Athens University of Economics and Business

A Behavioural Bank Run Model [*]

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Abstract

In our paper we investigate the determinants of banking crises. We review the relevant literature and we also construct and estimate a behavioural model that combines the two major views on banking crises. In our model, the market is populated by two groups of agents, the "fundamentalists" and the "nervous" agents. The former react to changes in economic fundamentals while the latter react to the actions of the rest of the agents. The interplay between these two groups creates interesting dynamics that could potentially explain bank runs.

[*]A paper submitted in partial fulfilment of the requirements for the Master of Science degree in the Master of Science Program in Business Mathematics. All Python code and documentation for the computational model is available at https://github.com/antonopoulos

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1 Introduction

Are banking crises a result of panic, a rational response or both? This question has been the main focus of research around banking crises. The severe impact of the financial crisis of 2007-2009 highlights the importance of understanding the drivers of such events. As this recent event showed, financial crises and more specifically banking crises, can have a huge impact on the economy as a whole and hence a meticulous analysis of the causes of such events is of the utmost importance.

When it comes to the drivers of banking crises, there are two schools of thought. On the one hand there are those who believe that crises are mainly panics, caused by some kind of "sunspot". This approach was formalized by Briant[1] and Diamond and Dybvig[2] according to which, crises are self-fulfilling phenomena and there is no solid connection between crises and fundamentals.

On the other hand, some claim that crises are exclusively driven by changes in economic fundamentals. There are a number of theoretical models (see among other Chari and Jagannathan[3]) and empirical studies (see among others Calomiris[4]) that support this opinion. According to this view, fundamentals either determine directly the actions of the agents or they act as "coordination devices".

One, more realistic approach is that crises are a result of the combined effect of panic and changes in fundamentals. More accurately, according to this view, changes in economic fundamentals act as a trigger of the self-fulfilling expectations.

Most of the papers that study bank runs, can be classified into two broad categories: There are the papers that propose game-theoretic models which try to explain the generating mechanisms behind bank runs. Moreover, there are also some other papers that focus on the macroeconomic and microeconomic determinants of bank runs, usually using some reduced form model (e.g. linear regression). However, we believe that despite their significant contribution to the literature, both approaches have flaws: Even though game-theoretic models propose plausible mechanisms, they cannot be easily estimated. Most of these models, are either not dynamic (e.g. 2 period "games") or use only unobservable variables, which makes their estimation impossible. On the other hand, reduced form models may have a high predictive power but such models, because of their simple form (usually linear), do not provide any insights about the agents' behaviour. This is why, in our paper, we propose a model that imposes some structure on the data (i.e. not a reduced form model) and which can be directly estimated from the data.

Building on the existing literature, we propose an alternative to the game-theoretic models that have been heavily used to explain banking crises by developing a behavioural model with heterogeneous agents. In this model, the level of bank deposits is endogenously determined by considering the interaction of market participants. More specifically, we assume that the market is populated by two distinct groups of agents, the "fundamentalists" and the "nervous" agents and that agents can switch groups after each period. The former, respond only to changes in economic fundamentals while the latter just observe the "lines" that are formed in front of them. The level of deposits in the banking system is determined by agents' demand and the interplay between these two groups can potentially result in a bank run. Finally, we also try estimate the parameters of our model using data from the Greek banking system.

The rest of the paper is organized as follows: In **Section 2** we review the most seminal papers in the bank run literature. **Section 3**, describes the model that we propose. In **Section 4** we describe the estimation process that we follow and **Section 5** presents the results that we obtain. Finally, **Section 6** concludes.

2 Literature Review

2.1 Causes of Banking Crises

Although funding and liquidity problems can trigger a crisis, the relevant literature shows that problems that arise in asset markets are also a usual cause. Banks often run into problems when many of their loans are non-performing or when securities lose their value. This is what happened in the Nordic banking crises in the late 1980s, the crisis in Japan in the late 1990s, and the recent crises in Europe. In the aforementioned instances, it was the non-performing real estate loans that led to the undercapitalization of these banks, which in turn, created the need for governmental support. Turbulence in asset markets, such as the subprime and other mortgage loans, also where the main culprits of the recent crisis. According to Claessens and Kose[5] these types of problems in asset markets can go undetected for some time, and a banking crisis often comes into the open through the emergence of funding difficulties among a large fraction of banks.

According to Gorton[6], banking crises, are rarely random events. It is more probable that a Banking Crisis will occur around the time of cyclical downturns, with recessions on the horizon. When depositors become aware of the risks, they start demanding cash from the banks. However, since banks cannot liquidate immediately their assets to satisfy the rising demand, a panic may occur. The banking crisis in the 1930s was attributed to shocks in the real sector and in many developing economies, banking crises were triggered by external events, such as sudden movements in capital flows, interest rates, which consequently led to an increase in the fraction of loans that were nonperforming.

A number of studies (Lindgren, Garcia and Saal[7], Barth, Caprio and Levine[8] among others) have identified a number of structural characteristics that are related to the development of banking crises. Some of them are: poor market discipline due to moral hazard and excessive deposit insurance, limited disclosure, weak corporate governance framework, and poor supervision. Furthermore, some other factors that are associated with bank crises are the following: large state-ownership and limited competition in the financial system and an undiversified financial system (World Bank, 2001). Nevertheless, it is quite difficult to assess the individual importance of these factors as, most of the time, they are observed simultaneously.

2.2 The Two Schools of Thought: Fundamental v Panic

One of the main questions that concerns researchers is whether banking crises are purely a result of panic or happen due to a deterioration of economic fundamentals.

The panic-based approach to banking crises was formalized by Bryant[1] and Diamond and Dybvig[2]. In the Diamond-Dybvig model (henceforth D&D), when investors withdraw money from a bank, they deplete the banks capital, reducing the amount available for investors who come in the future. This creates strategic complementarities, such that investors wish to withdraw when they think others will do so. The result is multiplicity of equilibria. There is an equilibrium in which all the investors withdraw and an equilibrium in which none of them does. This model implies that crises have a self-fulfilling nature as they occur only because investors believe they will occur and there is no connection between crises and fundamentals.

The fundamental-based (or information-based) approach has been modeled as well, for example, in Chari and Jagannathan[3], Jacklin and Bhattacharya[9], and Allen and Gale[10]. The main idea is that bad fundamentals (or negative information about fundamentals) lead banks balance sheets to deteriorate, inducing investors to run.

In the following sections, we present the D & D model, the most well-known sunspot-based model and also delineate the basic features of the asymmetric information-based models.

2.3 The Diamond Dybvig Model

Diamond and Dybvig were the first to develop a theory that would treat bank runs as self-fulfilling phenomena. According to D&D, banks issue short term liabilities so as to finance long-term productive projects. However, this process of maturity transformation is really special when it is being done by the banks since (1) agents must be served on a first-come first-served basis (2) agents' true liquidity needs remain private information. According to D&D, the aforementioned characteristics are the sources of bank fragility.

In the D&D model, agents possess an initial endowment of goods which can be invested and transformed into more goods in the future. If investment is left in place long enough, the net returns are positive. However, some agents will discover that they need to consume before the investment matures while other agents are patient and able to consume after investment has matured. Investment takes place before agents discover their intertemporal preference for consumption.

Diamond and Dybvig note that under ordinary circumstances, savers' unpredictable needs for cash are likely to be random, as depositors' needs reflect their individual circumstances. Since depositors' demand for cash are unlikely to occur at the same time, by accepting deposits from many different sources the bank expects only a small fraction of withdrawals in the short term, even though all depositors have the right to withdraw their full deposit at any time.

However a different scenario is also possible: The banks' assets are illiquid as their loans were, by assumption, used to finance long-term investments and cannot be called in quickly. Therefore, if all depositors attempt to withdraw their funds simultaneously, a bank will run out of money long before it is able to pay all the depositors. The bank will be able to pay the first depositors who demand their money back, but if all others attempt to withdraw too, the bank will go bankrupt and the last depositors will be left with nothing.

One of the most important implications of this model is that it shows that bank runs can occur even in a setting where we don't have any currency or a risky investment technology. Hence, one can conclude that it is not necessary for problems in the banking system to be related to such factors. In this model, even banks that are solvent are prone to bank runs. For instance, if a depositor expects all other depositors to withdraw their funds, then the bank's fundamentals are irrelevant since the depositor's rational response is to rush to take his or her deposits out before the other depositors do the same. In other words, in the D&D models, bank runs are self-fulfilling prophecies: each depositor's action depends on his/her expectation about the actions of the others.

For the purposes of our paper, these are the most important implications of the model that we should keep in mind. However, given the importance of this model in the literature of bank runs, we provide a more detailed analysis in the **Appendix**.

2.4 Fundamentals

The opposing view states that bank runs are exclusively driven by changes in economic fundamentals (Ennis[11]). The so called "asymmetric information" theories of bank runs assert that the cooperation failure between depositors can be attributed to informational asymmetries regarding the state of fundamentals.

Asymmetric information theory asserts that problems within the banking system originate from the fact the bank assets are opaque and depositors are not aware of the banks' portfolio composition. This lack of bank-specific information available to depositors, during times of high uncertainty, ”aggregate information” is used to assess the riskiness of individual banks (Gorton[6]). Hence, according to this view, panics, are actually rational responses by uninformed depositors when negative information arrives.

Moreover, Calomiris[4] also stresses that the macroeconomy plays an important role in shaping depositors' expectations. Chari and Jagannathan[3] also model runs where the uninformed depositors observe the actions of the informed ones (signal extraction). Referring to panic-based runs, they suggest that if individuals observe long lines at the bank, they correctly infer that there is a possibility that the bank is about to fail and precipitate a bank run.

Thus, these opposing theories suggest that bank runs, are not random phenomena, but rational responses. According to Chen[12], depositors are in an ”informational disadvantage” and respond to various sources of information, even before they become aware of the real value of their own bank's assets.

Goldstein and Pauzner[13] also model panic-based bank runs where the threshold levels of fundamentals of the economy determine the occurrence of a bank run. They criticize the D&D model for failing to provide tools to derive the probability of the bank-run equilibrium and they emphasise that the bank run outcome is still panic based, albeit determined by the realization of fundamentals which are not sunspots. In other words, in these models, fundamentals do not determine directly the actions of the agents but rather act as a ”coordination device”.

2.5 Empirical Evidence on the Role of Fundamentals

The empirical literature that studies banking crises, has identified a number of fundamental variables that could either determine or predict a crisis. In this section we will review the main findings of these studies.

Gorton[6], studies the national banking era in the United States between 1863 and 1914 and he asserts that crises were caused by depositors who were responding to an increase in perceived risk. He demonstrates that crises occurred whenever key variables that are linked to the probability of a recession reached a critical value and he asserts that the most important variable is the liabilities of failed firms. When the perceived risk of a recession (which is based on these variables), becomes high, depositors believe that their deposits are at risk which leads to mass withdrawals.

In their seminal paper, Demirguc-Kunt and Detragiache[14] examined the determinants of banking crises in a number of developed and emerging economies. They found out that variables that are related to the fundamentals of the economy are related to the occurrence of crises. Among the key predictors that they identify are: GDP growth, high real interest rates an inflation and the level of outstanding credit. They assert that crises cannot be attributed solely as self-fulfilling phenomena and that they are "tied" to the economy. Moreover, they note that the institutional environment of a country also affects the likelihood of a banking crisis.

While the aforementioned papers examine economy-wide variables, others focus on bank-specific variables and their relation with the withdrawals from specific banks. Schumacher[15], studies the runs in Argentinian banks following the devaluation of the Mexican currency in December 1994. The devaluation that took place in Mexico affected Argentina since it led to speculation that Argentina would do the same. These concerns about the currency quickly evolved to general concern about the soundness of the financial system and the economy as a whole. According to Schumacher, depositors transferred money from banks they considered "bad" to the "good" ones reacting on information they had about the ability of banks to survive a currency collapse. She notes that the "bad" banks were indeed fundamentally weaker, with poorer performance more non performing loans and lower liquidity.

Finally, Calomiris and Mason[16] study banking crises during the great depression and they find evidence that support the the "fundamental" view by showing that bank-specific variables such as leverage, asset risk, and liquidity affect the likelihood of failure, and so do variables that capture the local or regional economic situation. At the same time though, they also find that there is a significant unexplained residual when they try to explain crises which leads them to the conclusion that either the model of fundamentals is incomplete or that there was some element of panic involved.

