Social Networks and Macroeconomic Stability

Shu-Heng Chen, Chia-Ling Chang, and Ming-Chang Wen

Abstract

In this paper, the effect of the social network on macroeconomic stability is examined using an agent-based, network-based DSGE (dynamic stochastic general equilibrium) model. While the authors' primitive (first-stage) examination has the network generation mechanism as its main focus, their more in-depth second-stage analysis is based on a few main characteristics of network topologies, such as the degree, clustering coefficient, length, and centrality. Based on their econometric analysis of the simulation results, the authors find that the betweenness centrality contributes to the GDP instability and average path length contributes to the inflation instability. These results are robust under two augmentations, one taking into account non-linearity and one taking into account the shape of the degree distribution as an additional characteristic. Through these augmentations, the authors find that the effect of network topologies on economic stability can be more intriguing than their baseline model may suggest: in addition to the existence of non-linear or combined effects of network characteristics, the shape of the degree distribution is also found to be significant.
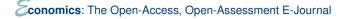
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1 Motivation

The purpose of this paper is to examine the effect of the social network on macroe-conomic stability using an agent-based, network-based macroeconomic model. We shall simulate the macroeconomy using the agent-based DSGE (Dynamic Stochas-tic and General Equilibrium) model, which is embedded with different network topologies. We then examine the effect of these different network topologies on the observed macroeconomic stability in terms of the GDP and inflation dynamics. Before we proceed, the general background to what this research pursues shall first be briefly reviewed.

1.1 The Two Lines of Research

A research subject on the relationship between social networks and macroeconomic stability can be examined from several different perspectives or channels. In terms of methodology, it does not have to rely on agent-based models. However, since agent-based models have interactions of agents as one of their essential ingredients, either explicitly or implicitly, (social) networks are naturally already there. In fact, by and large, there are two major lines of research being pursued in the literature on agent-based models; one relates to the *network-based agent-based models*, and the other to the *agent-based modeling of networks*.[1]
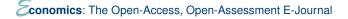
The pioneering study by Mark Granovetter (Granovetter, 1973), while, formally speaking, not involving an agent-based model, already incubated the idea of how interpersonal networks can affect the information flow of the distribution of job vacancies and how social networks can impact search and labor market behavior. Later on, this line of research was generalized into the familiar network-based discrete choice model or neighbors-based discrete choice model, as one of the most important classes of agent-based models. In fact, the earliest agent-based models, such as the checkerboard model or cellular automata, the Ising model, the percolation model, and the kinetic model, can be regarded as models explicitly built upon an interpersonal network upon which interactions of agents and the resultant decision-making can be defined and operated.[2]

In this line of research, network topologies are exogenously fixed or, in other words, are regarded as independent economic variables. The research question is then concerned with how the resultant endogenous economic behavior depends on the given network topologies, plus other given conditions. This line of research may be useful for providing us with some thought experiments (what-if scenarios) to see the possible economic effects of social network topologies; nevertheless, it does not address a more fundamental issue, i.e., how these networks got there in the first place.

Therefore, there is a second line of research which attempts to incorporate the formation of network topologies as part of the model. Examples directly related to

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[1] For the brief review of these two directions, the interested reader is referred to Chen (2006).

[2] For a review, see Chen and Li (2012).

our subject are Delli Gatti et al. (2010) and Delli Gatti et al. (2011), in which the networks of firms and banks are endogenously determined and evolving. Not only can this line of research be further connected to the increasing number of empirical studies on networks, but may also help us see that some measures normally built upon a given network, such as vulnerability, have to be updated over time.

Despite its potential generality and richness, few models are able to come up with a scale which can simultaneously determine the evolution of the networks of various economic agents (firms, banks, and households). What we have at this point is either a study focusing on the evolution of one kind of network, e.g., the interbank network, or the firm network, or else some very limited integration overarching firms and banks. It is not entirely clear whether we need a fully-fledged version of networks in our macroeconomic models, and, if so, to where and how far we can actually advance.

1.2   The Approach and the Model Taken

The approach taken by this specific study belongs to the first line of development. We take network topologies as given and, by means of thought experiments, study whether these network topologies may have macroeconomic impacts. As with other studies in the first-line research, the limitation is to assume away the possible upward causation, which, of course, can be open to further exploration, if this initial study can reveal its promising features.

Specifically, we take an agent-based version of the New Keynesian DSGE model.[3] In response to the recent criticisms (Colander et al., 2008; Colander, 2010; Solow, 2010; Velupillai, 2011; Stiglitz, 2011), some researchers have attempted to incorporate the three missing elements, i.e., bounded rationality, heterogeneity and interactions, into the DSGE models (Orphanides and Williams, 2007; Branch and McGough, 2009; Milani, 2009; Chen and Kulthanavit, 2010). This development leads to a kind of 'agentization' of the DSGE models, known as the agent-based DSGE models. These models are first initiated by De Grauwe (2010, 2011) and are further developed by Chang and Chen (2012) and Chen et al. (2014).

The latter differs from the former according to the level of analysis. The former (De Grauwe, 2010, 2011) starts at the mesoscopic level. It distinguishes agents by types and hence the interaction, learning and adaptation of agents are operated only based on the distribution over these types rather than going down to individual agents. Since individuals are not directly involved, social networks, i.e., the connections between these individuals, certainly have little role to play in this model. The latter, on the other hand, starts at the microscopic level (individual) level, and interaction, learning, adaptation and decision-making are all individually based. It is a manifestation of the network-based discrete choice model. Social

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[3]   There are a number of agent-based macroeconomic models directly formulated in the Keynesian spirit, while the network structure has not become an explicit part of it. See, for example, Dosi et al. (2010) and Dosi et al. (2013).

networks in this model are obviously indispensable, since they are the driving force behind the subsequent interactions of agents.

Chen et al. (2014) used the well-known Ising model, invented by the physicist Ernst Ising in his PhD thesis in 1924, as a model for interacting agents with regard to their mimetic behavior. This Ising model is operated with different embedded network topologies. In this paper, we shall use the same model to address the significance of network topologies to macroeconomic stability. Let us be more precise in regard to what we try to do here. We shall simulate the macroeconomy using the agent-based DSGE model augmented with the Ising model, which is embedded with different network topologies. We shall then examine the effect of these different network topologies on the observed macroeconomic stability in terms of the output and inflation dynamics.

As for the chosen network topologies, we consider two stages with different pursuits. In the first stage, we focus on *network generation mechanisms*, which include fully-connected networks, random networks, regular networks, small-world networks and scale-free networks. We then see whether there is any correspondence between macroeconomic stability and these generation mechanisms. The reason that we start with the network generation mechanism is because that earlier studies on agent-based economic models mainly focus on the network generation mechanisms (Albin and Foley, 1992; Wilhite, 2001). We should, however, realize that it is more informative to base our analysis upon *network characteristics* rather than network generation mechanisms. This is because the latter cannot uniquely define a network; two network generation mechanisms may happen to lead to the same network.

There are many network characteristics; in this study, we restrict ourselves to five frequently used characteristics, namely, degree, cluster coefficient, path length, betweenness centrality and closeness centrality. It is possible to include others, but we believe that this set of five serves as a good starting point for the key inquiry of the paper. Therefore, in the second stage, our purpose is to understand the possible correspondence between each of these characteristics and macroeconomic stability. This correspondence is established through the econometric analysis in the form of a simple linear regression with some extensions or augmentations. To do this, we need samples that are sufficiently diversified to cover a reasonable range of various network characteristics.

The remainder of this paper is organized as follows. In Section 2, we present the agent-based DSGE model, including the Ising modeling of learning and expectations formation with the embedded social networks. Section 3 gives a brief introduction to five network generation mechanisms (Section 3.1) as well as five network characteristics (Section 3.2) to be used in this paper. Section 4 then presents the simulation results and the related analysis and discussion, and is followed by the concluding remarks in Section 5.

2 The DSGE Model

2.1 The Standard DSGE Model

First, we describe the stylized New Keynesian DSGE framework. The model consists of the following three equations:

$$y_t = a_1 E_t y_{t+1} + (1 - a_1) y_{t-1} + a_2 (r_t - E_t \pi_{t+1}) + \varepsilon_t \tag{1}$$

$$\pi_t = b_1 E_t \pi_{t+1} + (1 - b_1) \pi_{t-1} + b_2 y_t + \eta_t \tag{2}$$

$$r_t = (1 - c_1)(c_2 + c_3(\pi_t - \pi_t^*) + c_4 y_{t-1}] + c_1 r_{t-1} + u_t \tag{3}$$

Equation (1) is referred to as the *standard aggregate demand* that describes the demand side of the economy. It is derived from the *Euler equation* which is the result of the dynamic utility maximization of a representative household and market clearing in the goods market. The notation in Equation (1) has the following meaning: y_t denotes the output gap in period t, r_t is the nominal interest rate and π_t is the rate of inflation. Here, we add a lagged output gap in the aggregate demand equation to describe habit formation (Fuhrer, 2000). E_t is the usual expectations operator, to which we will come back later.

Equation (2) is a New Keynesian Phillips curve that represents the supply side in the economic system. Under the assumption of nominal price rigidity and monopolistic competition, the New Keynesian Phillips curve can be derived from the profit maximization of a representative final goods producer and the profit maximization of intermediate goods producers which are composed of a number of heterogeneous households. To reflect the price rigidity, the intermediate goods producers can adjust their prices through the Calvo pricing rule (Calvo, 1983). By combining the first-order conditions of the final goods producer, the intermediate goods producer and the Calvo pricing rule, we can obtain the New Keynesian Phillips curve (Equation 2).

Equation (3) represents the *Taylor rule* commonly used for describing the behavior of the central bank (Taylor, 1993).[4] The idea is that the central bank reacts to deviations of inflation and output from targets. In Equation (3), π^* refers to the inflation target pursued by the central bank. The coefficients c_3 and c_4 represent the conflict resolution between the preference for price stability and economic growth; in the case that these two pursuits are equally important for the central authority, c_3 and c_4 are identical. The presence of the one-period-lagged interest rate is to take into account the smooth adjustment behavior of interest, and the coefficient c_1 gives the degree of smoothness.

Finally, ε_t, η_t, and u_t are all white noise added to aggregate demand, aggregate supply and the interest rate. Given these stochastic elements, E_t, in Equation (1) and Equation (2), is the expectations operator, denoting people's expectations of the GDP gap and the inflation rate.

