induced by the previous and subsequent grid changes in η, i.e. $\tilde{\eta}-1 \to \tilde{\eta}$ and $\tilde{\eta}+1 \to \tilde{\eta}+2$. (The discontinuity is called "upwards" if the induced change in the function is positive.) An analogous criterion for discontinuity will be used for any other parameter changes throughout.

We can now state the following conclusion:

Conclusion 1 *There exists decay rates α_1 and α_2, with $0 < \alpha_1 < 1 < \alpha_2$ such that, for all $\mu \geq 2$, the following statements hold:*

(i) If $\alpha \leq \alpha_1$, the function $\zeta_0(\cdot; \alpha, \mu)$ displays one, and only one, upward discontinuity.

(ii) If $\alpha \geq \alpha_2$, the function $\zeta_0(\cdot; \alpha, \mu)$ displays no discontinuities.

As mentioned, the validity of this conclusion is confirmed by an exhaustive analysis of the parameter space, which is illustrated by the diagrams displayed in Figure 11. Panels (a)-(c) pertain to its Part (i), while Panels (e) and (f) concern its Part (ii). On the other hand, Panel (d) considers a border case with $\alpha = 1$, where the change is discontinuous for large institutions but continuous for lower ones. Indeed, the fact that $\alpha = 1$ should mark such a qualitative change is as expected. For, as the reader may recall from Subsection 4.2, a unit value for α is precisely the point beyond which the probability mass associated to geographically close neighbors remains significant even for an arbitrarily large population.

In sum, the overall implication of our present analysis is that if geographic cohesion is low (i.e. α is small), some discontinuous upward shift in connectivity will occur at some threshold value of the innovation rate η, while the dependence on η will be continuous if α is high. This underscores the following point (which was already explained at some length when formerly discussing the simulations and the benchmark model). Whenever the *potential* for globalization exists (because α is low and thus profitable opportunities mostly arise globally) such a potential materializes abruptly. In effect, this sharp change is brought about by triggering a self-feeding process of network formation, which new links allow the creation of yet others, until a steady state with a much larger connectivity is attained.

Our early discussion also suggested that abrupt transitions are associated to hysteresis and, therefore, lead to equilibrium multiplicity and dependence of initial conditions. To confirm this early insight, we first need to verify that, indeed, the function ϕ computed as above always yields *at most two stable equilibria.* As before, denote by $\zeta_0(\eta; \alpha, \mu)$ the function that gives the lowest connectivity at a stable equilibrium for the corresponding parameter configuration. As a counterpart, now denote by $\zeta_1(\eta; \alpha, \mu)$ the function that gives the highest average degree at a stable equilibrium. Of course, in the absence of multiplicity we have $\zeta_0(\eta; \alpha, \mu) = \zeta_1(\eta; \alpha, \mu)$. But, in general, these functions may differ and then we shall be interested in the set $\Theta \equiv \{\eta : \ \zeta_1(\eta; \alpha, \mu) \neq \zeta_0(\eta; \alpha, \mu)\}$. In fact, this set will be found to define an interval (possibly an empty one) in Ψ_η, so we can define its length as $\theta \equiv \max\{\eta : \eta \in \Theta\} - \min\{\eta : \eta \in \Theta\}$. Being this length of the "multiplicity range for η " an endogenous variable, it can be conceived as a function of the remaining parameters of the model, α and μ, so we write $\theta(\alpha, \mu)$.

We are interested on the regularities displayed by the function $\theta(\cdot)$. Again we conduct a comprehensive analysis of the parameter space, and arrive at the conclusion that, for any particular μ, the function of α given by $\theta(\cdot, \mu)$ enjoys clear-cut regularities. The gist of this analysis is illustrated in Figure 12 and the conclusions are formally spelled out in Conclusion 2.

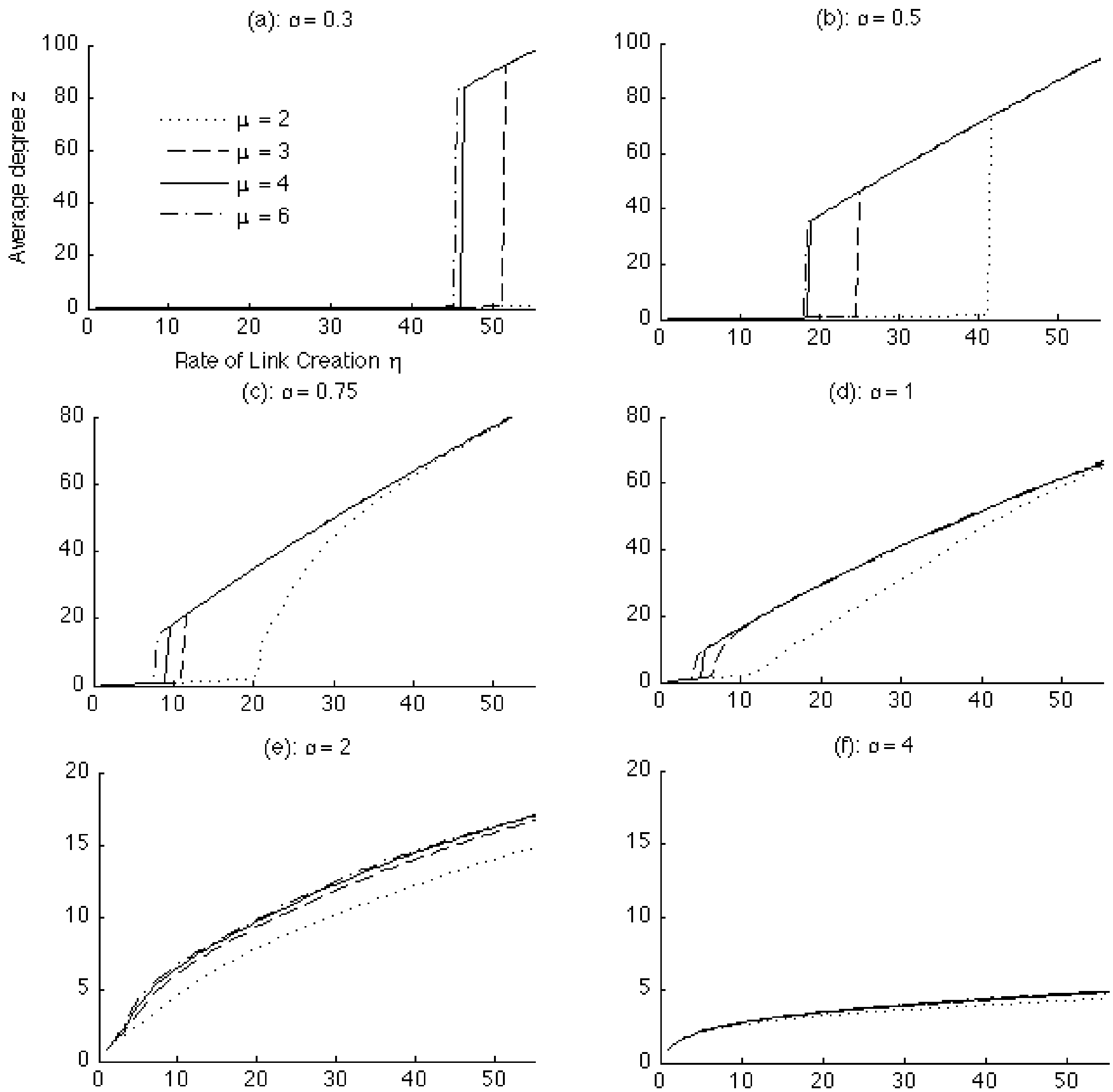


Figure 11: Numerical solution of the average network degree induced by the general model, as the innovation rate η rises, for different given values of the decay rate α and institutions μ (with $\lambda = 1$, $n = 1000$).

