UNIVERZITA KARLOVA V PRAZE

FAKULTA SOCIÁLNÍCH VĚD

INSTITUT EKONOMICKÝCH STUDIÍ

Diplomová práce

2012 Batnyam Damdinsuren

CHARLES UNIVERSITY IN PRAGUE

FACULTY OF SOCIAL SCIENCE

INSTITUTE OF ECONOMIC STUDIES

Master Thesis

ROLE OF FINANCIAL MARKET IN MACRO MODELING:
CASE OF MONGOLIA

Author: Batnyam Damdinsuren

Supervisor: Roman Horváth, PhD

Year: 2011/2012

Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

The author grants to Charles University permission to reproduce and to distribute copies of this thesis document in whole or in part.

Prague, May 18, 2012 Signature

Abstract

In this research we explored role of financial variables in macro modeling and their performance in case of Mongolia. We employed two different models for assessing performance of financial variables in macro modeling, structural VAR model and small scale macro model (SSMM). In doing so, we performed different analysis such as impulse response for seeing how financial variables fit into system and forecasting performance for how accurate model performs after introducing financial variables. So our result suggested that financial variables have substantial role on macro modeling and inclusion of financial variable is performing very good result in terms of forecasting in both models.

JEL Classification	C01, C51, C53, E12, E52, G17
Keywords	Financial markets, Small scale macro model, Structural VAR, Impulse response, Mean absolute errors.

Author's e-mail	batnyamd@gmail.com
Supervisor's e-mail	roman.horvath@gmail.com

Abstrakt

V této práci se zabýváme vlastnostmi a interpretací finančních proměnných v makroekonomickém modelování Mongolské ekonomiky. Pro odhadnutí finančních proměnných v makroekonomickém modelování jsme použili dva různé modely; strukturální model vektorových autoregresí (VAR) a základní makroekonomický model (SSMM). Pro analýzu odhadů jsme použili různé metody jako například impulzní odezvy k zjištění, jsou-li finanční proměnné adekvátní proměnné systému a zda-li, a jak, jejich zahrnutí do modelu ovlivní výsledek předpovědi. Naše výsledky ukazují, že finanční proměnné hrají podstatnou roli v mekroekonomickém modelování. Kromě toho zahrnutím těchto proměnných do modelování získáme velmi dobré a robustní výsledky při předpovědi obou použitých modelů.

Klasifikace JEL	C01, C51, C53, E12, E52, F47, G17
Klíčová slova	Finační trh, Základní makroekonomický model, Strukturální model vektorových autoregresí, Impulyní odezvy, Průměrná absolutní chyba

E-mail autora	batnyamd@gmail.com
E-mail vedoucího práce	roman.horvath@gmail.com

Contents

List of Tables

List of Figures

Master Thesis Proposal

Author	Batnyam Damdinsuren
Supervisor	Roman Horvath, PhD.
Proposed topic	The Role of Financial Market in Macro Economic Modeling: Case of Mongolia

Topic Characteristics: Before the credit crunch of August 2007, some researches were warning that interaction between macroeconomic and financial variables should be taken as a central issue in economics. Even though the lack of financial variables in macro models, especially in policy decision making level, became one of the most obvious shortcomings of macroeconomic theory (and the theory-based estimation of those systems) during the recent financial crisis, and led to fundamental critique.

In recent years, number of studies explored what it is the role of financial variables in macro economy and macroeconomic models such as T.Jacobson, J.Linde and K.Roszbach (2005); M.K.Brunnermeier and Y.Sannikovy (2011); G.D.Rudebusch (2010); S.G.Cecchetti, P.Disyatat and M.Kohler (2009); B.Christensen,O.Posch and M.Wel (2011) and R.Espinoza, F.Fornari and M.J. Lombardi (2009). But in more similar country case with Mongolia, T.Havranek, R.Horvath and J.Mateju (2010) have studied answer of question that “Do financial variables help predict macroeconomic environment?” in case of Czech Republic, small open economy with bank based financial sector. The study highlighted that financial variables have systematic effect on the macro economy and improves the forecast accuracy of real GDP and inflation, particularly, stock market index consistently improves forecast of both variables.

Based on all these theries and definitions, we will try to build small model to investigate role of financial variables in economic modeling in case Mongolia and check whether there is difference from previous studies if they exit. For usage of this study is not only for determining role of financial market, but also defining contribution of financial variables in macro forecasting.

Actually in last a few year, in Mongolia, financial market became more popular and taking more attention from public, because the Government decided to distribute evenly to a all the population some part of stocks of the company which owns the one of the

biggest coal mining resources in the world. So this recent attraction of financial market is motivating us to explore the role the financial market in the economic development.

Hypotheses: According to theory, existence of role financial variables has based on main assumption that:

- Tighter financial and credit conditions limit the potential for firms' activity to expand and for households to consume during harsh times.
- Asset prices capture expected firms' profitability, which is linked to the future rate of growth of the economy.

But in empirical level, we are assuming and checking:

- Existence of significant role of financial market in macro modeling
- Whether financial variables provide additional predictive power.

Methodology: There are various type of modeling approach can be used in this field of study such as semi or fully structural models (VAR type models, small macroeconomic models and general equilibrium models) etc.

Actually models are constructed for a purpose, and different models will be appropriate for different purposes, and have different areas of application, providing detail in one dimension at the expense of approximation in another dimension. In economics and finance, the purposes of the models include forecasting, policy analysis, communication with other specialists and evaluation of theories (R.P.Smith (2009)).

Although different models may be appropriate for each of these purposes, the purposes overlap enough that there are trade-offs. So it may be that the best forecasting model for inflation is a simple univariate model, e.g. So in sense of that, we will try to employ as simplest as possible model which is better in capturing macro-financial linkage.

Core Bibliography:

- Alan Kirman (2010), "The Economic Crisis is a Crisis for Economic Theory", *GREQAM, Université Paul Cézanne*, EHESS, IUF
- Haldane, A. G. (2009), "Rethinking the financial network", *Publication of Bank of England*.

- M. Lacoviello and S. Neri (2009) “Housing Markets Spillovers: Evidence from an Estimated DSGE Model” *American Economic Journal of Macroeconomics.*
- V. Cúrdia, M. Woodford (2009), “Credit spreads and monetary policy”, *Federal Reserve Bank of New York in its series staff reports with number 385.*
- R.P.Smith (2009), “Real-Financial Interactions in Macro-Finance Models“, *Quantitative and Qualitative Analysis in Social Sciences, Volume 3, Issue 1*
- R. Espinoza, F. Fornari And M.J. Lombardi (2009), ” The Role Of Financial Variables In Predicting Economic Activity”, *Working Paper Series, No 1108, ECB*

Author

Supervisor

1. Introduction

Before the credit crunch of August 2007, some researches were warning that interaction between macroeconomic and financial variables should be taken as a central issue in economics. Even though the lack of financial variables in macro models, especially in policy decision making level, became one of the most obvious shortcomings of macroeconomic theory (and the theory-based estimation of those systems) during the recent financial crisis, and led to fundamental critique[1].

