

MODEL RESPONSES TO CRISIS

**AN INVESTIGATION OF A BEHAVIOURAL FINANCE MODEL AND A
FINANCIAL FRICTIONS MODEL USING U.S. DATA**

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Abstract

This thesis aims to examine the response of a behavioural finance model and a financial frictions model to the financial crisis which was triggered in 2007. This thesis will test both models by using indirect inference as an evaluation method. The results of this study show that, when compared with the rational expectation model, behavioural expectation does not improve the model's ability to explain the real world. Therefore, behavioural expectation is unable to respond to the current crisis to form expectations. However, the financial frictions model which is suggested by the literature is found to be an efficient model that improves the model's overall performance. This thesis finds that although financial shocks contribute to the output gap variation during the crisis, it does not respond so much to the variations of inflation and policy interest rate.

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Chapter 1 Introduction

The recent credit crisis has been recognised as the worst economic crisis since the Great Depression of the 1930s. It began on 9 August 2007 when bad news from French bank BNP Paribas triggered a sharp increase of the lending rates. This made the financial world begin to realise just how serious the situation was. The crisis of 2007 led to the collapse of the financial services sector, bank bailouts, and the crash of stock markets around world. It also led to the failure of many business and, in particular, to numerous evictions, foreclosures, and prolonged high levels of unemployment. Due to the interaction among different markets and sectors, the crash resulted in large government deficits and a decline in economic activity in the U.S. This negative effect was quickly transmitted to the rest of the world. The effect was felt especially severely in the EU area, which experienced an adverse feedback impact on its loan books, asset valuations, and credit supply. Some of EU countries were more vulnerable than the others (e.g. Greece, Ireland, Portugal, Italy, and Spain). Consequently, these countries found it difficult to refinance their government debt, which led to the development of the European sovereign debt crisis.

A number of reasons have been proposed for the origins of this financial crisis. The first argument is that the financial crisis arose from the mistaken investments that were made and from peoples' lack of knowledge, this theory falls into the category of

behavioural finance studies. For example, Kindleberger (2003) argued that economic crises happen as a result of mob psychology or panic. In addition, the recent financial crisis can also be explained by herd behaviour. If the first class of investors can get higher profits from increasing asset values, then other investors will learn from this and also follow this behaviour, which causes even higher prices as more and more investors buy in the hope of getting similar profits. This herd behaviour finally leads to asset prices that are so far beyond their fair values that a crisis becomes unavoidable. Mainstream macroeconomists have been widely criticised as relying too much on rationality and market efficiency. In a rational world with an efficient market, a crisis could not happen in the first place. However, the behavioural school regards this financial crisis as a reflection of market inefficiency.

The second argument is that the financial crisis is considered to be rooted in the disorder of the banking sector. One common explanation made by Shin (2009) is that the banks became so heavily overleveraged that they could not afford to sustain the falling underlying asset prices at that time. The whole story started from individual banks who were busy extending credit to unqualified borrowers who wished to buy a house. The banks themselves did not care if the borrowers could pay back the loans or not because the underlying asset could guarantee the loss of foreclosure for banks when the asset price was rising. Additionally, the large investment banks could make a profit through issuing corporate debt based on these assets, which was called Col-

lateralised Debt Obligation (CDO). Investors bought these CDOs thinking that they were a much better investment strategy than holding treasury bonds. The large profits drove investment banks to require more and more assets. Then the lenders decided to ease the criterion of borrowing so that they could sell more default assets to the investment banks, which presented an excellent opportunity to make profits. This led to a fast expansion of housing loans. However, those who were unqualified for the loans eventually ended up holding the default. As more and more loans were defaulted, the banks held more and more mortgages. This created a higher supply in the housing market and, hence, much lower house prices. Consequently, a point was reached when the investment bankers no longer wanted to buy this debt. In addition, even prime-mortgages were thought to have become worthless because of higher borrowing cost rising and falling housing price. As a result, those investment banks who held the bad mortgages backed securities could no longer sell CDOs and they could not pay their loans back to the Fed. Meanwhile, the lenders held large amounts of assets that could not be sold. Lending at this point had almost stopped and interbank lending was nearly frozen. At this point the whole Western financial system faced collapse.

Besides banking sector disorders, it has also been suggested that the financial crisis was caused by the Fed's policy. The Fed policy rates were kept so low that it was easy for indebtedness to rise to unprecedented levels. Meanwhile, others have argued that the deregulation of financial institutions permitted excesses to develop in

the market. It has also been argued that it was government policy which encouraged even the poor to aspire to own their own homes that was a major factor in building the housing bubble. It has also been proposed that yet another factor has been the high propensity of the Chinese to put their money into savings (see Warnock and Warnock, 2006).

This thesis is motivated to find an appropriate model to explain the recent financial crisis. Based on the arguments stated above, it can be seen that many crisis models have been proposed. For example, behavioural finance models have argued that the agent's behaviour is not based on rational expectations but on heuristic rules of thumb or behavioural assumptions (see De Grauwe, 2010 and Kirman, 2011) while financial frictions models have been used by Bernanke, Gertler and Gilchrist(1999),¹ and Carlstrom and Fuerst (1997, 1998) that focuses if financial sector can amplify shocks. However, Davidson et al. (2010) argue that, even without the banking sector, this crisis can still be created by non-stationary shocks. They propose that macroeconomic data are generally non-stationary, at least in the quarterly data, which could explain the large uncertainty about the economy's future. They use a Real Business Cycle (RBC) model but allow the productivity shock to be non-stationary. Periods of crisis can then be created by this non-stationary shock.

¹ This paper is abbreviated as BGG in the later part of the thesis, which represents the style of the model in their paper.

Based on the proposed models, this thesis aims to test the model's response to financial crisis using U.S. data. The testing method is done by using indirect inference as an evaluation method. The main idea of testing is that it can simulate the data from the macroeconomic model if given the parameters of the macroeconomic model and the distributions of the errors (which can either be estimated or calibrated). The test is calculated from a comparison of the data observation with the data simulated from the structural model through an auxiliary model. In this thesis, VAR is used as the auxiliary model and tests are based on a function of the VAR estimates. The test statistic is computed from the distributions of these functions of the parameters or from these parameters themselves. The null hypothesis is that the macroeconomic model is correctly specified. Non-rejection of the null hypothesis implies that the macroeconomic model is not significantly different from that of the observed data. In this case, VAR estimates of the data generated by the model should match the VAR estimates estimated from the actual data. Rejection of the null indicates that the macroeconomic model cannot replicate the real world data significantly.

There are two kinds of models that are tested in this thesis, one is the behavioural finance model while the other is a financial frictions model. This will allow me to determine whether these models can explain recent crisis and recession.

This thesis is organised as follows: in Chapter 2, I survey the literature with regard to these two models. Meanwhile, Chapter 3 examines whether using behavioural

expectations can improve the model's encompassability of the data by comparing it with a rational expectation model. Chapter 4 will then test a financial frictions model that allows for the credit channel to influence the economy. This model is also compared with a non-credit channel model so that it is possible to determine whether the model performs better when credit is added in. Finally, Chapter 5 concludes this thesis.

Chapter 2 A Literature Review of Crisis Models

2.1 Introduction

Since the economic crisis began at the end of 2007, a major challenge to the standard RBC model or New Keynesian Smets-Wouters (SW) model has been its failure to forecast this crisis. Consequently, economists have had to search for alternative ways to model this crisis. Broadly speaking, two strands of literature have been proposed. One strand of the literature believes that human behaviour is not formed rationally, which contradicts the view of mainstream macroeconomics. This strand argues that there is no crisis in a rational expectation world, where people can predict correctly and markets are always efficient. This view is supported by a large number of behavioural finance studies. For example, Kindleberger (1978) argues that economic crises occur spontaneously as a result of mob psychology or panic. If everyone expects a crisis and acts as if it is about to occur, then the crisis becomes a self-fulfilling prophecy. Conversely, if no one expects a crisis, then this expectation is also self-fulfilling and no crisis occurs. Meanwhile, De Grauwe (2010) and Kirman (2011) assume that people suffer from cognitive limits, within which large volatility can be generated to form a crisis. This view is also supported by other sciences, such as psychology and neuro-

ogy, which are gradually showing that individuals suffer cognitive limitations (see, for example, Kahneman, 2002, Camerer et al., 2005, and Kahneman and Thaler, 2006). Since individuals can only understand limited information in the world, then it follows that when they are maximising their life time utility they will only consider a small amount of information.

The second strand of the literature believes that it is the banking model which challenges the standard RBC or SW model. This strand emphasises the incorporation of a financial market into the traditional model. Consequently, this kind of model means that I can analyse finance-related policy. In addition, the important transmission mechanism that is omitted by the traditional models can be recovered. Most of these financial frictions models originate in the studies of Bernanke, Gertler and Gilchrist (1999), and Carlstrom and Fuerst (1997, 1998). The introduction of a banking sector means that it is possible to find whether the existence of financial sector amplifies shocks, thereby accounting for the recent crisis. Credit frictions can have a significant impact on the transmission of shocks, either to the economy (which destroys collateral) or to the banking sector (which destroys credit availability). This kind of financial accelerator model propagates and amplifies shocks (such as productivity shocks or monetary shocks) to the economy.

However, Davidson et al. (2010) argue that, even without the banking sector, a crisis can be created by non-stationary shocks. They show that macroeconomic data

are generally non-stationary, at least in the quarterly data, which can explain the large degree of uncertainty about the economy's future. They use an RBC model but allow the productivity shock to be non-stationary. The periods of crisis can then be created by this non-stationary shock.

In an attempt to understand the recent credit crisis, this chapter aims to review the relevant models, especially those which respond to the recent crisis. Section 2.2 reviews the first strand of the crisis models, which is the behavioural model. Section 2.3 surveys the literature of financial frictions models. Finally, Section 2.4 summarises this chapter.

2.2 A Literature Survey of Behavioural Models

The first strand of models that challenge the standard RBC model is the behavioural finance model. Instead of discussing the literature of the behavioural model, I prefer to start this discussion by looking at the different means of modelling people's expectations. In terms of how rational a representative agent is, the categories to model expectations can be divided into fully rational expectations and imperfect rational expectations. The first category is very simple: it assumes that agents can fully understand the world, they can overlook the whole system and determine where they are and make a correct decision to optimise their welfare. Most of the rational expectation literature originates from Lucas and Sargent (1981). The second category is the

behavioural model, which assumes that investors are imperfectly rational. It assumes that individuals are suffering from cognitive limitations. In this model people forecast the future based on their past experience. If people observe that the asset price is going up for a certain period, then they start to believe that the price will continue to rise, which raises the demand to buy properties, thereby leading to an even higher asset price. Conversely, if they observe that the asset price falls then they think the price will continue to fall, which results in an even lower asset price. Consequently, large fluctuations of prices can happen in these models, which may cause financial crises.

Behavioural models can be supported by the other sciences, such as psychology and neurology. Camerer et al. (2005) assert that the establishment of a neural basis for some rational choice principles will not necessarily vindicate the approach as widely applied to humans. More and more economists are reverting from rational choice principles into a behavioural view that is anchored in limits on rationality, willpower, and greed. Della Vigna (2009) in his paper uses laboratory experiments combined with analysis of non-standard preferences to survey non-standard beliefs and non-standard decision making. He finds field evidence on three classes of deviations from these non-standard features. He also shows that most phenomena which are important in laboratory experiments also affect decisions in a variety of economic settings. He consequently proposes that economists should increasingly put more focus on behavioural

phenomena. Other literature that corroborates the cognitive limitations of human beings includes Kagel and Roth (1995), and McCabe (2003).

Considering support from psychology and neurology, many economists have started to challenge the mainstream macroeconomic world with rational expectation agents. For example, Hayek (1945) argues that any individual suffers unavoidable imperfect knowledge. The rational expectation models do not consider this knowledge imperfection, which may mislead people to believe the implications of these unrealistic models. He proposes to add knowledge imperfection into the central planner's problem. Meanwhile, Clark (1998) studies the recent developments of cognitive science and artificial intelligence. He claims that human intelligence is not considered as an abstract reasoning capability that is joined to a memory bank of facts, but rather as a device for controlling the body's varied set of adaptive behaviours in a way that helps the body cope with the particular environment that it finds itself in. He regards this view as "embodied, environmentally embedded cognition." Therefore, agents react to the optimisation problem via a simple chemical reaction which strengthens the neural processes that have been associated with improvements in the body's well-being and weakens those processes that have not.

The study of agent-based behaviour has a long history. Its origin can be traced to Pareto (1916), who wrote a chapter in his 'Treatise on Sociology' on non-rational behaviour. Pareto (1916) emphasises the importance of non-rational behaviour on the

economy. Meanwhile, Keynes (1936) in his 'General Theory' stresses that the form of expectation is important to determine the macroeconomic variable (such as output, employment and investment). He argues that people do not respond rationally if they cannot attach numerical probabilities to all of the possible consequences of their decisions. He adds that people tend to act by custom and convention; however, he does not provide an explicit model of how expectations are formed. A little later, Simon (1955) suggests that individuals suffer from limited cognition. He uses neurology in his paper to prove that the homo rational agent cannot be an accurate description of human behaviour. He cast doubt on the micro-founded model in terms of the representative agent which is assumed to be fully rational. Leijonhufvud (1981) argues that macroeconomic economy is full of risks. He likens forecasting inflation with a game of chess that is refereed by someone who announces that "from now on bishops move like rooks and vice versa . . . and I'll be back with more later" (Leijonhufvud, 1981, p. 264). Consequently, economic decisions that involve risks of losses from inflation are based on conventional or institutionalised rules of thumb instead of being based on rationality. Based on this idea, Leijonhufvud (1993) emphasises that these analytical limitations force economic theorists to exaggerate the rationality of the representative agent. He suggests, instead, the use of adaptive learning agents given the existence of massively parallel computers.

Recently, in response to the banking crisis, behavioural learning has been regaining its popularity. Rather than using rational expectation, Milan (2007) presents a Dynamic Stochastic General Equilibrium (DSGE) model where economic agents form their expectations behaviourally. He first estimates the model using Bayesian methods for obtaining relevant parameters in the forms of expectations and structural parameters. Using this learning model, the economy can endogenously generate time-varying macroeconomic volatility. He also shows that the model that includes this expectation can match the magnitude of the ‘Great Moderation’ in the mid-1980s.

In the light of recent crisis, the current macroeconomic models have all failed to encompass the sudden crisis. Kirman (2010) investigates the reasons for this, finding that it is either due to fundamental problems with the underlying General Equilibrium (GE) theory or to the unrealistic assumptions on which most models are based. He suggests dropping the unrealistic agent assumption (e.g. rational agents). He also proposes to model the economy as a complex adaptive system, which may at least provide us with an understanding of major ‘phase transitions’ in the economy, even if we cannot forecast when the crisis happens.

De Grauwe (2010) compares two different kinds of expectations, one uses an heuristic rule while the other is a rational expectation. He finds that the behavioural model generates correlations in beliefs, which then produces endogenous cycles. These beliefs are found to become more important when agents are willing to learn from the

errors produced by biased beliefs; however, the agent should be forgetful to influence the business cycle. He also shows that using a simple rule to form the model can produce the uncertainty of the monetary shock, which is different from rational expectation models. There is an extra dimension to uncertainty in the behavioural model that he studies, which comes from the degree of human behaviour.

Avgouleas (2009) argues that revising financial regulations (such as strict market discipline and enhanced capital base) have been proved to be less effective. Economists should consider the real reason, which is often ignored by the mainstream economists. He suggests including the behavioural elements of the crisis into the model. The behavioural aspect of the global financial crisis shown in the universal banks and international investment funds make a strong case for adoption of a behavioural approach for regulatory reform. The catastrophic consequences of the crisis and the findings of behavioural finance provide solid support for this proposal.

It is important to note that the behavioural model mentioned above is not the statistical learning approach that was pioneered by Sargent (1993). The statistical learning approach enables the representative agent with some cognitive limitation; however, when they forecast future, they act like statisticians or econometricians. Even if they cannot forecast future like statisticians or econometrician, they still can get the information from the media. This kind of model is described as a 'bounded rationality' model. Evans and Honkapohja (2001) find that, in many cases, statistical learning ap-

proach will converge to the rational expectation models. For example, they estimate the cobweb model by computing the sample mean from past prices. They conclude that expectations converge over time to the rational expectation value.

To summarise, an agent with full rationality is no longer considered to be a realistic assumption, a view which is supported by the other sciences. Following the failure to explain the current crisis, many economists have turned to behavioural models to form expectations. It has been suggested that using a simple rule to forecast future could be one way to explain the present crisis.

2.3 A Literature Survey of Financial Frictions Models

The second approach that disputes the standard RBC or SW model emphasises the necessity to include a financial sector in the model. It does not matter who owns the capital in traditional macroeconomic models while the asset market is not completely specified. Money in this kind of economy is only an ad hoc method which is incorporated, either by the utility function or by the cash-in-advance constraint. Consequently, we cannot draw any conclusion in terms of finance-related policy. In addition, macroeconomists suspect that an important transmission mechanism is omitted by the traditional macroeconomic models.

There had been a few attempts at modelling this interaction between financial markets and the macroeconomy before the financial crisis of 2007. Financial fric-

tions have a significant impact on the transmission of shocks, either to the economy (which destroys collateral) or to the banking sector (which destroys credit availability). According to the method to model borrowing constraints between firms and financial intermediaries, financial frictions can be divided into two approaches. One is the costly state verification set-up, which is shown in Townsend (1979) (see also: Bernanke, Gertler and Gilchrist, 1999; and Carlstrom and Fuerst, 1997 and 1998). In this kind of model there are bad states, which refer to those states where firms default on their debt; however, due to the limited liability, firms may also prefer to default on their borrowings in the other states. For the lenders, they have to pay a cost to verify whether the true states warrant default or not, this is what has been called ‘costly state verification’. Lenders will then require an external finance premium in steady state to compensate for this cost.

Bernanke and Gertler (1989) form a simple RBC model in which the condition of the borrower’s balance sheets is a source of output dynamics and amplifications. Meanwhile, Carlstrom and Fuerst (1997, 1998) develop a similar set-up as Bernanke and Gertler (1989). The innovation for their model is modelling long-lived entrepreneurs instead of living for only a single period, as is used in Bernanke and Gertler (1989). It is found by Carlstrom and Fuerst (1997, 1998) that endogenous agency costs can potentially influence business cycle dynamics. Bernanke, Gertler and Gilchrist (1999) develop their model by considering quantitative importance and long-lived agents. In

this study, they find the financial accelerator effect, through which shocks (such as productivity shocks or monetary shocks) can be amplified and propagated. Money is incorporated into their model so that the financial market may affect the transmission of monetary policy.

Similar work has been done by De Fiore and Tristani (2009), who present a simple extension of the basic New Keynesian setup in which the assumption of frictionless financial markets is relaxed. Their theory is simplified into a four-equation model, including an IS function, a Phillips Curve, a policy function, and a credit spread function. In this economy, asymmetric information and default risk leads banks to optimally charge a lending rate that is above the risk-free rate. The aggregate dynamics in this model are nested in the New Keynesian model. It also adopts costly state verification, as in Townsend (1979), to form the standard debt contract between firms and financial intermediaries. However, this model is different from the BGG because it stipulates a nominal debt contract instead of a real contract. The perspective of De Fiore and Tristani (2009) is not to study whether the model is appropriate for explaining the crisis, they use this model instead to find out whether monetary policy is optimal when adding credit frictions into the economy. In fact, they conclude that an aggressive easing policy is optimal in response to adverse financial market shocks. It should be noted that in Chapter 4, I will use this model to test whether it can be used to account for the recent crisis.

A large amount of empirical work has been done based on this kind of financial frictions model. For example, Meier and Muller (2006) adopt a BGG style financial accelerator set-up to analyse the monetary transmission mechanism. They estimate the model to match the model impulse response with the empirical impulse responses to monetary shock through VAR. Their results show that capital adjustment cost plays an important role in accounting for transmission of monetary shocks, but that there is not much effect from financial frictions. Neri (2004) also estimates a DSGE model, but with Carlstrom and Fuerst-style financial frictions that are constructed by Bayesian techniques. He shows that a model with both capital adjustment costs and financial frictions does better at explaining the data than either of these alone. Additionally, Christiano, Motto and Rostagno (2004) estimate a financial accelerator model of the U.S. economy during the Great Depression of the 1930s, but do not isolate its contribution in their findings. Furthermore, Christensen and Dib (2007) estimate and simulate a BGG like financial frictions model to evaluate the importance of the financial accelerator mechanism in fitting the data and its role in the amplification and propagation of transitory shocks. Structural parameters of two models (one with, and one without, a financial accelerator) are estimated by a maximum-likelihood procedure using post-1979 U.S. data. Their estimation and simulation results provide quantitative evidence in favour of the financial accelerator model while the model without a financial accelerator is statistically rejected in favour of the model that includes it. The presence

of the financial accelerator amplifies and propagates the effects of demand shocks on investment, but it dampens those of supply shocks. However, Christensen and Dib (2007) find that the importance of the financial accelerator for output fluctuations is relatively minor.

Another kind of financial frictions model specifies the constraints on borrowing by using costly enforcement. Kiyotaki and Moore (1997) build a model based on the work of Hart and Moore (1994), which presents the financial contract problem with ex post renegotiation and the inalienability of human capital. They claim that the financial contract borrowing limit is only viable up to the value of the net worth; consequently, a default cannot happen in equilibrium. The conclusion made for this model is similar to that of Bernanke, Gertler and Gilchrist (1999), which still amplifies the shocks and generates persistence of monetary shocks. Meanwhile, Cooley, Marimon and Quadrini (2004) also assume an incomplete enforceability constraint, which can also enlarge the impact of technological innovations on the aggregate output. This model indicates that economies with lower enforceability of contracts tend to have greater macroeconomic volatility. Although the costly enforcement model is easier to handle than the costly state verification model, in this kind of model there is no default in equilibrium and no credit spreads, which is not a realistic set-up.

After the Great Recession of 2007-2010, there is no excuse not to study the interactions between the macroeconomy and financial markets in much more detail.

Although a lot of recent studies have examined this topic, many of their models do not consider the breakdown of financial intermediation. For example, Gertler and Kiyotaki (2010) mention that a key feature of the recent U.S. crisis is the significant disruption of financial intermediation. The breakdown of the banking system has led to a sharp increase of financial costs. These high financing costs peaked after the Lehman Brothers collapse, which is considered a significant factor in the collapse of durable goods spending in the fall of 2008 that in turn triggered the huge contraction in the macroeconomic condition. The previous literature, such as Bernanke, Gertler and Gilchrist (1999) or Kiyotaki and Moore (1997), do not consider this to be an important factor to model the breakdown of a banking system. In addition, much of the previous studies are relevant to the current situation but have failed to forecast all of the empirical phenomena during the crisis.

Gertler et al. (2011) develop a macroeconomic model by incorporating a richer financial intermediation, especially when they examine liquidity. In their model, financial intermediaries can be issued outside equity and short term debt. This characteristic enables financial intermediaries to be highly exposed to the risk of adverse returns to their balance sheet in a way that is consistent with recent experience. The model is built on the framework of the agency problem between banks and savers in Gertler and Karadi (2011), and Gertler and Kiyotaki (2010). Therefore, within this framework, banks are allowed a meaningful trade-off between short term debt and equity. The

bank's decision relies on their perceptions of risks, which are measured by both the macroeconomic fundamental shocks and expectations about government policy. This model not only captures a crisis when financial intermediaries are vulnerable to risk but it also explains why banks adopt such a risky balance sheet in the first place.