Conclusion 2 *For all $\mu \geq 2$, there exists some $\alpha_1(\mu)$ and $\alpha_2(\mu)$ such that:*

(i) $f$or all $\alpha \leq \alpha_1(\mu)$, $\theta(\alpha, \mu) \equiv 0$

(ii) at $\alpha = \alpha_1(\mu)$, $\theta(\cdot, \mu)$ *displays an upward discontinuity;*

(iii) for all $\alpha > \alpha_1(\mu)$, $\theta(\cdot, \mu)$ *is monotonically nonincreasing;*

(iv) for $\alpha \geq \alpha_2(\mu)$, $\theta(\alpha, \mu) \equiv 0$.

The intuitive basis for the above conclusion is well understood by now. One of the effects of globalization is to introduce multiplicity within intermediate regions of innovativeness. Thus, the stronger the globalization that can be supported at equilibrium, the wider the range of η allowing for such multiplicity. This explains Parts (i) and (iv) in the above Conclusion. In Part (i), multiplicity does not arise because α is too low for globalization to be supportable at equilibrium. Instead, in Part (iv), the reason is that globalization is at all infeasible (even abstracting from social-network considerations), because the mechanism that generates new opportunities is too local. But, past the threshold value of α (cf. Part (ii)) where globalization is possible at equilibrium, the extent of it – and therefore the scope for multiplicity – falls as α grows. This explains Part (iii).

A further manifestation of the previous considerations concerns the effect of α on the characteristics of a globalized state – in particular, on its average connectivity. The main intuition here is that, provided the economy is in a globalized state, the lower is α the larger is the induced level of economic activity because linking opportunities are explored more globally (and therefore local saturation is less of an issue). But, of course, the trade-off is also clear: a lower value of α worsens performance in a non-globalized state and, even more importantly, makes it harder (i.e. requires a higher η) to trigger the transition to globalization.

A compact and useful way of capturing the essence of the former reasoning is by tracing the value of the functions $\zeta_0(\cdot, \alpha, \mu)$ and $\zeta_1(\cdot, \alpha, \mu)$ for any given μ and different values of α. The comparison of these functions has to be done relative to the point where globalization occurs (if it is occurs), as marked by the point of transition. For concreteness, denote by $\hat{\eta}(\alpha, \mu)$ the point where this transition occurs for given values of α and μ. That is, we define $\hat{\eta}(\alpha, \mu) \equiv \max\{\eta : \zeta_1(\eta, \alpha, \mu) \neq \zeta_0(\eta, \alpha, \mu)\}$.[10] Then, building upon the same analysis illustrated in Figure 12, we arrive at the following result.

Conclusion 3 *Given any $\mu \geq 2$ and α, α' with $\alpha' > \alpha > 0$, the following two conditions apply:*

(i) $\forall \eta > \hat{\eta}(\alpha, \mu), \;\; \zeta_1(\eta, \alpha, \mu) > \zeta_1(\eta, \alpha', \mu);$

(ii) $\forall \eta < \hat{\eta}(\alpha, \mu), \;\; \zeta_0(\eta, \alpha', \mu) \geq \zeta_0(\eta, \alpha, \mu).$

Part (i) simply states that past the point in η where the transition to globalization must have occurred (independently of initial conditions) for both instances of geographical cohesion under consideration, the economic activity induced by the lower value, α, is higher than that induced by the higher one, α'. In contrast, Part (ii) states that, below such a transition point, α yields lower performance than α' if the economy were to start at the *worst initial conditions* (say, an empty social network). Jointly, these two statements provide a clear-cut description of the two-sided impact that geographical cohesion has on the range and intensity of economic activity.

4.3.2 Transition to globalization and institutions

Now we turn to exploring the impact of institutions in the attainment of globalization. We find close formal parallelisms with the former Conclusion 1, but also novel features that are characteristic of institutional change. The analysis of the phenomenon, which is illustrated in Figure 13, leads to the following result.

[10] Note that $\hat{\eta}(\alpha, \mu)$ presumes that α and μ yield a discontinuous transition. Otherwise, this magnitude is not well defined and Conclusion 3 holds voidly.

Conclusion 4 *There exist an innovation rate $\bar{\eta}$ and decay rates α_1 and α_2, with $0 < \alpha_1 < 1 < \alpha_2$ such that the following statements hold:*[11]

(i) If $\alpha \leq \alpha_1$ and $\eta \geq \bar{\eta}$ the function $\zeta_0(\eta, \alpha; \cdot)$ displays one, and only one, upward discontinuity at some $\hat{\mu}$. For all $\mu \neq \hat{\mu}$, the function $\zeta_0(\eta, \alpha; \cdot)$ is "flat," i.e. $\zeta_0(\eta, \alpha; \mu + 1) - \zeta_0(\eta, \alpha; \mu) = 0$.

(ii) If $\alpha \geq \alpha_2$, the function $\zeta_0(\eta, \alpha; \cdot)$ displays no discontinuities.

Part (i) in the previous Conclusion indicates that, in line with what happens for changes in η, those in μ lead to discontinuous equilibrium transitions when geographical cohesion is not too strong. There are, however, two significant differences. A minor one concerns the requirement in Conclusion 4 that η be large enough. This is a mere consequence of the fact that, if the meeting rate is very weak, not even the best of circumstances (say, very good institutions) can deliver the minimum extent of connectivity that allows interaction to become global.

A second more interesting difference concerns the effect of institutions on the steady state *before* and *after* an abrupt shift to globalization has occurred. Part (i) of Conclusion 4 asserts that any improvements in institutions other than those that trigger the "globalization shift" have no significant effect on connectivity. In this sense, the only relevant consideration is whether institutions are good enough to reach the globalization threshold. Any changes short of that threshold or beyond it are inconsequential.

The subtle reason that explains such a stark behavior derives from insights gained from the standard theory random networks. It is well understood, specifically, that in any connected random network (i.e. a network with a single component) almost all pair of nodes lie at maximum network distance – its so-called *diameter*.[12] Hence in a globalized state (where, naturally, the underlying social network is connected) all nodes must lie at diameter distance. Thus the key requirement for its sustainability as a steady state must be that the institutions μ be no lower than the corresponding network diameter. When institutions reach the level of the maximum diameter of a globally connected network, the transition towards globalization can and does occur. Short of that, however, the transition is impossible and conditions remain essentially equivalent to those of an empty network – i.e. links can only be formed between immediate geographical neighbors. Finally, when institutions μ exceed the aforementioned threshold, essentially all pairs of nodes are at a distance where they can exploit *any* available opportunity and form a link. Hence any further increases in μ cannot improve this state and is thus irrelevant.