So the one of the main achievements from recent financial crisis for decision makers was an increased interest of re-defining interaction between financial market and macro economy in their macro models and weighting role of financial market in that relation. The linkage between the financial market and the real economic activity has drawn a substantial attention both in the economic and financial literature.

This study concentrates on interrelationship between financial sector and macro economy of Mongolia, most importantly, to assess how financial variables perform in macro model of small open economy in terms of theoretical consistency and predictive perspective. In recent years, number of studies explored what it is the role of financial variables in macro economy and macroeconomic models such as T.Jacobson, J.Linde and K.Roszbach (2005); M.K.Brunnermeier and Y.Sannikovy (2011); G.D.Rudebusch (2010); S.G.Cecchetti, P.Disyatat and M.Kohler (2009); B.Christensen,O.Posch and M.Wel (2011) and R.Espinoza, F.Fornari and M.J. Lombardi (2009). But in more similar country case with Mongolia, T.Havranek, R.Horvath and J.Mateju (2010) have studied answer of question that "Do financial variables help predict macroeconomic environment?" in case of Czech Republic, small open economy with bank based financial sector. The study highlighted that financial variables have systematic effect on the macro economy and improves the forecast accuracy of real GDP and inflation, particularly, stock market index consistently improves forecast of both variables. Other hand in case of Asian economy, W.Mahmood and N.Dinniah (2009) also studied dynamic relationship between stock prices and macroeconomic variables in six Asia-Pacific country cases. They found that interaction between output and stock price exits both in long and short run. However, there is no specific study carried on Mongolian

[1] Goodhart, C, A, Hofmann, B and Segoviano, M (2006).

case on this field so far. So this becomes the one of the main motivations for us to make this research.

Mongolian economy is small open economy and has its unique characteristic. Geographically land locked, small open economy has heavily dependent on external sector. Main export commodities are mineral raw goods such as copper, coal and gold, at the same time, Mongolia is consumer economy and more than 30 percent of CPI basket goods are imported. So these main features make the economy more insecure from any shock in international commodity market. At the same time, Mongolian financial market is strongly bank-based, but recently financial market became more popular and taking more attention from public, because the Government decided to distribute evenly to a all the population some part of stocks of the company which owns the one of the biggest coal mining resources in the world. So this recent attraction of financial market is motivating us to explore the role the financial market in the economic development.

We believe that main things for building macro model with financial variables would be theoretically consistency and empirically significant. If these preconditions fulfilled, then we can make further analysis with forecasting performance which will tell us whether financial variables bring any useful information to the model. In doing so, we compared forecasting performances of two different models with and without financial sector variables and with two different empirical approaches. The first model is the core macro model with only macro variables such as real GDP, inflation, exchange rate and short term rate and the second model is preferred as financial macro model which consists of financial variables addition to core model. As we mentioned above, we employed two different empirical approaches for creating the models such as structural vector autoregressive (SVAR) model for shorter term forecast and with monthly database, and small scale macro model (further will be called SSMM) for mid range forecast with quarterly database. These two approaches performed separately and assessed impulse response analysis and comparison of forecasting performances.

The our study result shows that monetary policy has significant effects on inflation, real demand and nominal exchange rate in short and long run, at the same time all those macroeconomic variables also have significant and consistent responses to

financial variable shocks. In addition to that, forecasting performance indicate that financial variables have substantial role on macro modeling and inclusion of financial variable is performing very good result in terms of forecasting in both SVAR and SSMM.

The rest of the paper is structured as follows: Chapter 2 presents literature review on inter linkage between macro and financial variables; Chapter 3 briefly describes theoretical motivation; Chapter 4 explains empirical methodology; Chapter 5 interprets dataset and empirical results and Chapter 6 provides conclusion. Finally, Appendixes gives additional results for estimation results.

2. Literature Review

Development of macro-financial linkage was one of the main topics in economic studying. From the time of existing financial markets, economists tried to define inter-linkage between financial and real sectors. The list of such literatures that determining linkage of macro financial sectors, begins from beginning of 20th century, because it is fair to say that first co-existence of financial turmoil and economic downturn occurred at that time.

Role of financial market in macro economy has been a main subject of macro research for long period. As mentioned in Fisher (1933), the Great Depression was in mainly because of excessive leverage before the crash and deflation afterwards. The further consequences can be listed as many items that also appear in the recent interest of macro research, such as bankruptcy, credit rationing, and precautionary saving.

Keynes (1936) stated a different approach to determine cause of the Great Depression by concentrating on the money supply and the confidence of investors. But Friedman and Schwartz (1963) argued that the money supply was a main force of production in time of the Great Depression. So contraction of monetary condition led to decrease of price and higher real interest rates, at the same time, demand for money was lower because of less investor confidence.

Representing the monetarist view, the Friedman and others concentrated on supply of money. They argued that portfolio composition does not matter in transmission mechanism of financial shocks in sense that borrowers have broader possibilities of rising money as either issuing bonds or commercial paper for themselves. So in that case, banks play only in role of money creator, and monetary policy has effects only on total amount of credit.

The monetarist view on real and financial market interaction had been dominant for about two decades. But after that, Mishkin (1978) and Bernanke (1983) showed that explaining depth of transmission of financial shocks with only monetary factors wasn't enough and illustrated that other financial variables such as bank lending (so called bank lending channel) also have independent effect addition to money supply.

The transmission channels between financial and real sectors go in both directions, more specifically effect of financial sector to real sector and effect of real sector to financial condition. Theoretical literature on effect of real sector to financial sector is defined in most of standard macroeconomic theories. Particularly, tighter macroeconomic conditions reduce profitability of firms and individuals' business and which results in more slow or decreasing phase of firms and individuals' financial conditions. The most economists consider this linkage as natural. Addition for that, worsened financial condition of firms and individuals' increases borrowers' default probabilities, which is again turn to affect to bank balance sheet and increase bank losses.

On the contrary, theoretical literature on effect of financial sector to real economy takes large portion of literatures on linkage of financial and real sectors. But it is worth to mention a one thing before we explain transmission channels from financial sector to real sector. A one can say that transmission channel form financial to real sector is so obvious since individuals or firms' spending decision is made based on discounted value of future incomes according to permanent income model and proper discount factor for this model is taken as an interest rate which is nominally financial variable. But we have to note that these financial variables only serve as transferring value of variable across the time and they have no other roles in standard macro models. It means that we are omitting financial frictions which exist in financial intermediation in real economy. In this manner, main purpose of studying transmission channel from financial market to real sector can be defined as exploring role of financial variables in decision making process.