In summary, it is crucial to include a mechanism of the financial sector so that the crisis can be properly explained. Based on the literature reviewed above, in Chapter 4, I will evaluate one of the financial frictions models so that it can be determined if a financial shocks and transmission mechanism can explain the recent crisis and the recession which followed.

2.4 Conclusion

Above all, in response to the crisis that started in 2007, the standard RBC or DSGE model is unable to provide an explanation for the recent crisis. Therefore, two sorts of crisis models are proposed. The first is the behavioural finance macroeconomic model, in which representative agents are assumed to form their forecast by using a heuristic rule instead of full rational expectation. In this kind of model the market is not efficient. There is a theoretical basis to think that a crisis can happen in this economy. The second model is formed by adding financial factors into the traditional DSGE model. These models provide an extra transmission mechanism of shocks, which may be able to explain the collapse of the banking system during the crisis.

Davidson et al. (2010) argued that, even without a banking sector, a crisis can be created by non-stationary shocks. Although periods of crisis can be created by this non-stationary shock, this kind of model is not in the scope or consideration of this thesis but it is offered instead as a recommendation for further research.

Chapter 3 Can Behavioural Finance Model Explain the Crisis?

3.1 Introduction

As reviewed in Chapter 2, the behavioural finance model is a crisis model in which the agent's behaviour is not based on rational expectations but which is based instead, for example, on heuristic rules of thumb or behavioural assumptions (see De Grauwe, 2010 and Kirman, 2011). The behavioural finance model challenges the mainstream macroeconomics models that use rational expectations, which assume that individuals can fully understand the interpretation of the whole world. The behavioural finance model criticises the inability of rational expectation models to explain the current economic crisis. In addition, the other sciences (such as psychology and neurology) are gradually showing that individuals suffer from cognitive limitations (see Kahneman, 2002, Camerer et al., 2005, Kahneman and Thaler, 2006). For example, Hayek (1945) claims that human beings have unavoidable imperfect knowledge and suggests that this knowledge of imperfection should be added into the central planner's problem. Meanwhile, Clark (1998) finds that the recent development of cognitive science and artificial intelligence enables us to believe that human intelligence is not considered as an abstract reasoning capability which is joined to a memory bank of facts, but is instead a

device for controlling the body's varied set of adaptive behaviours in a way that helps the body cope with the particular environment that it finds itself in. He defines this view as "embodied, environmentally embedded cognition." Therefore, agents respond to the optimisations problem through a simple chemical reaction instead of behaving with full rationality.

According to De Grauwe (2010), agents use a heuristic rule to forecast the future. This kind of model, which is based on the behavioural finance model, is called a bottom-up model in his paper. By contrast, in a top-down model the agents have extraordinary cognitive capacities so that individuals can memorise the whole system in a blueprint. Depending on their position in the system, agents can use this blueprint to maximise their utility. He also argues that the behavioural expectation model is a tractable approximation to the real world rather than asserting that people are totally knowledgeable of the model and the information to date. The reality is probably that there is a news-watcher who analyses data thoroughly and who allows people to see the forecasts at a very low cost. In this sense, agents are still rational. In addition, as reviewed in Chapter 2, the statistical approach of learning models can converge into rational expectation. Based on this debate, this chapter aims to determine whether the bottom-up (i.e. behavioural expectation) model can perform better than the top-down (i.e. rational expectation) model in terms of their capacity for encompassing data. This is done by using indirect inference as an evaluation method instead of using an esti-

mation method. Additionally, this chapter includes a description of the data sample covering the recent bank crisis. This chapter aims to see if behavioural expectation can generate large volatilities of macroeconomic variables during a crisis.

The question of how to test a calibrated or an estimated model has long been discussed. Most of the previous work on this subject is based on comparing particular features of the simulated data with actual data, such as moments comparison. In this study, the method borrows from the indirect inference estimation method (see Minford et al., 2009, Meenagh et al., 2009, Le et al., 2011). Given the structural parameters and the real data, structural shocks can be calculated for bootstrapping purposes. The simulated data are generated by bootstrapping the shocks a large number of times. The aim of the test is to compare the simulated data and the actual data through the auxiliary model. VAR is normally chosen as the auxiliary model because the structural model can always be represented as a restricted Vector Autoregressive-Moving-Average (VARMA) model, which is close to VAR representation. The null hypothesis is that the model is true for the economy. If the model is correct then the VAR estimates of the data generated by the model should match the VAR estimates that are generated using the actual data. The test statistic is based on the distributions of these functions of the parameters of the auxiliary model, or simply as a function of these parameters. A Wald statistic is used to reject or accept the structural model.

This chapter is organised as follows: Section 3.2 introduces the set-ups that are used for the behavioural and the rational expectation models, which are based on some of the specifications of De Grauwe (2010). Meanwhile, Section 3.3 explains the principles and procedures of the indirect inference method for evaluating models. Section 3.4 describes how the data is generated. It also describes the calibration of the structural models. Section 3.5 analyses the test results for both models. In this section, the bottom-up model and top-down model are compared in terms of their data encompassing ability. Section 3.6 is a further check of both models, which is conducted by estimating both models using indirect inference. The best structural parameters are found so that a fair comparison of the two models can be processed. Both models are then compared in Section 3.7, based on the estimated parameters. Finally, Section 3.8 concludes this chapter.

3.2 Model

The behavioural model is a stylised DSGE model that is similar to the model that is developed by De Grauwe (2010). It includes a standard aggregate demand equation, an aggregate supply function, and a policy rule equation, as follows:

$$\tilde{Y}_t = \tilde{E}_t \tilde{Y}_{t+1} - a_1(R_t - \tilde{E}_t \pi_{t+1}) + \varepsilon_{1t} \quad (3.1)$$

$$\pi_t = b_1 \tilde{Y}_t + \beta \tilde{E}_t \pi_{t+1} + k \varepsilon_{2t} \quad (3.2)$$

$$R_t = (1 - c_1)(c_2 \pi_t + c_3 \tilde{Y}_t) + c_1 R_{t-1} + u_t \quad (3.3)$$

where \tilde{Y}_t is the output gap, π_t is the rate of inflation, R_t is the nominal interest rate, and ε_{1t} is the demand error, ε_{2t} is the supply error, and u_t is the policy error. These errors are assumed to be autoregressive processes with coefficients that are calculated from the sample estimates. Equation 3.1 is the aggregate demand equation with an expectations operator in the behavioural model, where the tilde above \tilde{E} refers to expectations that are not formed rationally, as in De Grauwe (2010). The aggregate demand function is standard and it is determined by the expectation of output gap for the next period and real interest rate. Equation 3.2 is the aggregate supply function, which can be derived from profit maximisation by individual producers. The supply curve can also be interpreted as a New Keynesian Phillips Curve, which is a function of output gap and expected inflation for the next period. Finally, Equation 3.3 is the interest rate smoothing rule with a lagged interest rate that has been added into the classic form that is developed by Taylor (1993) to obtain smoothing behaviour.

The difference between the behavioural and rational expectation model lies in the formation of the expectation term. The expectation term in the behavioural model \tilde{E} is the weighted average of two kinds of forecasting rule. The first is the fundamental

forecasting rule, which enables agents to estimate the steady state value of the output or of inflation as their future forecasts. The second is the extrapolative rule, which enables individuals to extrapolate from previous states into the future. This means that they use their past experience to form an expectation of the future. The following equations give the fundamental rule and extrapolative rule, forming the expectations of output and inflation in the behavioural model:

$$\tilde{E}_t^f \tilde{Y}_{t+1} = 0 \quad (3.4)$$

$$\tilde{E}_t^e \tilde{Y}_{t+1} = Y_{t-1} \quad (3.5)$$

$$\tilde{E}_t^{tar} \pi_{t+1} = \pi^* \quad (3.6)$$

$$\tilde{E}_t^{ext} \pi_{t+1} = \pi_{t-1} \quad (3.7)$$

Equation 3.4 and 3.5 are the forecasting rules for output gap, while Equation 3.6 and 3.7 are the forecasting rules for inflation. The fundamental rule specifies that the steady state for the output gap is zero, while the extrapolative rule assumes that people forecast the future by extrapolating the previous output gap into the future. The expectation for inflation also includes the fundamental rule and the extrapolative rule. The fundamental rule assumes that the expected inflation should be the announced inflation

by the central banks. It is also called ‘inflation targeting’ rule, which is consistent with the central bank’s inflation target. Meanwhile, the extrapolative rule for forecasting inflation uses the previous period’s inflation as the future forecast.

In De Grauwe (2010), it is assumed that the market forecast is the weighted average of these two kinds of forecasting rules (i.e. the fundamental forecasting rule and extrapolative rule). Equation 3.8 is the market forecast for the output gap, while Equation 3.9 is the market forecast for inflation:

$$\tilde{E}_t \tilde{Y}_{t+1} = \alpha_{f,t} * 0 + \alpha_{e,t} Y_{t-1} = \alpha_{e,t} Y_{t-1} \quad (3.8)$$

$$\tilde{E}_t \pi_{t+1} = \beta_{tar,t} \pi^* + \beta_{ext,t} \pi_{t-1} \quad (3.9)$$

where $\alpha_{f,t}$ and $\alpha_{e,t}$ are the probabilities that agents use the fundamental rule and the extrapolative rule for forecasting the output gap, while $\beta_{tar,t}$ and $\beta_{ext,t}$ are the probabilities that agents use inflation targeting and extrapolative rule for forecasting inflation. In addition, the sum of the probability of being a fundamental rule and the probability of being an extrapolative rule is equal to one (see Equation 3.10 and 3.11).

$$\alpha_{f,t} + \alpha_{e,t} = 1 \quad (3.10)$$

$$\beta_{tar,t} + \beta_{ext,t} = 1 \quad (3.11)$$

These probabilities are defined according to discrete choice theory (see Anderson, de Palma, and Thisse 1992, and Brock and Hommes 1997), which analyses how individuals determine different choices. Agents compute the forecast performance of the different rules as follows:

$$U_{f,t} = - \sum_{k=1}^{\infty} \omega_k (Y_{t-k} - \tilde{E}_{t-k-1}^f \tilde{Y}_{t-k})^2 \quad (3.12)$$

$$U_{e,t} = - \sum_{k=1}^{\infty} \omega_k (Y_{t-k} - \tilde{E}_{t-k-1}^e \tilde{Y}_{t-k})^2 \quad (3.13)$$

$$U_{tar,t} = - \sum_{k=1}^{\infty} \omega_k (\pi_{t-k} - \tilde{E}_{t-k-1}^{tar} \pi_{t-k})^2 \quad (3.14)$$

$$U_{ext,t} = - \sum_{k=1}^{\infty} \omega_k (\pi_{t-k} - \tilde{E}_{t-k-1}^{ext} \pi_{t-k})^2 \quad (3.15)$$

where $U_{f,t}$ and $U_{e,t}$ are the forecast utilities for output gap of the fundamentalists and extrapolators, respectively; while $U_{tar,t}$ and $U_{ext,t}$ are the forecast performances for inflation of the fundamentalist and extrapolators, respectively. Actually, these are the Mean Squared forecasting errors (MSFEs) of the forecasting rules; ω_k are geometrically declining weights, which are defined as:

$$\omega_k = (1 - \rho)\rho^k \quad (3.16)$$

where ρ lies between zero and one, which is interpreted as a memory coefficient. The probability of using fundamental rule or an extrapolative rule is determined by these

utilities. If ρ approaches zero, it implies that agents tend to have no memory that the past errors cannot enter into the utilities. If ρ approaches one then it indicates that agents have an infinite memory that all the past errors are taken into account and share the same weight. Consequently, the past errors enter into the utility.

If using the above forecasting performances, the probabilities of the fundamentalist and extrapolator in forecasting output can be defined as:

$$\alpha_{f,t} = \frac{\exp(\gamma U_{f,t})}{\exp(\gamma U_{f,t}) + \exp(\gamma U_{e,t})} \quad (3.17)$$

$$\alpha_{e,t} = \frac{\exp(\gamma U_{e,t})}{\exp(\gamma U_{f,t}) + \exp(\gamma U_{e,t})} \quad (3.18)$$

While the probabilities of the inflation targeting rule and extrapolative rule are:

$$\beta_{tar,t} = \frac{\exp(\gamma U_{tar,t})}{\exp(\gamma U_{tar,t}) + \exp(\gamma U_{ext,t})} \quad (3.19)$$

$$\beta_{ext,t} = \frac{\exp(\gamma U_{ext,t})}{\exp(\gamma U_{tar,t}) + \exp(\gamma U_{ext,t})} \quad (3.20)$$

Equation 3.17-3.18 shows that if the forecast performance of the fundamental rule improves relative to the extrapolative rule, then the agents are more likely to choose the fundamental rule to forecast the future output gap. Therefore, the probability of using the fundamental rule increases. The inflation forecasting heuristic rule can be interpreted as a procedure for agents to find out how credible the central bank's

inflation targeting is. Equation 3.19-3.20 gives an idea how inflation targeting is credible. Since using the announced inflation target will produce good forecasts, the probability that agents rely on the inflation target rule will be high. If, on the other hand, the inflation target does not produce as good a forecast as an simple extrapolative rule, then the probability that agents use the inflation target rule will be small. Therefore, the mechanism driving the selection of the rules introduces a self-organising dynamic into the model. γ here is defined as the ‘intensity of choice’, which is assumed to be one in De Grauwe (2010). This measures the degree to which the deterministic component of utility determines actual choice.

The infinite sum in Equation 3.12 to 3.15 can be transformed into a recursive representation of the sum by the following:

$$U_{f,t} = -(1 - \rho)\rho(Y_{t-1})^2 - \rho U_{f,t-1} \quad (3.21)$$

$$U_{e,t} = -(1 - \rho)\rho(Y_{t-1} - Y_{t-k-3})^2 - \rho U_{e,t-1} \quad (3.22)$$

$$U_{tar,t} = -(1 - \rho)\rho(\pi_{t-1} - \pi^*)^2 - \rho U_{tar,t-1} \quad (3.23)$$

$$U_{ext,t} = -(1 - \rho)\rho(\pi_{t-1} - \pi_{t-k-3})^2 - \rho U_{ext,t-1} \quad (3.24)$$

The solution method to the behavioural model is obtained by substituting the expectation formation of Equation 3.8 and 3.9 into Equation 3.1 and 3.2; therefore, the model becomes

$$\tilde{Y}_t = \alpha_{e,t}Y_{t-1} - a_1(R_t - \beta_{tar,t}\pi^* - \beta_{ext,t}\pi_{t-1}) + \varepsilon_{1t} \quad (3.25)$$

$$\pi_t = b_1\tilde{Y}_t + \beta(\beta_{tar,t}\pi^* + \beta_{ext,t}\pi_{t-1}) + k\varepsilon_{2t} \quad (3.26)$$

$$R_t = (1 - c_1)(c_2\pi_t + c_3\tilde{Y}_t) + c_1R_{t-1} + u_t \quad (3.27)$$

With the definition for the probabilities in Equation 3.12-3.20, this model is a pure backward model, which can be solved directly. The IS curve then becomes:

$$\begin{aligned} \tilde{Y}_t = & (1 + a_1(1 - c_1)c_2b_1 + a_1(1 - c_1)c_3)^{-1}\{\alpha_{e,t}Y_{t-1} \\ & - [\beta(1 - c_1)c_2 - 1]a_1\beta_{ext,t}\pi_{t-1} - a_1c_1r_{t-1} + \varepsilon_{1t} - a_1u_t \\ & - a_1(1 - c_1)c_2k\varepsilon_{2t} - [\beta(1 - c_1)c_2 - 1]a_1\beta_{tar,t}\pi^*\} \end{aligned} \quad (3.28)$$

We can solve the model by substituting Equation 3.28 into a Phillips Curve and policy function.

The stylised DSGE model with rational expectation is defined as Equation 3.1-3.3, except that the expectations are formed rationally. All of the agents are assumed to understand where they are in the whole system and when they are in the long term horizon, so that they can make a correct decision to maximise their private utility. The

model can be solved by Dynare following Juillard's (2001) procedure, which can be written as:

$$Z_t = BZ_{t-1} + V_t \quad (3.29)$$

where Z_t is a vector of $\tilde{Y}_t, \pi_t, R_t, \varepsilon_{1t}, \varepsilon_{2t}$, and u_t .

3.3 Methodology

Indirect inference is used in this study to compare the effect of behavioural expectation and rational expectation. This method borrows from indirect inference estimation. It provides a framework for judging a calibrated or estimated model, which evolves the idea from the early literature of comparing the moments of the simulated data and actual data. However, indirect inference as an evaluation method provides a statistical criterion for rejecting or accepting models. Meanwhile, comparing a moments method cannot say how close the model is to the actual data.

Indirect inference is well known in the literature of estimation (e.g. Smith 1993; Gregory and Smith 1991, 1993; Gouriéroux et al. 1993; Gouriéroux and Montfort 1995; and, Canova 2005). When estimating the structural parameters, they are chosen so that when this model is simulated to generate estimates of the auxiliary model the results are similar to those obtained from the actual data. Indirect inference chooses

the parameters for the structural model so that it can minimise the distance between a given function of the two sets of estimates of the auxiliary model.

When using indirect inference for evaluating an existing structural model, the basic idea is that it can simulate the data from the macroeconomic model when given the parameters of the macroeconomic model and the distributions of the errors (which can be either estimated or calibrated). The test is based on a comparison of the data observation with the data simulated from the structural model through an auxiliary model. In this study, VAR is chosen to serve as the auxiliary model and the tests are based on a function of the VAR estimates. The reason to choose VAR as our auxiliary model is because the structural model can always be represented as a VARMA, which is close to a VAR representation. In addition, VAR also captures two features of the data, which are: the variance-covariance relation among the variables through the covariance matrix of the VAR disturbances, and the dynamic behaviour of the data via the dynamics and impulse response functions of the VAR. The test statistic is based either on the distributions of these functions of the parameters of VAR or on a function of these parameters. The null hypothesis is that the macroeconomic model is correctly specified. Non-rejection of the null hypothesis implies that the results of the macroeconomic model are not significantly different from those of the observed data. The VAR estimates of the data generated by the model should match the VAR esti-

mates estimated from the actual data. Rejection of the null hypothesis indicates that the macroeconomic model cannot replicate the data significantly.

A Wald test statistic is chosen to be the test statistic, which is used to reject or not reject the macroeconomic model. Following the notation of Canova (2005), y_t is defined as an $m \times 1$ vector of observed data ($t = 1, \dots, T$) and $x_t(\theta)$ is an $m \times 1$ vector of simulated data with S observations from the model, θ is a $k \times 1$ vector of structural parameters from the model. $S = T$ is always set, because the sample size of simulated data and the actual data has to be consistent. y_t and $x_t(\theta)$ are assumed to be stationary and ergodic. The auxiliary model is $f[y_t, \alpha]$, where α is a vector comprising elements of the VAR estimates and elements of the covariance matrix of y_t . Under the null hypothesis $H_0 : \theta = \theta_0$, the auxiliary model is then $f[x_t(\theta_0), (\theta_0)] = f[y_t, \alpha]$. The null hypothesis is tested through the $q \times 1$ vector of continuous functions $g(\alpha)$. Under the null hypothesis, $g(\alpha) = g(\alpha(\theta_0))$. a_T is defined as the estimator of using actual data and $\alpha_S(\theta_0)$ as the estimator of based on simulated data for θ_0 . Then we have $g(a_T)$ and $g(\alpha_S(\theta_0))$. The simulated data is obtained by bootstrapping N times of structural errors, so that there are N sets of simulated data. We can calculate the bootstrapped mean by $g(\overline{\alpha_S(\theta_0)}) = \frac{1}{N} \sum_{k=1}^N g_k(\alpha_S(\theta_0))$. The Wald statistic uses the distribution of $g(a_T) - g(\overline{\alpha_S(\theta_0)})$. The formula of the Wald statistic (WS) can be specified as:

$$WS = (g(a_T) - g(\overline{\alpha_S(\theta_0)}))' W^{-1}(\theta_0) (g(a_T) - g(\overline{\alpha_S(\theta_0)})) \quad (3.30)$$

where $W(\theta_0)$ is the variance and covariance matrix of the distribution of $g(a_T) - \overline{g(\alpha_S(\theta_0))}$.

The testing procedure has three steps. The first step is to derive the structural errors using the observed data and parameters calibrated or estimated in the model. Generally speaking, normal errors are not always assumed. If the model's equations have no future expectations, then the structural errors can be simply calculated using the actual data and structural parameters. If there are expectations in the model's equations, then rational expectation terms can be calculated using the robust instrumental variables methods of McCallum (1976) and Wickens (1982). The lagged endogenous data are used as instruments, which is effectively consistent with the auxiliary model VAR.

The second step bootstraps these errors N times to obtain N pseudo samples. The errors are always assumed to be autoregressive processes. The structural errors are estimated, and the relevant disturbance and autoregressive coefficients can be obtained. The model can be solved by Dynare using these coefficients. Using the solution from Dynare, the data can then be simulated using the N bootstrapped disturbances, so that we can get N sets of simulated data.

The Wald statistic is computed in the third step. The distribution of the estimates from the VARs is obtained by estimating the auxiliary model VAR on each pseudo sample. These sets of vectors represent the sampling variation that is implied by the

structural model, enabling its mean, covariance matrix, and confidence bounds to be calculated directly. N is normally set to be 1,000. Therefore, the estimates from the data and estimates from the models can be compared. In particular, the model's ability to encompass the dynamics and variances of the data can be examined. The dynamic properties are captured by VAR estimates, while the volatility properties can be captured by the variance of the main variables. For the individual estimates, the confidence interval (95%) is calculated directly from their bootstrapped distribution. For the model as whole, the statistic is calculated using Equation 3.30.

It should be noted that VAR(1) is selected as the auxiliary model. The reason to choose one lag for VAR estimation is due to the number of parameters. For example, there are three variables in the model. Consequently, the VAR(1) estimates would be nine. If at least these nine parameters cannot pass the test, then it is not necessary to proceed to test VAR(2) because it involves yet more parameters. If the test results of using VAR(1) cannot be rejected, then we can proceed to compare VAR(2). However, the model is normally rejected if using VAR(2) or more.

DSGE models generally do not perform well when tested against the full data behaviour. This finding is in line with the general rejection of these models that is found by using direct inference likelihood ratio tests (see Le et al. 2011). In this case, the Transformed Mahalanobis (TM) distances can be used to see how bad the model is, which is defined as:

$$TM = \frac{\sqrt{2M_a} - \sqrt{2p}}{\sqrt{2M_{s95\%}} - \sqrt{2p}} * 1.645 \quad (3.31)$$

where M_a is the Mahalanobis distance using the actual data, $M_{s95\%}$ is the 95% critical Mahalanobis distance from simulated data, and p is the number of parameters concerned or defined as degree of freedom. This formula is derived by transforming the Chi-square distribution into a standard normal distribution. The critical value for rejecting a model or not is 1.645. If TM is greater than 1.645, then the model is rejected, while if it less than 1.645 then it is not rejected. Normally this statistic is used when we cannot tell the relative performance between models. For example, if both of the models that are specified above are rejected, then it is necessary to calculate this so that we can determine the relative performance between the two models. In addition, we can see how bad the model is by looking at how far the TM deviates away from 1.645. The smaller the number is, the better the model fits.

