# Social Networks and International Policy Diffusion: A Multi-Agent Simulation Analysis

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## Introduction

This paper tries to identify the conditions in which international policy diffusion occurs, focusing on networks among nation-states. While policy diffusion has originally been observed and studied for various units, e.g. local governments or federal states, literature on "international" policy diffusion has also been increasing these days (Simmons et al. 2006; Jahn 2006).

Recently, international diffusion theorists have begun to pay attention to "network" as a condition in which diffusion occurs or as a variable which promotes it. (Polillo and Guillen 2005; Cao 2010). In other words, various networks among states have come to be considered as being promotive of international policy diffusion. The point here is that an agent is not necessarily affected by all the "others" in a given community, but particularly by those connected to this agent through its social networks. This seems a plausible assumption to account for policy adoption through diffusion.

In this paper, by using a computational technique called "Multi-Agent Simulation" (MAS), we provide new insights into the relationships between network and policy diffusion, or the effects of the latter on the former[1]. In particular, we reexamine a common view that "the denser the networks in a given community becomes, the easier it is for a policy to diffuse."As it conforms to intuition, previous researchers have almost "assumed" this view. However, by performing computer simulation, this paper reexamines this very assumption.

Performing computer simulation means conducting a kind of thought experiment. That is to say, in order to explore the relationship between network and policy diffusion, we construct a model in which policy diffusion occurs in interactions among states, which follow a set of simple and natural rules. By doing so, we experiment on parameters (here, network) which determine the model's behavior. Although most of the existing literature on policy diffusion has analyzed diffusion inductively, focusing on individual cases in which a policy diffuses successfully, we adopt a different approach. First, we conduct a deductive analysis by using a simulation model, rather than studying individual cases; second, we also pay attention to cases of failed diffusion as well as to successful ones.

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[1] MAS is a computer simulation method. MAS allows us to observe how a phenomenon at the macro-level (in this study "policy diffusion") emerges from the interactions between multiple agents (in this study "states").

## 1. Policy diffusion literature and social networks

### (1) Policy diffusion in international relations scholarship

In this paper, we rely on the definition by Simmons et al. (2006), which states that "international policy diffusion occurs when government policy decisions in a given country are systematically conditioned by prior policy choices made in other countries" (787). According to this definition, policy diffusion is characterized by path-dependence (in the sense that policy adoption is conditioned by prior decisions made by other countries), as well as by interdependence among states.

The history of policy diffusion literature dates back four decades, beginning with studies of diffusion among federal states in the U.S. (Walker 1969; Gray 1973) . From then, the literature has been variegated in scope and methods, such as through the incorporation of the adoption rate of neighboring states as an independent variable, or by means of statistical analysis (Berry and Berry 1990; Mintrom 1997). These studies have covered a wide variety of policies such as the abolition of death penalty; lottery; legalization of casinos; welfare policies; as well as environmental standards.

In contrast to the field of political science- where policy diffusion has long been well-established- it was only a decade ago that scholars in the field of international relations (IR) began to pay attention to this subject of study. (Of course, this remark is made with the exception of several studies on the diffusion of wars)[2]. It was the rise of constructivism in the 1990s, which provided the impetus for scholars in the field of IR to consider norm diffusion (Finnemore and Sikkink 1998). Subsequently, Simmons and Elkins (2004) brought the study of policy diffusion in the field of IR to greater heights, and it has since become a prominent topic of study in the field, especially in the scholarship on the international political economy (IPE). Among the policies that have been studied are pension privatization (Brooks 2005), social expenditure rates (Brooks 2005), central bank independence (Polillo and Guillén 2005), and reduction in corporate taxation (Cao 2010).

Most of these studies have tried to examine empirically "whether" there has been policy diffusion in a given field, and if so, "why" and "how" the policy diffusion occurred. (In particular, many studies have focused on individual case studies, in an attempt to identify the causal mechanisms of the diffusion). As a result, most scholars nowadays agree that the mechanisms for policy diffusion can be classified into four categories: (i) learning; (ii) competition; (iii) emulation; and (iv) coercion (Simmons et al. 2006). All of these mechanisms refer to the "bandwagon pressure" (Abrahamson and Rosenkopf 1997) which is imposed by the adopting states, on another

[2] For a representative study, see Most and Starr (1980)

given state. In other words, the more other states adopt an innovative policy, the more motivated a state becomes to adopt it.

However, while the existing literature has succeeded in classifying diffusion mechanisms, there has been few attempts to theorize how and when these mechanisms work[3]. Therefore, this is the task that we shall tackle in this paper.

**(2) Social networks**

This paper focuses on the subject of "networks," which has recently attracted attention in IR literature, as a factor that promotes policy diffusion[4]. Policies do not diffuse simply from one state to another, but rather through networks formed among states. For example, networks through bilateral trade and affiliation in international organizations (IOs) have been found to promote the diffusion of neoliberal economic policies (Cao 2010); and normative pressure from trade networks has been considered to help diffuse "central bank independence" (Polillo and Guillén 2005). A good example of networks studied in international relations would be the type of networks commonly observed in foreign relations, such as intergovernmental meetings and participation in common IOs. (This includes commercial ties through trade and investment.) Another example would be the links formed among non-state actors, such as business communities and NGOs. The close ties between states, brought forth by bilateral trade or IO affiliation, promote policy diffusion through learning or emulation (Cao 2010: 828-9; Henisz et al. 2005: 877).

This paper examines the effects that such networks have on policy diffusion. In particular, we consider the question of whether dense networks always promote policy diffusion. Previous literature has made the simplifying assumption that a linear relationship always exists between networks and policy diffusion; that is, with the assumption that denser networks among states always bring about more diffusion. In several cases, statistical analysis testing for the degree of dependence of the former on the latter has been conducted. Due to the seemingly intuitive nature of such an assumption, few scholar have questioned its validity.

However, it is not necessarily apparent that a policy diffuses more easily in a community with denser networks. Let us think of an incumbent state at the initial stage when the heralding state(s) (innovators) adopts (adopt) an innovative policy. In denser networks, an incumbent state has closer ties not only to the innovator(s), but also to those states that have not adopted the innovative policy as of yet. As a corollary, we cannot assume that a denser network always brings

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[3] For an exception, see Volden et al.(2008) using a formal model. However, they point to the similarity between the results of the two different mechanisms, "learning" and "emulation," and their main interest differs from ours.

[4] For network analysis in IR scholarship, see Hafner-Burton et al. (2009).

about a greater degree of policy diffusion, since the relationships between networks and policy diffusion that are observed in the real world prove to be far more complex than that.

We have so far clarified the problem that lies in policy diffusion studies, especially with regards to the way in which scholars have treated the effect of network density on policy diffusion. In this paper, we try to consider the relationship between network density and policy diffusion by using MAS, and we test whether these relationships are as simple as previous literature has assumed.

