Social networks, institutions, and the process of "globalization"

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Abstract

We propose a stylised dynamic model to understand the interplay of institutions and social networks in the phenomenon we call "globalization." This refers to the process by which even agents who are geographically far apart come to interact, thus overcoming what otherwise would be a fast saturation of local opportunities. But for such interaction to turn global, the social network must become global as well, since it acts as the social collateral that deters opportunistic behavior. This effect is modulated by institutions, which parametrize how social influence decays along the social network.

In this context, our main conclusions are that the transition towards globalization often occurs abruptly, it is a robust state of affairs once attained, and may crucially depend on initial conditions. That transformation, however, requires that the forces at work be balanced – in particular, geographical cohesion cannot be too high (for then global opportunities do not arise) nor too low (in which case there is too little social structure for the process to take off). The model is studied exhaustively by relying on tools and concepts of the modern theory of complex networks – analytically for a benchmark setup, and numerically for the general case.

Keywords: Social networks, Globalization, Institutions, 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 so much on trade – the typical focus of international economics – but on many other routes of interaction such as investment, communication, or research collaboration.[1] 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.

But, arguably, an advance on the theoretical front is needed as well if we are to progress in understanding this rich and multifaceted phenomenon. How should one measure globalization? Why should we care about it, and what are its economic implications? How does globalization come about? Should we expect it to be irreversible? Why may it fail to materialize in some cases? The aim of this paper is to undertake a preliminary step in addressing these questions within a theoretical framework.

Our approach stresses the role of social networks. In fact, we shall understand globalization as a topological feature of the underlying social network. In essence, it will refer to a situation where, irrespectively of how far agents lie in terms of some geographical (or other kind of fixed) distance, they tend to be relatively close in the social network. In our model, such network closeness is important because it bears on the ability of agents to form new links. And this, in the end, is what underlies their success in maintaining a dense (and therefore productive) pattern of economic interaction.

A key concept in our model is that of *social collateral* (see Karlan *et al.* (2009)), which is in the spirit of what Coleman (1990) labelled *network closure*. Coleman stressed, specifically, that the incentives of an individual to cooperate on any given relationship are often grounded on the fear/threat that, if she behaved opportunistically, this would trigger the collapse of other valuable relationships.[2] This, in turn, has important dynamic implications, since the topology of the current social network must then play a key role in its subsequent enlargement and maintenance. And, indeed, we shall find that these network feedback effects lead to some of the interesting dynamic features displayed by our model – e.g. the sharp transitions toward globalization (and hysteresis) observed as parameters change across certain regions.

Two additional factors enjoying a prominent role in our model are institutions and some underlying space (which could be of a geographical nature, or/and reflect other characteristics such as language or ethnic diversity). Institutions, on the one hand, are embodied by a parameter that determines the

[1] In fact, if we focus on trade, the presumed "revolution" of globalization appears less impressive when put in historical perspective. For example, as mentioned by Krugman (1995), the share of merchandise exports on GDP enjoyed a peak at the start of World War I and only recovered a similar level in the mid 1970's. And for a leading country such as the United Kingdon, even in the late 1980's the share of trade on GDP was significantly lower than that prevailing at the start of World War I.

[2] A famous example is provided by the wholesale diamond market in in New York City where, as Coleman (1988) explains, any instance of opportunistic behavior (e.g. the stealing or substitution of stones held in custody) would lead into ostracism by the tight network of family and business partners.

maximum social network distance below which other individuals can be used as social collateral. In a sense, as we shall explain, they can be regarded as capturing the degree to which agents internalize the cooperative social norm.

The role of space, on the other hand, is to provide some structure to the mechanism through which agents meet. If this mechanism is too local, it is apparent that globalization cannot possibly arise. This then leads to a rapid exhaustion of (local) possibilities for fruitful interaction and a thin social network. Turning to the opposite extreme, one of the most interesting insights derived from the model is that the meeting mechanism cannot bee too global either. For, in this case, the induced lack of meeting structure makes it virtually impossible for some network structure/closure to arise endogenously from a network with low connectivity. The implication is then that a thinly connected society becomes trapped into an absorbing deadlock. Thus, in the end, the conclusion is that only when agents meet at a suitably intermediate scale, the full potential for globalization is achieved.

The paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the 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 setup. 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.

2 Related literature

As advanced, the bulk of economic research on the phenomenon of globalization has been of an empirical nature. Often, the efforts have focused on a single dimension of the problem: 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 each particular "agent" rather than on their global interplay within the overall structure of interaction. Our model, instead, calls for systemic, network-like, measures of globalization.

A few papers in this vein that can be found in the recent literature are Kali and Reyes (2007), Arribas *et al.* (2009), and Fagiolo *et al.* (2010). They all focus on international trade flows (imports and exports)[3] and identify what could be interesting and economically relevant features of the network of trade, e.g. clustering, centrality, multistep indirect flows, or internode correlations. Their objective is mostly descriptive, although Kali and Reyes confirm (by extending the received growth regressions) that the network-based measures of integration they consider have a significant positive effect on growth rates. 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

Finally, since this paper is a strictly theoretical exercise, we briefly discuss some related literature that shares its theoretical bent. On the one hand, we may refer to those papers that, reflecting the aforementioned idea of network closure of Coleman (1990), have undertaken a formal and game-theoretic analysis of its effect and limitations. In addition to the paper by Karlan *et al.* (2009) already referred to, the issue has been studied, among others, by Greif (1993), Haag and Lagunoff (2006), Lippert and Spagnolo (2006), Vega-Redondo (2006), and Jackson *et al.* (2010).

These papers are quite different in some key respects. For example, they have considered different setups, e.g. fixed or endogenous network (itself static or dynamic). They also rely on different specific assumptions, e.g. players are either postulated to behave equally (say cooperatively) in all their interactions or their choice is partner dependent. And they use different equilibrium concepts, e.g. Nash equilibrium, coalition proofness, or pairwise stability. But they all highlight and shed useful light on the importance of the architecture of the social network in deterring opportunistic behavior in strategic population-wide interaction.

As outlined, a key feature of our approach is the contrast between some fixed (say "geographical") notion of distance and the endogenous social distance induced by the evolving social network. We end our discussion with two recent papers that, albeit relying on quite different social mechanisms, also bear on the effect of some fixed metric on the spread of cooperative behavior.

One is the paper by Dixit (2003), who studies a model of trade that 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 (i.e. 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

[3] In our last Section 5, we argue that our model favors the use of interaction flows – such as those reflection direct investment – where incentive issues are more prominent than for trade.

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 is Tabellini (2008), which 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 term associated to own cooperation whose size decreases with distance. Each individual plays this game only *once*. This allows the analysis to dispense with the features of Dixit's model that are tailored to repeated interaction (e.g. the assumption governing the spread of information). 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). As it turns out, cooperative behavior and "altruism" are, in a certain sense, strategic complements. This leads to interesting coevolving 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 is unique. However, in a variant of the model where the enforcement of cooperation (i.e. the detection and reversion of cheating) is the endogenous outcome of a political equilibrium, there can be multiple steady states and path dependence.

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 meeting probabilities decay sharply with distance), the level of interaction is severely limited 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 meet the enforcement issue. In Dixit (2003) and Tabellini (2008), such an enforcement is associated to 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 coevolving social network.

3 The model

In describing the model, we first present the underlying framework of agent interaction and then introduce the two forces (innovation and volatility) that govern the evolution of the economy 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 – see Figure 1 for an illustration. 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 $d(i,j)$.

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 it remains alive. For simplicity, let us suppose that the project vanishes, or becomes obsolete, at the rate λ that captures the volatility of the environment. While the project remains operational, the size the return flows it generates depend on the partners' efforts, which can be high (H) or low (L). If both exert high effort, let us normalize the flow received by each of them to unity. Instead, if both exert low effort, their individual return flow is equal to some positive $W < 1$.

To fix ideas, it is useful to conceive the bilateral situation that agents face at every point in time as a coordination game (say, of the classical stag-hunt or minimum-effort variety). Thus, if this game were played once and in isolation, either both agents choosing H or both choosing L would be the sole pure-strategy Nash equilibria. But, as we explain next, that game is played as part of a process of repeated interaction and is strategically embedded in the underlying social context. This, in effect, renders that simple coordination game as a mere component of an overall *population repeated game*.