According to numerous literatures, we can divide inter-linkage between financial and real sectors in some categories. For example, according to Basel Committee's working group[2], they identified three separate transmission channels to exist between financial and the real sectors such as borrower balance sheet, bank balance sheet and liquidity channels, and according to IMF research, they distinguished different approaches to financial markets' integration to macroeconomics such as efficient market hypothesis, imperfect capital markets, unstable finance approach and early warnings of

[2] BIS (2010).

financial crisis etc. Since our main topic is stated as defining role of financial market in macro modeling, we will focus more on the transmission channel from financial variables to real sector variables and will state our literature review in structure of Basel committee's subgroups which make it more understandable and well distinguishable between channels.

2.1 Theoretical Transmission Channels from Real to Financial Sector

It is fair to mention a few literatures about transmission channels from real to financial sector before we turn to our main topic. So in this section, we will review some literatures related with linkage that run from real sector to financial sector. More specifically, theory says that negative shock of real sector affect to individuals and firms' incomes and which results individuals and firms' business activity will be slowed down or in some cases decreases. Then this slow down of economic activity in individual level will cause to increase borrowers' default probabilities and to weaken banks' balance sheet further.

So in this context, balance sheet condition of borrowers' is very important, because whole financial sector depends mainly on the firms and individuals' balance sheet strength. As we explained before, weakness of borrowers' balance sheet can harm the balance sheet of banks, at the same time it can also affect to condition of capital markets negatively. Unfortunately it is very challenging to exploring this transmission channel the most of the time, because we have to work with very micro level data that balance sheet of individuals and firms' which is considerable more difficult to obtain than to study.

There are large amount of empirical work devoted to exam linkage runs from real sector to financial sectors. One of the important studies in this area is Pesaran et al (2006). They used Global VAR (GVAR) approach to estimate credit loss distributions of large number of firms in different regions of the world, conditional on global macroeconomic stance. One special feature of the model was that they developed model that is linked to a global macro econometric model that explicitly allows for the interdependencies that exist between national and international factors.

Another good study of this field is Jakubik and Schmieder (2008). They employed one-factor credit risk model for explaining credit risk based on dataset of Czech Republic and Germany. Main idea behind this type of model was to define the aggregated credit risk conditional on macroeconomic environment. Unlike linear models, this model is relatively simple non-linear model and better captures the highly complex relationships of economies which are hardly linear in the real world. As doing this study, authors tried to define macroeconomic variables which are the most important to explain credit risk, whether there are country-specific differences among that variables and what impact the occurrence of unfavorable macroeconomic circumstances can have on the macro and micro (portfolio) level. In later stage, outcome of the credit risk model is used for macro stress testing. The study finds that influence of macro shocks is higher in the Czech Republic than Germany, numerically there can be substantial increase in the corporate default rate (authors defined that modeling was meaningful for corporate sector, while this wasn't entirely case for household sector) more than 100% for Czech Republic and 40% for Germany in case of relative minor change in macroeconomic condition.

Drehman et al (2006) studied on possible impact of non-linearties on the aggregate credit risks which are formed as an aggregate liquidation rates and firm specific probability of defaults. They employed non-linear threshold VAR (TVAR) approach on the quarterly aggregate data of corporate credit in the United Kingdom and investigated non-linear transmission of macro shocks to aggregate corporate defaults and liquidation rates. They find that non-linearity is matter for level and shape of response of credit risk especially for small shocks which is leads to conclusion that linear models seem to overestimate credit risk for small shocks, whereas for large ones they tend to underestimate it. Moreover they also show that in the non-linear model starting values impact not only the level of projected credit risk, but they also influence the shape of the impulse response function.

Studies mentioned above were mainly based on finding some evidence of macro stress testing and examining links between macro models and corporate sector credit quality. So our next approach will focus more on the effect of real economic variables (such as employment, economic activity and asset market) on individuals, firms and

banks' balance sheet position, particularly through the borrowers' default and credit risk.

One of the pioneering work and prestigious impact on this field of study was Mishkin (1977). He attempted to investigate how household balance sheet behaved during the worst decline in prices of common stock in the postwar era. A substantial proportion of the decline in aggregate demand can be attributed to shifts in the aggregate household balance sheet and the depressive effect of the stock market on investment. He finds that household balance sheet could have affected aggregate demand during the recession (1973-75) which says household financial position did deteriorated during that period. Coupled with increased uncertainty, this deterioration may have turned consumers away from purchases of illiquid assets such as consumer durables and housing because the possible loss from holding them had increased a long with the probability of financial distress. Furthermore, he made conclusion about further effect of consumers' balance sheet such as the sharp deterioration in household balance sheets indeed appears to have been a major factor in the severity of the economic downturn, it was responsible for 40 percent of the depressive effects during the 1973-75 recession.

But Mishkin's study doesn't directly address to direct effect of borrowers' balance sheet to banks' balance sheet. To fill this gap, Qi and Yang (2009) studied on how loans perform in a general housing downturn, while defining how loss-given-default (LGD) is correlated with correlated with loan-to-value (LTV) ratios, and so on. So study stresses the importance of their finding for capital regulation. At origination, the LTV is an important determinant of potential LGD. Over time, the best capital regulation regime would rely on periodically updating current LTV and basing capital sufficiency calculations on this measure.

Jacobson (2005) examined interaction between real activity and firms' balance sheets in Sweden during period of 1990 to 1999. They find that financial stance of the economy do matter for real economic activity, more specifically interest rate, real exchange rate and output gap are important variables that explaining default risk of firms. So default risk is highly correlated with loss of credit which affects directly to bank balance sheet. Furthermore, they find strong evidence that most of the variation in balance-sheet variables are due to idiosyncratic shocks rather than aggregate shocks.

Goodhart et al (2006) explore the effect of changes in GDP growth and asset prices on credit growth directly on the default probabilities of banks in 18 countries. They find evidence that property markets play an important role in bank profitability and vice versa. In particular, they establish that in roughly half of the countries they study changing asset prices (both aggregate and housing prices) have a positive and significant effect on bank credit and changing bank credit has a slightly weaker positive and significant effect on asset prices. They also show that an increase in real GDP has a positive and significant effect on bank credit and asset prices. Their results also suggest that deviations in bank lending and asset prices from their trend relationship with GDP improve the estimation of bank default probabilities.

There are also bunch of studies which are more concentrated on either linkage between real economic activity and bank performance on specific sector or linkage between real sector and bank performance at regional and local level. We can call studies like Jordon and Rosenberg (2002), Meyer and Yeager (2001), Daly et al (2008) and Mayer et al (2008). But we prefer to skip these studies because these are too detailed and too specific.

