FINANCIAL CONTAGION: EVOLUTIONARY OPTIMISATION OF A MULTINATIONAL AGENT-BASED MODEL

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Abstract

Over the past two decades, financial market crises with similar features have occurred in different regions of the world. Unstable cross-market linkages during a crisis are referred to as financial contagion. We simulate crisis transmission in the context of a model of market participants adopting various strategies; this allows testing for financial contagion under alternative scenarios. Using a minority game approach, we develop an agent-based multinational model and investigate the reasons for contagion. Although the phenomenon has been extensively investigated in the financial literature, it has not been studied through computational intelligence techniques. Our simulations shed light on parameter values and characteristics which can be exploited to detect contagion at an earlier stage, hence recognising financial crises with the potential to destabilise cross-market linkages. In the real world, such information would be extremely valuable in developing appropriate risk management strategies.

Key Words: Financial Contagion, Minority/Majority Game, Agent-Based Model, Evolutionary Parameter Optimisation

JEL Classification: C63, C73, F37

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1. INTRODUCTION

Emerging markets have experienced a variety of financial crises over the past twenty years (e.g. Mexico in 1987, Asia in 1997, Russia in 1998, etc.), with shocks originating from one country being transmitted to its neighbours. This has been described as contagion or interdependence (King and Wadhwani, 1990; Forbes and Rigobon, 2002; Caporale et al., 2005). In order to distinguish between the two, one should compare linkages between markets in stable and crisis periods: a 'significant' increase in cross-markets linkages after a shock to a group of countries is defined as 'contagion' (Forbes and Rigobon, 2002), whilst stable linkages (through which the crisis is transmitted) are referred to as 'interdependence'. Detecting contagion at an early stage would make crisis management more effective. If shocks are transmitted through stable cross-market linkages, then countries experiencing them might be able to deal with crises by adopting policies to improve economic fundamentals. If instead shocks are propagated even though the fundamentals are sound, then IMF intervention might be appropriate (Caporale et al., 2005).

Since the seminal paper by Fama (1970), markets have often been thought of as being efficient. However, the empirical evidence is rather mixed (LeRoy, 1989). Consequently, agent-based models have become increasingly popular in recent years as an alternative approach to modelling financial markets (see LeBaron, 2000 for a review). Such models are based on artificial markets populated with heterogeneous agents with learning optimisation capabilities. They stress interactions, and learning dynamics in groups of traders learning about the relations between various factors. For example, Frankel and Froot (1988), Kirman (1991) and De Grauwe et al. (1993), focus on strategies that are used to trade a risky asset. Developments in computer technology have made it possible to model the behaviour of agents adopting a variety of complex strategies, allowing their behaviour to evolve over time in response to past performance. Lettau (1997) sets up an artificial financial market with a set of heterogeneous learning agents. The model is used to decide how to distribute wealth between a risky and a risk-free asset. A Genetic Algorithm (GA) is applied for obtaining the optimal parameters in various specifications for the portfolio policy. Generally speaking, these artificial markets with heterogeneous behaviour appear to be closer to real world markets. Shimokawa et al. (2007) build an agent-based equilibrium model which is consistent with the well-known stylized facts characterising financial markets; it appears that many of them can be explained by modelling traders as being loss-averse.

A branch of the literature on financial crises focuses on forecasting the outset of crises by developing early warning systems (Kaminsky et al., 1998; Kaminsky, 1999; Reagle and Salvatore, 2000). We build a multinational mixed-game agent-based model, as a first step in developing an early warning system for financial contagion. Existing studies have shown that irrational choices by noise traders lead to the emergence of herding behaviour and other risk factors (De Long et al., 1990; Cont and Bouchaud, 2000; Alfarano, 2006). Therefore we include noise traders and herding behaviour in our simulation setup in order to analyse contagion.

We take a mixed-game approach, which is based on the minority game model introduced by Challet and Zhang (1997) and then extended by Gou (2006). This is an effective framework for studying more realistic and complex markets. Evolutionary Programming (EP) is also adopted to obtain optimal estimates of the model parameters – this has already been used very successfully in many combinatorial optimisation problems (Yao et al., 1999). Our multinational model is estimated using time series data from the stock markets of Thailand, South Korea and Hong Kong up to the Asian crisis of 1997. The aim is to detect contagion at an early stage by analysing the simulation parameters and their characteristics, and therefore enable policy-makers to recognise financial crises with the potential to destabilise cross-market linkages. In the real world, such information would be extremely valuable for taking appropriate risk management decision. Thus our analysis will contribute to developing a framework for the management of financial crises.

2. MIXED-GAME MULTINATIONAL MODEL

2.1. Minority Game

The Minority Game (MG) was developed by Challet and Zhang (1997), and later on used to model the market behaviour of heterogeneous agents (Kalinowski et al., 2000; Challet et al., 2001; Johnson et al., 2001; Jefferies et al., 2004; Chen et al., 2008). While the formulation of the original MG model allows no communication, Kalinowski et al. (2000) develop a model where agents communicate with each other, and some of them are able to cooperate due to self-organization. Challet et al. (2001) analyse the stylized facts of financial markets using an MG based approach. Jefferies et al. (2001) and Johnson et al. (2001) build on minority games and develop Grand Canonical games, using that approach in a multi-agent game model to predict future movements in financial time-series. Improved forecasting accuracy is achieved when adding majority game agents, who play together with the minority game ones in a mixed-game model (Chen et al., 2008).

