Human behavior and tipping point of bank runs

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**HUMAN BEHAVIOR AND TIPPING POINT OF
BANK RUNS**

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SCHOOL OF SOCIAL SCIENCES

2019

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A thesis submitted to the Nanyang Technological University
in fulfilment of the requirement for the degree of
Doctor of Philosophy

2019

Statement of Originality

I certify that all work submitted for this thesis is my original work. I declare that no other person's work has been used without due acknowledgement. Except where it is clearly stated that I have used some of this material elsewhere, this work has not been presented by me for assessment in any other institution or University. I certify that the data collected for this project are authentic and the investigations were conducted in accordance with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

[31 March, 2019]

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Date

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[Huang Qiao]

Supervisor Declaration Statement

I have reviewed the content of this thesis and to the best of my knowledge, it does not contain plagiarised materials. The presentation style is also consistent with what is expected of the degree awarded. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accordance with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

[31 March, 2019]

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Date

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[Huang Weihong]

Authorship Attribution Statement

This thesis contains materials from 2 papers published in the following peer-reviewed article and journal where I was the main author.

Chapter 2 is published as Weihong Huang and Qiao Huang. "Liquidity Shock, Animal Spirits and Bank Runs." Essays in Economic Dynamics, Springer: 225-243 (2016). DOI: 10.1063/1.5022222.

Chapter 3 is published as Weihong Huang and Qiao Huang. "Connectionist agent-based learning in bank-run decision making." Chaos: An Interdisciplinary Journal of Nonlinear Science **28**(5): 055910 (2018). DOI: 10.1007/978-981-10-1521-2_13.

The contributions of the co-authors for both publications are as follows:

Associate Professor Weihong Huang is my supervisor, the initial idea of research came out from our discussion and exploration, the whole research was carried out by me under his supervision. The reason of putting his name as first author in the above-mentioned published papers is out of traditional respect and academic courtesy.

I confirm that I am the main author and contribute significantly for both publications.

[31 March, 2019]

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Summary

Since the end of WWII, economists generally believed that the phenomenon of bank runs had died away. However, sufficient evidences in last two decades indicate the revival of bank run, supported by the facts that numerous banking panics occurred repeatedly with the traditional and new styles. Examples include the runs on the American firm Countrywide Financial in August 2007, on Jiangsu Sheyang Rural Commercial Bank in March 2014, on all Greek banks in June 2015, on Home Capital Group in April 2017. Therefore, classical economic and financial theories about bank runs need to be challenged, and this thesis will explore the human behavior and tipping point of bank-run phenomenon.

It is a simple logic that bank runs happen when depositors fear losses, but there is no a clear signal in the market that when this fear will lead to a run on banks. First two contradictory views of bank-run classical models are reviewed here. Bank runs are caused by problems with fundamentals of banks (e.g. Allen and Gale ,1998; Calomiris and Mason, 2003) or coordination failure among depositors (e.g. Diamond and Dybvig, 1983). Facing the problems in these classical models, the animal spirit random variable, or sunspot equilibrium and tipping point of bank run are introduced. Animal spirit will trigger this risk, and bank runs will become

inevitable when passing the tipping point even the environment seems relatively good.

To consider the bounded rationality of human beings, a bottom-up behavioral model is built to model bank runs (Huang and Huang, 2016). It is shown with agent-based modeling approach that animal spirits of the depositors together with endogenous optimism and pessimism can cause liquidity shock. In particular, bank run will be triggered if the animal spirits reaches to a tipping point. The model is tested with a set of empirical data, which shows that the effect of animal spirits is significant in reality.

To further explore the internal mechanism of how the animal spirits can trigger the bank-run phenomenon, the nonlinear dynamic probabilities of bank runs based on the global games approach is simulated from the perspective of connectionist model of decision making. (Huang and Huang, 2018). In this framework, heterogeneous agents hold highly correlated but different beliefs about the real payoff. When real-world bank runs involve diverse elements, it is hard to conclude bank runs are merely because of miscoordination (e.g. Diamond and Dybvig, 1983) or the deterioration of the quality of the bank's assets (e.g. Allen and Gale, 1998). Besides, the probability of bank runs is neglected by the classical models. Therefore, an internal "mental model" that agents have integrated cognitive-affective network is proposed. As the affective processes play significant role in decision making, the pessimistic announcement may cause bank run even the fundamental economy is good. Both the rise of late payoff R and early payoff r will decrease the effect of affective processes. The increased risk sharing, that is, the increase of r might or might not increase PBR, which is based on the level of uncertainty. The increasing of late payoff is beneficial for preventing bank runs, but it is hard for bank to offer enough payoff when the economy is too bad.

After the conclusion that animal spirits exist in bank runs and an internal mental mechanism to show the reason behind this phenomenon has been proposed, there are still two key points for the estimation of PBR. First is the setting and robust check for affective processes. To be specific, the parameter in affective magnitude

section should be selected to effectively predict PBR. Second is the prediction of tipping point with different combination of early and late payoff. Thus, it is time to concern on the parameters and critical values in bank-run estimation. For the adjustment of affective-process parameters, the granger causality test and impulse response function are adopted. Based on the selected parameters, the results we have proved in the internal model are correct, and the affective-process effect becomes clearer. To figure out the tipping-point effect by threshold autoregressive (TAR) model, the result shows that the increased risk sharing, that is, the increase of early payoff r will cause this kind of effect, but it does not impact on the tipping-point value. On the other hand, the increase of late payoff R will increase the tipping point, which means that it will prevent even eliminate the bank-run phenomenon. Generally, when PBR passing 0.2, it is possible that bank run happens, and when PBR passing 0.25, it becomes very easy to run on bank and it is too late to restrain.

This study is one of pioneers that links agent-based computational economics, behavioral economics, neuroeconomics and econometrics. The findings in this research may shed some light on all the investors, bankers and policy makers. The further research will come from the setting for magnitude of announcement in different markets and the spread of this announcement in different social networks.

Chapter 1

Introduction

Ten years have passed from the financial crisis in 2007, but the crisis is never ending. Although the event is a disaster for the world's economy, it is also a historical opportunity for many new industries. During this decade, the economy recovers and many new forms generate, such as the Artificial Intelligence (AI) has become popular influencing on all-pervasive in life. Most of companies, organization or industries have to reform or disappear, especially in the financial sectors. However, our human nature is unchanged, and the joking mistakes or biases still happen in our daily life. As Warren Buffett's saying goes the time to be greedy is when others are afraid, and the time to be afraid is when others are greedy. Greed and panic are still the themes of human beings, which means the omnipotent economic man exists only in the assumption. The insurance for our deposit develops all the time, and our wealth becomes safer. However, every now and then we still hear the news about bank run, e.g. some countries or some places queue long outside the bank to withdraw money, the money in ATM drains in the country, the shadow bank run cause the new panic, etc. Bank run might have become outdated story, but it is still alive and happening all around the world.

1.1 Bank Run

Diamond and Dybvig (1983) (hereafter DD) proposed an influential analysis of bank runs. The driving force for a bank run is the fact that in a fractional reserve system, a bank does not hold enough liquid assets to serve all its depositors, should they all decide to withdraw their deposits at the same time. In other words, bank runs are the outcome of pure coordination failure. There are two self-fulfilling symmetric pure-strategic Nash equilibrium in DD's model. one equilibrium shows the situation that people withdraw money from bank only when they need cash. whereas the other equilibrium shows that all depositors run on the bank triggered by fear that the bank cannot return them. When depositors run on a bank, they make withdrawals that can overwhelm the bank and make the situation worse, which pushes the bank to fire sell its long-term investment and end up as a self-fulfilling prophecy. When this happens, even banks with good operation and healthy assets may be prone to bank runs because depositors believe they are, or might become, insolvent. This paper establishes the theoretical possibility that non-fundamental factors could be responsible for crisis outcomes.

The rivalrous view (e.g. Allen and Gale, 1998, hereafter AG) is that the main reason of bank runs is due to negative information on the banks asset quality and performance. They believed that bank runs arise endogenously as a consequence of the standard deposit contract in a world with aggregate uncertainty about asset returns. From DD perspective, bank runs can be pure sunspots, and the changes in the economic base may not be necessarily the reason of bank run, while AG believed that bank runs happens due to business cycle.

However, to empirically test these two classical theories of bank runs is difficult. It can be concluded that the cause of bank run is very ambiguous and opens to diverse interpretations. The classical model allows the existence of different possibilities of bank run, that is, bank run can be caused by panic or/and fundamental economic problems, yet no probability of such individual phenomenon is addressed. Yet, it is

obvious that knowing the probability of these possibilities of a bank run is crucial for policy making and investment analysis. Therefore, to have a model removes the multiplicity of equilibria is desirable. This kind of model allows us to identify an economically plausible equilibrium from the different equilibria, and it infers the probability of bank run from this equilibrium. To figure out this probability, as a human being, instead of just employing mathematics and strong economic analysis, some noneconomic factors would lead us to run on the bank without shyness and doubt. That is, a new foundation is needed to consider the interplay of heterogeneous agents (Lux and Westerhoff, 2009) and agents themselves (Chen, 2017).

1.2 Animal Spirits

The term Animal Spirits was introduced by Hume (1739) to seek the origins of human decision making as major field of human nature. However, we could hardly see any research of economics related to this concept until it is revisited by Keynes (1936). He suggested that human sentiments or feelings (e.g. optimism or pessimism) would drive the aggregate economy. Animal spirits, instead of just employing mathematics and strong economic analysis, would lead people to act without shyness and doubt, or even they would not react at all. This concept lays at the core of Keynes's explanation for the Great Depression, however, during 1970s, the New Classical Economics arose and criticized that animal spirits should be not considered at all.

During the waived period of animal spirits, the valuable development reappears in two new fields: Computational Economics and Behavioral Economics. In Computational Economics, adaptive learning mechanism, which consists of two kinds of rules: fundamentalist and chartist rules, has often been applied in literature (e.g. Brock and Hommes, 1997; Dawid, 1999; Grauwe and Grimaldi, 2006). In Behavioral Economics, it is called dual system theory (e.g. Epstein 1994; Stanovich

and West 2000; Peters and Slovic, 2000; Kahneman and Frederick, 2002; Loewenstein and O'Donoghue, 2004). This mechanism divided animal behavior into deliberative processes that assess options with a broad, goal-based perspective within the standard economic conception and affective processes encompassing emotions and emotional drives. It is noticed that the affective system is inherently myopic, while the deliberative system cares about both short-term and long-term outcomes. Pfajfar and Zakelj (2009) find out the experimental evidence in support of these two rules for inflation forecasts in a new Keynesian model. Some scholars begin to research the same topic with both methodologies together and get a more comprehensive result (e.g. Anufriev, Bao, Sutan and Tuinstra 2015; Anufriev, Bao and Tuinstra 2016)

Recently, the study of animal spirits was renewed by Akerlof and Shiller (2009) and began to raise greater concern. Different from seeking to minimize as much as possible in pure economic motivation and rationality, they explain the deviations that actually do occur and that can be observed. Besides, they generally account for the impact of animal spirits in the bank runs and point out that the dramatic loss of confidence is to be blamed to cause bank runs, and also inevitable even though some insurance measures have been set up. Grauwe (2012) brings animal spirits into the DSGE framework, and it is the first time that this concept is combined with new Keynesian model. He breaks the assumption of rational expectation that gives an endogenous shock with non-normal distribution. He also points out that when the sample is large enough, the uncertainty is transformed into measurable risk, which means that the deterministic trend is observable. Assenza, Brock and Hommes (2017) consider both animal spirits and expectations' heterogeneity together, and they mention that these two factors are indeed important drives of macroeconomic instability amplifying economic crises and slowing down recovery. Reiner and Westerhoff (2017) take a survey on rigorous modeling of animal spirits in macroeconomics. They distinguish that animal spirits are viewed from two different perspectives in these models, one points to a weak level of animal spirits when

agents choose one of two attitudes, strategies or similar alternatives; while the other considers agents with herd mentality and assuming the majority knows better. Therefore, with the development of animal spirits theory, considering the bank run phenomenon from the perspective of endogenous shock becomes possible.

1.3 Animal Spirits (Sunspots) in Bank Runs

Animal Spirits, or called Sunspot random variable, not the fundamental economy, can cause bank-run phenomenon. As heterogeneity of beliefs is an origin of sunspot equilibria (Cass and Shell 1983), bank runs might be caused by animal spirit as human nature in this scenario. The terms “animal spirits”, “sunspots”, “self-fulfilling beliefs”, etc. refer to the noise in the market that not related to economic fundamentals. Jevons (1884) first proposed the concept of "sunspot", which used the actual sunspot activity to explain the business cycle. The first sunspot model (Shell, 1977) worked out the sunspot equilibria for a government borrowing scheme in an overlapping generation model. At this point, sunspots purely represent extrinsic uncertainty that the economic fundamentals are assumed to be unaffected by the level of sunspot activity (Cass and Shell, 1983).

Some severe economic meltdown has been ascribed to ‘panics’ or ‘bursting bubbles’ in financial markets, such as the bank-run phenomenon. When the environment become chaotic, any information in the market might shift the strategies for the depositors. Diamond and Dybvig (1983) describe that there is a second equilibrium that depositors withdraw from the bank, although they have no immediate need for the money. They suggest that this might occur if one relies on some commonly observed random variable in the economy to choose from bank run equilibrium and the good equilibrium, e.g. there is a “sunspot” that may occur with positive probability less than one (Cass and Shell, 1983). Peck and Shell (2003, 2005) proved that sunspots will play a role in panic-based runs. Even when there is partial suspension of convertibility, panic based bank runs can be part of a sunspot equilibrium. If a sunspot occurs, the agents select the bank run equilibrium, and if

the sunspot does not occur, they select the good equilibrium. This suggests that the agents run on the bank due to the sunspot random variables.

1.4 Tipping Point

In 2000, Gladwell and Malcolm define tipping points as the moment of critical mass, the threshold, the boiling point. To be specific, it refers to one dramatic moment in an epidemic when everything can change all at once. Silver (2008) has pointed out that a Tipping-Point State is defined as a state that would be most likely to alter the outcome if it were decided differently. Besides, the latest and exhaustive interpretation has been given by Lamberson and Page (2012). They define tipping point as discontinuities in the relationship between present conditions and future states of the system. In other words, it is regarded as the action or outcome that dramatically reduces uncertainty about the future. The authors divide tipping point into two categorical distinctions, which describe the tipping point by scientific division. Beyond the pure theory, Sole (2011) has showed various models with the feature of tipping point in the phase transitions. Such process focuses on the properties of the interaction structure, which would undergo a dramatic shift when passing the tipping point. In the bank-run phenomenon, the spread of panic would increase dramatically when the surroundings is in chaos. Namely, some stimuli would tip the contagion, and bank runs is nearly formed above the tipping point. This implies the reason that why the economic behavior would always be explained by the unstable equilibrium, and actually in that case some forces in nature are driving us strikingly to a deterministic tendency.

Sometimes, the bank-run probability is very small, but the population that going to run on the bank still exists in our real world. This is what the prospect theory proposes that low probability is overweighting under risk. The probability weighting function under risk shows that the impact of change diminishes with the distance from the reference point (Tversky and Kahneman, 1992). Besides, by the principle of loss aversion, losses loom larger than corresponding gains (Tversky and

Kahneman, 1991). Based on different dependent source, the decision weights are diverse, so the shapes of the probability weighting function are variant (Kilka and Weber, 2001). Tversky and Kahneman (1979) mention the question that the sharp drops or apparent discontinuities of decision weights at the endpoints, and there is a limit to figure out how small a decision weight can be attached to an event. They call this as “quantal effect”, which is possible to give any weight at this area. In bank-run probability, we define this apparent discontinuity as the tipping point of bank runs. It refers to one dramatic moment in bank-run phenomenon when everything can change all at once. By the definition of Lamberson and Page (2012), the dramatical occurrence of bank runs will reduce uncertainty about the future.

1.5 Conclusion and Organization

Even lots of policies and insurances are implemented in banking system, the bank-run phenomenon still appears frequently. In this new environment, the financial risk become diversified and cryptic, therefore the reason of bank runs becomes complex and it is difficult to make a conclusion. Especially, many times the bank runs still occur when these financial institutions are in the good operating condition and quite well surroundings. Just some of extremely but small bad news, policies or events might also cause a great panic among the depositors, and then bank runs dramatically happen.