2.6 A Possible Explanation about the Role of Panic

Even though the evidence reviewed in the previous section provides a strong case that fundamentals matter and hence crises are not random events, the role of panic in these crises remains blurry. We should also highlight the fact that even if one finds correlation between fundamentals and crises, this is in no way a proof against the "panic" hypothesis.

One view is that, fundamentals act as a trigger of the self-fulfilling expectations. In other words, even though fundamentals can be associated with crises, a crisis would not occur without coordination failure. Hence, one could say that crises cannot be justified solely on the basis of fundamentals, since they could have resulted in a non-crisis outcome.

This can be better understood by the currency attack model by Morris and Shin[17]. In their model, the government maintains a fixed exchange rate regime at an overappreciated level. Speculators may choose to attack the regime by selling the local currency to the government and buying the foreign currency. The variable θ captures how strong the fundamentals of the economy are(a higher θ indicates stronger fundamentals and vice-versa). Speculators have to pay a transaction cost to attack the regime. They make a capital gain if the government abandons the regime and the government abandons the regime if the cost of maintaining it is higher than the benefit, where the cost is decreasing in the fundamental and increasing in the number of speculators who attack.

There are three regions of θ that determine the possible equilibrium outcomes (see **Figure 1**). There is a threshold $\tilde{\theta}$, below which there is a unique equilibrium where speculators attack the regime and the government abandons the regime. In this case, the fundamentals are so "poor" that the government will abandon the regime no matter what the speculators will do. The speculators understand that and choose to attack the currency. Above a threshold $\bar{\bar{\theta}}$ ($\bar{\bar{\theta}} > \tilde{\theta}$)the fundamentals are so good that the government will maintain the regime even if speculators choose to attack the currency. However, speculators also understand that and do not attack.

The most interesting part of the model is the region between $\tilde{\theta}$ and $\bar{\bar{\theta}}$.In this region we have multiple equilibria. At every level of fundamentals in this range, a crisis can either occur solely on the basis of self-fulfilling beliefs.Crises in this range can be referred to as "panic-based" because a crisis in this range is not necessitated by the fundamentals; it occurs because agents think it will occur, and in that sense, it is self-fulfilling. However, the occurrence of a self-fulfilling crisis here is entirely determined by the fundamentals. So, in this sense, the "panic-based" approach and the "fundamental-based" approach are not contradictory.

In sum, the discussion in the preceding paragraphs indicates that it is reasonable to assume that the fundamental-based argument, does not confront the panic-based approach. On the contrary, the two views complement each other: Poor fundamentals can cause crises, which, nevertheless, are still self-fulfilling in some degree.

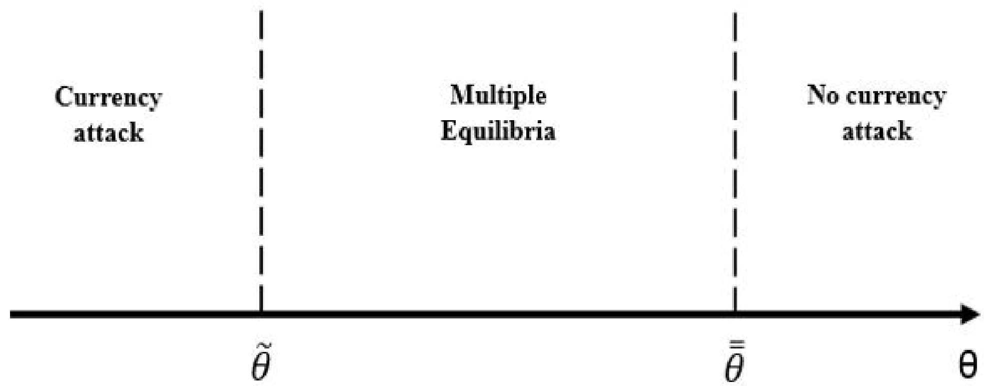

Figure 1: Morris & Shin Model.

This graph shows the three regions in the Morris & Shin model that determine possible equilibrium outcomes.

2.7 Distinguishing Panic and Information-based Bank Runs

According to the literature that we reviewed, bank runs can be instigated because of panic, information or both. Hence, the question is whether we can identify, empirically, the drivers of a bank run.

Being able to identify the drivers of a bank run has major policy implications. If bank runs are caused by panic (e.g. Diamond Dybvig[2], Peck & Shell[18], Postelwaite and Vives[19]), the policy measures should be deposit insurance or/and suspension of convertibility. If the fundamental-based hypothesis is true, then, policy options include ex ante imposition of balance sheet constraints or ex post recapitalization.

At first sight, this seems like a simple task. One could just try to show that agents withdrew their money simply because they observed other agents doing the same. However, this approach would have a serious flaw: If someone finds that investors are more likely to run when other investors run, is not a proof of panic as these agents could have observed some fundamental-related signal that made them withdraw their money in the first place (This issue is known as the "reflection problem", Manski [20]). Things get even more complicated when someone tries to "measure" the impact of panic during a bank run that was information-related.

Not surprisingly, there are not many papers that try to answer this question. One of the few papers that focuses on this subject is that of Graeve and Kara[21]. In their paper they use raw, micro-level, deposit data and compare the withdrawal rates across banks whose deposits are insured with banks that have uninsured deposits. In order to do that they construct a multivariate system (VAR) of deposits and interest rates. They conclude that conditional on a bank run, depositors run even on solvent banks which is a clear indication for panic. However, they also find that withdrawals in insolvent banks are four times larger than withdrawals on the solvent ones, which supports the information-based view.

In a different setting, Chen et al.[22] try to distinguish panic-related and fundamental-related outflows from mutual funds. When an investor wants to redeem her share form an open-end mutual fund, the fund must liquidate some of its assets. However, this cost is transferred to investors who remain in the fund. Hence, according to Chen et al.[22], if some agents expect that other agents will redeem their shares, they would also want to redeem their shares so as to avoid the damage. This incentive is stronger in funds with illiquid assets. Chen et al.[22] actually find that the response to a negative change in fundamentals is much stronger in funds with illiquid assets, which, essentially, is a proof for panic.

These two studies, using micro level data (i.e. account level data), were quite successful in distinguishing the two types of bank runs. However, there are two issues with these studies: First, such detailed data may not be always available to everyone. Secondly, it would be even better, if we could actually ”see” how the agents behave during these turbulent times. In other words, these studies just observe withdrawal rates, which is the ”final act” of an agent. However, we would also like to have a convincing answer about the exact mechanism that turns an information-driven ”run” to a widespread panic. Nevertheless, this can be done only if we impose some structure on the data and this is what we will try to do in the next pages.

3 The Model

3.1 Introduction

In order to construct a structural model for bank runs, we first have to take a stand about the level of rationality of the agents. There are two opposing views in the field of economics about this matter. Most of the bank run models that have been proposed until now share a common feature: In these models agents are fully rational and their actions depend on their expected utilities. However, there are many studies that challenge this view (see among others Thaler et al.[24]).

Many researchers argue (see among others Kirman[25]), that the traditional ”rational expectations” hypothesis is not suitable for modelling sudden changes in the environment and they highlight the need for models that are ”closer to reality”. Such need could be answered by a new class of models which are known as ”Agent Based Models”.

In these models, we do not have the ”all seeing” and ”all knowing” agents that we see in traditional economics. On the contrary, agents now follow some simple rules of thumb, that can tell them what to do in any given situation. Heterogeneous agent-based models have proved to be successful in simulating the fundamental properties of real economic systems and financial markets, which arise endogenously from the interaction of agents. These models have been used in fields like epidemiology, traffic congestion and crowd behaviour in building evacuations but also in the broader field of baking and finance. For instance, Lux[26] tried to simulate the interbank lending network, Giansante et al.[27] study the relation between liquidity and solvency of economic agents and Bookstaber and Paddrik [28] build an Agent-based Model that explains banking liquidity dynamics.

Even though, reduced-form models have proven to be very powerful in predicting a number of economic and financial phenomena, these models cannot explain in a clear way the generating dynamics of these events. However, Agent Based Models, just like any other structural model that imposes some kind of structure on the data, is more suitable in providing insights and explaining the behaviour of the agents.

As we saw previously, the ability to identify panic-based and fundamental-based banking crises is crucial for policy purposes and It is not surprising that many empirical papers have tried to distinguish the two types of crises in the data. In our paper we will try to construct a model with heterogeneous agents that identifies the basic mechanisms that can generate a bank run and that specifically distinguishes the two drivers (i.e. panic and fundamentals). In order to estimate the parameters of this model we will use data from the Greek banking sector.

In our model, we try to understand the dynamics of a bank run by modelling the course of deposits in the banking system. Our model assumes that the market is populated by two distinct groups of customers, the "nervous" customers and the "fundamentalists". The "nervous" customers observe the course of deposits in the banking system and tend to withdraw their money if they observe a decrease in deposits. On the other hand, the "fundamentalists" do not care about the level of deposits per se and observe a signal that proxies the fundamentals of the banking system. They tend to withdraw their money if these fundamentals deteriorate. Customers are able to shift between strategies at the start of each period. These two groups of agents reflect the two main schools of thought in the relevant literature. The "fundamentalists" represent the rational force of the market while the "nervous" agents are in a state of panic.

3.2 Evolution of the market shares

Let us start with the motion of the customer market fractions (i.e. the percentage of customers that are either "fundamentalists" or "nervous"). Let the number of agents in the market be N=1 (it is a matter of scaling and it could be any positive number). We define n_t^f and n_t^n as the percentages of "fundamentalists" and "nervous" customers respectively. In this model, customers can switch strategies in each period and their shares can be determined using a logit model. We can consider some payoff indices u_t^p and u_t^f which could be derived from past gains of the two groups. The market fractions can be then expressed as

$$n_t^f = \frac{e^{\beta u_{t-1}^f}}{e^{\beta u_{t-1}^n}+e^{\beta u_{t-1}^f}} \text{ and } n_t^n = \frac{e^{\beta u_{t-1}^n}}{e^{\beta u_{t-1}^n}+e^{\beta u_{t-1}^f}}$$

where β is the intensity of choice. Dividing these fractions by $e^{(\beta u_{t-1}^f)}$ and $e^{(\beta u_{t-1}^n)}$ respectively we obtain

$$n_t^f = \frac{1}{e^{-\beta(u_{t-1}^f - u_{t-1}^n)}+1} \text{ and } n_t^n = \frac{1}{e^{\beta(u_{t-1}^f - u_{t-1}^n)}+1}.$$

Note that the difference $(u_{t-1}^f - u_{t-1}^n)$ can be viewed as the relative attractiveness of the fundamentalist strategy. If we denote this attractiveness with a_{t-1}, the discrete choice approach is then given by

$$n_t^f = \frac{1}{e^{-\beta a_{t-1}+1}} \text{ and } n_t^n = \frac{1}{e^{\beta a_{t-1}+1}}.$$

Finally, without any loss of generality we can set $\beta = 1$ (it is just a matter of scaling) and we obtain:

$$n_t^f = \frac{1}{1+e^{-a_{t-1}}},\ n_t^n = \frac{1}{1+e^{a_{t-1}}} \text{ and of course } n_t^f + n_t^n = 1.$$

Note that the market fractions are directly related by the attractiveness level as an increase in a_{t-1} leads to an increase in the market share of the fundamentalists. Hence, we have to define the mechanism behind a_t.

Following the relevant literature, we assume that there are three forces that determine the relative attractiveness level of the fundamentalist strategy: (1) A certain predisposition towards one of the two strategies (i.e. agents could could inherently act more "rationally") (2) A herding mechanism, meaning that the more agents in one group, the more attractive this group becomes and (3) The withdrawal/deposit rate. Then, a_t is determined by:

$$\alpha_t = \alpha^* + \alpha_n(n_t^f - n_t^n) + \alpha_f(D_t - D_{t-1}),\ \alpha_n > 0,\ \alpha_f > 0 \quad (1)$$

The second term in the above equation captures the idea of herding. The more customers are already fundamentalists, the more attractive this group becomes. In reality, an agent cannot observe these groups directly. However, agents have at least a rough idea about the general behaviour of the public. For instance, they can understand whether their friends or family have started panicking or not, they watch the news etc. Hence, our assumption, that an agent can observe these two groups, is certainly a bit far-fetched but not totally unrealistic. We could, instead, assume that agents can observe some "noisy" signals about the groups' size, which would be closer to reality but we chose not to do that in order not to over-parametrize the model.