3.4 Data and Calibration

3.4.1 Data

In order to compare the test results of the behavioural and rational expectation models, this chapter employs quarterly U.S. data on output gap (\tilde{Y}_t), inflation rate (π_t), and

interest rate (R_t), covering the period from 1981Q4 to 2010Q4². The data are collected from the Federal Reserve Bank of St. Louis. In particular, the sample includes the early 1980s energy crisis and the recent financial crisis to allow for large fluctuations during crisis periods.

Output gap (\tilde{Y}) is defined by the percentage change of real GDP from the potential GDP. However, in practice, potential outputs are not observable. Although the question of how to estimate a potential GDP has long been discussed, no consensus has so far been arrived at. Different estimation methods of potential output and output gap can give different estimates. This difference is problematic when leading to policy recommendations. As summarised by the Economics Policy Committee (2001), broadly speaking there are two approaches to estimate this potential output and output gap, which are: the statistical detrending technique and the economic approach. The economic approach is undoubtedly more appropriate than pure detrending techniques to deal with well identified structural changes in the economy. In addition, a common practice in the recent literature is to estimate from the production function; however, this approach is impractical without a set of data, such as capital stock and productivity shock.

Considering the unavailability of a data set, this study will only consider statistical detrending techniques. A HP filter is the most commonly used tool to estimate

² Due to the calculation of performance variables, $U_{f,t}$, $U_{e,t}$, $U_{tar,t}$, $U_{ext,t}$, the data actually covers the period from 1970Q2 to 2010Q4.

the potential output. The HP filter identifies a trend output by minimising a criterion, and by combining the deviations from actual output and the fluctuations of the trend. The respective weights given to the two components of the criteria depend on an exogenous detrending parameter (usually referred to as λ), which defines the extent of smoothness of the trend. The advantage of using an HP filtered trend as a potential output is its simplicity and lack of a requirement for economic theory. This is a purely mechanical smoothing approach. The disadvantage is also due to its lack of a requirement for economic theory because since potential output is generated by a technique outside the model, it is not an appropriate estimator to model the true potential output.

Within detrending techniques, there are some previous studies that have suggested using a linear detrending of the output gap; however, this is not a ideal approach. Given the flexible economy of a DSGE model, the potential output can be solved as a function of technology shock (see Section 4.3 in Chapter 4). Although we do not know what a technology shock looks like, the probability that it is linear is very low. Therefore, HP filtered detrending with some degree of smoothing is more appropriate to estimate the potential output. A HP filtered trend is an appropriate and commonly used practice to estimate potential GDP and, hence, output gap. Therefore, it will be used in this study due to the unobservability of the potential GDP.

Inflation (π) is defined as the percentage change between current and previous quarter CPI, which can be calculated by differencing the logarithmic form of quarterly

CPI data. It should be noted that this inflation data is the quarterly inflation rate, while a risk free rate is collected as an annual rate; therefore, a necessary transformation from annual rate into quarter rate is needed in order to be consistent with quarterly inflation rate and quarterly output gap. This can be calculated using Equation 3.32.

$$R^q = (1 + R^a)^{\frac{1}{4}} - 1 \quad (3.32)$$

where R^q is quarterly interest rate and R^a is the annual interest rate. The risk free rate is collected as the effective federal funds rate. The data used for testing should all be stationary data; therefore, each variable has to be stationarised by detrending the data to determine if there is a significant trend. In this study it is proved that π_t and R_t has a significant trend. Linear detrending method is used here to smooth these two sets of data. All the data has then to be checked on their unit root properties by ADF tests. Figure 3.1 displays the time paths of the main three variables in the sample period after detrending. It shows that all of the three variables fluctuate around mean zero. Meanwhile, Table 3.1 gives the ADF test results, which show that they are all strictly stationary after detrending.

Variable	Options	τ statistics	Critical Value	Inference
Y	None	-2.137881	-1.94	stationary
π	None	-8.313042	-1.94	stationary
R	None	-4.300952	-1.94	stationary

Table 3.1: ADF Test Results of the Three Variables

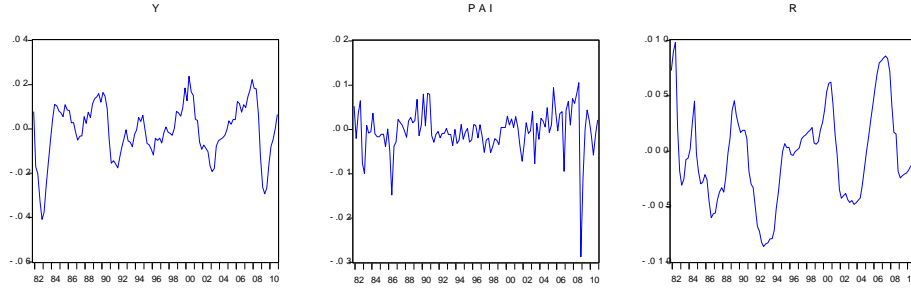


Figure 3.1: Time Paths of \tilde{Y} , π , R

3.4.2 Calibration

Table 3.2 gives the calibrations of both the behavioural model and the rational expectation model. The first part of the table shows the parameters that are common to both models, which follows Minford and Ou (2010). The second part of the table shows the parameters that are used specifically in the behavioural model. The value of γ and ρ are taken from De Grauwe (2010). The structural errors backed from actual data are found to be AR(1) significant in the behavioural model. It should be noted that the AR(1) coefficients in this table are obtained from sample estimates. The third part of this table shows the properties of the structural shocks for the rational expectation model. Similarly, all of these three errors are found to be AR(1) processes in the rational expectation model. The rational expectation model is solved and bootstrapped by assuming that the three errors are autoregressive processes with autoregressive coefficients, as specified in Table 3.2. Meanwhile, in order to obtain these residuals, the

rational expectation model requires an estimation of the rational expectation terms in the stylised model, which adopts McCallum-Wickens's IV method, which was proposed in McCallum (1976) and Wickens (1982), where the instruments used are the lagged data so that the IV equation is the VAR itself. Therefore, the expected future variables for output gap and inflation are approximated by the fitted values of VAR(1), which are linear combinations of the lagged main three variables.

BF/RE	Parameters	Definitions	Values
BF/RE	a_1	real interest rate elasticity on output gap	0.50
	b_1	coefficient of output gap on inflation	2.36
	π^*	inflation target	0
	β	discount factor	0.99
	κ	coefficient of supply shock on inflation	0.42
	c_1	interest rate persistence parameter	0.8
	c_2	policy preference on inflation	2.0
BF	c_3	policy preference on output gap	0.1
	γ	intensity of choice parameter	1
	ρ	memory parameter	0.5
	ρ_1	autoregressive coefficient for demand error	0.69
	ρ_2	autoregressive coefficient for supply error	0.84
RE	ρ_3	autoregressive coefficient for policy error	0.18
	ρ_1	autoregressive coefficient for demand error	0.89
	ρ_2	autoregressive coefficient for supply error	0.86
	ρ_3	autoregressive coefficient for policy error	0.18

Table 3.2: Calibration of Behavioural and Rational Expectation Model

3.5 Testing Results Based on Calibration

Given the data and calibration, the structural errors can be solved so that the model can be bootstrapped 1,000 times. The test statistics are calculated according to the distribution of these pseudo samples. This section aims to show the testing results using calibrated parameters. The test mainly examines three parts, which are: dynamic

properties, volatility properties, and full properties (which includes both). Firstly, the dynamic properties, VAR(1) is adopted as the auxiliary model, which is represented as in Equation 3.33:

$$\begin{bmatrix} \tilde{Y}_t \\ \pi_t \\ R_t \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{21} & \beta_{31} \\ \beta_{12} & \beta_{22} & \beta_{32} \\ \beta_{13} & \beta_{23} & \beta_{33} \end{bmatrix} \begin{bmatrix} \tilde{Y}_{t-1} \\ \pi_{t-1} \\ R_{t-1} \end{bmatrix} + \Omega_t \quad (3.33)$$

where the coefficients of the matrix are the testing concerns. These nine estimates characterise the model's dynamic properties. In addition to dynamic properties presented by this VAR(1), volatility properties are indicated by the variances of the main variables. Finally, a full properties test is conducted by combining dynamics parameters and volatility parameters together. This test is based on whether the coefficient estimates that use the actual data lie in the 95% confidence interval of the estimates based on the simulated data. A Wald statistic is then calculated to show whether the relevant properties can be rejected or not. It should be noted that the Wald statistics in the tables of the following sections are Wald percentiles. If the Wald percentile is higher than 95%, then it implies that the model can be rejected at a 5% significance level, while if it is lower than 95%, then the model cannot be rejected. A lower Wald value represents a better fit.

3.5.1 Behavioural Model

Table 3.3 presents the dynamic properties of the behavioural model, which obtained from the calibrated values. It gives the VAR(1) estimates using actual data and 95% bounds of VAR(1) estimates from the 1,000 simulated data. If sorting these 1,000 VAR(1) coefficients from these nine parameters, then 95% lower and upper bounds refer to the 50th and 950th VAR(1) coefficients. This table is included in order to examine whether the dynamics from the simulated data can capture the dynamics of the data observations. The following table tells that five out of nine parameters lie outside the 95% bootstrapped bounds, they are: interest rate sensitivity with lagged output gap, inflation and interest rate parameters with lagged inflation, and lagged interest rate. It is not surprising then that the overall dynamic properties are rejected by 100%, which indicates that the dynamic properties generated by the model cannot capture the real world dynamics.

VAR Parameters	Actual	95% Lower	95% Upper	IN/OUT
β_{11}	0.9145	0.7558	0.9319	IN
β_{21}	0.0205	-0.1187	0.0369	IN
β_{31}	-0.2214	-0.2041	-0.0148	OUT
β_{12}	0.0554	-0.1792	0.3909	IN
β_{22}	0.1214	0.9468	1.1706	OUT
β_{32}	0.1413	-0.7642	-0.3567	OUT
β_{13}	0.0336	-0.0583	0.1758	IN
β_{23}	-0.0073	0.3638	0.4656	OUT
β_{33}	0.8849	0.4953	0.6697	OUT
DW Dynamics	100%			

Table 3.3: Dynamic Properties of Behavioural Model Based on Calibration

Table 3.4 displays the volatility properties of the behavioural model. This is done by calculating the variances of the three variables from both the real data and from the simulated data. This table shows that only the variance of the output gap can be captured by the model. The variances of inflation and interest rate are far away from the 95% lower and upper bounds. The overall volatility properties are still rejected because the Wald percentile is higher than 95%. When the dynamic and volatility properties are combined together, the model is still rejected because the full Wald is 100%. Therefore, based on the calibration, the behavioural model is not found to be able to capture the reality. However, we cannot yet make a conclusion that the behavioural model is underperformed by the rational expectation model without looking at the testing results of the rational expectation model.

Variiances	Actual Values	95% Lower	95% Upper	IN/OUT
var(Y)	0.1584	0.0768	0.2512	IN
var(π)	0.0238	0.2270	0.8546	OUT
var(R)	0.0183	0.1605	0.5726	OUT
DW Volatility	96.4%			
Full Wald	100%			

Table 3.4: Volatility and Full Properties of Behavioural Model Based on Calibration

3.5.2 Rational Expectation Model

It is necessary to test the rational expectation model using the same sets of data in order to see if the behavioural model can outperform the rational expectation model. Table 3.5 gives the test findings in respect to the dynamic properties of this model. The overall dynamic properties are rejected by the Directed Wald of 95.6%, indicating

that this model cannot capture the dynamic properties of the VAR estimates using actual data; however, this is already close to a non-rejection level. Individually, only one out of nine parameters lies outside the 95% bootstrapped bounds (i.e. interest rate parameter to the lag of output gap). Individually, it can be seen that the rational expectation model can generate much better dynamic properties than the behavioural model, even though both are rejected jointly.

VAR Parameters	Actual	95% Lower	95% Upper	IN/OUT
β_{11}	0.9145	0.7143	0.9197	IN
β_{21}	0.0205	-0.3961	0.0963	IN
β_{31}	-0.2214	-0.2133	0.3020	OUT
β_{12}	0.0554	-0.0748	0.0779	IN
β_{22}	0.1214	0.1187	0.4813	IN
β_{32}	0.1413	-0.0620	0.3252	IN
β_{13}	0.0336	-0.0249	0.0471	IN
β_{23}	-0.0073	-0.0221	0.1614	IN
β_{33}	0.8849	0.7916	0.9481	IN
DW Dynamics	95.6%			

Table 3.5: Dynamic Properties of Rational Expectation Model Based on Calibration

In terms of volatility properties of rational expectation model, Table 3.6 shows that the volatility is not rejected at Directed Wald at 26.6%. This is a quite low Wald percentile, which represents that the rational expectations model can capture volatility much better than the behavioural model. Individually, all the three variances lie inside the 95% bounds. Above all, Table 3.6 finds that, with a Wald percentile of 90.4%, the model is not rejected jointly with dynamic and volatility properties.

An overall comparison between behavioural model and rational expectation model can be seen in Table 3.7. Based on the calibrated values, the first conclusion is made

Categories	Variiances	95% Lower	95% Upper	IN/OUT
$\text{var}(\tilde{Y})$	0.1584	0.0595	0.2265	IN
$\text{var}(\pi)$	0.0238	0.0150	0.0349	IN
$\text{var}(R)$	0.0183	0.0108	0.0443	IN
DW Volatility	26.6%			
Full Wald	90.4%			

Table 3.6: Volatility and Full Properties of Rational Expectation Model Based on Calibration

that the rational expectation model is much better than behavioural model in either dynamic or volatility properties of the models. In addition, the rational expectation model can replicate successfully all of the actual data in these two properties, while the behavioural model cannot do. However, this conclusion is only limited to the calibrated models. In order to have a fair comparison between the two models, it is necessary to do estimation for both models

Wald Categories	BF Model	RE Model
DW Dynamic	100%	95.6%
DW Volatility	96.4%	26.6%
Full Wald	100%	90.4%

Table 3.7: Comparison of Behavioural and Rational Expectation Model Using Calibration

3.6 Indirect Inference Estimation

The main idea of indirect inference as an evaluation method is to test the existing model to determine if the structural parameters θ_0 can generate the actual data. However, if this test cannot explain the data then another set of parameters might be needed to explain how the data is generated. If no set of parameters can be found under which the

model passes, then the model itself is rejected. If the models are already accepted then it is necessary to seek an alternative set of parameters that enables better testing results to be generated. According to the testing results of both models under calibration, the rational expectation model is much better than the behavioural model in every aspect. The rational expectation model is not rejected by the data, while the behavioural model is rejected totally based on the calibrated model parameters. Both of the models are estimated by indirect inference estimation in an attempt to have a fair comparison between these two models.

Indirect inference as an estimation method is used to obtain another set of parameters so that we can maximise the chances of the model passing the test. In estimation, the parameters of the structural model are chosen so that when this model is simulated it generates estimates of the auxiliary model that are similar to those obtained from the actual data. The optimal choice of parameters for the structural model are those that minimise the distance between a given function of the two sets of estimated coefficients of the auxiliary model. In this study, the auxiliary model is also chosen to be the VAR(1).

Estimation starts with a single set of parameters, without changing the signs of parameters searching over the whole parameter space. The minimum value of the Mahalanobis distance is calculated for each model over the sample period using a powerful algorithm that is based on Simulated Annealing. The search takes place over

a wide range around the initial values, with optimising search accompanied by random jumps around the space. The set of parameters that minimise the distance between the actual data and the simulated data in the aspect of dynamic and volatility properties are the optimal estimates, which can be used for further testing. Using these estimates to compare the models can help to avoid any unfair comparisons being made.

Table 3.8 displays the estimation results for the behavioural model, while 3.9 shows the estimation results for the rational expectation model. In both models, β is not allowed to vary. For the behavioural model in Table 3.8, all of the parameters in the IS, Phillips curve, and policy function vary by more than 40%, which indicates that the original calibrated values are not consistent with the data suggest. However, the parameters in forming behavioural expectation vary little. The calibrations of γ and ρ are much closer to the data suggest. Meanwhile, the autoregressive coefficients do not change too much. The estimation results in Table 3.9 tell that the rational expectation parameters do not change as much as those in the behavioural model, which suggests that the calibration is already approaching the values that are suggested by the data. Similarly with the behavioural model, all of the autoregressive coefficients for the three errors show little change. In addition, interest rate persistence does not vary much. There are only two parameters that are changed by more than 40%, which are output gap on inflation and policy preference on inflation. It is suggested by the data

that output gap should play a more important role in explaining inflation and that the central bank should place more attention on controlling inflation.

Parameters	Estimates	Calibration	Variation
a_1	0.7358	0.50	47%
b_1	3.4324	2.36	45%
k	0.5980	0.42	42%
c_1	0.4336	0.8	46%
c_2	2.9230	2.0	46%
c_3	0.0560	0.1	44%
γ	1.0397	1	4%
ρ	0.5304	0.5	6%
ρ_1	0.69	0.69	0%
ρ_2	0.85	0.84	1%
ρ_3	0.16	0.18	11%

Table 3.8: Estimation of Behavioural Model

Parameters	Values	Calibration	Variation
a_1	0.4307	0.50	14%
b_1	3.5046	2.36	49%
k	0.2935	0.42	30%
c_1	0.8190	0.8	2%
c_2	2.8641	2.0	43%
c_3	0.0804	0.1	20%
ρ_1	0.8849	0.89	1%
ρ_2	0.8677	0.86	14%
ρ_3	0.1736	0.18	4%

Table 3.9: Estimation of Rational Expectation Model

3.7 Testing Comparison Based on Estimated Parameters

It is necessary to conduct a testing comparison which uses estimated parameters for both models. Table 3.10 presents the individual properties for the behavioural model, while Table 3.11 shows the individual properties for the rational expectation model. From Table 3.10 it can be seen that there are six out of twelve parameters that are still

outside the 95% bounds. Meanwhile, Table 3.11 finds that all of the parameters lie inside the 95% bounds. Therefore, the behavioural model cannot simulate individual reality as successfully as the rational expectation model.

VAR Parameters	Actual	95% Lower	95% Upper	IN/OUT
β_{11}	0.9145	0.7136	0.9212	IN
β_{21}	0.0205	-0.4512	0.0343	IN
β_{31}	-0.2214	-0.1148	0.1964	OUT
β_{12}	0.0554	-0.0770	0.1309	IN
β_{22}	0.1214	0.4001	0.7728	OUT
β_{32}	0.1413	-0.2115	0.0668	OUT
β_{13}	0.0336	-0.0757	0.2062	IN
β_{23}	-0.0073	0.4943	1.0040	OUT
β_{33}	0.8849	0.2266	0.5977	OUT
$\text{var}(\bar{Y})$	0.1584	0.0634	0.2336	IN
$\text{var}(\pi)$	0.0238	0.0220	0.0729	IN
$\text{var}(R)$	0.0183	0.0543	0.1799	OUT

Table 3.10: Testing Details of Behavioural Model

VAR Parameters	Actual	95% Lower	95% Upper	IN/OUT
β_{11}	0.9145	0.7277	0.9316	IN
β_{21}	0.0205	-0.3817	0.1688	IN
β_{31}	-0.2214	-0.2566	0.3016	IN
β_{12}	0.0554	-0.0772	0.0756	IN
β_{22}	0.1214	0.0892	0.4276	IN
β_{32}	0.1413	-0.1136	0.2630	IN
β_{13}	0.0336	-0.0252	0.0420	IN
β_{23}	-0.0073	-0.0266	0.1429	IN
β_{33}	0.8849	0.8027	0.9525	IN
$\text{var}(\bar{Y})$	0.1584	0.0613	0.2514	IN
$\text{var}(\pi)$	0.0238	0.0119	0.0320	IN
$\text{var}(R)$	0.0183	0.0100	0.0408	IN

Table 3.11: Testing Details of Rational Expectation Model

Based on the estimated parameters, which were done by indirect inference estimation, it is possible to have a fair comparison of the model's ability to explain the

actual world. Table 3.12 presents the results of a comparison of Wald statistics between the behavioural model and the rational expectation model. The full Wald still rejects the behavioural model completely, while the rational expectation model is much improved with non-rejection of both dynamics and volatility. Clearly the behavioural method to form future expectation does not better help to explain the world. Mainstream macroeconomics can still account for the whole sample period, which covers the crisis.

Wald Categories	BF Model	RE Model
DW Dynamic	100%	90.0%
DW Volatility	96.0%	24.2%
Full Wald	100%	79.8%

Table 3.12: Comparison of Behavioural and Rational Expectation Model Using Estimated Parameters

Since a 100% full Wald is obtained using either calibration or estimates in the behavioural model, we cannot see if indirect inference estimation can improve the distance between the simulated worlds with the actual world. Although the behavioural model which uses estimates is rejected by 100% full Wald, the model is still improved. TM is calculated to measure how far away the model is from non-rejection. It is a normalised t-statistic which assumes that 1.645 is at the 95% percentile. This shows how far the behavioural model is away from the 95% bounds. If TM is higher lower than 1.645 then the model is rejected, while if it is lower than 1.645 then it is not rejected in the relevant properties. Table 3.13 shows the TM for the behavioural model for both calibration and estimates. Testing using calibration shows that the behavioural

model is very far away from non-rejection. Only the TM for volatility properties is close to being not rejected. If comparing calibration with estimate parameters, then it can be seen that the model is still improved due to the smaller TM for every case.

TM	Calibration	Estimates
TM (Dynamic)	32.00	5.55
TM (Volatility)	1.98	1.92
TM (Full)	30.01	5.93

Table 3.13: Comparison TM of Behavioural Model Using Calibration and Estimated Parameters

3.8 Conclusion

This chapter aims to determine if a behavioural model is better able to explain the recent crisis than the rational expectation model. The behavioural finance model has gained considerable popularity since the financial crisis of 2007, based on the assumption that agents have cognitive limitations in understanding the whole world. The world is not perfect, and this allows crises to happen; however, this view is not quite right. The rational expectation model allows shocks. If the shocks are large enough and frequent enough then negative shocks follow each other by chance, which can be felt as a 'crisis'. Furthermore, if using non-stationary data then unit root shocks (such as productivity) can produce a sharp change in the economy that is permanent. This amounts to a serious crisis because it is not just a 'bad downturn', which is a shift to a new and permanently worse output level. This seems to be happening at the moment. Davidson et al. (2010) finds that a non-stationary productivity shock can explain the

current crisis in the UK using rational expectations. Consequently, the rational expectation model is, in theory, able to explain crises.

Based on this motivation, this chapter has compared the testing results of a behavioural finance model with a rational expectation model. Indirect inference has been used as an evaluation method. Firstly, I tested the two models based on a calibration which had most of the parameters calibrated in common but with different expectation formations. These test results show that, based on the calibrated values, the rational expectation model is much better than the behavioural model in terms of either the dynamic or the volatility properties of the models. In addition, the rational expectation model can successfully replicate the actual data in these two properties, while the behavioural model cannot. Secondly, considering that the behavioural model is rejected due to the wrong specification of the structural parameters, I estimated both models by using indirect inference as an estimation method. The motivation to do this is to have a fair comparison of the two models. The test results based on the estimated parameters tell that each of the models is improved; however, the behavioural model is still rejected by the data. Therefore, it can be concluded that, although the behavioural model has gained considerable popularity during the recent crisis, it is still rejected by the data. Meanwhile, the rational expectation model is still better able to explain the data.