2.2 Theoretical Transmission Channels from Financial to Real Sector

Now we turn to our main topic which is transmission channels from financial sector to real sector. This channel explains response of macroeconomic variables to financial market shocks, more specifically how changes in balance sheet of both borrowers and banks can affect to real sector activity. In general, we can identify three different channels account for transmission of shocks originated in the financial sector to real economy such as borrower balance sheet channel; bank balance sheet channel; and liquidity channel. These three channels broadly explain not only transmission from financial sector to real sector, but also second round effect that from real sector to financial sector.

2.2.1 Borrower balance sheet channel

The borrower balance sheet channel rises from the when lenders are unable to monitor their investment fully, to assess all borrower's risk and enforce to repay debt in full amount. So this leads lenders to ask sufficient collateral from borrowers to cover debt, as doing this, borrower's equity and asset position affect to credit.

As defined in Cecchetti (1995), Central banks can directly affect balance sheets of borrowers by changing their net worth (the difference between assets and liabilities). Because interest rate increase reflection to monetary policy decision leads to affect firm's net worth, by decreasing expected value of firm and increasing real value of debt. Since firm has less net worth, it leads them to have less creditworthy. As a result, lenders will value firms as more risky and will ask more collateral or higher premium to make a loan. The asymmetry of information makes internal finance of new investment projects cheaper than external finance. This idea was formalized first with Bernanke and Gertler (1989) and supported and developed by Carlstrom and Fuerst (1997). Finalizing the idea of borrowers' channel to link with real economy is that economic shocks that affect to firms' net value will have effect on cost of borrower's financial activities, and then it will affect the potential level of expenditures that borrowers want to spend and thereby aggregate demand.

Another view of borrowers' balance sheet channel is formed in Kiyotaki and Moore (1997), so called financial accelerator model. They find that durable assets play dual role in the economy in which lenders can't force to borrowers to repay their debts unless debts are secured. So in this economy, assets serve as not only factor of production, but also collateral for loans. They state that interaction between asset price and limit of loan becomes very powerful transmission channel and thorough that channel, financial shock which leads to fall in asset price can also affect to real sector via this channel.

Overall, the all literatures which are made in this field of studies have a lack of evidence in role of financial variables in forecasting economic activity. In some sense, this can be related with vast possibilities of selection of indicators that represents financial markets and hence it seems difficult to pick the best combination of financial variables. Some authors have tried at very specific variables: for example, Liew and

Vassalou (2000) showed that composition of portfolios which covers long and short positions in some stock characteristics can help predict future US GDP. More recently, Guichard et al. (2009) had worked on determining possible effect of financial conditional index on GDP in case of United States, the euro area, Japan and the United Kingdom.

One of the remarkable works in this field of study is Gilchrist et al (2009). They examined existence of borrowers' balance sheet model by using FAVAR approach. Results indicate that credit spreads on senior unsecured corporate debt have a substantial predictive power for future economic activity relative to default-risk indicators such as the paper-bill spread or the high-yield credit spread. More precisely shocks to corporate bond spreads lead to quantitatively large swings in economic activity and real interest rates. Such credit market shocks explain a sizable fraction of the variance in economic activity at the two- to four-year horizon. These findings are consistent with the notion that an unexpected worsening of conditions in credit markets can cause a long-lasting economic downturn and that shocks to credit markets have played an important role in business cycle fluctuations in sample period.

More recently, Mateju et al (2011) investigate early warning indicators of economic crisis in 40 different country cases. They build early warning system for economic crisis which consists of both discrete and continuous models. They used extensive set of database of various types of economic crisis, and panel VAR approach for detecting significant indicators. They find that rising housing prices and external debt are important national risk factors for both crisis occurrence and crisis incidence while housing prices are a useful warning indicator for all clusters of countries.

Lastly for borrowers' balance sheet channel, we have to mention some evidence from non-linearities in this channel. There are plenty of studies those are used non-linear methods to detect power of financial variables related with borrowers' balance sheet to forecast real economic activities. For example, Gertler and Gilchrist (1994) examined importance of financial propagation mechanisms for aggregate activity taking account for asymmetries among the firms. They find significant difference between small and large firms on response to changes in monetary policy and evidence says that small firms play prominent role in slowdown of inventory demand.

Atanasova (2003) uses general non-linear VAR methodology to examine the response of credit market to monetary policy shocks in which system's dynamics change back and forth between credits constrained and unconstrained regimes in UK economic case. She could find significant evidence of asymmetric response of credit constrained and unconstrained regimes to monetary policy shocks.

2.2.2 Bank balance sheet channel

With bank balance sheet channel, we explain how financial institutions balance sheet can cause sharp contractions in credit and results of such having huge effect on economic activity (only condition has to be fulfilled is that there must be significant number of borrowers dependent on bank loan). Traditionally this channel was the most powerful channel to explain linkage from financial sector to real sector, therefore, big number of working papers devoted in this field of study. But as time goes by, transmission channels become more detailed and precise. One example is that now we divide traditional bank balance sheet channel in two separate channels such as traditional bank lending channel and bank capital channel. Moreover one channel that separated from bank balance sheet channel is liquidity channel which will be covered later.

Bernanke, Kashyap and Stein have a major contribution to the research which has been done on the bank lending channel. They find support for a bank lending channel whereas other researches find no support for it. Bernanke (1983) shows that the large fall in output during the great depression in the US is mostly attributed to bank panics and the large decline in loan supply associated with this. Bernanke and James (1991) show that this is the case in other 24 countries during different periods.

In the bank lending channel framework, monetary policy shocks have effects on supply of credit which go beyond the traditional effect through interest rates (interest rate channel effect goes through credit demand). In particular, negative monetary policy shock has effect on both sides of balance sheet of banks to decrease. For liability side, monetary tightening decreases money supply which is standard interest rate channel. But in asset side of balance sheet, it causes decline in credit supply which is called credit channel (Bernanke and Blinder (1988)).

According to Kashyap and Stein (1993), there are three assets involved in the bank lending channel: money, bonds and intermediated loans. According to this channel, the central bank has not only influence on money and bonds when using monetary policy but has also influence on loan supply and loan prices which are determined by intermediaries as banks. Moreover, there are three necessary conditions which should hold for the existence of a bank lending channel. The first condition is that bank loans and bonds are not perfect substitutes. Firms should not be able to totally offset the reduction in bank loans by borrowing from the bond market. If this is not the case then banks do not play an important role in lending to firms and monetary policy cannot influence the real economy through bank lending. Hence as the percentage of bank dependent firms in the economy increases monetary policy has a larger effect on loan volumes and loan prices. The second condition states that banks should not be able to totally offset the reduction in reserves by issuing certificate of deposit, bonds, stocks etc. If this is not the case again monetary policy has no effect on bank lending. The third condition is a more general one which also holds for the money view. In order for monetary policy to have a real effect on the economy prices should not change immediately. The slower the prices change the more impact there is on the real variables of the economy.