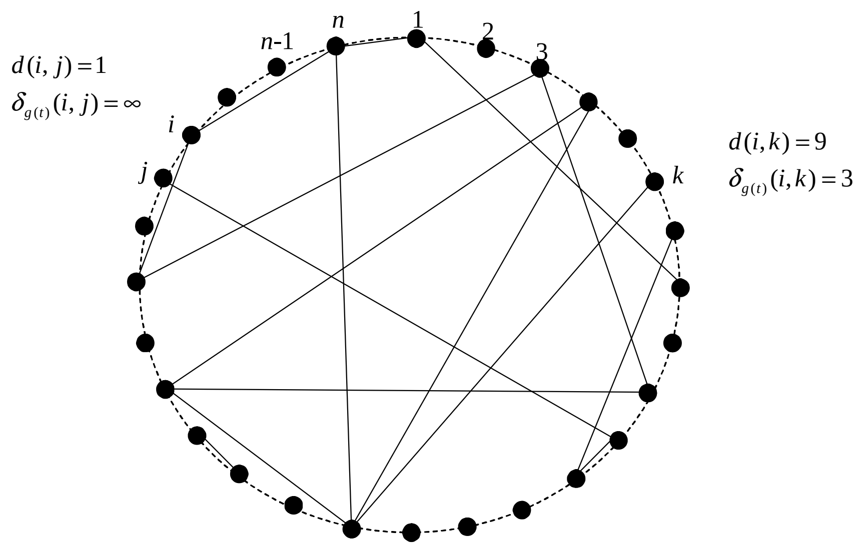

Figure 1: Snapshot of a situation at some t.

3.2 Dynamics

Over time, the network $g(t)$ – which may be conceived as the state of the system – changes due to two forces: innovation and volatility. The first one underlies 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 to be carried out with some partner. If such an idea does arrive to i, the probability $p_i(j)$ that the partner who is called for to carry it out is some particular j satisfies:

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

i.e. it decays with the geographical distance (geodistance, for short) between i and j, where the exponent $\alpha > 0$ modulates the effect of geodistance.

One possible motivation here is that the distance $d(\cdot)$ affects the probability that agents meet, and closer individuals meet more often. An important consequence is that, in general, the larger is α the more important will be geography in enhancing meeting correlations (e.g. between direct first-order meetings and those indirect ones of higher orders). Thus, in a sense, one may conceive α as a measure of "geographical cohesion" – a convenient phrase that we shall often use for concision. Another interpretation of such decay is that a longer distance decreases the probability that the agents are compatible or complementary. Then, the value of α would capture the extent to which geodistance reduces the complementarity/compatibility of skills – possibly because it widens the "cultural gap" – even if it does not affect necessarily the meeting probabilities.[4]

Once an idea has arrived to agent i and she has met a compatible partner j, there is the potential to undertake the corresponding project. In setting up this project, however, there are opportunistic incentives that must be overcome by these agents. Specifically, let us suppose that there is some fixed cost $2C$ to be incurred (once and for all) at the start of the project, and this cost can be either cooperatively shared or not. For simplicity, let us assume that this is no issue if i and j are immediate geographic neighbors. (A natural motivation is that their proximity allows enhanced monitoring or/and lower set-up costs.[5]) Instead, if i and j are not immediate neighbors, a genuine game is played at the start of their relationship, in which they independently decide whether to behave cooperatively or not in covering the set-up costs. If both decide to cooperate, then each covers C, half of the total those costs. Instead, if both defect, they are not covered at all and the project opportunity is irreversibly wasted. Finally, if one cooperates and the other defects, we assume that the former bears the full fixed cost $2C$ while the latter avoids it altogether. Thus, in essence, the strategic situation faced by agents i and j 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.

In principle, cooperation in the first stage could be supported by the threat of equilibrium punishment in the subsequent repeated coordination game. But, to focus on the most interesting case, we want to postulate payoffs that rule out this possibility (see below). This then implies that, unless freshly meeting agents can rely on the "collateral" afforded by the social network,[6] the opportunistic incentives they face cannot be overcome and the link will not be formed.

Consider first, as a benchmark, what would be the situation if every project had to be supported bilaterally, i.e. without resorting to the participation of a third party. Then, the most effective way in which an agent could induce her partner to share the start-up cost is by (credibly) threatening the latter to play the low-effort equilibrium for the whole duration of the project if she does not do so. 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. To guarantee that, as desired,

[4] A related possibility is that the stimuli triggering agents' creative ideas are more likely to be related to the environment they usually face. Thus, in general, the compatible skills required to carry them out are more likely to be held by agents close-by, whose environment is similar.

[5] For example, if the set-up cost for neighboring agents is $2\tilde{C} < 2C$, it may be assumed that the inequality (1) below is reversed, i.e. we have $\frac{W}{\rho} < \frac{1}{\rho} - \tilde{C}$. This would render it feasible for cooperation to be supported in a strictly bilateral fashion, as explained below.

[6] The felicitous term "social collateral" is borrowed from Karlan *et al.* (2009).

cooperation in this case *cannot* be enforced bilaterally we must postulate that

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

so that the payoffs obtained from initial defection (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 (and thus pay C) and then obtain a unit flow thereafter.

As advanced, our interest is on a context where, if any agent i and j who freshly meet can count on at least one other agent k to punish the defector, then it is better for both i and j to cooperate in sharing the start-up costs. By adapting the former line of argument, it is clear that this is implied by the following condition:

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

On the other hand, we must also guarantee that it is worthwhile to undertake the project if both agents cooperate in sharing the start-up costs but not if the partner free-rides. This is readily implied by

$$\frac{1}{\rho} - 2C < 0 < \frac{1}{\rho} - C. \tag{3}$$

Conditions (1)-(3) will be maintained throughout.[7] Third-party enforcement, therefore, is both necessary and sufficient to sustain cooperative behavior between any pair of agents. The question now is whether such mechanism is consistent with agents' incentives. And, even if this is the case, we may also want to consider whether it might be subject to some limits, e.g. associated to the speed at which information flows or the extent to which agents feel bound by the norm. These are concerns addressed by the following two assumptions:

A1. Agents play the equilibrium (i.e. incentive-compatible social norm)[8] such that, if it becomes common knowledge between two partners, i and j, that j has unilaterally defected upon a third player k, then i and j play the low-effort equilibrium of their stage game as long as their link remains active.

A2. There is some $\mu \in \mathbb{N}$ such that information about players' behavior "travels" (or remains effective) only $\mu - 1$ steps along the network. This means

[7] It is immediate to check that these conditions can be jointly satisfied if $1/2 < \rho C < 1$ and $1 - \rho C < W < 1 - \frac{1}{2}\rho C$.

[8] Note that, if the underlying network and other features of the situation are common knowledge, a situation where every pair of connected agents play *some* corresponding equilibrium of the (coordination) stage game at each point in time can be supported as an equilibrium of the overall intertemporal game played by the whole population. (See Lippert and Spagnolo (2006) and Vega-Redondo (2006) for a similar modelling approach.) It should be emphasized, however, that we are ruling out that agents be so sophisticated that they take into account the effect of their choices on the future changes of the social network – they are assumed to take the prevailing network as fixed.

that the behavior of any agent i with a partner j is effectively learned (instantaneously, for simplicity) only by agents k who are at no more than $\mu - 1$ links away from j in the social network.

The conjunction of A1-A2 and the payoff conditions (1)-(3) lead to the following link-formation rule:

LF (Link Formation) Any two previously unconnected individuals i and j who freshly meet choose to link (undertake a project) at any t if, and only if, their social distance in the prevailing network is at most μ.

The requirement that, in order for a link to be formed, the social distance between the new partners should not be too large is in the spirit of what Karlan *et al.* (2009) label the "circle of trust." In essence, it captures the idea that agents can be expected to respond to violations of a social norm (which is costly) only if they are sufficiently "attached" to the agents involved. In our model, the minimum degree of attachment required is given by the parameter μ, which we shall generally identify with "institutions." Conceivably, it could reflect the speed at which strategically relevant information flows, but we prefer to regard it as embodying how strongly agents internalize the social norm. Thus, only if the individual affected by a deviation of the cooperative norm is not too socially distant (i.e. no farther than $\mu - 1$ links away) the agent in question is ready to punish the deviating agent.

Such an interpretation is in line with the dichotomy put forward by Platteau (2000) between *generalized 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.

3.2.2 Volatility

Volatility is the second force governing the process, inducing project decay. As already mentioned, 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 channeled through the mechanism of link formation alone.

Thus, in a nutshell, the process modelled here can be succinctly described as the *struggle of innovation against volatility* to maintain a high level of economic interaction (i.e. connectivity). In this setup, our primary objective will be to understand how that struggle is affected by the different parameters of the model: η (the rate of innovation), α (the "geographical" decay of meeting) and μ (the strength of institutions).

4 Analysis

The discussion is organized in three parts. First, we present numerical simulations that highlight the wide range of interesting observations that arise in our setup. Second, we propose a theory that, even though directly applicable only to a extreme limiting case, it sheds light on the key mechanisms that underlie the aforementioned observations. Third, we devise a numerical approach to solving the model 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 leading 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 interesting observations, which in turn have guided the subsequent theoretical analysis presented in Subsections 4.2 and 4.3. In what follows, we focus on four main 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 and implications.