The third term is the percentage change of deposits[‡]. The intuition behind this factor is the following: if customers observe a decrease in deposits, α_t decreases. This means that the share of "fundamentalists", n^f_{t+1}, decreases and hence agents become more "nervous". Finally, when these two effects cancel out (i.e. when $n^f_t = n^n_t$ and $D_t = D_{t-1}$), then $\alpha_t = \alpha^*$, which is the predisposition parameter (which is positive if customers have a priori preference towards fundamentalism and vice-versa).

3.3 Stability Analysis

In order to understand the properties of the model, we believe that it would be useful to examine the equation that determines the attractiveness of the two groups. It is very important to be able to study how sensitive our model is to small perturbations or changes of initial conditions and of various parameters. Let us focus in the case where $D_t = D_{t-1}$, so that we can isolate the stochastic part of the model. Then, we have that:

$$\alpha_t = \alpha^* + \alpha_n(n^f_t - n^n_t) \iff \alpha_t = \alpha^* + \alpha_n\left(\tfrac{1}{1+e^{-\alpha_{t-1}}} - \tfrac{1}{1+e^{\alpha_{t-1}}}\right)$$

which is a difference equation of α_t and α_{t-1}. Rather than solving explicitly this difference equation, we will provide some numerical examples that will help us distinguish a few cases that we deem important.

For our first simulation we use $\alpha^* = 0$ and $\alpha_n = 7$ and an initial value $\alpha_0 = -10$. In the graph below we have plotted α_t against α_{t-1} and we can see that, the function has three equilibrium points (i.e. the points where

[‡]Throughout our analysis, we will take the natural logarithm of the levels of all variables. Hence, the difference of the log(levels) will be the percentage change

$\alpha_{t-1} = \alpha_t = \alpha$, for all t). One around $\alpha_t = 7$, one around $\alpha_t = -7$ and $\alpha_t = 0$. Since the market shares of the two groups of agents depend on α_t, we can also draw some conclusions about the market shares n_t. When $\alpha = 7$, the market is dominated by the "fundamentalists" since $n^f \approx 99\%$. When $\alpha = -7$, most of the agents have become "nervous" as $n_t^c \approx 99\%$. Finally, when $\alpha = 0$ the market is divided with $n^f \approx n^n \approx 50\%$. However, we should highlight that only the first two states are locally attractive while the third one is not stable. After trying different parameter values we can conclude that when the herding parameter $\alpha_n > 1$ and $\alpha* \approx 0$, this system has three equilibrium points, one with $n^f > 50\%$, one with $n^n > 50\%$ and one with $n^f \approx n^n$.

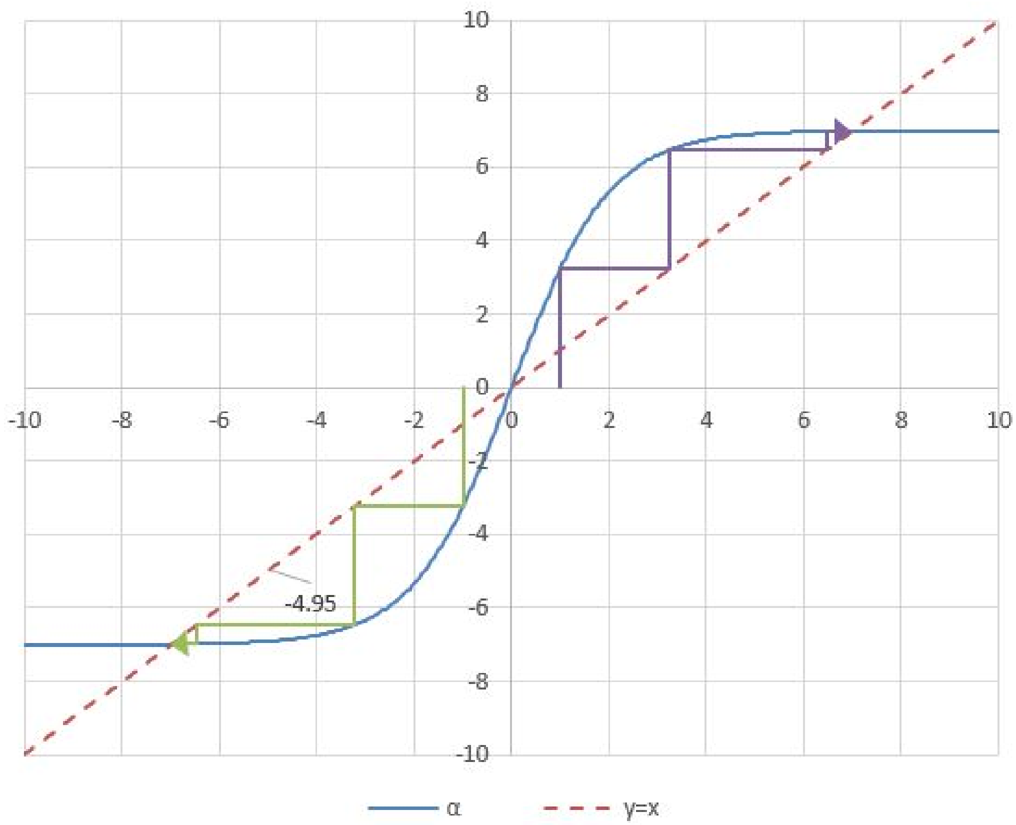

Figure 2: Cobweb 1.

We graph the deterministic part of the equation that determines α_t using $\alpha^* = 0$ and $\alpha_n = 7$. There are three equilibrium points where $\alpha_t = \alpha_{t-1}$ and two of them are locally attractive.

For the next simulation we set $\alpha^* = 0$ and $\alpha_n = 0.8$. Now, the system has only one equilibrium point, $\alpha = 0$, which locally stable. In general, we find that when $0 < \alpha_n < 1$ the system has only one equilibrium point, which is also locally attractive. Whether this equilibrium will be "dominated" by fundamentalists or "nervous" customers depends on the predisposition parameter α^*. As α^* becomes more negative, the graph shifts down and the system moves to regions where "nervous" agents dominate the market (where $\alpha_t < 0$) and vice-versa .

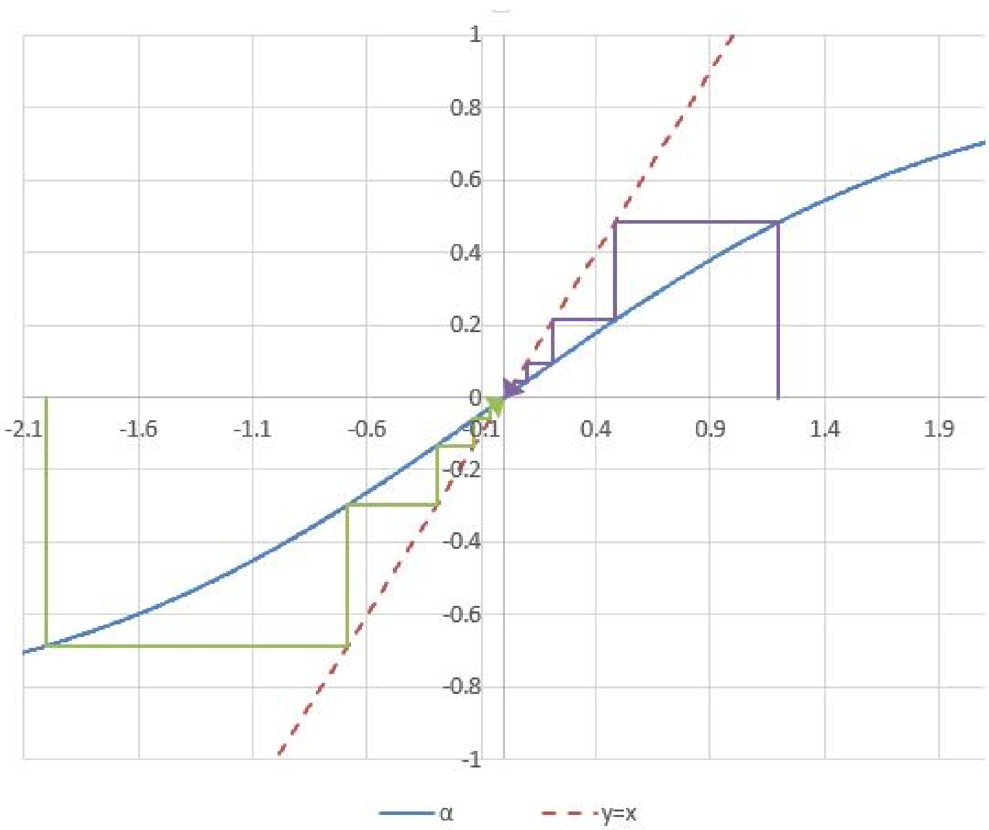

Figure 3: Cobweb 2.

For this graph we use $\alpha^* = 0$ and $\alpha_n = 0.8$. Now we have one equilibrium point at $\alpha_t = \alpha_{t-1} = 0$. We see that this point is locally attractive.

Lastly, we set $\alpha_n = 5$ and $\alpha^* = 5$ and we use $\alpha_0 = -15$ as an initial value and we obtain the following graph where we have only one equilibrium point (which is locally attractive) and where fundamentalists dominate the market. We conclude that when $\alpha_n > 1$ and $|\alpha^*|$ is sufficiently large, the system,again, has only one equilibrium point, where either fundamentalists or "nervous" agents dominate the market, depending on the sign of the predisposition factor α^*.

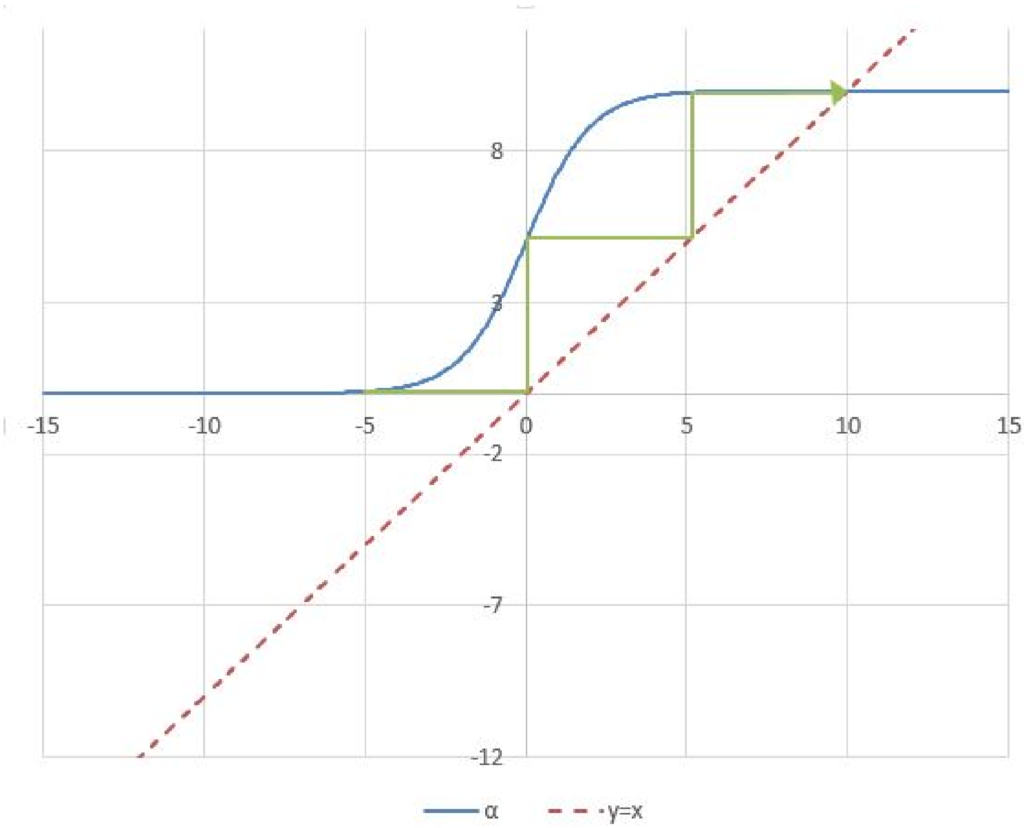

Figure 4: Cobweb 3.