This Chapter reviews two contradictory views of bank-run classical models. There is no doubt that if the quality of bank's asset is too bad, depositors are afraid that they cannot withdraw their money from the bank. On the other hand, when the panic forms even the bank is still in good operation, they will also run on the bank. Facing this scenario, the sunspot equilibrium exists, and animal spirit will play a significant role. The tipping point effect will appear and it is a crucial sign that the bank-run phenomenon is coming. That is, animal spirits will trigger this risk, and the bank run

will become inevitable when passing the tipping point even the environment seems relatively good.

In Chapter 2, a bottom-up behavioral model is built to model bank runs. It is shown with agent-based modeling approach that animal spirits of the depositors together with endogenous optimism and pessimism can cause liquidity shock. In particular, bank run will be triggered if the animal spirits reaches to a tipping point. The model is tested with a set of empirical data, which shows that the effect of animal spirits is significant in reality.

Chapter 3 simulates the stochastic dynamic probabilities of bank runs based on the global games approach, which mentions that heterogeneous agents hold highly correlated but different beliefs about the real payoff. When real-world bank runs relate to diverse elements, it is hard to conclude bank run is only because of miscoordination (e.g. Diamond and Dybvig, 1983) or the deterioration of the quality of the bank's assets (e.g. Allen and Gale, 1998). Besides, the probability of bank runs is neglected by the classical models. Therefore, an internal "mental model" that agents have integrated cognitive-affective network is proposed. As the affective processes play significant role in decision making, the pessimistic announcement may cause the bank-run even the fundamental economics is good. Both the rise of R and r will decrease the effect of affective process. The increased risk sharing might or might not increase PBR, which is based on the level of uncertainty, and the increasing of late payoff is beneficial for preventing the bank run.

Chapter 4 focuses on two unsolved questions for the estimation of PBR. First is the best setting for affective process, that is, the parameter in affective magnitude section, second is the tipping point with different combination of early and late payoff. Thus, this chapter concerns on the calibration of parameters and critical values in bank-run estimation. For the adjustment of affective-process parameters, the granger causality test and impulse response function are adopted. Based on the selected parameters, the results we have proved are correct, and the affective-process effect becomes clearer. To figure out the tipping-point effect by threshold autoregressive (TAR)

model, the result shows that the increased risk sharing, that is, the increase of early payoff r will cause this kind of effect, but it does not impact on the tipping-point value. On the other hand, the increase of late payoff R will increase the tipping point, which means that it will prevent even eliminate the bank-run phenomenon. Generally, when PBR passing 0.2, it is possible that bank run happens, and when PBR passing 0.25, it becomes very easy to run to bank and it is too late to restrain.

Chapter 5 concludes the specific contribution and the main findings of this thesis, and proposes the further research.

Chapter 2

Liquidity Shock, Animal Spirits and Bank Runs

2.1 Introduction

Liquidity is a prime concern in commercial banks. Strict liquidity requirement can prevent output fluctuations and avoid severe downturns. More strict liquidity rules are able to, at some degree, flatten out output fluctuations and keep serious downturns from happening. (Hoog and Dawid, 2017). It is not only a vital aspect for the safety of a single commercial bank, but also significant to the stability of the whole country and the global economy. Nowadays, although the consequence of liquidity shock, i.e., bank runs, has been superficially treated as a solved problem, not all credit institutions are covered by certain clinker-built system of defense. For example, during the Asian Financial Crisis in 1997, liquidity crisis occurred due to bank runs in many countries, which led to the bankruptcy of many commercial banks and the financial crisis in many economies. In addition, the shadow banking system has raised wide new liquidity concerns during the U.S. subprime mortgage crisis and the global financial crisis. At the same time, numerous traditional financial

institutions have begun to withdraw deposits from core financial institutions. Up to now, a lot of investors are still suffering from the panic of this turmoil though the economy has gradually recovered. Over the last two decades, these non-bank banks have grown up and begin to play a role similar as the commercial banks, investment banks and hedge funds. There can also be a run on shadow banks just as what happened to traditional banks in history, especially in the emerging market such as China where supervision is not foolproof. Hence, the classical economic theory about bank runs needs to be modified, and a theory involving the non-economic motivations that can explain the tipping point of the emergence phenomenon before bank failure are in dire need.

There are two main factors that may cause a bank failure: solvency shock and liquidity shock, and the latter, that is, temporary cash flow problem will also lead to bank run. Although many factors influence the liquidity of banks, there are two main perspectives. The first is the structure of a bank's assets and liabilities, which is based on the identity: $\text{Assets} = \text{Liabilities} + \text{Capital}$. When the depositors suspect that the bank cannot repay their deposits as the market value of assets is below liability, bank runs would happen if there is no additional liquidity provided. What's worse, when one of the representative banks bankrupts, people would be afraid of the bankruptcy of other banks. Depositors will panic and start withdrawing money from other banks even if those banks are well-managed. The second main factor is the policy of central bank. In the case of Northern Rock, before the breakout of a bank run, the Bank of England announced that it would provide emergency liquidity support. However, it was just after the central bank had the announcement that the depositors started queuing outside the bank. This revealed to us that the central bank could lose its capacity to play as the lender of last resort if the contagion has already been formed. Under such circumstance, it might aggravate the bank run phenomenon even more. In other words, both perspectives suggest that animal spirits might play an essential role in the phenomenon of bank runs.

When such crisis breaks out, human beings tend to fall into a state of chaos. As their willpower weakens, or surrounded by negative signals, two aspects of animal spirit -- emotion or emotional drives might play an essential role in their decision-making. Their confidence and stability in their action dramatically reduces after passing a critical value of mind state, and this threshold can be defined as the tipping point. In short, such striking change is driven by the animal spirits, a concept ever laid at the heart of Keynes's explanation for Great Depression, but was abandoned after the blooming of New Classical Economics. Although the reason of bank runs is still controversial, there is no doubt that the public lost confidence in the market though some of the banks are still well-managed, and all the people run on banks when the contagion of panic reaches a critical point. Therefore, the discovery and study of such tipping point is beneficial for us to effectively predict and prevent the occurrence of bank runs.

The optimal bankruptcy rules in monetary conditions are pioneered by Shubik and Wilson (1977), who have pointed out that the theory, as the severity of the penalties is varied, considered constraint of credit reappear in a variety of borrowing constraints in modern-equilibrium models. After that, based on Samuelson's pure consumption loans model, Bryant (1980) introduced an overlapping-generations model of borrowing and lending alone, without considering such factors as reserves, risky assets, or deposit insurance. In a word, this theory provides the basic strategy of game theory that has been cited in many papers about bank runs. The milestone of bank run theory is that of Diamond and Dybvig (1983) who have proposed the now-classic model based on Nash equilibrium, a model that demonstrates the reason why banks choose to issue deposits that are more liquid than their own assets and to understand the reason why banks are subject to runs. They pointed out the undesirable equilibrium in which all depositors panic and withdraw immediately. After that, the mainstream of academia explains and rationalizes their theory until now. The cost of illiquidity can be avoided with a fragile capital structure in bank (Diamond and Rajan, 2001a), however, when the bank failures appear, it will shrink

the common pool of liquidity, creating, or exacerbating aggregate liquidity shortages and lead to a contagion of failure (Diamond and Rajan, 2005).

There are two disparate fields in studying networks: graph theory and social science. In the social science, the set of contacts of an individual is their ‘neighborhood’, and the size of this neighborhood is the individual’s ‘degree’ (Keeling and Eames 2005). In random networks, the spatial position of individuals is irrelevant, and connections are formed at random (Bollobas, 2001). In the most simplified version of the random network, each individual has a fixed number of neighborhood through which infection can spread. In fact, the growing random network is more reliable, and the social science develops the mode by simulating the methodology of graph theory. The random graphs were first introduced by Erdos and Renyi (1959, 1960), who have given the probable structure of a random graph. In the development of their theory, they have found that there exists a probability distribution function with a regular sharp threshold. However, they could not find the precise condition of the critical value that the network would tip in their theory, and there are not the delicate trends of human nature considered in their model. After that, Schelling (1978) published *Micromotives and Macrobehavior*, where he is interested to find that a small and ostensible meaningless decisions and actions made by individuals often lead to dramatically unintended results for a large group. Similarly, Miller and Page (2004) set up a Standing Ovation Problem (SOP) that explains peer effect, which is the part of everyone’s common experience. It stresses some of the key themes caused in social systems, such as social learning, diffusion, heterogeneity, incentives, and networks. Even so, both the Schelling’s Segregation Model and the Standard Ovation Problem explaining the same individual behavior would lead to the unintended results at large group with the different condition. In addition, the agent-based modeling used in these models allow a variety of assumptions about information transmission, and it allows the researcher to easily alter the assumed behaviors and parameters in an effort to identify the key factors driving the results. As the great merit of agent-based modeling, many scholars nowadays attempt to

simulate the social network with the epidemic models. For the bank runs phenomenon, the driver of the dramatic chaos is driven by the animal spirits in nature, so the model should base on the condition and result of animal spirits. In a word, it is crucial to find out the tipping point that animal spirits would react prominently, and we should know which factor leading to this tip, which is direct or contextual.

2.2 The Generic Model

There are many households all simultaneously consuming, working and making saving, and households save by lending to financial institutions, in the form of deposits and bank capital. There are three components to consider when talking about an economy in this thesis, that is, entrepreneurs in firms, depositors in households and commercial banks that borrow from central bank. However, the action of central bank is assumed to have no impact on animal spirits here.

Figure 2 - 1 Circulation of Commercial Banks

It is assumed that a large number (L_t) of uncorrelated investment projects in an economy. The project lasts two periods and its price is Q_t . The projects required

funds providing from banks. Total bank loans for these projects ($L_t \times Q_t$) are equal to deposits (D_t) plus bank capital (BK_t), then aggregate bank balance sheet is:

$$Q_t L_t = D_t + BK_t$$

The deposit ratio $d_t = D_t / Q_t L_t$ and deposit rate is R_t , therefore gross deposit is $R_t d_t$.

Refer to Diamond and Rajan (2001a and 2001b) and Angeloni and Faia (2009, 2013), a present “liquidation value” of the assets equals to an expected value A_t plus a shock S_t , that is, it is interval is between 0 and 1. The “shock” here extends to the result of animal spirit effect, which is in a micro-level and is discussed in detailed in Part 2.3. In the previous literature, only the possible mathematic outcome or set as a constant number as a macro-level outcome are considered, neglecting the real effect from the psychological perspective. Thus, the assets is $A_t + S_t$. As the Figure 2 - 1 shown, the circulation of banking system should satisfy the function $A_t + S_t \geq R_t d_t$, otherwise the depositors might run on the banks.

Further, as the commercial bank has the professional knowledge about the project, it will have an advantage in figuring out the project value before it is completed compared with other lenders. Therefore, other lenders’ liquidation value can be set as $\lambda(A_t + S_t)$ where $0 < \lambda < 1$. $1 - \lambda$ acts as the fact that a household doesn’t possess professional knowledge on liquidation value of asset, which indicates the probability of liquidity shock. The reason is because there is no way for depositors or lenders to know how much is the actual return of the project as well as his/her own personal desire of consumption. In conclusion, there are two cases for the bank-run happening.

	Scenario	Range between the return of investment and saving	Returns of depositors and banks
Case 1	The depositors must run on bank as the outcome of the project is lower than the gross deposits (including interest)	$A_t + S_t < R_t d_t$	Depositors: $\frac{(1 + \lambda) \times (A_t + S_t)}{2}$ Bank: $\frac{(1 - \lambda) \times (A_t + S_t)}{2}$
Case 2	The other lenders figure out the outcome of project is lower than the gross deposit, but the calculation of the specific commercial bank is not	$\lambda(A_t + S_t) < R_t d_t < A_t + S_t$	Depositors: $\frac{A_t + S_t + R_t d_t}{2}$ Bank: $\frac{A_t + S_t - R_t d_t}{2}$

Table 2 - 1 Cases for the bank runs

In the first case, depositors alone would get $\lambda \times (A_t + S_t)$ by expectation, and the rest $(1 - \lambda) \times (A_t + S_t)$ share between depositor and the bank. The excess return is divided into half for each. The returns receive from the project investment is lower than gross deposit, which means the bank face the illiquidity risk. For the second case, the depositors run or not based on whether they believe the extraction of bank. At this time, the outcome of project seems uncertain for outsider. In the third case, if the outcome of project calculated by other lenders is higher than the gross return by deposit, that is $\lambda(A_t + S_t) > R_t d_t$, the depositor will not run the bank in this situation. In the following discussion, the third case is neglected as we only consider the scenario that bank run probably happened.

It is assumed that there is a random animal spirits might exist in the market, that is,

S_t is uniformly distributed in the interval $[-z, z]$ with probability $\frac{1}{2z}$. Thus, the

expected value of total payment to the depositors is maximized as follows:

$$\begin{aligned}
 \max_{d_t} \quad \tilde{E}p_t &= \frac{1}{2z} \int_{-z}^{R_t d_t - A_t} \frac{(1 + \lambda) \times (A_t + S_t)}{2} dS_t + \frac{1}{2z} \int_{R_t d_t - A_t}^z \frac{A_t + S_t + R_t d_t}{2} dS_t \quad (2.1) \\
 \text{s.t.} \quad \lambda \frac{A_t + z}{R_t} &< d_t < \frac{A_t + z}{R_t}
 \end{aligned}$$

The optimal value of deposit ratio can be solved

$$d_t = \frac{1}{R_t} \frac{A_t + z}{2 - \lambda} \quad (2.2)$$

The probability of bank run (PBR) occurring can be written as

$$PBR = \frac{1}{2z} \int_{-z}^{R_t d_t - A_t} dS_t = \frac{1}{2} \left(\frac{R_t d_t - A_t}{z} + \frac{z}{z} \right) = \frac{1}{2} - \frac{A_t(1 - \lambda) - z}{2z(2 - \lambda)} \quad (2.3)$$

PBR ranges between 0 and 1, impacted by the return of bank, the expectation of depositors and the shock in the market. The higher the expectation λ and shock z with the lower return A_t , the higher *PBR* happens.

The problem here is, for each of agents, they will have their own strategies to figure out the shock z in the market, and in micro-level an endogenous shock aroused by animal spirits is discussed in the following section.

2.3 Shock Caused by Animal Spirits

While the mainstream model assumes that agents are able to understand the whole world with the rational expectations, and here replaced by homo sapiens, the agents use the simple rules to portray the cognitive limitation and willingness to learn (e.g. Kirman, A. 2006; Brazier et al 2008; Grauwe 2012). In the other word, we will use heuristics (Tversky, A., & Kahneman, D. 1974) to decide the economic behavior with the adaptive learning mechanism, which can be simplified as two kinds of rules: One is the basic justifications underlying rational expectations, and the other is contrasting a great deal with the rational expectations forecasting rule. This is the basic mechanism that is applied for figure out the shock coming from animal spirits. What's more, each agent can use different forecasting rules. Therefore, there will be heterogeneity among agents. While rational expectations assume that agents understand the complex structure with understanding the only one "Truth" and allows builders of rational expectations models to focus on just one "representative agent", this heterogeneity creates interactions between agents and lead to a dynamics

that is absent from rational expectations models, which is more close to our real life. Here, two types of behavior rules (heuristics) could be assumed as follows: the first is “fundamentalist rule” that Agents estimate the future with uncertainty and only have too pessimistic and pessimistic biased estimates of it. The second is “chartist rule” that does not presuppose that agents have biased estimates. It is ambiguous for the future and predict by the previous observation.

As what has mentioned in *Part 2.2*, as the commercial bank has the professional knowledge about the project, it will have an advantage in figuring out the project value before it is completed compared with other lenders. Therefore, other lenders’ liquidation value can be set as $\lambda(A_t + S_t)$ where $0 < \lambda < 1$. The probability that the lender could get a liquidity shock is set as $1 - \lambda$. Based on the expected value A_t of assets, the liquidity shock at t is defined as $S_t = (1 - \lambda) A_t$. It is assumed that value A_t is fixed in all times, and the dynamics of the asset value is due to the shock caused by animal spirits S .

