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Social Networks and Macroeconomic Stability

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

Abstract

We construct an agent-based New Keynesian DSGE model with different social network structures to investigate the significance of network topologies to macroeconomic stability. According to our simulation results, we find that the more liquid the information flow, the higher the stability of the economy. Furthermore, the speed of information dissemination and the degree of clustering among agents may give rise to an adverse effect on economic stability. Finally, we find that the scale-free network will lead to the most dramatic economic fluctuations. The result is ascribed to the scale-free network's high centrality. It indicates that the opinion leaders may bring about a conglomerate effect that will cause fluctuations in the economy.

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1 Motivation

1.1 The Two Lines of Research

A research subject on the relation between social networks and macroeconomics can be studied 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, 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 is the network-based agent-based models, and the other is the agent-based modeling of networks.

The pioneering study by Mark Granovetter in 1973 (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, and the Ising model, the percolation model, and the kinetic model that all developed later 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.

In this line of research, network topologies are exogenously fixed or, in other words, they 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 is 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. An example directly related to our subject is Delli Gatti et al. (2010), in which the networks of firms and banks are endogenously determined and evolving. This line of research may not only be further connected to the empirical studies of networks piling up, 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

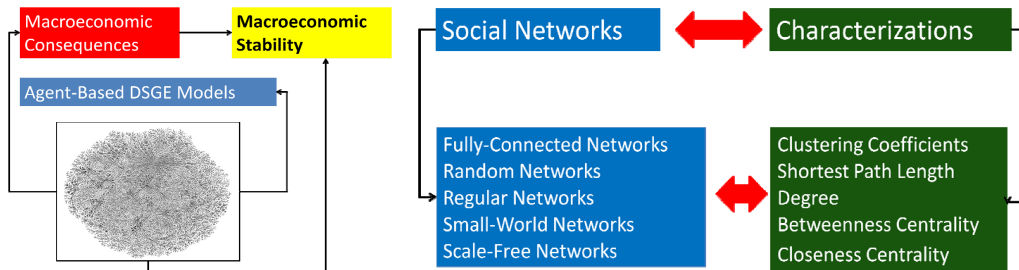


Figure 1 Research Skeleton

point is either a study focusing on the evolution of one kind of network, e.g., the interbank network, the firm network, or 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 (Dynamic Stochastic and General Equilibrium) model. 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 'agen-tization' of the DSGE models, known as the agent-based DSGE models. These models are first initiated by De Grauwe (2010a, 2010b) and are further developed by Chang and Chen (2012) and Chen, Chang and Tseng (2012).

The latter differs from the former according to the level of analysis. The former 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 networks in this model are obviously indispensable, since they are the key to drive the subsequent interactions of agents.

Chen, Chang and Tseng (2012) used the famous 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 (see also Figure 1, left panel). We shall simulate the macroeconomy using the agent-based DSGE model augmented with the Ising 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 output and inflation dynamics.

As for the chosen network topologies, we consider two stages with different pursuits. In the first stage, we choose some familiar classes of networks, which include fully-connected networks, random networks, regular networks, small-world networks and scale-free networks. We then want to see whether there is any correspondence to macroeconomic stability under these "big names". The question coming with this stage concerns why some network topologies are more stabilizing or destabilizing. To answer this question, we have to go beyond those big names to identify the key contributing factors in terms of various characterizations of social networks. There are many characterizations, and correlations up to different degrees may exist between them. In this study, we restrict ourselves to four frequently used characterizations, namely, degree, path length, cluster coefficient, closeness centrality and betweenness centrality. It is possible to include others, but we believe that this set of five serves as a good starting for the key inquiry of the paper.

Therefore, in the second stage (see Figure 1, the right panel), our purpose is to understand the possible correspondence between each of these characterizations and macroeconomic stability. This correspondence is established through statistical analysis in the form of a simple linear regression. To do this, we need samples that are sufficiently diversified to cover a reasonable range of the five characterizations.

A highlight of our results is briefly given here. We first find that network topologies matter as far as macroeconomic stability is concerned. When the social interaction is governed by the Ising model, the fully-connected network is most favorable to macroeconomic stability, whereas the scale-free network does the exact opposite. A further analysis shows that, among the key characterizations of network topologies, high (maximum) centrality indicators are a destabilizing

factor. In addition, the effects of cluster coefficients and average path length on macroeconomic stability may give rise to an adverse effect on economic stability.