## 2. Modeling Policy Diffusion

### (1) Threshold Model

#### A general explanation of the threshold model

In the previous section, we reviewed the existing literature on policy diffusion in political science. However, studies of policy diffusion have not been limited to political science. "Diffusion of innovation" has long been discussed in other fields, including sociology (Rogers 2003; Moore 1998). In this paper, we shall attempt to model the process of policy diffusion, based on the "threshold model" used by mathematical sociologists to analyze collective actions and diffusion of ideas (Granovetter 1978; Macy 1991). We use the threshold model because it is widely applied to the phenomenon of diffusion. Moreover, it is suitable for modeling the sort of "bandwagon pressure" that is commonly observed in policy diffusion. This refers to the pressure imposed upon a particular state to adopt an innovation, by the other states that have already adopted it.

In our model, all the agents (i.e. states) adopt the same policy at the initial unit of time. Consequently, some states (innovators) begin to adopt a new policy, which subsequently diffuses to the other states. When each state decides on whether to adopt a new policy, it refers to the diffusion rate in the group it belongs to. Each state has its own threshold value, and when the diffusion rate reaches that value, it chooses to adopt the new policy. These rules can be summarized as follows:

- At the initial time, each state adopts the existing policy (the diffusion rate of the new policy equals zero)
- At each time t, each state i chooses between two alternatives: to adopt or not to adopt the new policy.
- Each state i is assigned a threshold $x_i$ ! $[0,1]$ with which it compares the adoption rate $r_t \in [0,1]$ to make its choice at each time t. If $r_t \geq x_i$ then $i$ adopts the new policy.
- $x_i$ is fixed for all *t*.

Here, if a threshold follows a certain probability distribution function $f(r_i)$, the adoption rate at time t+1 can be represented as: $r_{t+1} = F(r_i)$, where $F(r_i)$ stands for the cumulative distribution function $f(r_i)$. In this paper, we assume that $f(r_i)$ follows a normal distribution. This is a reasonable assumption in view of the actual tendency observed in the diffusion of fashions, and is also the assumption upon which many diffusion studies are currently being based upon. Some prominent examples include the works of Granovetter, the founder of threshold models (see Granovetter and Soong 1983; and Abrahamson and Rosenkopf 1993).

Furthermore, the innovator explained above has a threshold 0 and thus adopts the innovative policy even when no other state has adopted it.

**Introducing the concept of a network**

In addition to the threshold model explained above, we introduce the concept of network. In Granovetter's model, an individual decides on whether to adopt a policy by comparing the adoption rate in the group and its own threshold value. However, as Granovetter himself has pointed out, we have to take into account the effects of social structure when considering diffusion of innovation (Granovetter 1978: 1429-1430). Where the original model does not treat personal ties between individuals, in the real world an individual may attach greater importance to the behavior of her/his friends (i.e. the adoption rate attached to her/his acquaintance) than to others.

For policy diffusion too, it is not difficult to find examples in which states are affected not equally by other states but rather by those states which they are connected to, through networks. For example, let us consider the example of central bank independence (CBI), a policy the recent proliferation of which has caused it to become widely studied by scholars in the field of IR. It is particularly relevant to our discussion to take note of the fact that between the time frame of 1990-1993, the policy of CBI took on a marked and distinct pattern of diffusion amongst the group of post-communist transitional economies (such as the former Soviet Union, as well as the group of Central / Eastern European countries). (Mcnamara 2002: 65). In marked contrast to the rapid spread of CBI amongst the group of post-communist transitional economies, was the limited diffusion of the same policy amongst other countries of the world. Apart from the United States and Germany, which had traditionally had independent central banks, and New Zealand, Chile and Turkey, which had already reformed their central banking systems in 1989, most other countries did not experience the rapid spread of CBI until after 1993. (This includes countries such as those in Western Europe and other advanced economies.)[5] The spread of CBI policy amongst the former socialist states during the period of 1990 -1993 can be seen as an excellent example of the diffusion of a policy through a local network.

In the same spirit as the case study discussed above, the agents in our model decide

[5] See tables in McNamara (2002: 71-75).

whether to adopt a new policy by comparing their individual threshold values with the adoption rate of the other agents which they are connected to, and not that of the group as a whole. This can be described as[6]:

$$r_t = \frac{\sum_{j=1}^{d} \delta_j}{d}$$

Where $\delta_j$ equals 1 if agent *j* is an adopter or 0 otherwise.

**(2) Multi-Agent Simulation[7]**

**The dependent variable and parameters of the model**

While Granovetter pointed to the importance of social structure and its complex effects on diffusion, he did not further analyze them systematically (Granovetter 1978). In this paper, we try to approach this complexity with MAS.

In our model, each agent (here, each state) acts according to the threshold model with social networks, as we have described above. We fix the number of agents at 100.[8] The dependent variable in our model is the "diffusion rate," i.e. the rate of the agents that have adopted the new policy in the model.

Each agent has its own threshold value which is assigned at random, and which follows a normal distribution. Following Granovetter's model, where an agent is assigned a value below zero (or over one), we assign a threshold value to each agent which can be either equal to 0 or 1) (Granovetter 1978: 1427). The mean and the standard deviation are $b_{mean}$ and $b_{stdev}$, respectively. The independent variable, or the parameter we manipulate in this paper, is "network." Our model introduces random networks[9] and we manipulate their "network density." Network density denotes the proportion of existing links to all the potential links between agents. When network density = 1.0, then the networks form a complete graph.

A major issue of consideration which we faced when running our simulation was the question of how to model the parameters of threshold distribution, namely $b_{mean}$ and $b_{stdev}$. This was an important matter, given that in threshold models, a slight change in distribution could very possibly bring about a huge difference in outcome. In consideration of this fact, and in order to

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6 For attempts to combine threshold models and networks, see for example Abrahamson and Rosenkopf(1997) Valente(1996), Chwe(1999), and Siegel(2009)

7 In this paper, we used artisoc ver2.6 in conducting the simulation. Please refer to Yamakage (2009) for more details on the simulator artisoc.

8 We set the number of agents as 100 because this paper analyzes policy diffusion among states.

9 On random networks, see Newman et al. (2001) and Callaway et al. (2000)

bring about an outcome that is as representative of as many parameters as possible, we conduct simulation runs with various sets of $b_{mean}$ and $b_{stdev}$.

Before setting $b_{mean}$ and $b_{stdev}$, we would like to explain the concept of "equilibrium" in a threshold model such as ours. An equilibrium here denotes a point where the diffusion rate stops increasing and becomes stable. This condition can be described mathematically as: $r_t = r_{t+1} = r^*$ . An equilibrium can be computed by locating a point where the cumulative distribution curve $F(r_i)$ crosses the 45 degree line. [10] The number of such points ranges from one to three. Threshold distributions could have two kinds of equilibrium: a "stable equilibrium," a point to which the diffusion rate converges, where $F(r_i)$ crosses the diagonal line from below,; and an "unstable equilibrium," a point from which the diffusion rate further distances itself, where $F(r_i)$crosses the diagonal line from above. Therefore, once the diffusion rate attains the level over an unstable equilibrium, it then increases dramatically. This level corresponds to the "critical mass" (Schelling 1978). Otherwise, if $F(r_i)$ is always above the 45 degree line, then the diffusion rate goes up constantly, even if the initial rate is zero.