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[4] There are different versions of the Taylor rule applied in the DSGE model, and the one which we adopt here is the same, for example, as the one in Kazanas et al. (2011).

The reduced form of the New Keynesian DSGE model is found by substituting Equation (3) into Equation (1) and then by rewiring in the matrix notation. This yields:

$$
\begin{bmatrix} 1 & -b_2 \\ 0 & 1 \end{bmatrix} \times \begin{bmatrix} \pi_t \\ y_t \end{bmatrix} = \begin{bmatrix} 0 \\ a_2(1-c_1)c_2 \end{bmatrix} + \begin{bmatrix} b_1 & 0 \\ -a_2 & a_1 \end{bmatrix} \times \begin{bmatrix} E_t\pi_{t+1} \\ E_t y_{t+1} \end{bmatrix}
$$
$$
+ \begin{bmatrix} 1-b_1 & 0 \\ a_2(1-c_1) & 1-a_1+a_2(1-c_1c_4) \end{bmatrix} \times \begin{bmatrix} \pi_{t-1} \\ y_{t-1} \end{bmatrix}
$$
$$
+ \begin{bmatrix} 0 \\ a_2c_1 \end{bmatrix} \times r_{t-1} + \begin{bmatrix} \eta_t \\ a_2u_t+\varepsilon_t \end{bmatrix}
$$

$$(4)$$

or, in a compact matrix notation,

$$\mathbf{AZ_t} = \mathbf{CON} + \mathbf{BE_t Z_{t+1}} + \mathbf{CZ_{t-1}} + \mathbf{br_{t-1}} + \mathbf{V_t} \tag{5}$$

where all notations above correspond one-to-one to the matrices in Equation (4) in an order from left to right. The solution to (5) in terms of $\mathbf{Z_t}$ is:

$$\mathbf{Z_t} = \mathbf{A^{-1}}[\mathbf{CON} + \mathbf{BE_t Z_{t+1}} + \mathbf{CZ_{t-1}} + \mathbf{br_{t-1}} + \mathbf{V_t}] \tag{6}$$

The solution exists only if matrix $\mathbf{A}$ is non-singular. By obtaining the inflation rate (π_t) and output gap (y_t) through Equation (6) and substituting them into Equation (3), the interest rate (r_t) can be determined accordingly.

2.2 The Agent-Based DSGE model

After describing the stylized New Keynesian DSGE model, we come to a variant initiated by De Grauwe (De Grauwe, 2010, 2011), which differs from the standard DSGE model in terms of the formation of expectations and its heterogeneity. In the standard New Keynesian DSGE model, the representative agent always has rational expectations. De Grauwe relaxed this stringent assumption and started the agent-based version of the DSGE model by replacing the homogeneous rational expectations of output with the heterogeneous boundedly rational counterparts.

This is done by using *a two-type agent-based model*, which is one of the most frequently used agent-based models in the literature (Chen et al. , 2012). This type of agent-based models starts with a description of the types of agents (Section 2.2.1), the determination of the meso-structure in terms of these types (Section 2.2.2), and the effect of the meso-structure on aggregate outcomes as well as the downward causation (Section 2.2.3).

2.2.1 The Two Types of Agents

In our context, we assume that there are only two states for expectations, referring to two types of agents. For the output (GDP gap) inflation, there are *optimists* and

pessimists. The former form their expectations biasedly and systematically in an upward manner, and the latter form their expectations with the same style but in a downward manner. Technically, their forecasting rules are specified as follows:

$$E_{o,t}y_{t+1} = g, \quad E_{p,t}y_{t+1} = -g, \tag{7}$$

where "*o*" is an abbreviation for the optimist and "*p*" is an abbreviation for the pessimist, and g ($g > 0$) denotes the degree of bias in the estimation of the output gap, which is a parameter to be specified later in the simulation table.

Similarly, there are two types of agents in the inflationary expectations. One is called the '*fundamentalist*', who tends to believe that the realized inflation will be the targeted inflation π^*, and the other is the '*chartist*', who simply behaves as a trend follower. Technically, these two expectations rules, $E_{f,t}$ and $E_{c,t}$, are described as follows:

$$E_{f,t}\pi_{t+1} = \pi^*, \quad E_{c,t}\pi_{t+1} = \pi_{t-1}, \tag{8}$$

where f and c are the abbreviations for the fundamentalist and the chartist.

2.2.2 The Meso-Structure and the Ising Model

Once after the two types of agents are specified, we need to know the size of each in the model, not just the absolute size, but also the relative size, i.e., the share of each in the market. While this size is treated as an exogenous variable in many earlier agent-based models and still so even recently, there are more and more models addressing it as a variable to be determined endogenously. The endogenous determination mechanism normally involves switches between different types of agents. If the types have been fixed, the learning and adaptation of agents are mainly manifested through this switching mechanism. In this paper, this switching or learning mechanism shall be modeled through the Ising model, to which we now turn.

The Ising model originated from the dissertation of Ernst Ising (1900–1998) (Ising, 1924). Ising studied a linear chain of magnetic moments, which are only able to take two positions or states, either up or down, and which are coupled by interactions between nearest neighbors. The model is strikingly successful in the search for the transition between the ferromagnetic and the paramagnetic states. In addition to physics, the model is also used in biology and the social sciences. In economics, it was first used in Follmer (1974), and has been used to model opinion dynamics (Orlean, 1995), financial markets (Iori, 1999, 2002) and tax evasion (Zaklan et al., 2009).

Our model is composed of a finite number of agents, say N agents, who are arranged in a specific network structure as we shall introduce in Section 3.1. The Ising model characterizes each individual's decision as a *stochastic discrete choice*. In our case, each agent's dual choice is influenced by his neighbor's (magnetic field)

in a stochastic manner. Specifically, in period t, agent i's probability of being an optimist ($i_y(t) = 1$) or a pessimist ($i_y(t) = -1$) and that of being a fundamentalist ($i_\pi(t) = 1$) or a chartist ($i_\pi(t) = -1$) is stochastically determined by his interactions with his neighbors in previous periods. For implementation, we further assume that this local interaction can be summed up by a few statistics, for example, the number of his optimists, pessimists, fundamentalists and chartists in agent i's neighborhood in period $t-1$. Then his choice in time t is assumed to be influenced by these local statistics. A simple formalization of this stochastic discrete choice for the output expectation, $i_y(t)$, is given by Equation (9).

$$Prob(i_y(t) = 1) = \frac{1}{1 + \exp(-2\lambda m_{i,y}(t))} \tag{9}$$

In Equation (9), the decision to be optimistic ($i_y(t) = 1$) or pessimistic ($i_y(t) = -1$) only involves one local statistic, i.e., $m_{i,y}(t)$. In line with the Ising model, this can typically be the weighted average of the local optimistic forces and pessimistic forces (or simply the *local market sentiment*), i.e., the market sentiment that agent i can experience from his neighbors (magnetic field). More concretely,

$$m_{i,y}(t) = \sum_{j=1, j \in \vartheta_i}^{N} w_{ij} j_y(t-1) \tag{10}$$

ϑ_i is the set of all *neighbors* of i.[5] w_{ij} is the weight that represents the interaction strength between i and j or j's influential power on i. In a very simple setting, we consider the uniform weight, i.e.,

$$w_{ij} = \frac{1}{\#\{j : j \in \vartheta_i\}} \tag{11}$$

Agent i's decision on inflationary expectations is determined is a similar manner.

$$Prob(i_\pi(t) = 1) = \frac{1}{1 + \exp(-2\lambda m_{i,\pi}(t))}, \tag{12}$$

where

$$m_{i,\pi}(t) = \sum_{j=1, j \in \vartheta_i}^{N} w_{ij} j_\pi(t-1) \tag{13}$$

In addition to the local statistics $m_{i,y}(t)$ and $m_{i,\pi}(t)$ (the forces in the magnetic field), the other variable appearing in Equations (9) and (12), is λ, the parameter

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[5] Later on, in Section 3, we shall formally introduce the notations related to the *network*. Borrowing the notations from there, the set ϑ_i can be formally defined as

$$\vartheta_i = \{j : b_{i,j} = 1\}.$$

which is normally known as the *intensity of choice* in the literature. The role of λ can be highlighted as follows.

$$Prob(i_y(t) = 1) \rightarrow \begin{cases} 1/2, & \text{if } \lambda \rightarrow 0. \\ 1, & \text{if } \lambda \rightarrow \infty \text{ and } m_{i,y}(t) > 0. \\ 0, & \text{if } \lambda \rightarrow \infty \text{ and } m_{i,y}(t) < 0. \end{cases} \tag{14}$$

Equation (14) is applicable to $Prob(i_\pi(t) = 1)$, except that $m_{i,y}(t)$ has to be replaced by $m_{i,\pi}(t)$. In terms of the Ising model, when λ is high, agents have the tendency to align with their neighbors, whereas when it is low, that tendency is disturbed and agents behave as if they are independent.

The switching mechanism characterized by stochastic choice models (9) and (12) will then be applied to each agent i ($i = 1, 2, ..., N$). Based on the choices stochastically made, in each period in time, our relative size of each type of agent is determined as:

$$\alpha_{o,t} = \frac{\#\{i : i_y(t) = 1\}}{N}, \quad \alpha_{p,t} = \frac{\#\{i : i_y(t) = -1\}}{N}, \tag{15}$$

and

$$\alpha_{f,t} = \frac{\#\{i : i_\pi(t) = 1\}}{N}, \quad \alpha_{c,t} = \frac{\#\{i : i_\pi(t) = -1\}}{N}. \tag{16}$$

These fractions, $\alpha_{o,t}$ and $\alpha_{f,t}$ ($\alpha_{p,t}$ and $\alpha_{c,t}$) then give the meso-structure of the economy at time t.