Two rules of S expectation can be listed as

(i) The fundamentalist rule is defined by

$$\text{The optimistic fundamentalist rule } \tilde{E}^{fo} S_{t+1} = b$$

$$\text{The pessimistic fundamentalist rule } \tilde{E}^{fp} S_{t+1} = -b$$

(ii) The chartist rule is defined by $\tilde{E}^c S_{t+1} = S_{t-1}$

The rules are simple in the sense that the agent are not to understand the whole picture, and just use the information they can understand. The experimental evidence has supported these two rules for inflation forecasts in a new Keynesian model (e.g. Duffy 2006). Although the agents could not figure out the whole picture of the market, they will have the adaptive learning ability that continually try to learn from their mistakes and choice the better rule they think, and generally, the market forecast is based on the weighted average of these two forecasts. This is the mechanism of animal spirits’ effect, which is driven by the memory and the

willingness to learn (intensity of choice). The shock in next period is written as $\tilde{E}S_{t+1}$ that

$$\tilde{E}S_{t+1} = \beta_{f,t} \tilde{E}^f S_{t+1} + \beta_{c,t} \tilde{E}^c S_{t+1} = \pm \beta_{f,t} \times b + \beta_{c,t} \times S_{t-1}, \text{ where } \beta_{f,t} + \beta_{c,t} = 1 \quad (2.4)$$

$\tilde{E}S_{t+1}$ is the weighted sum of two kinds of rule, so we should figure out the weight value firstly. Apply the discrete choice theory (Anderson et al., 1992), under pure rationality agents would choose the fundamentalist rule if $U_{f,t} > U_{c,t}$, and vice versa. $U_{f,t} / U_{c,t}$ is forecast utility of the fundamentalist/chartist rule separately. Yet, psychologists have gotten the result that when we make an alternative decision we are also influenced by our state of mind that is impacted by recent emotional experiences, environment, etc. Thus, we can derive the new probability of choosing the fundamentalist as

$$\beta_{f,t} = P(U_{f,t} + \varepsilon_{f,t} > U_{c,t} + \varepsilon_{c,t})$$

$\varepsilon_{f,t}$ and $\varepsilon_{c,t}$ are the component that will aggrandize the animal spirits, and a more precise expression can specify as the logistically distributed (Anderson et al. 1992, p. 35):

$$\begin{aligned} \beta_{fo,t} &= \frac{\exp(\gamma U_{fo,t})}{\exp(\gamma U_{fo,t}) + \exp(\gamma U_{fp,t}) + \exp(\gamma U_{c,t})} \\ \beta_{fp,t} &= \frac{\exp(\gamma U_{fp,t})}{\exp(\gamma U_{fo,t}) + \exp(\gamma U_{fp,t}) + \exp(\gamma U_{c,t})} \\ \beta_{c,t} &= \frac{\exp(\gamma U_{c,t})}{\exp(\gamma U_{fo,t}) + \exp(\gamma U_{fp,t}) + \exp(\gamma U_{c,t})} \end{aligned} \quad (2.5)$$

If the $U_{f,t} / U_{c,t}$ improves greater than the outcomes of chartist/fundamentalist rule, the people prefer the fundamentalist/chartist rule. The parameter γ refers to willingness to learn from the past performance, and it shows as the intensity of choice in economic behavior. It is related to the variance of $\varepsilon_{f,t}$ and $\varepsilon_{c,t}$. When

the variance is large, γ approaches 0. In this situation, agents choose the rule randomly and the probability of fundamentalist/ extrapolator equals to 0.5 as the time goes on. The variance becomes small when γ increases, and the utility is then fully deterministic. In the other words, the willingness to learn is 0 when $\gamma=0$, and it will increase with the size of γ . In this adaptive learning mechanism, only those rules that pass the fitness test remain in place, or kick out.

$$\begin{aligned}
U_{fo,t} &= - \sum_{k=0}^{\infty} w_k (S_{t-k-1} - \tilde{E}_{fo,t-k-2} S_{t-k-1})^2 \\
U_{fp,t} &= - \sum_{k=0}^{\infty} w_k (S_{t-k-1} - \tilde{E}_{fp,t-k-2} S_{t-k-1})^2 \\
U_{c,t} &= - \sum_{k=0}^{\infty} w_k (S_{t-k-1} - \tilde{E}_{c,t-k-2} S_{t-k-1})^2
\end{aligned} \tag{2.6}$$

For $U_{f,t} / U_{c,t}$, the geometrically declining weights is introduced, because the agents would forget and give lower weight to errors made far in the past compared with errors made recently. Therefore, they are the negative value of geometrically declining weights (w_k) times mean squared forecasting errors of the fundamentalist and chartist rules respectively. To be specific, the $w_k = (1-\rho)\rho^k$ ($0 \leq \rho \leq 1$) is defined, and the equation can be written as follows:

$$\begin{aligned}
U_{fo,t} &= \rho U_{fo,t-1} - (1-\rho)(S_{t-1} - \tilde{E}_{fo,t-2} S_{t-1})^2 \\
U_{fp,t} &= \rho U_{fp,t-1} - (1-\rho)(S_{t-1} - \tilde{E}_{fp,t-2} S_{t-1})^2 \\
U_{c,t} &= \rho U_{c,t-1} - (1-\rho)(S_{t-1} - \tilde{E}_{c,t-2} S_{t-1})^2
\end{aligned} \tag{2.7}$$

When $\rho = 0$, there is no memory, which means that only performance in last period impacts on the forecasting rule, and the memory increases with the growth of ρ . When $\rho = 1$, the agent has infinite memory and the weight allocated to each period is the same and approaches to 0. At this time, the agents forget nothing, but

the impact of new information can be also ignored. The animal spirit might disappear in this situation.

2.4 Tipping Point Simulation

Based on the random social network, the possibility shocked by animal-spirit effects can be simulated by heterogeneous agent-based modeling. As the rumor between depositors becomes more frequent under the uncertain circumstance, the information in links would increase convexly (Figure 2-2-(a)). The vertical axis of d means the degree (information number) of each depositor, and the horizontal axis of n represents the probability of group panic. At the beginning, when the panic group is small, the neighbor is almost zero as almost no one will care about the bad situation and each one is isolated from others. If the group becomes larger, the depositors start to concern about more information, which would increase infinitely when the major group focuses on it. The links between depositors increase convexly, because human

Figure 2 - 2 (a) the degrees each depositor when the population of panic is increasing; (b) the relationship between real probability of individual depositor withdraw rationally and the probability of individual withdraw in fact

being would become very sensitive to changes in the low probability and be impacted by the dramatic loss of confidence. Based on the prospect theory, there are

overweighting of small probability and the underweighting of large probability. When the expectation begins to deviate the reference point, people would become sensitive observably, and they react much more strongly than the rational necessity. In Figure 2-2-(b), the probability of rational withdrawal of individual depositor P_r is expressed as the horizontal axis, and the probability of reality is the vertical axis. During the uncertain period, the panic people are likely to withdraw their money when they believe other people were also withdrawing. As a result, they withdraw

Figure 2 - 3 Tipping Point of Bank Runs

the money at high level in reality, while the rational choice still closes to zero. Further, as people become less sensitive to changes in probability that moves away from the reference point, the willingness of withdrawal will decrease gradually. After this change driven by animal spirits, the new equilibrium in standard economic would appear.

In reality, individual withdrawal gradually changes in the normal situation, however, there exists the extreme scenario when passing a critical value that leads to a discontinuous jump to the whole withdrawing behavior. The moment of jumping is the tipping point (TP), which appears due to the fact that animal spirits has played an essential role in human decision making. What we can see in Figure 2-3-(a) is that the degree of shock caused by animal spirits (p) is the horizontal axis, and the probability of bank runs ($P(p)$) showing as vertical axis is increasing slowly and then becomes drastic. Bank run phenomenon forms when the $P(p)$ gets 1 rapidly.

Regarded as the equilibrium problem in Figure 2-3-(b), the probability 0 and 1 of $P(p)$ are two stable equilibrium similar to the Nash equilibrium in Diamond and Dybvig model. However, when the $P(p)$ is larger than TP , it will tend to probability 1, or when the p is less than TP , the tendency to 0 would happen. In other words, the TP is an unstable at the lower p . However, when the change arrives at the tipping point, the effect of animal spirit becomes positive to cause the bank runs. The vertical axis P_w is the effect of animal spirit. The negative value indicates it will prevent the happening of bank run, while the positive value will boost the bank-run phenomenon. The larger the number is, the higher probability the bank-run caused. Thus, it is necessary for us to find out the tipping point and then recognize the tendency of bank runs.

Figure 2 - 4 Simulation Results

Now it is ensured that after passing the tipping point, the withdrawal dramatically grows to cause a social bank run phenomenon impacted by the extremely enlarging of animal spirits, and the simulation result of agent-based modeling is demonstrated with different assumptions. To simplify, there are 4 connections for each agent that have the same probability to deliver the information (80%), and 39507, the amount of withdrawing agents is selected arbitrarily. In Figure 2-4, the horizontal axis is the animal-spirit effect, and the vertical axis is the percentage of withdraw, that is, the probability of bank runs. Initially, driven by the animal spirits, the tipping point,

around 40% is just one possibility that becomes much stronger, and the real tipping point is based on the emotional change of human being. Nevertheless, the insurance mechanism, here it is to decrease the probability to deliver the pessimistic information from 80% to 60%, shows effective to delay the tipping point. Even when the panic occurs, it can help keep the confidence among some depositors. As is seen from the Figure 2-4, the tipping point appears later, with several fluctuations before the process of dramatic change. Hence, it can leave the time to stop the tips in this scenario. Furthermore, there is no more than 80% withdrawal, which implies that more effective insurance might control the occurrence of bank-run in a low degree.

2.5 Data Analysis

Figure 2 - 5 CSI and BI

From the discussion above, the US real data is used with the equation

$$PBR = \frac{1}{2} - \frac{A_t(1-\lambda) - z}{2z(2-\lambda)}.$$

The KBW Bank Total Return Index (KBW BTRI), which

is abbreviated as BI below, is set as the return of bank A_t , and the Michigan

Consumer Sentiment Index (CSI) is regarded as the ratio of other lenders' value λ (Figure 2-5). It is the monthly data from Jan. 1993 to April 2015.

The number of bank failure is treated as the proxy of bank runs tendency. Influenced by the saving and loan crisis during the 1980s to 1990s, a lot of banks failed during the two decades. In Figure 2-6, orange line is the trend of yearly real data in US, and by the simple calculation there are 2362 banks closed between year 1980 and year 1995. After that, US entered a boom time that only 50 banks failed until 2006. However, the breakout of financial crisis revisits this kind of old story that the illiquidity risk in bank strikingly increases.

Figure 2 - 6 Modeling Probabilities and Real Results of Bank Runs

The result of the model is shown in blue line. Coinciding with the real data, after the peak around year 1989, the risk got down gradually and the strong shock with animal spirits effect still existed until year 1995. The probability of bank runs became lower than 50% and continuous decreased after that year. Yet, between the end of 1990s and the beginning of 20th century, a small number of bank run cases still appeared because the adjustment was implemented before the boom time. Since year 2000, the bank crisis got down till the eruption of subprime crisis. Obviously, there is a discontinuous jump of the bank run risk just as what the real story tells us in financial

crisis. Behind this result, the shock aroused by animal spirits might guide the central bank effectively, and the detailed analysis is expressed in the following.

Overall, it is clear that following the shock of animal spirits dramatically increases, the bank runs phenomenon would erupt. The result of real data is shown in Figure 2-7. Before the probability of bank runs (in red line) jumps, the animal-spirit effect (in blue line) dramatically increase ahead during the year 2007. Luckily, before the tipping point of animal spirits appears, there might be some inflection point that makes the economic statement become chaotic, and this is the signal that the central bank should implement or swift the monetary policy for preventing the following crisis.

Figure 2 - 7 Animal Spirits and Bank Runs

As mentioned in the model section, animal spirits are determined by the memory and the intensity of choice. When $\rho=0$, there is no memory, and the memory increases with the growth of ρ . When $\rho=1$, the agents forget nothing, they can remember all the things with the same weight. The animal spirit might disappear in this situation as they don't have any cognitive limitation. Computing the correlation between bank runs and animal spirits for consecutive values of ρ , the animal spirits

arise when they try to remember the history. The better memory the agents have, the higher animal spirits exists. One possible explanation for this is that the analysis will become very complex and it is difficult to take an optimal decision, when the agents can remember more and more scenarios but can not capture the whole picture. However, after ρ approaches to 0.95, it will dramatically drop to almost zero (Figure 2-8-(a)). This shows that when agents can remember most of the happenings, they can avoid the most of the uncertainty with their high cognitive capability. This proves that the agents should have the cognitive limitation that forgets something to generate the animal spirits.

The parameter γ refers to the intensity of choice that comes from the willingness to learn from the past performance (including themselves and other agents). When γ approaches 0, agents choose the rule randomly and the probability to be fundamentalist (or extrapolator) is exactly 0.5 as the time goes on. When γ increases, the willingness to learn will increase. To check the importance of this γ in creating animal spirits the simulated result is plotted in Figure 2-8-(b). It shows that at the beginning, the correlation between bank runs and animal spirits is very low and would get down to a negative value first. This reveals that when agents have little willingness to learn, the effect of animal spirits will go down, even have the negative effect on willingness to learn when γ is around 0.1 and 0.3. At this interval, people would like to learn from the past performance with little animal spirits if the willingness is small. In the data, it is because that γ can be low only if the economic environment is good enough, and at that time the agents do not want to learn too much from the market. In the contrast, the γ turns to be quite high when the market become uncertain. At this time, the animal spirits arise, which means that the agents need a minimum level of willingness to learn for animal spirits to emergence and to influence the fluctuation of banking system.

(a)

(b)

(c)

Figure 2 - 8 Correlation between Bank Runs and Animal Spirits

So far, it is ensured that the cognitive limitation and the willingness to learn would shock the banking system. What's more, considering the longitudinal effect of animal spirits by taking the impulse response function in Figure 2-8(c), the effect is significant and lasting for 100 steps. The agents need a short time to react, so the effect is zero but increases fast at the beginning. Around the 10th step the effect becomes largest and then declines gradually for a long time. Overall, it shows that the shock of animal spirits is quite significant and long lasting.

Figure 2 - 9 Distribution of Animal Spirits

In a good environment, the economic activities are frequent because it is easy to earn money, and the animal spirits are low. Normally, the economic world is working in line with the law. Figure 2-9 shows the monthly distribution of animal spirits, and it is easy to find that the major distribution is allocated at the lower level of animal spirits. Yet, just a few values are between 0.4 and 0.6, because people become very prudent when the economic environment is not good or bad, and they do not try to switch their choice or learn from the history. And then there is a small peak from 0.6. During the crisis, people would like to swift their wealth to a safer way, so the

activities are also relatively frequent. They will try to learn from the aftermath of the history and they will take the extreme reaction when this kind of contagion forms and spreads. Figure 2-10 is the yearly data of real bank-run numbers in US and the trend of animal spirits. In the simulation result, before the financial crisis from 2007, animal spirits increase dramatically, and the bank-run numbers rapid grow in the following. Also, the decrease of animal spirits is delayed compared with the bank-run phenomenon. This reveals that the agents are still scaled the happening of bank run, so the recovery of economics needs a longer time.

Figure 2 - 10 Bank-Run Numbers and Animal-Spirit Trend

Figure 2 - 11 Bank Runs and its Corresponding Animal Spirits

Figure 2-11 is plotted the corresponding animal spirits when probability of bank runs is from 0 to 1. There is an increase with the increasing rate from the value around 0.5 of bank-run probability. What's more, the value becomes very oscillatory until getting the higher level, and the animal spirits will tip when it is around 0.5.

Figure 2 - 12 Ascending order of Bank-run Probability

In addition, to figure out the tipping point of bank-run phenomenon, the probability of bank runs is plotted with the ascending order in Figure 2-12. It is clear that there is a discontinuous jump. What's more, before the jumping the probability is concave shape that increases with the decreasing rate. However, after the jump around 0.53, the shape becomes convex that increases extremely fast. Therefore, this point of discontinuous jump is the tipping point of bank runs.

In Figure 2-13, taking the animal spirits with ascending order with the corresponding value of bank runs, the animal spirits jump when the value is around 0.3 and then the banking system becomes chaotic at first. At this time, the central bank would like to solve the problem, and the banking system turns to stable for a while. However, as the real financial situation exacerbate and the animal spirits is larger than 0.5, the trend of bank runs turns into deterministic that to be a higher level, and the so called bank-run phenomenon is formed in this case.