Over last 2 decades, there is broad debate on existence of bank lending channel and actually debate didn't reach its ultimate consensus. As we mentioned before, there were a lot of attempts to prove existence of bank lending channel. Since possibility of selection of variable is quiet rich from bank specific balance sheet, every attempt has different results. For example according to selection of variable and using econometric methodologies, there are two separate class are developed in recent studies. One is methodology using aggregate dataset of banking sector and real sector variables and distinguishing bank loan supply from loan demand. Another one is that using disaggregates or bank level data and focuses more on their balance sheet structure and what these differences imply for the strength of the bank lending channel. This approach comes from idea that transmission of bank lending channel can be different in light of firm's size or even bank's size.

Literatures working with aggregate data are lead by Bernanke and Blinder (1988) and follows with very successful one was Hulsewig et al (2002). They examined relevance of bank lending channel in the transmission of monetary policy in Germany within structural vector error correction (VECM) on the basis of aggregate bank loan data. They use identification restriction on cointegration vector to distinguish bank loan supply and demand. The results of studies show that they could identify two separate cointegration vectors which are interpreted as long-run loan supply and demand, even though long run effect of monetary policy on bank loan supply was relatively weak.

While Kashyap et al (2000) and Oliner and Rudebusch begin to focus more on differential reliance of firms of different size on the bank credit. Kashyap and Stein (2000) seek to identify whether there are important cross sectional differences in the way that banks with varying characteristics respond to policy shocks. They find that small banks respond to changes in monetary policy stronger than other larger banks because their balance sheets are less liquid than others and they are more dependent from the banks. Moreover, they find at least some evidence of implied difference across the banks on the response to monetary shocks.

In later stage of this kind of study, researchers started to concentrate more on bank specific characteristics, such as bank capitalization, liquidity and bank size. Kishan and Opiela (2000) study bank capitalization and monetary policy by looking at lending by banks segregated into different asset-size and capital leverage ratio groups. Their analysis finds that small undercapitalized banks have the largest response of loans to monetary policy shocks but the smallest response of large-time deposits, indicating that small, poorly capitalized banks are unable to raise alternative funds to sustain lending levels when monetary policy contracts.

By using similar analysis with Kashyap and Stein (2000) and Kishan and Opiela (2000), number of authors supported existence of bank lending channel in their country cases such as Kakes et al (1999) in Germany, Leo De Haan (2003) in Netherland, Hernando and Pages (2001) in Spain and so on.

Another angle of bank balance sheet channel is how bank balance sheet reacts to regulation induced changes. This type of study is started from 1990-1992 capital

crunches and so called bank capital channel. Actually it doesn't necessarily show how bank loan growth changes as response monetary policy, but it shows how bank balance sheet response to exogenous changes in their capitalization. However, number of authors devoted their works to define enough evidence to existence of bank capital channel, existence of this channel doesn't broadly accepted or proved. Obviously, it is very problematic and very difficult thing to solve that distinguishing reduction of bank loan due to regulatory capital constraints from other factors.

Recent studies have attempted to distinguish between lending reductions due to regulatory capital constraints and reductions stemming from market forces, by using bank-specific capital requirements set by bank supervisors as a measure of regulatory capital constraints. For example, Ediz et al (1998) studied on UK bank data from the period 1989 to 1995 and found that banks whose risk-weighted capital ratio fell within a "regulatory pressure zone" of one standard deviation above the trigger tended to raise their capital ratios, consistent with the hypothesis that banks attempt to maintain a buffer of capital over regulatory minima.

And the last but not least, Borio and Zhu (2007) introduced very interesting idea about bank balance sheet channel. They investigate link between monetary policy and the perception and pricing of risk by economic agents, so called risk taking channel.

2.2.3 Liquidity channel

The recent financial crisis has highlighted the importance of liquidity as an influence on banks' ability to extend credit and thereby on economic activity. In liquidity channel, high leverage ratios and large maturity mismatches in banks' balance sheets are a critical element for suffering any type of liquidity shocks and banks would struggle to fund new lending to real economy. As stressed in Fisher (1933), there is strong linkage between bad assets and bank's health and which confirms features of asset price and bank balance sheets. The basic feature stated that bank responds to liquidity or solvency shock as selling assets they have. This creates excess supply of assets in the market and leads to decrease of asset price. As making spiral, falling asset price direct more and further asset sell in the market and so on.

In the light of current crisis, a lot of authors tried to describe origin of recent crisis link with liquidity shocks. There are several empirical evidences that proved the existence of liquidity channel in recent crisis. Brunnermeier and Pederson (2009) studied on model which link asset market liquidity and traders funding liquidity. Funding liquidity is defined as liability of bank balance sheet and can be formulated as ability of finding funds in short run by selling assets and new borrowing to fulfill its obligations. Market liquidity is defined as asset side of bank balance sheet and shows the assets that can be traded. As a result of their study, they find some characteristic of market and funding liquidity, but most interesting to us is that they stated that "Central banks can help mitigate market liquidity problems by controlling funding liquidity. If a central bank is better than the typical financiers of speculators at distinguishing liquidity shocks from fundamental shocks, then the central bank can convey this information and urge financiers to relax their funding requirements". Meanwhile, Drehmann and Nikolaou (2009) defined evidence on funding liquidity risk are typically stable and low, with occasional spikes, especially during the recent crisis.

3. Theoretical Model - Small Open Economy Model

Our theoretical model is based on work of A.Berg, P.Karam and D.Laxton (2006). We start with presenting simple New Keynesian type small open macro model. Basic model consists of four equations such as aggregate demand or IS curve, price setting or Phillips curve, Rule for policy interest rate and economy opening variable exchange rate. Addition to that, we add 3 more equations which are representing financial market, namely, LM curve, equation for stock market index and stock market capitalization.

Let's start from aggregate demand equation. Output gap depends on its expected and lagged values, real exchange rate and real interest rate.

[1] $$gap_t^{GDP} = \alpha_1 \cdot gap_{t+1}^{GDP} + \alpha_2 \cdot gap_{t-1}^{GDP} + \alpha_3 \cdot (rir_{t-1} - rir_{t-1}^*) + \alpha_4 \cdot (rer_{t-1} - rer_{t-1}^*) + \varepsilon_t^{GAP}$$

where gap_t^{GDP} is output gap, rir_t is real interest rate in percent, rer_t is a real exchange rate and ε_t^{GAP} is output gap shock or aggregate demand shock. Since the model is based on output gap paradigm model, (*) denotes the equilibrium level of corresponding variables. Real exchange rate is measured as foreign exchange rate, so increase of exchange rate means depreciation of domestic exchange rate, moreover, output gap is calculated as a deviation of real GDP from its potential level in percentage points. Sign of the parameters are expected to be positive except parameter of real interest rate.