2.2.3 The Aggregate Effect of the Meso-structure

Given the fractions of the optimists and pessimists, $\alpha_{p,t}$ and $\alpha_{o,t}$, and the fractions of the fundamentalists and chartists, $\alpha_{f,t}$ and $\alpha_{c,t}$, the aggregated expected output gap and the aggregated expected inflation in period $t+1$ can then be regarded as the *weighted average* of the expectations held by the two types of agents, weighted by their fractions, as shown in Equations (17) and (18).

$$E_t y_{t+1} = \alpha_{o,t} E_{o,t} y_{t+1} + \alpha_{p,t} E_{p,t} y_{t+1} = (\alpha_{o,t} - \alpha_{p,t}) g \tag{17}$$

$$E_t \pi_{t+1} = \alpha_{f,t} E_{o,t} y_{t+1} + \alpha_{c,t} E_{p,t} y_{t+1} = \alpha_{f,t} \pi^* + (1 - \alpha_{f,t}) \pi_t \tag{18}$$

2.2.4 Remarks on Theoretical Foundations

Here we come to an intriguing point. Given the heterogeneity of the agent's expectations, while it is quite usual to use the weighted average, weighted by the fraction of each type, as the aggregate expectations or the equivalent expectations of the representative agents (Chen and Yeh, 2002), it is not entirely clear on what grounds this weighted average can actually replace the expectations, $E_{i,t} y_{t+1}$ and

$E_{i,t}\pi_{t+1}$, appearing in the DSGE model, Equations (1) and (2), originally derived under the individual optimization scheme.

One possible justification is to treat or assume these two equations, the aggregate demand and the Phillips curve, as emergent properties from an agent-based macroeconomic model. In fact, this assumption is not totally stringent. In agent-based models, the relationships among all economic variables are emergent and not assumed or imposed. These include the famous Phillips Curve, Beverage Curve and Okun's Law. Unlike the conventional equation-based models which take these relationships as given, agent-based models allow these relations to be studied as endogenously emergent properties (Russo et al., 2007; Lengnick, 2013; Delli Gatti et al., 2011).[6] In this way, we shall say that there is indeed a mapping between the weighted expectations and other aggregate variables. Of course, the exact form of the emergent equations may depend on the details of the specific agent-based model.
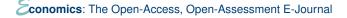
There is an another constraint to our approximation. The agent-based models, as well demonstrated by Wolfram (2002), can generate four types of dynamics. In addition to the fixed points, limit cycles, and chaos (pseudo randomness), it can also generate the pattern known as "on-the-edge-of-chaos" and is computationally irreducible. So far, no single agent-based macroeconomic model has formally demonstrated the "on-the-edge-of-chaos" property in their model; nonetheless, due to this possibility, it is likely that the emergent aggregate properties may constantly change with the evolution of the economy, and hence there is no time-invariant form of the functional relation, such as Equations (1) and (2). In this case, the effective time horizon which can legitimize our approximation cannot be infinitely long or can be rather limited.

In sum, without getting to these much more sophisticated models, one can take Equations (1) and (2) as an approximation to the possibly emergent laws (equations). The modeling strategy based on this simplification allows us to take a first step toward the exploration of the possible effects of network topologies. Having known this restriction, we shall proceed by assuming that the two expectations appearing in Equations (1) and (2) can be replaced by the two in the form of (17) and (18).

3   Social Networks

In this section, we give a brief description of each network employed in this study (Section 3.1). They are not exhaustive, and one can always add others, but as a pioneering study, we believe that the ones considered are representative enough to

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[6] That the equation-based model can be given an agent-based interpretation has also been frequently seen in other social sciences. For example, Uri Welinsky, the founder of NetLogo, frequently used the famous Lokta-Volterra equation, a prominent equation in ecology, as an example to illustrate how the same kind of phenomena can be generated by agent-based models (Wilensky and Reisman, 2006) (see NetLogo Models Library: Sample Models/Biology, Wolf Sheep Predation). However, because of the inclusion of geographical specifications, the Lokta-Volterra equation can only be considered as an approximation of the result dynamics generated by the agent-based model.

cover different characterizations of network topologies (Section 3.2). Later on, our agent-based DSGE model will be embedded within these different network settings, and their effects on macroeconomic behavior will be simulated and studied.

3.1 Network Generation Mechanisms

So far, the most powerful mathematical treatment of social networks is mathematical graph theory. To recap, a graph (G) or a network $G(V,E)$ is defined by a set of vertices (nodes) V and a set of edges (links) E. In many social applications like ours, each node corresponds to a single agent, and $V = \{1,...,N\}$ denotes the set of all the agents considered in the economy. The number N is then the cardinality of the set V or the size of the network. The set E can be represented as an $N \times N$ binary matrix. $E = \{b_{ij} : i, j \in V\}$ denotes the pairwise connections existing among the agents; normally, $b_{ij} = 1$ if such a connection exists between i and j, and zero if there is no such connection. In addition, since self-connection has little application value, we normally assume that $b_{ii} = 0$. The network is *undirected* if the matrix E is symmetric, i.e., $b_{ij} = b_{ji}$. All the social network topology considered in this paper is *undirected*.[7]

Following the current practice in the social network analysis, we consider a number of frequently used network topologies in the literature. These network topologies are at most served for the purpose of thought experimentations; it would be hard to take any of it literally from an empirical viewpoint. Presumably, the best use of them is simply to help us have a rough idea or a picture of the effect of social networks on the macroeconomic performance. With this scope in mind, we have considered the following network topologies: the fully-connected network, the circle and the regular network, the small-world network, and the scale-free network. Each of them will be briefly described as follows. All these networks are also depicted in Figure 1.

Fully-connected network   The fully-connected network has the feature that agents are completely connected with each other. In other words, each agent has $N - 1$ links. An example of the fully-connected network is given in Figure 1 (first row, left).

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[7]   The decision heuristic which we use in this paper is a very standard neighborhood-based decision model, i.e., each agent's decision is influenced by his neighbors. Since the neighboring relation is symmetric, the network interests us is undirected. Needless to say, there are variations of this setting which can lead to directed networks.
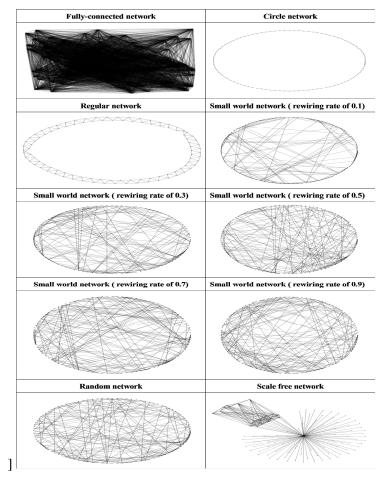
Figure 1 Social Network Topologies

Circle and Regular Network   In the fully-connected network, all interactions are global; however, in many realistic settings, interactions are rather local and are confined to the geographical constraints. There are a number of spatial networks, such as cellular automata, that may be a better representation of these constraints. We, however, consider an alternative with similar virtues but that is much less computationally demanding, which is known as a *regular network*. In a regular network, all agents are distributed and placed like a ring (Figure 1, first right and second left) and each agent is connected with his k neighbors both on the left and the right; k is a constant. A special case called the circle appears when the interaction is extremely limited and $k = 1$ (Figure 1, first right). In addition to this extreme case, a regular network with $k = 2$ is also considered (Figure 1, second left).

Small World and Random Network   The regular network focuses only on local interactions. It captures a kind of clustering activity, but does not allow for

interactions crossing clusters. Nevertheless, inter-cluster interactions are important in reality. Sociologist Mark Granovetter first noticed its significance in the labor market and proposed the so-called *weak-tie connection* (Granovetter, 1973). A network which allows for both local and bridging interaction was first proposed by Watts and Strogatz (1998) and is known as the *small-world network*.

The small-world network combines the ideas of random networks and regular networks. These two kinds of networks can be interestingly compared by the two essential characterizations of network topologies, namely, the *clustering coefficient* and the *average distance*. The clustering coefficient is a formal measurement of the extent to which *friends of mine are also friends of each other*. The average distance, denoted as the average length of the shortest path between two nodes, is used to measure the average distance between two nodes, which corresponds to the degree of separation in a social network. Watts and Strogatz (1998) show that regular networks tend to have a larger clustering coefficient and also a larger diameter; random networks of the equivalent size tend to have a smaller diameter and also a smaller clustering coefficient.

To have a network with a large clustering coefficient but also a small average distance, Watts and Strogatz proposed a network generation algorithm as follows. Firstly, it generates a regular network with N nodes, each with 2κ neighbors. Secondly, a rewiring probability, p, is applied to each link of each agent. If rewiring takes places, then that link will be disconnected and rewired to a randomly selected agent. By fine-tuning the probability parameter, p, a spectrum of small-world networks, which has the random network and the regular network as two extremes, can be generated. In fact, when $p = 0$, we have the regular network and, when $p = 1$, we have the random network (Figure 1, first on the fifth row). In this study, small-world networks with p equal to 0.1, 0.3, 0.5, 0.7, and 0.9 are employed and they are exemplified in Figure 1 (right on the second, the two on the third and fourth). Small-world networks, as compared to other random graphs with the same number of nodes and edges, are characterized by clustering coefficients significantly larger than expected and average shortest-path lengths smaller than expected.

Scale-Free Network   Now, we have networks with a mixture of local and bridging connections, each up to a different degree. In addition, due to the randomness introduced by the rewiring parameter, nodes (agents) can have different numbers of connections, a property which is not shared by the regular networks. This phenomenon, known as the *degree distribution* (see the definition below), corresponds well with what we experience in real social settings: some agents have many more connections than others. However, the way the degree distribution is introduced by the rewiring parameter is basically *random* rather than by a certain social mechanism. Therefore, one cannot directly control the degree distribution in a manner that mimics the empirical degree distribution observed in real social contexts, such

as the *power law distribution*.[8] The power law distribution of the degree has been found in many social contexts, such as the citation network of scientific publications (Redner, 1998), the World Wide Web and the Internet (Albert et al., 1999; Faloutsos et al., 1999), telephone call and e-mail graphs (Aiello et al., 2002; Ebel et al., 2002), and in the network of human sexual contacts (Liljeros et al., 2001).

A scale-free network is a network with the power law property. Thus, the number of links originating from a given node follows a power law distribution represented by $p(k) = k^{-\gamma}$ where k is the number of links. The *scale-free network* was first proposed by Barabási and Albert (1999), and hence is also known as the *BA model* (the Barabási-Albert model). Barabási and Albert (1999) proposed an algorithm, known as *preferential attachment*, to generate a scale-free network. The idea of *preferential attachment* is similar to the classical "*rich get richer*" model originally proposed by Simon (1955). By this algorithm, the network is initialized with N_0 agents with some initially randomly-generated connections and then new agents are sequentially added to the network, one at a time. The new agent, say, i (the ith agent entering the network), is then linked to each of the existing agents, j $(j = 1, ..., i-1)$, with a probability that is positively related to the number of connections (degree) that agent j has. Equation (23) is an example of the preferential attaching probability

$$Prob(\{b_{i,j} = 1)\}) = \frac{(k_j)^\theta}{\sum_{j=1}^{i-1}(k_j)^\theta}, \qquad (23)$$

where θ is a scaling factor. An example of the scale-free network with $\theta = 1$ is shown in Figure 1 (right, the last row).