4.3.3 Institutions and the optimal level of geographical cohesion

Throughout the discussion of the general model conducted in this section, we have stressed that the interplay of institutions and innovativeness with geographical cohesion is one of the main forces at work in the model. Here, we explore this interplay in more detail by focusing on what we informally described in Subsection 4.1) as the optimal level of geographical cohesion (OGC). Denoted by $\alpha^*(\eta, \mu)$, the OGC is now precisely identified with the value of α that, for given η and μ, maximizes $\zeta_0(\eta, \alpha, \mu)$.

[11] As in many of the cases depicted in Figure 13 below, the discontinuity may occur at the very first value of $\mu = 2$. Then, our notion of discontinuity is taken to apply strictly for changes above this value and voidly to changes below it.

[12] Heuristically, this is a consequence of the fact that, if we consider any given node, the number of other nodes that can be reached at (minimum) distance y grows exponentially with y. Thus, for large networks, the number of nodes lying on layers that are relatively closer to that node is an insignificant fraction of those lying on more distant ones. See Bollobás (1985)

The analysis on the dependence of OGC on μ and η is respectively illustrated by Panels (a) and (b) in Figure 14. In both cases we find that the OGC falls as the underlying conditions (institutions or innovativeness) improve. This is a reflection of the fact that, in general, optimality of α requires that the geographical structure be as global as it permits the effective attainment of *globalized interaction*. Thus, how far the economy should go in this direction is limited by the quality of the environment. An interesting point to note is that, if the environment is good enough (either concerning institutions or innovativeness), the OGC is lower than unity. This, as explained in Subsection 4.2, implies that if the population is very large, new linking opportunities involving geographically close individuals arise with only a vanishing small probability.

More precisely, the previous discussion is formally captured by the following results.

Conclusion 5 *Given any η, the OGC $\alpha^*(\eta, \cdot)$ is monotonically nonincreasing in μ. Moreover, there exist lower bounds $\bar{\eta}$ and $\bar{\mu}$ such that, if $\eta \geq \bar{\eta}$ and $\mu \geq \bar{\mu}$, then $\alpha^*(\eta, \mu) < 1$.*

Conclusion 6 *Given any μ, the OGC $\alpha^*(\cdot, \mu)$ is monotonically nonincreasing in η. Moreover, there exist a lower bound $\bar{\eta}$ such that, if $\eta \geq \bar{\eta}$, then $\alpha^*(\eta, \mu) < 1$.*

5 Summary and conclusions

The paper has proposed a "spatial" theoretical framework to study the relationship between globalization and economic performance. The main feature of the model is that *connections breed connections*, for it is the prevailing social network that provides the support to the materialization of new economic/linking opportunities (either by providing agents with information, granting them access, or conveying trust). In a steady state, only if the economy is able to exploit these opportunities at a fast enough rate can it sustain a high level of connectivity and the correspondingly intense process of obsolescence that renders pre-existing links redundant.

But in order for the economy to attain such a high rate of link creation, the social network is to turn global, i.e. social distances between agents must become short. Otherwise, only local opportunities can be materialized and the growth potential is bound sharply by local saturation. To understand the way in which this phenomenon of globalization comes about has been the primary concern of the paper. We have found, specifically, that it may occur quite abruptly, that history (initial conditions) may shape the long run, and that the interplay of "geography" and the social network may be quite subtle. Concerning the latter, for example, an important insight is that *some* geographic cohesion, despite acting as a local anchor of interaction, may play a crucial role in launching global interaction from an originally sparsely and locally connected economy.

This paper represents a first step in what we hope will be a multifaceted research program, both with a theoretical and empirical side to it. From a theoretical viewpoint, one of the tasks ahead should be to enrich the microeconomic foundations of the model. This will require, among other things, to describe in more detail the way in which information flows through the social network, and the incentives that agents have to respond to it. Other valuable lines of extension would be to allow for some agent heterogeneity (the basis for most economic interaction, possibly tailored to the underlying space), as well as the operation of canonical economic institutions (e.g. markets) in interplay with the evolutionary network dynamics.

Finally, another important route to pursue is of an empirical nature. As discussed in Section 2, there is a substantial empirical literature on the phenomenon of globalization but a dearth of complementary theoretical work supporting these efforts. The present paper aims at contributing to closing the gap, by developing a network-based theory that suggests what variables to measure and what predictions to test. And, as briefly outlined, our companion paper, Duernecker, Meyer, and Vega-Redondo (2010), has built upon this theory to construct network measures of economic globalization that turn out to be robust and very significant explanatory variables of the contrasting economic (growth) performance of the different world economies over the last decades. An elaboration and refinement of this preliminary research is also an important item in our research agenda.

Appendix A

We start this Appendix with an interpretation of our model that is based on a game-theoretic motivation of the (same) law of motion of the system postulated in Subsection 3.2. The process by which new linking opportunities arrive continues to be interpreted as a form of innovation, with an "idea" arriving to each agent i at the rate η and the partner j who is required to carry it selected as specified in (1). And again we posit that any ongoing project becomes obsolete and vanishes at the exogenous rate λ.

The key difference now is that every such ongoing interaction is conceived as a repeated coordination game, in which the return flow generated per unit time depends on whether each partner exerts a hight effort H or a low one L. For simplicity, let us normalize to unity the net flow received by each agent if both exert low effort, while their individual return flow is assumed equal to some positive $W < 1$ if both exert low effort. (The specific payoffs associated to asymmetric effort profiles are immaterial for the discussion, provided they make the symmetric profiles the only pure-strategy equilibria of the game.) If any two agents were to play such repeated game in isolation, then it is clear that, for example, any pattern of play where they choose to play the same symmetric action profile – either (H, H) or (L, L) – during the whole life of the project would trivially define an equilibrium. Thus, to make the problem interesting, we enrich the strategic situation as follows. First, we assume that there are opportunistic gains to be made at the start of the project that may even prevent the project from "taking off." Second, we allow for the possibility that players embed their bilateral situation in a whole-population game where, as we shall see, the social network may play a key role in overcoming opportunism. Next, we describe in turn each of these new dimensions of the problem.

Suppose that, at the time a new partnership is to be established between any two agents, there is some fixed cost $2C$ that must be incurred (once and for all) to set up the corresponding project. If the agents are immediate geographic neighbors, we assume that they can implement an equal sharing of these costs – the assumption here is that geographic proximity allows close monitoring and prevents opportunistic behavior. But, instead, if they are not neighbors, the assignment of the set-up costs is determined in a initial set-up stage that precedes the operation of the project itself. In this first stage of their relationship, each agent decides independently whether to cooperate or not. If both cooperate, then each covers C, half of the total cost. Instead, if both defect, the cost is not covered at all, the consequence being that the project does not start and the economic opportunity is irreversibly wasted. Finally, if one cooperates and the other defects, we assume that project starts but the former agent bears the full fixed cost $2C$ while the latter avoids it altogether. Thus, in essence, the full strategic situation faced by the agents can be succinctly described as a Prisoner's Dilemma followed by a repeated coordination game (as explained above) once the project is set up and running.