The basic MG structure involves an odd number N of market players, each of whom has to choose an action (buy or sell) every time period. The two possible actions are denoted as $\{+1,-1\}$. The players who have made the minority choice win the game in the corresponding period. Market participants work with limited memory, and can only rely on information about the winning side choice in the last M periods. An agent makes the next-step decision, based on his own strategy table (private information), and on the M-size record (public information) available to all market participants. The M-size string at time t is denoted by μ_t, $\mu_t = (\chi_{t-m-1},\ldots,\chi_{t-1})$, where χ_t stands for the winning sign in period t. There are 2^M possible winning-choice histories that can be assigned to the string μ_t, as shown in the first column of Table 1. That results in 2^{2^M} possible strategies for each player. Each agent works with K strategies in his decision table, where $K << 2^{2^M}$, and is not aware of the decision tables of other players. In a decision table, a strategy recommends a fixed action for each possible history string μ_t. At time t, an agent i selects one of the strategies available to him, and takes the action recommended by that strategy. The selection is based on the string μ_t, and the action taken is denoted by $\alpha^{\mu_t}_{\pm,i}$.

Table 1: *Example decision table of agent i, for M=3, K=2.*

μ_t	$S_{1,i}$	$S_{2,i}$
-1, -1, -1	-1	+1
-1, -1, +1	+1	-1
-1, +1, -1	-1	+1
-1, +1, +1	+1	+1
+1, -1, -1	-1	-1
+1, -1, +1	-1	+1
+1, +1, -1	-1	+1
+1, +1, +1	+1	-1

We randomly draw K strategies for each player, and as the strategy pool is quite large, this assures that players have heterogeneous decision tables. Strategy j for player

i is denoted with $S_{j,i}\ (j=1...K, i=1...N)$. Table 1 shows a decision table when the number of available strategies to an agent is $K=2$, and the size of the memory or history string μ_t is $M=3$. Furthermore, each strategy collects a virtual point if its predicted action is on the winning side. A player makes the decision of $+1$ or -1, following the strategy with the highest virtual score in his decision table.

Finally, we summarize the actions of the population of agents at time t, and get the excess demand $A_t = (\alpha_1^\mu + \alpha_2^\mu + ... + \alpha_N^\mu)$. The minority side wins the game, therefore the sign chosen by the minority of market participants at time t is $\chi_t = -sgn(A_t)$. The new history string is then constructed as $\mu_{t+1} = (\chi_{t-M+1}, ..., \chi_t)$.

2.2. Model Structure

Gou (2006) extends the MG by adding majority game players and formulating a mixed-game model. The odd number of agents N is divided into two groups, where $N1$ is the number of majority game players and $N2$ is the number of minority game players. Similarly, $M1$ and $K1$ denote the memory size and the size of strategy tables for majority game players, while $M2$ and $K2$ denote the same properties for minority players. The approach adopted by the majority players only differs in the condition of win: an agent wins if his action is on the majority side. Thus the two types of players will record opposite winning signs for the same market move. Fox example, a price increase implies that the majority of players have selected to buy, and the minority to sell. The winning action for a majority player is buying, and for a minority player is selling. Therefore, the sign χ_t chosen by majority players for the record string μ_t at time t is $\chi_t = sgn(A_t)$. The agents also collect virtual points for their strategies over time windows denoted with *T1* for majority players and *T2* for minority players. The price P_t at time *t* depends on the excess demand A_t, as formulated in (1):

$$P_t = \delta \sum_{i=1}^{N} a_{s_i}^{\mu_t} + P_{t-1}, \tag{1}$$

where the parameter δ is a scale factor.

For the purpose of simulating the linkage between two markets, we extend the mixed-game model and allow players to make investment decision based on information from both the domestic and the foreign market. The players still invest in the domestic market, and not in the foreign market. Let us assume that for player *i*, $i = 1,...,N_A$, the domestic market is *A*, and *B* is the foreign market. Therefore, player *i* faces two possible actions, based on the two strings μ_A and μ_B, from markets *A* and *B*, respectively. The probability $\pi_{i,t}^{A}$ of player *i* choosing an action at time *t* based on the domestic market *A* is given by equation (2), and the probability $\pi_{i,t}^{B}$ of that agent choosing an action based on the foreign market *B* by (3) (Serguieva and Wu, 2007; Caporale et al., 2008):

$$\pi_{i,t}^{A} = \frac{exp\left(\lambda^A \omega_{i,t}\right)}{exp\left(\lambda^A \omega_{i,t}\right) + exp\left(-\lambda^A \omega_{i,t}\right)} \tag{2}$$

$$\pi_{i,t}^{B} = 1 - \pi_{i,t}^{A}, \tag{3}$$

Here, λ^A is a scale factor, and the parameter $\omega_{i,t}$ corresponds to the virtual points. These depend on whether the player is winning or not in the domestic and foreign markets. If at time *t* the action based on the domestic market is the same as that based on the foreign market, then the parameter $\omega_{i,t}$ does not change. If the action based on market A wins the game and that based on market B loses then $\omega_{i,t}$ increases, otherwise $\omega_{i,t}$ decreases. All actions are taken in the domestic market.