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[8] A power law distribution is a density function which is proportional to a power function, i.e.,

$$y = f(x) = Prob(X = x) \sim x^{-\gamma}, \qquad (19)$$

where X is a random variable. A nice feature of the power distribution is that it is *scale free*. A random variable X is called *scale free* or said to have a scale-free distribution if

$$f(bx) = g(b)f(x). \qquad (20)$$

Intuitively, the shape of the distribution in an interval $[x_1, x_2]$ is the same as that of $[bx_1, bx_2]$ except for a multiplicative constant. The definition above obviously applies to the power-law distribution since

$$f(bx) = (bx)^{-\gamma} = b^{-\gamma}x^{-\gamma}. \qquad (21)$$

The power law distribution has been cited as *Pareto's Law* when what interests us is the tail distribution of Equation (19), i.e.,

$$Prob(X \geq x) \sim x^{-\beta}, \qquad (22)$$

where $\beta = \gamma - 1$.

3.2 Characterizations of Network Topologies

To facilitate the later simulation study, it would be useful to characterize the chosen network topologies by a few key variables, and then examine the effects of these variables on the resultant macroeconomic behavior. Based on what we have discussed throughout this section and also the literature on social network analysis, we restrict our attention to the following five major characterizations, namely, average degree, average clustering coefficient, average path length, betweenness centrality and closeness centrality. They shall be briefly described as follows.

Degree Distribution and Average Degree The degree of a specific vertex is the number of links emanating from that vertex. A degree distribution $f(k)$ gives the probability of a randomly chosen vertex which has exactly k links. The power law distribution discussed earlier, which has the form $f(k) = k^{-\gamma}$, is one example of the degree distribution.[9] When the network has a finite size, $f(k)$ can also be read as a histogram that gives the percentage of the agents who have exactly k links. The average degree is the mean associated with distribution $f(k)$. When V is finite, it is simply

$$\bar{k} = \frac{\sum_{i=1}^{N} k_i}{N}, \tag{24}$$

where N is the size of the network (the total number of agents in the network) and k_i is the number of the degrees of agent i.

Average Clustering Coefficient The clustering coefficient measures the tightness of the local connection. Specifically, we are asking: if agent j is connected to i, and l is also connected to i, is j also connected to l? Let ϑ_i be the set of neighbors of agent i,

$$\vartheta_i = \{j : b_{ij} = 1, j \in V\} \tag{25}$$

Then the *clustering coefficient* of agent i, C_i, is defined as follows.

$$C_i = \frac{\#\{(h,j) : b_{hj} = 1, h, j \in \vartheta_i, h < j\}}{\#\{j : j \in \vartheta_i\}} \tag{26}$$

The definition of the *average clustering coefficient* is thus straightforward.

$$\bar{C} = \frac{1}{n} \sum_{i=1}^{n} C_i \tag{27}$$

By Equation (26), if agent i's neighborhood is fully connected then the clustering coefficient C_i is 1; otherwise, if they are poorly connected, then C_i is closer to zero. Hence, the average clustering coefficient $\bar{C}$ gives a general picture of how well agents are locally connected.

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[9] See footnote 8.

Average Path Length   Average path length, defined as the average length of the *shortest path* connecting two vertices, is used to measure the average distance between two nodes, which corresponds to the degree of separation in a social network. Given $G(V,E)$, let $d(i,j)$ be the length of the shortest path between the vertices i and j. Then the mean shortest length of $G(V,E)$ is simply the mean of all $d(i,j)$,

$$L = \frac{1}{\frac{1}{2}N(N-1)} \sum_{i \geq j} d(i,j). \tag{28}$$

The definition above may be problematic if there is an isolated vertex which actually has no edge on any other vertices. So, $G(V,E)$ with isolated vertices are not considered here.

Centrality   Centrality concerns the significance of individual agents in their relation to the entire network. Intuitively, given a network topology, to identify the leaders, the most influential persons, the most alerted agents, or the most vulnerable positions of the network, centrality is the key measure to look at. The idea was initiated by sociologist Linton Freeman (Freeman, 1977), who used a star network to point out the three mainstays of centrality, namely, degree, betweenness and closeness. The later development was to generalize the notion of centrality from the star network to general network topologies. Along this line of development, the two most crucial measures are *betweenness centrality* and *closeness centrality*, to which we now turn.

Betweenness centrality measures how many times an agent sits on the shortest path connecting two other agents. Formally, let $n_{s,t}$ be the total number of the shortest paths connecting vertices s and t, and let $n_{s,t}^i$ be those passing through i. Then the centrality of node i is defined as

$$C_B(i) = \sum_{s,t \neq i} \frac{n_{s,t}^i}{n_{s,t}} \tag{29}$$

The other key node centrality measure in networks is closeness centrality (Freeman, 1978; Opsahl et al., 2010; Wasserman and Faus, 1994). It is defined as the inverse of farness, which in turn, is the sum of the distances to all other nodes. As the distance between nodes in disconnected components of a network is infinite, this measure cannot be applied to networks with disconnected components. Equation (30) represents its mathematical formula where $d(i,j)$ is the shortest distance between i and j. Thus, the more central a node is, the lower is its total distance to all other nodes. Closeness can be regarded as a measure of how quickly information can be spread from s to all other nodes sequentially.

$$C_c(i) = \sum_{i \neq j} \frac{1}{d(i,j)} \tag{30}$$

4   Simulation Results and Analysis

In this section, we try to study the relationship between the social network and macroeconomic stability. We shall use the agent-based (network-based) DSGE model to generate the time series of two major macroeconomic variables, the output gap and inflation, and then study the effects of the network topology on their stability (volatility).[10] To do so, we propose a two-stage analysis. A small-scale experiment, like a pilot experiment, is attempted in the first stage. In this stage, we quickly generate 10 different networks and obtain a quick grasp of their possible effect on economic stability. As we shall see in Section 4.2, this initial exploration does suggest some network effects and prompts us to go further to identify its possible sources. Therefore, in the second stage (Section 4.3), we carry out a large-scale simulation based on a large sample of networks with diversified characteristics. An econometric analysis is applied to examine the effect of each network characteristic.

4.1   Simulation Design

The parameter setting involves two parts, one for the DSGE model and one for the social interaction within the embedded social networks. The parameter values of these two parts are given in the upper panel and the middle panel of Table 1. While we take a simulation approach, to make the simulation results reasonably interesting, the parameter values fed to the DSGE model are those actually studied in the literature. In this paper, we take the values from De Grauwe (2010) and Kazanas et al. (2011). Regarding the middle panel, our agent-based (network-based) DSGE model is built upon the five different network topologies reviewed in Section 3, namely, the fully connected network, the regular (circle) network, the random network, the small-world network, and the scale-free network. The parameters given in the middle panel are those required for generating various network topologies.

In this article, the size of the networks is identically set to 100. Hence, the degree for the fully connected network is 99, but that for others varies. It is set as two for the circle network, and four for the regular, random, and small-world networks.[11] To have a full spectrum between the regular network and the random network, we consider the five rewiring rates ranging from low to high for small-world networks. Finally, for the scale-free network, we grow the network with an initial set of 10 nodes with a probability of 0.5 of being connected to each other. We then introduce new nodes one after the other and make them connect to the existing nodes with a preferential attachment scheme (23) with the scaling parameter $\theta = 1$. The last entry of the middle panel gives the value of the key parameter in the stochastic choice model, i.e., the intensity of choice.

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[10] Since the behavior of the central bank (the agent) is not part of our social network modeling, the interest rate volatility due to the Taylor rule is not brought into the analysis.

[11] For the random and small-world network, instead of controlling the degree per agent directly, what we actually did is control the average degree of the network.

Table 1 Parameter Settings of the Network-Based DSGE Models

The DSGE Model		
π^*	0.02	The central bank's inflation target
a_1	0.5	Coefficient of expected output in output equation
a_2	-0.2	The interest elasticity of output demand
b_1	0.5	Coefficient of expected inflation in inflation equation
b_2	0.05	Coefficient of output in inflation equation
c_1	0.8	Interest smoothing parameter in Taylor equation
c_2	2	Constant in Taylor equation
c_3	0.5	Coefficient of inflation gap in Taylor equation
c_4	0.5	Output gap smoothing parameter in Taylor equation
$\bar{q}$	0	Threshold of output gap
g	0.01	Output forecasts of optimists
$\varepsilon_t, \eta_t, u_t$	0.005	The size (standard deviation) of shocks (GDP, inflation and Taylor's rule)
Social Networks and Interaction		
N	100	Number of agents
$k(\bar{k})$	4	Average degree (random, regular, small-world)
p	0.1, 0.3, 0.5, 0.7, 0.9	Rewiring rate (small-world)
N_0	10	Initial size (scale-free)
p_0	0.5	Initial connecting probability (scale-free)
θ	1	Scaling factor (scale-free)
λ	0.1, 0.3, 0.5 0.7, 0.9	Intensity of choice (Ising)
Others		
T	300	Number of simulation periods for each calibration experiment
R	100	Number of experiments for each calibration

Based on the parameter values given in the middle panel, we generate 10 networks as exemplified in Figure 1. The five characteristics, reviewed in Section 3.2, of the ten generated networks are summarized in Table 2.[12] The agent-based (network-based) DSGE model is then embedded with these networks, and for each of these networks we run 100 times of simulation ($R = 100$), and each run lasts for 300 periods ($T = 300$), as indicated in the bottom panel of Table 1. In this way, at the end of each run, we will have the time series of the following three variables: the output gap, inflation and the nominal interest rate. Each variable has 300 observations. We then compute the volatility (variance) of each series, and further compute the average of these volatilities over 100 samples. The analysis is then based on these sample volatility averages.

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[12] It is worth noting that there is such a possibility that i and j have no path connecting the two. In this case, $d(i,j)$ obviously has no finite distance, which may make the average path length problematic. While in the literature it will be considered as infinity, that cannot help distinguish all network topologies with different isolated components (nodes). In this article, the way in which we deal with this problem is to assign a large distance, large enough to make such a distinction. Specifically, with a network size of 100, we set $d(i,j) = 999$ if there is no path traveling through i and j, which is ten times higher than the largest possible finite distance.