Consider first the scenario where the repeated relationship associated to each project is conceived (in particular, by the agents themselves) as an independent bilateral game. Then, in principle, cooperation between non-neighbors in its first set-up stage could be supported by the threat of a suitable punishment in the continuation repeated coordination game. However, to focus on the most interesting case, we postulate that the prevailing payoffs rule out this possibility. This amounts to saying that not even the most "severe punishment" that can be credibly implemented with a (pure-strategy)[13] equilibrium of the continuation repeated game – i.e. play the effort profile (L, L) for ever – can compensate the gains that may be reaped by deviating from a cooperative arrangement in the initial set-up stage.

To be more precise, denote by $\rho = \delta + \lambda$ the effective discount rate used by players in evaluating the intertemporal payoffs derived from any particular project, where δ is the rate at which they discount the future and, as will be recalled, λ is the volatility rate at which projects are discontinued. The payoff conditions that rule out that cooperation may be enforced bilaterally at equilibrium are:

$$\frac{W}{\rho} > \frac{1}{\rho} - C. \tag{6}$$

Simply, the above inequality guarantees that the payoff gains obtained from defection at the initial stage (which saves the cost C) and an indefinite play of the low-effort equilibrium (which generates a constant payoff flow of W) is higher than the payoff obtained from sharing the start up cost (paying C) and then obtain a unit flow thereafter.

Under the payoff circumstances given by (6), cooperation in the set-up stage requires that, after a deviation, any punishment must involve more than the affected partner himself. For simplicity, we posit that it is enough that one other partner implements a punishment (by moving to the low-effort profile in the ongoing relationship) to deter such a deviation. It is easy to check that this amounts to positing that

$$\frac{2W}{\rho} < \frac{2}{\rho} - C. \tag{7}$$

Finally, we want to make the natural assumption that

$$\frac{1}{\rho} - 2C < 0 < \frac{1}{\rho} - C. \tag{8}$$

which merely says that an equal sharing of set-up costs makes the project worthwhile for both of the agents involved but a full burden does not. This condition makes the issue of whether a possible project/link with be undertaken/formed crucially hinge upon the fact of whether the set-up costs will be shared or not. Conditions (6)-(8) define a (non-empty)[14] scenario where any new project opportunity faced by two agents will be pursued if, and only if, each of them has at least one other ongoing partner who would punish a deviation by switching to the low-effort continuation equilibrium. Third-party enforcement, therefore, becomes both necessary and sufficient to sustain the formation of new links among non-neighboring agents (and, therefore, a fortiori, sufficient for neighboring agents as well). The question now is whether such multilateral enforcement is consistent with agents' incentives, i.e. part of well-specified equilibrium of an overall game played by the whole population.

To see that the postulated third-party enforcement can be sustained at an equilibrium of the population game, it is enough to note that, for every contingency other than at an initial set-up stage, agents are required to play an equilibrium of the stage coordination game confronted by every pair of ongoing partners.

[13] The restriction to pure-strategy equilibria is adopted for simplicity. Nothing essential would be affected by the consideration of equilibria in mixed strategies.

[14] It can be checked that those conditions are jointly satisfied if, for example, $1/2 < \rho C < 1$ and $1 - \rho C < W < 1 - \frac{1}{2}\rho C$.

Trivially, therefore, it always defines an equilibrium of the continuation game. There is however, an implicit but important informational assumption that underlies such equilibria, namely, that the past behavior of every agent is common knowledge among all of its partners. In general, it is natural to assume that such information will flow though the social network itself. Thus, if we suppose that no deviating agent will report his deviation to his other partners, we must count on other agents (starting by the agent who originally suffered the deviation) to spread that information.

But if the spreading of such information is to rely on the social network, it is natural to consider some limitations – either on how fast that information travels or how far it goes. A simple way to model such considerations is to posit that strategic information only travels a certain number of steps, say $\mu - 1$ links, where μ is a parameter of the model. Then, the key behavioral assumption we make is that an agent i will punish a partner j who has deviated with some other agent k if, and only if, there is a path between i and k that does not involve j and consists of no more than $\mu - 1$ steps. And, from the previous considerations, it is important to emphasize that, after j's deviation, such a behavior can indeed be supported as part of an equilibrium since the following two points hold:

- It is common knowledge for both j and k that j has deviated with i. (Here, we assume that the prevailing social network is common knowledge.)
- Indefinite play of the effort profile (L, L) can be supported as part of an equilibrium of the continuation game. (Thus it is optimal for each of them to choose L if the other is anticipated to do likewise.)

In the end, the former considerations may be translated into a network formation rule that is exactly as described by (a)-(b) in Subsection 3.2.1. To do so, we contemplate a network-formation set-up where, at the time a linking opportunity arises, agents evaluate this opportunity in isolation, given the prevailing network. Thus, in particular, they do not contemplate how the the creation of the new link may affect linking possibilities in the future by adding to the amount of social collateral at their disposal.[15] This, for example, provides a strategic foundation to the postulate (c.f. (b.1)) that two agents who receive the opportunity to form a new link will do so if their social social distance is no higher than μ. For, in this case, each of them is no further away than $\mu - 1$ steps from a current partner of the other. Thus, under our maintained assumptions, both of these partners can be relied upon to punish (and thus deter) deviations from a cooperative sharing of set-up costs.

As explained, one possible interpretation for the parameter μ is informational – i.e. it may be related to the speed at which strategically related information moves along the network, specifying the maximum number of steps that it can advance before the triggered reaction arrives too late to be effective in deterring deviations. Another plausible and interesting interpretation has to do with the extent to which agents internalize the cooperative norm and thus are ready to act in order to uphold it. More specifically, $\mu - 1$ could be viewed as the furthest away (socially speaking) that an individual may be from an agent who has been "exploited" by other and still be ready to punish the latter. This is in the spirit of what Karlan *et al.* (2009) label the "circle of trust," which embodies the idea that agents can be expected to respond to violations of a social norm with third-party costly punishments only if they are sufficiently "attached" to the agents involved. It is also in line with the dichotomy put forward by Platteau (2000) between *generalized*

[15] This, in effect, introduces two time scales into the process. One is the scale at which agents' repeated interaction takes place; the second one, implicitly much slower, is the time scale at which opportunities arrive. This separation of time scales is a common simplification used when an evolutionary approach is applied to the study of repeated games – see, for example, Binmore, Samuelson and Vaughan (1995).

morality (moral sentiments applied to abstract people) and *limited-group morality* (which is restricted to a concrete set of people with whom one shares a sense of belonging). In fact, the importance of this distinction was already stressed by Banfield's (1958) celebrated study of Southern Italy. There he argued that the persistent backwardness of this region was largely due to a pervasive *amoral familism*, i.e. the *exclusive* concern for the well-being of the close family as opposed to that of the community at large.