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 depict the effect of changes in η on four endogenous variables that, in combination, provide a good account of the main characteristics displayed by the corresponding *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,

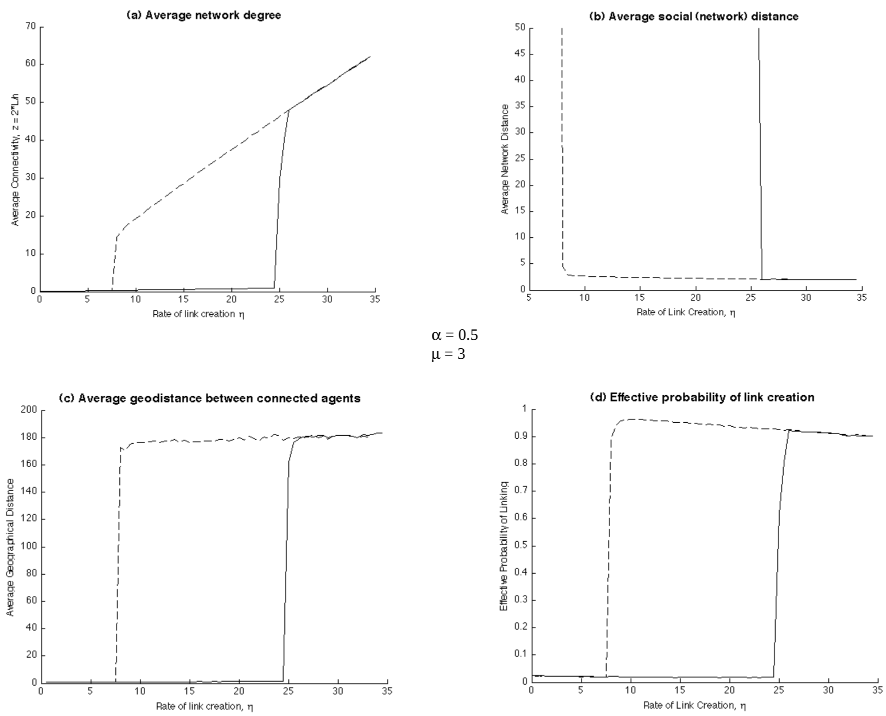

Figure 2: Discontinuous transition in network connectivity, and hysteresis, as the innovation η rate changes for given (low) $\alpha = 0.5$ and $\mu = 3$ (with $\lambda = 1$, $n = 1000$).

whenever any two agents meet, they actually form a new link.[9]

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 $n = 1000$. (See the Appendix for a detailed description of the algorithm used to compute the steady state values of each of the variables displayed here.) 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 slowly, while the dashed line corresponds to very slow *decreases* in η. More 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,

[9] Note that, in general, 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.

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 α, interagent *meeting* is global – i.e. a large fraction of the agents who meet are geographically quite apart. Thus, if institutions μ are weak and the original network is quite sparse, social distances between meeting agents also tend to be quite high. Their meetings, therefore, tend to be "wasted" and links are not formed, which perpetuates a low-connectivity state. The same state of affairs continues 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 meeting agents and 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. Under these conditions, with the social distance among even far-way agents much reduced, further increases in η translate into a sustained (almost proportional) increase in connectivity. A new regime has set in, which is what we called *globalization.* In fact, within a some intermediate region for η (the interval $(7, 25)$ in our case) whether such a regime sets in or not depends on whether the initial conditions embody a globalized state or not. This corresponds to what is often described as hysteresis. Conceptually, it amounts to saying that transitions are robust, i.e. not reversed by small changes in the parameter η in either direction. It can also induce strong path-dependencies, with "history" playing a key role in explaining why the economy is at its current state.

In fact, our intuitive understanding of the phenomenon 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 α, meeting is quite global 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 institutions are strong (μ relatively large) and/or interagent meeting local (α high), then neither globalization is so crucial (because strong institutions decrease the importance of social collateral) nor possible (since most of the partners are found locally). This implies that the effect of the innovation rate η on economic activity is gradual and no multiplicity arises. Moreover, local saturation becomes an important issue, and the fraction of meetings that give rise to new projects decreases as η grows.*

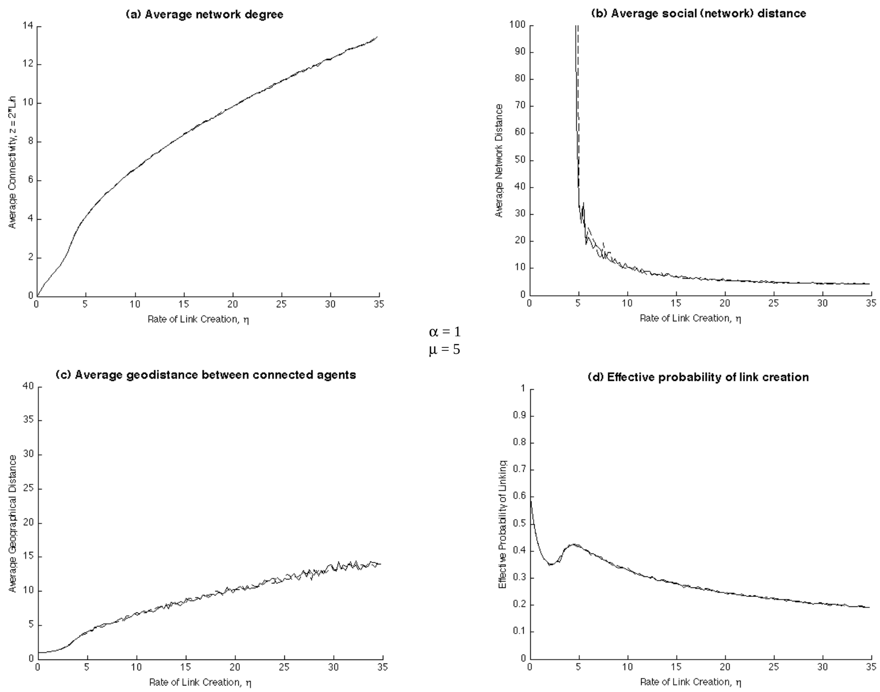

Figure 3: Continuous change in network connectivity, without hysteresis, as the innovation η rate changes when $\alpha = 1$ and $\mu = 5$ are relatively high ($\lambda = 1$, $n = 1000$).

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 distance 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 some 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 $\alpha = 2$, the fraction of global meetings is negligible and, therefore, there is not even the *potential* for globalized interaction. Thus the bulk of the process unfolds locally and most of the meetings between nearby agents who are not already connected lead to the formation of a new link. (This is helped by the fact that, since $\mu = 5$, institutions are relatively strong.) Therefore, as η grows, the rise in the average connectivity occurs continuously, and is unaffected by the network considerations – i.e. the sharp reconfiguration of the network topology – that underlie the transition to globalization in the former case.

This understanding of the situation is reflected by Panels (b)-(d) in Figure 3. In Panel (c) we see that links are mostly local – their average geodistance is low and 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. But probably the most interesting feature is found in Panel (d). There we see that the effective linking probability tends to fall with η. 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 the positive network effects. These effects, akin to those underlying the transition to globalization, are nevertheless not strong enough to offset the curse of too-local interaction: the saturation of profitable opportunities, which in the end irreversibly dominates.

Observation 3: *Globalization can materialize only if the probability of long-distance meetings is significant. But the extent to which such global meetings are beneficial depends on the strength of institutions. If μ is high, the optimal geographical range of meetings is indeed long, and this mitigates local saturation. However, if μ is low, it is better that meetings be more local so that the structure provided by "geography" can offset the stronger opportunistic incentives induced by weak institutions.*

This observation is illustrated in Figure 4. It depicts the average network connectivity as a function of the meeting decay 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 $\alpha \in (0, 5]$, with high values of α entailing that most meetings are local and thus the typical meeting scale is small. While low values imply that most meetings are between geographically distant agents and thus the induced meeting scale is small.

Let us refer to the value α^* at which the level of economic 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

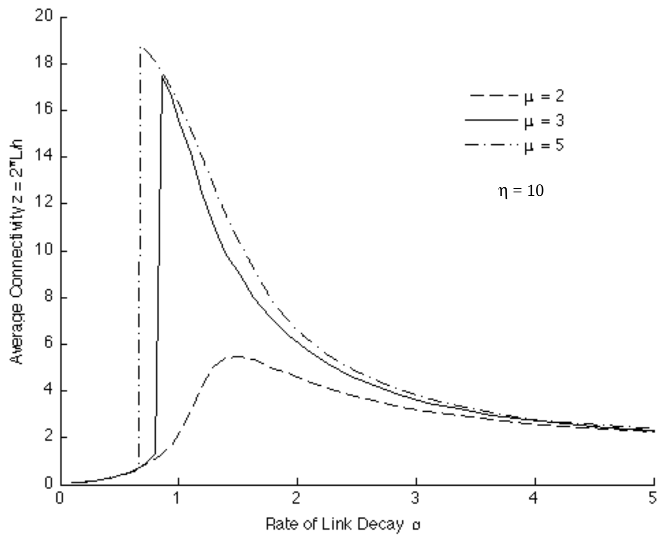

Figure 4: Network connectivity as the decay parameter α grows, for a given value of $\eta = 10$ and different values of institutions μ ($\lambda = 1$, $n = 1000$).