I am going to focus on rational expectation in the next chapter because it is still a better method to form the model. Rational expectation is the basic assumption of forming expectations in the financial frictions model; therefore, in the next chapter, I will determine if adding financial frictions matters when accounting for a crisis.

Chapter 4 Does It Matter When Adding Credit Channel?

4.1 Introduction

Chapter 3 has analysed the first category of crisis models and it has found that behavioural expectation is not an appropriate method to model the current economic crisis. Meanwhile, it found that rational expectation, which is a mainstream macroeconomic model, is still not rejected, even during the crisis period. In this chapter, I am going to investigate the other strand of crisis models, which is the financial frictions model that is formed by rational expectations. My aim is to investigate whether including a financial sector transmission can account for the recent crisis.

In this chapter I adopt a simple extension of the basic New Keynesian setup, in which the assumption of frictionless financial markets is relaxed, following the example of De Fiore and Tristani (2009). The financial frictions model has four equations, which are: IS function, Phillips Curve, policy function and credit spread function. In this economy, asymmetric information and default risk leads banks to optimally charge a lending rate which is above the risk-free rate. The aggregate dynamics in this model are nested within the New Keynesian model. This model is different from the traditional three-equation model because of the addition of a credit channel. It is also

different from the IS function and Phillips Curve in the standard three-equation model because when the credit channel is added the credit spread and nominal interest rate play a role in the real economy and inflation. Consequently, this chapter is motivated to examine if this financial frictions model is superior to the standard three-equation model when using the same set of data covering the recent crisis period.

Credit frictions have been shown to have a significant impact on the transmission of shocks, either to the economy (which destroys collateral) or to the banking sector (which destroys credit availability) (e.g. Bernanke, Gertler and Gilchrist 1999; and Carlstrom and Fuerst 1997 and 1998). This kind of financial accelerator model propagates and amplifies shocks (such as productivity shocks or monetary shocks) to the economy. The key mechanism involves the presence of credit frictions, in the form of an external finance premium, on the demand for capital investment. This model relies on the costly state verification that was set-up in Townsend (1979) to characterise the optimal real debt contract between firms and financial intermediaries. Meanwhile, the model that was developed by De Fiore and Tristani (2009) assumes nominal debt contract.

The methodology that was used for evaluating the credit model and the non-credit model is accomplished by using indirect inference as a testing method. Although the question of how to test a calibrated or an estimated model has long been a point of debate, most of the literature is based on comparing particular features of the simulated

data with the actual data (particularly moments comparison). The method that is used in this chapter borrows from the indirect inference estimation method in that, given the structural parameter, simulated data from the model and actual data are compared through the auxiliary model. The auxiliary model is often chosen to be VAR because the structural model can always be represented as a VARMA, which is close to a VAR representation. The null hypothesis is that the model is true for the economy. If the model is correct then the VAR estimates of the data generated by the model should match the VAR estimates using the actual data.

In this chapter, I will compare the simplified credit model and the stylised reduced form of the DSGE model. This chapter proceeds as follows. In Section 4.2, I will introduce the microfoundations of the credit model following the work of De Fiore and Tristani (2009). Section 4.3 shows the reduced form credit model and its calibrated values for the model parameters. Section 4.4 explains the data properties and reports the test findings for the credit model. Meanwhile, Section 4.5 presents the three-equation form model without involving financial frictions. I will also report the test results using indirect inference for this model. In Section 4.6 both models are compared to see if one of the models performs better than the other. Section 4.7 will look at the question of a parameter uncertainty, which is one of the problems that have been examined by the testing process. Indirect inference is then used as an estimation method to determine the sets of values that enable both of the models to work

efficiently. In addition, both models are tested using estimated sets of parameters. Section 4.8 will then analyse crisis period in terms of variance decomposition and shock contribution to the main macroeconomic variables during crisis period. Finally, a conclusion is drawn in Section 4.9.

4.2 Microfoundations of Credit Model

4.2.1 Environment of Credit Model

The microfoundation of the credit model that is studied in this chapter is taken from De Fiore and Tristani (2009). It is formed by an indefinitely-lived representative household, owning firms who produce differentiated goods in the retail sector, and a continuum of risk-neutral entrepreneurs who produce homogeneous goods in the wholesale market. It is assumed that the financial market is imperfect, with asymmetric information and costly state verification, which influences the activity of wholesale firms. Meanwhile, the firms produce with inputs of labour and idiosyncratic productivity shocks. Entrepreneurs have to pay workers in advance of production by raising external finance. The risk of default on their debts is due to the idiosyncratic shocks. A perfectly competitive financial intermediary ensures their lending behaviour. Firms and banks stipulate debt contracts, which are the optimal contractual arrangements in a costly state verification environment.

The timing of the economy is as follows. At the beginning of the period, the financial market opens with the aggregate shocks. Households then make their portfolio decisions by allocating their wealth (including existing assets, bond and deposits). The banks keep these deposits, which are used to finance the production of firms. Each wholesale firm stipulates a contract with a bank in order to pay their labour costs. In the second period, the goods market opens. Wholesale firms produce homogeneous goods, which are then sold to the retail sector. If profits are adequate to repay the debt, then the firms will place the remaining revenues into the financing of entrepreneurial consumption. If the revenues are not sufficient to repay the debt, then they will default and their production is seized by the banks. Firms in the retail sector buy the homogeneous goods from wholesale entrepreneurs in a competitive market and they use them to produce differentiated goods at no cost. Retail firms have some market power due to the differentiation of their goods. However, they are not free to change their price because prices are subject to Calvo contracts. The retail goods are then purchased both by households and wholesale entrepreneurs for their own consumption.

4.2.2 Household

Each household maximises their life time utility function

$$E_0\left(\sum_0^{\infty} \beta^t [u(c_t) + \kappa(m_t) - v(h_t)]\right) \quad (4.1)$$

subject to budget constraint

$$M_t + D_t + E_t[Q_{t,t+1}Z_{t+1}] \leq W_t \quad (4.2)$$

where D_t is deposits, M_t is money or existing nominal assets, W_t is nominal wealth, Z_{t+1} is a portfolio of nominal state-contingent bonds each paying a unit of currency in a particular state in period $t + 1$, and $Q_{t,t+1}$ is the price of bonds. The total wealth includes money, deposits and the expected return of state-contingent bonds. W_{t+1} is defined as:

$$W_{t+1} = Z_{t+1} + R_t^d D_t + R_t^m (M_t + P_t w_t h_t + V_t - P_t c_t - T_t) \quad (4.3)$$

where w_t is the real wage, h_t is the total working hours, V_t are the nominal profits that are transferred from retail producers to households, T_t is tax, and R_t^d and R_t^m are interest paid on deposits and money holdings.

If defining $\Delta_{m,t} = \frac{R_t^d - R_t^m}{R_t^d}$ and $\pi_t = \frac{P_t}{P_{t-1}}$, the optimal conditions can be derived by choosing between consumption and working hours, and allocating wealth of deposits, bonds investment and money holding:

$$\frac{v_h(h_t)}{u_c(c_t)} = w_t \quad (4.4)$$

$$\frac{1}{R_t} = E_t[Q_{t+1}] \quad (4.5)$$

$$R_t = R_t^d \quad (4.6)$$

$$u_c(c_t) + \kappa_m(m_t) = \beta R_t = \beta R_t E_t \left\{ \frac{u_c(c_{t+1}) + \kappa_m(m_{t+1})}{\pi_{t+1}} \right\} \quad (4.7)$$

$$\frac{\kappa_m(m_t)}{u_c(c_t)} = \frac{\Delta_{m,t}}{1 - \Delta_{m,t}} \quad (4.8)$$

4.2.3 Wholesale Sector

In the wholesale sector, a continuum of firms (which is indexed by i) are owned by entrepreneurs, who face a linear technology production function that is specified as:

$$y_{i,t} = A_t \omega_{i,t} l_{i,t} \quad (4.9)$$

where A_t is an aggregate productivity shock and $\omega_{i,t}$ is an idiosyncratic productivity shock with log-normal distribution function Φ and density function of ϕ . This production function can be seen as an abstraction from capital accumulation, which is different with BGG style financial frictions mode where entrepreneurs are assumed to decide in the period t defines how to allocate their profits to consumption and investment expenditures. The value of the stock of capital in period $t + 1$ provides the firm with a certain net worth (i.e. internal funds) that can be used in that period's production. In this environment, aggregate shocks can affect the evolution of a firm's net worth, thereby creating endogenous persistence. In De Fiore and Tristani's (2009) model, it is assumed that each firm receives a constant endowment τ at the beginning

of each period, which can be used as internal funds. The firms need to raise external finance because these funds are insufficient to finance their desired level of production. Therefore, financial frictions also have important effects in this economy. A spread arises endogenously between the loan rate charged by financial intermediaries to firms and the risk-free rate, which reflects the existence of a default risk.

4.2.4 Labour Demand

It is assumed that firms should pay wages by raising external finance before profiting from the sale of retail goods. In this study, the financial contract is stipulated with financial intermediaries before observing the idiosyncratic productivity shock and after observing the aggregate shocks. The amount of external finance is $P_t(x_{i,t} - \tau)$, which means that the total funds at hand are $P_t x_{i,t}$. The financial constraint should then satisfy the following:

$$x_{i,t} \geq \omega_t l_{i,t} \quad (4.10)$$

where \bar{P}_t is the wholesale price and $\frac{\bar{P}_t}{P_t} = \chi_t^{-1}$ is the relative price between wholesale price and retail goods price. Each firm i can then maximise its profit as:

$$\frac{\bar{P}_t}{P_t} E[A_t \omega_{i,t} l_{i,t}] - \omega_t l_{i,t} \quad (4.11)$$

subject to the financial constraint in Equation 4.10, where the expectation $E[\cdot]$ is taken with respect to the idiosyncratic shock, which is unknown at the time of labour hiring decision, and w_t denotes the payment of labour services, which are measured in terms of the final consumption goods. The Lagrangian multiplier on the financing constraint is denoted as $(q_{i,t} - 1)$. The optimal conditions are solved as:

$$q_{i,t} = q_t = \frac{A_t}{\omega_t \chi_t} \quad (4.12)$$

$$x_{i,t} = \omega_t l_{i,t} \quad (4.13)$$

implying that:

$$\varepsilon[y_{i,t}] = \chi_t q_t x_{i,t} \quad (4.14)$$

Equation 4.13 indicates that it is profitable for the firms to use all of the funds to produce, which also means that the firms can minimise their chances of default. Equation 4.14 implies that intermediate firms must sell at a mark-up $\chi_t q_t$ over the production costs so as to cover for the presence of monitoring costs and for the monopolistic distortion in the retail sector.

4.2.5 Financial Contract

The optimal financial contract is to choose a contract of $(x_{i,t}, \bar{\omega}_{i,t})$, which solves the costly state verification problem by maximising the entrepreneur's expected profits, as follows:

$$\bar{P}_t \chi_t q_t f(\bar{\omega}_{i,t}) x_{i,t} \quad (4.15)$$

subject to the lender's incentive constraint:

$$\bar{P}_t \chi_t q_t g(\bar{\omega}_{i,t}; \mu_t) x_{i,t} \geq R_t^d P_t (x_{i,t} - \tau) \quad (4.16)$$

feasible condition:

$$\bar{P}_t [f(\bar{\omega}_{i,t}) + g(\bar{\omega}_{i,t}; \mu_t) - 1 + \mu_t \Phi(\bar{\omega}_{i,t})] \leq 0 \quad (4.17)$$

and the entrepreneur's incentive constraint:

$$\bar{P}_t \chi_t q_t f(\bar{\omega}_{i,t}) x_{i,t} \geq P_t \tau \quad (4.18)$$

The optimal condition for the financial contract is solved as:

$$q_{i,t} = \frac{R_t}{1 - \mu_t \Phi(\bar{\omega}_{i,t}) + \frac{\mu_t f(\bar{\omega}_{i,t}) \Phi(\bar{\omega}_{i,t})}{f_{\bar{\omega}}(\bar{\omega}_{i,t})}} \quad (4.19)$$

$$x_{i,t} = \left\{ \frac{R_t}{R_t - q_t g(\bar{\omega}_{i,t}; \mu_t)} \right\} \tau \quad (4.20)$$

where $\bar{\omega}_{i,t}$ is a threshold for the distribution of the idiosyncratic productivity shock, below which firms go bankrupt; $f(\bar{\omega}_{i,t})$ are the expected shares of output accruing to

the entrepreneur and $g(\bar{\omega}_{i,t})$ are the expected shares of output accruing to the bank; and, μ_t is the share of input value that is lost due to monitoring costs.

The gross interest rate on loans can be backed out from the debt repayment, which requires:

$$\bar{P}_t \bar{\omega}_t \chi_t q_t x_t = R_t^l P_t (x_{i,t} - \tau) \quad (4.21)$$

By combining 4.16 and 4.21 together, the credit spread is derived as:

$$\Delta_t = \frac{R_t^l}{R_t^d} = \frac{\bar{\omega}_t}{g(\bar{\omega}_{i,t}; \mu_t)} \quad (4.22)$$

It can be seen that the credit spread is determined by the bankruptcy threshold and monitoring cost.

4.2.6 Entrepreneurs

If they do not default, entrepreneurs pay their debt at the end of each period. The remaining profits will support their consumption, which is:

$$e_t = f(\bar{\omega}_t) q_t x_t \quad (4.23)$$

Using the results from financial contract in Equation 4.19 and 4.20, the consumption of entrepreneur can be derived as:

$$e_t = \tau R_t \left(1 + \frac{\mu_t \Phi(\bar{\omega}_t)}{f_{\bar{\omega}}(\bar{\omega}_t)}\right) \quad (4.24)$$

Equation 4.24 shows that entrepreneurial consumption depends only on the nominal interest rate, bankruptcy threshold, and monitoring cost. An increase in the nominal interest rate has no direct effect on loans and it affects financial conditions mainly by inducing an increase in the mark-up q_t . This reflects in the firm's higher profits, so that a higher R_t leads to an increase in entrepreneurial consumption.

4.2.7 Retail Sector

In the retail sector, a continuum of monopolistically competitive retailers buy wholesale goods from entrepreneurs in a competitive market and then differentiate it at no cost. The profits are distributed to households, who own retail firms. Price setting is subject to a Calvo contract. It is assumed that each retailer adjusts its price with a probability of $1 - \theta$. $Y_t(j)$ is defined as the quantity of output sold by retailer j and $P_t(j)$ is defined as the retail price set by retailer j . Each retailer maximises their expected discounted profits as:

$$E_t \left[\sum_{k=0}^{\infty} \theta^k \bar{Q}_{t,t+k} \frac{P_t(j) - \bar{P}_{t+k}}{P_{t+k}} Y_{t+k}(j) \right] \quad (4.25)$$

where:

$$\bar{Q}_{t,t+k} = \beta \frac{u_c(c_{t+1}) + \kappa_m(m_{t+1})}{u_c(c_t) + \kappa_m(m_t)} \quad (4.26)$$

The optimal conditions are:

$$1 = \theta \pi_t^{\epsilon-1} + (1 - \theta) \left(\frac{\epsilon}{\epsilon - 1} \frac{\Theta_{1,t}}{\Theta_{2,t}} \right)^{1-\epsilon} \quad (4.27)$$

where:

$$\Theta_{1,t} = \frac{1}{\chi_t} Y_t + \theta E_t [\pi_{t+1}^\epsilon \bar{Q}_{t,t+k} \Theta_{1,t+1}] \quad (4.28)$$

$$\Theta_{2,t} = Y_t + \theta E_t [\pi_{t+1}^{\epsilon-1} \bar{Q}_{t,t+k} \Theta_{2,t+1}] \quad (4.29)$$

4.2.8 Market Clearing Conditions

The money clearing conditions are defined as follows:

Money:

$$M_t^s = M_t \quad (4.30)$$

Bonds:

$$Z_t = 0 \quad (4.31)$$

Labour:

$$h_t = l_t \quad (4.32)$$

Loans:

$$D_t = P_t(x_t - \tau) \quad (4.33)$$

Wholesale goods:

$$y_t = \int_0^1 Y_t(j) dj \quad (4.34)$$

Retail goods:

$$Y_t(j) = c_t(j) + e_t(j) \quad (4.35)$$

4.2.9 Systematic Equations

The model can be loglinearised around their steady states as the following,

$$\hat{Y}_t = E_t \hat{Y}_{t+1} - \varphi_1(\hat{R}_t - E_t \pi_{t+1}) - \varphi_2(\hat{\Delta}_t - E_t \hat{\Delta}_{t+1}) - \varphi_3(\hat{\chi}_t - E_t \hat{\chi}_{t+1}) + \eta_{1t} \quad (4.36)$$

$$\pi_t = -\gamma_1 \hat{\chi}_t + \beta E_t \pi_{t+1} \quad (4.37)$$

$$\hat{\Delta}_t = \mu_1 \hat{Y}_t - \mu_2 \hat{R}_t + \eta_{2t} \quad (4.38)$$

$$\hat{\chi}_t = -\lambda_1 \hat{\Delta}_t - \lambda_2 \hat{R}_t - \lambda_3 \hat{Y}_t + \eta_{3t} \quad (4.39)$$

where a hat represents the log-deviation of a variable from its steady state, all the $\varphi, \gamma, \mu,$ and λ are combinations of parameters derived from microfoundation and $\eta_{1t}, \eta_{2t}, \eta_{3t}$ are combination of shocks.

4.3 Credit Model

Following the example of De Fiore and Tristani (2009), the reduced form of credit model is rearranged in this study into a specification of output gap \tilde{Y}_t , as in the following equations:

$$\tilde{Y}_t = E_t \tilde{Y}_{t+1} - a_1(R_t - E_t \pi_{t+1} - \hat{r}_t^e) - a_2(\hat{\Delta}_t - E_t \hat{\Delta}_{t+1}) + a_3(R_t - E_t R_{t+1}) + \epsilon_{1t} \quad (4.40)$$

$$\pi_t = b_1 \tilde{Y}_t + \bar{\kappa} R_t + b_2 \hat{\Delta}_t + \beta E_t \pi_{t+1} - \bar{\kappa} \epsilon_{2t} \quad (4.41)$$

$$\hat{\Delta}_t = c_1 \tilde{Y}_t - c_2 R_t + c_3 \epsilon_{3t} \quad (4.42)$$

$$R_t = (1 - d_1)(d_2 \pi_t + d_3 \tilde{Y}_t) + d_1 R_{t-1} + u_t \quad (4.43)$$

where $\pi_t, R_t, \hat{\Delta}_t$ represent inflation, nominal interest rate, and credit spread between loan rate and risk free rate, respectively; $\epsilon_{1t}, \epsilon_{2t}$ and ϵ_{3t} represent demand shock, supply shock, and shock to the credit market, respectively; and, u_t represents the policy disturbance. It is assumed that the four errors are AR(1) processes. It should be noted

that \tilde{Y}_t is the output gap, which is equal to output minus the potential output from the flexible economy (\hat{Y}_t^e). Meanwhile, \hat{r}_t^e is the real interest rate from the flexible economy where monopolistic distortions are eliminated. Consequently, \hat{r}_t^e can be solved from the flexible price economy, which is specified as:

$$\hat{Y}_t^e = E_t \hat{Y}_{t+1}^e - \sigma \hat{r}_t^e \quad (4.44)$$

$$(\sigma^{-1} + \varphi) \hat{Y}_t^e = (1 + \varphi) a_t - \hat{r}_t^e \quad (4.45)$$

where a_t is the technology shock and σ, φ are the parameters from the utility function. By solving the flexible economy model it can be seen that \hat{r}_t^e is a combination of technology shocks. Therefore, \hat{r}_t^e can enter into the demand shock of v_t in Equation 4.40 and it becomes:

$$\tilde{Y}_t = E_t \tilde{Y}_{t+1} - a_1 (R_t - E_t \pi_{t+1}) - a_2 (\hat{\Delta}_t - E_t \hat{\Delta}_{t+1}^3) + a_3 (R_t - E_t R_{t+1}) + \epsilon_{1t} \quad (4.46)$$

where \hat{v}_t is the shock to the aggregate demand that is created by including the real interest rate from the flexible economy.

³ When using Equation 4.7 and 4.35 to form $E_t \tilde{Y}_{t+1}$ on the right hand side of IS curve,

$$E_t \tilde{Y}_{t+1} = E_t c_{t+1} + E_t e_{t+1} \quad (4.46)$$

There is no $E_t e_{t+1}$ from whole sector consumption; therefore, if adding $E_t \tilde{Y}_{t+1}$ to the right hand side, we should minus a term of $E_t e_{t+1}$. The expected terms of $E_t \hat{\Delta}_{t+1}$ and $E_t R_{t+1}$ then come from $E_t e_{t+1}$.

Equation 4.41 is the extended Phillips Curve. The same as the standard New Keynesian Phillips Curve, this model also includes output gap and expected inflation to determine inflation. However, the coefficient of output gap enters differently by including the presence of entrepreneurs in the economy. In contrast to the standard New Keynesian Phillips Curve, this model gives a role to the nominal interest rate and credit spread in determining inflation (see Equation 4.39 and Equation 4.37). Both terms exert a downwards pressure on economic activity. A higher nominal interest rate will push up marginal costs and, hence, inflation. Additionally, the credit spread also has a positive effect on inflation because a higher spread implies a higher cost of external finance for wholesale firms and, therefore, it exerts independent pressure on inflation. Both the nominal interest rate and the credit spread act as cost-push factor to the economy.

Equation 4.42 indicates that credit spread between loan rate and policy rate is affected by output gap and nominal interest rate. Credit spread increases with aggregate demand but falls with nominal interest rate. An excess demand for retail goods or wholesale goods implies an implicit tightening of the credit constraint. Due to the given amount of internal funds, firms have to use their internal funds to finance a higher level of debt. This would raise the default risk and, hence, a larger spread would develop. The relationship between credit spread and nominal interest rate is negative.

Increasing the nominal interest rate will reduce aggregate demand and, therefore, reduce the credit spread.

Equation 4.43 is the policy rule that is used in this model. It is still an interest rate smoothing rule that is generated by adding persistence of interest rate. This is exactly the same rule, with the same coefficients that has been used in Chapter 3.

Equation 4.46 is the new version of the IS curve that describes how the output gap depends on expected future gap and expected real interest rate, which is the same in the standard New Keynesian model. In contrast, output gap also depends on the expected changes of credit spread and nominal interest rate. Firstly, a higher credit spread between the loan rate and deposit rate will raise the probability of bankruptcy. This leads to the shrinking of entrepreneurial consumption, which in turn reduces aggregate demand. Secondly, a higher nominal interest rate can raise the financial mark-up and, therefore, generate higher profits to consume (see Equation 4.19). Meanwhile, $E_t \hat{\Delta}_{t+1}$ has a positive effect on aggregate demand because a higher expectation of credit spread between t and $t + 1$ can lead to lower than expected entrepreneurial consumption. Expected future household consumption would increase for a given aggregate resource constraint in Equation 4.35. As assumed, households are forward looking and the increased future consumption will feed through the current households' consumption; therefore, leading to an expansion of aggregate demand. Although $E_t R_{t+1}$ has a similar effect on aggregate demand, it is transmitted in the opposite way. A higher expected

nominal interest rate between t and $t + 1$ can increase financial mark-up and entrepreneurial consumption. For a given aggregate resource constraint, the future households consumption will be reduced, which also feeds through to a reduction of current household consumption.