Next, we consider simulating herding behaviour, as it has been identified as a major factor behind contagion. Herding behaviour arises due to irrational investment choices made by noise traders (Bouchaud and Cont, 1998; De Long et al., 1990). Such behaviour has been described and simulated using agent-based models (Alfarano et al., 2006; Serguieva and Wu, 2007). Kaizoji (2001) investigates the impact of herding behaviour on financial crises between correlated markets. We introduce here a proportion of noise traders into the multinational mixed-game model. They have a tendency to follow the sign of the final change in all markets. For example, in market A, the probability $\pi^{A}_{n,t,buy}$ of noise traders to take a buy action is defined by equation (4) (Caporale et al., 2008):

$$\pi^{A}_{n,t,buy} = \frac{exp(\zeta^{A}_{t})}{exp(\zeta^{A}_{t}) + exp(-\zeta^{A}_{t})}, \tag{4}$$

where

$$\zeta^{A}_{t} = \left(\frac{P^{A}_{t-1} - P^{A}_{t-2}}{P^{A}_{t-2}}\right)\tau^{A,A} + \left(\frac{P^{B}_{t-1} - P^{B}_{t-2}}{P^{B}_{t-2}}\right)\tau^{A,B}. \tag{5}$$

Here, P^{A}_{t} or P^{B}_{t} is the price in market A or B, respectively. The parameters $\tau^{A,A}$ and $\tau^{A,B}$ measure the sensitivity of noise traders in market A towards the market movement in A and B, respectively. If we extend the multinational model to more than two markets, then the definition of parameter ζ^{A}_{t} is given by equation (6):

$$\zeta^{A}_{t} = \sum_{z=A}^{Z}\left(\frac{P^{z}_{t-1} - P^{z}_{t-2}}{P^{z}_{t-2}}\right)\tau^{A,z}, \tag{6}$$

where $z \in \{marketA, marketB, marketC, ..., marketZ\}$. Finally, the probability $\pi^A_{n,t,sell}$ of noise traders in market A to choose a sell action is $\pi^A_{n,t,S} = 1 - \pi^A_{n,t,B}$.

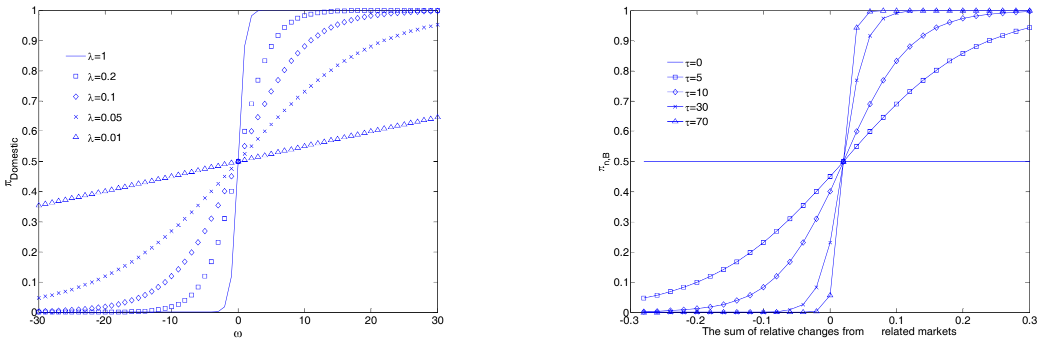

Figure 1. *The effect of the sensitivity factor and the scaling factor*
Left: the probability of smart traders taking action based on the domestic market, $\pi_{Domestic}$ calculated with equ. (2) for different values of the scale factor λ.
line $\lambda=1$; square $\lambda=0.2$; diamond $\lambda=0.1$; cross $\lambda=0.05$; triangle $\lambda=0.01$
Right: the probability of noise traders selecting to buy, $\pi_{n,B}$ calculated with equ. (4) for different values of the sensitivity factor τ.
line $\tau=0$; square $\tau=5$; diamond $\tau=10$; cross $\tau=30$; triangle $\tau=70$.

The features of definitions (2) and (4) are summarized as follows. At the very beginning, $\omega_{i,0} = 0$ in formula (2), and agents have the same probability to take an action based on the domestic or foreign market. If the action based on the domestic market wins the game and that based on foreign market loses, then the parameter is updated from 0 to $\omega_{i,1} > 0$. This will increase the probability $\pi^A_{i,1}$ of taking in the next period the action based on the domestic market. If such situation happens continually, that probability will get close to 1. If the opposite situation occurs, the probability will decrease until near 0, but meanwhile the probability of taking the action based on the foreign market will increase up to near 1. Considering definition (4), at the beginning or in equilibrium, the relative sum of market changes $\zeta^A_0 = 0$ and noise traders choose to buy or sell with the same probability. If changes in related markets sum up to a positive $\zeta_t^A > 0$, then the probability of noise traders deciding to buy is larger than that of choosing to sell, and vice versa. As Figure 1 shows, the factors λ and τ can be employed to adjust the speed of the probability getting close to 1 or 0. Therefore, λ and τ can be used to describe characteristics of different markets.