For this simulation we use $\alpha^* = 5$ and $\alpha_n = 5$ and we see that we obtain one equilibrium point which is locally attractive.

We believe that for the purposes of our analysis, cases (2) and (3) are not very interesting. In these cases, we would have a market that is persistently dominated either by fundamentalists or "nervous" agents and this is not a reasonable assumption.

As we saw previously, according to the relevant literature, the fundamental-based argument does not confront the panic-based approach, as poor fundamentals can cause crises which will still be self-fulfilling in some degree. It is possible, that agents oscillate between rational and more irrational or "nervous" behaviours. This is exactly what we want to capture with this model and this is why we believe that we should focus in case (1) where we can obtain multiple equilibria.

Of course, when we add the stochastic part of the model, this kind of analysis gets more difficult but after a number of simulations we conclude that these three general rules that we presented, hold even in the full specification of the model.

3.4 Determination of Deposits

The level of deposits is determined by demand and supply, were demand (supply) is the precise amount of money that is withdrawn (deposited) per period. The specific demand of each customer group is kept simple in the form of the demand per customer in that group[§](a more detailed analysis of these demand functions is provided in the **Appendix**).

Fundamentalists, want to withdraw their money if the fundamentals of the banking system deteriorate. On the other hand, the "nervous" agents, observe only the change in the deposits and they would withdraw their money if deposits decrease (i.e. observing withdrawals rates is like observing the "lines" that are formed in front of them. Hence, "nervous" agents essentially base their actions on the actions of others). However, when the fundamentals improve and deposits increase, the average demand of the two groups remains constant. Thus, we model group specific demands as follows:

$$d_t^f = c + \phi(X_t - X_{t-1})\mathbb{I}_{[(X_t - X_{t-1})<0]} + \epsilon_t^f, \quad \epsilon_t^f \quad \sim N(0, \sigma_f^2), \quad \phi > 0 \ (2)$$

$$d_t^n = c + \chi(D_t - D_{t-1})\mathbb{I}_{[(D_t - D_{t-1})<0]} + \epsilon_t^n, \quad \epsilon_t^n \quad \sim N(0, \sigma_n^2), \quad \chi > 0 \ (3)$$

where, X_t is a variable that reflects the state of the fundamentals of the banking system and it will be exogenous to the model (we will specify it later) and D_t the log-level of deposits at time t. Moreover, d_t^f and d_t^n is the demand per customer in each group and ϕ and χ capture the "aggressiveness" of the the customer in the two groups. The constant c, is the average demand of the two groups when deposits increase and fundamentals improve (i.e. when

[§]The group-specific demand is the total demand over the number of agents in that specific group

$(X_t - X_{t-1}) > 0$ and $(D_t - D_{t-1}) > 0)$. This constant essentially reflects some other factors (e.g. macroeconomic factors) that are not captured by this model. The intuition behind these asymmetric demand functions is that, during relatively calm periods (i.e. when the fundamentals improve and deposits increase), we expect deposits to be driven by GDP growth, taxation etc. However, when problems arise, we expect people to behave differently. Some of the agents will focus on the fundamentals of the economy and some on the behaviour of others (i.e. on withdrawal rates).

Lastly, each trader in each group could diverge from these trading rules and hence, each demand component has a group-specific noise term which reflects the within-group heterogeneity.

The total demand, d_t^{TOT}, (normalized by the population size) can be obtained if we multiply each group specific demand with the respective market shares:

$$d_t^{TOT} = n_t^f d_t^f + n_t^n d_t^n \ (4)$$

The total demand (d_t^{TOT}) can be either positive (net deposit of money) or negative (net withdrawal) and the total deposits are adjusted according to the following equation:

$$D_{t+1} = D_t + d_t^{TOT} \ (5)$$

In sum, the model works as follows: In each period, the customers observe the size of each group and the percentage change of deposits. The attractiveness of the fundamentalist strategy (α_t) is determined from equation (1). Then the two groups of customers are formed and each group forms has own demand (equations (2) and (3)). Finally, the new level of deposits is determined endogenously by the model from equation (5) (a more detailed analysis of the computational solution of the model is provided in the **Appendix**).

3.5 Qualitative Features of a Sample Run

Before we proceed to the estimation part, it would be useful to explore the qualitative features of the model by running two simulations. For the first simulation we run the model without any stochastic noise (i.e. $\sigma_n = 0$, $\sigma_f = 0$), while for the second simulation we run the full model. These two simulations highlight two important aspects of the model. We will see that when we use the deterministic version of the model, bank runs are the result of a deterioration of the fundamentals. However, in the full version (with stochastic noise), a bank run can occur even when economic fundamentals are not deteriorating. In other words, when we add noise in the model, a random event (e.g. a relatively large withdrawal) can cause panic that results in a large scale bank run.

The numerical parameters used for the first simulation can be found in **Table 1**. We run the model for 194 periods.

Table 1: Model Parameters- 1st Simulation

c	α^*	α_n	α_f	ϕ	χ	σ_n	σ_f
0.007	0	2	2	0.3	0.6	0	0

In the graph below you can see the the variable that captures the economic fundamentals, X_t. For the purposes of this simulation we assume that this variable initially increases, then experiences a sharp drop and finally, it continues its upward course.

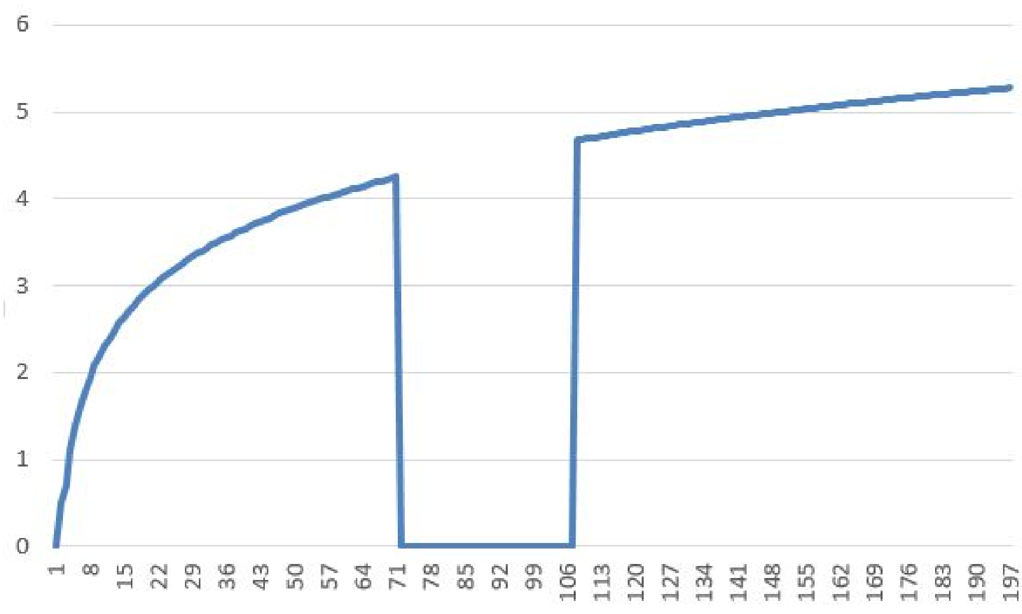

Figure 5: Economic Fundamentals- 1st Simulations.

While the fundamentals of the economy improve, the market is dominated by fundamentalists ($n_f > 0.5$, see **Figure 6**). When the economy experiences a sharp deterioration of its fundamentals, we have two effects. The fundamentalists, that dominate the market, respond to this deterioration and start withdrawing money from the banking system (see **Figure 7**) (remember that the demand of fundamentalists depends only on the change in the variable X_t). This decrease in deposits makes fundamentalism less attractive and in the next period, nearly all agents have become "nervous" (see **Figure 6**). In turn, the "nervous" agents withdraw more money from the banking system (see **Figure 8**), as a response to the decrease in deposits (remember that the demand of the "nervous" agents depends on the change in deposits).

This simple (and extreme) example highlights that panic can be present even in a "run" that is caused by a deterioration of fundamentals: The crisis, first manifests as a result of the sharp deterioration in fundamentals. This deterioration then causes a decrease in deposits and this decrease makes most of the agents "nervous". Finally, these agents withdraw more money from the banking system, and these withdrawals magnify the severity of the crisis.

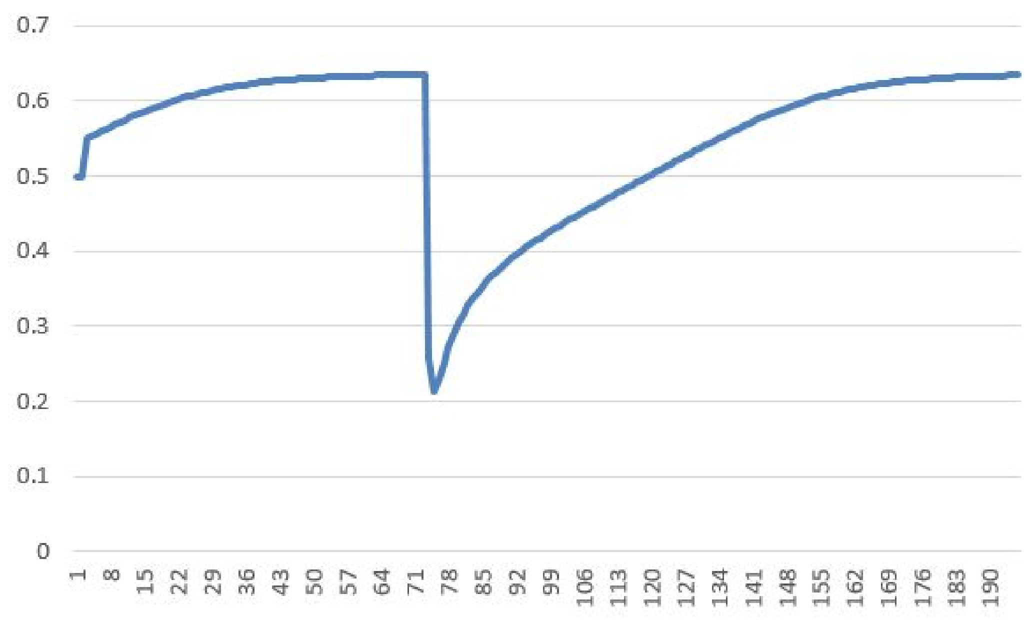

Figure 6: Share of Fundamentalists- 1st Simulations.

This graph shows the share of fundamentalists throughout the periods. We can discern a sharp decline around the 74th period,right after the banking system experiences a strong negative shock. When the fundamentals of the economy start improving, the fundamentalists, once again, dominate the market.

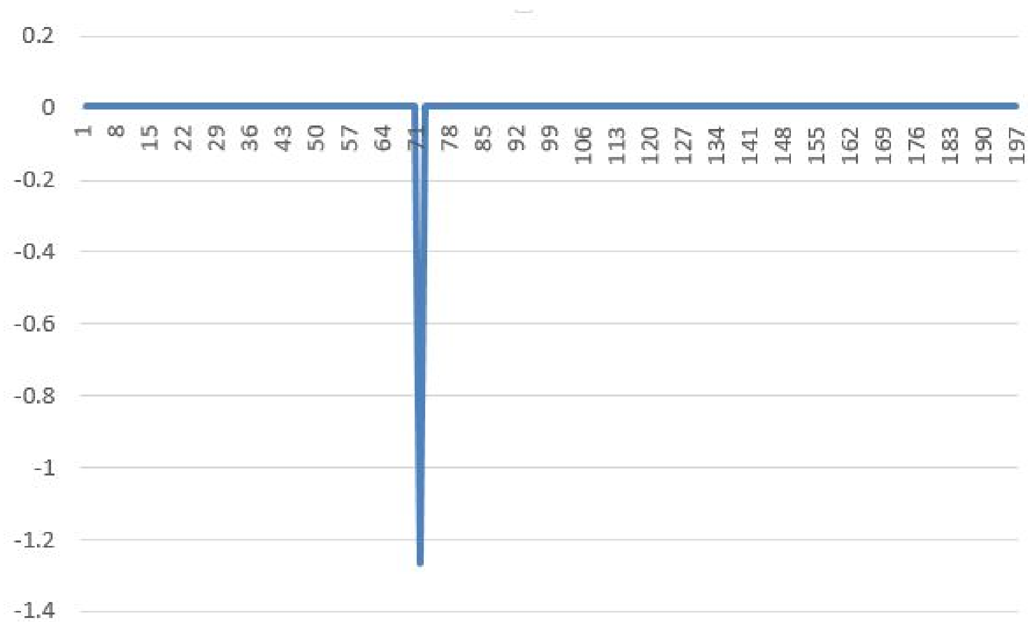

Figure 7: Average Demand of Fundamentalists- 1st Simulation.