Figure 2 - 13 Ascending Animal Spirits and its Corresponding Bank Runs

2.6 Discussion and Conclusion

The effect of animal spirits shows us that small changes could have big, and desirable, consequences. From the result of agent-based simulation, we can see that the policy intervention might be effective if the policy can be actualized before the tip of animal spirits. Mostly, human beings are naive, and preferences often fluctuate as a result of purely present-bias effect (Loewenstein, 1996). When the crisis occurs, people normally pay attention to the recent depression, instead of the gain in the future, and then the tips of bank runs might easily emerge. On the other side, sophistication effect means sophisticates are fully aware of any self-control problems they might have in the future, and this awareness can influence behavior now. Thus, sophisticates are influenced by the sophistication effect in addition to the present-bias effect. However, a person with projection bias understands the qualitative nature of change in her preferences but underestimates the magnitude (Loewenstein, O'Donoghue and Rabin, 2000). Thus, while people believe the crisis gradually recovers nowadays, they are still too prudent for the risk free investment. Further, Loewenstein and O'Donoghue (2004) model the behavior motivated by animal spirits as the interaction between deliberative system (assesses options with a broad, goal-based perspective) and affective system (experiences emotions, such

as anger and fear, and motivational drives, such as hunger and sex). The deliberative system may expand willpower to exert influence on the myopic affective system. However, it is a limited cognitive resource that may have an impact on exercising self-control. Individuals have a finite amount of willpower, which is used for all kinds of tasks. Ego depletion theory postulates that willpower (or ego) depletes when using it, but is replenished after a while (like a muscle). Exercising self-control now impacts self-restraint later, e.g., individuals can maintain their diet discipline for some time, but not over long time (Baumeister et al., 1998). To solve the self-control problem, the potential benefits of commitments suggested by Gul, F., & Pesendorfer (2001) and Thaler and Benartzi (2004), and this result supports Diamond and Dybvig (1983). Therefore, a good commitment can control the shocks aroused by animal spirits to avoid this kind of disaster, and this has explained the current situation in China that the banking system is very stable due to the strong commitment from central bank. Yet, although China can be regarded as the symbol with strong commitment, as the inclusive financial system strikingly developing, the mechanism to figure out the probability of crisis breakout is still necessary and attractive, let alone in the open system for most of countries. Hence, this study pays attention on the threshold of time that central bank should implement a stronger intervention for banking system, and discovering the animal-spirit effect is quite remarkable.

With the thriving of the complex banking system and its unsound supervision, the risk of bank runs should be considered again. This paper attempts an exploratory study about how the shock caused by animal spirits can tip the bank run occurrence based on the adaptive learning mechanism. The effect of animal spirit does not come from the irrational expectation, instead, it is from the fact that the agents are eager to learn from the mistake they ever have with the bounded memory ability. Yet, those agents could not capture all the information in the complex market, and they only use the information they can understand driven by both the optimal/pessimistic and extrapolated motivation. Thus, such kind of animal spirit lays at the core of the banking crisis, and it will dramatically rise when the economic environment

deteriorates. The distribution of animal spirits shows that economic activities are frequent in both good and bad situation, and the shock caused by animal spirits explains that when the tipping point is passed, the financial contagion takes places even if there is intervening policy. On the other hand, the result of agent-based simulation reveals that the preventative policy is helpful in preventing the arrival of tipping point, and central bank should implement rescue policies before that point. The tipping point and long run effect of animal spirits demonstrates the reason why crisis is difficult to recover in a short time once it is formed. This has explained why the bank run phenomenon still occurs in Northern Rock even after the announcement of the central bank, and why the public is still scared when we talk about financial crisis.

Overall, this behavior model with endogenous waves of optimism and pessimism accounts for the micro-behavior with the animal spirits —the shock caused by cognitive limitation and willingness to learn—in the bank run phenomenon, and the signal from this kind of shock is beneficial for central bank's monetary policy.

Chapter 3

Connectionist Agent-Based Learning in Bank-Run Decision Making

3.1 Introduction

We have witnessed a new wave of bank runs across the world during the recent financial turmoil. Examples include the runs on Northern Rock in September 2007, on Busan II Savings Bank in February 2011, on Greek banks in June 2015, on Home Capital Group in April 2017. There are, broadly speaking, two opposing views about the cause of bank runs, that is, bank run is due to miscoordination or the deterioration of the quality of the bank's assets. However, Real-world bank runs tend to involve various factors, which makes it difficult to conclude the cause. Besides, there are no probabilities attached to these possibilities in the classical models. In contemporary behavioral economic theories, the well-known dual-system theory proposes that human behavior comes from the interaction of cognitive and affective

processes. With the development of agent-based modeling, agents heterogeneity in their cognitive capacity can be simulated by Artificial Neural Networks (ANNs), which is a solution for the shortcoming of behavioral economic mechanism. This paper applies an ANNs nonlinear dynamic model with the global game framework to figure out the integrated cognitive-affective processes in bank-run decision making. Therefore, fully capturing the heterogeneous nature of human behavior, this internal “mental model” figures out the dynamic processes for bank-run phenomenon.

Carlsson and Damme (1993) introduced the theory of global games. The theory provides a framework (see Morris and Shin 2005 for an overview) that considers the probability of bank runs. Classic panic-based bank run models include an important assumption that everyone knows with certainty the return of the deposit. However, in reality, people usually do not know exactly how much is the return. In fact, different but highly correlated beliefs exist among people about the true payoff. The global games approach made it is closer to reality by assuming that every agent receives a noisy-provide-signal which provide certain information on the true fundamental base of the economy yet does not allow them to determine the exact value of the payoff. In such an environment, agents will play threshold strategies, which is when the signal that they received is above certain level of threshold, they will withdraw their deposit, vice versa, when the signal is below a certain level of threshold, they keep their money in the bank. The idea behind this behavior is that agents will form their assumption about signals received by other players based on their own signals. However, there exists a kind of signal that is intermediate showing that there is no difference between keeping the money in the bank and withdrawing the money given the assumption on other player's probable action. The signals above mentioned define a threshold strategy equilibrium if the threshold for each player is the best response to the threshold of the other players.

The global games approach integrates the panic-based and fundamental view of bank runs, which is also an improvement from classical model. These two related

but different views can be found in Chapter 1 on bank runs. The panic-based view sees bank run can be caused by pure sunspot random variables, which means bank run may occur when there are no changes in the real economy. In traditional belief, a good economic fundamental prevents the occurrences of bank runs, however, there are still runs due to strategic uncertainty about others' beliefs.

As described earlier, one of the very attractive feature of the global games approach is that it includes the probability of bank run (PBR). Therefore, policy maker can adjust the parameters in the related bank run model by adopting the global games approach. For example, policy makers are able to make corresponding policies by calculating the PBR by using different level of return of bank deposit or liquidity requirement. Attention need to be paid that global games approach can only work properly if it provides a good prediction of human behavior.

Although contemporary behavioral economic theories try to incorporate cognitive and emotional factors to better describe human economic decisions, they still cannot fully capture the heterogeneous nature of human behavior. For example, what prospect theory from Kahneman and Tversky (1979) describes is the pattern observed from the majority of their subjects, giving no explanation concerning the behavior of the minority (14-35 percent of their subjects). Recent experimental studies strongly suggest that it is no longer appropriate to assume homogeneity in either risk preference or time preference. For example, both Benjamin and Shapiro (2005) and Christelis, Jappelli and Padula (2010) showed that people with higher cognitive abilities participate more in financial markets. If this is the case, together with the finding by Frederick (2005) that the risk attitudes of the subjects with higher cognitive ability are exactly the opposite of the prospect theory from Kahneman and Tversky (1979), the foundation of modeling financial market participants according to prospect theory might not be well grounded.

The solution for the shortcoming in behavioral economic theories is to make artificial agents heterogeneous in their cognitive capacity by agent-based modeling. Computational agents can be as rational (or irrational) as real people, with learning

models that range from simple reactive reinforcement learning (“If this happens, what should I do?”) to sophisticated anticipatory learning (“If I do this, what might happen?”) (Chen, 2017). To be specific, there are several types of agent cognition: reflexive agents, utility-based agents, and adaptive agents (Russell and Norvig, 1995). Often, these types of cognition are thought of in increasing order of complexity, with reflexive agents being the simplest, and adaptive agents the most complex.

According to the agent-based mechanism, we can explicitly take into account learning process so that cognitive capacity become transparent. Technically, to achieve this we should combine agent-based modeling with machine learning, which is inspired by the work done by Herbert Simon on bounded rationality and satisficing in “Administrative Behavior” and “Sciences of the Artificial” (Simon, 1947, 1955, 1959 and 1969). Simon is first to apply machine learning techniques to economic decision-making problems, and he is also one of the founders of modern-day Artificial Intelligence (AI). Artificial Neural Networks (ANNs) use the machine learning to simulate computational parallels of biological neurons, which seems only appropriate that in applying ANNs to decision making problems (e.g. Chen and Lu, 1999; Binner, Kendall and Chen, 2004). We rely on various aspects of Simon’s path-breaking work in this study.

The well-known dual-system theory (e.g. Epstein, 1994; Stanovich and West, 2000; Peters and Slovic, 2000; Kahneman and Frederick, 2002; Loewenstein and O’Donoghue, 2004) typically incorporates the bounded rationality into economic behavior. It proposed that a person’s behavior is determined by an interaction between cognitive processes that access options with a broad, goal-based perspective, and affective processes that encompass emotions and other motivational states. A single integrated system approach has been advocated by a smaller number of theorists (e.g. Damasio et al., 1994; Mellers et al., 1997; Gray, 2004). According to this, emotions provide dynamic signals that feed into and help guide the cognitive system over time for making decisions. To describe exactly how this temporal

integration and interaction occurs is a major challenge for this viewpoint. Busemeyer, Dimperio and Ryan (2007) extend their decision field theory (Busemeyer and Townsend, 1993, Busemeyer, Townsend and Stout, 2002), which has been successfully used to explain data in traditional decision-making tasks, to provide dynamic mechanisms for integrating fast emotional signals with slower cognition information to guide decisions. Their model assumes that emotions, motivations, and cognitions interact to produce a decision, as opposed to being processed independently and in parallel. Emotions are temporary states reflecting changes in motivational levels. Affect is an evaluation of an emotional state according to a positive (approach) or negative (avoidance) feeling (movement tendency). The dynamic nature of emotions present challenges to traditional static theories of decision making, and the model attempts to address these dynamic characteristics formally.

Based on the chapter 2 (Huang and Huang, 2016), the so-called animal spirits of depositors can cause the tipping point of bank run, and here we try to figure out the dynamic psychological foundation for this phenomenon at intra-individual level. Therefore, this chapter applies an ANNs dynamic model with the global game framework to figure out the integrated cognitive and affective process in bank-run decision making. In different level of uncertainty, the effect of cognitive/affective process in decision making is concerned, and the effect of changing of early/late payoff will be tested.

The rest of this chapter is organized as follows. In section 3.2, we discuss the theoretical bases of the format and process of decision making in bank run. The global game of bank runs shows the logic of the decision making, and the dual-process dynamic decision making of bank runs is based on the ANNs agent-based modeling for the decision processes of heterogeneous depositors. Section 3.3 reveals the specific parametrization and design, and then analyzes the results of the simulation. In section 3.4, we will come to a conclusion.

3.2 Global Game of Bank Runs

Payoff Withdrawal	No Run ($e < \hat{e}$)	Bank Run ($e \geq \hat{e} \equiv \frac{N}{r}$) Payoff
in Period $n+1$	r	r (with probability of $\frac{\hat{e}}{e} = \frac{1}{r}$) 0 (with probability of $1 - \frac{\hat{e}}{e}$)
in Period $n+2$	$\frac{N - r \times e}{N - e} R$ (with probability of θ) 0 (with probability of $1 - \theta$)	0

Table 3 - 1 Global Game of Bank Runs

N = numbers of agents; e = number of withdrawer; $\hat{e}$ = threshold number of withdrawers; r = early payoffs; R = late payoff; θ = probability of getting late payoffs

Table 3-1 above shows the global game of bank runs. It is assumed that all N agents are patient agents. Although human beings' rationality is bounded, which will lead to the bias, however, it does not equal to irrational. To some degree, all the depositors are "strategic" players in the market, so we set all the depositors patient. If the number of withdrawers e exceeds the threshold number of withdrawers $\hat{e} = \frac{N}{r}$, the bank will not have enough money to pay every withdrawer the promised rate r . Therefore, the bank runs will occur if $e \geq \hat{e}$.

As DD model (1983) shows, banks can offer a demand-deposit contract to achieve risk sharing. To simplify it, the logic of contract is in the following. Firstly, agents deposit their endowment in bank in period n . Then, they will make a decision in period $n+1$, withdrawing the money or waiting until period $n+2$. The early payoff is

r , and the late payoff is $\frac{N - r \times e}{N - e} R$. If there are no early withdraws, late payoff will become R .

In period $n+1$, when there is no bank run (number of withdrawers is less than the threshold number of withdrawers), the payoff for all agents is r , which is the promised fixed return, and most of the agents will withdraw their money in next period. However, when there is bank run (number of withdrawers equals to or exceeds the threshold number of withdrawers), there is some probability that agents will still be paid r , and some probability that agents will be paid nothing. When bank run happens, all agents will go to withdraw, therefore when $e \geq \hat{e}$, it will result as

$e = N$. The probability of getting early payoff r equals to $\frac{\hat{e}}{e} = \frac{N/r}{N} = \frac{1}{r}$.

In period $n+2$, when there was bank run in period $n+1$, the payoff for agents will be zero. When there is no bank run in period $n+1$, agents will receive the payoff of $\frac{N - r \times e}{N - e} R$ with probability of θ , where the interval for θ is $(0, 1)$ (Goldstein and Pauzner, 2005).

In the case of no bank run in period $n+1$, the likelihood of being paid nothing still exist. That is, $\theta=0$. The probability of θ is introduced to represent the fundamental of economy. In the situation that fundamental of economy is good, θ approaches 1, that is, the environment is clear, and the chance of occurrence of bank run is certainly slim. On the other hand, when θ becomes smaller, which means the depositors are likely to get nothing in this period, this will cause panic and ultimately bank run. Therefore, if θ is sufficiently small (large), all players have a dominant strategy to withdraw early (late). However, when θ is in indeterminacy region, the strategy becomes uncertainty.

At any point in time, each agent will make their own evaluation on this two-stage demand-deposit contract. In the following simulating test, r and R are fixed in each of simulation, however, the factor θ , which reflects the fundamental of economy,

might be changed. It is assumed that agents repeatedly make evaluation and choices whether to withdraw in period $n+1$ or in period $n+2$. This can be further elaborated that agents study the outcome and make choices between these two periods in period $n+1$. And this behavior will repeatedly happen over infinite periods of time. Therefore, the iteration of the model includes both of these two stages.

However, the announcements in the market will impact on agents. When making decision, the agents cannot precisely predict θ , and they can just concern on any information they can receive from the market. Based on the information they have, they try their best to make the optimal decision, but this information might be also harmful to make a rational decision. The global game approach can only work properly if it provides a good prediction of human behavior. Additionally, it is also difficult to predict the existing number of withdrawers e , and when depositors will become the withdrawers e is not answered in the existing literature.

Generally, as θ is unknown, the agents make their decision to run on the bank or not based on two factors: the fundamental of economy that they already have general idea on and announcements from market which will have impact on their decision making. Based on the global-game framework above, to find out the probability of bank run impacted by these two factors, an intra-individual level connectionist model with dual processes is proposed in the following section.

3.3 Dual-Process Decision Making of Bank Runs

Agents can never make a “so called” optimal decision, only a satisfactory decision can be achieved. This concept of “bounded rationality” is introduced by Simon (1947), who assumes that the human being as a system of behavior is quite simple. The apparent complexity of our behavior is largely a reflection of the complexity of the environment in which we live in. Thus Simon (1955) proposed to use the “thinking machine”, that is, an artificial intelligence model, to simulate our internal system. It is not necessarily related to biological functioning, but it helps to

understand the processes of our decision making. Simon (1961) further concludes that central motivation of artificial neural network (ANN) is to investigate human processes of decision making. In other words, ANN can be loosely defined as artificial intelligence models inspired by analogy with the brain and realizable in computer programs.