2.3. Evolving Model Parameters

Modelling real market movement requires optimal parameter configurations. With appropriate configurations, artificial markets can reproduce stylized features and phenomena of financial time series, such as fat tails (Bouchaud and Cont, 1998; Guillaume et al., 1997) or financial contagion (Caporale et al., 2008). Various parameter configurations can also be used to describe the characteristics of different markets. Evolutionary Programming (EP) is one of a class of paradigms for simulating evolution by iteratively generating increasingly appropriate solutions. It was introduced by L. Fogel (1962), and has been successfully applied to many numerical and combinatorial optimization problems (D. Fogel, 1991; D. Fogel, 1993). The EP procedure involves two major steps (Yao, 1999):

a) populations are generated as parents generate respective offspring via mutation;
b) better individuals from the parents and offspring populations are selected as parents for the next generation.

Following this procedure, we first initialize the population. Table 2 lists the parameters in the multinational agent-based model. Each individual in the initial population corresponds to a parameter configuration, where the values of the parameters are randomly initialised.

Table 2: *Parameters of the artificial stock market*

Parameters	*Description*	*Constraints*
N1	number of majority game players	N/2<N1<N, integer
N2	number of minority game players	1<N2<N/2, integer
N_noise	number of noise traders	0<=Nnoise<N/2, integer
M1	memory size of majority game player	2<M1<M2, integer
M2	memory size of minority game players	M2<10, integer
K1	strategy table size of majority game players	2<K1<K2, integer
K2	strategy table size of minority game players	K2<10, integer
T1	time widow of majority game players	30<T1<T2, integer
T2	time window of minority game players	T2<100, integer
δ	scale factor for pricing	$0<\delta<10$
τ	sensitivity factor	$0<=\tau$

Note: It is currently assumed that $\lambda=1$; in the future that parameter will also be included in the optimisation procedure.

The initial population is regarded as the parents of the first generation. For each parent, a single offspring is generated through mutation. Then, the fitness of all individuals is evaluated, and a tournament selection is applied to both parents and offspring, to generate the next parent population. The repetition of mutation and selection steps stops if the halting criterion is satisfied (see the pseudo-code below):

```
1. t = 0;
2. Initialize: Parents^t (N1, N2, Nnoise, M1, M2, K1, K2, T1, T2, δ, τ);
3. Iterate {
        Mutation: Offspring^t() = Mutation(Parents^t());
        Evaluate: FitnessFunction(Parents^t(), Offspring^t());
        Selection: P^(t+1)() = Selection(FitnessFunction(Parents^t(), Offspring^t()));
        If (halting criterion is satisfied)
              Stop;
        otherwise:
              t = t+1;
        }
```

In order to evaluate the fitness of individuals, we measure the performance of parameter configurations. The time series generated with the artificial stock market under particular parameter configuration are compared with the real time series of the target market. We use one individual parameter configuration for a number of simulations of the artificial market, and consider the mean fitness of those simulations as the final fitness value of the corresponding parameter configuration. Thus the fitness function of an individual in the population is formulated in (7):

$$f(P_{sim}) = \sum_{i=1}^{\theta}\sum_{t=1}^{T}\left|P_{real}(t) - P_{sim}^{i}(t)\right| \Big/ (\theta \cdot T)), \qquad (7)$$

where θ stands for the number of repetitive simulation, and the i th simulation's price time series is denoted by $P_{sim}^{i}(t)$, $i = 1,\ldots,\theta$. Also, the real time series in the target market is denoted by $P_{real}(t)$, and T stands for the size of the series used to estimate the model.

3. SIMULATION AND ANALYSIS

Our aim is to simulate the occurrence of financial contagion during a financial crisis. We focus on the behaviour of simulated price series under various parameter configurations. Under some configurations, the simulated series for the target market show little interdependence with the crisis-origin market, under any conditions. For other parameters, the simulated price series for the affected market exhibit strong linkages with the behaviour of the crisis origin, whether during a stable or a crisis period. Those behaviours do not simulate the most important feature of financial contagions, i.e. the significant increase in cross-market linkages.

The EP procedure outlined above is applied to the mixed-game multinational model in order to optimize parameter configurations for target real markets, and then those parameters are used to simulate the occurrence of contagion during the Asian financial crisis of 1997. The crisis originated in Thailand, and affected the markets in South Korea, Hong Kong, Indonesia, Malaysia and other Asian countries. Figures 2 and 3 show the behaviour of the markets in South Korea and Hong Kong in respect to

Thailand, over a horizon of 222 trading days, from 25/02/1997 till 31/12/1997. The first 111 days correspond to the pre-crisis phase, and the following 111 days represent the crisis phase. During the first phase, Thailand suffers an initial tumble and then rebounds, while South Korea and Hong Kong do not follow that tumble and their markets are unaffected. During the second phase, Thailand suffers another plunge and this is quickly reflected in the behaviour of South Korea and Hong Kong, and other Asian markets. We will simulate the markets in South Korea (SK) and Hong Kong (HK) as target real markets, in relation to the movement of the Thailand's (TH) stock market.