The above consideration suggests that a slight change in $b_{mean}$ or $b_{stdev}$ could produce a big difference in the diffusion rates, depending on how $F(r_i)$ and the 45 degree line cross.[11] Therefore, when we vary $b_{mean}$ and $b_{stdev}$, we conduct two types of runs, namely simulation A, where "$F(r_i)$ and the 45 degree line cross at three points", and simulation B, where "$F(r_i)$ is always above the 45 degree line. " To put it more definitely, we conduct simulation A-1 ($b_{mean}$=0.3, $b_{stdev}$ ,=0.15) and simulation B-1 ($b_{mean}$=0.3, $b_{stdev}$ ,=0.2). $F(r_i)$ in each simulation and its relation to the 45 degree line are shown in Figure 1.

**[Figure 1]**

A slight difference in the standard deviations between A-1 and B-1 results in a big difference in eventual diffusion rates, because the former has an unstable equilibrium while the latter does not[12].This is an important feature of threshold models.

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[10] For further accounts of threshold distributions and equilibria in thresholds see Granovetter and Soong (1983) and Yin (1998).

[11] Besides, this also indicates that threshold models depend on initial values, as well as threshold distributions. Namely, if the initial rate is above (even if only slightly) the unstable equilibrium, then it would reach the level of the stable equilibrium above. However, as the initial adoption rate in our model is 0, we do not have to deal with this problem so far.

[12] Take note that in figure 1, the number of agents is considered infinite. One may ask whether

To summarize our point, this paper tries to clarify the relationships between network density and diffusion rates. In performing computer simulation for each sets of threshold distributions, namely A-1 and B-1, we vary network density from 0 to 0.5, conduct 1,000 runs for each network density, and observe the shift in the average diffusion rates.

**Interpretation**

Finally, we discuss how to interpret $b_{mean}$, $b_{stdev}$, and "network density" in the context of international policy diffusion. First, as smaller $b_{mean}$ means lower average threshold and thus results in more diffusion, $b_{mean}$ could be interpreted as the average level of satisfaction with the existing policy (i.e. higher $b_{mean}$ means higher satisfaction level). Second, if we consider that each state's level of satisfaction with the existing policy depends on the socio-economic environment surrounding it, $b_{stdev}$ could be interpreted as the socio-economic diversity among states.[13] And finally, "network density" could be interpreted as density of relations or communication in international society. This refers to the frequency of intergovernmental meetings, networks of bilateral trade, or transnational solidarity of NGOs, as we have argued above.

Besides, following these interpretations of $b_{mean}$ and $b_{stdev}$, we could label simulation A1 as "small international diversity model" and B1 as "great international diversity model."

## 3. Simulation results and mechanisms

### (1) Simulation results

First, in Figure 2, we show the results of simulations A1 and B1. The dotted line in Figure 2 plots the diffusion rate in the original threshold model (in our model, this means complete graph at network density = 1.0). As network density increases, network gets more and more similar to complete graph, so that the diffusion rate eventually converges to this dotted line.

**[Figure 2]**

Figure 2 shows two interesting results. First, in simulation A-1 (small international diversity model), the diffusion rate reaches its peak as early as at network density = 0.05, and then declines

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the arguments above can be applied to our models, which have 100 agents each of which is assigned a threshold randomly. To answer this, we have conducted simulation for simple threshold models (with complete graph) and the diffusion rates averaged over 1,000 runs are; 0.16 in A-1 and 0.89 in B-1. Therefore, it is obvious that A-1 and B-1 are essentially different.

[13] On this point, see also Yin (1988: 542). Yin argues that $b_{stdev}$ could also be interpreted as radicality of policy B, as well as diversity of agents' properties as we interpret it.

very rapidly, converging to that of the complete graph. Until around network density = 0.5, the diffusion rate in A-1 remains higher than that of the complete graph. Second, in simulation B-1 (great international diversity model), the diffusion rate reaches the value of the complete graph at a very low network density (network density = 0.05), and then remains stable. In other words, the diffusion rate in B-1 reaches that of the complete graph even when each state is linked to no more than 5 states out of 99.

Both of these results clarify the point that "denser networks do not always promote diffusion," for in each simulation, the peak comes at network density = 0.5, and as the network density increases further, the diffusion rate declines rapidly (A1) or remains stable (B1). These findings are interesting, because they contradict the assumption of existent literature and widely-held intuition. In particular, in a community with small diversity among its members, it is sparse relationships, not dense ones, that promote innovation diffusion.

### (2) Mechanisms

What accounts for these outcomes? We would like to explain here the mechanisms behind the simulation results. We have conducted 11,000 runs in total (1,000 runs for each network density, which ranges from 0, 0.05, 0.1, … to 0.5), and in addition to the average diffusion rates plotted in Figure 2, we show the scattergrams and the rates of cascade (over 90 % diffusion) occurrence in Figure 3.

**[Figure 3]**

As is clear from Figure 3, the diffusion rates exhibit bipolarity. In other words, an innovation either diffuses to all or nearly all the agents (cascade), or, does not diffuse at all (no cascade), and the rate of cascade occurrence determines the average diffusion rate. Therefore, to understand the mechanisms, it is necessary to inquire into the factor that determines this bipolarity.

For each of the 1,000 runs conducted for each network density, all the parameters show different values. For example, "the number of the innovator" varies within a certain range. Also, the network structure under a certain network density varies from one simulation to another. Of all these parameters, we focus on "EA" (early adopter), based on Watts (2002), a representative scholar of complex networks. In this paper, an EA refers to (i) an agent which is linked to one of the innovators, and (ii) an agent which is easily affected (with a low threshold value). To put it more definitely, an EA is described as an agent $\phi_i \le a_i / k_i$, where $\phi_i$ denotes agent $i$'s threshold, $a_i$ the number of the links connecting $i$ to innovators, and $k_i$ the degree of distributions. In each run, EA adopts the innovation right at the first step, immediately after the innovators. Simply said, an EA is "an agent which adopts the innovation at the first step." In contrast, when there is no EA, only the innovators adopt the innovation, so that no diffusion occurs. Watts, who studies diffusion in random networks, points to EAs' importance, and argues that it is the presence of EAs, rather than innovators, that determines innovation diffusion.[14]

As is clear from the above definition of an EA, the number of EAs is 0 when network density = 0. Then, as the network density increases, at first the number of EAs also increases, but after a certain point it begins to decline. This is because $a_i$ ceases to increase after a certain point whereas $k_i$ increases constantly in proportion to the network density.[15]

Figure 4 shows the relationship between the number of EAs and the diffusion rates. In Figure 4, we superpose the shifts in EAs' ratio for each network density with the diffusion rates shown in Figure 2.

**[Figure 4]**

Figure 4 gives us significant implications about the mechanisms. First, in A-1 EAs' ratio is highly correlated with the diffusion rate. This indicates that the bipolarity mentioned above is to a significant extent determined by EAs' ratio. Second, however, for B1 the diffusion rate remains stable even as the EAs' ratio declines. This difference in the relationships between EAs and the diffusion rates leads to the diffusion rate in A-1, which peaks at network density = 0.05 and then declines very rapidly, and B-1, which peaks at network density = 0.05 and then remains stable. What accounts for such a difference?