Table 2 The Five Characteristics of the Ten Generated Networks

Network	AD	ACC	APL	MBC	MCC
Fully-Connected	99	1.000	1.0000	0.0000	0.0101
Regular	4	0.500	12.8789	588.0000	0.0008
Circle	2	0.000	25.2525	1200.5000	0.0004
Random	4	0.036	3.4442	472.3707	0.0037
SW01	4	0.254	4.1230	687.2087	0.0031
SW03	4	0.098	3.5271	496.9631	0.0036
SW05	4	0.003	23.3632	556.2843	0.0038
SW07	4	0.265	3.4489	611.5324	0.0038
SW09	4	0.270	3.4358	364.1322	0.0034
Scale-Free	4.52	0.147	2.0513	4681.2521	0.0095

Some abbreviations are used in the table. SW01, SW03, SW05, SW07, and SW09 refer to the small-world network with the rewiring rates 0.1, 0.3, 0.5, 0.7, and 0.9, respectively. "AD", 'ACC', "APL", "MBC", and "MCC" are the abbreviations for the average degree (24), average clustering coefficient (27), average path length (28), maximum betweenness centrality (29), and maximum closeness centrality (30), respectively.

4.2 Results: Initial Exploration

The mean volatility of the GDP gap and inflation over the 100 samples are given in Tables 3 and 4. Numerically, these values seem to be close. To examine whether they are statistically significantly different, we conduct the test in a 10-fold manner. Basically, in each test, the volatility of one specific network is tested against the remaining nine as a group to see whether the former is from the same distribution defined by the latter, and we do this one by one for each network.[13] The t statistic for testing the null that it is from the same distribution is given in the parentheses in the tables. Furthermore, we follow the statisticians' convention to use the symbol $*$ if the p-value of the test is less than a certain threshold, and a significance level of 0.05 is chosen here.

From both tables, some results stand out. First, we can see that most networks fail to distinguish themselves in regard to their effect on economic stability; however, they are some networks for which the effect is rather significant. The most evident one is the scale-free network. It is significantly different from others in terms of the output gap volatility under all intensities of choice (λ) and in terms of the inflation volatility when λ is large enough. Second, if we take the regular network and the random network as the two extremes of a spectrum, then we can see that the in-between results (the results of those small-world networks) exhibit a similar pattern. For example, the regular network has almost no idiosyncratic effect on

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[13] Since we have a sample of 100 observations for each network, it is still possible to conduct the test for each pairs of network. However, if we do so there will be 225 tests altogether, and presenting the results will then become too overwhelming. Hence, as an alternative, we decide to test the null that a single network comes from the distribution defined by the other nine. We then do this in a ten-fold manner.

Table 3 The Network Effect on the Volatility of Output Gap

Network	$\lambda = 0.1$	$\lambda = 0.3$	$\lambda = 0.5$	$\lambda = 0.7$	$\lambda = 0.9$
Fully	0.44099	0.43847	0.43591	0.43445	0.43210
	(3.28)*	(1.27)	(1.22)	(1.06)	(0.70)
Regular	0.44119	0.43861	0.43601	0.43418	0.42507
	(-4.84)*	(0.95)	(1.12)	(1.21)	(4.76)
Circle	0.44102	0.43839	0.43653	0.43464	0.43289
	(1.99)	(0.28)	(0.61)	(0.92)	(0.30)
Random	0.44103	0.43852	0.43612	0.43471	0.43199
	(1.64)	(1.21)	(1.01)	(0.88)	(0.75)
SW01	0.44102	0.43838	0.43593	0.43431	0.43275
	(2.03)	(1.58)	(2.54)*	(1.12)	(0.37)
SW03	0.44106	0.43889	0.43588	0.43475	0.43260
	(0.51)	(0.36)	(1.22)	(0.85)	(0.44)
SW05	0.44116	0.43891	0.43616	0.43429	0.43258
	(-3.37)*	(0.21)	(0.97)	(1.06)	(0.45)
SW07	0.44111	0.43856	0.43616	0.43485	0.43249
	(-1.34)	(1.16)	(0.97)	(0.79)	(0.50)
SW09	0.44096	0.43873	0.43648	0.43442	0.43229
	(4.73)*	(0.67)	(0.66)	(1.06)	(0.60)
Scale-free	0.44120	0.44247	0.44640	0.45076	0.45012
	(-5.40)*	(-7.91)*	(-129.94)*	(-208.07)*	(-22.35)*

The numbers shown above are the mean variances of 100 time series, each having 300 observations obtained from the DSGE simulation using the respective network shown in the first column and intensity of choice shown in the first row. The numbers shown inside the parentheses are the *t*-values of the null that the mean variance in question is sampled from the same distribution which generates the other nine. We follow the statisticians' convention to use ∗ if the *p*-value of the test is less than 0.05.

either of the two volatilities; hence, neither do SW1 and SW3. Similarly, the random network has no idiosyncratic effect in all scenarios, and this result is almost copied by SW7 and SW9. Third, however the two extremes can hardly help harness the one in the middle, i.e., SW=0.5, which shows its consistent idiosyncratic effect on inflation volatility. Fourth, one may assume that the effect of the circle network and the regular network should be very close, since the latter only differs from the former in k (degree) by two. Nevertheless, this is not entirely the case and their distinction can be found in the inflation scenario when λ is high. Fifth, one may expect very different behavior from the fully connected network given its large number of degrees, but its distinction can be found only in the inflation scenario. Sixth, leaving the network topologies aside, we also find that the parameter (λ), the intensity of choice, plays a role here; however, its effect is rather uncertain, and differs from one volatility to the other. For example, in the case of the GDP volatility, the idiosyncratic effect of each network becomes quite prevalent when λ is small, while it goes the other way round in the case of inflation volatility.

Table 4 The Network Effect on the Volatility of Inflation

Network	$\lambda = 0.1$	$\lambda = 0.3$	$\lambda = 0.5$	$\lambda = 0.7$	$\lambda = 0.9$
Fully	0.56061	0.51181	0.46553	0.42581	0.39581
	(1.04)	(2.19)	(4.49)*	(5.88)*	(5.83)*
Regular	0.56063	0.51207	0.46685	0.42859	0.39881
	(0.99)	(1.52)	(1.55)	(1.42)	(1.63)
Circle	0.56049	0.51257	0.46834	0.43122	0.40245
	(1.30)	(0.29)	(-1.28)	(-1.97)	(-2.47)*
Random	0.56080	0.51222	0.46698	0.42885	0.39934
	(0.63)	(1.15)	(1.30)	(1.08)	(1.03)
SW01	0.56063	0.51213	0.46664	0.42850	0.39923
	(0.99)	(1.10)	(1.97)	(1.54)	(1.15)
SW03	0.56063	0.51216	0.46713	0.42895	0.39926
	(0.99)	(1.30)	(1.01)	(0.95)	(1.12)
SW05	0.56534	0.51622	0.47069	0.43238	0.40239
	(-174.75)*	(-28.21)*	(-7.38)*	(-3.66)*	(-2.39)*
SW07	0.56062	0.51201	0.46692	0.42901	0.39946
	(1.02)	(1.37)	(1.42)	(0.88)	(0.90)
SW09	0.56058	0.51250	0.46713	0.42889	0.39950
	(1.10)	(0.46)	(1.01)	(1.03)	(0.41)
Scale-free	0.56066	0.51322	0.47043	0.43480	0.40650
	(0.94)	(-1.29)	(-6.4)*	(-9.28)*	(-10.50)*

The numbers shown above are the mean variances of 100 time series, each having 300 observations obtained from the DSGE simulation using the respective network shown in the first column and intensity of choice shown in the first row. The numbers shown inside the parentheses are the *t*-values of the null that the mean variance in question is sampled from the same distribution that generates the other nine. We follow the statisticians' convention to use * if the *p*-value of the test is less than 0.05.

In sum, Tables 3 and 4 do indicate the existence of the network effect on economic stability, but the perplexing nature of the initial exploration does make it hard to attribute the effect *directly* to the network generation mechanisms and hence the family of networks. This is so because even under the same generation mechanism (same family) the networks can still have very different characteristics. For example, Table 2 clearly shows that SW05 can have an unusually longer average path length, longer even than that of the regular network of the same k.[14] In additinion, if one is pondering why the scale-free network is so much different from others, Table 2 may immediately suggest that the betweenness centrality and the closeness centrality are things that draw attention.

Hence, a better way to form the question is *not* to ask what network generation mechanism may contribute to economic stability or instability, but more fundamentally, to ask what network characteristics may do. Once the essential characteristics are identified, one can then check what characteristics a specific network generation mechanism can feature and gauge its possible network effects. Therefore, in the rest of this section, we shall start by generating a large sample of networks with

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[14] See footnote 13 for the appearance of this discrepancy.

varying characteristics (Section 4.3.1). We will then run the DSGE model embedded with these networks, and derive the volatility statistics as we did in Section 4.1. A multivariate regression model is then applied to examine the possible contribution of each characteristic to the observed volatilities (Section 4.3.2).

4.3   Significance of Network Characteristics

Coming to this stage, we have formally formulated our research question as to the contribution of network topology to economic stability in terms of the five major characteristics. In other words, we ask what the relationship is between the economic stability and degree, clustering coefficient, average path length, betweenness centrality and closeness centrality. It is this question which we believe no one, at least, known to us, has asked before, and which makes this work a pioneering one in the literature.

A formal econometric examination of the effect of network characteristics on economic stability will involve a review of the possible functional form between the stability variables and the characteristics included. One, therefore, has to address what would be the appropriate functional form to do this, and what are those characteristics to be included in the function. A rigorous treatment demands a rather exhaustive work which cannot be completed in a single paper. The strategy which we shall be trying here is to begin with a *benchmark*, which may not be sufficient but could be minimal (necessary). We will then see what the fundamental results which we can have from this minimal setup, and then go further to examine whether these fundamental results are sensitive to some possible augmentations.

The two augmentations which we have in mind are the possible influence of the more complex function (*non-linearity*) and the inclusion of other important characteristics (omitted variables). However, even the exploration of the two augmentations of the baseline model should be very limited; as we already notice, a thorough exploration really requires exhaustive research, and there is obviously more that is needed to be done in the follow-up studies.