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 incentive issues, the meeting mechanism should be as global as possible: this would minimize the detrimental effects of local saturation. But if, as postulated, opportunistic incentives are indeed an issue, too large a meeting scale is suboptimal. The problem is that the population would then be unable to develop enough social structure from scratch to support cooperation. This can be partially remedied if meeting takes place at a smaller scale. Then, the population can rely upon the "geographical structure" provided by the meeting mechanism to offset some of the opportunistic incentives.

In the end, the optimal compromise between the two previous considerations is reached at some intermediate level, the OGC α^*. And, naturally, the "price" to be paid in the form of localness must be tailored to the quality of institutions. As Figure 4 shows, the OGC falls (i.e. meeting becomes more global) the stronger are institutions. This is because the higher is μ, the less severe are the incentive problems and, therefore, the less detrimental it is to aim for a global meeting mechanism.

Observation 4: *If the meeting decay α is sufficiently low, the path of institutional improvement is dichotomic (i.e. involves just two states), with a shift at a certain threshold on μ. Below the threshold, globalization fails to materialize and any institutional improvement is ineffectual. Past the threshold, where globalization has already obtained, the same occurs and* *further institutional improvements are ineffectual.*

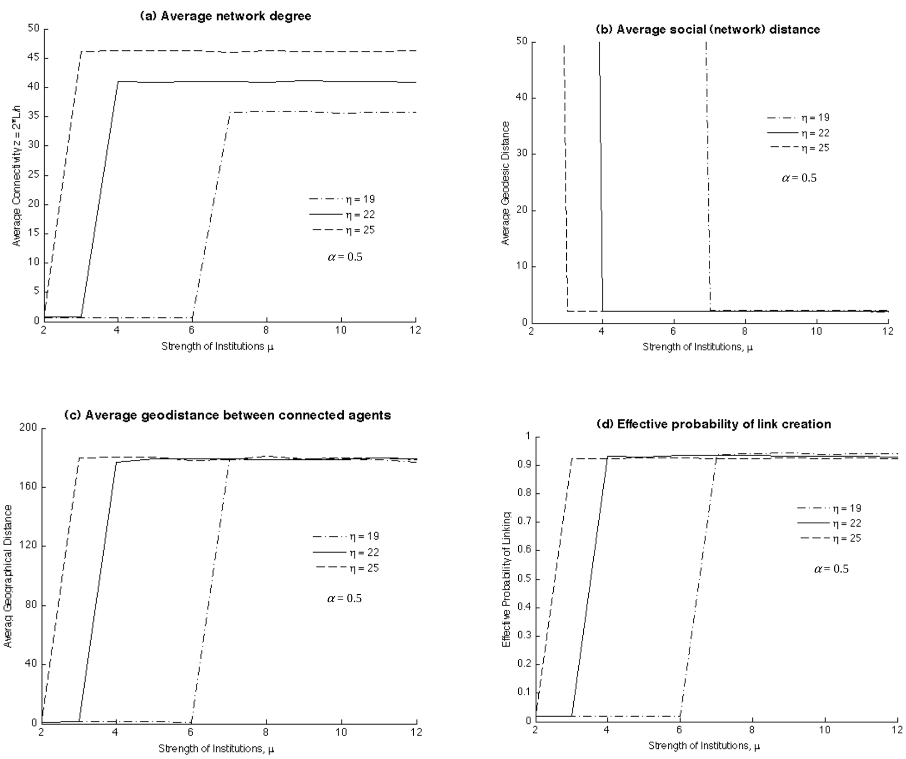

Figure 5: Discontinuous transition in network connectivity as institutions μ improve, for a given (low) value of $\alpha = 0.5$ and different values of the innovation rate η (with $\lambda = 1$, $n = 1000$).

This observation is illustrated in Figure 5. As usual, the reported outcomes are population averages of connectivity, social distance, geodesic distance, and effective linking probability, here computed for $\alpha = 0.5$ and $\mu \in \{2, 3, ..., 12\}$. We consider, moreover, three different values of the innovation rate, $\eta \in \{19, 22, 25\}$. The simulations depict a path of institutional improvement where μ grows gradually. More precisely, at each value of μ the model is simulated from the steady state obtained for the preceding value until a new steady state is reached.

Indeed, as Observations 1 and 2 suggest, globalized interaction requires that meeting be sufficiently global (low α) and institutions well developed. But how developed institutions need to be? In general, of course, this depends on the other parameters – specifically, on the innovativeness of the environment, as captured by η. But the stark point made by Figure 5 is that the *only* essential effect of institutional improvement is to allow for the materialization of globalization. If this situation is *not* achieved, better or worse institutions are mostly ineffectual. And if globalization is indeed achieved, this is all that institutions are really called for – further improvements are of little consequence as well.

The basis for such step-like conclusion is related to the following well-known feature of (asymptotically large) random networks (see Subsection 4.2). If any such network is connected (i.e. all nodes belong to a single component), every pair of nodes are at maximum distance: the so-called diameter of the network. In our (finite but large) context, when globalization occurs, the network approximates such a situation and, for most pairs of nodes, their distance cannot exceed the prevailing institutions.[10] This then explains that further institutional improvements are essentially irrelevant and hence we have the flat segment of the functions depicted in Figure 5 past the transition threshold. An analogous idea explains the flat segments of those functions to the left of the transition threshold. Below this threshold, essentially all pairs of nodes are at distances higher than institutions, and this remains in place with identical implications until the shift to globalization (and the abrupt reduction in the network diameter) can materialize.

An illustrative support for the above line of reasoning is found in Panels (b) and (d) of Figure 5. There we see that, as long as μ lies below the threshold, the network distance remains uniformly high – in particular, higher than μ – and thus the effective linking probability stays at a uniform low level. This happens because most meetings occur between agents who are geographically close (see Panel (c)) but whose social distance exceeds μ. Nothing in this respect changes up to the point where μ reaches the threshold. Beyond that point, the typical network distance becomes drastically lower (in particular, lower than μ) and the effective linking probability attains a uniform high level.

In sum, therefore, we find that there is a threshold for the strength of institutions that marks the frontier between two *homogenous* regions that are *qualitatively* distinct, one characterized by globalized connections and the other by localized interaction. Finally, note that the globalization threshold depends on the innovation rate η in the natural fashion: if new ideas come up more frequently (higher η), the system can reach the globalized state under weaker institutions. This reflects a substitutability between the quality of the environment and that of institutions, which we discuss at some length below.

4.2 Benchmark theory: low geographical decay

In this section, we consider a benchmark extreme case where the meeting mechanism is unaffected by geographic distance – i.e. a context with a vanishingly small α . Our prior understanding of this case will help highlight 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).

[10] For a theoretical discussion of this property, see the last part of Subsection 4.2.

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 its two nodes.) 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:

$$\phi = \frac{1}{2\eta} z. \tag{4}$$

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)[11] 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, assuming that the population is very large – formally, in the limit $n \to \infty$ – the overall (statistical) properties of the network are fully captured by the average degree of the network z. And therefore, we may conceive $\phi = \phi(z)$ as a function of z as well. Then, the equilibrium condition (4) becomes 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 will be to single out the solutions of the equation that are stable, which are the only ones that are truly relevant as dynamic predictions of the model.

In an Erdös-Rényi (ER) network, it is well known that if the average degree is large enough, there is a unique[12] component of the network that has a significant fractional size, i.e. encompasses a fraction of nodes that is bounded above zero as $n \to \infty$ – see, e.g., Bollobás (1985). 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)):

$$\chi = 1 - e^{z\chi}, \tag{5}$$

inducing the function $\chi(z)$ that is depicted in Figure 6.

[11] As shown in Lemma 7 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 and 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 8). These distortions, however, do not affect the qualitative behavior of the model for low α, as confirmed in Subsection 4.3.

[12] Therefore, all other components have an insignificant (vanishing) fractional size as $n \to \infty$.