Figure 5 clearly answers this question. Figure 5 plots the ratio of EAs ratio in the x-axis, against the diffusion rates (averaged over 11,000 runs) in the y-axis. Here, it is remarkable that when An interesting finding is that when the ratio of EAs is greater than 0.05 or 0.06, the diffusion rate almost always reaches 1.0. In other words, when there are more than 5 or 6 EAs in the community, diffusion rate almost always converges to unity. Therefore, no matter how dense the networks are, a cascade occurs when EAs' ratio is above a certain value. Otherwise, the diffusion rate depends on the number of EAs. For example, a decrease in the EAs' ratio from 0.08 to 0.06 has no effect on the resulting diffusion, which explains the outcome in B-1. As is shown in Figure 4, in B-1 EAs' ratio certainly decreases, but the minimum ratio is around 0.06. This is the reason why in B-1 the diffusion rates do not reflect the decrease in the number of EAs, in contrast to A-1.

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[14] Watts (2002). However, Watts' definition of EA is slightly different from ours, described as: $\phi_i \leq 1/k_i$. We modify this definition because our model, particularly its degree distributions of networks, differ from those of Watts.

[15] The numbers of innovators averaged over 11,000 runs are 2.27 in A-1 and 6.68 in B1.

[Figure 5]

We have hitherto explained the mechanisms that produce the difference between A-1 and B-1 shown in Figure 2. The mechanisms are briefly summarized in Figure 6: EAs' ratio is determined by two factors, namely distribution of thresholds (in our model, A-1 or B-1) and network structure (whether agents which could be easily affected are linked to the innovator(s)). A subsequent outcome is that the rate of policy diffusion is to a large extent determined by the ratio of EAs.

[Figure 6]

The results of our simulation suggest that denser relationships do not necessarily lead to more innovation diffusion in a given community. Conversely, if the peak of diffusion comes early, further links among agents do not contribute to the rate of diffusion. With regards to the question of what mechanisms cause these findings, we have demonstrated that network structure, namely the ratio of EAs, play a major role in determining diffusion rates .

### (3) Robustness checks

Thus far, we have observed interesting results that emerge from adding network structure to the threshold model. To verify that these results do not depend on particular sets of variables, we perform robustness checks by varying two variables; (1) distribution of thresholds, and (2) number of agents.

First, we are going to verify that the above results are not limited to the particular distributions of thresholds (A-1 and B-1). By fixing $b_{mean}$ and changing $b_{stdev}$, we derived A-1, which has an unstable equilibrium and B-1, which does not. In this section, we change A-1's $b_{mean}$ to derive B-2 ($b_{mean}$=0.25, $b_{stdev}$=0.15), which has no unstable equilibrium. Following our interpretations above, B-2 could be named "conservative community model". In addition, we derive A-2 ($b_{mean}$=0.25, $b_{stdev}$=0.1) which exhibits unstable equilibrium and conduct the same sets of runs as above for A-2 and B-2.

The results of A-2 and B-2 are shown in Figure 7. Figure 7 exhibits the same features observed in the base runs; in A-2, the diffusion rate comes at the peak so early as at network density = 0.05, and then declines very rapidly, converging to that of complete graph; and in B-2, the diffusion rate reaches the value of the complete graph at a very low network density (network density = 0.05), and then remains stable. Likewise, we can observe the same correspondence between the diffusion rates and the EAs' ratio. These results allow us to conclude that with the exception of minor differences, the results of our model are generally robust with regards to threshold distributions.

**[Figure 7]**

Second, we test the model's robustness on the number of the agents. In the base runs we set the number of the agents as 100, but in the international society there exist a lot of smaller communities. On the other hand, there are some world-wide communities like the United Nations. Therefore, it is important to see if the same results could be derived from communities with different scales.

Hence we conduct the same runs for two models with 50 and 150 agents. We used threshold distributions of A-1 and A-2. The results are shown in Figures 8 and 9. The characteristics we have observed in the base runs are basically maintained. This allows us to conclude that our findings are also robust on community scales.

**[Figure 8, 9]**

## 4. Implications

The model which we have presented thus far is very simple, but it is this very simplicity which helps to clarify a pitfall in the existing literature. In this section, we would like to summarize the findings of our model, and the implications which its results have on policy diffusion studies.

It is intriguing that a slight difference in the standard deviation of distribution of thresholds (between A-1 and B-1) or a slight difference in the mean of their distribution (between A-1 and B-2) leads to a big difference in the diffusion rate in absolute terms. This suggests that a slight change in diversity among states or in satisfaction with the existing policy could actually bring about a stark difference in the result. However, this observation could be made without conducting simulation, since it is in fact intuitive, as suggested by the shape of $F(r_i)$. It has also been pointed out by scholars of collective action and diffusion, such as Granovetter (1978). Two important contributions that we have made especially with our model are as follows.

First, denser networks do not always lead to more diffusion. Based on this finding, we further exemplify how the effects of policy diffusion is in fact dependent on other factors apart from network density, such as the degree of diversity among states, and the average level of satisfaction with the existing policy.

This finding modifies the common view that "denser networks always lead to more diffusion." As the view that "network density is positively correlated with the rate of policy diffusion" is not counter-intuitive, it has not been questioned before. Existing studies regarding the "diffusion of innovations" too, have been based upon the common assumption that network density is linearly related with the policy diffusion rate.[16] However, as our simulation results indicate, the relationship between these two variables are in fact quite complex. This suggests that there is the potential for selection bias if we infer these relationships from individual cases,[17] for each individual case corresponds merely to a single plot in our graphs.

Turning our attention to the implication of our results for the real world, it can be said that our findings provide a novel way with which to understand the literature on "globalization and policy convergence". There has been a long-standing debate in IR whether globalization promotes policy convergence among states.[18] Increase in "network density" in our model could be interpreted as globalization (or at least one of the dimensions of globalization), as it implies a higher density of networks among states. However, as is clear from our results, this increase does not necessarily contribute to policy diffusion or convergence.[19] Therefore, globalization and the resultant network of interstate relationships on their own do not necessarily promote policy convergence.

The second finding is that whether easily affected states are linked to the innovators or not determines the rate of policy diffusion to a great extent. Therefore, network structure, rather than the characteristics of individual states, is the real key to understanding the mechanisms of policy diffusion. If applied to the real world, our results can be interpreted as follows: in a sparsely connected world, even if an innovative policy is initially adopted by only a small fraction of states (innovators), some other states connected to the innovators will consider the policy as prevailing worldwide (or as an "international standard") and thus adopt it. This is because in the social networks of these states, the policy has indeed won a majority; and their adoption of the policy then leads to its sequential diffusion across the entire community of states. In contrast, when the degree of connection between states is higher, each agent will be able to correctly recognize that the number of states which have adopted the policy is in fact small. This recognition allows each agent to base its decision of whether or not to adopt a new policy on the trends prevailing in the whole community. As a result, there will be no cascade in terms of policy diffusion rate. Such findings are certainly coherent with real world observations.

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16 For example, see Abrahamson and Rosenkopf (1997: 298).