With this blueprint in mind, our baseline model should be a linear function of the five characteristics as reviewed in Section 3.2. This baseline model and the related estimation will be detailed in Section 4.3.2 with a discussion of the fundamental findings. We will then move to a specific variation of the linear form in a direction toward non-linearity, namely, a polynomial Taylor-expansion form (Section 4.3.3). Finally, we will attempt to add additional characteristics related to the degree distribution to our baseline model (Section 4.3.4).

4.3.1   Network Generation

The idea of the second-stage simulation is to have a more extensive sampling so that a thorough examination of the effect of various network characteristics is possible. To achieve this goal, we first have to decide an ideal size of network sample and the generation mechanism. Regarding the first point, given a degree of arbitrariness, we

Table 5 Parameter Setting for Network Random Generation

Parameter	Parameter Space	
General		
N	100	number of agents
λ	0.5	intensity of choice
T	300	number of simulation periods for each calibration experiment
Small-World Networks (437)		
p	[0,1]	rewiring rate
κ	[2,45]	number of neighbors on the left and on the right
Random Networks (36)		
$Prob(\{b_{i,j} = 1\})$	{ 0.5 }	probability of connecting any random pair
Scale-Free Networks (27)		
N_0	[5,90]	initial size (scale-free)
p_0	0.5	initial connecting probability
θ	[0.2, 100]	scaling factor

What are inside the parentheses are the numbers generated from the respective networks. There are 437 samples from the family of small-world networks, 36 from the family of random networks, and 27 from the family of scale-free networks.

decided to have a sample of 500 networks. We consider this size to be pragmatically large enough for rigorous statistical analysis. Second, to have a large diversity of network characteristics, of the five discussed in Section 3.1, we involve three network generating mechanisms, namely, small-world networks, scale-free networks, and random networks.[15] Since each network can be characterized by a few parameters, the idea of the random generating mechanism is simply to randomly select a set of parameter values from the parameter space and then generate the network based on the chosen parameter values. In Table 5, the parameter space for each type of network is specified. Among the three network families, 437 are sampled from the small-world networks, 36 from the random networks, and 27 from the scale-free networks.[16]

Through this network random generation mechanism, we are able to generate networks with an average degree from 2 to 80, an average cluster coefficient from 0 to 0.8240, an average path length from 1.1919 to 87.0463, a maximum betweenness centrality from 13 to 4681, and a maximum closeness centrality from 0.003 to 1.

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[15] This is because the regular and the fully connected networks are largely fixed, and have little room for generating varieties.

[16] We actually generated more than 500 samples. This was so because the average path length can be rather large when many components are disconnected. To try not to involve these "ill-behaved" networks in our samples, we excluded some networks with gigantic average path length. Ideally, we would hope to restrict the island type of samples since based on experience they are rarely seen in modern societies with their advanced communication technology.

Table 6 Characteristics of the Randomly Generated Networks: Basic Statistics

Network Characteristics	Min	Max	Mean	Variance
AD	2	80	39.6134	523.0591
ACC	0	0.8240	0.4288	0.0485
APL	1.1919	87.0463	3.4512	100.9276
MBC	13.0940	4681.677	277.9621	835680
MCC	0.0030	1	0.0090	0.0020

The above table shows the basic statistics of the five network characteristics over the 500 networks, which are randomly generated using Table 5. "AD", 'ACC", "APL", "MBC", and "MCC" are the abbreviations for the average degree (24), average clustering coefficient (27), average path length (28), maximum betweenness centrality (29), and maximum closeness centrality (30), respectively.

These ranges together with other statistics are shown in Table 6. This large range and variation will certainly facilitate our regression analysis that is to be discussed later (Section 4.3.2).

Notice that the large-scale simulation is all based on a single value of λ, i.e., $\lambda = 0.5$ (Table 5, the fourth row). As for this specific choice, some remarks are made here. First of all, in Section 4.2, we have already highlighted the uncertain effect of this parameter on volatilities. This may suggest that a fully fledged analysis should also take a large range of λs into account. However, if we do so, it will make the current paper oversized. Second, given the pioneering nature of the paper, the main goal is to establish a benchmark in the literature so that further visits and more comparison work can be provided a basis with which to start. Therefore, a choice of λ which is not large, and also not too small, serves this purpose well.

4.3.2 Regression Analysis

To examine the effect of network characteristics on economic stability, we may begin with Equations (31) and (32), and estimate the coefficients of the two equations *individually*, say, by ordinary least squares (OLS).

$$
\begin{aligned}
Var(\text{output gap}) = \beta_{y,0} + \beta_{y,1} \times AD + \beta_{y,2} \times ACC + \beta_{y,3} \times APL \\
+ \beta_{y,4} \times MBC + \beta_{y,5} \times MCC + \xi_y
\end{aligned}
\tag{31}
$$

$$
\begin{aligned}
Var(\text{inflation}) = \beta_{\pi,0} + \beta_{\pi,1} \times AD + \beta_{\pi,2} \times ACC + \beta_{\pi,3} \times APL \\
+ \beta_{\pi,4} \times MBC + \beta_{\pi,5} \times MCC + \xi_\pi
\end{aligned}
\tag{32}
$$

However, in our case, there is reason to believe that the shock affecting the output gap volatility may spill over and also affect the inflation volatility, and vice versa, since they are generated by the same DSGE model. Hence, estimating these equations as a set, using a single large equation, should improve efficiency. The

Table 7 Multivariate Regression Analysis: Explained and Explanatory Variables

Notation	Variables
Explained Variables	
V_y	Output Gap Volatility
V_π	Inflation Volatility
Explanatory Variables	
X_1	Average Degree (AD)
X_2	Average Cluster Coefficient (ACC)
X_3	Average Path Length (APL)
X_4	Maximum Betweenness Centrality (MBC)
X_5	Maximum Closeness Centrality (MCC)

latter approach is the familiar *seemingly unrelated regression estimation* (SURE). SURE can be useful when the error terms ξ_y and ξ_π are correlated. In this paper, we do find the error terms of different volatility equations to be correlated; therefore, SURE is applied. To do so, we rewrite the set of equations (31) and (32) into a single equation as in (33). Equation (33) is written in a compact form. For all notations used in this compact form, one can find their correspondence in Table 7.

$$\Gamma = \beta_0 + \beta\Psi + \Xi \tag{33}$$

where

$$\Gamma = \begin{pmatrix} V_y \\ V_\pi \end{pmatrix}, \beta_0 = \begin{pmatrix} \beta_{y,0} \\ \beta_{\pi,0} \end{pmatrix}, \beta = \begin{pmatrix} \beta_y & 0 \\ 0 & \beta_\pi \end{pmatrix}, \Psi = \begin{pmatrix} \mathbf{X} \\ \mathbf{X} \end{pmatrix}, \Xi = \begin{pmatrix} \xi_y \\ \xi_\pi \end{pmatrix}.$$

and

$$\mathbf{X}' = \begin{pmatrix} X_1 & X_2 & X_3 & X_4 & X_5 \end{pmatrix},$$
$$\beta_y = \begin{pmatrix} \beta_{y,1} & \beta_{y,2} & \beta_{y,3} & \beta_{y,4} & \beta_{y,5} \end{pmatrix},$$
$$\beta_\pi = \begin{pmatrix} \beta_{\pi,1} & \beta_{\pi,2} & \beta_{\pi,3} & \beta_{\pi,4} & \beta_{\pi,5} \end{pmatrix}.$$

Table 8 gives the SURE regression results. From this table, we can see that not all network characteristics can have an effect on economic stability. The only characteristic which has a consistent effect on both GDP fluctuations and inflation fluctuations is centrality. Interestingly enough, the two centrality measures have an opposite effect. The betweenness centrality plays a destabilizing role, whereas the closeness centrality plays a stabilizing role. On the other hand, all five characteristics can significantly contribute to the inflation stability or instability. The ones playing the stabilizing role are the cluster coefficient and the maximum closeness centrality, whereas the ones playing the destabilizing role are the average degree, average path length, and maximum betweenness centrality.

Table 8 The SURE Results

	Output gap($\times 10^{-6}$)			Inflation($\times 10^{-6}$)		
Intercept	420163	(2507.24)	*	468401	(15015.9)	*
AD	-6.7	(-0.5)		12	(4.75)	*
ACC	824	(0.5447)		-1370	(-5.40)	*
APL	9.713	(0.2297)		213	(141.43)	*
MBC	2.382	(27.59)	*	0.9817	(61.09)	*
MCC	-5160	(-3.05)	*	-9820	(-31.16)	*
R^2		0.67066			0.98559	
Adj R^2		0.66732			0.98544	

The table above shows the SURE regression results. The second and the fifth columns are the estimated coefficients in the output gap equation and the inflation equation. The third and the sixth columns are the *t* values of the respective coefficients. The fourth and the seventh columns denote the statistical significance at the 5% level with the symbol "*".