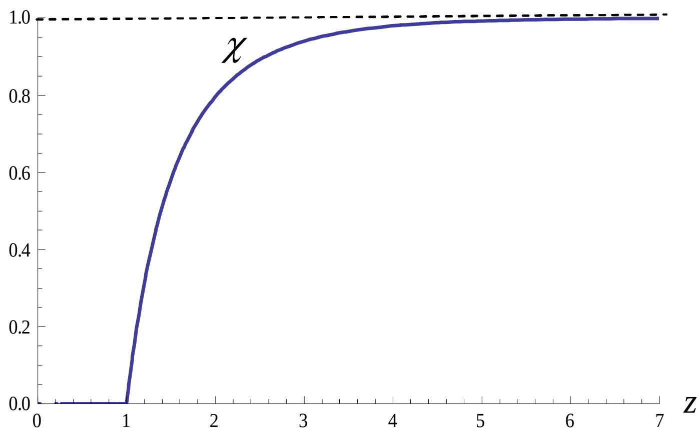

Figure 6: The fractional size $\chi = \chi(z)$ of a Poisson random network, as a function of the average degree z.

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. Specifically, note that the *conditional* probability ϕ that any agent i, upon receiving an idea, establishes a link to the selected agent j is no higher than 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 (5). This allows us to write:

$$\phi(z) \leq [\chi(z)]^2,$$

which is the indicated upper bound for the effective linking probability.

For the sake of focus, let us provisionally abstract from the dependence on institutions by assuming that, albeit being finite, μ is arbitrarily large.[13] Then, we can invoke the above inequality with equality and the steady state condition (4) can be formulated as follows:

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

As explained, expression (5) determines $\chi(z)$ as depicted in Figure 6, in turn leading to the graphical representation of the steady-state condition that is illustrated in Figure 7.

Steady states are represented in Figure 7 by intersections of the sigmoidal-like function $[\chi(z)]^2$ and the ray of slope $1/(2\eta)$. If η is small enough (such

[13] This entails, in particular, that μ must grow as n grows. But, relying on standard arguments in the theory of random networks, it can be seen that it is enough that μ grows as slow as $\ln(n)$ for the validity of the ensuing logic.

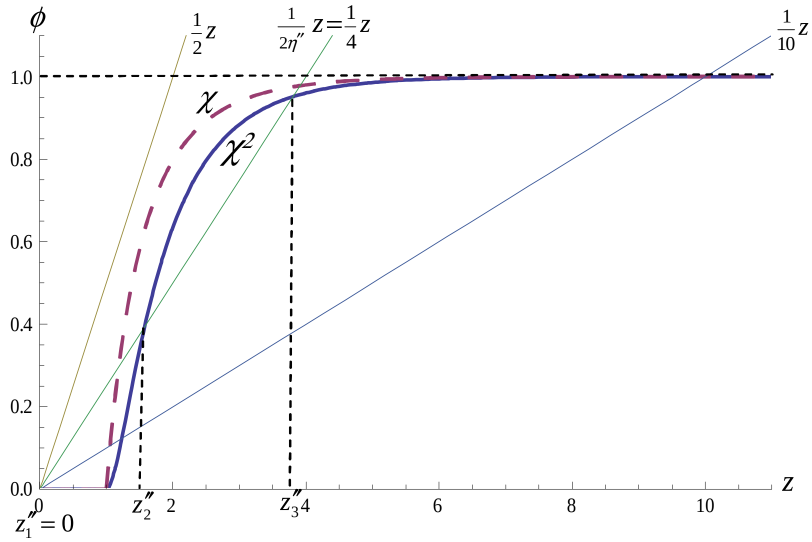

Figure 7: Equilibrium condition for the benchmark model for three different values of the innovation rate: $\eta' = 1$, $\eta'' = 2$, $\eta''' = 5$. For the intermediate η'', there are three equilibria, whose corresponding average degrees are denoted by $z_1''(= 0)$, z_2'', and z_3''. While the first and third are stable, the one associated to z_2'' is unstable.

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''' in Figure 7 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 point to note is that, for every value of η, the zero-degree equilibrium is *locally stable*, no matter how high is the value of η. This makes the following very important point. If the system starts with a very low average connectivity, it will never be able to escape that situation through local adjustment, *even if the underlying conditions become arbitrarily positive.* The economy, in other words, is stuck in a low-activity trap, from which it cannot free itself by relying on the the individual incentives formation alone. As we shall now explain, the root of the problem is that, because $\alpha = 0$, the mechanism of network formation cannot be supported the the underlying geographic structure. And some such structure is crucial in the process through which an originally low-interaction economy can become global and thus sustain a high level of interaction!

To shed further light on the problem, let us see what happens when geography genuinely affords the required structure. This is modulated by the value of the parameter α that determines the distance-associated decay in meeting probabilities. As it turns out, the precise threshold beyond which a new qualitative situation arises in this respect is $\alpha = 1$. For, 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 $n \to \infty$. To see this, note that, for any given $\bar{d}$, the probability of meeting a partner within this distance as the population grows can be approximated by

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

and therefore

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

because the function $x^{-\alpha}$ is not integrable (i.e. does not have a bounded integral) over the range $[1, \infty)$ when $\alpha \leq 1$. This implies that the local stability properties of the empty network are unchanged in very large populations as long as the decay parameter α does not exceed 1. That is, a zero-degree equilibrium continues to be locally stable for any finite value of η.

Matters are quite different when $\alpha > 1$. In this case, the probability that any agent i meets her close geographic neighbors is positive – in particular, the probability of meeting either of the two immediate ones is (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 8.

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 $\hat{\eta} \simeq 0.1$, 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 setup, 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. As will be recalled, this is indeed 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 in understanding many interesting properties of the globalized phase itself. By way of illustration, we now focus on the remarkable regularity displayed in Figure 9. It shows that, once globalization has been triggered by a sufficient improvement in the innovation rate η, the network average degree grows linearly

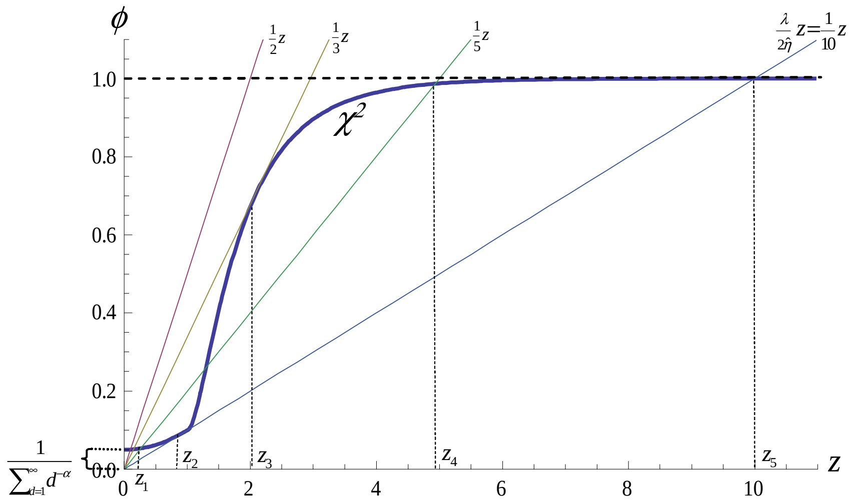

Figure 8: Destabilization of the low-activity equilibrium in the benchmark model for $\eta > \hat{\eta} = 0.1$

as η increases further, with a *common slope* (slightly below 2) for *every value* of the institutional parameter μ. In this sense, therefore, we can say that there is a fixed rate at which growing innovativeness translates into higher economic activity that only depends on the economy having become globalized – not on the details of how such state has been attained.

To see how the benchmark model illuminates this conclusion, first note that, in a globalized state, almost all nodes are part of the (single) giant component of the network. Thus, under the assumption that it is an Erdös-Rényi network, almost every pair of nodes can be supposed to lie at the network distance given by the diameter of the giant component, which can be estimated as follows:

$$\text{diam}(z, n) \simeq \frac{\ln n}{\ln z}$$

where recall that n is the population size (a parameter) and z is the average degree (an endogenous value). Since, at every globalized state, we find that institutions indeed satisfy:[14]

$$\mu \geq \frac{\ln n}{\ln z}, \tag{6}$$

we can associate to each of those states an effective linking probability ϕ that is uniformly close to one. Thus, from the steady-state condition (4), we may

[14] This inequality is to be conceived as a condition of the endogenous variable z that must be satisfied for globalization to materialize under such connectivity (and the parameters n and μ).