17 See also, Siegel(2009: 129).

18 See, for example Collingsworth et al. (1994) as convergence theorists; and Vogel (1995) as skeptics.

19 Of course, "globalization" means not only network expansion, but also, increase in "velocity" of circulation of goods, money, people and information. Our reflection from the simulation results is limited to the former, and does not deny that the latter would promote policy diffusion.

Our findings indicate that "network structure" is an important variable in determining policy diffusion. According to our simulation results, the number of innovators or easily affected agents (in our model, agents with low thresholds) are not important on their own. Rather, what really determines policy diffusion is how closely these two types of agents are connected. While intuition suggests that more innovators may lead to more diffusion, what in fact counts is network structure. The existing literature on policy diffusion lacks this perspective. For example, in qualitative analyses using panel data, the dependent variable has been "whether a given state has adopted the policy". Likewise, independent variables have been defined to take into account bilateral factors only, such as the adoption of a policy by investor states or states in affiliation through IOs. Such a perspective assumes that each single state is an independent unit in itself. Therefore, existing studies have not considered "the adoption rate in the whole community" as a dependent variable[20], or, systemic factors such as "network structure" as independent variables.

## Conclusion

Previous studies on policy diffusion have limited the scope of their analyses to successful cases of diffusion. They are therefore unable to pin-point the cases where diffusion actually occurs. Using agent-based simulation, we have clarified the conditions which determine international policy diffusion, particularly the effects of network structure. The most important finding derived from the simulation results is that "denser networks do not always lead to more diffusion." One may speculate that among a given community of states, more frequent intergovernmental meetings or a higher volume of trade among them would usually lead to more diffusion of an innovative policy. However, as our simulation results have shown, when the diffusion rate reaches its peak, denser networks do not promote further diffusion of an innovation.

These results suggest that the effects of networks on policy diffusion are not as simple as the existing studies have assumed, but are in fact very complex. At least, it is not proper to infer relationships between networks and policy diffusion from one single case of successful diffusion. Moreover, our findings can provide a key to the understanding of puzzling incidents (puzzling from the viewpoint of previous literature, at least) in the real world, such as in cases where "diffusion has occurred in spite of low network density" or in cases where "denser networks have not led to further diffusion".

Another significant finding from our simulation is the importance of EAs in determining diffusion. This suggests that "network structure," namely whether easily affected agents are

[20] This is because previous studies have only picked up cases of successful diffusion and tried to explain "why such diffusion has occurred."

connected to innovators, greatly conditions policy diffusion. As existing studies have not paid attention to this factor, future researchers need to take it into account.

In this paper, we have conducted a kind of thought experiment. In order to construct a theory or a hypothesis, researchers commonly rely on a thought experiment. However, thought experiments in human brains often go wrong, whereas computer simulation frequently gives us counter-intuitive results. For this reason, by performing computer simulation, we have conducted an "accurate" kind of thought experiment on relationships between networks and policy diffusion. In previous studies, denser networks have been thought to lead to more diffusion. This assumption conforms to intuition, but our thought experiment using computer simulation, not human brains, has disclosed complex relationships between networks and diffusion. By presenting novel results that depart from the existing premises, our analysis has plainly revealed the significance of introducing computer simulation. In addition, it is also meaningful that our simple model, with only networks added to the basic threshold model, has produced such complex results.

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Figure. 1 The Equilibrium Points of Threshold Distributions