This graphs shows the average demand, d_t^f, of the fundamentalists. As we can see the average demand decreases rapidly around the 71th period, right after the decrease in X_t.

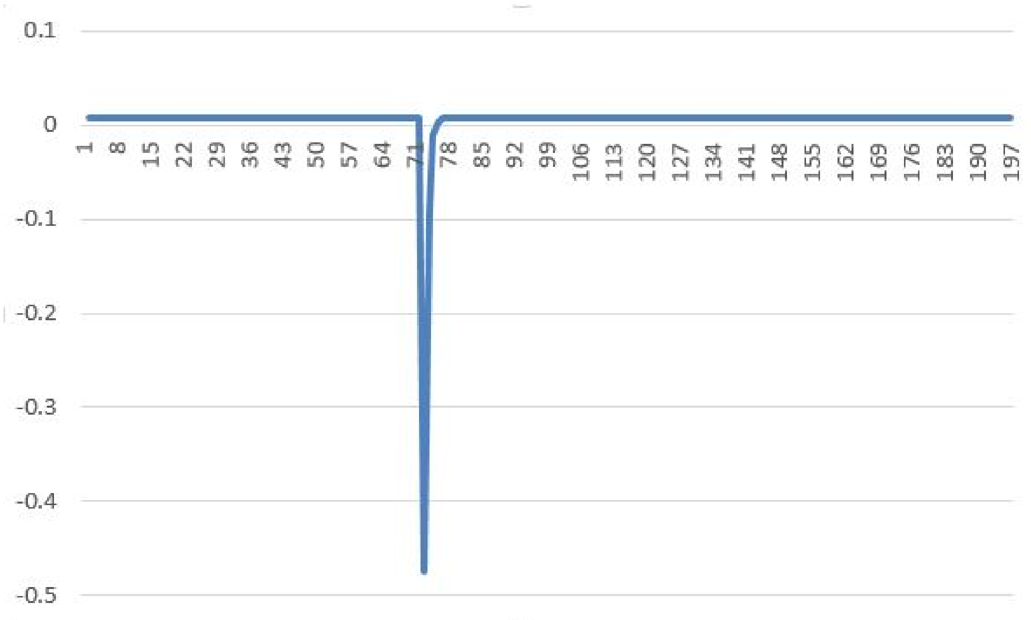

Figure 8: Average Demand of "Nervous" Agents- 1st Simulation.

This graph depicts the course of the average demand, d_t^n, of the "nervous" agents. Even though it is not easily seen from the chart, the demand of these agents decreases sharply on the 72th period, right after the decrease that we saw in the average demand of the fundamentalists. This means that after the initial response of the fundamentalists to the decrease in fundamentals, we have a second wave of withdrawals from the agents that have now become "nervous".

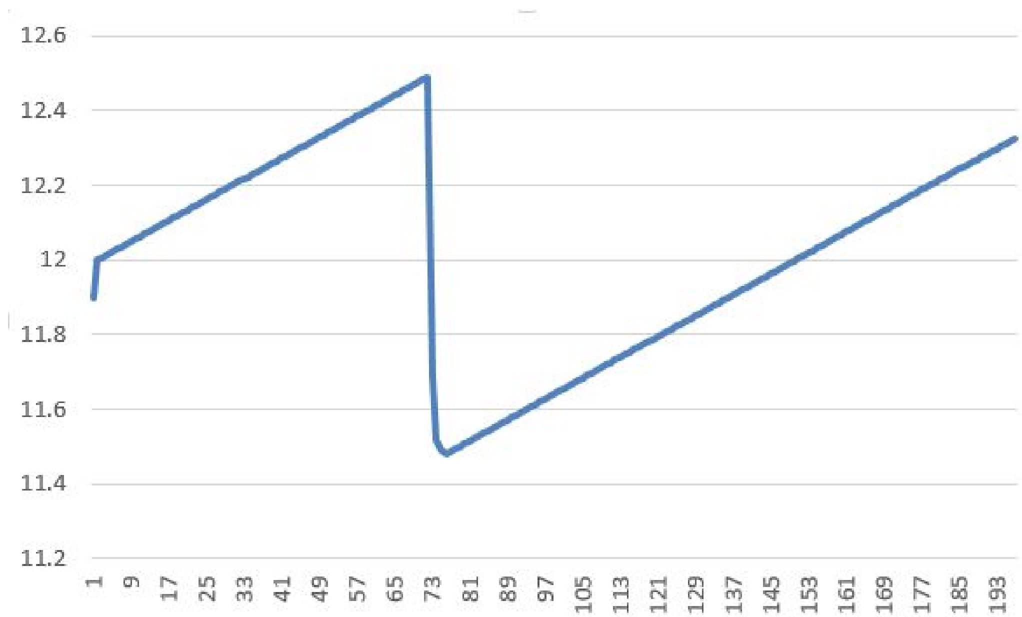

Figure 9: Level of (log) Deposits- 1st Simulation.

The level of deposits in the banking system. We can understand that when we do not include stochastic shocks, the course of deposits is determined solely by the course of the economic fundamentals.

Now, we are going to run a second simulation but this time the demand functions will include stochastic shocks. Again, we run the model over 194 days. In **Figure 10** we see the variable that captures the fundamentals of the banking system, X_t, while **Figure 11** shows the level of (log) deposits, D_t, generated by the model. **Figure 12** shows the percentage of customers that are fundamentalists, over time.

In **Figure 11**, we have highlighted two instances were deposits drop sharply. These two events can be considered as bank runs. One run starts around period 25 and a second one after period 125. However, we will see that the mechanisms that generated these two events were very different.

As we can see in **Figure 10**, around period 25, there is no significant change in the fundamentals of the banking system. Why did we observe a large decrease in deposits then? Around this period, agents observed a large deposit withdrawal, which was the result of random market forces. At the same time, we can see that the share of "fundamentalists" decreases rapidly (see **Figure 12**), as a decrease in deposits makes the agents more "nervous". As a result, the "nervous" agents dominate the market right after the 25th period. Then, the "nervous" agents responded to the initial large withdrawal, with an even larger withdrawal (remember that the demand of the "nervous" agents depends on $D_t - D_{t-1}$) which caused an even sharper decrease in total deposits. This created a negative spiral which made almost everyone in the market more "nervous" and resulted in this bank run.

On the other hand, the second bank run is different. We can see that around the 150th period, the fundamentals of the banking system deteriorate significantly. Around that time, the "fundamentalists" respond by withdrawing their money, and total deposits start decreasing. Then, the "nervous" agents respond to this decrease by withdrawing more money and as the aggregate level of deposits drops more and more, agents become "nervous" and continue withdrawing money.

These two "runs" that we just studied are very different: The first bank run that we observed was the result of pure panic. A random event created a negative spiral that resulted in the withdrawal of massive amounts of money from the banking system. However, the second bank run, started as a rational response to the deterioration of economic fundamentals and was exacerbated through the effect of herding and panic.

Table 2: Model Parameters- 2nd Simulation

c	α^*	α_n	α_f	ϕ	χ	σ_n	σ_f
0.007	0.05	2.00	2.35	0.157	1.29	0.14	0.01

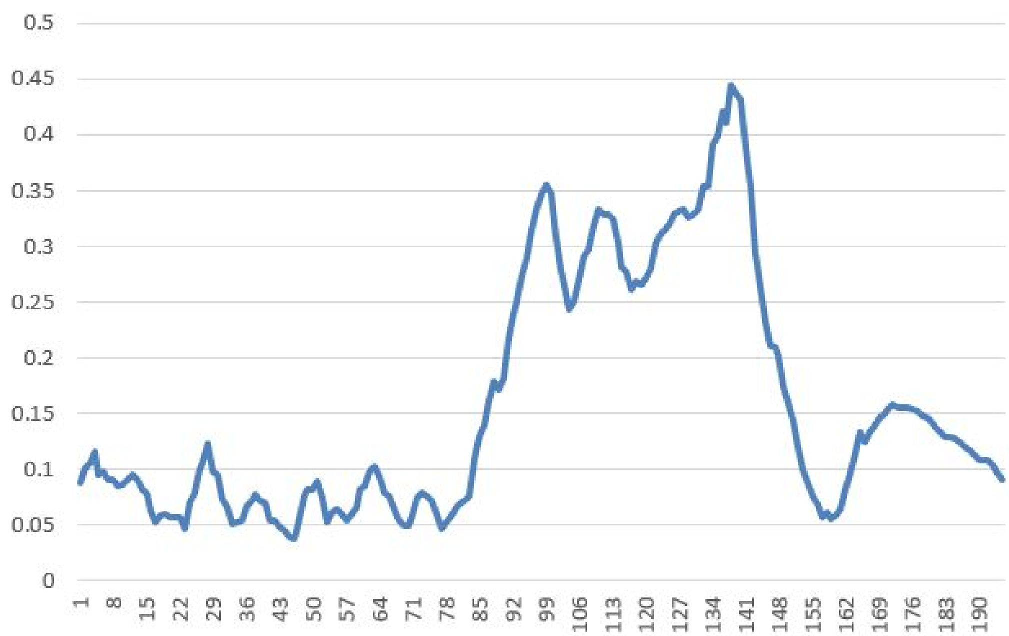

Figure 10: Economic Fundamentals- 2nd Simulation.

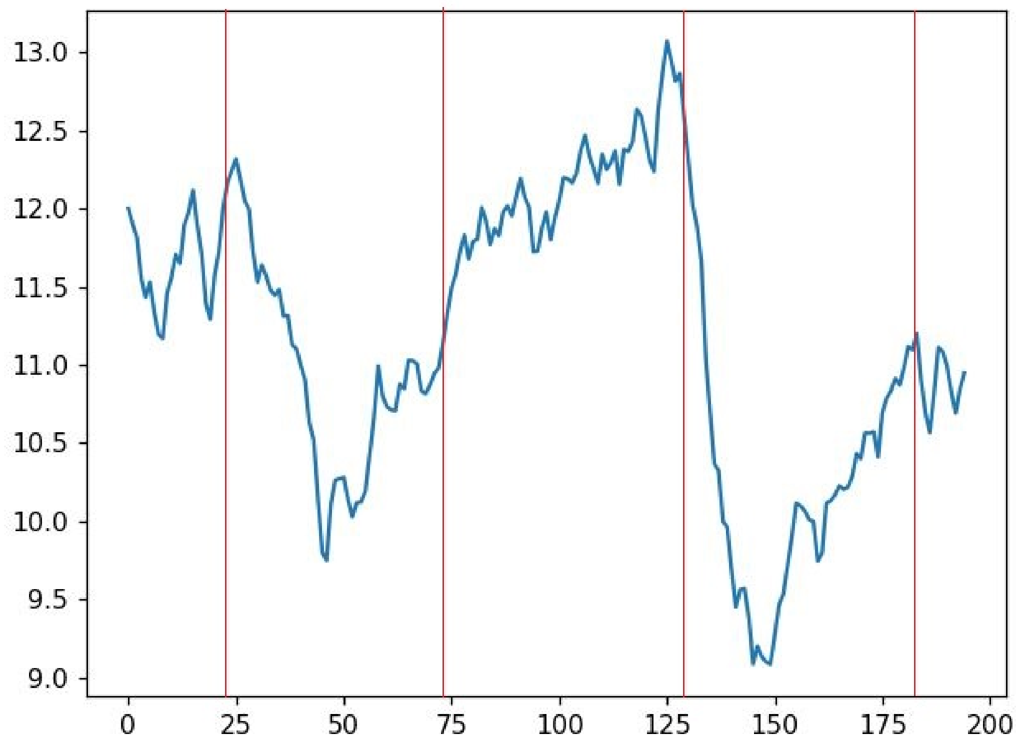

Figure 11: Level of (log) Deposits- 2nd Simulation.