The remainder of this paper is organized as follows. In Section 2, we present the agent-based DSGE model. Next, we describe the Ising modeling of learning and expectations formation with social networks. In Section 4, we simulate different network structures and present the results. Finally, in Section 5 we conclude.

2 The Agent-Based DSGE Model

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

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

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

$$r_t = c_1 (\pi_t - \pi_t^*) + c_2 y_t + c_3 r_{t-1} + u_t \quad (3)$$

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 for aggregate demand is as follows: 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 logged output gap in the aggregate demand equation to describe habit formation (Fuhrer, 2000). E_t is the expectations operator, which we use to describe how people form their expectations. In the standard New Keynesian DSGE model, the representative agent always has rational expectations.

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).

Next, we follow the setting of Kazanas et al. (2011) to establish the Taylor rule to describe the behavior of the central bank in the standard New Keynesian DSGE model and it can be found in Equation (3). Based on Taylor's rule, the central bank reacts to deviations in inflation and output from targets. π^* refers to the inflation

target of the central bank. In order to get closer to the real world, π^* is set to be equal to 2. In addition, the one-period lagged interest rate in Equation (3) represents the smoothing behavior and we set $c_1 = 0.8$. Furthermore, we assume that the inflation target is as important as the output gap. Therefore, we set $c_3 = c_4 = 0.5$. Finally, as the DSGE model is the DGE (Dynamic General Equilibrium) model with stochastic terms, ε_t , η_t and u_t are all white noise disturbance terms.

According to the aforementioned equations, we can substitute Equation (3) into Equation (1) and rewrite the matrix notation. Thus, the reduced form can be written as:

$$\begin{aligned} \begin{bmatrix} 1 & -b_2 \\ 0 & 1 \end{bmatrix} \times \begin{bmatrix} \pi_t \\ y_t \end{bmatrix} &= \begin{bmatrix} 0 \\ a_2(1-c_1)c_2 \end{bmatrix} + \begin{bmatrix} b_1 & 0 \\ -a_2 & a_1 \end{bmatrix} \times \begin{bmatrix} E_t \pi_{t+1} \\ E_t y_{t+1} \end{bmatrix} \\ &+ \begin{bmatrix} 1-b_1 & 0 \\ a_2(1-c_1) & 1-a_1+a_2(1-c_1c_4) \end{bmatrix} \times \begin{bmatrix} \pi_{t-1} \\ y_{t-1} \end{bmatrix} \\ &+ \begin{bmatrix} 0 \\ a_2c_1 \end{bmatrix} \times r_{t-1} + \begin{bmatrix} \eta_t \\ a_2u_t + \varepsilon_t \end{bmatrix} \end{aligned} \quad (4)$$

or

$$\mathbf{AZ}_t = \mathbf{CON} + \mathbf{BE}_t\mathbf{Z}_{t+1} + \mathbf{CZ}_{t-1} + \mathbf{br}_{t-1} + \mathbf{V}_t \quad (5)$$

According to the above, we can have the solution Z_t for the system.

$$\mathbf{Z}_t = \mathbf{A}^{-1}[\mathbf{CON} + \mathbf{BE}_t\mathbf{Z}_{t+1} + \mathbf{CZ}_{t-1} + \mathbf{br}_{t-1} + \mathbf{V}_t] \quad (6)$$

After obtaining the inflation rate (π_t) and output gap (y_t) through Equation (6), we have to substitute the solution for Equation (3) and to arrive at the interest rate (r_t).

Finally, we must emphasize that the difference between the stylized New Keynesian DSGE model and the agent-based DSGE models is the difference between the expectations of the output gap and inflation. In this paper, agents have different expectations. The individual expectations are based on the social network structure. Both the social network structures and the heterogeneous expectations in the agent-based DSGE model are introduced in Section 3.

3 Ising Modeling of Learning and Expectations Formation with Social Networks

3.1 Social Networks

The purpose of this paper is to discuss the economic effects of different social networks. Therefore, in Section 3.1.1, the network topology is first briefly introduced. Then, the statistical properties of the social network structure are presented in Section 3.1.2.

3.1.1 Network Topology

In order to depict the social network's formation and its structure, we apply the concept of graph theory. Thus, a network $G(V, E)$ is defined by a set of agents N and a set of links E . More specifically, $V = \{1, \dots, n\}$ denotes all agents connected in some network relationship, and the number n refers to the size of the network. E denotes which pairs of agents are linked to each other so that $E = \{b_{ij} : i, j \in V\}$ encodes the relationship between any two agents in the network. Customarily, we use $b_{ij} = 1$ to indicate that there exists an edge (connection, relation) between i and j ; otherwise it is zero. For this reason, we can use an $N \times N$ matrix to describe the network structure. However, we set $b_{ij} = b_{ji}$, which is known as a non-directed network in our model. Therefore, we can have a symmetric network matrix and the network formation algorithm for each specific social network structure as follows. In addition, the graph of these different network structures can be found in Figure 2.