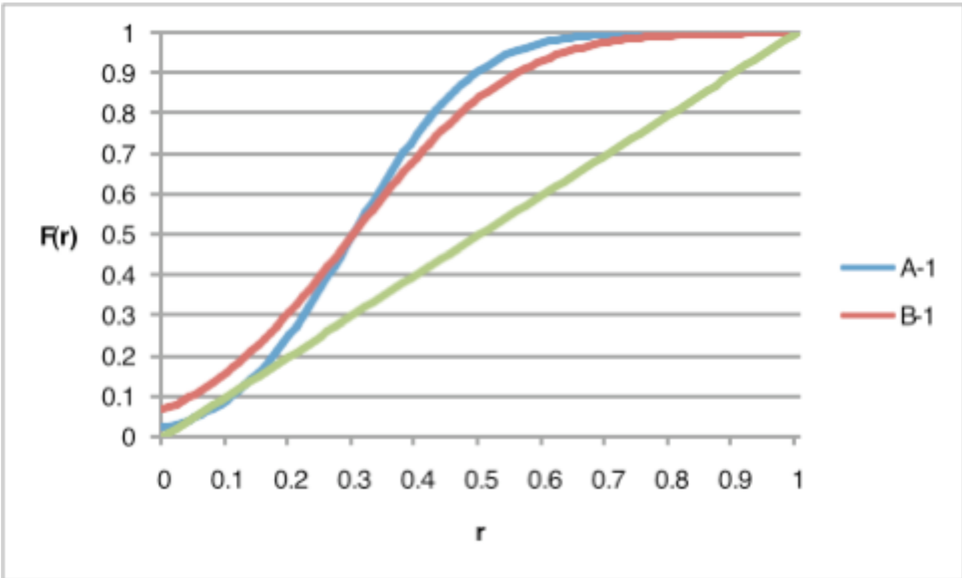



Figure. 2 Average Diffusion Rates

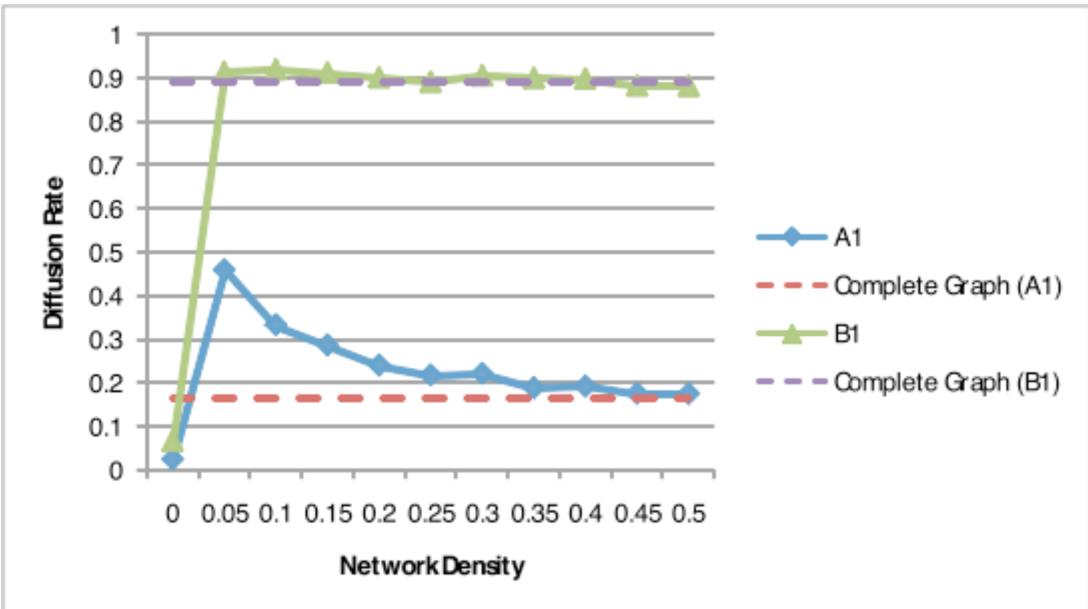
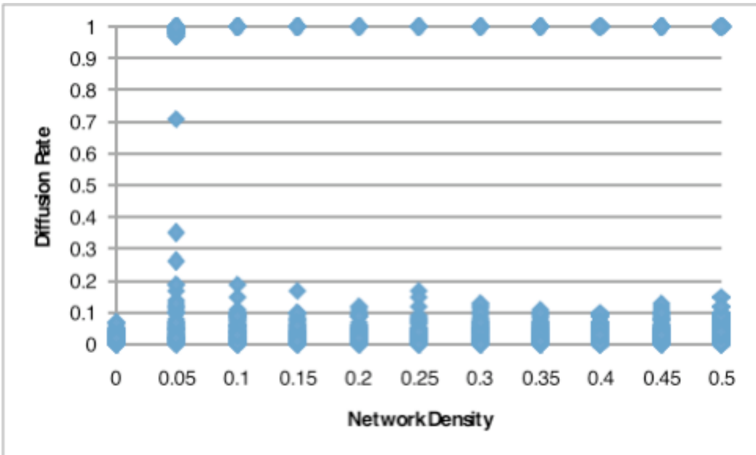
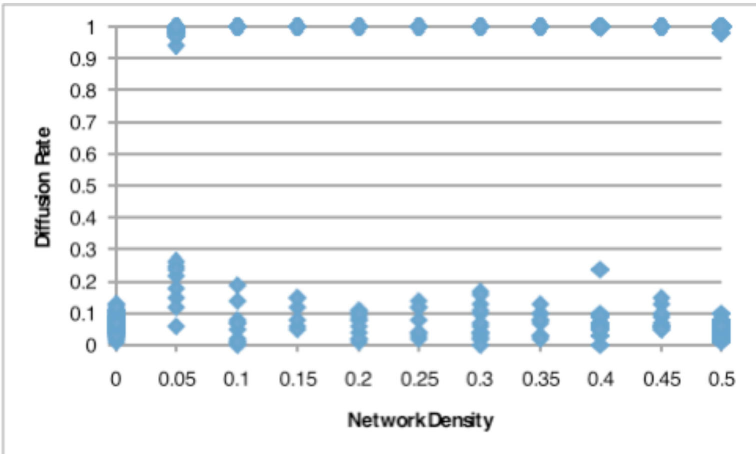


Figure.3 Scattergrams and Cascade Rates

Scattergram A-1




Scattergram B-1




Cascade Rates

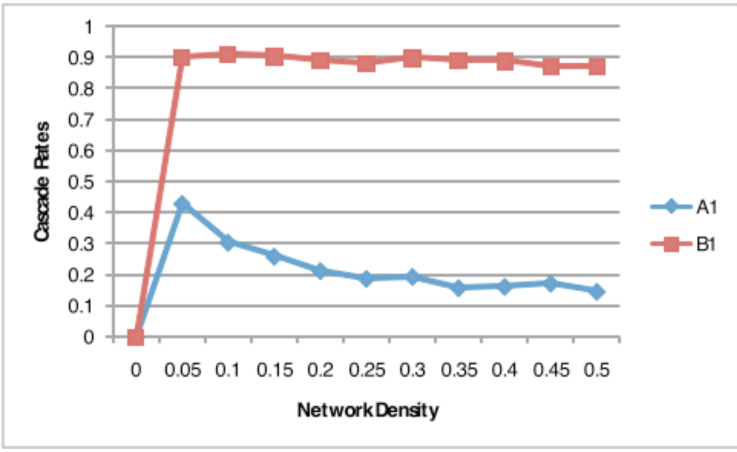
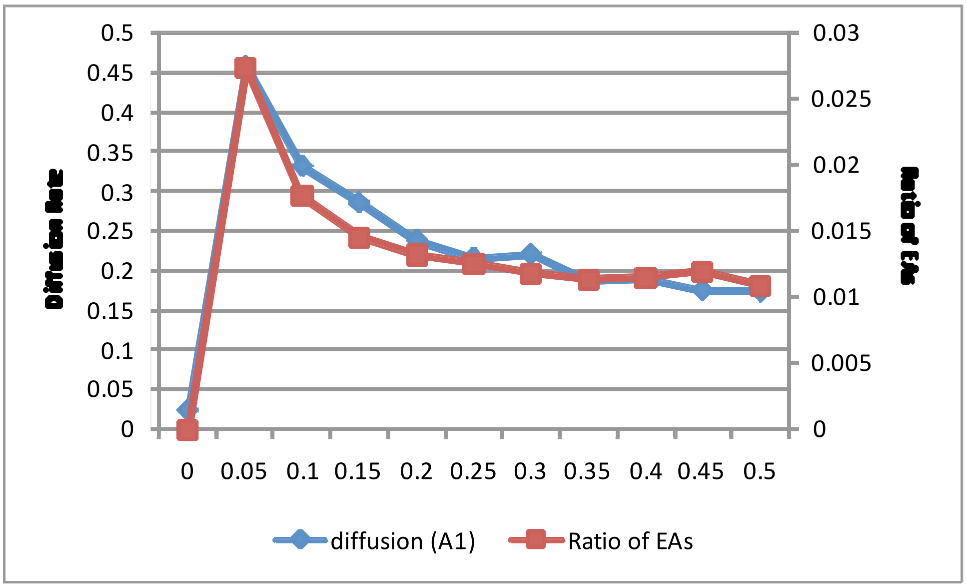