4.3.1 Summary of Credit Model

The intuition of this model's workings goes as follows. Banks lend to entrepreneurs this model allows the banks to lend entrepreneurs (who have only a fixed exogenous and inadequate sum as their own wealth) the money needed to finance their wage bill. The credit rate for this is an add-on spread to the risk-free rate, which rises wage bills, nominal interest rate, and other elements risk factors (such as the threshold for bankruptcy and monitoring costs, which is generally assumed to be fixed). Firstly, as the wage bill (i.e. employment) rises, the size of possible bankruptcy rises and credit spread rises. Secondly, as the risk-free rate rises, the banks' cost of funds rises and this is passed on to firms. Then a higher cost makes it harder for the firms to pay back the funds and so default probabilities rise. As can be seen from impulse response functions in Figure 4.1, the effect of output on credit spread is stronger than that of nominal interest rate. However, the policy shock impulse response functions show that there is still some effect from interest rates. Regarding the financial shock

impulse responses, normally financial shock should lower nominal interest rate but in this model it acts as a cost factor and raises inflation and so raises nominal interest rate.

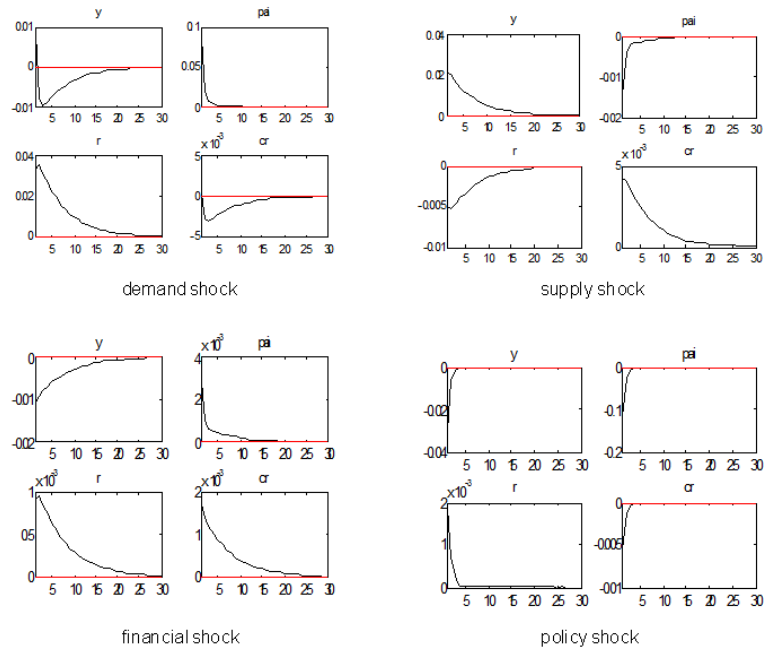


Figure 4.1: Impulse Response Function to Each Shock

Following the intuitive logic above, the model therefore asserts that the credit spread depends mainly on activity (employment) and secondly on interest rates, both positively. By contrast the BGG accelerator depends on available funds as well as investment demands; in the boom investment demand rises and raises the external premium but also available funds rise and this works the opposite way. Hence the behaviour of the spread with respect to the business cycle is ambiguous there (presum-

ably it is negative in the early phase when profits are rising faster than investment, but reverses in the later phase as the investment boom takes hold and profits are flattening off) whereas here in the De Fiore and Tristani (2009) model it is positive since in the boom both activity and interest rates rise. The positively relationship between the boom and credit spread might be considered to be a flaw of the model; however, this can only be assessed in terms of its overall performance (i.e. its ability to track the joint behaviour of output, inflation and interest rates).

4.3.2 Calibration of Credit Model

Table 4.1 summarises the calibrated value in the credit model. This model is calibrated following the example of De Fiore and Tristani (2009). The idiosyncratic shock from the firm side follows log-normal distribution with mean and standard deviation calibrated so as to ensure the quarterly steady state credit spread is equal to 0.5% and 1% bankruptcy rate for each quarter. All of the other structural parameters are standard and consistent with the literature. From this table the unique parameters in the aggregate demand and aggregate supply of credit model are a_2 , a_3 , κ , b_2 . It can be seen that credit spread has a large effect on output and inflation. It should also be noted that the AR(1) coefficients are estimated using the actual data backed from the structural model. The demand, supply error, as well as financial error have high persistence, while the policy error has less persistence.

Parameters	Definitions	Values
β	discount factor	0.99
a_1	interest rate elasticity on output gap	1.54
a_2	credit spread coefficients on output gap	3.82
a_3	interest surprise coefficient on output gap	0.54
b_1	coefficient of output gap on inflation	1.49
κ	coefficient of interest rate on inflation	1.49
b_2	coefficient of credit spread on inflation	9.45
c_1	coefficient of output gap on credit spread	0.19
c_2	coefficient of interest rate on credit spread	0.04
c_3	financial market shock parameter	0.075
d_1	interest rate persistence parameter	0.8
d_2	policy preference on inflation	2.0
d_3	policy preference on output gap	0.1
ρ_1	autoregressive coefficient for demand error	0.85
ρ_2	autoregressive coefficient for supply error	0.84
ρ_3	autoregressive coefficient for financial error	0.86
ρ_4	autoregressive coefficient for policy error	0.18

Table 4.1: Calibration of Credit Model

4.4 Evaluating Calibrated Credit Model

4.4.1 Data

The variables involved in this model are: output gap (\tilde{Y}), inflation (π), credit spread ($\hat{\Delta}$) and nominal interest rate (R). Therefore, the data collected includes \tilde{Y} , π , R_l and R . The data sample covers the period from 1981Q4 to 2010Q4, which has the same set of data as \tilde{Y} , π and R in Chapter 3. Output gap is estimated by using an HP filtered trend, which is the same as that used in Chapter 3. Credit spread is generated by the difference between loan rate (R_l) and risk free rate (R). The loan rate is represented by the bank prime loan rate. All of the data are collected from Federal Reserve Bank of St. Louis.

In order to make sure that the structural error is stationary, each variable has to be stationarised by detrending to determine if there is a significant trend. All of the data has then to be checked on their unit root properties by ADF tests. Figure 4.2 displays the time paths of the four variables in the sample period after detrending. For the first impression, the four variables are stationary and fluctuating around zero. Table 4.2 gives the ADF test results, which also confirm they are all strictly stationary after detrending.

It should be noted that credit spread is less volatile when compared with the early 1980s. However, the early 1980s is indeed a turbulent period. By 1979, inflation reached a startling 11.3% and in 1980 soared to 13.5%. The Federal Reserve chief Paul Volcker was appointed in 1979 to fight this high inflation as his primary objective. He restricted the money supply and introducing credit controls for a short period to fight inflation. He also raised interest rate, which was about 11% in 1979, rose to 20% by June 1981. The prime interest rate, a highly important economic measure, eventually arrived 21.5% in 1982. All these measurements could be the reason to cause this high volatile credit spread.

Variable	Options	τstatistics	Critical Value	Inference
\tilde{Y}	None	-2.137881	-1.94	stationary
π	None	-8.313042	-1.94	stationary
R	None	-4.300952	-1.94	stationary
$\tilde{\Delta}$	None	-2.816015	-1.94	stationary

Table 4.2: ADF Test Results of the Four Variables

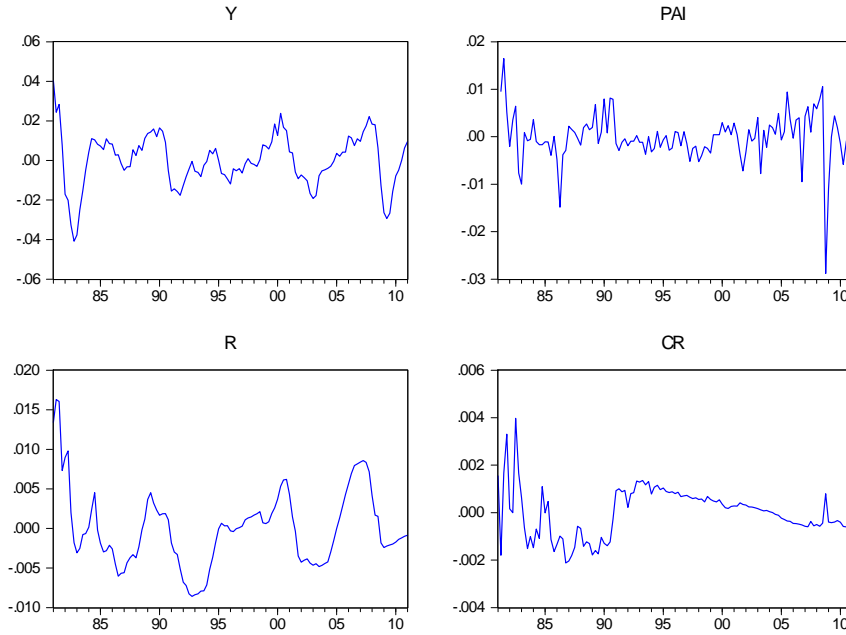


Figure 4.2: Time Paths of \tilde{Y} , π , R , $\hat{\Delta}$

4.4.2 Testing Results

The test is based on a comparison of the data observation with the data simulated from the structural model, concerning both dynamic and volatility properties. Firstly, VAR(1) is used as an auxiliary model for the dynamic properties. It should be noted that the auxiliary model is used only for a limited number of key variables \tilde{Y}_t, π_t, R_t . The reason for this is to compare the relative performance of common variables in the credit and non-credit model. If only a limited number of the variables are considered in the model, then the Wald statistic that is used is the Directed Wald statistic (instead of the full Wald statistic). In addition to the dynamic properties that are presented

by this VAR(1), I will also look at the volatility properties which are indicated by the variances of the main variables. The full test is based on whether these coefficients estimates using the actual data lie in the 95% confidence interval of the estimates based on the simulated data using both VAR(1) estimates and variances.

Table 4.3 presents the test results with respect to the dynamic properties of the credit model. The overall dynamic properties are captured by the Direct Wald statistics of 85.5%, indicating that this credit model can capture the dynamic properties of the VAR estimates from the actual data (given a 5% significance level). Individually, three out of nine parameters lie outside of the 95% bootstrapped bounds, which are: output gap, inflation and interest rate response to the lag of output gap. The dynamic overall is not rejected, even though there are three VAR(1) coefficients which are outside the bounds. This is the key idea of indirect inference as a testing method. The other testing methods (such as comparing the moments) only consider the individual variable and they ignore the covariance between variables. This variance-covariance matrix is the reason for this non-rejection of dynamic properties.

Secondly, Table 4.4 shows that the credit model can also capture the joint distribution of the actual data variances. The Directed Wald for the variances is 79.0%, indicating non-rejection of the model volatilities. Individually, only one out of the three variances (i.e. the variance for inflation) lies outside the 95% bounds. However, the actual variance of inflation is close to the 95% lower bound.

VAR Parameters	Actual	95% Lower	95% Upper	IN/OUT
β_{11}	0.9145	0.7221	0.9134	OUT
β_{21}	0.0205	-0.3485	0.0076	OUT
β_{31}	-0.2214	-0.2152	0.3704	OUT
β_{12}	0.0554	-0.1444	0.0754	IN
β_{22}	0.1214	0.0032	0.3855	IN
β_{32}	0.1413	-0.3940	0.3138	IN
β_{13}	0.0336	-0.0354	0.0363	IN
β_{23}	-0.0073	-0.0273	0.0865	IN
β_{33}	0.8849	0.7384	0.9327	IN
DW Dynamics	85.5%			

Table 4.3: Dynamic Properties of Credit Model

Above all, with non-rejection of the dynamics and variances, the model is not rejected with much lower Directed Wald (see Table 4.4).

Variances	Actual Values	95% Lower	95% upper	IN/OUT
var(\tilde{Y})	0.1584	0.0680	0.2602	IN
var(π)	0.0238	0.0245	0.0875	OUT
var(R)	0.0183	0.0085	0.0336	IN
DW Volatility	79.0%			
Directed Wald	83.4%			

Table 4.4: Volatility and Full Properties of Credit Model

4.5 Evaluating Calibrated Three-Equation DSGE Model

It is meaningful to compare these results with those of a model without a credit sector, which is a simple three-equation reduced form of the DSGE model that can be written as follows:

$$\tilde{Y}_t = E_t \tilde{Y}_{t+1} - a_1(R_t - E_t \pi_{t+1}) + \varepsilon_{1t} \quad (4.47)$$

$$\pi_t = b_1 \tilde{Y}_t + \beta E_t \pi_{t+1} + k \varepsilon_{2t} \quad (4.48)$$

$$R_t = (1 - d_1)(d_2 \pi_t + d_3 \tilde{Y}_t) + d_1 R_{t-1} + u_t \quad (4.49)$$

where all of the variables are the same as those in the credit model; ε_{1t} is the error from the demand side; ε_{2t} is the shock from the supply curve; and, u_t is the policy error. It is also assumed that all three errors are AR(1) processes. In the IS curve, the economy output gap is standard and it is not affected by the expected changes of credit spread and nominal interest rate. Based on the standard Phillips Curve, it can be seen that this model is not affected by nominal interest rate and credit spread. The policy function is the same across both models.

The calibrated value for this model is standard and consistent with the literature, which is presented in Table 4.5. Although the magnitudes of the parameters are different from the credit model, the signs of the parameters are the same as those of the credit model. It is similar to the credit model in that the AR(1) coefficients of demand and supply error are relatively large when compared with the coefficient of policy error. The data used for testing the three-equation model is the same set of data as those used in the credit model. Theoretically, a credit spread can affect the whole economy through the credit channel; therefore, if correct, the credit model can perform better

than the traditional three-equation DSGE model with respect to explaining the output gap, and the inflation and interest rates.

Parameters	Definitions	Values
a_1	real interest rate elasticity on output gap	0.50
b_1	coefficient of output gap on inflation	2.36
β	inflation expectation on inflation	0.99
k	coefficient of supply shock on inflation	0.42
d_1	Interest rate persistence parameter	0.8
d_2	policy preference on inflation	2.0
d_3	policy preference on output gap	0.1
ρ_1	autoregressive coefficient for demand error	0.89
ρ_2	autoregressive coefficient for supply error	0.86
ρ_3	autoregressive coefficient for policy error	0.18

Table 4.5: Calibration of Three-equation Model

Table 4.6 gives the test findings of the dynamic properties. The overall dynamic prosperity is rejected by the Directed Wald of 95.6%, implying that this model cannot replicate the dynamic properties of the actual data VAR estimates. However, this is already close to a non-rejection level. Individually, only one out of nine parameters lies outside of the 95% bootstrapped bounds. If compared with the credit model, individually this model is better but it has worse joint performance of VAR coefficients.

VAR Parameters	Actual	95% Lower	95% Upper	IN/OUT
β_{11}	0.9145	0.7143	0.9197	IN
β_{21}	0.0205	-0.3961	0.0963	IN
β_{31}	-0.2214	-0.2133	0.3020	OUT
β_{12}	0.0554	-0.0748	0.0779	IN
β_{22}	0.1214	0.1187	0.4813	IN
β_{32}	0.1413	-0.0620	0.3252	IN
β_{13}	0.0336	-0.0249	0.0471	IN
β_{23}	-0.0073	-0.0221	0.1614	IN
β_{33}	0.8849	0.7916	0.9481	IN
DW Dynamics	95.6%			

Table 4.6: Dynamic Properties of Three-equation Model

Table 4.7 shows that the volatility is not rejected at Directed Wald at 26.6%. It also tells us that this three-equation DSGE model can better capture the volatility of the three variables jointly than the credit model. Individually, all of the three variances lie inside the 95% bounds. Above all, Table 4.7 also shows that the model is not rejected jointly with dynamic and volatility properties, with a Wald percentile of 90.4%.

Categories	Variances	95% Lower	95% upper	IN/OUT
$\text{var}(Y)$	0.1584	0.0595	0.2265	IN
$\text{var}(\pi)$	0.0238	0.0150	0.0349	IN
$\text{var}(R)$	0.0183	0.0108	0.0443	IN
DW Volatility	26.6%			
Full Wald	90.4%			

Table 4.7: Volatility and Full Properties of Three-equation model

4.6 Comparing Credit Model with DSGE Model Based on Calibration

The two results tested by indirect inference are compared in order to see if adding a credit channel can make the model perform better. This comparison is based on the calibrated parameters. Table 4.8 shows that, overall, the credit model is slightly better than the traditional three-equation model, although both are not rejected at 5% significance level. The three-equation model can explain the variances of the three variables better than the credit model. With regard to the dynamic part, the credit model fits the data better than DSGE model. Therefore, generally speaking, including a credit spread into the model is slightly better able to explain the data. However,

in order to see if there is a fair comparison, a further examination using estimated parameters to the testing is necessary.

Wald Categories	Credit Model	Non-Credit Model
DW Dynamic	85.5%	95.6%
DW Volatility	79.0%	26.6%
Full Wald or DW	83.4%	90.4%

Table 4.8: Comparison of Credit and Non-credit Model Using Calibration

4.7 Parameter Uncertainty

If the models are already accepted, then it is necessary to seek an alternative set of parameters that are able to produce better testing results. According to the testing results of both models under calibration, overall the credit model is slightly better than the three-equation model but it is worse in the aspect of volatility. In order to have a fair comparison between the two models, both models are estimated by using indirect inference estimation.

In the following subsections I will use indirect inference as an estimation method to obtain another set of parameters so that the chances of the model passing the test can be maximised. In the estimation, the structural parameters are chosen so that when this model is simulated it generates estimates of the auxiliary model that are similar to those obtained from actual data. The optimal choice of parameters for the structural model are those that minimise the distance between a given function of the two sets of

estimated coefficients of the auxiliary model. The auxiliary model is also chosen to be the VAR(1).

4.7.1 Indirect Inference Estimation

Table 4.9 shows the estimated parameters for the credit model and Table 4.10 gives all of the estimates in the three-equation model. The basic principle to do this estimation is to keep the signs of parameters unchanged and allow the parameters to change into a set of values that can minimise the distance between the actual data and simulated data through VAR(1). For both models, β , the discount factor is not allowed to vary.

Table 4.9 and Table 4.10 also present the variations of the estimated parameters compared with calibrations. Similarly, in both models, none of the AR(1) coefficients change much when compared with the calibration. In addition, the real interest rate coefficients in the IS curve do not change much. This indicates that the calibrated values of real interest rate in both models are quite consistent with reality. In contrast, in the credit model most of the parameters estimated are much larger than the calibrated ones in their absolute values (such as a_2, a_3, b_2). These parameters are unique in the credit model. This implies that the effects of nominal interest rate and credit spread are underestimated using previous calibration. Therefore, most of the calibration underestimates these credit spread and credit channel parameters. Meanwhile, in the three-equation model, there are no large variations except the parameter of output

gap in the Phillips Curve. This implies that the calibration underestimates the effect of output on inflation.

Parameters	Estimates	Calibration	Variation
a_1	1.6055	1.54	4%
a_2	1.9145	3.82	50%
a_3	0.7968	0.54	48%
b_1	0.8454	1.49	43%
κ	1.7292	1.49	16%
b_2	14.1591	9.45	50%
c_1	0.2829	0.19	49%
c_2	0.0603	0.04	51%
c_3	0.0390	0.075	48%
d_1	0.7123	0.8	11%
d_2	2.6123	2.0	31%
d_3	0.0570	0.1	43%
ρ_1	0.8681	0.85	2%
ρ_2	0.7881	0.84	6%
ρ_3	0.8667	0.86	1%
ρ_4	0.1549	0.18	14%

Table 4.9: Estimates of Credit Model

Parameters	Estimates	Calibration	Variation
a_1	0.4307	0.50	14%
b_1	3.5046	2.36	49%
k	0.2935	0.42	30%
d_1	0.8190	0.8	2%
d_2	2.8641	2.0	43%
d_3	0.0804	0.1	20%
ρ_1	0.8849	0.89	1%
ρ_2	0.8677	0.86	1%
ρ_3	0.1736	0.18	4%

Table 4.10: Estimates of Three-equation Model

Using the estimated parameters, Figure 4.3 charts each residual term in the model equations against the real data. The left side of this figure refers to the credit model, while the right side relates to the charts in the non-credit three-equation model. Firstly, when compared with the residuals in the IS curve, the credit model captures a better

movement of the real data of the output gap. Secondly, the residuals of the Phillips Curve in the non-credit model have much larger variation when compared with the inflation data. This large error could come from the omitted credit channel. Comparing these two charts of Philips Curve, we can see that the large error is created by the omitted credit channel with nominal interest rate and credit spread. Finally, the policy errors which are calculated using the estimated parameters do not show much difference between the credit and non-credit models. Therefore, according to this figure, we can see that the structural errors in credit model seem to capture a better movement of the real data. In order to see whether this can be proved by statistical testing, I need to compare them using indirect inference testing based on the estimated parameters.

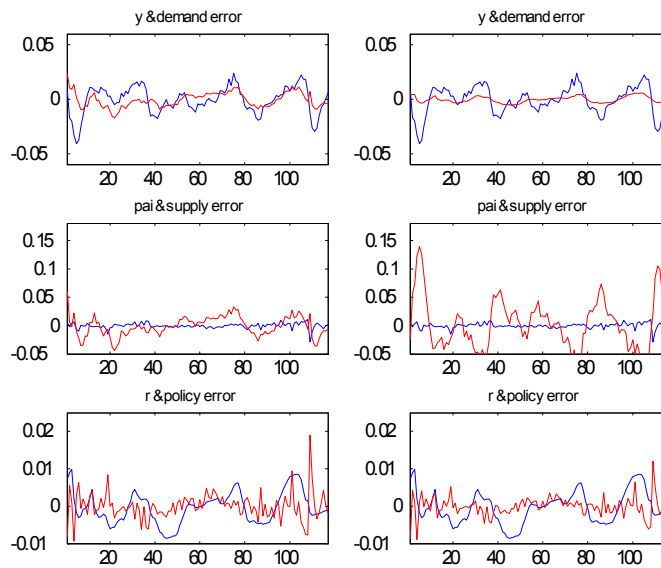


Figure 4.3: Residuals (red) against Real data (blue)

Table 4.11 and 4.12 show the individual parameters and their 95% bounds in the credit model and in the standard three-equation model. It can be seen that after estimation all of the parameters in both models (including dynamic parameters and volatility parameters) lie inside 95% bounds. When under calibration, there are three VAR(1) coefficients lying outside 95% bounds, while there is only one parameter in non-credit model outside the bounds. These results indicate that after estimation the individual parameters are improved in the credit model. However, we cannot make a conclusion about whether adding credit into the model can be better performed just by looking at these tables.