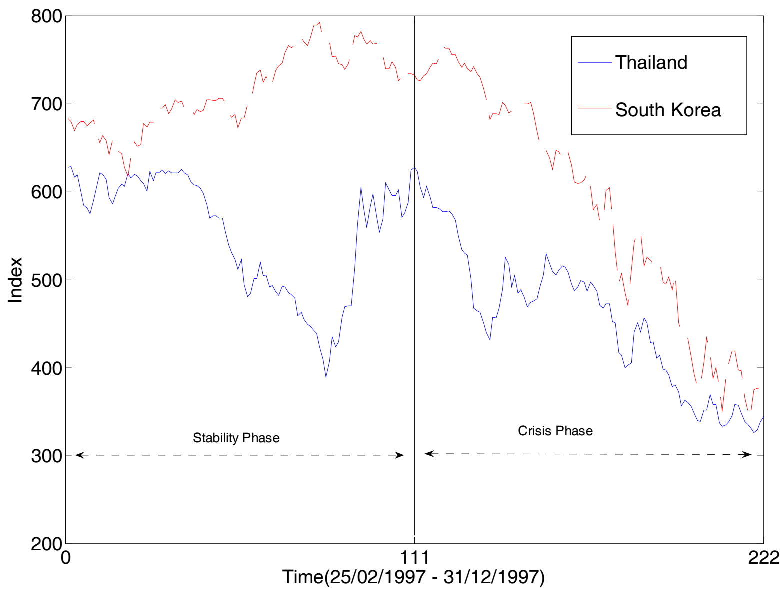

Figure 2. *Indices of Thailand's and South Korea's stock market, 25/02/1997 - 31/12/1997.* The solid blue line corresponds to the country where the crisis originated, Thailand, and the dash red line represents an affected market, South Korea. The left side corresponds to the pre-crisis phase, and the right side represents the crisis phase.

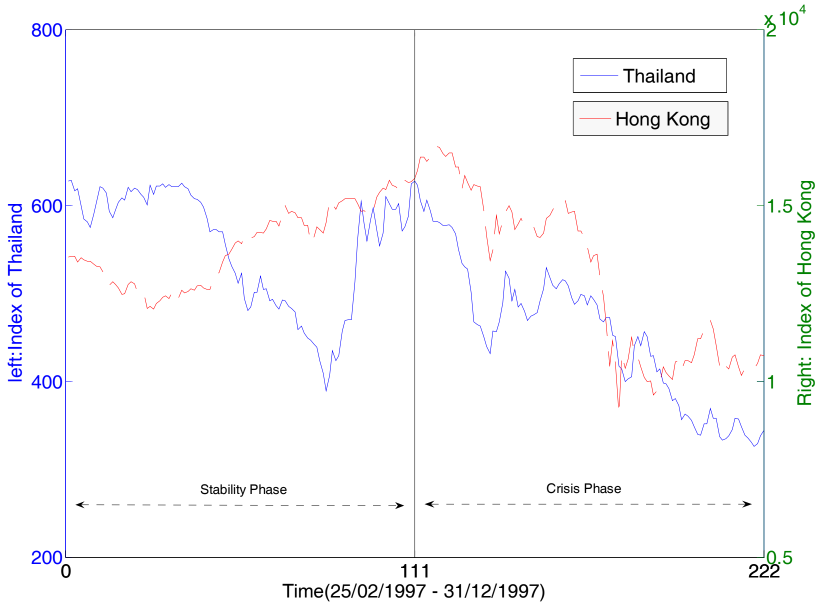

Figure 3. *Indices of Thailand's and Hong Kong stock market, 25/02/1997 - 31/12/1997.* The solid blue line corresponds to the country where the crisis originated, Thailand, and the dash red line represents an affected market, Hong Kong. The left side corresponds to the pre-crisis phase, and the right side represents the crisis phase.

Simulated markets are very sensitive to some of the parameters, e.g. N_{noise}, δ and τ. For the purpose of investigating their effects, we design some experiments under typical values for the rest of the parameters. The simulated price series of the affected market are shown in relation to the TH real market, and the real series of SK serves as the reference frame. Figure 4 depicts 10 simulations under an extreme configuration where there exists only one noise trader $N_{noise}=1$, while Figures 5 and 6 present another extreme configuration with a large number of noise traders $N_{noise}=99$ (the maximum for $N=201$). The simulations in Figure 4 do not reveal any linkages with the crisis-origin market. The results there correspond to a very small number of noise traders, and we can conclude that the sensitivity factor τ would not affect the simulations. The results in Figure 5 correspond to a very large number of noise traders; however, the parameter configuration includes an extremely small sensitivity factor $\tau=0$. These simulations still show no linkages between the affected market and the one where the crisis originated.

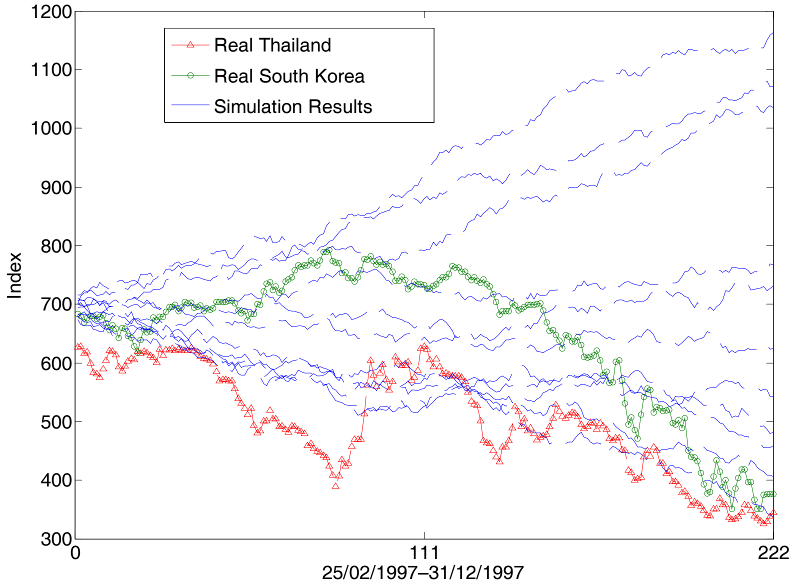

Figure 4. *Affected market simulation under a minimum number of noise traders $N_{noise}=1$.*
The adopted typical values for the rest of the parameters are:
N1=99, N2=101, N=201, M1=3, M2=6, K1=3, K2=6, T1=20, T2=60, δ=5, τ=3.