(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 2 (First row, left).

(2) Circle and regular network

In the fully-connected network, all interactions are global; however, in many realistic settings, interactions are rather local and are connected 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

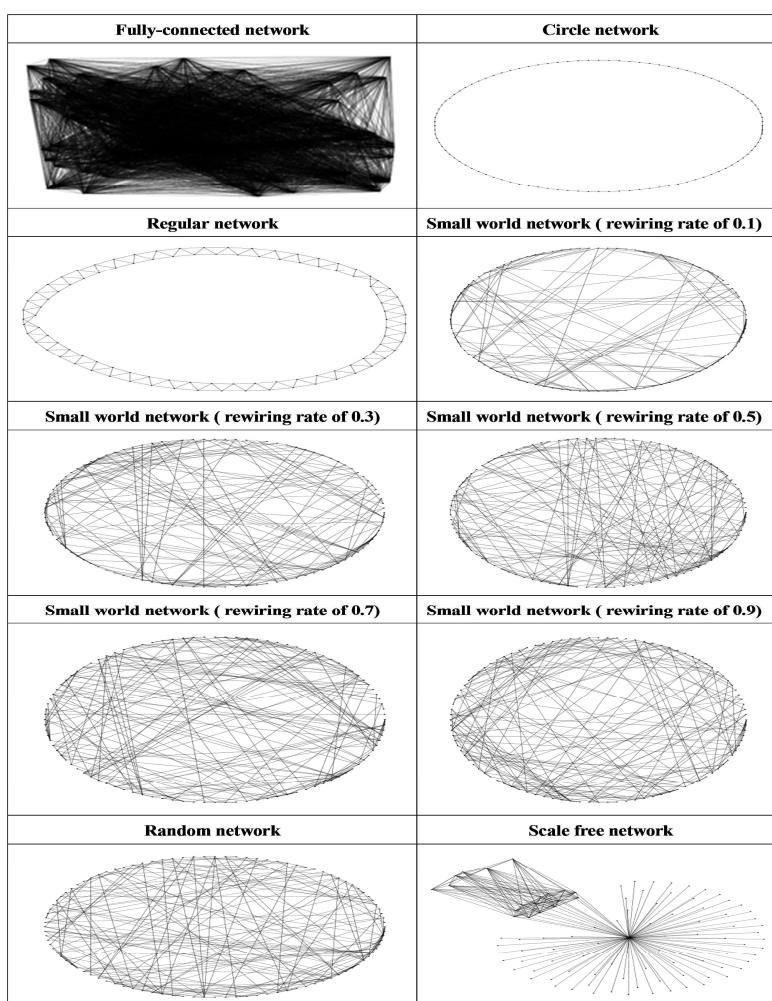


Figure 2 Social network structures

$k = 1$ (Figure 2, first right). In addition to this extreme case, a regular network with $k = 2$ is also considered (Figure 2, second left).

(3) 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 those 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 smaller clustering coefficient.

(4) Scale-free network

A scale-free network is a network with the power law property. Thus, the number of links originating from a given node denotes a power law distribution represented by $p(k) = k^{-\gamma}$ where k denotes the number of links. The idea of a scale-free network comes from observations of many social contexts, e.g., the citation network among scientific papers (Redner, 1998), the World Wide Web and the Internet (see, e.g., Albert et al., 1999; Faloutsos et al., 1999), telephone call and e-mail graphs (Aiello et al., 2002; Ebel et al., 2002), or the network of human sexual contacts (Liljeros et al., 2001). All of them show that only a few agents have many friends; most agents in the network have only a few friends. The most popular method to construct a scale-free network is the preferential attachment of Barabási and Albert (1999), which starts with m_0 agents and then progressively adds one new agent, i , to an existing network and builds links to existing agents with preferential attachment, according to Equation (7), that describes the rich as getting richer; the probability of linking to a given agent is proportional to the number of existing links that a node has.

$$prob(\text{linking to agent } i) = \frac{k_i}{\sum_j^{N-1} k_j} \quad (7)$$

3.1.2 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, basically, average degree, average clustering coefficient, average path length, betweenness centrality and closeness centrality. They shall be briefly described as follows. The basic statistics of simulated social networks are shown in Table 1.