We end this Appendix with the statement and proof of the lemma invoked in Subsection 4.2 and a related remark.

LEMMA **1** *For large n, in a steady state where almost all nodes belong to the giant component, the degree distribution is Poisson.*

Proof: Note that for every pair of nodes, i and j, the rate at which they create a link at any given t is (for large n) approximately equal to

$$\gamma_{ij} = 2\eta \frac{1}{n-1} \tag{9}$$

where we assume that both i and j belong to the giant component and also use the fact that, since n is arbitrarily large, the probability that i and j have a link is essentially zero (thus conditioning on that link not being in place is inconsequential). Given any $t > 0$, let t' be the latest previous time ($t' < t$) at which an ij-link formation event occurred. Now given such t', let t'' be the first subsequent time ($t'' > t'$) at which an event of destruction for the ij-link occurs. Clearly, we can write

$$P\{ij \in g(t)\} = P\{t'' > t\}.$$

Hence, since the ij-link creation events occur at the rate γ_{ij} given in (9) while its decay events occur at the rate $\lambda = 1$, we have

$$P\{ij \in g(t)\} \to \frac{\gamma_{ij}}{\gamma_{ij} + 1} \simeq \frac{1}{n} 2\eta,$$

where the last expression retains the leading term in the limit $n \to \infty$. Thus, since the events $\{ij \in g(t)\}$ are independent for all for $j \neq i$, and each occurs with the above probability, the degree distribution is Poisson, as claimed.

REMARK **1** *When the fractional size of the giant component $\chi < 1$, there will be a positive correlation between the degree of a node and its being part of the giant component, which biases upwards the probability of forming new links for high-degree nodes. This will in turn bias the degree distribution towards having more links across nodes of high degree than what would be entailed by a Poisson network with the same average degree.*

Appendix B: Computational Algorithm

In this Section we describe the algorithm that is used to numerically compute the equilibrium of a network[16]. Essentially, the algorithm computes the equilibrium by performing a simulation of the network. It proceeds in two successive steps which are repeated until certain termination criteria are met. The first

[16]The MATLAB code implementing the algorithm is available upon request.

step selects and implements a particular adjustment event (which can be either an innovation draw or a link destruction) and the second step checks whether or not the system has reached a stationary equilibrium.

As mentioned at the outset, we normalize the rate of link destruction $\lambda = 1$, moreover, we fix the population size at $N = 1000$. The free parameters of the model are, thus, given by the triplet (α, η, μ). The state of the network at any point is characterized by the $N \times N$ dimensional adjacency matrix A. An element of which, denoted by $a(i, j)$, takes the value of 1 if there exists an active link between the nodes i and j, and it is 0 otherwise. L denotes the total number of active links in the network. By construction, L has to equal the number of non-zero elements in the state matrix A. In what follows, we systematically explain each of the steps the algorithm runs through. The initial state of the network is given by A[17].

- **Step I:** At the start of each simulation step, $t = 1, 2, ...$, an adjustment event is randomly selected: This can be either an innovation draw or a link destruction. The two events are mutually exclusive, that is, in each simulation step only one event can occur. The rate at which either of the two events realize are fixed and equal to λ and η. Every node in the network is equally likely to receive an innovation draw. Conversely, all existing links are equally likely to be destructed. Therefore, the flow of innovation draws and destroyed links are, respectively, given by ηN and λL, and the probability of an innovation draw to occur is, thus, $\frac{\eta N}{\eta N + \lambda L}$. Depending on the actual realization, the routine proceeds either to Step A.1. (innovation draw) or Step B.1. (link destruction)
  - A.1. To start with, the routine randomly selects a node $i \in N$ which receives the project draw. All nodes in the network are equally likely to receive the draw, therefore, the success probability for a particular node is N^{-1}.
  - A.2. Next, a "partner" node $j \neq i \in N$ is selected, which is called upon to carry out the project. The probability that the partner is some particular j satisfies $p_i(j) \propto d(i, j)^{-\alpha}$. This can be translated into an exact probability - which equals $p_i(j) = B \times d(i, j)^{-\alpha}$ - using the scaling factor B. To determine B we exploit the fact that $\sum_{j \neq i \in N} p_i(j) = 1$ which leads to $p_i(j) = \left(d(i, j)^{\alpha} \sum_{j \neq i \in N} d(i, j)^{-\alpha} \right)^{-1}$. The routine randomly picks a specific node j according to $p_i(j)$[18].
  - A.3. If $a(i, j) = 1$, there is already a connection in place between i and j. In that case the innovation draw is wasted, and the algorithm proceeds to **Step II**. If, instead, $a(i, j) = 0$ the algorithm proceeds to A.4
  - A.4. In this step, the algorithm examines whether or not it is (technically) feasible to establish the connection between i and j. To this end, it, first, determines the geodesic distance between i and j, denoted $\delta_A(i, j)$, given the current state A, If it finds that $\delta_A(i, j) \leq \mu$ then the link ij ($= ji$) is created and the corresponding elements in the adjacency matrix, A, $a(i, j)$ and $a(j, i)$ are set equal to 1. If $\delta_A(i, j) > \mu$, the link is not created and the state matrix A remains unchanged. To determine the geodesic distance we use a breadth-first search algorithm, which we describe in

[17] The initial state can either be an empty network (with A containing only zeros), or, the network obtained for a certain vector of parameters.

[18] Since the nodes are located along a ring, there exist two different nodes j and j' for which $d(i, j) = d(i, j')$ holds. We break the tie by, first, selecting a specific distance d according to $p_i(j)$, and then "flipping a coin" to select one of the two nodes at this distance.

detail below. Notice that since $\mu \geq 1$, all links between neighboring nodes (for which $d(i, j) = 1$) are created with probability 1, conditional on not being in place. With Step A.4. the link creation process is finalized and the algorithm proceeds to **Step II**.

- B.1. If the event selected in **Step I** involves a link destruction, the algorithm randomly picks one of the existing links in the network and dissolves it. The state matrix is updated accordingly by setting $a(i, j)$ and $a(j, i)$ both equal to 0. All existing links in the network are equally likely to be destructed. Thus, for a specific link the probability of being selected is L^{-1}. Once the link destruction process is completed, the algorithm moves on to **Step II**.