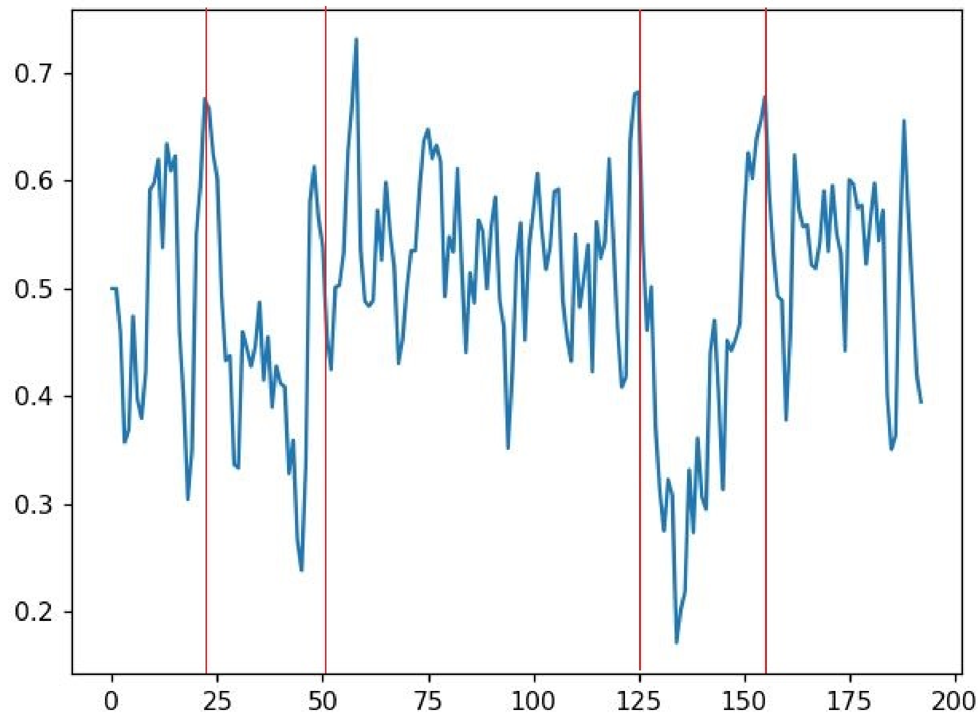

Figure 12: Percentage of Fundamentalists- 2nd Simulation.

In the deterministic version of the model (i.e. in the first simulation), we cannot have panic-based runs since the behaviour of the agents is entirely determined by the course of fundamentals. If economic fundamentals improve, then there is no reason for the agents to withdraw their money. A bank run occurs only when these fundamentals deteriorate.

However, when we include stochastic shocks in the model, we are able to generate "panic-based" runs as well as bank runs driven by economic fundamentals. Now, the course of deposits can be different from the course of fundamentals since, some random event ("sunspot"), can create wide-spread panic that results in massive withdrawals.

This simple example showed how the "fundamental-based" and the "panic-based" approaches could work in practice. The structure that we imposed on the data, allows us to keep track of the "behind the scene" market dynamics and because of that we can clearly identify panic-based and fundamental-based bank runs.

The identification of these two drivers of bank runs has major policy implications since they imply different kinds of remedies. As we already noted, a bank run that is driven solely by panic can be addressed by some sort of capital controls (e.g. temporary suspension of withdrawals). While, in the case of fundamental-driven runs, such measures would be totally inefficient. In that case, a suspension of withdrawals would not alter the behaviour of agents, as agents would be still worried about the fundamentals of the economy.

4 Estimation

In this section we will discuss the numerical estimation of our model using one of the most well-known methods, the Simulated Method of Moments (SMM). For an overview of SMM see the work of Lee and Ingram[29].

4.1 The Objective Function

Just like the Generalized Method of Moments[30], SMM refers to a set of descriptive statistics which are called moments and tries to make the model generated moments as close as possible to their empirical counterparts. However, the difference with GMM is that in SMM, model moments arise from simulations. In models like the one we propose (which is quite non-linear), estimation by Maximum Likelihood or GMM could be infeasible or at least intractable. Hence, estimation by simulation is a reliable alternative.

Let m^{mod} and m^{emp} be the model-generated and empirical moments respectively and let the objective function that we want to minimize be the following:

$$J = (m^{mod} - m^{emp})^T W (m^{mod} - m^{emp}) \quad (9)$$

where W is the optimal weighting matrix (which we will specify later). Until now, this looks exactly like GMM but the now, the difference is that the model moments will be equal to the average of the moments from each simulation: $m^{mod} = \frac{1}{S}\sum_{i=1}^{S} m_s$.

A weighting matrix for our objective function is optimal, if it provides the smallest asymptotic covariance for the estimator. In other words, it is a matrix that downweights the moments with high variability since the higher the variability of a moment, the higher the difference between m^{mod} and

m^{emp} that is still treated as insignificant. A typical choice for this optimal weighting matrix is the inverse of an estimated variance-covariance matrix of the moments, $\hat{\Omega}^{-1}$.

Lastly, when performing an optimization, there is always the case of being trapped in a local minimum/maximum. Hence, in order to make sure that we will avoid this error, we will restart the procedure several times with new initial values until we observe that the results from the minimization do not change significantly.

4.2 Selection of Moments

The purpose of our estimation is to examine whether we can obtain some parameter values that are realistic and meaningful. We want our model to be able to capture, to some extent, the dynamics of bank deposits and withdrawals and in order to do that we will use data from the Greek banking system. We will use monthly deposit data from 2000 to 2016,obtained from the Central Bank of Greece, which means that our sample consists of 194 monthly observations.

Usually, when using GMM or SMM to estimate model parameters, the moments that one chooses reflect some "stylized" facts of the empirical data. However, in our case such "stylized" facts do not exist. In other words, we do not have some empirical findings about withdrawal rates, that are consistent across periods and markets and thus, we will follow our intuition in selecting the moments that we will use.

Our model has a total of eight parameters and we will estimate all of them. In order to simulate the course of bank deposits we will use ten moments and hence, our model will be slightly over-identified. The first moments that we will use are the Standard Deviation of the percentage change of deposits and the autocorrelation functions of the percentage change of deposits for three different lags $\tau = 1, 3, 6$. Moreover, we will also use Kurtosis and Skewness to capture the "fatness" of the tails and any possible asymmetries. We also want to capture the volatility of deposits and withdrawals and hence we will use the autocorrelation functions of the absolute percentage changes at three different lags $\tau = 1, 5, 10$ (since the absolute percentage change is a proxy for volatility). Finally, we want our model to be able to scale the level of deposits and thus, the average level of deposits is also considered.

5 Results

As already mentioned, we try to fit the monthly deposit series for the Greek Banking system, where 194 monthly observations from January 2000 to February 2016 are considered. For the variable X_t, that is exogenous to the model and which captures the fundamentals of the banking system, we chose the Financial Soundness Indicator (FSI) obtained from the ECB which is a proxy for the quality of the economic fundamentals[¶]. Proceeding with the minimization (9) as described above and after trying a number of different initial guesses we are confident that we found a minimum and our results summarized in **Table 3** (rounded to two digits after the decimal point). We also provide the standard errors of all estimated parameters (in parentheses). **Table 6**, in the **Appendix**, shows the empirical moments and the model-generated moments.

Firstly, let us focus on **Table 3**. We can see that the results are really intuitive. For instance, the standard deviation of the fundamentalists' demand is approximately zero and certainly much lower that the one for the nervous agents. This means that the fundamentalists are more "confident" about their actions and have a much less volatile demand. Lastly, the predisposition parameter α^* is positive and around 0.02, which means that the agents are (slightly) predisposed to follow a fundamentalist approach.

In **Figure 13**, we can compare the generated deposits, obtained from the estimated model and the actual deposits. Even though, the fit is not perfect, we have to note that the model captures the general course of deposits: The upward slope until 2009, the slow decline until 2013 and the sharp decrease in 2015. In **Figure 14**, we also plot the estimated share of fundamentalists across time. We see that throughout all periods, the market is balanced between fundamentalists and chartists ($n^f \approx 50\%$) but around the 170th period, the fundamentalist share starts to decline rapidly and more and more agents become "nervous". This drop actually coincides with the sharp decrease in deposits in 2015.

From these graphs we can draw one some important conclusions: In **Figure 13** we can see that there are two instances where deposits decrease. The first "phase" starts around 2009, when deposits start decreasing slowly. The second instance is in late 2014, where deposits decrease sharply. However,

[¶]After estimating the model using different indices, we chose this index since it provided the best fit only during the second "run" we observe an increase in the share of "nervous" agents. During both periods, the fundamentals of the banking system deteriorate (see **Figure 16** in the **Appendix**) and hence this makes the fundamentalists withdraw their money. However, in 2015, apart from the fundamentalists that withdrew their money, we also had a strong "panic" effect, as indicated by the share of "nervous" agents, that resulted in a much more severe and rapid bank run.

As far as the generated moments are concerned, there seems to be room for improvement. As we can see from **Table 5** (see **Appendix**), the model fails to capture the kurtosis of the data (4.10 instead of 2.00), the skewness (-1.65 instead of -0.83) and the standard deviation (0.042 instead of 0.019). However, we have to note that the average deposit level ("dMean") as well as the estimated autocorrelation functions ("rAC" and "vAC") are close to their empirical counterparts. In order to test whether our results are robust we also use two outside moments[‖], namely the percentage of changes in deposits below -5% and the second order autocorrelation function of the percentage changes, with mixed results. As we can see in **Table 6** (see **Appendix**), the model manages to capture the autocorrelation function but fails to capture the percentage of observations.

Table 3: Estimated Parameters

	c	α^*	α_n	α_f	ϕ	χ	σ_n	σ_f	$\mathscr{J}(\theta)$
Param.	0.03	0.02	1.19	4.19	4.64	0.01	0.69	0.00	5.20
(St.Dev)	(2.31)	(1.00)	(1.08)	(1.00)	(1.00)	(1.00)	(1.09)	(1.16)	

[‖]Outside moments are moments that are not used in the estimation process

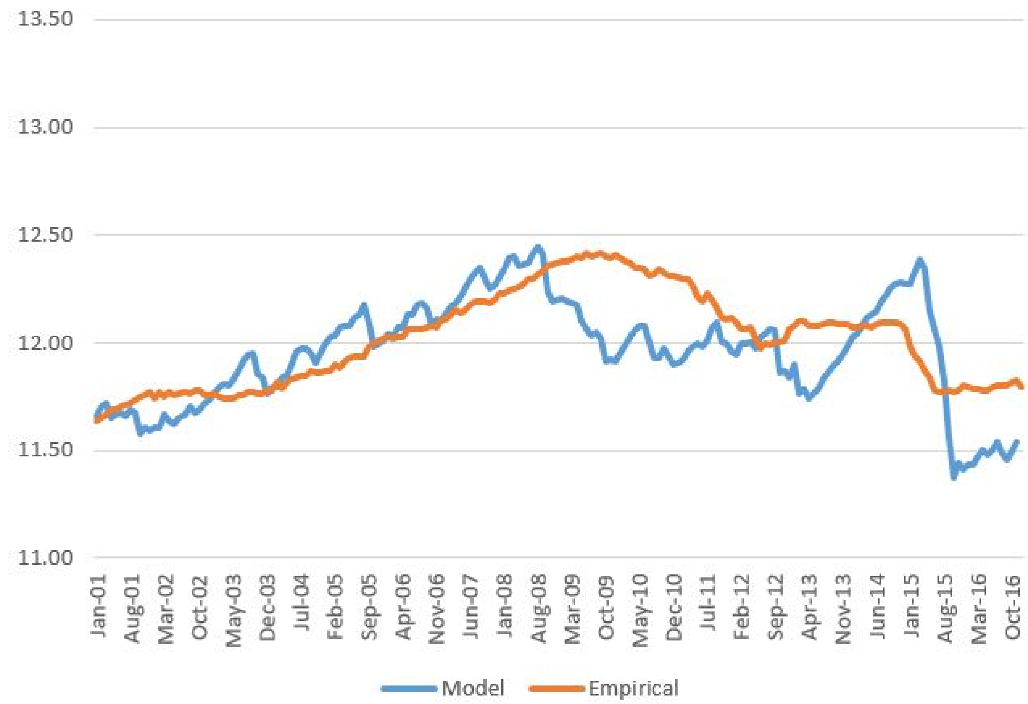

Figure 13: Estimated and Actual Deposits.