To incorporate the bounded rationality into economic behavior, the dual-system theory has been accepted by the mainstream scholars. Now, it is time to revisit Simon's spirit that simulates our internal system with this frontier theory. Therefore, to better understand the actual human decision making in bank-run phenomenon, a "connectionist" artificial neural network model capturing the dual-system theory will be applied with the global game framework.

To be specific, this setting is one kind of single integrated systems that can capture the dual-system theory. It makes the dual-system theory in agent-based modeling that fully consider the heterogeneous nature of human behavior. The fundamental thought comes from the decision theorists (Keeney and Raiffa, 1993) that each decision result can be characterized by numbers of attributes with different weights and values. In Busemeyer, Townsend and Stout (2002), this thought improves to the based mechanism that this chapter is applied, which can go back to Grossberg (1988) and Rumelhart and McClelland (1986). In Busemeyer, Dimperio and Ryan (2007), the affective (emotional) processes is introduced into this kind of dynamic connectionist model of decision making. Mainly based on these references, I develop to the cognitive-affective processes model in bank run phenomenon as follows.

It is clear that when the environment is certainly good or bad, depositors will easily choose to "run" or "no run". However, the world we are living in is much more complicated than we thought. It is impossible for us to capture and analyze all the emerging information, let alone to make an optimal decision. When we are making a decision, it is not only captured by our cognitive processes in our mind, but also by affective processes, which happens simultaneously. Cognition by itself cannot

produce action to influence behavior, and the cognitive processes must operate via the affective processes (Camerer et al., 2005). In most complex situation, the affective processes are even with greater impact on our decision making.

Decision making in bank runs emerges from a continuous interplay of two broad types of decision processes, which capture the difference between deliberative/cognitive thinking and impulsive/affective decision. In contrast to most formal models in economics, such processes codetermine the decision making at the intra-individual level (Alos-Ferrer and Strack, 2014). The interactions between the cognitive and affective processes can be captured by one integrated system (Figure 3-1).

Figure 3 - 1 Connectionist Interpretation of Dual-Process Bank Run's Decision Making

M: payoffs; **W**: weight; **C**: contrast; **O**: cognitive processes; **G**: announcement; **F**: following of announcement; **T**: affective magnitude; **A**: affective processes; **PBR**: probability of bank run.

For cognitive processes, agents will make an evaluation for the payoff. Firstly, the early payoff $\mathbf{M}_e$ and late payoff $\mathbf{M}_l$ will be disclosed by banks, and there are two scenarios which are run on banks ($\mathbf{M}_{er}$ and $\mathbf{M}_{lr}$) or no-run on banks ($\mathbf{M}_{enr}$ and $\mathbf{M}_{lnr}$). Agents run on banks when they find that it is unlikely to get their promised returns. Thus, for both run and no-run scenarios, they will evaluate the weight/probability to get their payoff at early ($\mathbf{W}_{er}$ and $\mathbf{W}_{lr}$) or late period ($\mathbf{W}_{enr}$ and $\mathbf{W}_{lnr}$). A comparison will be made based on the evaluation, which will result as **C**, and the cognitive process **O** will then be formed.

Besides, any information in market will have an impact on agents' decision, and most of the time they find the information is ambiguous. This is when the affective process works. In many existing literature, it is regarded as sunspot random variables that may cause the panic-based bank run (e.g. Diamond and Dybvig, 1983, Cass and Shell, 1983, Peck and Shell, 2003, 2005), and here the vector $\mathbf{D}(\mathbf{t})$ plays as a special case of "sunspot random variables", which can capture the affective effect of agents especially when panic appears. This basic setting also comes from Busemeyer, Dimperio and Ryan (2007), that is, agents have their own affective goal, denoted as the probability to get the pessimistic announcements vector $\mathbf{G}(\mathbf{t})$, and the affective status quo, denoted as impact from the announcement vector $\mathbf{F}(\mathbf{t})$. The impact of announcements is denoted as $\mathbf{D}=\mathbf{G}-\mathbf{F}$.

With the influence by the announcements, the emotion and emotional state of agents will become different. Thus, the affective magnitude **T** is introduced to measure the emotion and the emotional state. The two components (**D** and **T**) form the affective process **A**, which, together with **O**, will achieve the decision making **PBR**. When **PBR** is larger than 0.5, it means that bank-run phenomenon probably exists in the market, and it is updated and becomes historical feedback in the following period.

At any moment in time, the choice of “run” or “no run” is determined by the Probability of Bank Run (PBR). A new state of $\mathbf{PBR}(t+1)$ is formed at each moment from the previous state $\mathbf{PBR}(t)$ and the new input cognitive vector $\mathbf{O}(t+1)$ and affective vector $\mathbf{A}(t+1)$, according to the following stochastic difference equation:

$$\mathbf{PBR}(t+1) = \mathbf{A}(t+1) \circ \mathbf{PBR}(t) + \mathbf{O}(t+1) \quad (3.1)$$

where $\circ$ means Hadamard product.

Based on this simple updating equation, the PBR for “run” or “no run” form a PBR state matrix, denoted as $\mathbf{PBR}(t) = [PBR_r(t) \ PBR_{nr}(t)]$. The dynamic probability at time t , denoted $PBR_i(t)$, represents the integration of cognitive and affective processes considered for choice $i=r$ or nr up to that point in time. Cognitive process is a stochastic dynamic mechanism, while the affective one is nonlinear dynamic. Generally, the integration is one kind of dynamic learning in bank-run decision making.

A. Cognitive Process

At any moment in time, each “run” or “no run” choice is associated with a cognitive process value. The cognitive processes for option i at time t , denoted $O_i(t)$, represent the momentary advantage or disadvantage of option i when compared with other option on payoff under consideration. The ordered set of cognitive processes for “run” or “no run” choice forms a cognitive vector, denoted $\mathbf{O}(t) = [o_r(t) \ o_{nr}(t)]'$, and it is formed by the following matrix product:

$$\mathbf{O}(t) = \mathbf{C} \times \mathbf{M}(t) \circ \mathbf{W}(t) \quad (3.2)$$

This vector is determined by three different components.

The first component of cognitive processes is the personal evaluation of early and late payoff, denoted by vector:

$$\mathbf{M}(t)=[m_r(t) \quad m_{nr}(t)]' \quad (3.2a)$$

If the early payoff is higher than late payoff, that is, $m_e(t) > m_l(t)$, depositors will choose to run on the bank. In no run situation, agents must receive payoff $r > 1$, but in run situation they will receive 0 with $1 - 1/r$ probability.

The second component is weight of personal evaluation attached to early and late payoff, denoted by vector:

$$\mathbf{W}(t)=[w_r(t) \quad w_{nr}(t)]' \quad (3.2b).$$

With high level of certainty, the depositor can easily choose to run or no run. For example, with the no-run situation considered, it will become $w_l(t)=0$ or $w_l(t)=1$ when the fundamental economy is extremely bad or good.

The matrix product of probability and payoff, $\mathbf{M}(t)\mathbf{W}(t)$, determines the weighted payoff of run or no-run outcomes at each time point.

The third and final component used to determine the cognitive processes of each option is the comparison process that contrasts the weighted payoff of each option. This comparison process is needed to determine the relative advantage or disadvantage of each choice on the payoff considered at that moment. The cognitive processes for each option are produced by contrasting the weighted payoff of “no run” against “run”. This comparison process can be represented by a simple contrast matrix:

$$\mathbf{C}=\begin{bmatrix} 1 & -1/2 \\ -1/2 & 1 \end{bmatrix} \quad (3.2c)$$

B. Affective Processes

At any moment in time, each “run” or “no run” choice is also associated with an affective process value. The affective processes for option i at time t , denoted by $A_i(t)$, represents the effect of pessimistic/optimistic announcement with different

affective magnitude. The ordered set of affective processes for “run” or “no run” choice forms an affective vector, denoted by $\mathbf{A}(t)=[a_r(t) \ a_{nr}(t)]'$, and it is formed by the matrix product:

$$\mathbf{A}(t)=\mathbf{D}(t) \circ \mathbf{T}(t) \quad (3.3)$$

The first component $\mathbf{D}(t)$ is the impact of announcements, which is the public information that will impact agents but not the fundamental of economy. The component of depositors reacting from diverse information follows an exogenous random process. this component consists of two parts. The first part is the announcements (or called information) that is denoted by vector $\mathbf{G}(t)=[g_r(t) \ g_{nr}(t)]'$. The other is reaction (or called decision) from the announcements denoted by vector $\mathbf{F}(t)=[f_r(t) \ f_{nr}(t)]'$. Agents are heterogenous, so different agents receive diverse information in the market resulting in various level of impact.

Therefore, the impact of announcements for “run” or “no run” outcome is denoted by:

$$\mathbf{D}(t) = \mathbf{G}(t) - \mathbf{F}(t) = [g_r(t) - f_r(t) \ g_{nr}(t) - f_{nr}(t)] \quad (3.3a)$$

In our assumption, the announcements, rather than the fundamental of economy, may cause bank-run phenomenon as well. When it is in economically good times, normally the pessimistic announcements are rare, and bank runs are not likely to happen in this market. However, there are times when rumors are spread and lots of pessimistic announcements exist in a strong market. If most of agents believe the information is reliable, they might still choose to run on banks even in economically sound market. To find out the effect of panic, it is assumed that there is 80% probability to get the pessimistic announcements and 20% probability for the optimistic ones. This assumption is based on the fact that no matter how good the market is, bad news will fill with the whole market once it is formed. By this

assumption, it is easy for us to find out the clear effect of pessimistic announcements that the non-fundamental factors could be responsible for bank runs.

The famous Reference-Dependent Model (Tversky and Kahneman, 1991) proposed that losses loom larger than corresponding gains, which means that the bad announcements have bigger impact than good announcements. Therefore, it is assumed that the depositor will accept the pessimistic announcements with 80% probability and 20% for the optimistic one.

The second component is affective magnitude. By human nature, the change of our affective magnitude is nonlinear. To guarantee a late withdrawal, the agents who choose to wait have to receive a higher payoff than those who choose to withdraw, that is, $\frac{N - r \times e}{N - e} \times R(\theta) > r$. If θ is sufficiently small, all players have a dominant strategy to withdraw early. However, when θ is in indeterminacy region or the pessimistic announcements are too strong, the strategy becomes uncertain. The effect of θ is nonlinear, and the larger θ is, the more certain environment becomes.

Affective magnitude will decrease with θ increasing, so the effect of θ is set as a decreasing function θ^γ , where $0 \leq \gamma \leq 1$. In other words, smaller late payoff is needed when θ becomes larger to prevent bank-run phenomenon. Here, we simplify this effect as $\theta^{0.6}$ where $\gamma=0.6$. Considering the effect of θ , to equalize the payoff associated with “withdraw” and “wait”, that is, $r = \frac{N - r \times e}{N - e} \times R \times \theta^{-0.6}$, we can get the threshold withdrawal fraction to avoid occurrence of bank-run, that is

$$\frac{e}{N} = \frac{R \times \theta^{0.6} - r}{r \times (R \times \theta^{0.6} - 1)}.$$

Besides, the panic will be spread at different degree when the

amount of the agent changes, and this nonlinear effect can be denoted as $PD = \sqrt[\delta]{N}$ where $\delta > 1$. Here we simplify this effect as $PD = \sqrt[4]{N}$ where $\delta=4$. Therefore, combining the effect from the threshold withdrawal fraction to avoid bank-run and the amount of agents, we define the Affective Magnitude as:

$$AM = \frac{e}{N} \times \sqrt[4]{N} = \frac{(R \times \theta^{0.6} - r) \times \sqrt[4]{N}}{r \times (R \times \theta^{0.6} - 1)}$$

Thus, the vector is denoted by:

$$\mathbf{T} = \left[\frac{(R \times \theta^{0.6} - r) \times \sqrt[4]{N}}{r \times (R \times \theta^{0.6} - 1)} \quad 1 - \frac{(R \times \theta^{0.6} - r) \times \sqrt[4]{N}}{r \times (R \times \theta^{0.6} - 1)} \right] \quad (3.3b)$$

In each period t , $t = 100$, the following sequence of events takes place:

1. The evaluation on the value and the probability of each payoff, and the contrast of each decision will form the cognitive process all at once.
 - a) Each agent can receive the early and late payoff from the market, and then they should estimate the probability of getting each payoff;
 - b) Firstly, they should guess whether the bank run would happen. If there is no run, they must get r payoff in early period. If there is run, they can get r with the probability of $1/r$;
 - c) Secondly, if with no run, they should figure out the probability θ of getting the payoff $\frac{N - r \times e}{N - e} R$ in late period.
 - d) There is a deliberative contrast in our brain, and then form the cognitive process.
2. The impact of announcements and the affective magnitude will influence the affective process together.
 - a) The announcements will shift the decision of bank run. There is 80% probability to get the pessimistic announcements and 20% probability for the optimistic one;
 - b) Each agent makes different or unique decisions even when they receive the same information. The depositor will accept the pessimistic announcements with 80% probability and 20% for the optimistic one.

- c) In the affective process, the panic of bank run will come from two parts after the announcements, how much they can get from each payoff and how many depositors withdraw when the bank run occurs.

Integrating the effect of the cognitive process and the affective process, PBR is updated and becomes historical feedback for each agent in the following period.

3.4 Simulation

3.4.1 Parametrization and Design

To examine the behavior of the model and its robustness, simulations are conducted for a large number of parameter values in Table 3-2:

Symbol	Assignment	Description
T	100	length of a simulation
N	10, 100 and 1000	number of agents
r	1.20, 1.32, 1.45, 1.60	the early payoff with 10% incremental ratio
R	2.0, 2.20, 2.42, 2.66	the late payoff with 10% incremental ratio
θ	between 0 and 1	the probability of getting late payoff, fixed or randomly to test the fundamental economics
G	between 0 and 10	announcement, 0 means extremely optimistic and 10 means extremely pessimistic
F	between 0 and 10	reaction on announcement, which is the difference with G

Table 3 - 2 Parameter Values

The probability of getting late payoff θ might be set randomly within different intervals to check the result at different level of uncertainty, e.g. θ is in indeterminacy region, such as between 0.3 and 0.7. In the timeline, the sequent θ has 0.8 probability to keep the same rate, and changes with 0.2 probability. If agents are completely rational, the runs only occur when θ is relatively low. However, the impact of announcement in the market will have great impact on the bank run phenomenon, such as the announcement before the Northern Rock in September 2007. It shows that the noise in the market will lead to the bank run, even when bank and market are good enough.

3.4.2 Simulating Results

In this section, we analyze the simulating results. First, the comparison is made between single cognitive process and cognitive-affective process in bank-run decision making. Second, the details of cognitive-affective processes are figured out. Last but not the least, the effect of increased risk sharing (r), the greater late payoff (R) and the recovering of fundamental economics (θ) will be tested. In the beginning, the benchmark initial value is set as: $r = 1.2$, $R = 2$ and $n = 100$.

If the agents can precisely analyze the whole picture of market, bank-run only occurs when the fundamental economy is terrible. From the left-hand side of Figure 3-2, the result of single cognitive processes is plotted. When agents have complete rationality, they will swift their strategy with the changing of real economy. When θ equal to 0.6, the probability of bank run (PBR) is around 0.5. The agents will fully consider the risk about the payoff, and they will have 50% probability choosing to run or no run. Therefore, the risk of bank-run can be clearly figured out by real economy (shown in the lower left of Figure 3-2), and it is impossible to occur if the bank works well. However, the stories that the depositors run on the well-run banks is not rare. Therefore, the introduction of integrated cognitive-affective processes is crucial, and the results are plotted in the right-hand side of Figure 3-2, which is obvious that the PBR is fluctuating within a large scale while the fundamental

economy is stable. Influenced by our emotion, the announcement in the market will have dramatical impact on our decision making. even when the bank works well, PBR might jump to a high level as well (shown in the lower right of Figure 3-2).

Figure 3 - 2 Comparison of Cognitive and Cognitive-Affective Processes

To check the general effect from fundamental economy, θ varying from 0 to 1 with 1000 different values is simulated (Figure 3-3). The prediction is made 1000 times at each time point, and then take the average of PBR. As the result, fundamental economy will decide the average level of PBR, and there is a clear linear negative

relationship between θ and PBR.