- **Step II:** If we start with an empty network (with A containing only zeros) and let the two forces - innovation and volatility - operate, then network gradually builds up structure and gains in density. If this process is run long enough, eventually, the network attains its equilibrium. An important question in this context is, when to terminate the simulation? Or put differently, how can we find out that the system has reached a stationary state? **Step II** of the algorithm is concerned with this issue. Strictly speaking, the equilibrium of the network is characterized by the constancy of all the endogenous variables. That is, in equilibrium, the structure of the network, as measured for instance by the average connectivity, remains unchanged. However, a computational difficulty arises from the random nature of the processes involved. Link creation and destruction are the result of random processes, which imply the constancy of the endogenous variables only in expectations. In other words, each adjustment step leads to a change in the structure of the network, and consequently, the realization of each of the endogenous outcomes fluctuate around a constant value. To circumvent this difficulty, the algorithm proceeds as follows:

  - C.1. At the end of each simulation step t , the routine computes (and stores) the average connectivity prevailing in the current network as $z(t) = \frac{2 \times L(t)}{N}$.
  - C.2. Every T steps it runs an OLS regression of the $\underline{T}$ most recent values of z on a constant and a linear trend.
  - C.3. Every time the slope coefficient changes its sign from plus to minus, a counter n is increased by 1.

Steps I and **II** are repeated until the counter n exceeds the predetermined value of $\overline{n}$. For certain parameter combinations, mainly for those that imply high and globalized interaction, the transition process towards the equilibrium can be very sticky and slow. For that reason and to make sure that the algorithm does not terminate the simulation to early we set $\underline{T} = 5 \times 10^5$, $T = 10^4$ and $\underline{n} = 10$.

Breadth-first search algorithm: In Step A.4. we use a breadth-first search algorithm to determine if, starting from node i, the selected partner node j can be reached within at most μ steps. The algorithm is structured in the following step-wise fashion:

- Step $m = 1$: Construct the set of nodes which are directly connected to i, Formally, this set is given by $X_1 = \{k \in N : \delta_A(i, k) = 1\}$. Stop the search if $j \in X_1$ otherwise proceed to Step $m = 2$

- Step $m = 2, 3, ...$ For every node $k \in X_{m-1}$ construct the set $x_k = \{k' \in N \setminus \{i\} : \delta_A(k, k') = 1\}$. Let X_m be the union of these sets with all the nodes removed which are already contained in X_{m-1}.

Formally: $X_m = \left\{ \bigcup_{k \in X_{m-1}} x_k \right\} \setminus X_{m-1}$. By construction, all nodes $k' \in X_m$ are located at geodesic distance m from the root i, i.e. $\delta_A(i, k') = m$, $\forall k' \in X_m$. Moreover, all elements in X_m are nodes that were not encountered in any of the previous $1, 2, ..., m-1$ steps. Stop the search if (a) $j \in X_m$, (b) $m = \mu$, or (c) $X_m = \emptyset$, otherwise proceed to Step $m+1$. Case (a): Node j has been found within distance μ. Case (b): A continuation of the search is of no use as $\delta_A(i, j) > \mu$ in which case the creation of the link ij is infeasible. Case (c): No new nodes are encountered along the search which implies that i and j are disconnected from each other.

The search is continued until one of the three cases occurs.

In the text we report the equilibrium outcomes of four endogenous variables, which are: the average connectivity in the network, the average geographical and geodesic distance and the effective probability of link creation. We next show how each of these are computed.

1. To compute the average connectivity in the network we simulate the equilibrium of the system for $t = 1, 2, ...\bar{t}$, with $\bar{t} = 5 \times T$, steps and take the average of $z(t)$ over all $\bar{t}$ realizations.

2. Similarly we compute the average geographical distance between connected nodes in the network as the average of $\left\{ \frac{1}{L} \sum_{ij \in g(t)} d(i, j) \right\}_{t=1}^{\bar{t}}$.

3. Formally, the average geodesic distance in the network should be computed as, $\frac{1}{N} \sum_{i,j \in N} \delta_g(i, j)$. However, in the current context this approach is not advisable, due to the potential existence of disconnected sub-parts in the network. Any two nodes, i and j, which are not jointly located on such a sub-part would - literally - be $\delta_g(i, j) = \infty$ steps away from one another. To account for that we randomly draw N pairs of (i, j) and compute $\delta_g(i, j)$ for each of them. If i and j happen to be disconnected we set $\delta_g(i, j)$ equal to a high number $\bar{\delta} < \infty$. The randomization also helps to economize on computational speed, since computing $\delta_g(i, j)$ for all possible pairs (i, j) would imply a substantial computational burden.

4. The effective probability of link creation is computed as the ratio of the number of innovation draws which lead to a successful link creation to the total number of innovation draws obtained in $\bar{t}$ simulation steps.

References

[1] Arribas, I., F. Pérez and E. Tortosa-Ausina (2009): "Measuring globalization of international trade: theory and evidence," *World Development* **37**, 127-145.

[2] A.T. Kearney/Foreign Policy Magazine (2006): The Globalization Index, http://www.foreignpolicy.com.

[3] Banfield, E.C. (1958): *The Moral Basis of a Backward Society*, New York: The Freepress.

[4] Binmore, K., L. Samuelson, and R. Vaughan (1995): "Musical Chairs: Modelling Noisy Evolution," *Games and Economic Behavior* **11**, 1-35.

[5] Bisin, A. and T. Verdier (2001): "The economicsof cultural transmission and the dynamicsof preferences," *Journal of Economic Theory* **97**, 289-319.

[6] Bollobás, B. [1985] (2001): *Random Graphs* (2nd. Edition), Cambridge (U.K.): Cambridge University Press.

[7] Borensztein, E., J. de Gregorio, and J.-W. Lee (1998): "How does foreign direct investment affect economic growth?," *Journal of International Economics* **45**, 115-135.

[8] Centre for the Study of Globalisation and Regionalisation (2004): The CSGR Globalisation Index, http://www2.warwick.ac.uk/fac/soc/csgr/index/.

[9] Coleman, J. S. (1988): "Social Capital in the Creation of Human Capital," *American Journal of Sociology* **94**, 95-120.

[10] Coleman, J. S. (1990): *Foundations of Social Theory* , Cambridge, MA: Harvard University Press.

[11] Dollar, D. and A. Kraay (2001): "Trade, growth, and poverty," *World Bank Discussion Paper*, Washington, D.C..

[12] Dreher, A. (2006): "Does globalization affect growth?", Evidence from a new index of globalization, *Applied Economics* **38**, 1091-1110.

[13] Dreher, A., N. Gaston and P. Martens (2008): *Measuring Globalization: Gauging its Consequences*, New York: Springer .

[14] Dixit, A. (2003): "Trade Expansion and Contract Enforcement," *Journal of Political Economy* **111**, 1293-1317.

[15] Duernecker, G., M. Meyer and F. Vega-Redondo (2011): "An network-based empirical analysis of economic globalization," work in progress, University of Mannheim and European University Institute.

[16] Fagiolo, G., J. Reyes, and S. Schiavo (2010): "The evolution of the World Trade Web," *Journal of Evolutionary Economics* **20**, 479-514.

[17] Greif, A. (1993): "Contract enforceability and economic institutions in early trade: the Maghribi traders' coalition," *American Economic Review* **83**, 525-48.

[18] Haag, M. and R. Lagunoff (2006): "Social norms, local interaction, and neighborhood planning," *International Economic Review* **47**, 265-96.

[19] Jackson, M., T. Rodriguez-Barraquer and Xu Tan (2010): "Social capital and social quilts: network patterns of favor exchange," mimeo, Stanford University.