Table 1 The network characteristics statistics

NAME	A.D.	A.C.C.	A.P.L.	M.B.C.	M.C.C.
Circle	2	0.000	25.2525	1200.5000	0.0004
SW05	4	0.003	23.3632	556.2843	0.0038
Random	4	0.036	3.4442	472.3707	0.0037
SW03	4	0.098	3.5271	496.9631	0.0036
Scale-free	4.52	0.147	2.0513	4681.2521	0.0095
SW01	4	0.254	4.1230	687.2087	0.0031
SW07	4	0.265	3.4489	611.5324	0.0038
SW09	4	0.270	3.4358	364.1322	0.0034
Regular	4	0.500	12.8789	588.0000	0.0008
Fully	99	1.000	1.0000	0.0000	0.0101

(1) Average degree

The average degree is based on the number of neighbors. It shows how many neighbors a node in the network has on average. It can be calculated by Equation (8) where N is the total number of nodes in the network and $d(V_i)$ denotes the number of neighbors of node i .

$$\bar{d} = \frac{\sum_{i=1}^N d(V_i)}{N} \quad (8)$$

(2) Average clustering coefficient

Roughly speaking, the clustering coefficient measures how well neighbors are connected to each other. Specifically, if agent j is connected to i , and k is also connected to i , is j also connected to k ? Formally, the set of neighbors of agent i is defined as Equation (9).

$$\vartheta_i = \{j : b_{ij} = 1, j \in G\} \quad (9)$$

Then the clustering coefficient of an agent can be defined as Equation (10)

$$C_i = \frac{\#\{(h, j) : b_{hj} = 1, h, j \in \vartheta_i, h < j\}}{\#\{j : j \in \vartheta_i\}} \quad (10)$$

Thus, the average cluster coefficient can be calculated by Equation (11)

$$\bar{C} = \frac{1}{n} \sum_{i=1}^n C_i \quad (11)$$

According to the mathematical formula of the average clustering coefficient, if the neighborhood is fully connected, then the clustering coefficient is 1. However, if

the average clustering coefficient is close to 0 that means that there are hardly any connections in the neighborhood.

(3) *Average path length*

Average path length is a concept in network topology that is defined as the average number of steps along the shortest paths for all possible pairs of network nodes. It can be computed by Equation (12) where $d(i, j)$ is the shortest distance between i and j .

$$APL = \frac{\sum_{i,j} d(i, j)}{n(n-1)} \quad (12)$$

(4) *Centrality indices*

If we want to consider the node's importance to the social network rather than just connectivity, the centrality indices can be good measures (Opsahl et al. (2010)). In this paper, we discuss the effects of betweenness centrality and closeness centrality. The betweenness centrality is generally attributed to sociologist Linton Freeman (1977) which is a measure of a node's centrality in a network equal to the number of shortest paths from all vertices to all others that pass through that node. According to the idea, betweenness centrality can be calculated by Equation (13) where σ_{st} is the total number of shortest paths from node s to node t and $\sum_{s \neq t \neq i} \sigma_{st}(i)$ denotes the number of those paths that pass through i .

$$C_B(i) = \sum_{s \neq t \neq i} \frac{\sigma_{st}(i)}{\sigma_{st}} \quad (13)$$

The other key node centrality measure in networks is closeness centrality (Freeman, 1978; Opsahl et al., 2010; Wasserman and Faust, 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 (14) 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.

$$C_c(i) = \sum_{i \neq j} \frac{1}{d(i, j)} \quad (14)$$

3.2 Ising Modeling of Learning and Expectations Formation

To make the macroeconomic models more realistic, economists have started to relax the standard New Keynesian DSGE model and have built the agent-based

version. In this paper, the heterogeneous expectations of inflation and the output gap follow De Grauwe (2010a, 2010b). To describe the different behavioral rules of the expected output gap, we assume that the agents do not fully understand how the output gap is determined, and so the agents use simple rules, say, the optimistic rule and the pessimistic rule, to forecast the future output gap. Therefore, in the agent-based DSGE model, forecasts of optimistic agents systematically bias the output upwards and forecasts of pessimistic agents systematically bias the output downwards. Specifically, the optimists' rule is defined by $E_{o,t}y_{t+1} = g$ and the pessimists' rule is defined by $E_{p,t}y_{t+1} = -g$, where $g > 0$ denotes the degree of bias in the estimation of the output gap.