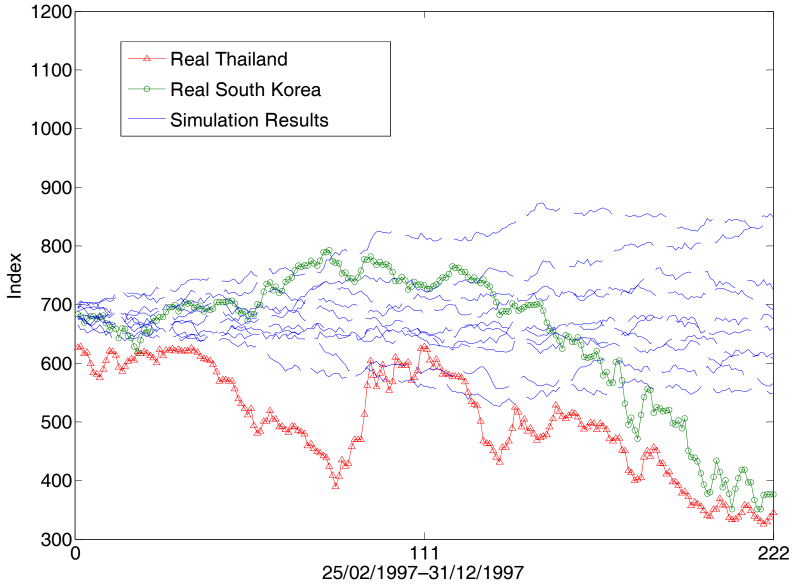

Figure 5. *Affected market simulation under a large number of noise traders and a minimum sensitivity factor, $N_{noise}=99$ (maximum for N=201) and τ=0.*
The adopted typical values for the rest of the parameters are:
N1=1, N2=101, N=201, M1=3, M2=6, K1=3, K2=6, T1=20, T2=60, δ=5.

Comparing the two figures, the fluctuation range of the simulated price in Figure 5 is narrower than that in Figure 4. This is because the parameter configuration in Figure 5 corresponds to markets without sensitivity $\tau=0$. Therefore, noise traders have equal probability to choose to buy or sell, and the maximum number of noise traders in the parameter configuration drives the simulated price series closer to random walks. In the next experiment, we increase the sensitivity factor up to $\tau=8$, while the other parameters stay fixed as in the configuration in Figure 5. Now the simulations in Figure 6 present a clear tendency to follow the crisis-origin market. A large number of noise traders combined with a high sensitivity factor result in the high interdependence between the simulated market and the crisis-origin market.

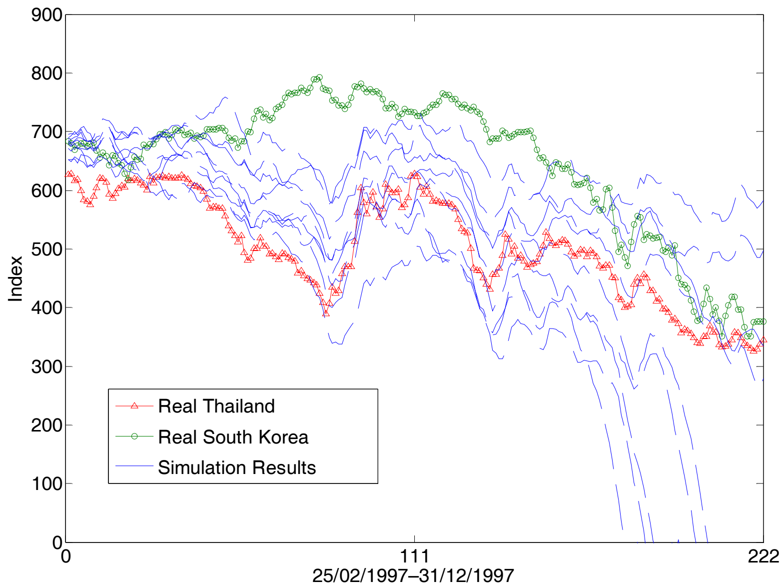

Figure 6. *Affected market simulation under a large number of noise traders and a high sensitivity factor* $\tau=8$.
The adopted typical values for the rest of the parameters are:
$N_{noise}=99, N1=1, N2=101, N=201, M1=3, M2=6, K1=3, K2=6, T1=20, T2=60, \delta=5.$

In the above three experiments, we have observed how the effect of the parameter N_{noise} is related to the effect of the sensitivity factor τ. Now consider the scaling factor δ. Due to the different market indices and trading volumes in each market, δ needs to be adjusted to assure that the simulated fluctuations are within the range of the specific targeted real market. For example, the experiments in Figure 7 are performed for different values of δ, under a typical parameter configuration of $N1=80$, $N2=101$, $N_{noise}=20$ and $\tau=10$. The results show that the fluctuation range of the simulated price series is quite sensitive to the scaling factor.