[20] Kali, R. and L. Reyes (2007): "The architecture of globalization: a network approach to international economic integration," *Journal of International Business Studies* **38**, 595-620.

[21] Lane, P. and G. M Milesi-Ferretti (2001): "The external wealth of nations: measures of foreign assets and liabilities for industrial and developing countries," *Journal of International Economics* **55**, 263-94.

[22] Lippert, S. and G. Spagnolo (2006): "Networks of relations, word-of-mouth communication, and social capital, SSE/EFI Working Paper in Economics and Finance no. 570. [[Check recent publication]]

[23] Karlan, D., M. Mobius, T. Rosenblat, and A. Szeidl (2009): "Trust and Social Collateral," *Quarterly Journal of Economics* **124**, 1307-1331.

[24] Platteau, J. P. (2000): *Institutions, Social Norms, and Economic Development*, Amsterdam: Hardwood Academic Publishers and Routledge.

[25] Tabellini, G. (2008): "The scope of cooperation: values and incentives," *Quarterly Journal of Economics* **123**, 905-950

[26] OECD (2005*a*): Measuring Globalisation: OECD Handbook on Economic Globalisation Indicators, June 2005.

[27] OECD (2005*b*): Measuring Globalisation: OECD Economic Globalisation Indicators, November 2005.OECD (2005*b*): Measuring Globalisation: OECD Handbook on Economic Globalisation Indicators, June 2005.

[28] Vega-Redondo F. (2006): "Building up social capital in a changing world," *Journal of Economic Dynamics and Control* **30**, 2305–2338.

[29] Vega-Redondo, F. (2007): *Complex Social Networks*, Econometric Society Monograph Series, Cambridge: Cambridge University Press.

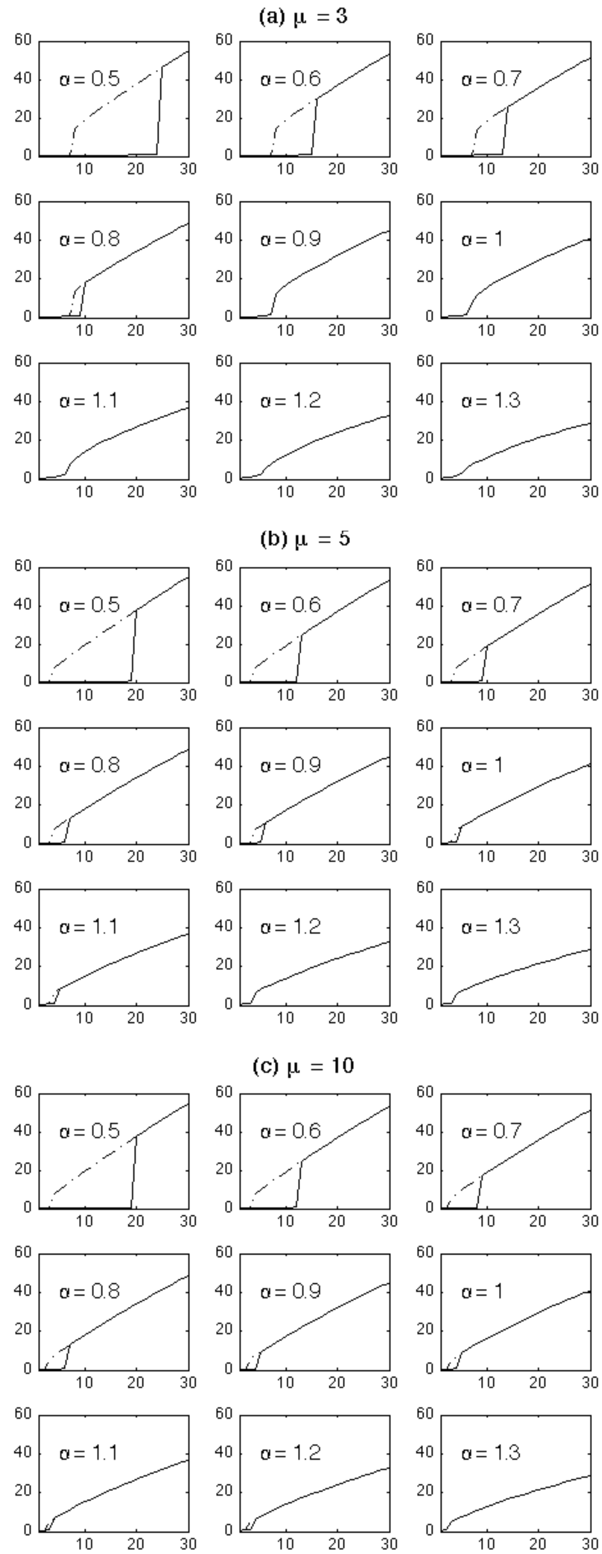


Figure 12: Numerical solution induced by the general model for the transition in the average network degree – including possible hysteresis – as the innovation η rate changes for different given values of α and μ (with $\lambda = 1$, $n = 1000$).