4.3.3 Non-Linearity

It is appropriate to say that Equation (33) serves only as a starting point. The effects of network characteristics on economic stability can be much more complex than what Equation (33) can represent. However, there are infinite numbers of ways to work with non-linear models. Our attempt here is, therefore, limited and is guided by two basic inquiries: first, the presence or the absence of the non-linear effects, and second, the robustness of the linear effects to the presence of the former. With these goals in mind, we consider a general representation form of the universe of non-linear models, namely, the *polynomial approximation* (the *Taylor approximation*). Specifically, our two inquiries can be effectively addressed by some linear models using Taylor expansion up to the second and the third order, as shown in Equations (34), (35), and (36).

$$\Gamma = \beta_0^2 + \beta^2 \Psi + \gamma^2 \Psi^2 + \Xi_2 \tag{34}$$

$$\Gamma = \beta_0^3 + \beta^3 \Psi + \gamma^3 \Psi^3 + \Xi_3 \tag{35}$$

$$\Gamma = \beta_0^{(q)} + \beta^{(q)} \Psi + \gamma^{(q)} \Psi^{(q)} + \Xi_{(q)}, \quad q = 1, 2, 3, 4, 5 \tag{36}$$

where

$$\Psi^2 = \begin{pmatrix} \mathbf{X^2} \\ \mathbf{X^2} \end{pmatrix}, \Psi^3 = \begin{pmatrix} \mathbf{X^3} \\ \mathbf{X^3} \end{pmatrix}, \Psi^{(q)} = \begin{pmatrix} \mathbf{X^{(q)}} \\ \mathbf{X^{(q)}} \end{pmatrix} \quad (q = 1, 2, 3, 4, 5),$$

and

$$\mathbf{X^{2}}' = \begin{pmatrix} X_1^2 & X_2^2 & X_3^2 & X_4^2 & X_5^2 \end{pmatrix},$$

$$\mathbf{X^{3}}' = \begin{pmatrix} X_1^3 & X_2^3 & X_3^3 & X_4^3 & X_5^3 \end{pmatrix},$$

$$\mathbf{X^{(1)}}' = \begin{pmatrix} X_1 X_2 & X_1 X_3 & X_1 X_4 & X_1 X_5 \end{pmatrix},$$

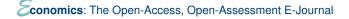$$\mathbf{X^{(2)}}' = \begin{pmatrix} X_2 X_1 & X_2 X_3 & X_2 X_4 & X_2 X_5 \end{pmatrix},$$

$$\mathbf{X^{(3)}}' = \begin{pmatrix} X_3 X_1 & X_3 X_2 & X_3 X_4 & X_3 X_5 \end{pmatrix},$$

$$\mathbf{X^{(4)}}' = \begin{pmatrix} X_4 X_1 & X_4 X_2 & X_4 X_3 & X_4 X_5 \end{pmatrix},$$

$$\mathbf{X^{(5)}}' = \begin{pmatrix} X_5 X_1 & X_5 X_2 & X_5 X_3 & X_5 X_4 \end{pmatrix}.$$

These equations are the augmentations of the original linear model (33) with the quadratic form (34), the cubic form (35), or the cross-product forms (36). Our SURE of these seven different polynomial models suggest that non-linear effects do in fact exist. These results are very voluminous; to keep the presentation smooth, we, therefore, have decided to leave the details in the appendix (Tables 11 and 12), and only highlight a few observations here.

From Table 11, we can see that the non-linear effects of the network characteristics on the GDP stability are mainly manifested through the two centrality measures, a result which is very similar to what we have in the baseline model. The two centrality measures are not only significant in the quadratic form ($\beta_{y,4}^2$, $\beta_{y,5}^2$) and the cubic form ($\beta_{y,4}^3$, $\beta_{y,5}^3$), but are also significant in many combined terms. In fact, the combined terms which are significant all have centrality as a part of them (such as $\beta_{y,14}^{(1)}$, $\beta_{y,24}^{(2)}$, $\beta_{y,25}^{(2)}$, $\beta_{y,41}^{(4)}$, $\beta_{y,42}^{(4)}$, $\beta_{y,45}^{(4)}$, $\beta_{y,52}^{(5)}$, $\beta_{y,53}^{(5)}$, and $\beta_{y,54}^{(5)}$). Therefore, for the GDP stability, centrality seems to be the most important characteristic; it impacts the GDP stability not only linearly, but also non-linearly.[17] The prominent role of centrality in economic stability can also be found in the inflation equation. The two centrality measures are again significant in either the quadratic or cubic forms, and most combined terms having centrality as a part are found to be significant. Nonetheless, the effect of centrality on inflation stability is less certain since the sign of its linear term flips from one equation to the other.

With the presence of these nonlinear effects, we then further examine the robustness of the results obtained from Equation (33) (Table 8). The SURE augmented with the quadratic, cubic and the cross-product terms are shown in Table 11 and Table 12. By comparing these tables with our baseline results (Table 8), we can see that the signs of some coefficients flip, from either positive to negative or negative to positive. To have a better picture, a summary of these flips is given in Table 9. There we denote the term by "0" if the sign of the respective coefficient changes from the baseline model to the augmented model; otherwise, we denote it by "1" if there is no such flip.

---

[17] The non-linear effect of network characteristics is also found in other studies of economic networks; for example, in a different setting, Gai and Kapadia (2010) found that the network connectivity (degree) has a non-linear effect on the probability of contagion in the interbank network.

Table 9 The SURE Augmented with Higher Order Terms

Network Characteristics	Ψ	Ψ^2	Ψ^3	$\Psi^{(1)}$	$\Psi^{(2)}$	$\Psi^{(3)}$	$\Psi^{(4}$	$\Psi^{(5)}$
output gap								
AD	-	0	0	1	0	1	1	0
ACC	-	1	1	1	1	0	1	1
APL	+	0	1	1	1	1	1	0
MBC	+	1	1	1	1	1	1	1
MCC	-	0	0	1	1	0	0	0
inflation								
AD	-	0	0	0	0	1	0	0
ACC	-	1	1	0	1	1	0	0
APL	+	1	1	1	1	1	1	1
MBC	+	0	0	1	1	1	1	0
MCC	-	1	1	0	1	0	1	1

The second column shows the sign of the coefficient of each network characteristic under the baseline model (33). The following columns show the robustness of these signs when the liner model is augmented with the quadratic form (34), the cubic form (35), and the five different cross-product forms (36). The "zero" cell indicates that the sign has flipped, whereas the "one" cell indicate that the sign remains unchanged. Details of the SURE results of the non-linear augmentations can be found in Tables 11 and 12.

For the GDP stability, since only the two centrality measures are significant in the linear model (Table 8), our robustness check is, therefore, limited to these two measures. Of the two centrality measures, it is interesting to notice that, even with the augmentation in seven different directions, the effect of the betweenness centrality remains statistically positive, whereas the closeness centrality seems rather sensitive to the augmentations and it flips five times in the seven augmented models. In addition, for the inflation stability, originally in Equation (33), all five characteristics are significant; hence we run through all of these five to see their robustness. Unlike the GDP equation, both centrality measures are somewhat sensitive to the augmentations and flip between positive and negative. The only characteristic that shows the robustness is the average path length. It consistently demonstrates the adverse effect of the average path length on the inflation stability.

4.3.4 Other Characteristics

While the five characteristics used in this study very often appear in the network literature, there is little doubt that they are not exhaustive. Some other characteristics may exist and even may even play a role. We keep this possibility open, but, as before (Section 4.3.3), we are interested in knowing whether the addition of the other characteristics will affect our fundamental findings established in Section 4.3.2. Therefore, in this section, we try to include one more characteristic, i.e., the

shape of the degree distribution, which may provide us with additional information that is not revealed via the average degree and the other four characteristics.

However, the immediate problem which we encounter is that there is no well-known characteristic in the network literature to capture the general information of the degree distribution. Therefore, depending on what we are searching for, different measures can be developed. In this article, we propose a measure which has economic meaning, i.e., a measure in line with income distribution or wealth distribution. We believe that the degree distribution, to some extent, can represent income distribution through the social capital connection. Hence, a measure developed in this way may indirectly enable us to inquire into the relationship between income distribution and economic stability.

If so, then a measure which is frequently used and can be easily calculated is the ratio of the wealthy people's income to the poor people's income, as shown in Equation (37).

$$DIP = \frac{k_{75}}{k_{25}}, \tag{37}$$

where *DIP* stands for the degree distribution in terms of percentiles and k_{75} and k_{25} refer to the 75th and the 25th percentiles of the distribution in question. One can also go further to have the measure of the inequality in a more extreme position as in Equation (38).

$$DIE = \frac{k_{max}}{k_{min}}, \tag{38}$$

where *DIE* stands for the degree distribution in terms of the extremes and k_{max} and k_{min} refer to the maximum and minimum values of the degree distribution, respectively.

With these two additional characteristics, we rerun SURE (33) and the results are shown in Table 10. By comparing Table 10 with Table 8, we can find that the results originally found in Table 8 remain unchanged. Those significant variables remain significant with the signs unchanged. This shows that our earlier results are very robust. It seems that the degree of inequality does in fact enhance the instability of the economy, as the coefficients of *DIP* and *DIE* are all positive; however, they are significant only in the GDP equation, and not the inflation equation.

Table 10 The SURE Augmented with the Shape of the Distribution

	Output Gap($\times 10^{-6}$)			Inflation($\times 10^{-6}$)		
Intercept	417525	(435.19)	∗	46267	(2606.96)	∗
AD	-8.53	(-0.64)		12	(4.72)	∗
ACC	9650	(0.71)		-1360	(-5.38)	∗
APL	9.748	(1.21)		213	(141.30)	∗
MBC	2.384	(27.46)	∗	0.9741	(60.24)	∗
MCC	-5180	(-3.07)	∗	-9820	(-31.11)	∗
DIP	2707	(2.73)	∗	117	(0.63)	
DIE	516	(2.25)	∗	17	(1.29)	
R^2		0.67588			0.98565	
Adj R^2		0.67126			0.98545	

The above SURE is the SURE (33) augmented with two additional explanatory variables related to the shape of the distribution, *DIP* and *DIE*. Other variables are defined in Table 7. Columns 2 and 5 are the estimated values, and Columns 3 and 6 are the associated *t* values. The coefficients which are significant at the 5% level are marked by ∗ in Columns 4 and 7, respectively.

5   Concluding Remarks

While the rapid growth in the literature on social networks indicates the relevance of the network topologies to economic performance, there is no formal thorough examination of the effect of these network topologies on macroeconomic stability. To the best of our knowledge, this is the first work in this direction. Given the daunting nature of this research, we have adopted a strategy which can allow us to at least have a foot in the door before we can move into the hall.

The strategy is to choose the macroeconomic model which is most accessible to the inclusion of different network topologies of economic units. Having said that, we are aware that most agent-based macroeconomic models would have such network topologies, explicitly or implicitly, as part of their models, but not all of them make it easier for the expansions to facilitate a large-scale simulation with a large variety of network topologies as in the case in this paper. It turns out that the agent-based DSGE model as initiated by De Grauwe (De Grauwe, 2010, 2011) becomes a straightforward choice at this initial stage.

In this paper, we construct an agent-based New Keynesian DSGE model with different social network structures to investigate the effects of the networks on macroeconomic fluctuations. The network topologies used in this article are mainly introduced for us to conduct thought experiments. While these networks may potentially correspond to some real economic or social networks, there is no attempt to provide them with any empirical ground or calibration, which requires a framework very much different from the current setting. Hence, serious treatments of these networks in the parlance of economics or endowing the associated parameters with economic meaning can be superficial. Under this situation, to make the model not unnecessarily complex, the network topologies employed here are *undirected*
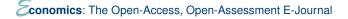
and *discrete* (*equal-weighted*), serving as a starting point for this line of research. For pure thought experiments, it is certainly interesting to explore the directed and weighted network topologies. This is a subject for further studies.