Figure 3 - 3 Average-Diminishing PBR and its Corresponding θ

Besides, the fluctuation of the PBR comes from affective process, and it is combined by two components: the impact of announcement and affective magnitude. The results are listed in three diagrams in Figure 3-4.

For the first component impact of announcement, there are ten levels about the signal from the market, that is, 0.1 means the most optimistic (0 can be ignored) and 1 means the most pessimistic (Figure 3-4b). The level 0 is neglected, as it is impossible there is no impact from market. The market is complex, even in the best/worst period, there is still some bad/good news in the market. Therefore, it is rare to receive the extreme good/bad announcement, and then lowest/highest value of impact is rare. Most of values distribute between 0.4 and 0.9 locating at higher level of PBR, and this shows that the pessimistic announcement might increase PBR significantly.

The second component is affective magnitude, and it has a positive relationship with PBR (Figure 3-4c). One explanation for this is that while the fundamental economy goes down, depositors get panic easily, and their decision making will be much more greatly impacted by their emotion in the short term. After agents receive the

pessimistic information from the market, they become more scared when they feel the environment is terrible.

Figure 3 - 4 PBR and Affective Factors

For the whole affective process effect, the pessimistic announcement will lead to the dramatical jump of PBR (Figure 3-4a). The Figure shows that while the announcement becomes more pessimistic (higher value of announcement impact), the affective processes have greater impact on a higher level of PBR rather than the lower level. Therefore, the line of affective processes becomes flatter when the value increases. This means that at the same level of announcement, the affective-process effect is stronger at high level of PBR.

Figure 3 - 5 PBR and its Corresponding Cognitive-Affective Processes

Based on the whole analysis above, Figure 3-5 reveals the result that the average level of PBR is shifted by the fundamental economy, but whether the bank-run phenomenon occurs is significantly impacted by the cognitive-affective process. The former shows AG's opinion that bank run is caused by the deterioration of the bank's assets quality, and the later explains DD's perspective that bank run is due to miscoordination. If the economy is really terrible, there is no doubt that bank runs is bound to happen as human beings have the cognitive capability. While the affective effect is dramatically increasing, the bank-run still occurs even the fundamental economy is quite good. In a nutshell, with the theoretical framework of behavioral economics, the cognitive-affective process here shows a psychological basic for both DD perspective and AG perspective.

Based on the common sense, the increase of risk sharing should increase PBR; the greater late payoff should decrease PBR; the recovering of fundamental economy should decrease PBR as well. In the following, the effect of increased risk sharing (r), greater late payoff (R) and recovering of fundamental economics (θ) are tested. In all scenarios, both the increased risk sharing (r) and late payoff (R) will decrease the effect of affective processes, and increase the effect of cognitive processes (see Appendix). This illustrates that the adjustment of both early and late payoff is a strong long-term signal influencing the bank-run phenomenon. However, the direction and magnitude of influence is obviously different.

With a high level of uncertainty, that is, when θ is very low (smaller than 0.3) and the fundamental economy is bad, the adjustment of both r and R is useless at this scenario (see Appendix A1 and A2). At this time, the environment is so clear that agents are bound to go to run, so the affective effect can be ignored. Although the increase of R will decrease PBR a little, the value is still significantly high.

With an intermediate uncertainty, when θ is between 0.3 and 0.7, the increase of R will reduce PBR as the effect of affective processes will be decreased even negligible. When R is large enough, the effect of cognitive process will dominate PBR (see Appendix B1), and AG is correct at this moment. At this time, the increased risk sharing will shift PBR up, and the effect of affective process still impacts PBR (see Appendix B2). At this time, the increased risk sharing is a disaster to the market.

With a low level of uncertainty, the increase of R can eliminate the bank run phenomenon (see Appendix C1). The increase of r will decrease the effect of affective process, so the fluctuation of PBR become small, and this effect will shift PBR down. On the other hand, the increased risk sharing will move the average of PBR up (see Appendix C2). Therefore, the comprehensive effect is quite unclear, and the reaction of the increased risk sharing is small proved by the experiment result (Klos and Sträter 2012).

The simulating result is in line with DD's perspective that bank runs still occur even the fundamental of economy is good. Figure 3-6 below is an example of low level of uncertainty, that is, θ is between 0.7 and 0.9. Most of the points locate at either very low or high level, which shows the dynamic version of DD's model indicating that there are two self-fulfilling symmetric pure-strategy Nash equilibria. At this scenario, the fundamental of economy is relatively good, yet there exist lots of pessimistic announcements in the market. It is concluded from the stimulation that if PBR is smaller than 0.23 (the red line in the upper panel), it is quite stable at the low level. However, if PBR is larger than 0.23, PBR dramatically jumps to a high level.

Figure 3 - 6 Corresponding Cognitive-Affective Processes and Tipping Point
 $\theta=0.7\sim0.9; R=2.0; r=1.2$

Tipping point effect of bank-run phenomenon proposed in our previous work (Huang and Huang, 2016) explained the above. It refers to one dramatic moment in bank-run phenomenon when everything can change all at once. Our recent work finds that this effect exists at both low and middle level of uncertainty. While, in high level of uncertainty, bank run is likely to happen, thus this kind of effect is neglected. Generally, this is a dynamic process that the historical results will influence the updating PBR. However, the affective processes are temporary states that are impacted by the announcements. Therefore, there exist high probability that PBR will tip to a high level in two conditions: 1) the impact of affective processes increase to a high level; 2) PBR passes the tipping point. If bank-run has formed and the pessimistic announcements remain over a long period time in the market, PBR will stay at very high level. At this time, as we proposed above, both the increasing of late payoff value and the recovery of fundamental of economy are useful to solve this disaster. The best is to take the intervention ahead of PBR passing the tipping point.

3.5 Conclusion

This chapter focuses on certain probability of bank runs, that is neglected by the classical model. The global game of bank runs shows the logic of the decision making, and the heterogeneous agents hold highly correlated but unidentical beliefs about the true payoff. The dynamic decision process integrates the well-known dual-system theory into an ANNs agent-based modeling system.

The pessimistic announcements will cause the bank-run even when the fundamental of economy is good, because the affective process plays significant role in decision making. Both the rise of R and r will decrease the effect of affective process. However, with the change of r , the announcements in the market still dramatically switch the depositors' strategies despite the lower level of uncertainty. The increased risk sharing might or might not increase PBR, which depends on the level of uncertainty. The increase of late payoff is beneficial for preventing the bank run if

the environment is not extremely terrible, even it can prevent the bank-run when the fundamental of economy is good. This simulation result is robust for different number of agents. Therefore, when the bank-run phenomenon happens, banks should take strategy that increase the late payoff and government must recover fundamental of economy as soon as possible. For the policy makers and financial analysts, to find out the tipping point of bank run is a creative and practical solution in the more and more complicated banking system.

This chapter is one of pioneers that links agent-based computational economics to behavioral economics, and the findings in this research may shed some light on investor's analysis, banker's adjustment, central bank's monetary policy and government's economic policy. The future research will further explore the tipping point of bank-runs when r or R changes with different level of θ . With different tipping points, the effect of cognitive-affective process will be varied, and the relationship with PBR should be figured out.

Appendix

A1. Different R with high level of uncertainty

PBR with Different 'R' and its Corresponding Cognitive-Affective Process

$r=1.2$, θ is between 0.1 and 0.3

A2. Different r with high level of uncertainty

PBR with Different ' r ' and its Corresponding Cognitive-Affective Processes

$R=2.0$, θ is between 0.1 and 0.3

B1. Different R with middle level of uncertainty

PBR with Different 'R' and its Corresponding Cognitive-Affective Process

$r=1.2$, θ is between 0.3 and 0.7

B2. Different r with middle level of uncertainty

C1. Different R with low level of uncertainty

PBR with Different 'R' and its Corresponding Cognitive-Affective Process

$r=1.2$, θ is between 0.7 and 0.9

C2. Different r with low level of uncertainty

PBR with Different ' r ' and its Corresponding Cognitive-Affective Processes

$R=2.0$, θ is between 0.7 and 0.9

Chapter 4

Calibration of the Tipping Point in Bank Run Models

4.1 Introduction

Chapter 2 proposes the tipping point of bank run will be triggered by the shock aroused by animal spirit (Huang and Huang, 2016). The agents are eager to learn from the mistakes that they have made with the bounded memory ability, which, however, could not capture all the information in the complex market, and they only use the information they can understand driven by both the optimal/pessimistic and extrapolated motivation. Thus, this kind of animal spirit lays at the core of the banking crisis, and it will dramatically rise when passing the tipping point. To understand the origin of animal spirits, Chapter 3 introduces an internal “mental model” to consider the interaction of cognitive and affective processes in bank-run decision making (Huang and Huang, 2018). When the environment is chaotic, the affective process plays a significant role in decision making, and the pessimistic announcement will have strong and clear impact on probability of bank run (PBR). This is the scenario that the sunspot equilibrium exists. Even the fundamental

economy is good, the bank-run phenomenon may happen. At this time, the affective-process effect still exists and it will tip the PBR when passing the tipping-point value, which shows the learning process that forms the sunspot equilibrium.

In previous studies, to make the mechanism as simple as possible to get the clear conclusion, some settings are simplified as some specified numbers after many times of computational experiments, but it is still not confirmed with a precise check. For calibration of the tipping point in bank run models, there are still two unsolved questions. Firstly, what is the best setting for affective process, that is, the parameter in affective magnitude section. Secondly, what is the tipping point with different combination of early and late payoff. In this chapter, the statistical mechanisms, that is, the granger causality test as well as impulse response function (IRF) in vector autoregressive (VAR) model for the first question and threshold autoregressive (TAR) models for the second question will be applied.

From equation (3.1) in Chapter 3, A_{t-1} is influencing P_{t-1} , which in turn influences P_t . Besides, the last sentence in Part 3.3 has further explained for this dynamic mechanism that “Integrating the effect of the cognitive process and the affective process, PBR is updated and becomes historical feedback for each agent in the following period.” This means that the affective variables A_{t-1} to A_{t-p} might still impact on P_t . Therefore, to fully consider the historical feedback, the granger causality test as well as impulse response function are introduced to get the best setting for affective process, which play a key role in bank-run phenomenon, especially in the DD’s scenario. In this chapter, with different combinations of parameters in affective process setting, the granger causality and IRF relationship between Probability of Bank Run and affective process is tested.

The Granger causality test is a statistical concept of causality test to investigate the causality relationship of two variables, e.g., if one variable can be used to forecast another in a time series, proposed by Granger in 1969. Further, Hacker and Hatemi-J (2006) has developed a method from granger causality test and made it less easily influenced by deviations due to the fact that we assumed the error term has a

characteristic of normal-distribution, which can be applied in financial economics, as most of financial variables are non-normally distributed (Mandelbrot and Benoit 1963). In order to distinguish the positive changes' causal impact from negative ones', asymmetric causality testing suggested in the literature (Hatemi-J, 2012). Dumitrescu and Hurlin (2012) developed the Granger causality to panel data model. Human behavior is performed by brain networks, the dynamics of which are controlled by various probabilities which can be treated as random processes. Despite the fact that many researches have been conducted on causality, limited information on the size of the effect, from where to where the information moves, as well as the time effect was drawn (Kim et al., 2011). At this time, Bressler and Seth (2011) found that Granger causality is useful to address neural network issues. To further check the best combinations of parameters in affective process setting, IRF is adopted to trace the time path of affective-process effect of structural shocks on PBR. The seminal Sims (1980) proposed the impulse responses for the dynamic analysis of VAR, and it has been widely used in the neural network analysis (e.g. Widrow and Winter, 1988; Lazzaro et al., 1989; Nerguizian et al., 2006) and artificial neural decision making (e.g. Hawley et al., 1990; Blakemore and Robbins, 2012).

After adjusting the affective-process parameters, the tipping-point effect, which is about the difference in direction and steepness between two regimes can be estimated. A Threshold Autoregressive (TAR) models can be used to find out the tipping point, which are commonly used in the nonlinear time-series research. The reason is because it is easy to identify the variables, and estimate the result compared to other nonlinear time-series models. By adopting TAR, asymptotic confidence intervals form when estimating tipping point (Hansen, 1997). Tong (1983, 1990) initiated that a threshold autoregression can be used to approximate a general nonlinear autoregressive structure when the number of regimes is small. Tipping point effect is related to the behavior of non-linear discontinuity waves, but when a smooth transition function replaces the discontinuity of the tipping point, TAR model can be inferred to the Smooth Transition Autoregressive (STAR) model (e.g.

Granger and Terasvirta, 1993). If we reduce the tipping-point effect as the sample size becomes larger, we are able to obtain the predicted tipping-point' sampling distribution with an asymptotic distribution with no noisy parameters. In a similar way, for tests on hypotheses regarding the tipping point, if the distribution of the likelihood ratio statistic is limited, the same will be completely free of nuisance parameters. This makes it easy to have confidence intervals of the tipping point: the function of the tipping point can be presented as plot the likelihood ratio; draw in the pre-defined confidence level the critical value; and finally the tipping point with likelihood ratios that lie below the critical value can then be marked.

Based on the methodologies above, the calibration of PBR will be tested in this chapter. The rest of the paper is organized as follows. In section 4.2, we discuss the theoretical foundation of the calibration. First is to test the parameter for affective-process section, and then find out the tipping-point values. Section 4.3 reveals the specific parametrization and design, and then analyzes the results of the simulation. A large number of results will be listed and compared. In section 4.4, we will come to a conclusion.

4.2 The Calibration Mechanism

4.2.1 Affective Magnitude

At time t , the dynamic behavior, denoted as $P_i(t)$, describes the integration of cognitive and affective processes considered for choice i up to that point in time. Cognitive process is a stochastic dynamic mechanism, while the affective one is nonlinear dynamic. Generally, the integration is one kind of dynamic learning in bank-run decision making. The affective process for option i at time t , denoted by $A_i(t)$, represents the effect of pessimistic/optimistic announcement with different affective magnitude. The affective vector is formed by the matrix product:

$$\mathbf{A}(t) = \mathbf{D}(t) \circ \mathbf{T}(t) \quad (4.1)$$

where $\circ$ means Hadamard product.

The first component impact of announcement $\mathbf{D}(t)$ is the noise from the market, and the second component affective magnitude will be nonlinear change by human nature. The affective magnitude vector is denoted by:

$$\mathbf{T} = \left[\frac{(R \times \theta^\gamma - r) \times \sqrt[\delta]{N}}{r \times (R \times \theta^\gamma - 1)} \quad 1 - \frac{(R \times \theta^\gamma - r) \times \sqrt[\delta]{N}}{r \times (R \times \theta^\gamma - 1)} \right] \quad (4.1a)$$

If agents wait until period 2, they will receive the late payoff with probability of θ , where the interval is $(0, 1)$ (Goldstein and Pauzner, 2005). When the fundamental economy is well, θ is close to 1, that is, the environment is total certainty, and this is the common scenario that bank run is rare. On the other hand, when θ becomes smaller, which means the depositors are likely to get nothing in the later withdrawal, this panic will spread and the bank run will occur. Therefore, if θ is sufficiently small, all players have a dominant strategy to withdraw early. However, when θ is in indeterminacy region or the pessimistic announcement is too strong, the strategy becomes uncertain. The effect of θ is nonlinear, and it is defined as θ^γ where $0 \leq \gamma \leq 1$. Besides, the panic will be spread with different degree when the amount of the agent changes, and this nonlinear effect can be denoted as $PD = \sqrt[\delta]{N}$ where $\delta > 1$. Therefore, the combination of γ and δ with the most significant impact on PBR must be checked, and granger causality test and impulse response function (IRF) will be applied in the following.

If the PBR and affective process are endogenous for each other, the VAR/VEC model should be used. For the unit root-test we can check whether the data is stationary or not. If the data is not stationary but cointegration, the VECM can be adopted. On the other hand, as the data in simulation is stationary tested by Dickey–Fuller test,

VAR model is applied here.