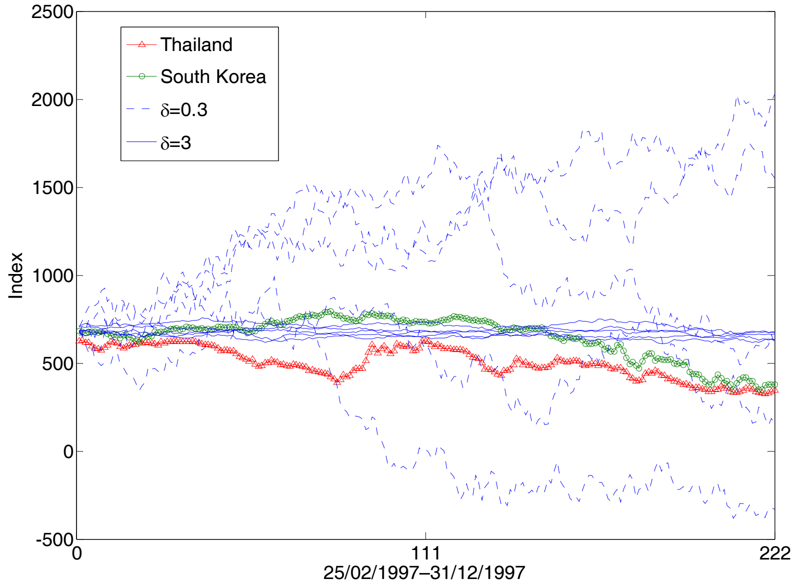

Figure 7. *Affected market simulation under different values of the scale factor* δ.
Five simulations are performed with δ=0.3 and another five simulations with δ=3.
The adopted typical values for the rest of the parameters are:
$N_{noise}=20$, $N1=80$, $N2=101$, $N=201$, $M1=3$, $M2=6$, $K1=3$, $K2=6$, $T1=20$, $T2=60$.

According to the definition of financial contagion given in Forbes and Rigobon (2002) and Caporale et al. (2005), this occurs when the correlation between the original market and the affected market increases significantly from a period of relative stability to a period of crisis; otherwise the phenomenon is defined as interdependence. Let us consider the correlation coefficient between the country from which the crisis originated, i.e. Thailand, and one of the affected markets, South Korea. The correlation coefficient in the pre-crisis phase is *-0.64*, while in crisis it is *0.92* (see Table 3). In the case of the other affected market, Hong Kong, the correlation coefficient pre-crisis is *-0.85*, and during crisis *0.86* (see Table 3).

Table 3. *Estimated parameter configurations*

			Random Estimation	EP Estimation	Target Value
South Korea	Parameters	$N1$	25	7	
		$N2$	151	174	
		N_{noise}	25	20	
		$M1$	3	3	
		$M2$	6	8	
		$K1$	4	4	
		$K2$	6	7	
		$T1$	12	80	
		$T2$	60	131	
		δ	2.2	2.36	
		τ	30	18.1459	
	Correlation Coefficient	Pre-crisis	0.63	0.28	-0.64
		Crisis	0.94	0.91	0.92
Hong Kong	Parameters	$N1$	28	4	
		$N2$	131	190	
		N_{noise}	42	7	
		$M1$	3	5	
		$M2$	6	8	
		$K1$	4	4	
		$K2$	6	7	
		$T1$	12	18	
		$T2$	60	106	
		δ	0.2	0.04368	
		τ	40	12.264	
	Correlation Coefficient	Pre-crisis	0.48	-0.11	-0.52
		Crisis	0.96	0.84	0.86

To be able to simulate contagion, we estimate optimal parameter configurations for the artificial stock market, applying the EP procedure. In the procedure, the number of generations is sets to 200, the population size is 20, the number of competitors for to tournament selection is to 10, and the number of repetitions for each individual parameter configuration is 10. The optimal parameter configurations are presented in Table 3. In the case of SK and TH, the optimal parameter configuration is *N1=7*, *N2=174*, *N3=20*, *M1=3*, *M2=8*, *K1=4*, *K2=7*, *T1=80*, *T2=131*, δ*=2.36* and τ*=18.1459*. Simulations with this configuration are shown in Figure 8. In the case of HK and TH, the optimal configuration is *N1= 4*, *N2=190*, *N3=7*, *M1=5*, *M2=8*, *K1=4*, *K2=7*, *T1=18*, *T2=106*, δ*=0.04368* and τ*=12.264*. Simulations with these parameters are plotted in Figure 9. Both Figures reveal that the simulations track reasonably well the contagion-affected markets, and that the optimal parameter configurations allow the simulation of financial contagion.