For the heterogeneous expectations of inflation we follow De Grauwe (2010a, 2010b) in allowing for two inflation forecasting rules. One rule is based on the announced inflation target. In other words, the inflation target believer's rule is defined by $E_{t,t}\pi_{t+1} = \pi^*$ and the extrapolator's rule is defined by $E_{e,t}\pi_{t+1} = \pi_{t-1}$.

In order to describe the social interaction behavior among agents, we use the Ising model as our interaction model. The Ising model originated from the dissertation of Ernst Ising (1900-1998). 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 has been strikingly successful in the search for the transition between the ferromagnetic and the paramagnetic state. 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; Iori, 2002) and tax evasion (Zaklan et al., 2009).

In this paper, the Ising model is composed of a finite number of agents and arranged in a specific network structure. Each agent can either move up (optimistic rule/ inflation target rule) or move down (pessimistic rule/extrapolating rule). Therefore, the probability of agent i using the optimistic rule (inflation target rule) can be represented by Equation (15) (Equation 16).

$$prob(x_1(t) = o) = \frac{1}{1 + \exp(-2\lambda m_{1,i})} \quad (15)$$

$$prob(x_2(t) = t) = \frac{1}{1 + \exp(-2\lambda m_{2,i})} \quad (16)$$

According to Equation (15) and Equation (16), two variables will affect the behavior for each agent. The first is $m_{1,i}/m_{2,i}$ which is a function of the interaction influence of the neighbors of each agent. w_{ij} is the interaction strength between agents i and j , which depends on how many neighbors agent i has.

$$w_{ij} = \frac{1}{\#\{j : j \in \mathcal{D}_i\}} \quad (17)$$

To be brief, $m_{1,i}$ and $m_{2,i}$, could be represented by Equation (18) and Equation (19) where $Z_1(i, j)$ and $Z_2(i, j)$ are the action of output gap expectations and inflation for neighbor j .

$$m_{1,i} = \sum_{j=1}^N w_{ij} Z_1(i, j) \quad \text{where} \quad (18)$$

$$Z_1(i, j) = \begin{cases} 1 & \text{if } j \text{ uses the optimistic rule} \\ 0 & \text{if } j \text{ uses the pessimistic rule} \end{cases}$$

$$m_{2,i} = \sum_{j=1}^N w_{ij} Z_2(i, j) \quad \text{where} \quad (19)$$

$$Z_2(i, j) = \begin{cases} 1 & \text{if } j \text{ uses the inflation target rule} \\ 0 & \text{if } j \text{ uses the extrapolating rule} \end{cases}$$

The other variable is the intensity of choice (λ). If $\lambda \rightarrow \infty$ then $prob(x_1(t) = o)$ (or $prob(x_2(t) = t)$) $\rightarrow 1$. However, if $\lambda \rightarrow 0$, then $prob(x(t) = o)$ (or $prob(x_2(t) = t)$) $\rightarrow \frac{1}{2}$. In other words, the agents have the tendency to align with their neighbors at the high intensity of choice. However, at the low intensity of choice, the tendency of the agents to align with their neighbors is disturbed, so that the agents become independent of each other; some of them take on the optimistic rule (or inflation target rule) and some of them take on the pessimistic rule (or extrapolating rule).

4 Collaborations and Simulation Results

4.1 Parameters Setting

In simulations, we follow the parameters setting of De Grauwe (2010a) and Kazanas et.al.(2011) for the stylized New Keynesian DSGE model. Details of the parameters in the agent-based DSGE model and the parameter values of different network structures can be found in Table 2.

Table 2 Parameters Setting of the Calibrated Models model

Parameters setting of the agent-based 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
ρ_k	0.5	the speed of declining weights omega in mean squared errors
$\varepsilon_t, \eta_t, u_t$	0.005	standard deviation shocks of output gap, inflation and Taylor's rule
λ	0.1, 0.3, 0.5 0.7, 0.9	intensity of choice
Others		
N	100	number of agents
T	300	number of simulation periods for each calibration experiment
R	100	Number of experiments for each calibration

4.2 Simulation Results

In this section, we try to study the relationship between the social network and macroeconomic stability. For this reason, we calculate the volatility (variance) of the output gap and inflation and perform a two-stage analysis. In the first stage of the research, we simulate only 10 different networks and establish the hypothesis through the preliminary study. In the second stage, we carry out a large-scale simulation and conduct a regression analysis to verify the previous hypothesis. 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. The results of the first stage can be found in Section 4.2.1 and the results of the simple regression can be found in Section 4.2.2.