VAR Parameters	Actual	95% Lower	95% Upper	IN/OUT
β_{11}	0.9145	0.7164	0.9220	IN
β_{21}	0.0205	-0.3510	0.1124	IN
β_{31}	-0.2214	-0.2516	0.3140	IN
β_{12}	0.0554	-0.0933	0.0726	IN
β_{22}	0.1214	-0.0716	0.3144	IN
β_{32}	0.1413	-0.0486	0.3972	IN
β_{13}	0.0336	-0.0334	0.0411	IN
β_{23}	-0.0073	-0.0718	0.0909	IN
β_{33}	0.8849	0.7897	0.9658	IN
$\text{var}(\bar{Y})$	0.1584	0.0687	0.2429	IN
$\text{var}(\pi)$	0.0238	0.0155	0.0318	IN
$\text{var}(R)$	0.0183	0.0108	0.0427	IN

Table 4.11: Testing Details of Credit Model Based on Estimated Parameters

Table 4.13 details the test results of both models under estimated parameters. Firstly, the test of the credit model which uses estimated parameters shows that the Direct Wald for the dynamic part is much improved (i.e. it is reduced from 85.5% to

VAR Parameters	Actual	95% Lower	95% Upper	IN/OUT
β_{11}	0.9145	0.7277	0.9316	IN
β_{21}	0.0205	-0.3817	0.1688	IN
β_{31}	-0.2214	-0.2566	0.3016	IN
β_{12}	0.0554	-0.0772	0.0756	IN
β_{22}	0.1214	0.0892	0.4276	IN
β_{32}	0.1413	-0.1136	0.2630	IN
β_{13}	0.0336	-0.0252	0.0420	IN
β_{23}	-0.0073	-0.0266	0.1429	IN
β_{33}	0.8849	0.8027	0.9525	IN
var(Y)	0.1584	0.0613	0.2514	IN
var(π)	0.0238	0.0119	0.0320	IN
var(R)	0.0183	0.0100	0.0408	IN

Table 4.12: Testing Details of Three-equation Model Based on Estimated Parameters

63.8%), which indicates non-rejection of the dynamic properties of the credit model. Secondly, the Directed Wald for the volatility properties is found to be much better than that using calibrated values. Thirdly, the credit model cannot be rejected jointly with much lower Wald level. Although the test of the non-credit model shows that the Directed Wald for dynamics is improved, the improvement is only slight (i.e. from 95.6% to 90.0%). In addition, the volatility Wald reaches a higher non-rejection level. The full Wald is around 80%. It can be seen from these results that the credit model is better than the non-credit model in every aspect. Therefore, this proves that adding a credit channel improve model's ability to explain the real world. Adding a credit channel allows for an extra transmission mechanism of the macroeconomic fundamentals.

Wald Categories	Credit Model	Non-credit Model
DW Dynamic	63.8%	90.0%
DW Volatility	12.3%	24.2%
Full Wald	45.4%	79.8%

Table 4.13: Comparison of Credit and Non-credit Model Using Estimated Parameters

4.8 Subsample Analysis of The Credit Model: Crisis Period

From above analysis, it can be seen that credit channel model performs better than the standard non-credit DSGE model under both calibrated values and estimated parameters from indirect inference estimation. This section will examine if financial shock or financial transmission mechanism can explain the financial crisis covering from 2006Q1 to 2010Q4. Firstly, I am going to see the stochastic variance decomposition of each shock to each variable in this crisis episode. Then I will look at the shock contributions using real time analysis, which uses the actual shocks in this period.

4.8.1 A Stochastic Variance Decomposition of Crisis Period

Table 4.14 shows the variances decomposition for each variable in the credit channel model during the crisis period. It can be seen that financial shock plays an important part in explaining the variance for output gap. In addition, it proves that financial shock is the main reason behind the recent recession in the U.S. economy. Even though the spread movement was less than in the early 1980s, it is still responsible for the crisis. By implication, if the same analysis was done for the early 1980s it would show that the spread was responsible for a large part of the sharp recession that was experienced at that time. However, it has little influence on the inflation and interest rates. Most of

the variance of inflation is explained by the policy shock, while interest rate is driven by demand shock.

Variances	\dot{Y}	π	R
demand shock	2.3%	13.4%	84.6%
supply shock	17.4%	4.7%	8.1%
financial shock	75.3%	4.6%	6.9%
policy shock	5.0%	77.3%	0.4%

Table 4.14: Variance Decomposition: 2006Q1-2010Q4

4.8.2 Accounting for This Particular Crisis Period

The standard variance decomposition can only show the proportional effect among the four shocks. A further examination of the variance decomposition is conducted in order to see the contribution of this credit model by specifically using the actual shocks in the crisis period. The three lines in the following figures are the total predicted (blue), the predicted total without financial shocks (green), and the total predicted without financial transmission (red). The total predicted is charted by bootstrapping actual shocks in this episode to get the time path of main three variables. The predicted total without financial shocks is obtained by bootstrapping actual shocks without financial shock. When simulating the total predicted without financial transmission, all the financial transmission parameters are closed by setting $a_2 = 0, a_3 = 0, k = 0$, and $b_2 = 0$.

According to Figure 4.4, there is a significant distance between the predicted output gap and the predicted without financial shock or transmission. The distance

can be explained by the financial factors. Compared with the other two figures of inflation and interest rate (Figure 4.5 and Figure 4.6), there are not so much difference between the predicted total and those without financial factors. Compared with the total without financial transmission and total without financial shocks, the latter two figures hardly differ, implying that financial transmission of non-financial shocks is modest in this episode: the effect of the non-financial shocks is occurring through the usual non-financial channels. The financial effect is coming from the financial shocks themselves. However, there is relatively larger difference between these two lines in Figure 4.4. This indicates that financial transmission of non-financial shocks to aggregate demand is relatively larger in this crisis period, which means that financial effect is coming from other shocks as well.

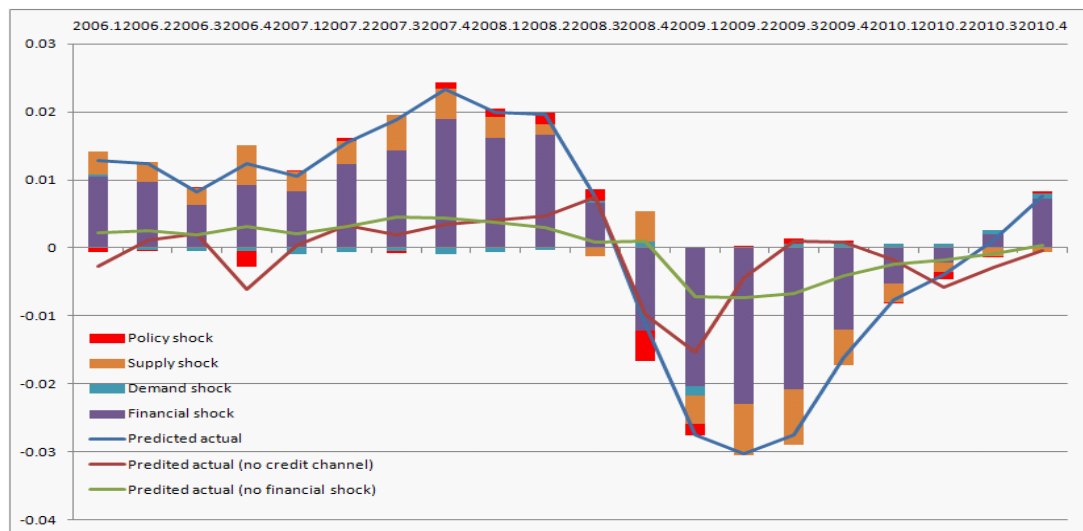


Figure 4.4: Shock Decomposition for Output During Crisis Period

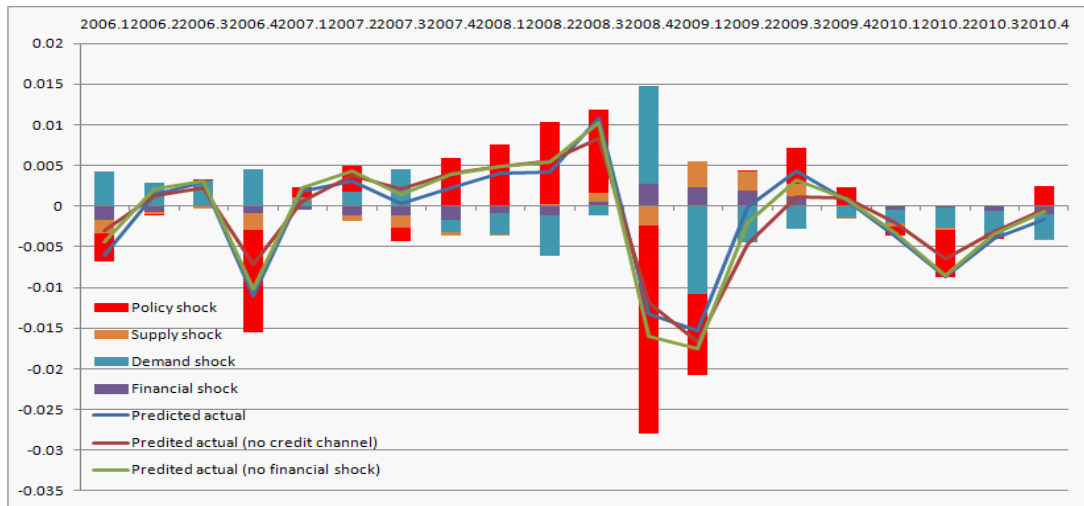


Figure 4.5: Shock Decomposition for Inflation During Crisis Period

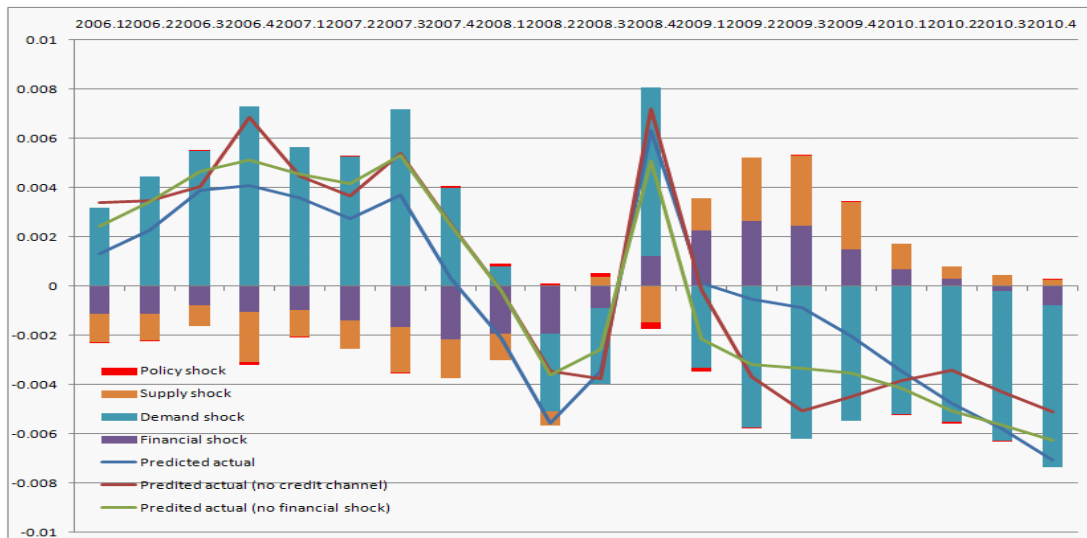


Figure 4.6: Shock Decomposition for Interest Rate During Crisis Period

The bars in these figures show the decomposition of each shock to each variable in each period. This is done by closing each individual shock and simulating variables. The difference between the total predicted variables and total predicted variables without a specific shock is the contribution of each shock.

Firstly, in Figure 4.4, if we focus on the bottom of recession in 2009Q2, financial shock contributes 2.3% to the downturn, while supply shock contributes around 0.7%. Demand shock is tiny in this period. If we look at the whole episode, financial shock is still the main driving force of the aggregate demand. The deep recession is due to this financial shock. The main channel through which the adverse financial shock is transmitted to the real economy has to do with the fact that firms survive. If firms do not go bankrupt, then they need to make higher profits to finance the higher cost of finance. It is the ensuing reduction in real wages which produces the main squeeze on aggregate demand.

Secondly, according to Figure 4.5, policy shock dominates the crisis period. As oil price and commodity prices surged before financial crisis, policy and supply shock are all positive. From 2008Q4, as commodity price falls sharply in 2008Q4, supply and policy shock becomes negative. Then when the economy enters into deep recession, inflation increases in 2009Q3, when policy, supply and demand shock take almost equal contribution. However, policy and supply shock are positive, while demand shock is negative.

Finally, in terms of interest rate (see Figure 4.6), demand shock dominates policy interest rate. In 2008Q4, policy interest rate reached its highest point followed by a sharp decrease onwards, leading to a deep recession of U.S. economy. It contributes about 0.5% to 0.6% to the interest rate after 2009Q2, when the recession starts. The second largest shock in this period is the financial one. When crisis happens, the financial shock depresses output but raises interest rates due to its effect on inflation where it acts as a cost-push shock in this model. Taylor rule shock is hardly seen in this period.

4.9 Conclusion

In this chapter, I have used indirect inference to test whether adding a credit channel to the three-equation model can enable the model to perform better. For this purpose, I have compared a credit model with a standard three-equation model, which does not have the mechanism of financial frictions. Both models are in a reduced form, which can be derived from microfoundations. The data used for evaluating both models are the same set of data, covering the time from the early 1980s energy crisis to the recent bank crisis which began in 2007.

Both models are tested using their calibrated values. Although it is found that both models are not rejected by the data, the credit model is found to be slightly superior to the three-equation model. In order to have a fair comparison, I have extended

the models by varying the structural parameters. Both models are estimated by indirect inference by allowing a certain degree of searching in a Simulated Annealing algorithm. The role of estimation is to maximise the chances of the model passing the test or improving the test. When using the estimated parameters to test the models, it is suggested that both models are improved in terms of their Wald statistics. The test also indicates that the credit model performs better in explaining output gap, inflation, and policy interest rate.

With the whole sample analysis, the credit model achieves a better fit of the data than the non-credit model. In order to see the contribution of this credit model to the crisis, a subsample analysis is conducted (which covers from 2006Q1 to 2010Q4). A conclusion is drawn that financial shock contributes much of the variation of aggregate demand but quite limited effect on inflation and interest. Inflation is dominated by policy shock, while policy interest rate is dominated by demand shock.

Chapter 5 Conclusion

This thesis is motivated to find an appropriate model to explain the current economic crisis. The standard RBC or SW models fail to forecast this crisis because the financial crisis started in 2007. Consequently, many economists have been searching for an alternative to account for this crisis. To date, two kinds of models have been proposed, which are the behavioural finance model and the financial frictions model. In the behavioural finance model the agent's behaviour is not based on rational expectations but on, for example, heuristic rules of thumb or behavioural assumptions. Meanwhile, the financial frictions model is either based on costly verification state or on incomplete enforcement constraint. By introducing a financial sector, these models can provide an extra transmission mechanism of the shocks, which may explain the collapse of the banking system during the current crisis.

Based on the proposed models in the literature, in this study I have tested one of the behavioural models using a heuristic rule. The testing method is done by using indirect inference as an evaluation method. The main idea for testing is that, given the parameters of the macroeconomic model and the distributions of the errors (which are either estimated or calibrated), it can simulate the data from the macroeconomic model. The test is based on a comparison of the data observation with the data that is simulated from the structural model through an auxiliary model. I have decided to

use VAR as the auxiliary model and have based the tests on a function of the VAR estimates. The test statistic is calculated from the distributions of these functions of the parameters of VAR, or of a function of these parameters. The null hypothesis is that the macroeconomic model is correctly specified. Non-rejection of the null hypothesis implies that the macroeconomic model is not significantly different from that of the observed data. VAR estimates of the data generated by the model should match the VAR estimates estimated from the actual data. Rejection of the null hypothesis indicates that the macroeconomic model cannot replicate the data significantly.

Firstly, I have adopted indirect inference as a testing method to evaluate the relative performance of rational expectation and behavioural expectation using US data covering the period from 1981Q4 to 2010Q4. It is found that, based on either the calibration or estimated parameters, the rational expectation model performed better than the behavioural model. Meanwhile, when using estimated parameters, the behavioural model is still rejected by the data while the rational expectation model is not rejected. Although the behavioural model has gained considerable popularity due to the recent crisis, in this study it has failed to explain the crisis. Meanwhile, although rational expectation has been found in this study to be better able to model people's expectations, many mainstream economists have argued that rational expectation models allow iid shocks, and if the shocks are large enough and enough negative ones follow each other by chance then they can become a 'crisis'. Furthermore, if using non-stationary data,

unit root shocks (such as productivity shocks) can produce a sharp change in the economy. These shocks are also permanent. The result is a significant crisis, which is not just a 'bad downturn' but also a shift to a new, permanently worse output level, which seems to be happening at the moment. Davidson et al. (2010) find that a non-stationary productivity shock can explain the current crisis in the UK using rational expectations. This view is confirmed by the testing results in this study.

Secondly, in this study I have used indirect inference to test whether adding a credit channel to the three-equation model enables a better performance. A credit model is compared with a standard three-equation model that does not have the mechanism of financial frictions. Both models are in a reduced form, which can be derived from microfoundations. The data used for evaluating both models are the same set of US data, covering the period from the early 1980s energy crisis through to the recent bank crisis which began in 2007. Both models are tested using calibrated values. Although the results show that both models are not rejected by the data, the credit model is slightly superior to the three-equation model. Therefore, to achieve a fair comparison, I have extended both models by varying the structural parameters. By using the estimated parameters to test the model, it has been found that both models are improved in terms of Wald statistics. This also suggests that the credit model is better able to explain the output gap, and the inflation and policy interest rate. The results of the whole sample analysis show that the credit model achieves a better fit of the

data than the non-credit model. In order to see the contribution of this credit model to the crisis, I have proceeded with a subsample analysis (which covers the period from 2006Q1 until 2010Q4). It is found that financial shock only contributes much of the variation of aggregate demand but quite limited effect on inflation and interest. Inflation is dominated by policy shock, while policy interest rate is dominated by demand shock.

References

- [1] Anderson, S., De Palma, A. and Thisse, J.F. 1992. *Discrete Choice Theory of Product Differentiation*, MIT Press, Cambridge, Mass.
- [2] Avgouleas, E. 2009. The global financial crisis, behavioural finance and financial regulation: in search of a new orthodoxy. *Journal of Corporate Law Studies*, 9(1), pp. 23-59.
- [3] Bernanke, B., Gertler, M. and Gilchrist, S. 1999. The financial accelerator in a quantitative business cycle framework. in J.B. Taylor, and M. Woodford, eds., *Handbook of Macroeconomics*. Amsterdam: North-Holland.
- [4] Brock, W. and Hommes, C. 1997. A rational route to randomness, *Econometrica*, 65, pp. 1059-1095.
- [5] Carlstrom, C.T. and Fuerst, T. 1997. Agency costs, net worth, and business fluctuations: a computable general equilibrium analysis. *American Economic Review*, 87, pp. 893-910.
- [6] Carlstrom, C.T. and Fuerst, T. 1998. Agency costs and business cycles. *Economic Theory*, 12, pp. 583-597.
- [7] Camerer, C., Loewenstein, G. and Prelec, D. 2005. Neuroeconomics: how neuroscience can inform economics. *Journal of Economic Literature*, 63(1), pp. 9-64.
- [8] Christiano L.J., Motto, R. and Rostagno, M. 2004. The great depression and the Friedman-

- Schwartz hypothesis. *NBER Working Papers*, No. 10255.
- [9] Christensen, I. and Dib, A. 2008. The financial accelerator in an estimated New Keynesian model. *Review of Economic Dynamics, Elsevier for the Society for Economic Dynamics*, 11(1), pp. 155-178.
- [10] Clark, A. 1998. *Being There: Putting Brain, Body and World Together Again*. Cambridge: MIT Press.
- [11] Cooley, T., Marimon, R. and Quadrini, V. 2004. Aggregate consequences of limited contract enforceability. *Journal of Political Economy*, 112(4).
- [12] Davidson, J., Meenagh, D., Minford, P. and Wickens, M. 2010. Why crises happen?- nonstationary macroeconomics. *Cardiff Working Paper Series*, E2010/13.
- [13] De Grauwe, P. 2010. Top-down versus bottom-up macroeconomics, *CESifo Economic Studies*, 56(4), pp. 465-497.
- [14] De Fiore, F. and Tristani, O. 2009. Optimal monetary policy in a model of the credit channel. *Working Paper Series 1043*, European Central Bank.
- [15] Della Vigna, S. 2009. Psychology and economics: evidence from the field. *Journal of Economic Literature*. 47(2), pp. 315–372.
- [16] Economic Policy Committee. 2001. Report on potential output and output gap. Available at: http://europa.eu/epc/pdf/finaloutput_en.pdf [Accessed: 27 July 2012]
- [17] Evans, G. and Honkapohja, S. 2001. *Learning and Expectations in Macroeconomics*.

Princeton University Press.

- [18] Gertler, M., Kiyotaki, N. and Queralto, A. 2011. Financial crises, bank risk exposure and government financial policy. Available at: <http://www.hec.unil.ch/documents/seminars/deep/312.pdf> [Accessed: 31 March 2012].
- [19] Gertler, M. and Kiyotaki, N. 2010. Financial intermediation and credit policy in business cycle analysis. In Friedman, B. and Woodford, M. (Eds.), *Handbook of Monetary Economics*. Amsterdam: Elsevier.
- [20] Gertler, M. and Karadi, P. 2011. A model of unconventional monetary policy. *Journal of Monetary Economics*, January.
- [21] Gourieroux, C., Monfort, A. and Renault, E. 1993. Indirect inference. *Journal of Applied Econometrics*, 8, pp. 85-118.
- [22] Gourieroux, C. Monfort, A. 1995. Simulation Based Econometric Methods. *CORE Lectures Series, Louvain-la-Neuve*.
- [23] Gregory, A. and Smith, G. 1991. Calibration as testing: Inference in simulated macro models. *Journal of Business and Economic Statistics*, 9, pp. 293-303.
- [24] Gregory, A. and Smith, G. 1993. Calibration in macroeconomics, in: Maddala, G. (Ed.), *Handbook of Statistics*, 11, Elsevier, St. Louis, Mo., pp. 703-719.
- [25] Hart, O. and Moore, J. 1994. A theory of debt based on the inalienability of human capital. *Quarterly Journal of Economics*, 109(4), pp. 841-879.

- [26] Hayek, F. 1945. The use of knowledge in society. *American Economic Review*, XXXV, no. 4, pp. 519-530.
- [27] Juillard, M. 2001. DYNARE: a program for the simulation of rational expectations models. *Computing in Economics and Finance 213*. Society for Computational Economics.
- [28] Kagel, J.H. and Roth, A.E. 1995. *Handbook of Experimental Economics*. Princeton, NJ: Princeton University Press.
- [29] Kahneman, D. 2002. Maps of bounded rationality: a perspective on intuitive judgement and choice. *Nobel Prize Lecture*, December 8, Stockholm.
- [30] Kahneman, D. and Thaler, R. 2006. Utility maximisation and experienced utility, *Journal of Economic Perspectives*, 20, pp. 221-234.
- [31] Kindleberger, C.P. 1978. *Manias, Panics, and Crashes*, 1st ed. New York: Basic Books.
- [32] Kindleberger, C.P. 2003. *Manias, Panics, and Crashes: A History of Financial Crises*. 4th ed. Palgrave Macmillan.
- [33] Kirman, A. 2011. Learning in agent-based models. *Eastern Economic Journal*, 37(1), pp. 20-27.
- [34] Keynes, J.M. 1936. *The General Theory of Employment, Interest, and Money*. London: Macmillan.