Figure. 4 Juxtaposing Diffusion Rates to Ratio of EAs

A-1




B-1

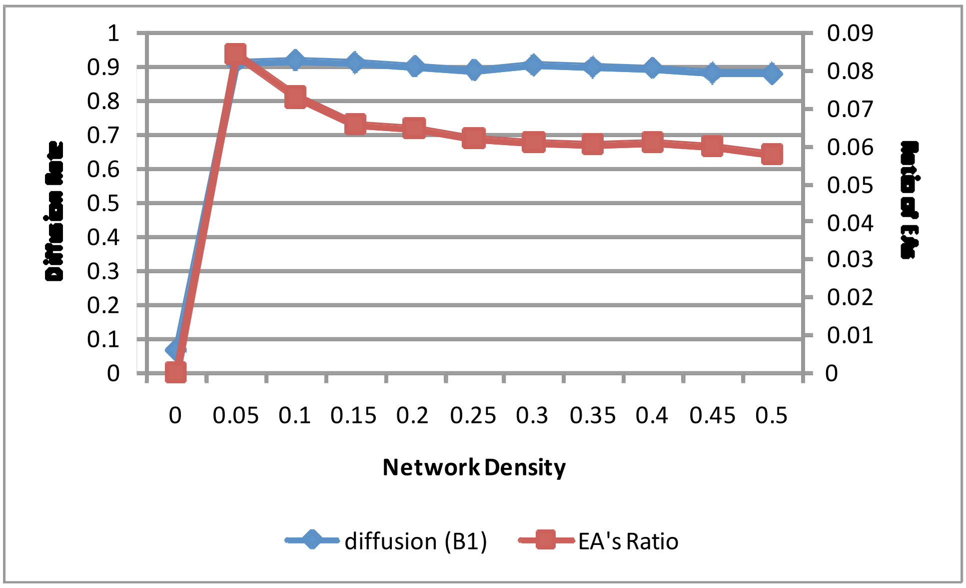



Figure. 5 Plotting Ratio of EAs against Averaged Diffusion Rates

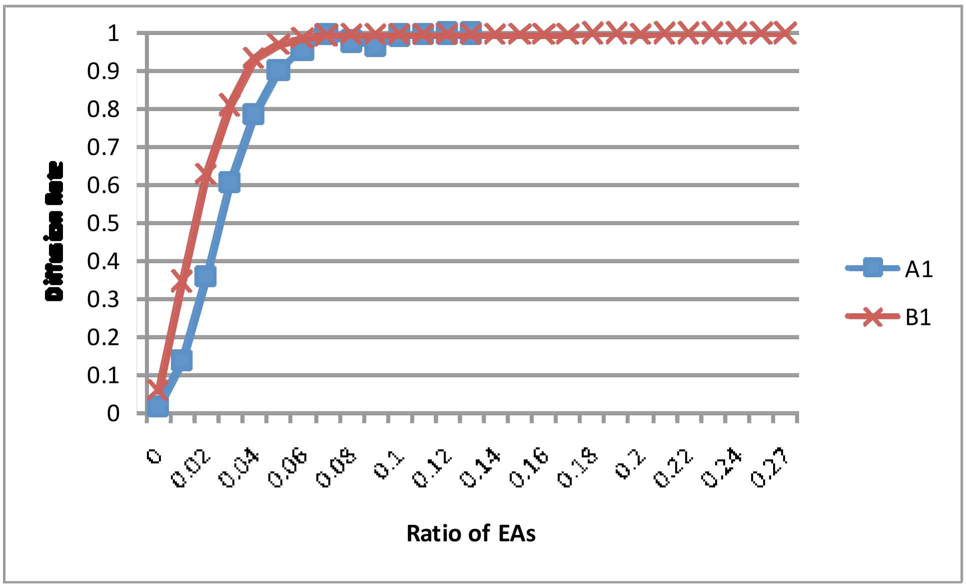


図6　Mechanisms

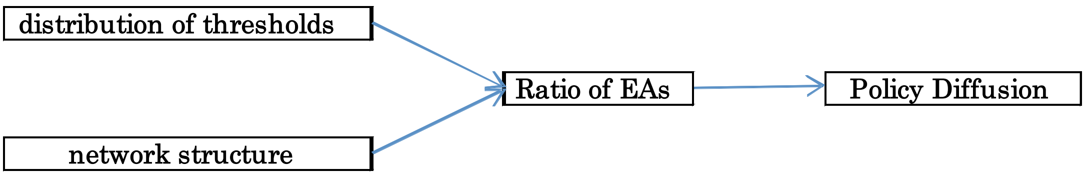
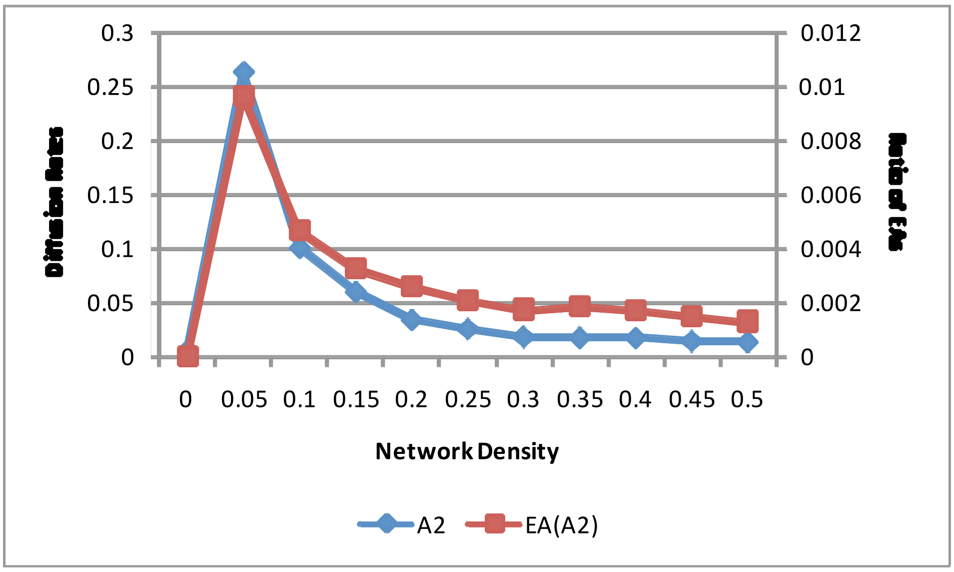



Figure.7 Relationships between Diffusion and Ratio of EAs (A-2 and B-2)

A-2



B-2

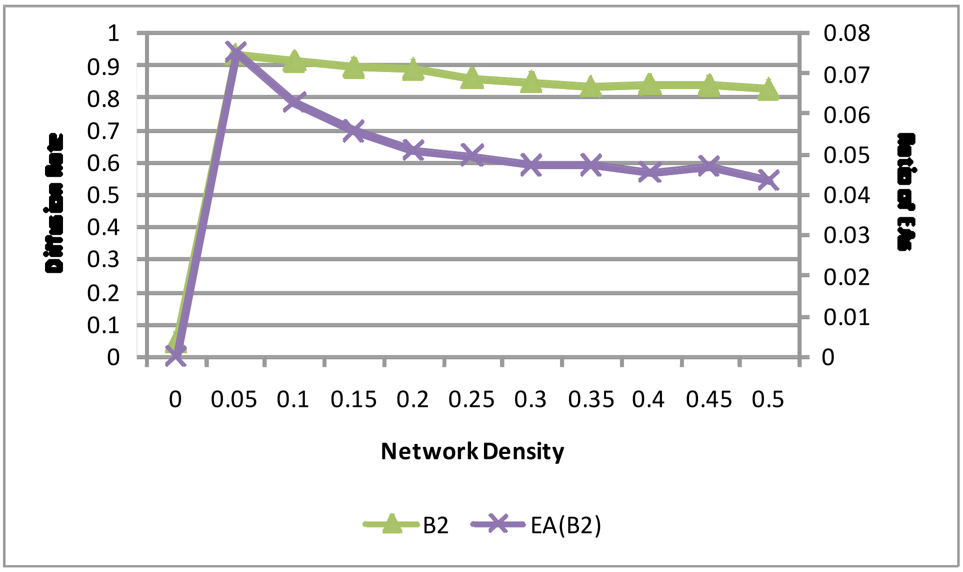
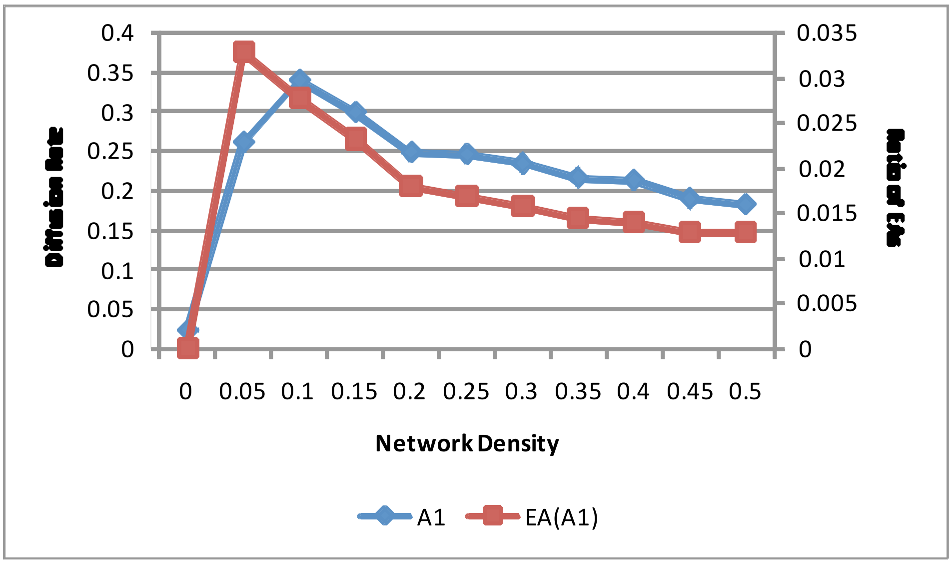