This graph shows the actual (log) deposits of the Greek Banking system (blue line) and the (log) deposits that are generated from the model that we estimated. Even though the generated data seem to overestimate and under-estimate the level of deposits most of the time, the model manages to capture the general course of deposits and most importantly, the sharp drop around the end of 2014.

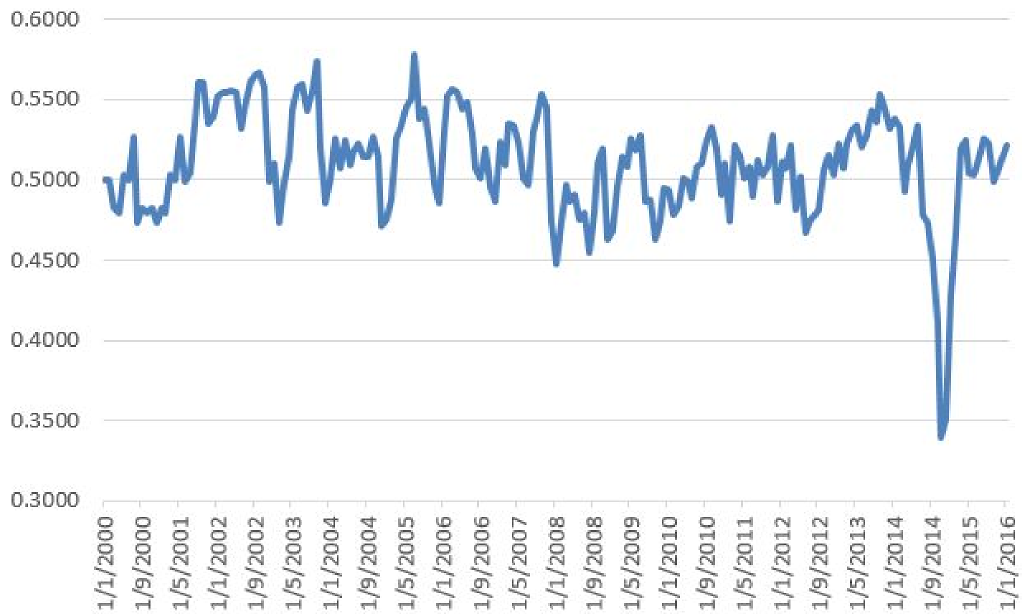

Figure 14: Share of Fundamentalists- Estimated.

The graph shows the estimated share of fundamentalists in the market, throughout the time. In general, there is a balance between fundamentalists and "nervous" agents while the share of fundamentalists decreases rapidly around the end of 2014.

6 Conclusion

In this paper we reviewed the main studies that focus on the causes of banking crises and we presented the debate around economic fundamentals and random panics. The one school of thought claims that crises are driven mainly by changes in economic fundamentals while, others, believe that they are just panics, caused by some kind of "sunspot". However, many theoretical and empirical studies have also shown that these two determinants could have a joint effect. Then, the question arises: what is the mechanism behind the interplay of these two factors and how can we capture it empirically?

In order to answer these questions, we developed a model in order to simulate bank deposits with an aim to capture market dynamics. We were interested in simple structures that can potentially reproduce the most important empirical findings to a high degree and which are quantitatively close to the real ones. We described and evaluated a structural behavioural model that simulates bank deposits and where agents follow simple strategies. First, we presented its key mechanisms and their particular roles in the model structure and then we estimated the model using data from the Greek banking system that went through a severe crisis recently. The parameters of the model were obtained following an estimation method known as the Simulated Method of Moments (SMM). Indeed, we saw that the "fundamentalists" v. "nervous" structure that we proposed could potentially capture important aspect of the empirically observed behaviour of the agents.

To date, we have discussed a model were agents behaviour is determined endogenously by a herding component and the change in the level of deposits. However, we have to acknowledge that the model has some major flaws too. First of all, in our model, macroeconomic factors are not captured explicitly. Instead, we tried to capture the effect of these factors through the constant c, in the demand functions of the two groups. Nevertheless, in order for a structural model to be complete, one should also make explicit assumptions about the effects of GDP growth and taxation on the level of deposits.

Moreover, the variable that proxies the quality of the fundamentals of the economy is considered to be exogenous to the model. However, in reality, the quality of the fundamentals and the behaviour of the agents in the system are interrelated. For instance, a large drop on the level of deposits would have a negative impact on the fundamentals of the banking system, and these "feedback" effects are essentially ignored in our model.

Finally, in our estimation we used monthly data which is not ideal for the kind of model that we try to estimate. Since we examine sudden changes in the banking system, the ideal dataset would consist of raw, micro level data with a daily frequency, so that we could focus only on the uninsured accounts. However, since we could not gain access to such dataset, we chose to estimate the model with monthly data so as to see whether it produces realistic parameter values.

In sum, our analysis indicates that such behavioural models, as the one that we proposed, could be a reliable alternative in explaining the dynamics of bank runs and also in distinguishing fundamentals-driven and panic-driven crises. As we already said, the correct "remedy" for such crises, that occur every now and then, depends on the right "diagnosis", which up to date, has been a very difficult task.

A-7 APPENDIX

A-7.1 A detailed analysis of the D&D model

The model assumes that there are three periods and that each consumer has a unit endowment of goods in period 0. The consumers can invest their endowments and can earn $R > 1$, they invest until the last period (period two). However, if they liquidate their investment before period two, they earn 1 (their initial endowment). Hence, consumers can choose in period 1, whether they will liquidate their investment or wait until period 2.

D&D assume that each consumer can be either patient or impatient. A consumer is impatient with probability p and derives utility from consumption in the first period, while a consumer can be patient with probability 1-p. Patient consumers derive utility from consumption in period 2 only.

The utility of the impatient consumers is $u(c_1)$ and for the patient is $\rho u(c_1 + c_2)$. The utility of the patient consumers depends on $c_1 + c_2$ since their consumption consists on what they store from T=1 plus what they obtain in period 2. All agents have CRRA utility functions and D&D also assume that $1 \geq \rho \geq R^-1$. The categorization of consumers into patient and impatient is made simply to reflect the fact that liquidity needs are not always predictable.

In competitive equilibrium, when each customer learns his/her type in period 1, impatient customers stop investing and their consumption will be $c_1^i = 1, c_2^i = 0$ (the superscript "i" denotes "impatient"). The consumption allocation of the patient consumers will be $c_1^p = 0, c_2^p = R$. It is important to note that in competitive equilibrium $c_1^i = 1$ while $c_2^p = R$ and hence $u(c_1^i) \leq \rho u(c_2^p)$. So under these assumptions, impatient agents are unlucky since the utility that they derive is lower that that of the patient consumers.

If we solve the social planners problem we will see that this allocation is not socially optimal. The planner's problem is:

$$\begin{gathered} \max \; pu(c_1^i) + (1-p)\rho u(c_2^p) \\ \text{s.t. } (1-p)c_2^p - R(1 - pc_1^i) = 0 \end{gathered}$$

Using the F.O.Cs we obtain $u'(c_1^{*i}) = \rho R u'(c_2^{*p})$ and since $\rho R > 1$ we get that $1 < c_1^{*i} < c_2^{*p} < R$. Hence, in this (optimal) allocation, the impatient consumers have higher consumption than before while the consumption of the patient ones is lower. This result means that it would be optimal for agents to "collaborate" and insure against the risk of having to liquidate their investment in period 1, because they are impatient and here is where banks will play an important role.

Banks can act as intermediaries and offer r_1 to anyone who wants to withdraw in period 1 and r_2 to anyone who wants to withdraw in the second period. If a fraction $f < r_1^{-1}$ of the agents want to liquidate their investments in period 1, then the bank can liquidate fr_1 projects and give them their goods. Then, the remainder goods will be $R(1 - fr_1)$ in the second period and they will be distributed among the rest of the agents (i.e. among 1-f of the agents).

We can see that, with this contract, we can achieve the same allocation with the social planner. Assume that $r_1 = c_1^*$ and that $f = p$. We also know that only impatient agents are willing to withdraw in period 1. This means that the resources left i period 2 are $\frac{R(1-pc_1^*}{1-p}$ which is c_2^* from the planner's problem.

This result shows that banks, as financial intermediaries, can increase welfare by providing insurance, something which the market did not generate.

However, this equilibrium is not the only one in the model. Suppose now that all the patient consumers decide to withdraw their "money" in period 1. Since the impatient agents would withdraw in period 1 too, the bank can only give c_1^{*-1} of the claims for c_1^*. Hence, each agent will receive c_1^* with probability c_1^{*-1} and zero with probability $1 - c_1^{*-1}$. An agent that waits until period 2 to withdraw will receive nothing since the bank will have liquidated all investments. This is a second Nash equilibrium since if all patient consumers withdraw in the firs period, a patient consumer will have no incentive to wait until period 2. In other words, in this case, a patient consumer has nothing to gain if he/she waits until period 2. We should also note that this allocation is even worse than the allocation achieved in the competitive equilibrium.

According to D&D, this problem can be solved if the bank suspends its payments in the first period. Suppose that the bank decides to pay c_1^{*-1} to the number of agents $(\hat{f})$ that want to withdraw in period 1, where $p \leq \hat{f} < c_1^{*-1}$. If only impatient consumers withdraw in period 1, then we have that $f = p$ and $c_2^* = \frac{R(1-pc_1^*)}{1-p}$, which it is the superior Nash Equilibrium.

If the agents that withdraw in period 1 are $f > \hat{f}$, then an agent that chooses to withdraw in the first period will receive c_1^* with probability $\frac{\hat{f}}{f} < 1$ and zero with $(1 - \frac{\hat{f}}{f})$ probability. However, if a patient consumers waits until the second period he/she will receive $\frac{R(1-fc_1^*)}{1-f}$. In order to understand the agent's decisions let's take a closer look to the payoffs. The expected payoff in period 1 is $E(return) = (\hat{f}/f) \times c_1^* + (1 - \hat{f}/f) \times 0$, which decreases as f increases. The payoff in the second period $\frac{R(1-fc_1^*)}{1-f}$, is certain and increasing with f. We already know that if $\hat{f} = p$, then we avoid the bad equilibrium and we can see that if $f > \hat{f}$, the incentive to withdraw early gets weaker. Hence, it is easy to see, that when banks can suspend withdrawals, the only possible equilibrium is the superior one.

From this short review of the D&D model, we can draw to major conclusions that are germane to our paper: First of all, D&D showed, that even in a system with no currency and with risk-free investments, a bank run can occur. Moreover, they showed that this bank run has actually a self-fulfilling nature and it is a result of "panic".

A-7.2 The Greek Banking System

Data collected from the Bank of Greece and form the European Central Bank, regarding deposits and loans in Greece and the Eurozone, is evident of the deteriorating state of Greek Financial institutions.

The data paints an astonishing picture. After the Greek Government was unable to refinance its public debt from private creditors, the country entered an austerity program which demanded extended market reforms. As we can see in Figure 1, deposits follow a downward path after that point. We also see a sharp drop of deposits right before the 2012 elections, when the fear of a possible default was high. After the elections, deposits were stabilized before they decrease again in the months leading to the elections of January 2015 and the referendum of July 2015. We should also note that the Load to Deposits ration (LTD) was 145% when "normal" levels are around 120% (Van den End[23]). Put together, these figures demonstrate the distress of the Greek banking sector and show that the system is in fact in crisis.

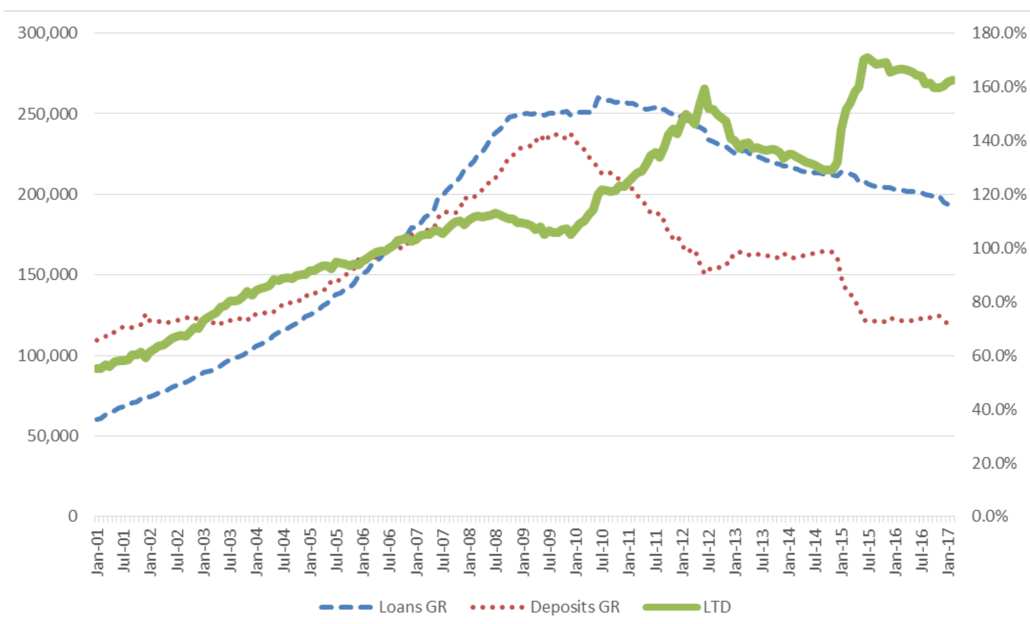

Figure 15: Greek Banking Sector.