Table 3 Variance of output gap

Network	$\lambda = 0.1$	$\lambda = 0.3$	$\lambda = 0.5$	$\lambda = 0.7$	$\lambda = 0.9$
Circle	0.44102	0.43839	0.43653	0.43464	0.43289
SW05	0.44116	0.43891	0.43616	0.43429	0.43258
Random	0.44103	0.43852	0.43612	0.43471	0.43199
SW03	0.44106	0.43889	0.43588	0.43475	0.43260
Scale-free	0.44120	0.44247	0.44640	0.45076	0.45012
SW01	0.44102	0.43838	0.43593	0.43431	0.43275
SW07	0.44111	0.43856	0.43616	0.43485	0.43249
SW09	0.44096	0.43873	0.43648	0.43442	0.43229
Regular	0.44119	0.43861	0.43601	0.43418	0.42507
Fully	0.44099	0.43847	0.43591	0.43445	0.43210

Table 4 Variance of inflation

Network	$\lambda = 0.1$	$\lambda = 0.3$	$\lambda = 0.5$	$\lambda = 0.7$	$\lambda = 0.9$
Circle	0.56049	0.51257	0.46834	0.43122	0.40245
SW05	0.56534	0.51622	0.47069	0.43238	0.40239
Random	0.56080	0.51222	0.46698	0.42885	0.39934
SW03	0.56063	0.51216	0.46713	0.42895	0.39926
Scale-free	0.56066	0.51322	0.47043	0.43480	0.40650
SW01	0.56063	0.51213	0.46664	0.42850	0.39923
SW07	0.56062	0.51201	0.46692	0.42901	0.39946
SW09	0.56058	0.51250	0.46713	0.42889	0.39950
Regular	0.56063	0.51207	0.46685	0.42859	0.39881
Fully	0.56061	0.51181	0.46553	0.42581	0.39581

4.2.1 A Quick Look into the Effects of Network Topologies

According to Table 3, we find that the output gap volatility is the minimum under the fully network structure and the maximum under the scale-free network structure. Similarity, the volatility of inflation exhibits the same phenomenon (Table 4).

Table 5 Sorting of economic fluctuations

	$\lambda = 0.1$			$\lambda = 0.3$			$\lambda = 0.5$			$\lambda = 0.7$			$\lambda = 0.9$		
	output gap	inflation		output gap	inflation		output gap	inflation		output gap	inflation		output gap	inflation	
Circle	*	***		**	+		++	+		+		++	++		++
SW05	+	+++		++	+++			+++		++			+		+
Random		++										**	**		
SW03				+			***					+			
Scale-free	+++	+		+++	++		+++	++		+++		+++	+++		+++
SW01				***	***		*	**		*	**	*	+		*
SW07					**					++					
SW09	***	**					+								
Regular	++			*	*		***	*		*	*	***	***		**
Fully	**	*		*	***		**	***		***	***	***	*		***

*** denotes the smallest value of volatility among different networks, ** the second smallest one, and * the third smallest one. +++ denotes the largest value of volatility among different networks, ++ the second largest one, and + the third largest one.

Table 6 Social network and macroeconomic stability

A.D.	A.C.C.	A.P.L.	M.B.C.	M.C.C.
Circle	Circle	Fully	Fully	Circle
SW05	SW05	SW01	SW09	Regular
Random	Random	Regular	Random	SW01
SW03	SW03	Random	SW03	SW09
SW01	Scale-free	SW09	SW05	SW03
SW07	SW01	SW03	Regular	Random
SW09	SW07	SW07	SW07	SW07
Regular	SW09	Scale-free	SW01	SW05
Scale-free	Regular	SW05	Circle	Scale-free
Fully	Fully	Circle	Scale-free	Fully

Table 5 is a summary of Tables 3 and 4. According to the above, we find that the scale-free network shows the largest value of volatility among different networks, whereas the fully connected network does the exact opposite. Furthermore, we find that the economy is relatively stable under the fully-connected network, the regular network and the small-world network with a rewiring rate equal to 0.1. However, if the social network is a scale-free, circle, and small-world network with a rewiring rate equal to 0.5, the economic fluctuations will be relatively large. To understand how the network topology influences the economic fluctuations, we build up Table 6 and all of the network properties are sorted from the small routes to the large. In addition, the yellow grid represents the network which generates a relatively stable economy and the green grid represents the network which generates a volatile economic environment. According to the information offered by Table 6, we propose the following four hypotheses:

Hypothesis 1 (Information Flows): The more liquid the information flow, the higher the stability; more specifically, the higher the degree of the network topology, the higher the stability.