If affective process, A_{t-j} where $j > 0$ can help explain / forecast Probability of bank run, PBR_t , then A is said to Granger cause. Statistically speaking, A granger causes PBR , if we reject the null hypothesis that all b_i are zeros. We assume a particular autoregressive lag length p and estimate

$$PBR_t = c_0 + \alpha_1 PBR_{t-1} + \dots + \alpha_p PBR_{t-p} + b_1 A_{t-1} + \dots + b_p A_{t-p} + \varepsilon_t \quad (4.2a)$$

And the restriction function

$$PBR_t = c_1 + \alpha_1 PBR_{t-1} + \dots + \alpha_p PBR_{t-p} + u_t \quad (4.2b)$$

We use a standard F -test of the hypothesis

$$\begin{aligned} H_0 : b_1 = b_2 = \dots = 0 \\ H_1 : \text{at least one } b \text{ is not zero.} \end{aligned}$$

To calculate the sum of squared residuals for both equation (4.2a) and (4.2b)¹

$$\text{Sum of squared residuals from (4.2a) : } RSS_1 = \sum_{t=1}^T \hat{\varepsilon}_t^2$$

$$\text{Sum of squared residuals from (4.2b) : } RSS_2 = \sum_{t=1}^T \hat{u}_t^2$$

$$F = \frac{(RSS_2 - RSS_1) / p}{RSS_1 / (T - 2p - 1)} \quad (4.2c)$$

If F is greater than 10% critical value for an $F(p, T-2p-1)$ distribution, then the null hypothesis is rejected that A does not Granger-cause PBR .

After the Granger causality is confirmed, the specific effect of variable is concerned.

To trace the time path of the affective-process effect A of structural shocks on current and future PBR , we can get the impulse response functions (IRF), which trace the impact effect of 1 unit change in structural innovations.

¹ t runs from 1 to T as indicated

Refer to Enders (2008), the simultaneous equations are set as follows

$$\begin{aligned} PBR_t &= c_{10} + \alpha_{11}PBR_{t-1} + \dots + \alpha_{1(t-p)}PBR_{t-p} + b_1A_{t-1} + \dots + b_{1(t-p)}A_{t-p} + \varepsilon_{1t} \\ A_t &= c_{20} + \alpha_{21}PBR_{t-1} + \dots + \alpha_{2(t-p)}PBR_{t-p} + b_1A_{t-1} + \dots + b_{2(t-p)}A_{t-p} + \varepsilon_{2t} \end{aligned}$$

We can express as

$$\begin{bmatrix} PBR_t \\ A_t \end{bmatrix} = \begin{bmatrix} c_{10} \\ c_{20} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \dots & \alpha_{1(t-p)} & b_{11} & \dots & b_{1(t-p)} \\ \alpha_{21} & \dots & \alpha_{2(t-p)} & b_{21} & \dots & b_{2(t-p)} \end{bmatrix} \begin{bmatrix} PBR_{t-1} \\ \dots \\ PBR_{t-p} \\ A_{t-1} \\ \dots \\ A_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

We apply the iteration method and get

$$x_t = (I + C_1 + \dots + C_1^n)C_0 + C_1^{n+1}x_{t-n-1} + \sum_{i=1}^n C_1^i \varepsilon_{t-i}$$

When $n \rightarrow \infty$, we can write as the stability condition is met, we can write x_t as follows:

$$x_t = \mu + \sum_{i=0}^n C_1^i \varepsilon_{t-i}, \text{ where } \mu = \begin{pmatrix} \overline{PBR} \\ \overline{A} \end{pmatrix} = \begin{pmatrix} \overline{PBR} \\ \overline{A} \end{pmatrix}$$

More explicitly

$$\begin{aligned} x_t &= \begin{bmatrix} PBR_t \\ A_t \end{bmatrix} = \begin{bmatrix} \overline{PBR} \\ \overline{A} \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \alpha_{11} & \dots & \alpha_{1(t-p)} & b_{11} & \dots & b_{1(t-p)} \\ \alpha_{21} & \dots & \alpha_{2(t-p)} & b_{21} & \dots & b_{2(t-p)} \end{bmatrix}^i \begin{bmatrix} \varepsilon_{1t} \\ \dots \\ \varepsilon_{1t} \\ \varepsilon_{2t} \\ \dots \\ \varepsilon_{2t} \end{bmatrix} \\ &= \begin{bmatrix} \overline{PBR} \\ \overline{A} \end{bmatrix} + \sum_{i=0}^{\infty} \frac{1}{1 - b_{12} \times b_{2p} \times \dots \times b_{(t-p-1)1} \times b_{(t-p)1}} \begin{bmatrix} \alpha_{11} & \dots & \alpha_{1(t-p)} & b_{11} & \dots & b_{1(t-p)} \\ \alpha_{21} & \dots & \alpha_{2(t-p)} & b_{21} & \dots & b_{2(t-p)} \end{bmatrix}^i \\ &\quad \times \begin{bmatrix} 1 & \dots & 1 & -b_{1p} & \dots \\ \dots & 1 & -b_{2p} & 1 & \dots \\ 1 & \dots & 1 & \dots & \dots \\ -b_{(t-p)1} & 1 & \dots & 1 & \dots \end{bmatrix} \begin{bmatrix} \varepsilon_{PBRt} \\ \dots \\ \varepsilon_{PBRt} \\ \varepsilon_{At} \\ \dots \\ \varepsilon_{At} \end{bmatrix} \end{aligned}$$

$$\text{where } \begin{bmatrix} \varepsilon_{1t} \\ \dots \\ \varepsilon_{1t} \\ \varepsilon_{2t} \\ \dots \\ \varepsilon_{2t} \end{bmatrix} = e_{t-i} = B^{-1} \varepsilon_{t-i} = \frac{1}{1 - b_{12} \times b_{2p} \times \dots \times b_{(t-p)1} \times b_{(t-p)1}} \begin{bmatrix} 1 & \dots & 1 & -b_{1p} \\ \dots & 1 & -b_{2p} & 1 \\ 1 & \dots & 1 & \dots \\ -b_{(t-p)1} & 1 & \dots & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{PBRt} \\ \dots \\ \varepsilon_{PBRt} \\ \varepsilon_{At} \\ \dots \\ \varepsilon_{At} \end{bmatrix}$$

To measure the effects of ε_{PBRt} and ε_{At} shocks on the entire time paths of the $\{PBR_t\}$ and $\{A_t\}$ sequences, we define

$$\Phi(i) = \frac{1}{1 - b_{12} \times b_{2p} \times \dots \times b_{p1} \times b_{p1}} \begin{bmatrix} \alpha_{11} & \dots & \alpha_{1p} & b_{11} & \dots & b_{1p} \\ \alpha_{21} & \dots & \alpha_{2p} & b_{21} & \dots & b_{2p} \end{bmatrix}^i \begin{bmatrix} 1 & \dots & 1 & -b_{1p} \\ \dots & 1 & -b_{2p} & 1 \\ 1 & \dots & 1 & \dots \\ -b_{p1} & 1 & \dots & 1 \end{bmatrix} \quad (4.3)$$

$\Phi_{jk}(i)$ is called the impact multipliers, known as IRF, which trace the impact effect of 1 unit change A for PBR .

4.2.2 Tipping Point

The fundamental economy is good, but with many pessimistic information in the market, depositors easily get panic and their decision making will be greatly impacted by their emotion in the short term. After agents find some of depositors go to run on the bank, they become more scared because they are afraid that the environment becomes terrible. Thus, all of depositors will run on the bank if passing the tipping point of bank run.

Refer to Hansen (1997), the PBR is $(PBR_1, \dots, PBR_n)$, with initial conditions $(PBR_0, PBR_{-1}, \dots, PBR_{-p+1})$.

To find out the tipping point, a two-regime Threshold Autoregressive (TAR) model is reasonable to be proposed as follows:

$$\begin{aligned} PBR_t = & (\alpha_0 + \alpha_1 PBR_{t-1} + \dots + \alpha_j PBR_{t-j}) I(q_{t-1} \leq \mu) \\ & + (\beta_0 + \beta_1 PBR_{t-1} + \dots + \beta_j PBR_{t-j}) I(q_{t-1} > \mu) + e_t \end{aligned} \quad (4.4)$$

Basically, as shown in the above equation, $1(\cdot)$ can be treated as the indicator function. $q_{t-1} = q(PBR_{t-1}, \dots, PBR_{t-j})$ is regarded as a recognized PBR function.

The order of the autoregressive model is $j \geq 1$, Schwert (2002) suggested that we can set the number of lags not bigger than $j_{\max}$, where

$$j_{\max} = (12 \times (\frac{n}{100})^{\frac{1}{4}}) \quad (4.5)$$

The threshold parameter is defined as μ . Therefore, the parameter α_j are the slopes of the model when $q_{t-1} \leq \mu$. Otherwise, we use β_j instead of α_j when $q_{t-1} > \mu$.

Two alternative representations of Equation (4.4) will be applied. Let

$$x_t = (1 \quad PBR_{t-1} \quad \dots \quad PBR_{t-j})'$$

and

$$x_t(\gamma) = (x_t' 1(q_{t-1} \leq \mu) \quad x_t' 1(q_{t-1} > \mu))'$$

Thus we can show Equation (4.4) as either

$$PBR_t = x_t' \alpha 1(q_{t-1} \leq \mu) + x_t' \beta 1(q_{t-1} > \mu) + e_t \quad (4.6)$$

or

$$PBR_t = x_t(\mu)' \eta + e_t \quad (4.6a)$$

where $\eta = (\alpha' \beta)'$.

If the threshold parameter μ has been known, η can be estimated

$$\hat{\eta}(\mu) = (\sum_{t=1}^n x_t(\mu) x_t(\mu)')^{-1} (\sum_{t=1}^n x_t(\mu) y_t),$$

Here, from the above estimation, the residual is known as $\hat{e}_t(\mu) = y_t - x_t(\mu)' \hat{\eta}(\mu)$,

we can as well know the residual variance as

$$\hat{\sigma}_n^2(\mu) = \frac{1}{n} \sum_{t=1}^n \hat{e}_t(\mu)^2 \quad (4.7)$$

To minimizes Equation (4.7), μ can be estimated

$$\hat{\mu} = \arg \min_{q_{t-1} \in \Gamma} \hat{\sigma}_n^2(\mu) \quad (4.7a)$$

where the interval can be defined as $\Gamma = [\underline{\mu}, \overline{\mu}]$. We can therefore have the residuals

$$\hat{e}_t = y_t - x_t(\mu)' \hat{\eta} \quad \text{and variance} \quad \hat{\sigma}_n^2 = \hat{\sigma}_n^2(\hat{\mu}).$$

For this estimation, with a particular integer $d \in [1, \overline{d}]$, the variable of threshold is $q_{t-1} = PBR_{t-d}$ for. Integer d is the delay lag, and it is unknown. One of following key jobs is to estimate this delay lag. For inferring on the tipping point, we predict a fixed d first because the LS estimate $\hat{d}$ is super-consistent.

To test the existing of tipping point, it is to figure out whether Equation (4.7a) is statistically significant relative to a linear $AR(p)$ or not, so there is the null hypothesis

$$H_0 : \alpha = \beta_0$$

The difficulty of identifying threshold μ under H_0 is a shortcoming of this testing. To solve this problem, the below F-statistic showed that the test is near-optimal for alternatives which are distant from the null hypothesis

$$F_n(\mu) = n \left(\frac{\hat{\sigma}_n^2 - \hat{\sigma}_n^2(\hat{\mu})}{\hat{\sigma}_n^2(\hat{\mu})} \right) \quad (4.8)$$

The asymptotic distribution of F_n is not χ^2 in the case that we can't define μ ,

but it can be approximated by bootstrap procedure (Hansen 1996). Setting that ρ_t^* , $t=1, \dots, n$ are iid $N(0,1)$, where ρ_t^* , $t=1, \dots, n$ are random selected, and $PBR_t^* = \rho_t^*$. We can observe that x_t , $t=1, \dots, n$, so in order to find the residual variance $\hat{\sigma}_n^{*2}(\mu)$, we use PBR_t^* regress on x_t . The F-statistic will become

$$F_n^*(\mu) = n(\tilde{\sigma}_n^{*2}(\mu) - \hat{\sigma}_n^{*2}(\mu)) / \hat{\sigma}_n^{*2}(\mu)$$

and $F_n^* = \sup_{\mu \in \Gamma} F_n^*(\mu)$.

If the error e_t is heteroskedastic in certain condition, we will need to use a heteroskedasticity-consistent Wald test instead of the F -statistic.

$F_n(\mu)$ with Similarly, making $PBR_t^* = \hat{e}_t \rho_t^*$, $R = (I \quad -I)$, $M_n(\mu) = \sum x_t(\mu) x_t(\mu)'$, and $V_n(\mu) = \sum x_t(\mu) x_t(\mu)' \hat{e}_t^2$.

As the result, we can obtain the pointwise Wald statistic as follows:

$$W_n(\mu) = (R\hat{\eta}(\mu))' [R(M_n(\mu)^{-1} V_n(\mu) M_n(\mu)^{-1}) R']^{-1} R\hat{\eta}(\mu)$$

Also take the test for H_0 and get

$$W_n = \sup_{\mu \in \Gamma} W_n(\mu) \quad (4.9)$$

In order to test the hypothesis $H_0: \mu = \mu_0$, the likelihood ratio (or F) statistic is applied:

$$LR_n(\mu_0) = n \left(\frac{\hat{\sigma}_n^2(\mu) - \hat{\sigma}_n^2(\hat{\mu})}{\hat{\sigma}_n^2(\hat{\mu})} \right) \quad (4.10).$$

For construct confidence intervals for μ , it is to define a conservative procedure that the convexified region is $\Gamma = [\hat{\mu}_1, \hat{\mu}_2]$, where $\hat{\mu}_1 = \min_{\mu} \hat{\Gamma}$ and $\hat{\mu}_2 = \max_{\mu} \hat{\Gamma}$.

4.3 Simulation and Estimation

To examine the affective-process effect and tipping point with robustness, tests are conducted for a large number of parameter values.

Symbol	Assignment	Description
T	100, 500 and 1000	length of a simulation
N	10, 100 and 1000	number of agents
r	1.20, 1.32, 1.45, 1.60	the early payoff with 10% incremental ratio
R	2.0, 2.20, 2.42, 2.66	the late payoff with 10% incremental ratio
θ	between 0 and 1	the probability of getting late payoff, fixed or randomly to test the fundamental economics
γ	0, 0.2, 0.4, 0.6, 0.8, 1	the exponent of θ effect
δ	3, 4, 5, 6, 7	n^{th} root about the nonlinear effect of agent amount

Table 4 - 1 Parameter Value

4.3.1 Affective-Process Effect

In this part, different combinations in affective magnitude section will be tested. To robust check that this effect exists in different environment, the interval of θ is from 0.3 to 0.9. When θ is smaller than 0.3, it means that the environment is too terrible and bank run must occur. Thus, the analysis is neglected here. In the timeline, the

sequent θ has 0.8 probability to keep the same rate, and changes with 0.2 probability. In our previous research, it has been found that the affective-process effect is obvious when R is from 2.0 to 2.2 and $r=1.2$ keeps unchanged. Therefore, for each combination, two points of Granger Causality test will be made, that is, when $R=2.0$ and $R=2.2$ (Table 4-2). In simulation, there are 100 agents and in 1000 sequence timeline. At the result, there are three potential combinations have significant p -value at 10% level: $\gamma=0.6, \delta=4$; $\gamma=0.8, \delta=3$; $\gamma=1, \delta=6$. To figure out the best one, a further IMF should be checked among these three choices.