- [35] Kyotaki, N. and Moore, J. 1997. Credit cycles. *Journal of Political Economy*, 105, pp.211-248.
- [36] Le, V.P.M., Meenagh, D., Minford, P. and Wickens, M. 2011. How much nominal rigidity is there in the US economy? testing a New Keynesian DSGE Model using indirect inference, *Journal of Economic Dynamics and Control*, 35(12), pp. 2078-2104.
- [37] Leijonhufvud, A. 1981. *Information and Coordination*. New York: Oxford University Press.
- [38] Leijonhufvud, A. 1993. Towards a not-too-rational macroeconomics. *Southern Economic Journal*, 60, pp. 1-13.
- [39] Lucas, R. E. and Sargent, T. J. 1981. *Rational Expectations and Econometric Practice*. HarperCollins Publishers.
- [40] McCabe, K. 2003. Neuroeconomics. in: L. Nadel, Ed., *Encyclopedia of Cognitive Science*. New York: Macmillan Publishing. pp. 294-298.
- [41] McCallum, B. T. 1976. Rational expectations and the natural rate hypothesis: some consistent estimates. *Econometrica*, 44, pp. 43-52.
- [42] Meier, A. and Muller, G. J. 2006. Fleshing out the monetary transmission mechanism: output composition and the role of financial frictions. *Journal of Money, Credit, Banking* 38, pp. 1999–2133.
- [43] Meenagh, D., Minford, P. and Wickens, M. 2009. Testing a DSGE Model of the EU,

- Open Economies Review*, 20(4), pp. 435-471.
- [44] Milan, F. 2007. Learning and time-varying macroeconomic volatility. *Working Papers*, 070802, University of California-Irvine, Department of Economics.
- [45] Minford, P., Theodoridis, K. and Meenagh, D. 2009. Testing a model of the UK by the method of indirect inference, *Open Economies Review*, 20(2), pp. 265-291.
- [46] Minford, P. and Ou, Z. 2010. Testing the monetary policy rule in US: a reconsideration of Fed's behaviour, *Cardiff University Working Paper Series*, E2009/12, October 2009, updated in 2010.
- [47] Neri, S. 2004. Agency costs or costly capital adjustment DSGE models. a Bayesian investigation. *Bank of Italy Draft*.
- [48] Pareto, V. 1916. *Trattato di Sociologia Generale*, 4 vols, Florence: Barbera. Translated into English and edited by Arthur Livingston as *The Mind and Society*. New York: Harcourt Brace & Co., 1935.
- [49] Sargent, T. 1993. *Bounded Rationality in Macroeconomics*. Oxford University Press.
- [50] Shin, H.S. 2009. Reflections on Northern Rock: the bank run that heralded the global financial crisis. *Journal of Economic Perspectives*, 23, pp. 101–119.
- [51] Simon, H.A. 1955. A behavioural model of rational choice. *The Quarterly Journal of Economics*, 69(1), pp. 99-118.
- [52] Smith, A., 1993. Estimating nonlinear time-series models using simulated vector au-

- toregressions. *Journal of Applied Econometrics*, 8, pp. 63-84.
- [53] Taylor, J.B. 1993. Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy*, 39, pp.195-214.
- [54] Townsend, R. 1979. Optimal contracts and competitive markets with costly verification. *Journal of Economic Theory*, 22, pp. 265-293.
- [55] Warnock, F. and Warnock. V. 2006. International capital flows and US interest rates. *International Finance Discussion Paper* No. 860, International Finance Division, Board of Governors of the Federal Reserve System (September).
- [56] Wickens, M.R. 1982. The efficient estimation of econometric models with rational expectations. *Review of Economic Studies*, 49, pp. 55-67.

Appendix A Behavioural Model

A.1 Calibration

A.1.1 Estimates of the AR Process for Each Error

Errors	AR(1) Coefficient	T-statistics
demand error	0.6949	10.9660
supply error	0.8422	17.7043
policy error	0.1827	2.0312

Table A.1: AR(1) Estimation of Each Error in the Behavioural Model Using Calibration

A.1.2 The Model's Deterministic Impulse Response Functions

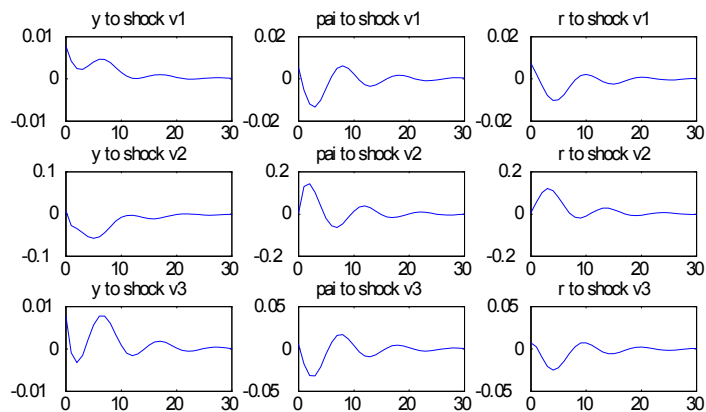


Figure A.1: IRF to Each Shock

A.1.3 A Selection of Bootstrap Samples shown Against the Actual Data for Each Variable

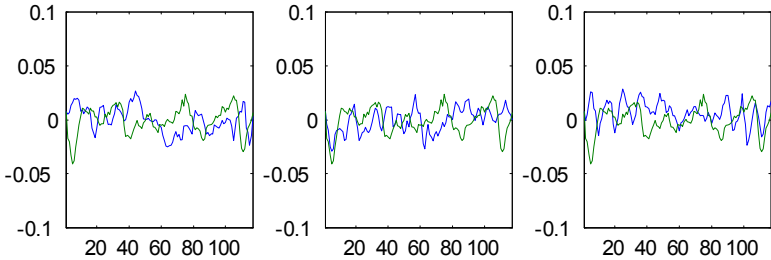


Figure A.2: Actual Data with Bootstrapping Sample: \tilde{Y}

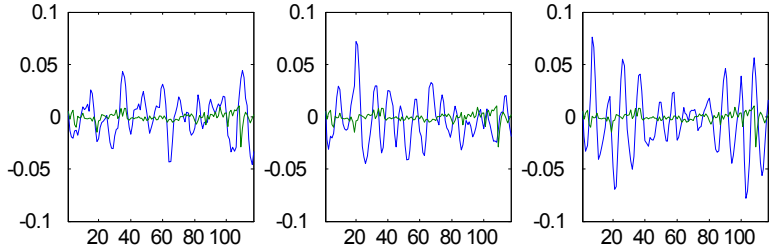


Figure A.3: Actual Data with Bootstrapping Sample: π

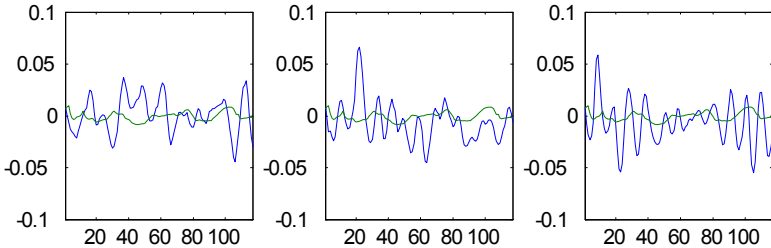


Figure A.4: Actual Data with Bootstrapping Sample: R

A.1.4 VAR Impulse Response Functions and Their 95% Bounds

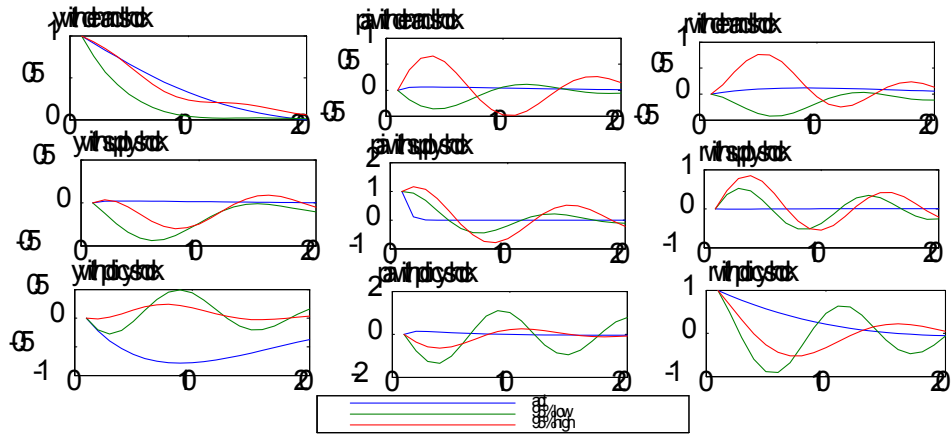


Figure A.5: VAR IRF and 95% Bounds

A.1.5 Cross-moments and Their 95% Bounds

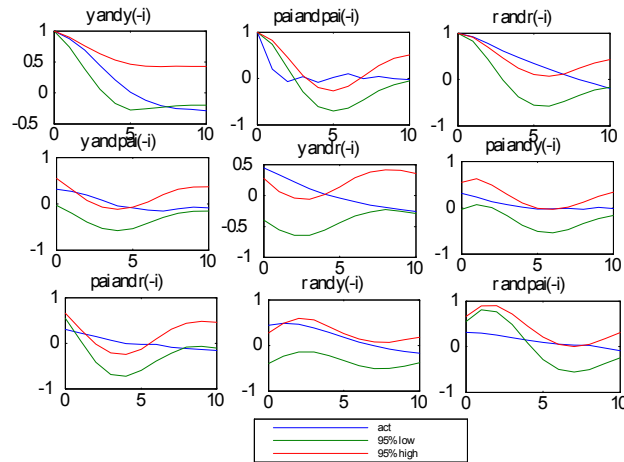


Figure A.6: Cross-moment and 95% Bounds

A.2 Estimated Parameters

A.2.1 Estimates of the AR Process for Each Error

Errors	AR(1) Coefficient	T-statistics
demand error	0.6914	10.9383
supply error	0.8536	18.7792
policy error	0.1567	1.7527

Table A.2: AR(1) Estimation of Each Error in the Behavioural Model Using Estimated Parameters

A.2.2 The Model's Deterministic Impulse Response Functions

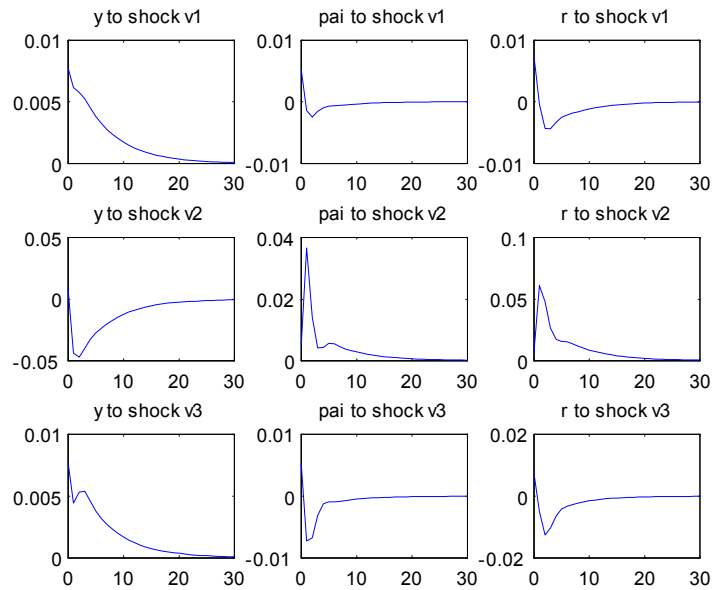


Figure A.7: IRF to Each Shock

A.2.3 A Selection of Bootstrap Samples Shown Against the Actual Data for Each Variable

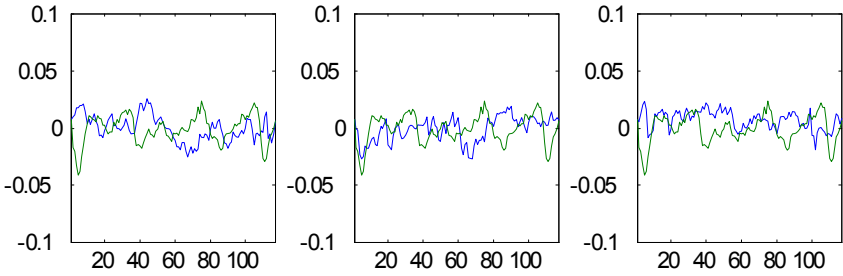


Figure A.8: Actual Data with Bootstrapping Sample: \tilde{Y}

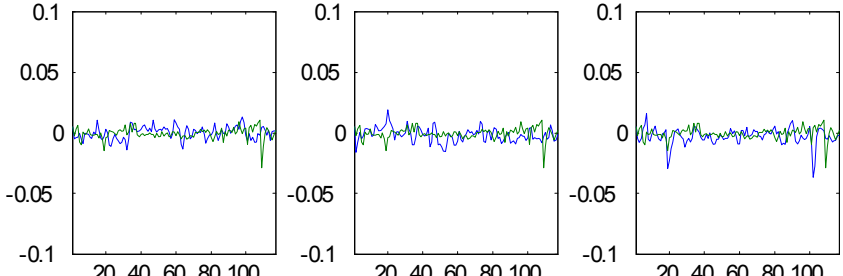


Figure A.9: Actual Data with Bootstrapping Sample: π

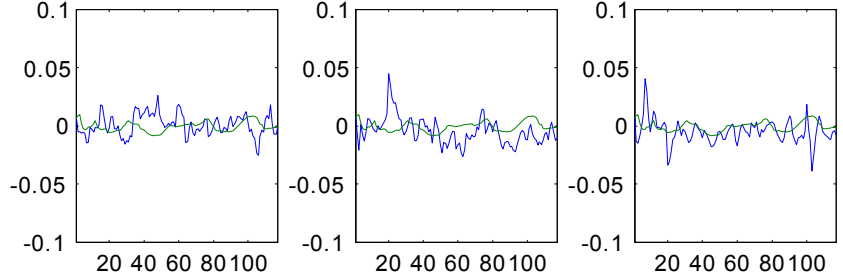


Figure A.10: Actual Data with Bootstrapping Sample: R

A.2.4 VAR Impulse Response Functions and Their 95% Bounds

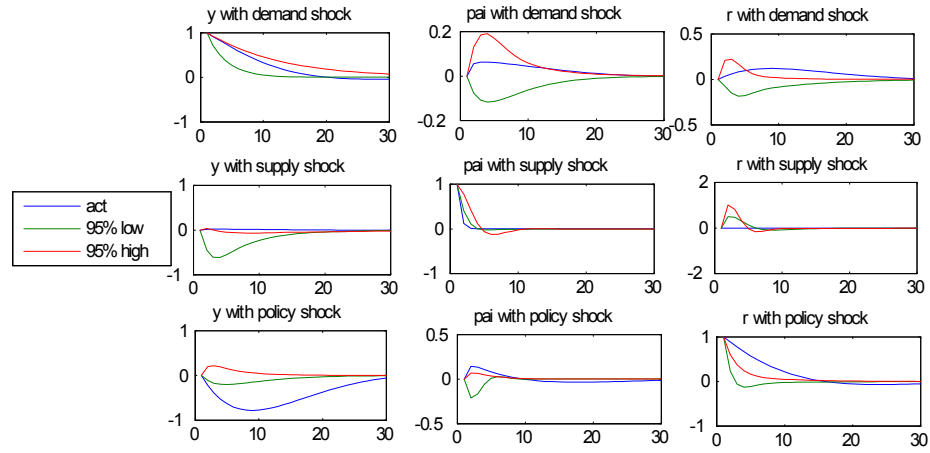


Figure A.11: VAR IRF and 95% Bounds

A.2.5 Cross-Moments and Their 95% Bounds

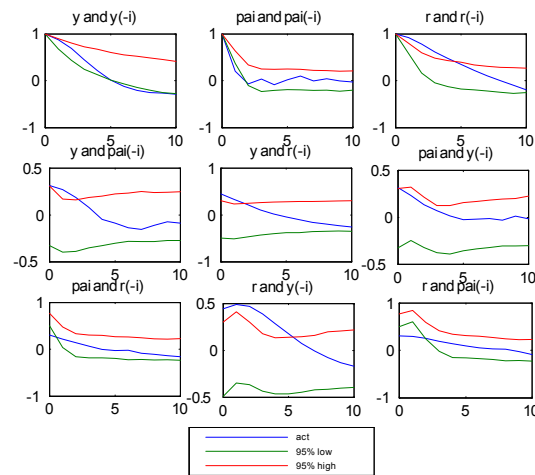


Figure A.12: Cross-moments and 95% Bounds

Appendix B Rational Expectation Model

B.1 Calibration

B.1.1 Estimates of the AR Process for Each Error

Errors	AR(1) Coefficient	T-statistics
demand error	0.8554	24.6479
supply error	0.8641	19.5548
policy error	0.1827	2.0312

Table B.3: AR(1) Estimation of Each Error in the RE model Using Calibration

B.1.2 The Model's Deterministic Impulse Response Functions

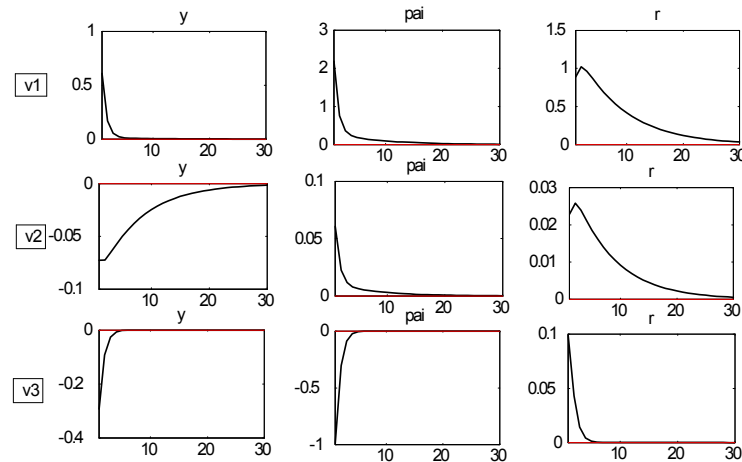


Figure B.1: IRF to Each Shock

B.1.3 A Selection of Bootstrap Samples Shown Against the Actual Data for Each Variable

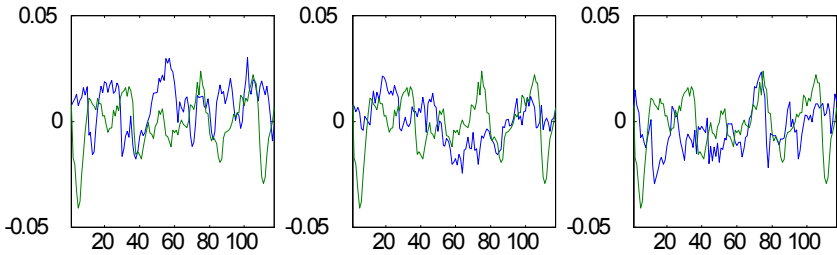


Figure B.2: Actual Data with Bootstrapping Sample: \tilde{Y}

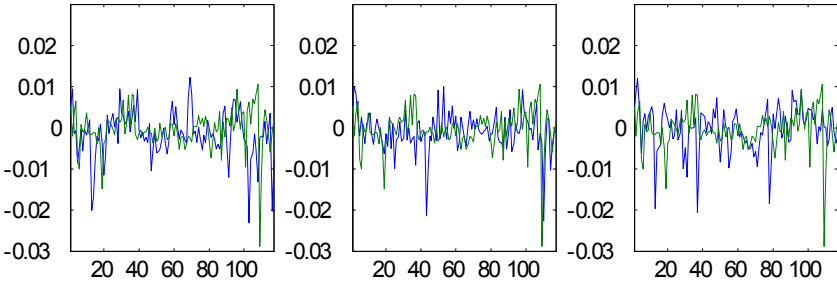


Figure B.3: Actual Data with Bootstrapping Sample: π

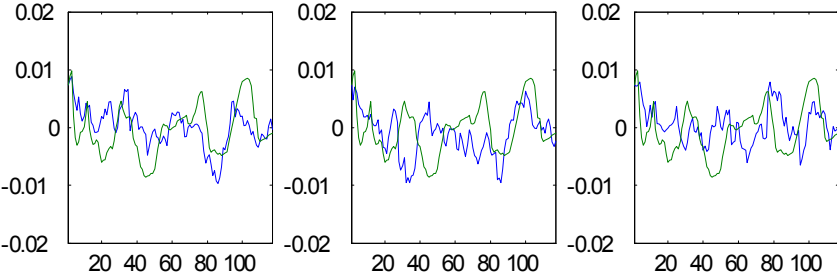


Figure B.4: Actual Data with Bootstrapping Sample: R

B.1.4 VAR Impulse Response Functions and Their 95% Bounds

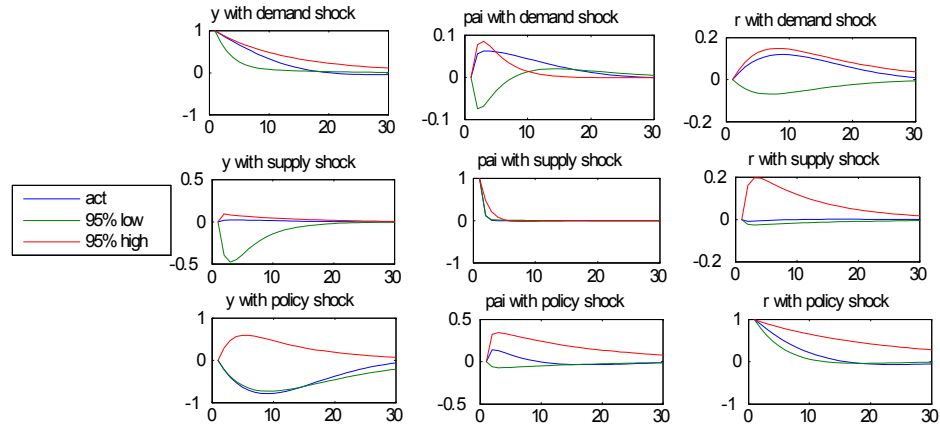


Figure B.5: VAR IRF and 95% Bounds

B.1.5 Cross-Moments and Their 95% Bounds

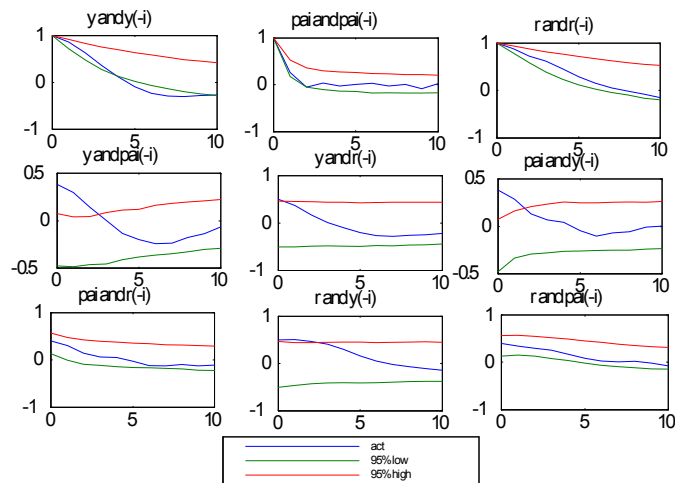


Figure B.6: Cross-moments and 95% Bounds

B.2 Estimated Parameters

B.2.1 Estimates of the AR Process for Each Error

Errors	AR(1) Coefficient	T-statistics
demand error	0.8849	27.4867
supply error	0.8677	19.9553
policy error	0.1736	1.9425