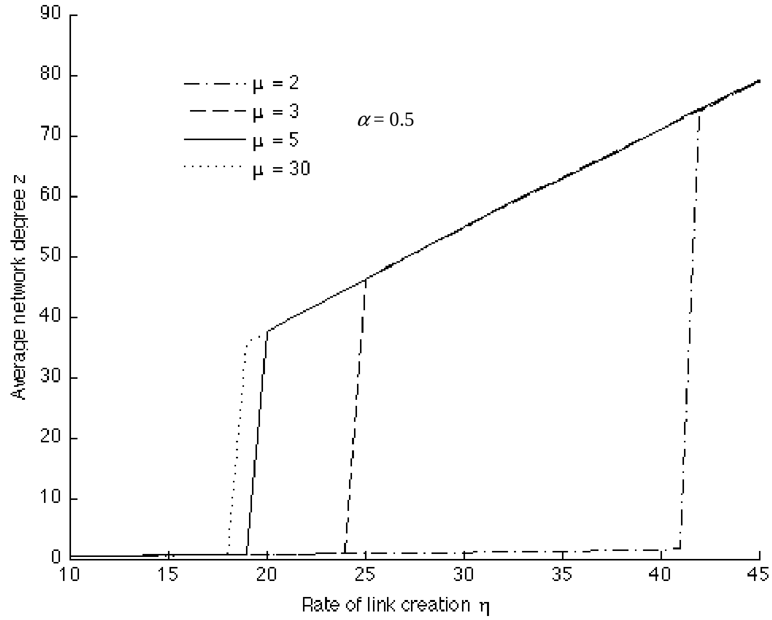

Figure 9: Network connectivity as the innovation rate η rises, for a given (low) value of $\alpha = 0.5$ and different values of institutions (with $\lambda = 1$, $n = 1000$).

conclude that the linear expression

$$z = 2\eta \tag{7}$$

must hold approximately at any globalized state, independently of the underlying institutions, as indeed displayed in Figure 9.[15]

The benchmark model considered in this subsection has been conceived as the idealization of a context where the decay parameter α is small and thus geography plays a little role. And, indeed, we have seen that it works well to reproduce and understand many of the regularities observed for numerical simulations under such circumstances. It has proven useful, in particular, to understand the sharp transitions and hysteresis that characterizes the behavior of the process in this case. For higher values of α, however, we have encountered a quite different behavior: continuous transitions and no hysteresis (recall e.g. Figure 3). To shed light on this different behavior, we can no longer rely on

[15] The fact that the slope displayed in Figure 9 is slightly below 2 (roughly, 1.7) 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.

the benchmark model discussed here and we need to develop a more general approach. This is the objective of Subsection 4.3.

4.3 From the benchmark model to the general approach

The benchmark model provides a stylized and large-population account of the main forces at work when the meeting decay α is small. But, of course, in general we are interested of understanding the phenomenon even when the population is not very large and, most importantly, when the decay parameter α is high. A key feature of the model is the interplay between α and the other parameters of the model – most crucially, the quality of institutions as captured by μ.

For such a general setup, our approach elaborates on the route pursued for the benchmark model. Specifically, we shall rely on the steady-state condition (4) 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, to proceed in this fashion, we first need to determine the function $\phi(z)$ that gives the effective linking probability associated to different values of z. But, in contrast with the approach pursued for the benchmark model, now we do not aim at approximating this function through a stylized account of the situation (the Erdös-Rényi framework). Rather, we base the analysis on an accurate estimate of the function ϕ that is obtained through numerical methods.

Specifically, given some fixed parameter configuration, the value $\phi(z)$ associated to any value of z is obtained as follows. First we simulate the process starting from an empty network and putting the volatility component on hold, until the average degree z in question is reached. Thereafter, we bring in random link destruction so that, at each point in time, the average degree remains uniformly equal to z.[16] As the simulation proceeds in this fashion, we record the fraction of times that a link is created between meeting 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 it specifies the "notional" rate of project creation that would ensue (normalized by population size) *if* such average degree z were stationary. And when, indeed, 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. Again the situation can be diagrammatically illustrated as a point of intersection between the function ϕ and a ray of slope equal to $1/(2\eta)$. Figure 10 includes different panels where such intersections are depicted for different values of α and μ and a fixed ratio $1/(2\eta)$.

As a quick and informal advance of the systematic analysis that will be undertaken below, note that Figure 10 shows the expected effect of the parameters

[16] More specifically, at each instant in which a link is created, another link is chosen *at random* to be eliminated (i.e. 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

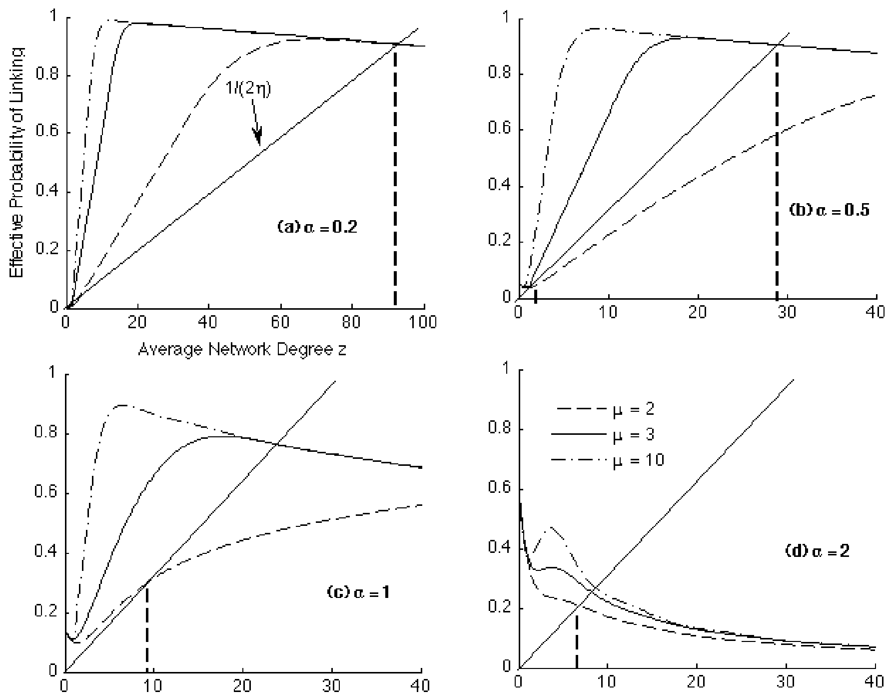

Figure 10: Graphical representation of the equilibrium condition (4) in the general framework. The diagrams trace the steady states as points of intersection between a fixed ray of slope $1/(2\eta)$ and the function $\phi(z)$ computed for different instutions μ (within each panel) and decay parameters α (across panels).

of the model. Specifically, *ceteris paribus*, better institutions enhance economic activity, with the effect being essentially dichotomic for low values of α and gradual for larger values. Also note that the transition towards a more globalized state is abrupt for low values of α but gradual for larger ones. Specifically, consider the panel for $\alpha = 0.5$ where, for the value of η being considered, the system is at a point of a discontinuous transition. This situation contrasts with that displayed in the panels for larger α where, if η were to change, it would trace a continuous change in the equilibrium. Finally, observe that as α changes and one compares the equilibria obtained (for fixed η) across the different panels of Figure 10, the effect is non-monotonic. First, the equilibrium average degree increases with α, which reflects the positive impact of globalization; then it decreases, which is the familiar effect of local saturation arising as the meeting mechanism becomes too local.

It is reassuring to confirm that there is a precise correspondence – not just qualitative but also *quantitatively* very accurate – between the stable points derived from the steady-state condition and those identified by our numerical simulations. Such a close match involves, in particular, a correct identification of the transition points, the magnitude of the induced changes, and the range of hysteresis. This is illustrated in Figure 11 below by focusing on the simulation results that led to the four observations of Subsection 4.1.

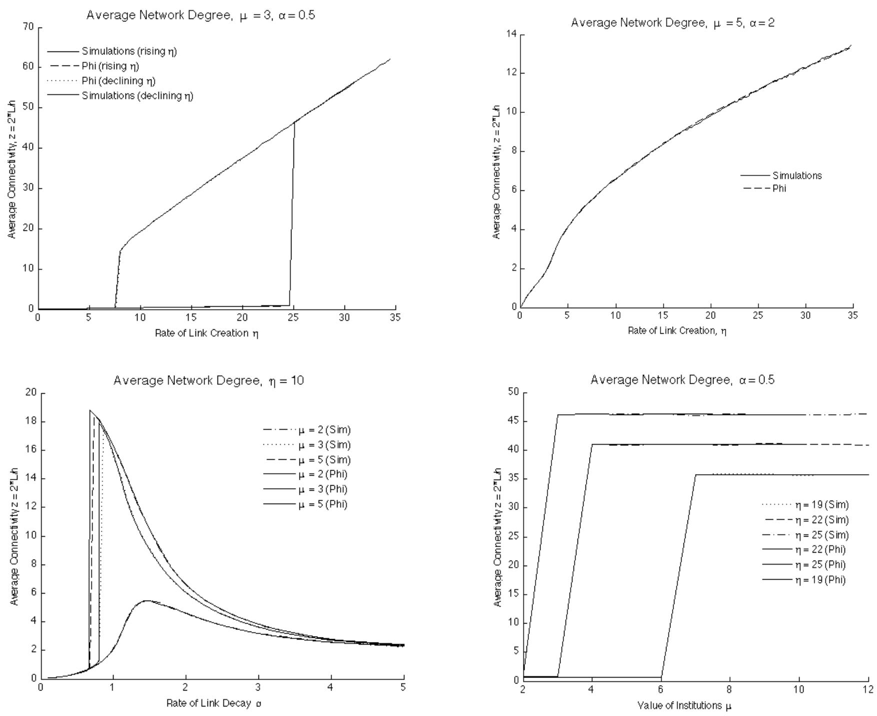

Figure 11: Comparison between the theoretical predictions and the numerical simulations for each of the parameter-dependence exercises conducted in Observations 1-4.