This simple but fundamental setting allows us to have several findings which are worth summarizing. First, we find that the network characteristics can have some effects on the economic stability, and different economic variables may be sensitive to different characteristics. Second, we also find, however, that few characteristics are robust to different settings, in particular, with the non-linear augmentations. Third, putting the two together, we do not find any single characteristic which is universally important to both GDP and inflation. While the two centrality measures consistently show their prominence in both the GDP and inflation equations, but the signs are not robust across different equations. Fourth, the effect of the network topology on economic stability is not limited to the five basic characteristics. In addition to them, the shape of the degree distribution is also found to be important. Fifth, more subtly, the effects of the network characteristics can exist in a nonlinear fashion, with quadratic, cubic or combined effects. Without monotonicity, our understanding and forecasting of the network effects certainly becomes more challenging. Sixth, despite these perplexities, two characteristics quite clearly stand out throughout the analysis, i.e., the (maximum) between centrality on the stability of GDP and the average path length on the stability of inflation. It remains to be answered what underlies these causal mechanisms. This actually calls for a theory of economic stability in terms of network topologies, which deserves an independent study.

As we have said at the very beginning of the paper, there are many different perspectives from which to look at the relationship between social networks and the macroeconomy. The path which we have taken here is very much in the spirit of sociologists, particularly Mark Granovetter, who are more interested in the information functionality of social networks. This information perspective of social networks has become the essence of a large class of agent-based models, namely, network-based (neighbor-based) discrete choice models. Within this framework, there have been various explorations into the effects of social networks, such as the consumer's choices of products, the producer's choices of technology, and the investor's choice of stocks and investment strategies. In this vein, this paper is simply an extension of these studies to agent-based macroeconomic models, specifically, the agent-based DSGE model.

However, the network effect should not be limited to the information flow, and hence we would like to add two remarks at the end of this paper. First of all, in this paper, we do not consider the *production perspective* of social networks, which economists and game theorists are most interested in. Many social networks, broadly defined, such as interbank networks, supply chains, and company networks, have a real production functionality. The vulnerability of an economy is often investigated from this perspective. However, the current agent-based version of the DSGE models, or, probably, the entire set of DSGE models, is not suitable for exploration in this direction. Eurace (Cincotti et al. , 2012) or other agent-based macroeconomic models may serve the purpose even better.

This, then, brings us to our final remark. While in this paper we are able to identify the economic significance of some essential characterizations of network topologies, such as betweenness centrality and average path length, we, however, have to express reservations on these findings in the sense that they are all from a highly stylized economic model. As to whether these characterizations can be neutral in other settings, in particular, those with specific institutional arrangements, has yet to be addressed. When mathematicians, sociologists and physicists began to characterize the network structures in their hands, they may or may not have understood their full significance. It is then left for us to constantly search for the unexplored deeper meanings with the possible serendipities of finding out other missing characterizations.

Appendix

In this appendix, we present the qualitative results of our non-linear augmentations of the baseline model (33), as specified in Equations (34), (35), and (36). Since there are a total of seven equations to run and each has 6 to 11 coefficients to estimate, the presentation of all the estimates would be overwhelming. We have, therefore, decided to skip the numerical details and only give the sign of the coefficient with its significance. While the SURE estimates the GDP and the inflation equations together; for convenience, the results of the seven GDP regressions are grouped together and are given in Table 11, and the inflation regression results are also grouped together and are given in Table 12 in the counterpart position.

There are seven SURE equations. All seven equations have the baseline model as part of it and are then augmented with different non-linear components. Tables 11 and 12 can be divided into eight panels. The first panel consists of the estimation results of all the coefficients of the baseline part, including the baseline model itself. $\beta_{y,i}$ ($i = 1, ..., 5$) and $\beta_{\pi,i}$ ($i = 1, ..., 5$) are the coefficients corresponding to the characteristic X_i in the GDP equation (denoted by y) and the inflation equation (denoted by π), respectively. The characteristic X_i is defined in Table 7. Panels 2 to 8 then show the regression results of the additional coefficients coming from the specific non-linear augmentations, denoted by Ψ^2, Ψ^3, and $\Psi^{(q)}$ ($q = 1, ..., 5$), notations which are consistent with those in Equations (34) to (36).

These augmentation specifications are indicated in the first row of both tables. The columns led by these symbols, Ψ^2, Ψ^3, and $\Psi^{(q)}$, then give the regression results of the specific non-linear augmentation. In addition to the baseline part which is already shown in the first panel, the results of other coefficients are shown in the respective panels, from Panels 2 to 8 corresponding to the augmentation Ψ^2, Ψ^3, and $\Psi^{(q)}(q = 1, ..., 5)$. The additional coefficients are coded in a very intuitive way. We use $\beta_{y,i}^2$ and $\beta_{y,i}^3$ $(i = 1, ..., 5)$ to denote the coefficient corresponding to the square of X_i (X_i^2) or the cube of X_i (X_i^3) in the GDP equation. We then use $\beta_{y,qi}^{(q)}$ $(i = 1, ..., 5; i \neq q)$ to denote the coefficient corresponding to the cross term $X_q X_i$ appearing in the GDP equation. The same coding scheme applies to Table 12, except that y is replaced by π.

The two tables do not show the numerical values, only the sign of the coefficient and its significance. The latter is denoted by $*$ if it is significant at the 5% level. Notice that the second column led by Ψ is simply the baseline model, which is already shown in Table 8; we simply replicate the sign and the significance level here in order to facilitate the robustness check.

Table 11 SURE Results of the Nonlinear Augmentations: GDP

Coefficients	Ψ	Ψ^2	Ψ^3	$\Psi^{(1)}$	$\Psi^{(2)}$	$\Psi^{(3)}$	$\Psi^{(4)}$	$\Psi^{(5)}$
$\beta_{y,1}$	-	+	+	-	+	-	-	+(*)
$\beta_{y,2}$	-	-	-	-	-(*)	+	-	-(*)
$\beta_{y,3}$	+	-	-	+	+	+	+	-(*)
$\beta_{y,4}$	+(*)	+(*)	+(*)	+(*)	+(*)	+(*)	+(*)	+(*)
$\beta_{y,5}$	-(*)	+(*)	+	-	-(*)	+	+(*)	+(*)
$\beta^2_{y,1}$		-						
$\beta^2_{y,2}$		+						
$\beta^2_{y,3}$		+						
$\beta^2_{y,4}$		-(*)						
$\beta^2_{y,5}$		-(*)						
$\beta^3_{y,1}$			-					
$\beta^3_{y,2}$			+					
$\beta^3_{y,3}$			+					
$\beta^3_{y,4}$			-(*)					
$\beta^3_{y,5}$			-(*)					
$\beta^{(1)}_{y,12}$				-				
$\beta^{(1)}_{y,13}$				+				
$\beta^{(1)}_{y,14}$				+(*)				
$\beta^{(1)}_{y,15}$				+				
$\beta^{(2)}_{y,21}$					-			
$\beta^{(2)}_{y,23}$					+			
$\beta^{(2)}_{y,24}$					+(*)			
$\beta^{(2)}_{y,25}$					+(*)			
$\beta^{(3)}_{y,31}$						+		
$\beta^{(3)}_{y,32}$						-		
$\beta^{(3)}_{y,34}$						-		
$\beta^{(3)}_{y,35}$						-		
$\beta^{(4)}_{y,41}$							-(*)	
$\beta^{(4)}_{y,42}$							+(*)	
$\beta^{(4)}_{y,43}$							-	
$\beta^{(4)}_{y,45}$							-(*)	
$\beta^{(5)}_{y,51}$								-(*)
$\beta^{(5)}_{y,52}$								+(*)
$\beta^{(5)}_{y,53}$								+(*)
$\beta^{(5)}_{y,54}$								-(*)

Table 12 SURE Results of the Nonlinear Augmentations: Inflation

Coefficients	Ψ	Ψ^2	Ψ^3	$\Psi^{(1)}$	$\Psi^{(2)}$	$\Psi^{(3)}$	$\Psi^{(4)}$	$\Psi^{(5)}$
$\beta_{\pi,1}$	+(*)	-(*)	-	-(*)	-(*)	+(*)	-(*)	-(*)
$\beta_{\pi,2}$	-(*)	-	-	+	-	-(*)	+(*)	+
$\beta_{\pi,3}$	+(*)	+(*)	+(*)	+(*)	+(*)	+(*)	+(*)	+(*)
$\beta_{\pi,4}$	+(*)	-(*)	-(*)	+(*)	+(*)	+(*)	+(*)	-(*)
$\beta_{\pi,5}$	-(*)	-(*)	-(*)	+(*)	-(*)	+(*)	-	-(*)
$\beta_{\pi,1}^2$		+(*)						
$\beta_{\pi,2}^2$		+						
$\beta_{\pi,3}^2$		+						
$\beta_{\pi,4}^2$		+						
$\beta_{\pi,5}^2$		+(*)						
$\beta_{\pi,1}^3$			+					
$\beta_{\pi,2}^3$			+					
$\beta_{\pi,3}^3$			+					
$\beta_{\pi,4}^3$			+(*)					
$\beta_{\pi,5}^3$			+(*)					
$\beta_{\pi,12}^{(1)}$				-				
$\beta_{\pi,13}^{(1)}$				-				
$\beta_{\pi,14}^{(1)}$				-(*)				
$\beta_{\pi,15}^{(1)}$				+(*)				
$\beta_{\pi,21}^{(2)}$					+			
$\beta_{\pi,23}^{(2)}$					+			
$\beta_{\pi,24}^{(2)}$					-(*)			
$\beta_{\pi,25}^{(2)}$					+(*)			
$\beta_{\pi,31}^{(3)}$						-(*)		
$\beta_{\pi,32}^{(3)}$						-		
$\beta_{\pi,34}^{(3)}$						-(*)		
$\beta_{\pi,35}^{(3)}$						-		
$\beta_{\pi,41}^{(4)}$							-(*)	
$\beta_{\pi,42}^{(4)}$							-(*)	
$\beta_{\pi,43}^{(4)}$							-(*)	
$\beta_{\pi,45}^{(4)}$							+	
$\beta_{\pi,51}^{(5)}$								+(*)
$\beta_{\pi,52}^{(5)}$								-(*)
$\beta_{\pi,53}^{(5)}$								-(*)
$\beta_{\pi,54}^{(5)}$								+(*)

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