$\delta \backslash \gamma$		0	0.2	0.4	0.6	0.8	1
R=2.0	3	0.017	0.193	0.122	0.361	0.002	0.221
R=2.2		0.189	0.493	0.344	0.014	0.086	0.190
R=2.0	4	0.833	0.131	0.654	0.057	0.654	0.592
R=2.2		0.250	0.442	0.009	0.035	0.009	0.148
R=2.0	5	0.389	0.717	0.115	0.014	0.483	0.331
R=2.2		0.386	0.140	0.459	0.742	0.253	0.667
R=2.0	6	0.177	0.159	0.431	0.086	0.446	0.070
R=2.2		0.075	0.024	0.008	0.594	0.000	0.087
R=2.0	7	0.431	0.100	0.078	0.071	0.307	0.264
R=2.2		0.007	0.176	0.766	0.193	0.063	0.214

Table 4 - 2 Granger Causality Test

There are two scenarios to compare the IMF, the first is in the general environment, and the other is in the low level of uncertainty, which the tipping-point effect exists. Based on the granger causality test setting, there is one more consideration that $R=2.1$. The affective-process effect is in the short-run, so the lag terms will be chosen as parsimoniously as possible. To compare AIC/BIC criteria, the general scenario is lag 4 and low uncertain scenario is lag 2. In the general scenario (see Appendix A1), the effect from last two combinations is much more significant. e.g. for the second combination ($\gamma=0.8, \delta=3$), the maximal impact is near 0.4 in 95% confidence interval when $R=2.0$. And we continue to compare the result in low uncertainty (see Appendix A2), the second combination also has the best and stable performance that the maximal impact is close to 0.2 in 95% confidence interval when R changes from

2.0 to 2.2. Therefore, the second combination is selected, and the affective magnitude vector is denoted by:

$$\mathbf{T} = \left[\frac{(R \times \theta^{-0.8} - r) \times \sqrt[3]{N}}{r \times (R \times \theta^{-0.8} - 1)} \quad 1 - \frac{(R \times \theta^{-0.8} - r) \times \sqrt[3]{N}}{r \times (R \times \theta^{-0.8} - 1)} \right] \quad (4.11)$$

4.3.2 Tipping Point

In low level of uncertainty that θ ranges from 0.7 to 0.9, similar to affective process, the tipping point also plays an important role. When the fundamental economy is relatively good, the bank-run phenomenon are not likely to happen. At this time, the runs will occur only if PBR pass some critical value. To be specific, the average of PBR is smaller than 0.50 in this scenario, and PBR will tip to a high level impacted by both affective-process effect and tipping-point effect. There are two characteristics of affective-process effect at this time: first is that affect-process only have very short-run effect. Secondly, the value of affective-process effect become smaller, however, any little increase of affect-process effect will lead to the dramatical jump of PBR.

Figure 4- 1 Difference θ and its Ascending PBR

Figure 4-1 shows the simulating result with the initial setting $R=2.0$ and $r=1.2$. There are 100 agents in 500 sequence time. In the simulation, it is clear to see that when θ is in low level, PBR gradually increases in very high level. That is, if θ is sufficiently small, bank run must happen. To be specific, when the average of PBR is larger than 0.50, which means that the occurrence of bank-run is obvious, the tipping point effect can be ignored due to that the fluctuation only keeps in the high level. On the other hand, when the average of PBR is smaller than 0.50, tipping point effect comes out. In low level of uncertainty (θ is close to 1, that is when the economy is relatively good), it seems that the bank-run phenomenon is difficult to happen. However, this tipping-point effect will dramatically increase this probability. When passing this threshold value, bank run becomes easy to occur. Therefore, the estimation of when the bank run will tip is very meaningful in the real world. When R and r have been announced, the tipping point will locate at some stable interval, based on different level of R and r . Therefore, the tipping point and its 95% confidence interval when these two payoff changing should be estimated.

There are 100 agents in 500 sequence time. Firstly, the lag term should be selected. Based on Schwert (2002), $\text{lag} \leq 16$, and then we check the stability of significance from 1 to 16. The sum of squares errors (SSE) will be smaller when the lag term increases, and the significance becomes the most stable when $\text{lag}=15$. Therefore, $\text{lag}=15$ is selected. Secondly, the delay parameter has to be figured out. By Hansen, Bruce E. (1997), the delay parameter is decided by Bootstrap P -Value < 0.05 , which means that LM-test (F-test) for threshold rejects linearity as F sequence exceeds 95% critical value. The conservative 95% confidence intervals for μ is to be defined as the convexified region $\Gamma = [\hat{\mu}_1, \hat{\mu}_2]$ where $\hat{\mu}_1 = \min_{\mu} \hat{\Gamma}$ and $\hat{\mu}_2 = \max_{\mu} \hat{\Gamma}$. To test the tipping point when both the early and late payoff change, the setting of early payoff r will range from 1.2 to 1.6 with 0.1 added one by one and late payoff R will range from 2.0 to 2.6 with 0.1 added one by one (see Appendix B).

	R	r	y_{t-d}	μ	p -value	Confidence interval
1	2	1.2	y_{t-3}	0.278684	0	[0.270305, 0.278729]
2	2.1	1.2	y_{t-2}	0.292955	0.024	[0.176925, 0.292955]
3	2.2	1.2	y_{t-2}	0.311447	0.011	[0.252327, 0.5426]
4	2.3	1.2			NA	
5	2.4	1.2			NA	
6	2.5	1.2			NA	
7	2.6	1.2			NA	
8	2	1.3	y_{t-10}	0.204476	0.039	[0.202056, 0.337864]
9	2.1	1.3	y_{t-9}	0.280163	0.042	[0.27513, 0.292324]
10	2.2	1.3	y_{t-5}	0.284656	0	[0.281456, 0.433581]
11	2.3	1.3	y_{t-4}	0.273291	0.094	[0.269896, 0.499907]
12	2.4	1.3			NA	
13	2.5	1.3			NA	
14	2.6	1.3			NA	
15	2	1.4	y_{t-13}	0.24236	0.006	[0.216541, 0.997183]
16	2.1	1.4	y_{t-13}	0.297154	0.034	[0.297154, 0.297154]
17	2.2	1.4	y_{t-5}	0.195254	0.092	[0.184347, 0.213508]
18	2.3	1.4	y_{t-3}	0.377731	0.024	[0.224994, 0.421843]
19	2.4	1.4	y_{t-11}	0.318085	0.016	[0.29893, 0.457382]
20	2.5	1.4			NA	
21	2.6	1.4			NA	
22	2	1.5	y_{t-14}	0.27762	0.001	[0.264037, 0.333525]
23	2.1	1.5	y_{t-1}	0.218584	0.016	[0.21105, 0.301928]
24	2.2	1.5	y_{t-11}	0.390941	0.022	[0.322573, 0.986502]
25	2.3	1.5	y_{t-13}	0.235156	0.016	[0.227398, 0.723273]
26	2.4	1.5	y_{t-1}	0.260246	0.015	[0.253091, 0.269042]
27	2.5	1.5	y_{t-7}	0.349609	0.034	[0.287009, 0.363233]
28	2.6	1.5			NA	
29	2	1.6	y_{t-5}	0.297769	0.038	[0.224099, 0.301269]
30	2.1	1.6	y_{t-2}	0.30768	0.026	[0.264038, 0.317864]
31	2.2	1.6	y_{t-14}	0.23617	0.004	[0.232431, 0.27901]
32	2.3	1.6	y_{t-3}	0.227326	0.028	[0.221881, 0.460945]
33	2.4	1.6	y_{t-5}	0.260543	0.022	[0.231419, 0.383147]
34	2.5	1.6	y_{t-7}	0.266304	0.026	[0.2219, 0.346758]
35	2.6	1.6	y_{t-13}	0.328891	0.024	[0.287034, 0.392176]

Table 4 - 3 Tipping Points and the Corresponding Confidence Interval

In Table 4-3, most of tipping points are located between 0.25 and 0.35. In the relative low risk sharing level, that is, r is small, the tipping point will be disappear and at

this time the maximal $PBR < 0.5$ when R is increasing, e.g. $R=2.3$ and $r=1.2$, $R=2.5$ and $r=1.4$.

Figure 4- 2 Tipping Point Trend

When r increases by 0.1, R should increase by 0.1 for preventing the tipping-point effect. e.g. when $r=1.2$, the tipping-point effect disappears when $R=2.3$, when $r=1.3$, the tipping-point effect can be eliminated when R increase to 2.4. This reveals that the increased risk sharing will increase the probability of tipping-point effect. In our previous research, we have found that the increase of r will decrease the fluctuation of PBR, however, the PBR seems more unpredictable as the tipping-point effect exists. Besides, the tipping-point value is not impacted by the change of risk sharing. This means that the increased risk sharing just influence on the existance of tipping-point effect, but not the threshold value. In other words, only the change of R have significant impact on the changing of tipping-point value. Thus, we can take the average value with the same R but different r , and look at the relationship between R and the tipping-point value. Two critical value should be focused, the tipping-point estimation value and the lower bound of 95% confidence interval. At the result, there is a positive trend that the increased R (from 2.0 to 2.6) will increase the tipping-point value of bank-run occurrence (Figure 4-2). These detailed numbers show that

it becomes more difficult to run on the bank when the late payoff can be larger, and this supports our previous main finding that the increase of R will reduce even eliminate PBR. In addition, this increase trend is not a linear relationship, which means that some of increased R is more useful for preventing bank-run phenomenon, such as R increases from 2.0 to 2.1, from 2.5 to 2.6. This is the result with 1000 times bootstrap replications, so the 95% confidence interval is reliable. This means that other estimation will probably locate within this interval, and the PBR might tip when passing the minimum level of tipping-point value, which is around 0.2 and 0.3. Generally, when the fundamental economy is quite good but PBR exceeds 0.2, it is possible that the tipping-point effect of bank run exists. Therefore, the financial institutions and central bank should be careful to prevent the occurrence of bank run when the tipping point is coming.

4.4 Conclusion

Animal-spirit random variables can trigger the bank-run phenomenon. Even in good environment, the tipping-point effect will cause bank run dramatically. Our internal “mental model” consider the interaction of cognitive and affective processes. The cognitive-process effect can be strong only when the market is good and has little noise, otherwise, it is probably that affective-process effect dominates the decision making in the short run. Therefore, this study focuses on the parameters and critical values in bank-run estimation. For the adjustment of affective-process parameters, the granger causality test and impulse response function are adopted. As the result of granger causality, there are three combinations, then one of which is selected by impulse response function. Based on the selected parameters, the results we have proved in previous chapters are correct, and the affective-process effect becomes clearer. When the uncertainty is in the low level, the bank run occurs only when the tipping-point effect exists. The increased risk sharing, that is, the increase of early payoff r will cause this effect, but it does not impact the tipping-point value. On the

other hand, the increase of late payoff R will increase the tipping point, which means that it will prevent or even eliminate the bank-run phenomenon. Generally, when PBR passing 0.2, it is possible that bank run happens, and when PBR passing 2.5, it is very easy to run on banks because it is probably passing the tipping point. As tipping-point effect is a discontinuous jump dramatically, it is too difficult to prevent bank run after passing it. Thus, the financial institutions, central bank, depositors and investors should pay attention to the animal-spirit random variables in the market. Even in a stable environment, it is a warning if these random variables are close to the tipping point.

Appendix

Appendix A1. Impulse Response Function for Three Potential Choices ($\theta = 0.3 \sim 0.9$)

$\gamma=0.6, \delta=4$

$\gamma=0.8, \delta=3$

$\gamma=1, \delta=6$

Appendix A2. Impulse Response Function for Three Potential Choices ($\theta = 0.7 \sim 0.9$)

$\gamma = 0.6, \delta = 4$

$\gamma = 0.8, \delta = 3$

$\gamma = 1, \delta = 6$

Appendix B F -test for Threshold and the Corresponding Confidence Interval

$R=2, r=1.2$

$R=2.1, r=1.2$

$$R=2.2, r=1.2$$

$$R=2, r=1.3$$

$R=2.1, r=1.3$

$R=2.2, r=1.3$

$R=2.3, r=1.3$

$R=2, r=1.4$

$R=2.1, r=1.4$

$R=2.2, r=1.4$

$R=2.3, r=1.4$

$R=2.4, r=1.4$

$R=2, r=1.5$

$R=2.1, r=1.5$

$R=2.2, r=1.5$

$R=2.3, r=1.5$

$R=2.4, r=1.5$

$R=2.5, r=1.5$

$R=2, r=1.6$

$R=2.1, r=1.6$

$R=2.2, r=1.6$

$R=2.3, r=1.6$

$R=2.4, r=1.6$

$R=2.5, r=1.6$

$$R=2.6, r=1.6$$

Chapter 5

Summary

To figure out the reason why bank-run phenomenon still frequently occur, this thesis provides insights from animal spirits that have been repeated calls with great attentions in economics (e.g. Loewenstein and O'Donoghue, 2004; Akerlof and Shiller, 2009; Grauwe, 2012). This term used in economics goes back as far as Keynes (1936). Animal spirits, instead of just employing mathematics and strong economic analysis, would lead people to act without shyness and doubt. When the environment is in chaos, the animal spirits will be large and this so-called sunspot equilibrium exists in the market. When the environment seems to be highly safe, the trigger of animal spirits is nonlinear, and occurrence of bank run will become unpredictable. At this time, there is a tipping point of bank runs. Before the formation of bank run, there is an inevitable trend if a threshold value is passed.

Real world bank runs tend to involve various factors, and it might be due to miscoordination or/and deterioration of the quality of the bank's assets. Both solvency shock and illiquidity shock will become the bank's disaster. It is clear that solvency shock in the market might cause a bank failure, while insolvency is much

more serious because even if the banks have access to temporary funds it can't solve the underlying problem of excess debts such as the Lehman Brothers and Greece. On the other hand, liquidity shock shows a temporary cash flow problem, which can cause insolvency in the long term. Liquidity shock will also trigger the bank-run phenomenon although sometimes banks are still in good operation. Impacted by both of insolvency and illiquidity, the noneconomic factors might play a crucial role for running on banks.

Chapter 1 concludes two mainstream perspectives of bank-run theories, however, it is debatable which one is the real reasons of bank runs. This study shows that bank-run phenomenon might come from both reasons, that is, the miscoordination or/and deterioration of the quality of the bank's assets. To better understand the mechanism behind these two causes, the term animal spirits is revisited. The bad economic situation can cause the run on the bank, and sometimes the nonfundamental factors can cause this phenomenon as well, that is the sunspot-equilibrium scenario. Especially when the economic environment is relatively good, the happening of bank run will appear dramatically. The tipping-point effect is important and it is concerned in this study.

Chapter 2 figures out the existence of animal spirits in bank-run phenomenon. Replaced by economic man, the agents use the simple rules to portray the cognitive limitation and willingness to learn (e.g. Kirman, A. 2006; Brazier et al 2008; Grauwe 2012). The agents just use the information they can understand, which can not capture the whole picture. Both the simulation and real data results show the effect of animal spirits that small changes could have big, and desirable consequences. The shock aroused by animal spirits can tip the bank run based on the adaptive learning mechanism. The effect of animal spirits does not come from the irrational expectation. Instead, it is from the fact that the agents are eager to learn from the mistake they ever have with the bounded memory ability.

Chapter 3 further explores the internal mechanism of animal spirits, and proposes a "mental model" that agents have integrated cognitive-affective neural network. In

the simulation result, the average level of PBR is shifted by the fundamental economy, and this can come from the single cognitive process. All of these are in accordance with AG's opinion that bank run is caused by the deterioration of the quality of the bank's assets. On the other hand, the fluctuation of PBR is significantly impacted by the cognitive-affective process, especially it is due to the affective process. This means that the animal-spirit random variable will have significant influence on our affective process while the pessimistic announcement appears in the market. In this scenario, it is in accordance with DD's perspective that bank run is due to miscoordination, and it is not related to fundamental economy. This chapter explains both of the contradictory views of bank-run classical models. Besides, there are several conclusions for the adjustment of early payoff r and late payoff R . Both the rise of r and R will decrease the affective-process effect. The increased risk sharing (increase r) might or might not increase PBR, which is based on the level of uncertainty. The rise of late payoff R must be beneficial for preventing the bank run.

Chapter 4 takes the estimation of PBR by solving two questions, the checking of affective-process parameter and the prediction of tipping point. By this robust check, it is nonlinear dynamic for affective magnitude in affective-process section. By 1000 times bootstrap replications, 25 sets of tipping point and its corresponding 95% confidence interval are estimated. In the simulation result, the increased risk sharing will cause the tipping-point effect, but it does not impact the tipping-point value. On the other hand, the increase of late payoff R will increase the tipping point, and it will prevent the happening of bank run if R is large enough. Generally, when PBR passing 0.2, it is possible that bank runs occur, and when PBR passing 0.25, it becomes very dangerous and too late to restrain.

This thesis develops from the psychological foundation of human behavior, and gives explanation for bank-run phenomenon with the framework combined computational economics, behavioral economics, neuroeconomics and econometrics. Based on sets of simple parameters, the model is built to take the precise explanation and estimation of bank-run occurrence. The further research will

come from two points. Firstly, the magnitude of announcement in the market is different. Secondly, the spread of this announcement can go with different social networks.

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