Inflation depends on expected and lagged level of inflation, exchange rate and output gap levels and formed as follows:

[2] $$\pi_t = \beta_1 \cdot \pi_{t+1} + (1 - \beta_1) \cdot \pi_{t-1} + \beta_3 \cdot (rer_t - rer_{t-1}) + \beta_4 \cdot gap_{t-1}^{GDP} + \varepsilon_t^{\pi}$$

Here π_t denotes CPI inflation and ε_t^{π} is inflation shock or cost push shock. Specificity of this equation is sum of parameters of expected and lagged inflation is always one. It says that if output and exchange rate gaps are zero, then any level inflation would be solution of this equation. Moreover, this expression indicates that coefficient of forward looking inflation should be positive which shows how good central bank anchors the inflation. Monetary policy effects the inflation through the exchange rate and output

level. So parameters of those variables should be greater than zero. If country is open, then exchange rate pass thorough coefficient would be bigger.

We assume that exchange rate equation follows the covered interest parity (IP) condition.

[3] $$rer_t = E_t(rer_{t+1}) - \left(rir_t - rir_t^{for} - prem_t\right) + \varepsilon_t^{rer}$$

where rir_t^{for} is foreign interest rate, $prem_t$ is country risk premium and ε_t^{rer} is exchange rate shock.

Finally, monetary policy rate is based on short term nominal interest rate and is set by central bank in order to keep inflation as close as to targeted inflation (π^*). So we assume that central bank sets its policy rate according to Taylor type rule.

[4] $$i_t = \gamma_1 \cdot i_{t-1} + (1-\gamma_1) \cdot (rir_t^* + \pi_t + \gamma_2 \cdot [\pi_{t+1} - \pi_{t+1}^*] + \gamma_3 \cdot gap_t^{GDP}) + \varepsilon_t^i$$

Here, ε_t^i is monetary policy shock and π_t^* is a targeted inflation. Parameter of lagged nominal interest rate indicates persistency of monetary policy decision. Moreover, response of monetary policy to exceeded inflation from its target level and positive real GDP gap will be increase of policy rate. So parameters are expected to be positive.

Addition to core economic model, I also defined financial variables according to other literatures. For example, as one of financial variables, money demand or broad money is defined as standard LM curve which depends on real interest rate and output gap.

Main part of financial inclusion is stock market capitalization equation and stock market index equation. For stock market capitalization equation we employed model from Calderon-Rossell, R Jorge (1990, 1991) and later it extended by Garcia and Liu (1999) and Charles (2008) by adding macro factors into model.

[5] $$cap_t = \epsilon_1 \cdot cap_{t-1} + \epsilon_2 \cdot gap_{t-1}^{gdp} + \epsilon_3 \cdot T_{t-1} + \epsilon_4 \cdot M_{t-1} + \epsilon_5 \cdot F_{t-1} + \varepsilon_t^{cap}$$

where cap_t is stock market capitalization, T_t is variables that represent liquidity of stock market such as turnover ratio, M_t is variable represents macroeconomic stability like inflation, exchange rate, international reserves etc, F_t represents banking sector characteristics such as broad money, loan outstanding and so on and ε_t^{cap} is stock market capitalization shock. Sign of the parameters can't be defined same, it can vary depend on selection of variables.

The last but not least, stock market price equation defined according to Modigliani and Miller (1961)'s Dividend Discount Model (DDM).

[6] $$P_t = \vartheta_1 \cdot M_{t-1} + \vartheta_2 \cdot \pi_{t-1} + \vartheta_3 \cdot ir_{t-1} + \vartheta_4 \cdot ner_{t-1} + \vartheta_5 \cdot P_{t-1}^{exp} + \varepsilon_t^p$$

Here P_t denotes stock price index, M_t is money supply, ner_t is nominal exchange rate, P_t^{exp} is export price and ε_t^p is stock price shock.

4. Empirical model – Structural Vector Autoregression

Since important work from Sims (1980), SVAR model became so popular among the economic researchers due to extensive ability to show dynamic response of macro variables to particular structural shocks Leu (2011). In general, setting the group of restrictions which are widely consistent with macro economic theory, on normal VAR model is called SVAR model. We followed methodology from paper of Sims et al (1990) and estimated VAR model with imposing restrictions. The selection of variables which are used in our SVAR model is based on equation [1] – [4]. As mentioned in Sims et al (1990) estimated in level. Our system equation with 4 variables ($gap_t^{GDP}, \pi_t, rer_t, i_t$) and four structural shocks ($\varepsilon_t^{Gap}, \varepsilon_t^{\pi}, \varepsilon_t^{rer}, \varepsilon_t^{i}$) is considered as empirically identified.

We begin with defining general specification and identification of SVAR which is linear and stochastic dynamic form. We assume that y_t is covariance stationary process and restricted form of moving average for y_t which is containing vector of original shocks.

[7] $$y_t = D(L) \cdot \varepsilon_t$$

where, L is lag operator, $D(L)$ is matrix polynomial and ε_t is vector of structural disturbance or shocks such as aggregate demand shock, cost push shock, exchange rate shock and monetary policy shock ($\varepsilon_t = \varepsilon_t^{Gap}, \varepsilon_t^{\pi}, \varepsilon_t^{rer}, \varepsilon_t^{i}$). Structural shocks are serially uncorrelated and variance-covariance matrix is diagonal matrix whose diagonal elements are variance of structural shocks.

Vector of structural shocks are not observable directly from data we have. But we have one way to observe shocks, is to estimate reduced-form VAR model.

[8] $$y_t = A(L) \cdot u_t$$

where $A(L)$ is matrix polynomial in lag operator and u_t is vector of residual of reduced form VAR with covariance matrix (Ω). So if we assume that there exits non-singular matrix D_0, then u_t can be written in form of linear combination of structural shocks ε_t.

[9] $u_t = D_0 \cdot \varepsilon_t$

where elements of D_0 matrix shows how structural shocks effect to reduced form residuals of y_t vector contemporaneously.

Obviously, we need to identify D_0 matrix to explore structural shock ε_t from estimated residual of VAR model u_t. Since we know that $D(L) = A(L)D_0$, thus D_0 should be identified and equation [5] will be derived.