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 setup of 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.

Given the numerical estimation of the function ϕ underlying our theoretical approach, in order to formulate precise statements 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 unit step (i.e. $\eta = 1, 2, \ldots$) while for α the grid step is chosen equal to 0.05. 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 raised in Subsection 4.1 when discussing Observation 1, i.e. the conditions (as given by α and μ) under which the transition to globalization as η changes 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 specify when the function $\zeta_0(\cdot; \alpha, \mu)$ behaves discontinuously as η changes discretely along its *grid* $\Psi_\eta = \{1, 2, , ...\}$. 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 $\tilde{\eta}+1 \to \tilde{\eta}+2$. 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 $\mu \in \Psi_\mu$ the following statements hold:*

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

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

As mentioned, the validity of this conclusion is confirmed by an exhaustive analysis of the parameter space, illustrated by the diagrams displayed in Figure 12. Panels (a)-(c) illustrate its Part (i), while Panels (e) and (f) illustrate 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. Interestingly, 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 local meetings remains significant even for an arbitrarily large population.

In sum, the overall implication here 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 point already explained at some length when discussing the simulations and the benchmark model. When the potential for globalization exists (because α is low and thus meeting is global) such potential will materialize abruptly, by triggering a self-feeding process of network formation.

Our early discussion also suggested that abrupt transitions are associated to hysteresis and, therefore, equilibrium multiplicity and dependence of initial conditions. To study this issue, we first confirm that the form computed for the function ϕ guarantees that there are always *at most two stable equilibria*. The

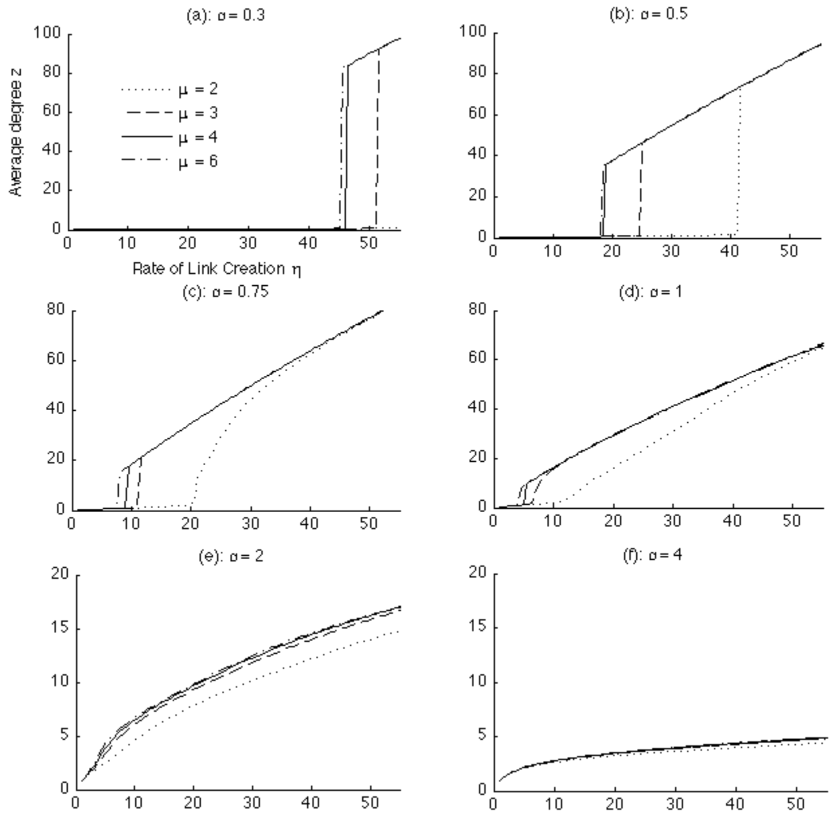

Figure 12: Numerical solution of the average network degree induced by the general model, as the innovation rate η rises, for different given values of the decay rate α and institutions μ (with $\lambda = 1$, $n = 1000$).

one with the lowest connectivity has its average degree given by the function $\zeta_0(\eta; \alpha, \mu)$ introduced above. Then define by $\zeta_1(\eta; \alpha, \mu)$ the counterpart function that specifies the highest average degree at a stable equilibrium. Of course, in the absence of multiplicity we have $\zeta_0 = \zeta_1$. But, in general, they may differ and then we are interested in the set $\Theta \equiv \{\eta \in \Psi_\eta : \zeta_1(\eta; \alpha, \mu) \neq \zeta_0(\eta; \alpha, \mu)\}$. This set can to be seen to form an interval (possibly an empty one), so we can correspondingly define the length of that interval as $\theta \equiv \max_{\theta \in \Theta} \theta - \min_{\theta \in \Theta} \theta$. Being this length an endogenous variable, it is 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, given any particular μ, the function $\theta(\cdot, \mu)$ enjoys clear-cut regularities. The gist of the analysis is illustrated in Figure 13 and the conclusions are formally spelled out in Conclusion 2.

Conclusion 2 *For all $\mu \in \Psi_\mu$, 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 should be 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 supported at equilibrium. Instead, in Part (iii), the reason is that globalization is unfeasible given the too-local meeting mechanism. But, past the threshold value of α (cf. Part (ii)) where it is possible at equilibrium, the extent of globalization – 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.

Indeed, the previous intuitive understanding of matters is essentially right, and a compact and useful way of capturing the essence of it 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. More precisely, we can identify this point as $\hat{\eta}(\alpha, \mu) \equiv \max\{\eta : \zeta_1(\eta, \alpha, \mu) \neq \zeta_2(\eta, \alpha, \mu)\}$.[17] Then, building upon the same analysis illustrated in Figure 13, we arrive at the following result.

Conclusion 3 *Given any $\mu \in \Psi_\mu$ and $\alpha, \alpha' \in \Psi_\alpha$ with $\alpha < \alpha'$, the following two conditions apply:*

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

[17] 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.

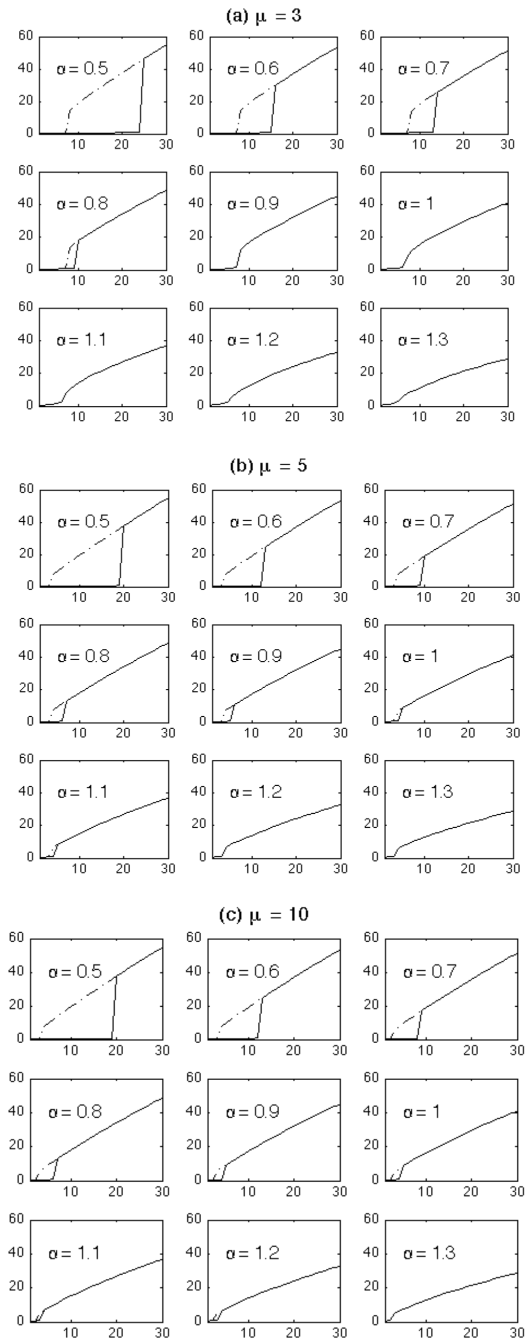

Figure 13: Numerical solution induced by the general model for the transition in the average network degree – including possibe hysteresis – as the innovation η rate changes for different given values of α and μ (with $\lambda = 1$, $n = 1000$).