Due to the neoclassical assumptions of perfect information, we infer that the more liquid information flow will contribute to the stability of the economy. Therefore, we use the average degree as the information liquid indicator and detect whether the more average the degree is, the more stable the economy will be. There is no doubt that the information diffusion of a fully-connected network is the most liquid. According to Table 6, the fully-connected network and the regular network belong to the high average degree group and the economic systems under those two

network structures are relative stable.¹ On the other hand, the circle network and small-world network with a rewiring rate equal to 0.5 are within the low average degree group and the economic fluctuations in the economy are relatively high. For this reason, we infer that the relationship between the average degree and economic fluctuations should be negative.

Hypothesis 2 (Herding): The higher the average clustering coefficient, the easier it will be to facilitate the herding effect.

If we just observe the average clustering coefficient of the network for the highest (lowest) three economic fluctuations, our findings will tend to suggest that more clustering of the agents will lead to fewer economic fluctuations. In other words, the average clustering coefficient and economic fluctuations are negatively correlated. However, if we check the economic fluctuations of the small-world network with a rewiring rate equal to 0.7 and a small-world network with a rewiring rate equal to 0.9, the economic fluctuations of those two networks are not low but their average clustering coefficients are high and thus the average clustering coefficient and economic fluctuations can be positively correlated. According to the above, we do not obtain a clear insight into how the average clustering coefficient affects the economic fluctuations in the preliminary study. Therefore, a more clustered group of agents will more easily facilitate the herding effect leading to a deterioration in the economic stability and the exchange of information to stabilize the economy has to be confirmed further.

Hypothesis 3 (Information Dissemination): The faster the information is disseminated, the more stable is the economy.

In this paper, we use the average path length to represent the speed of information transmission. According to Table 6, a higher average path length tends to lead the larger economic fluctuations. We therefore suggest that the relationship between average path length and economic fluctuations should be positive.

Hypothesis 4 (Conglomerate Effect): If the social network structure exists as the opinion leader, the fluctuations in the economy will be larger.

¹ For the Scale-free network, the average degree of the Scale-free network is relatively high; however, there are some points with more links that will result in the average degree possibly being biased.

Table 7 The network properties statistics

Network Characteristics	Minimum	Maximum	Mean	Variance
A.D.	2	80	39.6134	523.0591
A.C.C	0	0.8240	0.4288	0.0485
A.P.L.	1.1919	87.0463	3.4512	100.9276
M.B.C.	13.0940	4681.677	277.9621	835680
M.C.C.	0.0030	1	0.0090	0.0020

First of all, we want to know why the scale-free network generates the largest fluctuations. Therefore, we go back to check the property of each network structure. We find that the scale-free network is not prominent in terms of the average degree, average clustering coefficient and average path length. However, its maximum betweenness centrality and maximum closeness centrality are the largest (Table 1). Thus, the scale-free network structure exists as the opinion leader. If the leader’s opinion changes, large numbers of people will be influenced and their action will be changed. For example, in the subprime crisis, the credit rating agencies played a very important role at various stages of the crisis. At the beginning, the rating agencies gave a top triple-A rating to the derivatives which were correlated to the subprime mortgage, such as mortgage-backed securities (MBS) and collateralized debt obligations (CDO). However, when the rating agencies observed that such derivatives were overvalued and lowered the rating, many investors’ opinions were changed. Then, the financial crisis occurred. According to the above inference, the centrality indicator and the economic fluctuations can be positively correlated.

4.2.2 Regression analysis: the economic effects of social network topologies

In the studies discussed above, we thus obtain a preliminary analysis of the impact of various network indicators on economic fluctuations. However, the sample in the first stage is too limited to confirm our conjectures. Therefore, to have a more thorough examination of these characterizations, a second-stage simulation with more extensive sampling is conducted to understand the above-mentioned hypothesis. To address those issues, we generate 500 networks with different network properties. By attempting as much as possible to include different values of the network characteristics, 437 small-world networks, 27 scale-free networks and 36 random networks are selected. The descriptive statistics of the network characteristics are presented in Table 7.