Figure 16: Financial Soundness Indicator.

The Financial Soundness Indicator (FSI) from January 2000 to February 2016, obtained from the ECB. As we can see, as the 2008 financial crisis started unfolding, the soundness of the Greek banking sector started deteriorating. The fundamentals of the Greek banking system improved for a while until they started deteriorating again after 2014.

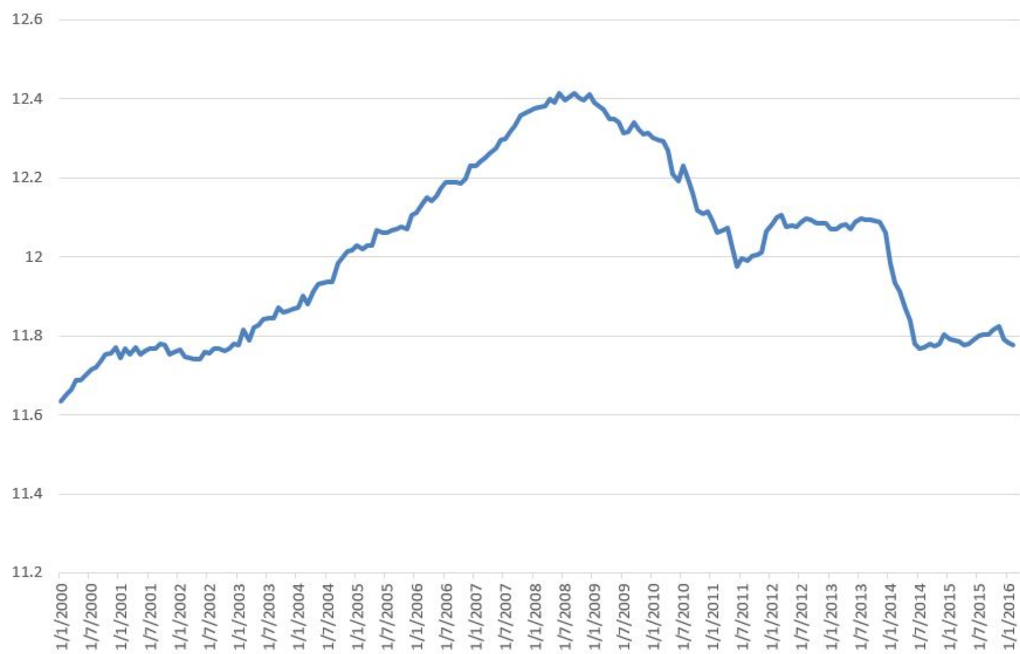

Figure 17: (log) Deposits Levels.

The graph shows the levels of (log) deposits of the Greek banking system from January 2000 to February 2016. There are two periods where deposits decline: One, that starts around 2009 and ends around 2011 and a second one, which is much more rapid, that starts around 2014.

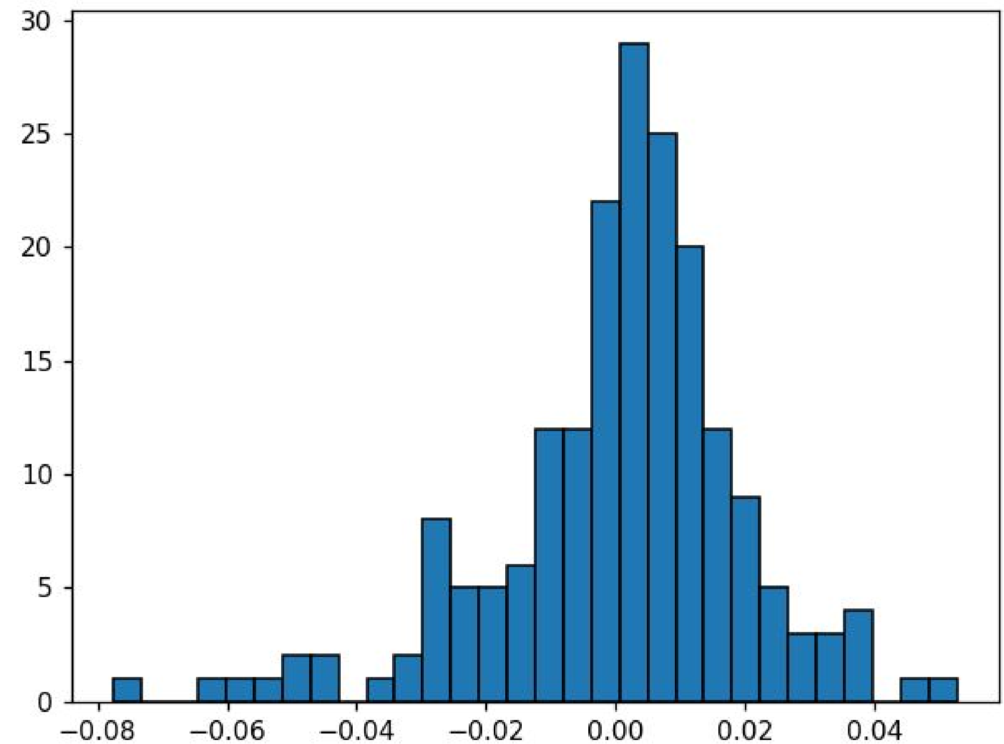

Figure 18: Distribution of %change in deposits.

The graph shows the distribution of the %changes in the level of deposits of the Greek Banking System. We see that the distribution is left skewed with fat tails.

A-7.3 Estimation Results

Table 4: Variance-Covariance Matrix

	c	α^*	α_p	α_f	ϕ	χ	σ_n	σ_f
c	5.36	0.18	-0.86	-0.43	0.00	-0.01	-0.89	-2.62
α^*		1.00	0.04	-0.01	0.00	0.00	0.04	-0.05
α_p			1.17	-0.09	0.00	0.00	-0.18	-0.52
α_f				1.00	0.00	0.00	-0.07	-0.01
ϕ					1.00	0.00	0.00	0.00
χ						1.00	0.00	0.00
σ_n							1.19	-0.42
σ_f								1.35

This is the variance-covariance matrix of the estimated parameters.

Table 5: Correlation Matrix

	c	α^*	α_p	α_f	ϕ	χ	σ_n	σ_f
c	1.00	0.08	-0.34	-0.19	0.00	0.00	-0.35	-0.97
α^*		1.00	0.04	-0.01	0.00	0.00	0.04	-0.04
α_p			1.00	-0.08	0.00	0.00	-0.17	-0.46
α_f				1.00	0.00	0.00	-0.07	-0.01
ϕ					1.00	0.00	0.00	0.00
χ						1.00	0.00	0.00
σ_n							1.00	-0.38
σ_f								1.00

The correlation matrix of the estimated parameters. Most of the correlations are in small which indicates that there are not identification problems in our estimation.

Table 6: Data & Model Moments.

	St.Dev.	Skew	rAC			Kurt	dMean	vAC		
			1	2	3			1	5	10
Empirical	0.019	-0.83	0.25	0.25	0.06	2.00	12.02	0.28	0.03	0.01
Model	0.042	-1.65	0.28	0.25	-0.05	4.10	12.00	0.27	0.04	-0.05

This table presents the moments obtained from the empirical data and the moments that are generated from the model. "dMean" is the average level of (log) deposits, "Skew" is the skewness of the %change of deposits, "rAC" is the autocorrelation function of the %change of deposits in three different lags, "Kurt" is the kurtosis of %change of deposits and "vAC" is the autocorrelation function of the absolute %change of deposits in three different lags.

Table 7: Outside Moments.

	%Obs.	rAC-2
Empirical	0.03	0.24
Model	0.10	0.23

In order to test whether our estimation is robust, we use two outside moments."%Obs." is the percentage of changes in deposits below -5% and rAC-2 is the second order autocorrelation function of the %change of deposits.

A-7.4 Demand Functions

Let the total number of agents be N=1 and let N^f and N^n be the number of agents that are fundamentalists and "nervous" respectively. We model the average demands, d_t^f and d_t^n, for each group as follows:

$$d_t^f = \frac{d_t^{f*}}{N_t^f} = c + \phi(X_t - X_{t-1})\mathbb{I}_{[(X_t - X_{t-1})<0]} + \epsilon_t^f$$

$$d_t^n = \frac{d_t^{n*}}{N_t^n} = c + \chi(D_t - D_{t-1})\mathbb{I}_{[(D_t - D_{t-1})<0]} + \epsilon_t^n$$

where d_t^{f*} and d_t^{n*} are the total demands for each group. Then, the total demand (from both groups) will be the sum of the total demand of the two groups: $d_t^{TOT} = d_t^{f*} + d_t^{n*}$. Since N=1 we get that:

$$d_t^{TOT} = d_t^{f*} + d_t^{n*} \iff$$

$$d_t^{TOT} = \frac{d_t^{f*}}{N} + \frac{d_t^{n*}}{N} \iff$$

$$d_t^{TOT} = \frac{N_t^f}{N_t^f}\frac{d_t^{f*}}{N} + \frac{N_t^n}{N_t^n}\frac{d_t^{n*}}{N} \iff$$

$$d_t^{TOT} = \frac{N_t^f}{N}\frac{d_t^{f*}}{N_t^f} + \frac{N_t^n}{N}\frac{d_t^{n*}}{N_t^n}$$

This can be written equivalently as $d_t^{TOT} = n_t^f d_t^f + n_t^n d_t^n$, where $n_t^f = \frac{N_t^f}{N}$ and $n_t^n = \frac{N_t^n}{N}$ are the "market shares" of the two groups.

A-7.5 Computational Solution of the Model

The model consists of two main equations. The first equation determines,α_t which is the attractiveness of the two strategies:

$$\alpha_t = \alpha^* + \alpha_n(n_t^f - n_t^n) + \alpha_f(D_t - D_{t-1})$$

If we substitute n_t^f and n_t^n we obtain:

$$\alpha_t = \alpha^* + \alpha_n(\tfrac{1}{1+e^{-\alpha_{t-1}}} - \tfrac{1}{1+e^{\alpha_{t-1}}}) + \alpha_f(D_t - D_{t-1}) \quad \text{(A)}$$

The second equation determines the level of (log) deposits:

$$D_{t+1} = D_t + d_t^{TOT}$$

If we substitute d_t^{TOT} we get:

$$D_{t+1} = D_t + n_t^f d_t^f + n_t^n d_t^n \iff$$

$$D_{t+1} = D_t + \tfrac{\phi(X_t - X_{t-1}) + \epsilon_t^f}{1+e^{-\alpha_{t-1}}} + \tfrac{\chi(D_t - D_{t-1}) + \epsilon_t^n}{1+e^{\alpha_{t-1}}} \quad \text{(B)}$$

In order to estimate the model we do the following: We use two initial guesses for D_0 and D_1 and one initial guess for α_0. Then, for a given set of parameter values, we solve (A) and obtain α_1. The values of X_t are known since X_t is exogenous to the model. For some random ϵ_1^f and ϵ_1^n, we can obtain D_2 from (B). Now we know α_1, D_0, D_1 and D_2.

The next step is to obtain α_2. We can see from (A) that α_2 will depend on D_2 and D_1 which are known. Hence we can solve for α_2 and repeat the process recursively. For the initial guesses D_0 and D_1 we use the first two values of the (log) deposit levels from the empirical data and we set $\alpha_0 = 0.5$.

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