Figure.8 Relationships between Diffusion and Ratio of EAs (50 states)

A-1




B-1

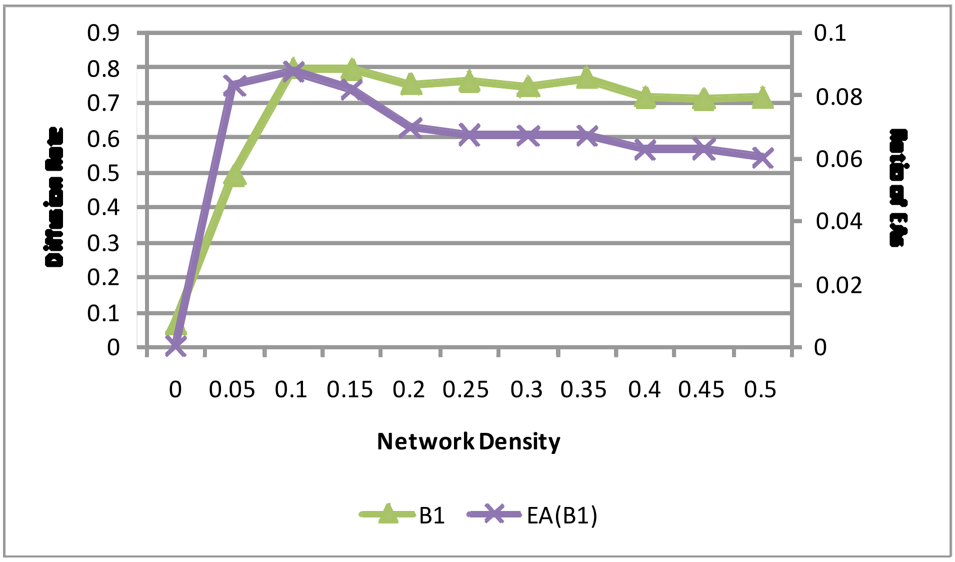
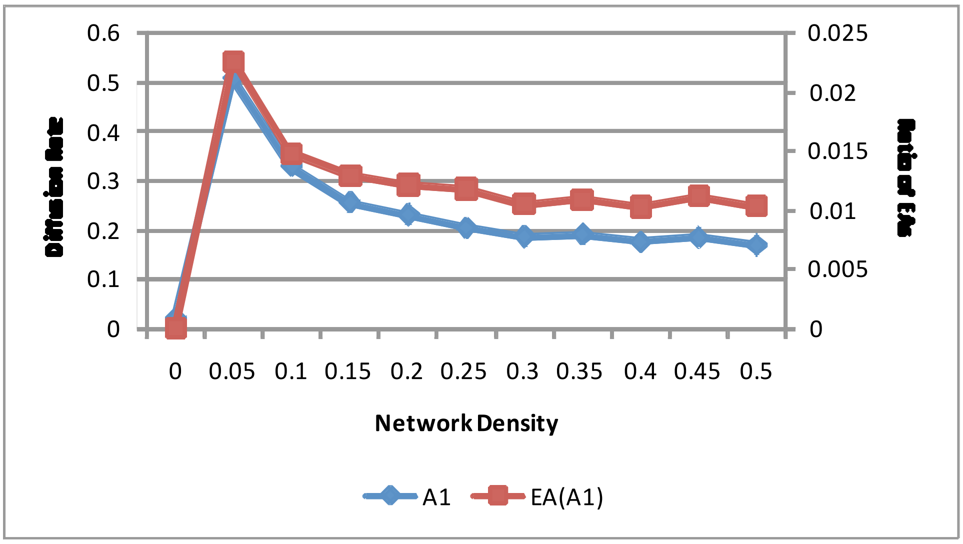
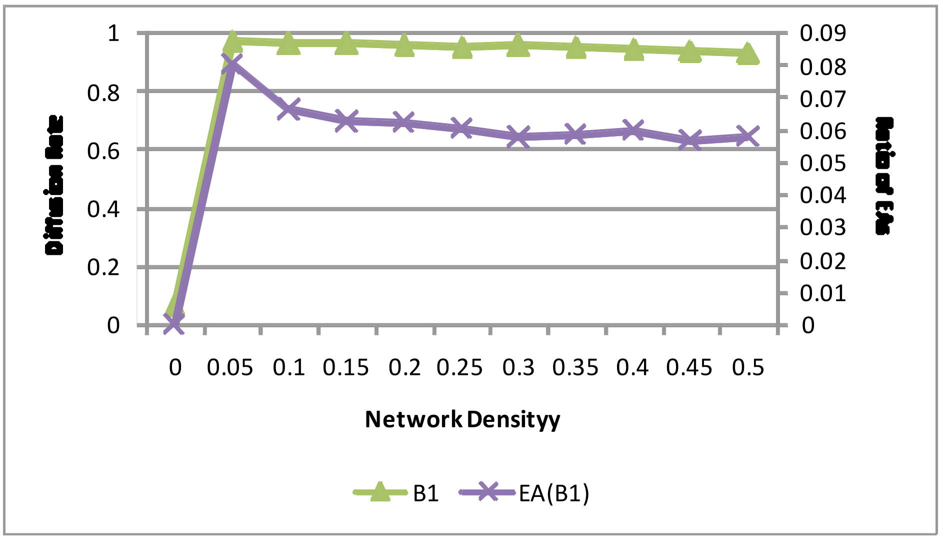



Figure.9 Relationships between Diffusion and Ratio of EAs (150 states)

A-1




B-1


Diffusion Rate
Ratio of EAs
Network Densityy
B1
EA(B1)