Table B.4: AR(1) Estimation of Each Error in the RE Model Using Estimated Parameters

B.2.2 The Model's Deterministic Impulse Response Functions

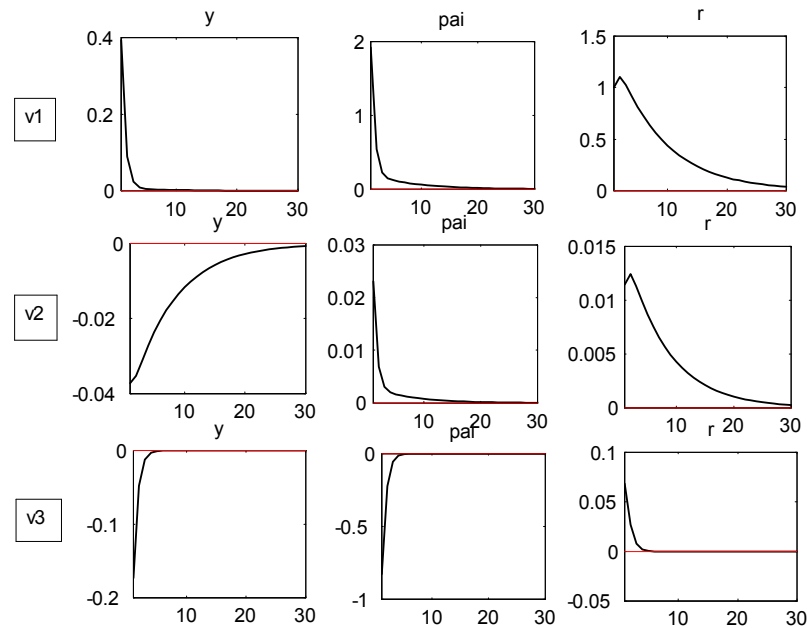


Figure B.7: IRF to Each Shock

B.2.3 A Selection of Bootstrap Samples Shown Against the Actual Data for Each Variable

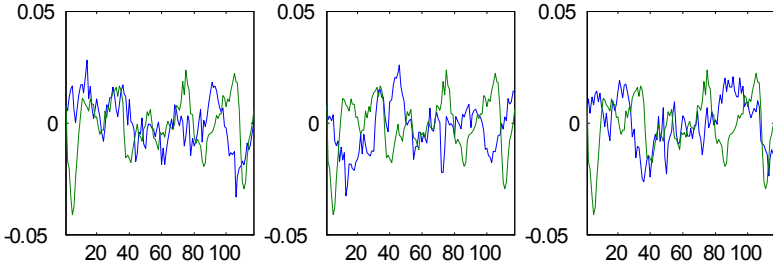


Figure B.8: Actual Data with Bootstrapping Sample: \tilde{Y}

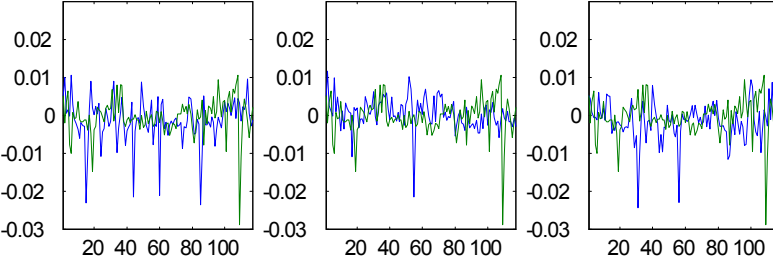


Figure B.9: Actual Data with Bootstrapping Sample: π

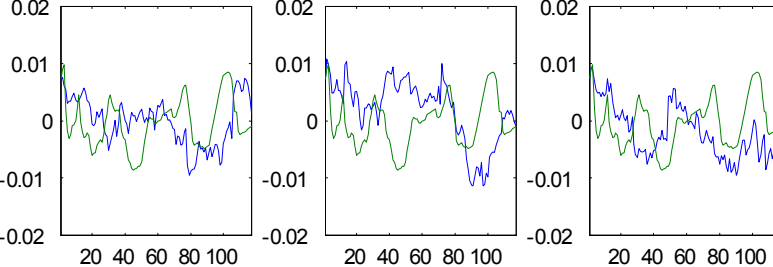


Figure B.10: Actual Data with Bootstrapping Sample: R

B.2.4 VAR Impulse Response Functions and Their 95% Bounds

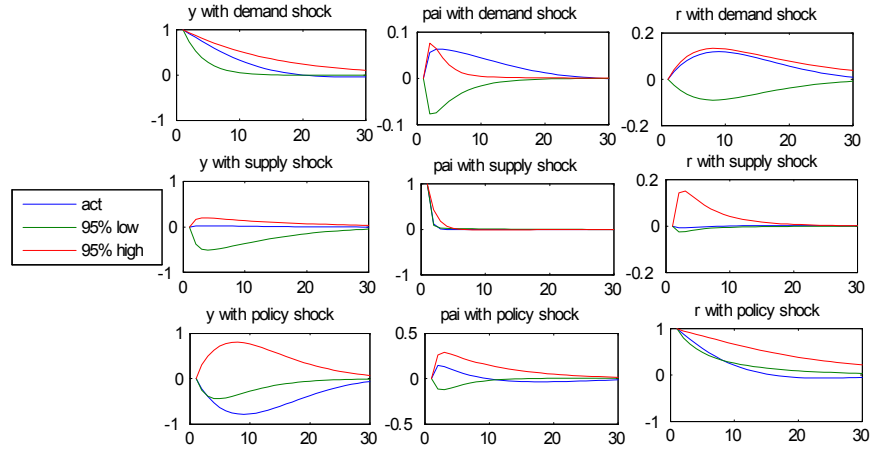


Figure B.11: VAR IRF and 95% Bounds

B.2.5 Cross-Moments and Their 95% Bounds

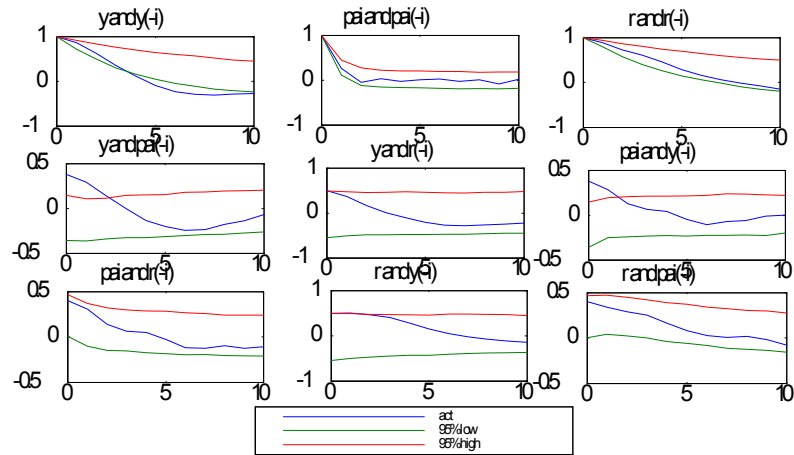


Figure B.12: Cross-moments and 95% Bounds

Appendix C Credit Model

C.1 Calibration

C.1.1 Estimates of the AR Process for Each Error

Errors	AR(1) Coefficient	T-statistics
demand error	0.8459	17.7457
supply error	0.8398	17.6333
financial error	0.8599	19.3875
policy error	0.1827	2.0312

Table C.5: AR(1) Estimation of Each Error in the Credit Model Using Calibration

C.1.2 The Model's Deterministic Impulse Response Functions

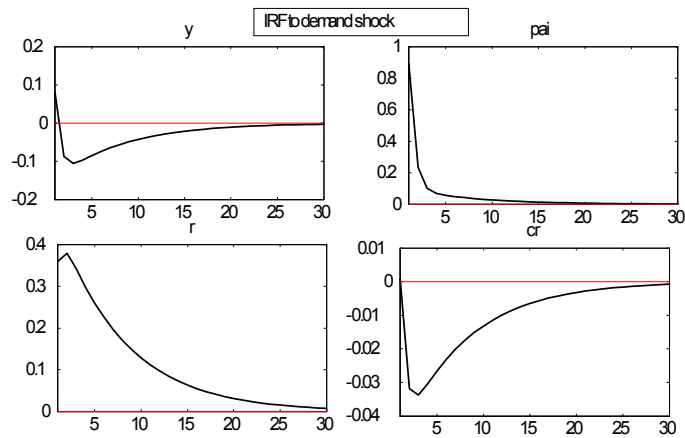


Figure C.1: IRF to Demand Shock

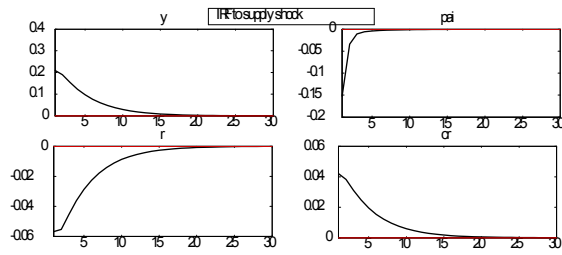


Figure C.2: IRF to Supply Shock

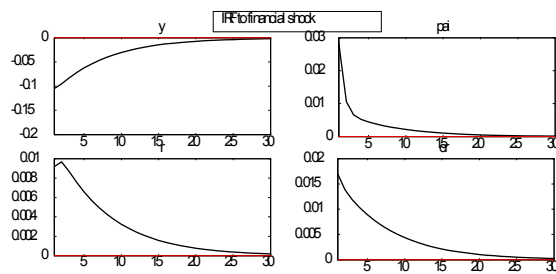


Figure C.3: IRF to Financial Shock

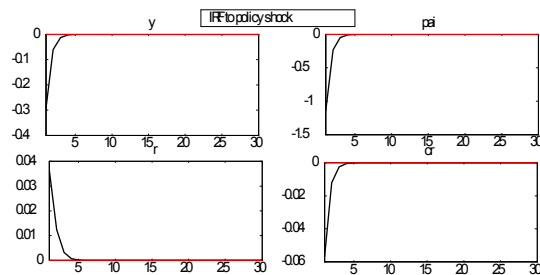


Figure C.4: IRF to Policy Shock

C.1.3 A Selection of Bootstrap Samples Shown Against the Actual Data for Each Variable

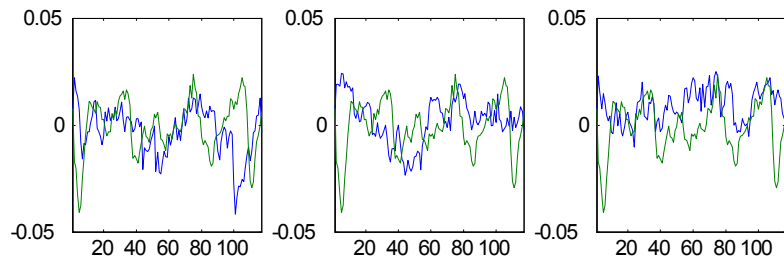


Figure C.5: Actual Data with Bootstrapping Sample: \tilde{Y}

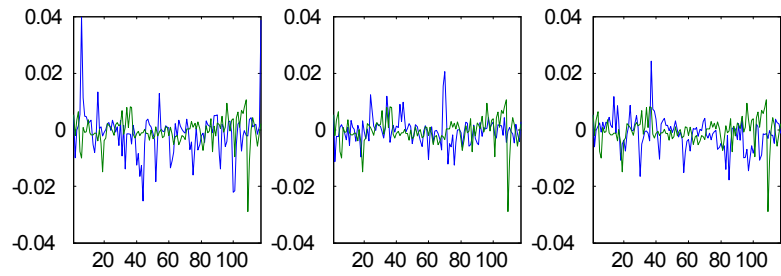


Figure C.6: Actual Data with Bootstrapping Sample: π

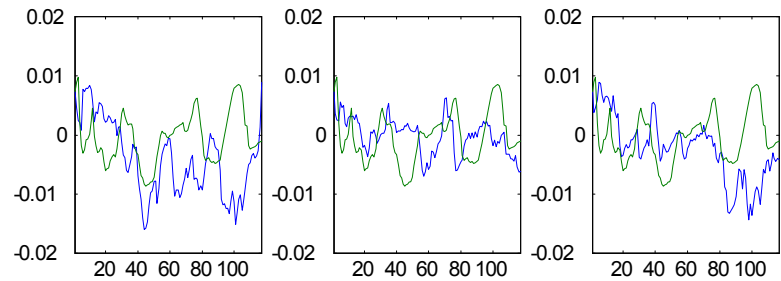


Figure C.7: Actual Data with Bootstrapping Sample: R

C.1.4 VAR Impulse Response Functions and Their 95% Bounds

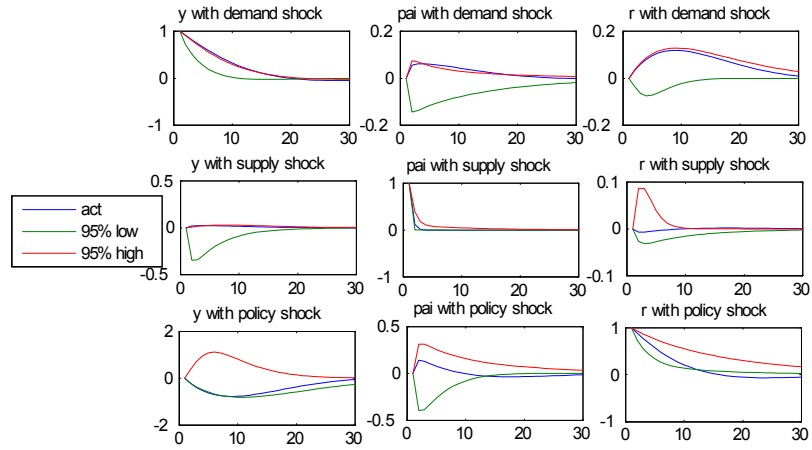


Figure C.8: VAR IRF and 95% Bounds

C.1.5 Cross-Moments and Their 95% Bounds

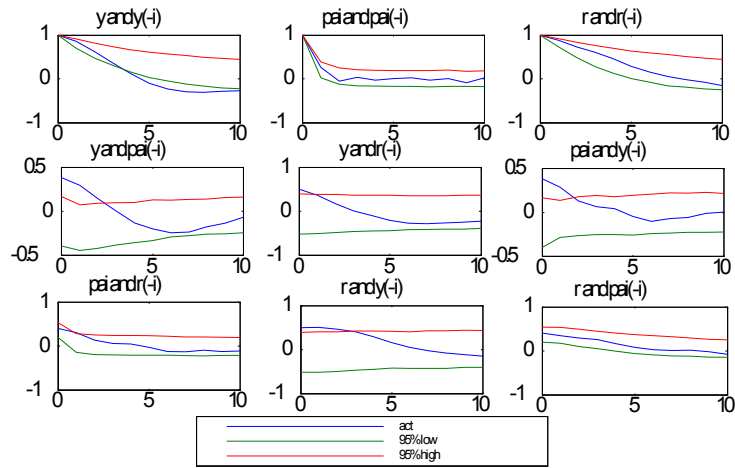


Figure C.9: Cross-moments and 95% Bounds

C.2 Estimated Parameters

C.2.1 Estimates of the AR Process for Each Error

Errors	AR(1) Coefficient	T-statistics
demand error	0.8681	20.1399
supply error	0.7881	14.0396
financial error	0.8667	19.9640
policy error	0.1549	1.7270

Table C.6: AR(1) Estimation of Each Error in the Credit Model Using Estimated Parameters

C.2.2 The Model's Deterministic Impulse Response Functions

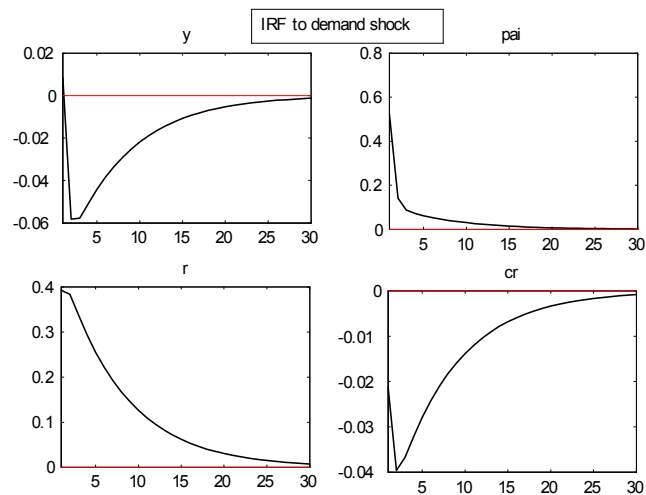


Figure C.10: IRF to Demand Shock

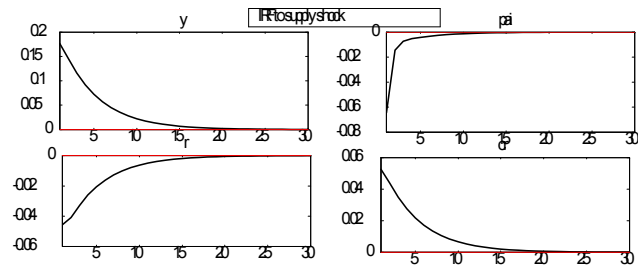


Figure C.11: IRF to Supply Shock

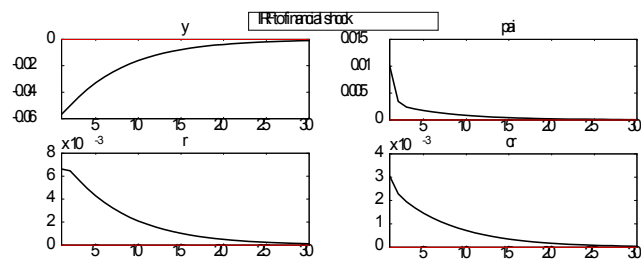


Figure C.12: IRF to Financial Shock

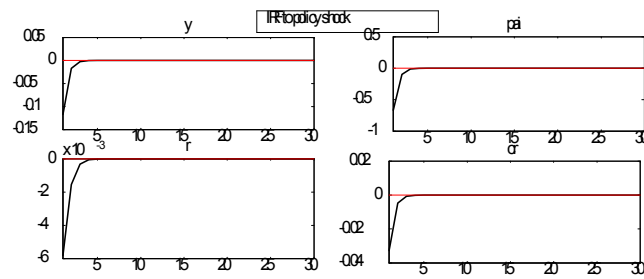


Figure C.13: IRF to Policy Shock

C.2.3 A Selection of Bootstrap Samples Shown Against the Actual Data for Each Variable

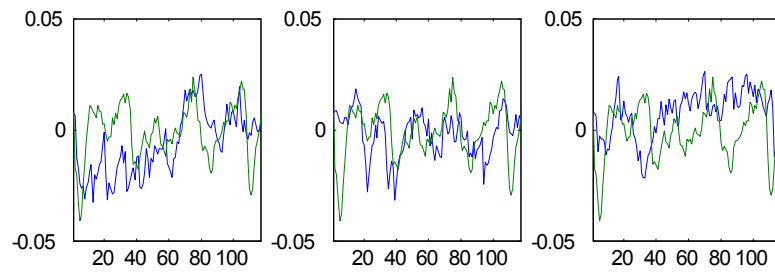


Figure C.14: Actual Data with Bootstrapping Sample: \tilde{Y}

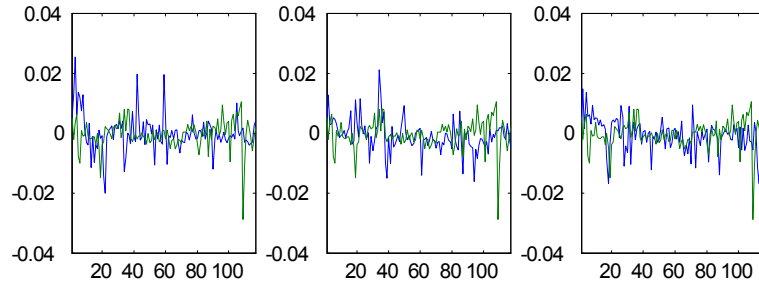


Figure C.15: Actual Data with Bootstrapping Sample: π

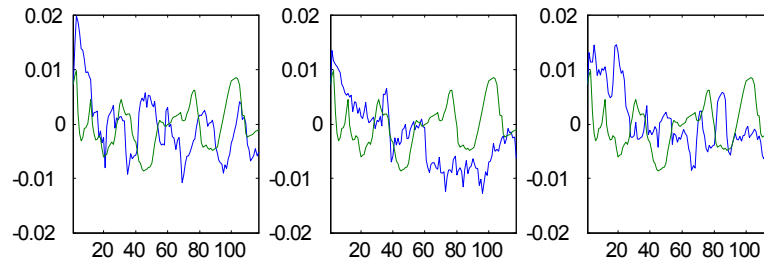


Figure C.16: Actual Data with Bootstrapping Sample: R

C.2.4 VAR Impulse Response Functions and Their 95% Bounds

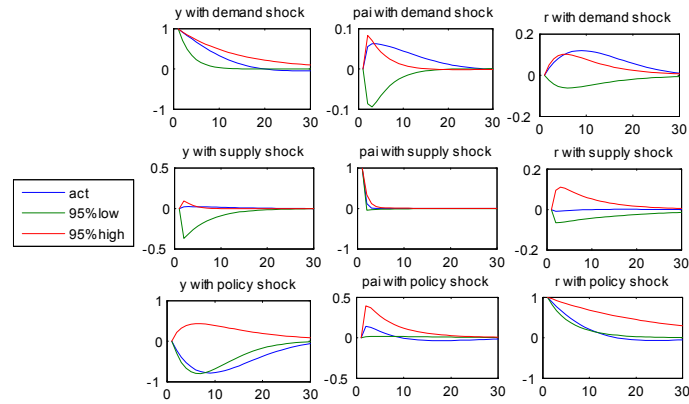


Figure C.17: VAR IRF and 95% Bounds

C.2.5 Cross-moments and Their 95% Bounds

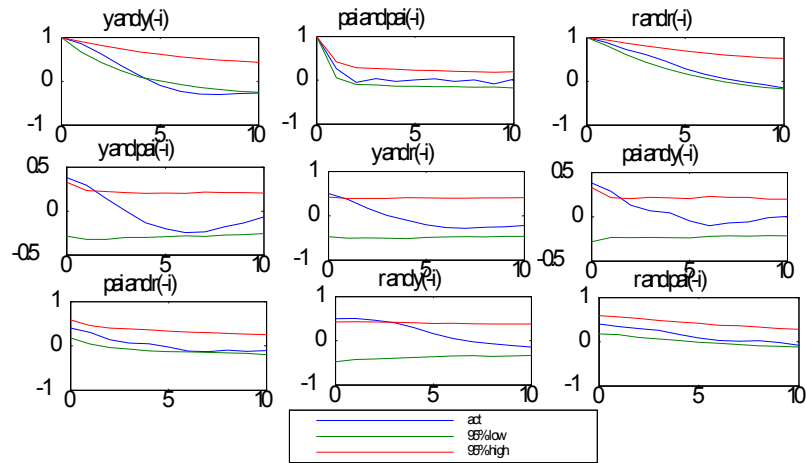


Figure C.18: Cross-moments and 95% Bounds