As far as, we defined variance-covariance matrix is identity matrix, covariance matrix of residuals can be stated as $\Omega = D_0 D_0^{'}$. So since we have 4 variables, we need to impose 6 more restrictions on D_0 and the restrictions will be determined on long run multiplier of $D(L)$. For imposing restrictions, we employed most straight forward approach so called Choleski identification and ordered variables as follows:

[10] $$\begin{bmatrix} u_t^{gap} \\ u_t^{\pi} \\ u_t^{i} \\ u_t^{rer} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ D_{21} & 1 & 0 & 0 \\ D_{31} & D_{32} & 1 & 0 \\ D_{41} & D_{42} & D_{43} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^{gap} \\ \varepsilon_t^{\pi} \\ \varepsilon_t^{i} \\ \varepsilon_t^{rer} \end{bmatrix}$$

So explaining restrictions in economic sense, all shocks except exchange rate shock has long run effect on exchange rate and the price is influenced only by aggregate demand shock. But of course, if we change the order of variables, we will have different results.

5. Data and Empirical Results

5.1 Data descriptions

Since we are estimating both SVAR and small scale macro models, our dataset consist of two different kind of frequency such as monthly and quarterly. But compositions of variables are more or less same for both models. The sample in monthly data which is used in SVAR analysis includes of 168 observations from January 1998 to December 2011 and the sample of quarterly data which is used in small scale macro model consists of 56 observations from first quarter of 1998 to fourth quarter of 2011. Sample selection is based on fact that quality and robustness of estimation will increase with the length of the database and the other hand this was the longest and finest sample period with any major structural breaks. All the macroeconomic and financial market data are collected from publicly available reports and database of domestic institutions such as Central Bank of Mongolia (BOM) and National Statistical Office of Mongolia (NSO). Detailed description and sources of variables are given in Appendix 1.

Dataset has two main components like macro variables and financial variables. Macro economic variables such as real Gross domestic product (GDP), inflation, short term interest rate and exchange rates, represent whole economic characteristics. The financial variables set consists of broad money growth, banking sector loan growth, share of non-performing loan in total loan, loan loss provision, liquidity assets in banking sector and was collected from banking sector reports (monthly bulletins, loan reports and consolidated balance sheet of banking sector) of BOM. Addition to that, stock market variables such as market capitalization and harmonized stock market index, TOP20 index, are collected from NSO's monthly bulletins.

A core models are only consists of macroeconomic variables. Since real GDP is given only in quarterly basis, we used real gross industrial output as proxy of GDP in monthly database, log-linearized and seasonally adjusted. For quarterly model, we used real GDP to calculate potential GDP level (by using Kalman filter) and GDP gap from its potential level. GDP gap represents economic cycle. Moreover, log-linearized consumer price index (CPI) is used as measure of price; 7-day central bank bill rate is used as short term interest rate which is also considered as policy rate of central bank

(BOM) and log of nominal exchange rate of US dollar against Tugrug (Mongolian national currency, MNT) is used as exchange rate. All variables mentioned above are given in monthly basis, so for transforming monthly data to quarterly data, we took end of period values as representing corresponding quarter. For example, March, June, September and December represent first, second, third and fourth quarters respectively.

A financial model has 8 more variables from banking sector and stock market addition to core model. Selection of financial variables is mainly based on fact that financial market in Mongolia is almost bank based and stock market is playing only in minor role. At the same time, recent rapid growth of stock market illustrates further importance of financial market in economic growth. For banking sector data, we chose annual growth of money supply and total loan in percentage points, liquidity assets (Tier-I assets) and loan loss provision as share of total assets in banking sector, share of foreign currency denominated deposit in total deposit, and total non-performing loan in share of total loan. For stock market variables, both market capitalization and Top20 index are log-linearized. Transformation from monthly data to quarterly data is exactly same as variables in core models, end of the period.

Report of empirical results is structured as follows: First, we present Structural Vector Autoregression (SVAR) model without any financial item (core macro model) and its performance in detail. Since procedure of estimation of model is same with models which have financial variables, we will briefly explain difference from core model in terms of impulse response. Second, we will show estimation result of core and financial small scale macro models. Lastly, we will evaluate the performance of financial variables in forecasting main macro variables such as real industrial production, GDP gap and CPI inflation.

5.2 Estimation result of Models

5.2.1 Structural Vector Autoregression model (SVAR)

To specify and define proper VAR model, some properties usually need to be checked for those time series which are used in models, namely, stationarity and cointegration[3].

[3] At the same time, some literatures also suggest that stationarity and cointegration conditions are not always necessary to be fulfilled in case of whole system is stable itself.

The stationarity condition is tested by using Augmented Dickey-Fuller (ADF) test in monthly database. Table 5.1 gives ADF statistics for all endogenous variables in system.

Table 5.1: ADF unit root test results (1998M1 – 2011M12)

Variables	# of optimal lags	ADF statistic	Probability
	General Economic Variables		
cpi_l	1	- 3.22 [c, t]	0.084
Δcpi_l	0	- 6.87	0.000
er_l	1	- 3.17 [c, t]	0.093
Δer_l	0	- 7.79	0.000
ir_cbb	0	- 3.12 [c, t]	0.106
Δir_cbb	0	- 12.43	0.000
IP_l	0	- 12.10 [c, t]	0.000
	Financial Market Variables		
$loan\_l$	2	- 2.21 [c, t]	0.480
$\Delta loan\_l$	2	- 3.56	0.000
$M2\_l$	0	- 2.59 [c, t]	0.284
$\Delta M2\_l$	2	- 3.80	0.000
$top20\_l$	1	- 2.35 [c, t]	0.403
$\Delta top20\_l$	0	- 8.50	0.000
mrk_cpt_l	1	- 1.73 [c, t]	0.734
Δmrk_cpt_l	0	- 10.36	0.000

Notes: *c and t in square brackets represent the inclusion of constant and time trend in regression of the test. Optimal lag length of ADF test regression was chosen by SIC criteria and maximum lag is up to 13.*

The ADF test is performed up to maximum 13 lags with and without constant and time trend. Selection of optimal lag is chosen based on BIC (Bayesian Information Criteria). The ADF test results show that null hypothesis of I(1) is not rejected at one percent significance level for all variables. But for I(0) case, null hypothesis is rejected almost for all variables except industrial production.

Estimating VAR model, lag level has to be selected carefully. We performed number of tests to select lag length, such as sequential modified LR test, Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC), Hannan-Quinn information criterion (HQ) and Lag exclusion Wald test. For core macro model, all test results suggested us to use VAR(2) model. But for confirming test result, we also ran VAR(1) and VAR(3) models and compared diagnostics tests of those models.

Diagnostic test results show that test can’t reject joint hypothesis of no serial correlation and no heteroskedasticity in VAR(2) model which has the best test result out

of three different VAR specification. All these results together support decision of choosing VAR(2) which will be used in further analysis.