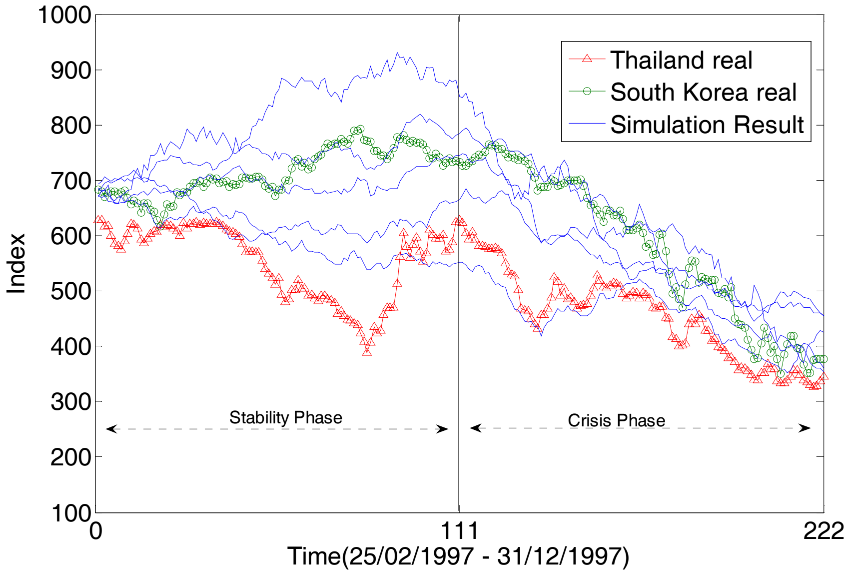

Figure 8. *Simulations with the optimal parameter configuration for South Korea as the affected market and Thailand as the contagion-origin market.*
triangle line: real index movement in the contagion-origin market of Thailand, circle line: real index movement in the contagion-affected market of South Korea, solid line: simulated index for the contagion-affected market of SK based on the parameters in Table 3 (time horizon 25/02/1997-31/12/1997)

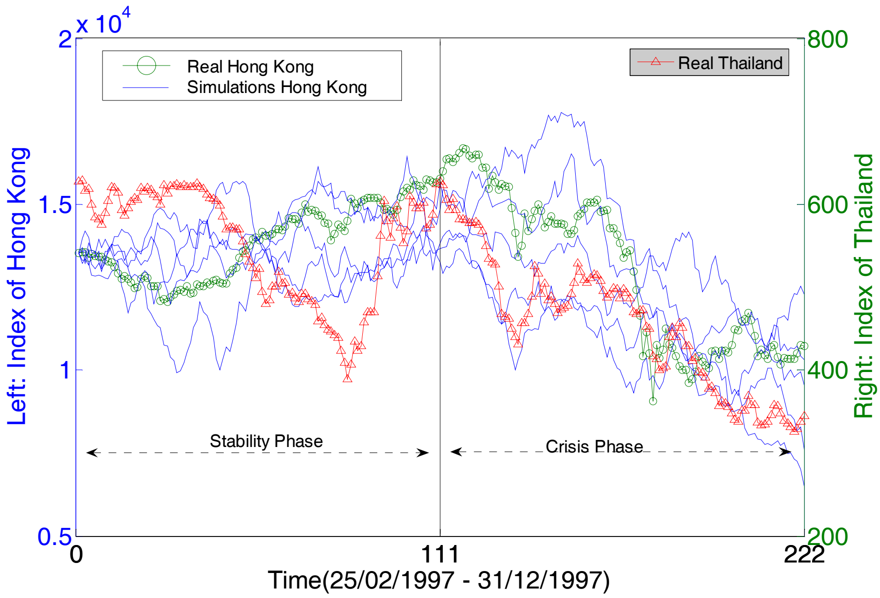

Figure 9. *Simulations with the optimal parameter configuration for Hong Kong as the affected market and Thailand as the contagion-origin market.*
triangle line: real index movement in the contagion-origin market of Thailand, circle line: real index movement in the contagion-affected market of HongKong, solid line: simulated index for the contagion-affected market of HK based on the parameters in Table 3 (time horizon 25/02/1997-31/12/1997)

In our previous work (Caporale et al., 2008), we identify appropriate parameter configuration, adopting a procedure outlined in Gou (2006). That approach is referred to here as random estimation. Table 3 summarizes the simulation results under parameter configurations identified through random estimation and EP estimation. With the EP estimation, the average correlation coefficient between the contagion-origin TH market and the simulated affected SK market is *0.28* in the pre-crisis phase rising to *0.91* in crisis. Comparing these with the corresponding correlation values of *0.63* and *0.94* under random estimation, we conclude that the EP procedure approximates better the real correlation values of *-0.64* and *0.92*, respectively. A similar conclusion can be drawn when considering the simulated affected HK market. Under EP estimation, the correlation coefficient with the contagion-origin TH market is

-0.11 pre-crisis rising to *0.84* during the crisis, while the corresponding values under random estimation are *0.48* and *0.96*. The EP procedure better approximates the real correlation coefficients of *-0.52* pre-crisis and *0.86* during crises. Notice that the correlation coefficient is not explicitly targeted when evaluating the fitness of individual configurations in the EP procedure. In conclusion, the empirical cases provide evidence that the EP estimation performs significantly better and is more suitable for simulating contagion.

4. CONCLUSIONS

In this paper, we propose a multinational agent-based model to simulate contagion occurring during financial crises. The aim is to capture characteristics of linked financial markets contributing to the occurrence of contagion. These are captured by identifying configurations of the agent-based model capable of simulating contagion. We use real data for Thailand, where the Asian crisis of 1997 originated, and simulate the movements of the affected markets of South Korea and Hong Kong. The simulation results are particularly sensitive to some of the parameters in the multinational agent-based model, and their effect is further investigated. Then an evolutionary programming algorithm is adopted for estimating the optimal parameter configuration. The experimental results indicate that EP estimation outperforms earlier procedures suggested in the literature.

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