(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 where the transition to globalization occurs for the lower value of α, the economic activity induced by this lower value is higher than that induced by the higher α'. In contrast, Part (ii) states that, below such a transition point, α yields lower performance than α'. Note that the latter statement accounts, in particular, for the fact that the transition towards globalization occurs at a lower η value for α' than for α. Jointly, these two statements provide a clear-cut description of the two-sided impact that the decay rate 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 14, leads to the following result.

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:*[18]

(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 in* Ψ_μ *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* $\zeta_0(\cdot; \alpha, \mu)$ *displays no discontinuities in* Ψ_η.

Part (i) of the previous Conclusion indicates that, in line with what happens for η, changes in μ lead to discontinuous equilibrium transitions when the meeting mechanism is sufficiently global. There are, however, two significant differences. One concerns the requirement that η be large enough. This is a mere consequence of the fact that, if the the meeting rate is very weak, not even the best of circumstances (say, very powerful institutions) can deliver the minimum extent of connectivity that renders interaction global.

A second difference is that, when interaction becomes indeed global and thus an abrupt upward transition occurs, this is the only point at which change takes place. That is, away from this point of discontinuity, no improvement of institutions has any effect whatsoever on the connectivity displayed (as traced by the lowest-degree equilibrium). The intuition for this behavior is the same as explained in Subsection 4.1, so we shall not elaborate on it further. In sum, the key point to emphasize is that, even though institutions and innovativeness are forces that operate in quite different ways, improvements in either of them trigger similar self-feeding effects. Thus, under low geographical cohesion, they both lead to sharp transitions towards globalization and hysteresis.

[18] As in many of the cases depicted in Figure 15 below, the discontinuity may occur at the very first value of $\mu = 2$. Then, our notion of discontinuity is taken to apply for changes above this value and (voidly) to changes below it.

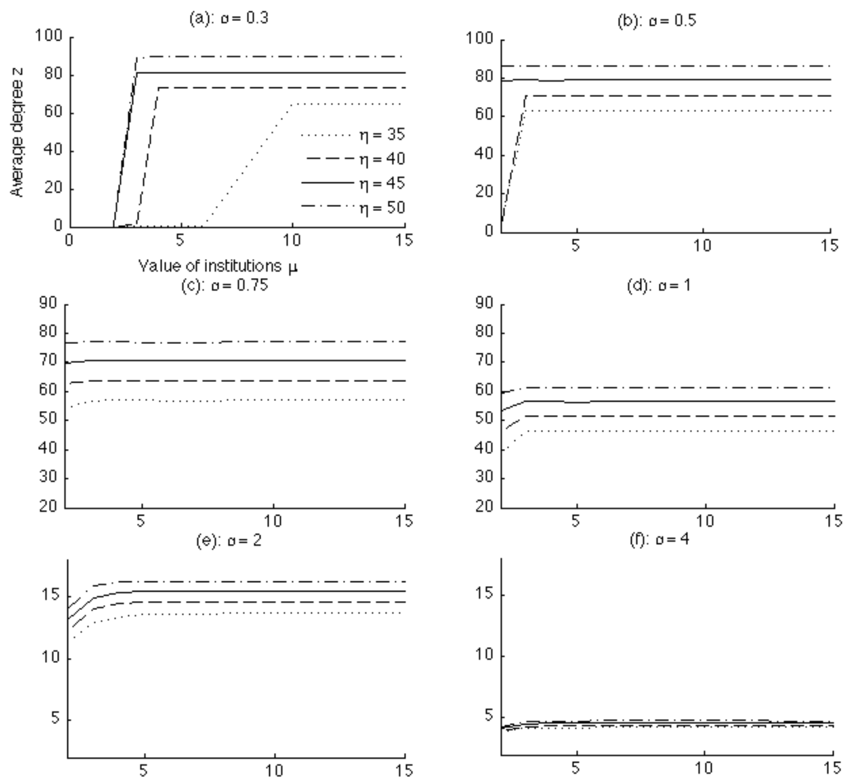

Figure 14: Numerical solution of the average network degree induced by the general model, as institutions improve, for different given values of the innovation rate η and the decay rate α (with $\lambda = 1$, $n = 1000$).

4.3.3 Institutions and the optimal level of geographical cohesion

Throughout our discussion of the general model, the interplay of institutions and innovativeness with geographical cohesion has been highlighted as one of the main forces at work. Finally, we explore this interplay in more detail here, by focusing on what we label (in analogy with the same term used in Subsection 4.1) the optimal level of geographical cohesion (OGC), denoted by $\alpha^*(\eta, \mu)$. It is identified with the value of α that, for given η and μ, maximizes $\zeta_0(\eta, \alpha, \mu)$.

The analysis on the dependence of OGC on μ and η is respectively illustrated by Panels (a) and (b) in Figure 15. 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 requires that the meeting structure be as global as is consistent with 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. In a very large population, therefore, only a vanishing small probability is associated to close-by meetings.

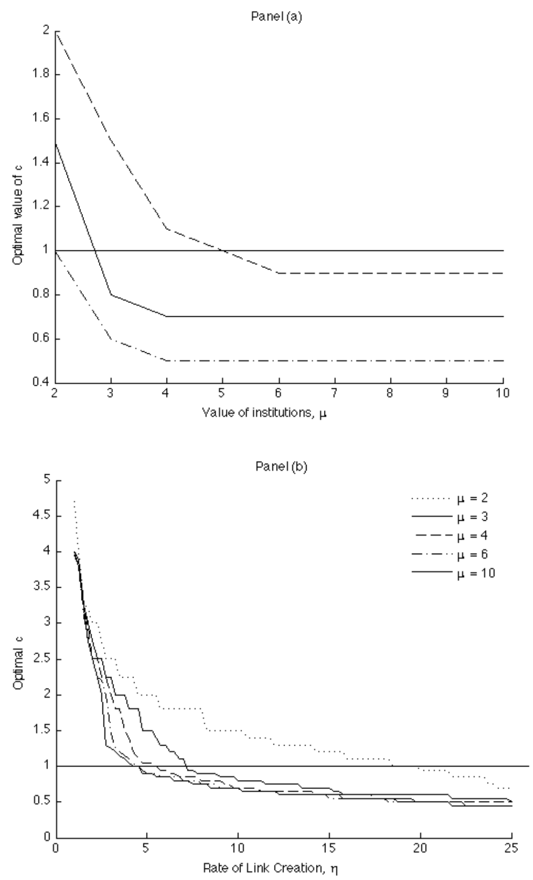

Figure 15: Optimal level of geographical cohesion (OGC), as a function of institutions μ (Panel (a)) and the innovation rate η (Panel (b)).

More precisely, the previous discussion is 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 stylized "spatial" model to study the relationship between institutions, globalization, and economic interaction. The main feature of the model is that connections breed connections, offsetting the opportunistic incentives that would otherwise make collaboration unfeasible. Such social collateral, in turn, renders it possible for economic interaction to span long distances, thus alleviating the saturation of local opportunities.

But in order for such a beneficial process to unfold, the social network must become global – i.e. globalization must arise as a self-sustainable state of affairs. To understand the way in which this phenomenon comes about has been the primary concern of the paper. We have seen, for example, that it may occur quite abruptly, that history (initial conditions) may shape the future, and that the interplay of "geography" and institutions may be quite subtle. In particular, we have found that *some* geographic cohesion, despite acting as a local anchor of interaction, may play a crucial role in triggering global interaction.

This paper is to be viewed as merely a first step in what we hope could be a multifaceted research program. From a theoretical viewpoint, an obvious and much-needed task is to enrich the microeconomic/strategic foundations of the model. This will require, among many 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 features to be enriched in the future concern the extent to which one allows for heterogeneity (the basis for most economic interaction), how it is tailored to the underlying space, and how canonical economic institutions such as markets operate in this context.

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 may help in this task, by suggesting what variables to measure and what predictions to test. Specifically, our model highlights network interaction measures and stresses the importance of direct and indirect connections as a way of promoting cooperative behavior. Ongoing work by Duernecker, Meyer, and Vega-Redondo (2010) is starting to pursue this path, by constructing network measures of foreign direct investment (for which incentive considerations are important) and relating them to different measures of economic activity and performance.

Appendix A

Lemma 7 *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

$$\gamma_{ij} = 2\eta \frac{1}{n-1} \tag{8}$$

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 (8) 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 8 *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[19]. 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 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

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

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[20].

- **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 $p_i(j)$[21].
  - 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

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

[21] 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.

search algorithm, which we describe in 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 subparts in the network. Any two nodes, i and j, which are not jointly located on such a subpart 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 $\overline{\delta} < \infty$. 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 $\overline{t}$ simulation steps.

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