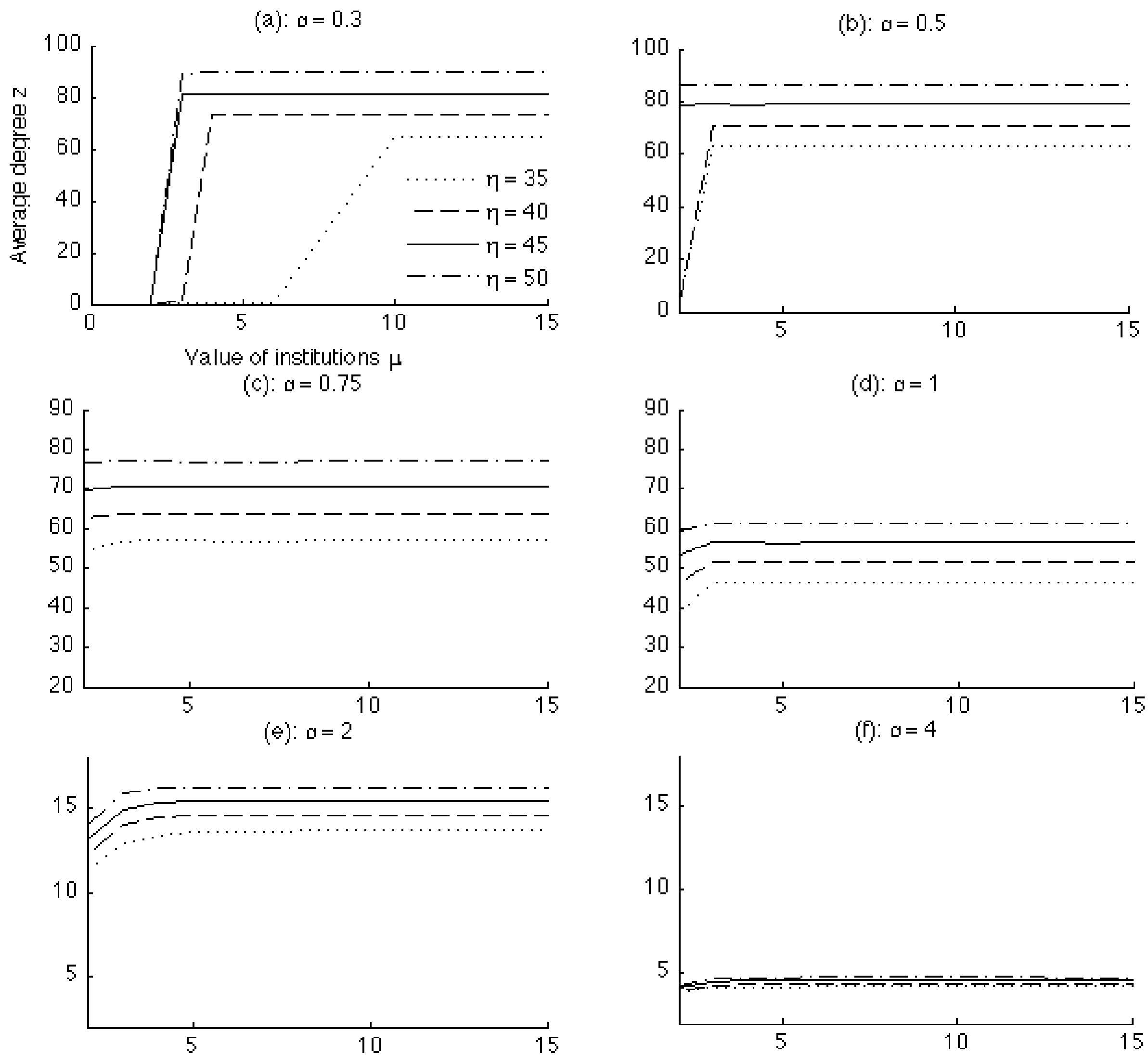
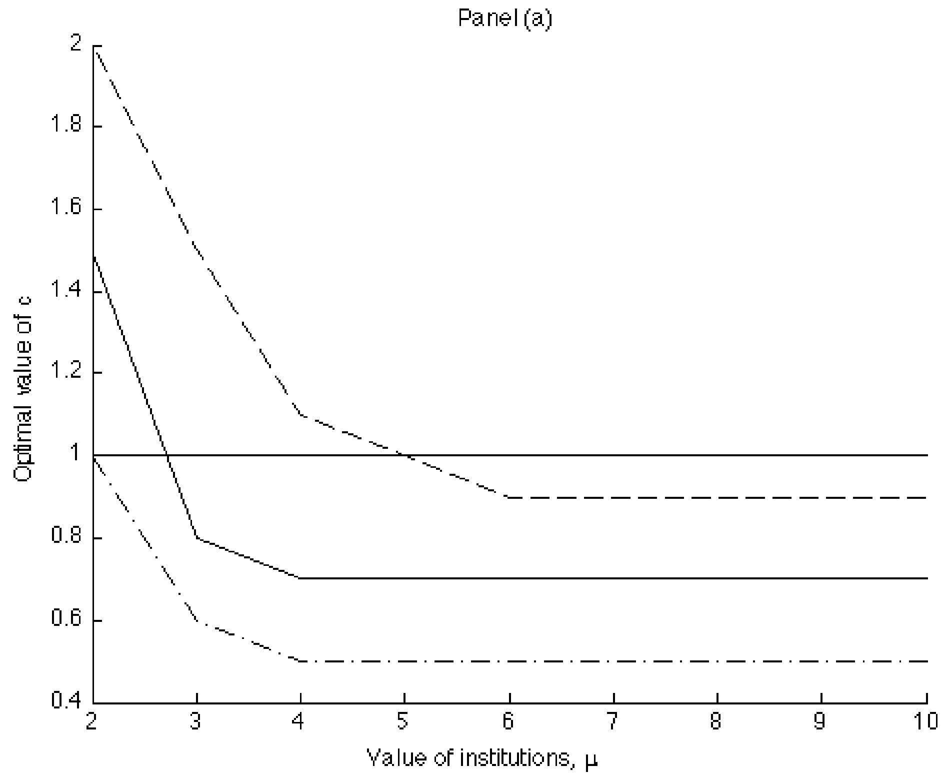


Figure 13: Numerical solution of the average network degree induced by the general model, as institutions improve, for different given values of the innovation rate η and the decay rate α (with $\lambda = 1$, $n = 1000$).



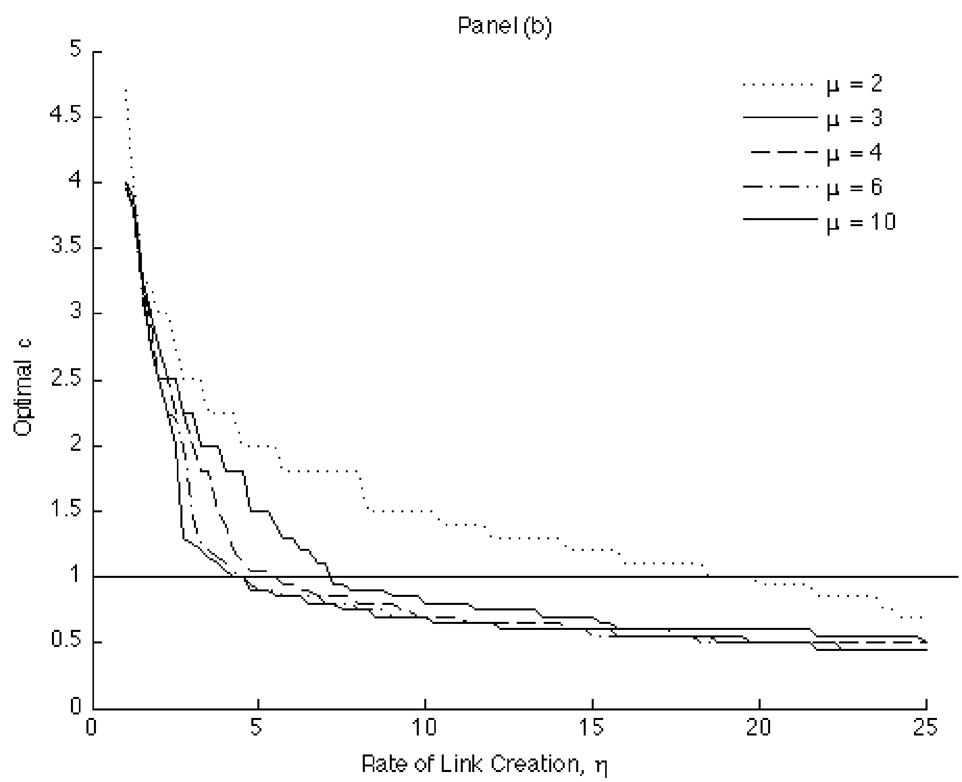


Figure 14: Optimal level of geographical cohesion (OGC), as a function of institutions μ (Panel (a)) and the innovation rate η (Panel (b)).