Table 8 Regression results

	Output gap($\times 10^{-2}$)			Inflation($\times 10^{-2}$)		
Intercept	-79.631	(-60.74)	***	49.290	(250.85)	***
A.D.	-0.278	(-2.13)	***	-0.09238	(-4.71)	***
A.C.C.	0.148	(2.00)	***	0.02737	(2.48)	***
A.P.L.	-0.0553	(-1.81)	**	0.307	(66.9)	***
M.B.C.	1.441	(9.83)	***	0.00494	(0.55)	
M.C.C.	0.336	(5.63)	***	0.449	(20.41)	***
R^2	0.6419			0.9411		
Adj R^2	0.6382			0.9405		

* The first column represents all of the independent variables, the second column shows the parameter estimates of the output gap model, the third column is the T-ratio, *** represents the coefficients that are statistically significant at the 5 per cent level, and ** the coefficients that are statistically significant at the 10 per cent level.

Furthermore, the empirical regression models are introduced in Equations (20) and (21) to examine the relation between the economic fluctuations (the variance of the output gap and the variances of inflation) and the average degree, average clustering coefficient, the average path length, the maximum betweenness centrality and the maximum closeness centrality. In addition, a natural log transformation is applied for the dependent variable and independent variables.

$$\ln[\text{var}(\text{output gap})] = \beta_0 + \beta_1 \times \ln AD + \beta_2 \times \ln ACC + \beta_3 \times \ln APL + \beta_4 \times \ln MBC + \beta_5 \times \ln MCC \quad (20)$$

$$\ln[\text{var}(\text{Inflation})] = \beta_0 + \beta_1 \times \ln AD + \beta_2 \times \ln ACC + \beta_3 \times \ln APL + \beta_4 \times \ln MBC + \beta_5 \times \ln MCC \quad (21)$$

Table 8 provides a summary of the regression results. First, we find that the macroeconomic stability is highly correlated with the social network structure. Both of the R squares of the output gap stability model and inflation stability model are high. In addition, we find that the estimated coefficients of the average degree are negative and significant for both the variance of the output gap and inflation. Therefore, we have successfully verified Hypothesis 1, which argues that the more liquid the information flow, the higher the stability. In addition, as we experience in the first-stage simulation, we also find that the centrality indicators

and the economic fluctuations are positively correlated and thus we can deduce that if the opinion leaders exist in the economic system, their actions will affect a lot of people and thus the economic fluctuations will be larger. Furthermore, in the preliminary study of the first-stage, we cannot observe the relationship between the average clustering coefficient and the economic fluctuations directly. We do not know that the increased clustering of agents will give rise to the herding effect, thereby bringing about a deterioration in the economic stability or exchange the information to stabilize the economy. This therefore has to be confirmed in the second stage. According to Table 8, the estimated coefficients of the average clustering coefficient both have a positive effect on the variance of the output gap and inflation and thus the empirical results tend to support the view that more clustering among agents may bring about the herding effect and exacerbate the economic fluctuations. For Hypothesis 3, we want to examine whether the more quickly the information is diffused, the more stable the economy will become. We find that the path length has an adverse effect on the output stability but a positive effect on the price stability. In other words, the more rapid diffusion of information can contribute to the stability of the price level but harm the output stability.

5 Conclusion

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. Several of these findings are worth summarizing. First, according to our simulation results, we find that economic stability depends on the social network topology. We find that the more liquid the information is, the more it will contribute to the stability of the economy. Therefore, if the network structure is closer to the perfect information which is the key assumption of the neoclassical economists, the economy will be more stable. Furthermore, the speed of information diffusion and the degree of clustering among agents may give rise to an adverse effect on economic stability. Finally, the results also show that a scale-free network will lead the most dramatic economic fluctuations. In going back to check the property of each network structure, we find that the scale-free network is not prominent in relation to the average degree, average clustering coefficient and average path length. However, its centrality is the largest. Due to the high centrality, the scale-free network structure serves as the opinion leader. If the leader's opinion changes, many people's thoughts will be influenced and they will make different decisions. Therefore, we infer that if the social network structure serves as the opinion leader, the fluctuations in the economy will be larger. Our empirical results also support the hypothesis that the centrality indicators have a negative effects on the economic stability. In this paper, we separately discuss

the impact of the economic stability of individual network statistics, but we do not rule out the possibility that all network properties may jointly work together. This paper does not consider this complex situation.

As we have said at the very beginning of the paper, there are many different perspectives to look at in terms of the relationship between social networks and the macroeconomy. The path which we take 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 into agent-based macroeconomic models, and, in this sense, the agent-based DSGE model. There are two remarks we would like to add 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 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 cluster coefficients, betweenness centrality and 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 probably an unfinished business then for us to search for their deeper meanings with the possible serendipities of finding out other missing characterizations.

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