Table 5.2: Diagnostic test results for different VAR specifications

Diagnostic test	VAR(1)	VAR(2)	VAR(3)
Serial Correlation (Q test, 5)	206.97	62.38	63.66
	(0.00)	(0.43)	(0.18)
Serial Correlation (LM test,5)	32.25	23.37	21.80
	(0.01)	(0.10)	(0.15)
Heteroskedasticity (ARCH test)	135.83	189.96	282.89
	(0.00)	(0.14)	(0.07)

Notes: *p-values are given in parenthesis.*

As a next step of analysis, cointegration between variables in the VAR(2) model is tested with Johansen-Juselius maximum likelihood procedure. Test results are shown in Table 5.3. Both Trace and Maximum Eigen value test results showed that there can be 2 potential conintegration relationship among the variables in VAR(2) at the 5% confidence level. But number of conintegration variables is less than number of variables in the system,

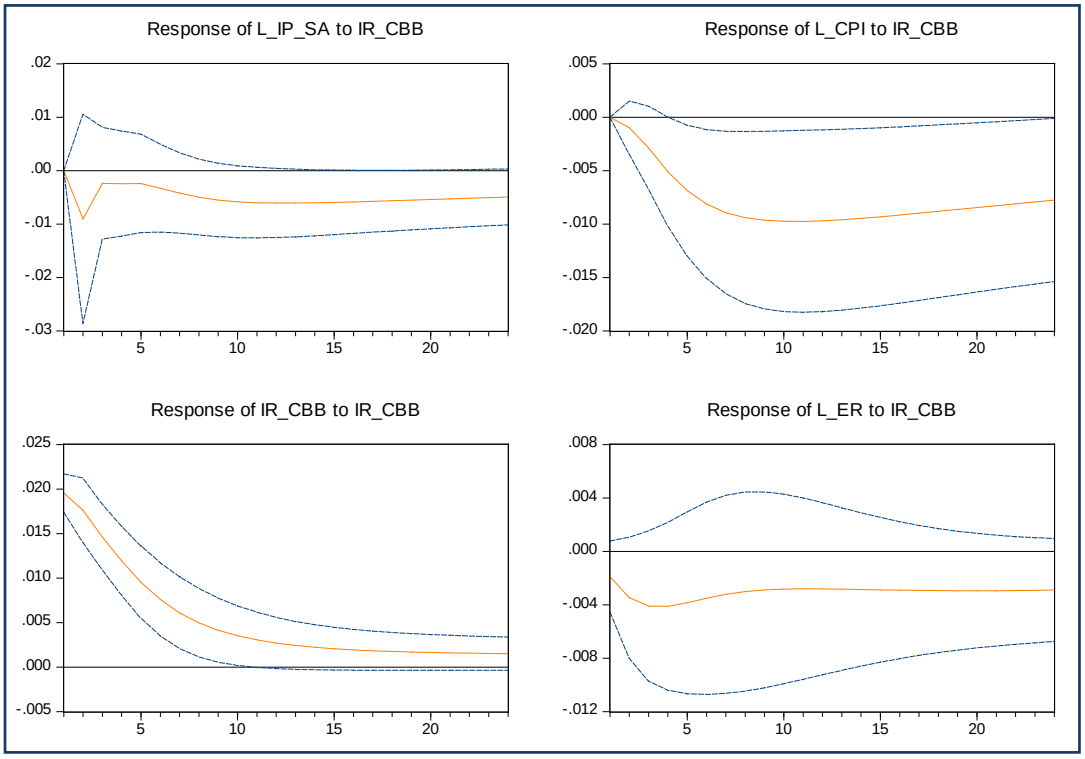
Table 5.3: Johansen conintegration test results

	Trace test		Maximum Eigen value test	
Hypothesized Number of Cointegrations	Trace statistics	Critical Value at 5%	Max-Eigen Statistics	Critical Value at 5%
None*	85.22	47.86	49.66	27.58
At most 1*	35.57	29.79	21.51	21.13
At most 2	14.06	15.49	11.79	14.26
At most 3	2.26	3.84	2.26	3.84

Notes: ** denotes rejection of the hypothesis at the 5% level.*

The estimated parameters of core macro SVAR model, implying structural shocks' contemporaneous and long run impacts on the variables are shown in Appendix 2, together with all other financial SVAR models. So we run impulse responses from VAR model to check consistency of model estimation in theoretical manner. The dynamic responses of industrial production, CPI inflation and exchange rate the short run interest rate or monetary policy rate shock of one standard deviation are shown in following Figures 5.1 – Figure 5.6. The scale between two dashed lines represents 90% of confidence interval, reflecting uncertainty of the estimated coefficients.

Figure 5.1: Impulse responses: Effect of Monetary policy rate shock on macro variables



The responses to the shock are consistent and according with theory. As concern Figure 5.1, unexpected increase in policy interest rate leads to sharp and persistent drop in CPI and starting from 5th month, impact of monetary policy is well significant. The response of industrial production to monetary policy tightening is negative and not significant. Industrial production reaches its lowest point after 2 months and stays below zero line afterwards. The foreign exchange rate reaction to the monetary policy tightening is also negative and not significant, but rather weak compared to industrial production and CPI responses. So as we mentioned before, all the responses of macro variables in the core SVAR model to monetary tightening are consistent with other monetary business cycle literature. When monetary tightening takes place, inflation and real economic activity slow down and foreign exchange rate depreciates.

So far, we only mention about core SVAR model estimation and its impulse response. After estimating core model, we introduced financial variables into our system one by one. Reason of that was first, if we put all variable into system at the same time, we would face problem of degree of freedom, second, as putting it separately, we able to track impact of each financial variable to system separately. Addition to that, we used 4

financial variables out of 8 variables as endogenous variables. Other four variables, namely, loan loss provision, share of non-performing loan to loan, share of foreign currency denominated deposit in total deposit and share of liquid assets in total assets are employed as exogenous variables.

Procedure of estimating financial SVAR models is exactly same as core SVAR model. Results of financial SVAR models are little bit different than core SVAR model in terms of coefficient. But number of lags used and other diagnostic test results were almost identical. So we claim that it can be so because our core model is build strong and stable. In the next section, we present impulse response analysis of other SVAR models which include financial variables, and further they will be called as a financial SVAR. We show 2 different block of impulse response for each financial SVAR models. The one is block of impulse responses of variables to monetary policy shock (increase of policy rate by one of standard deviation), and the other one is block impulse response of macroeconomic variables to corresponding financial variable shock. Since blocks of monetary policy shock are more or less similar in every financial model, we present first block of impulse response in only case of broad money and second block of impulse response for every financial model[4].

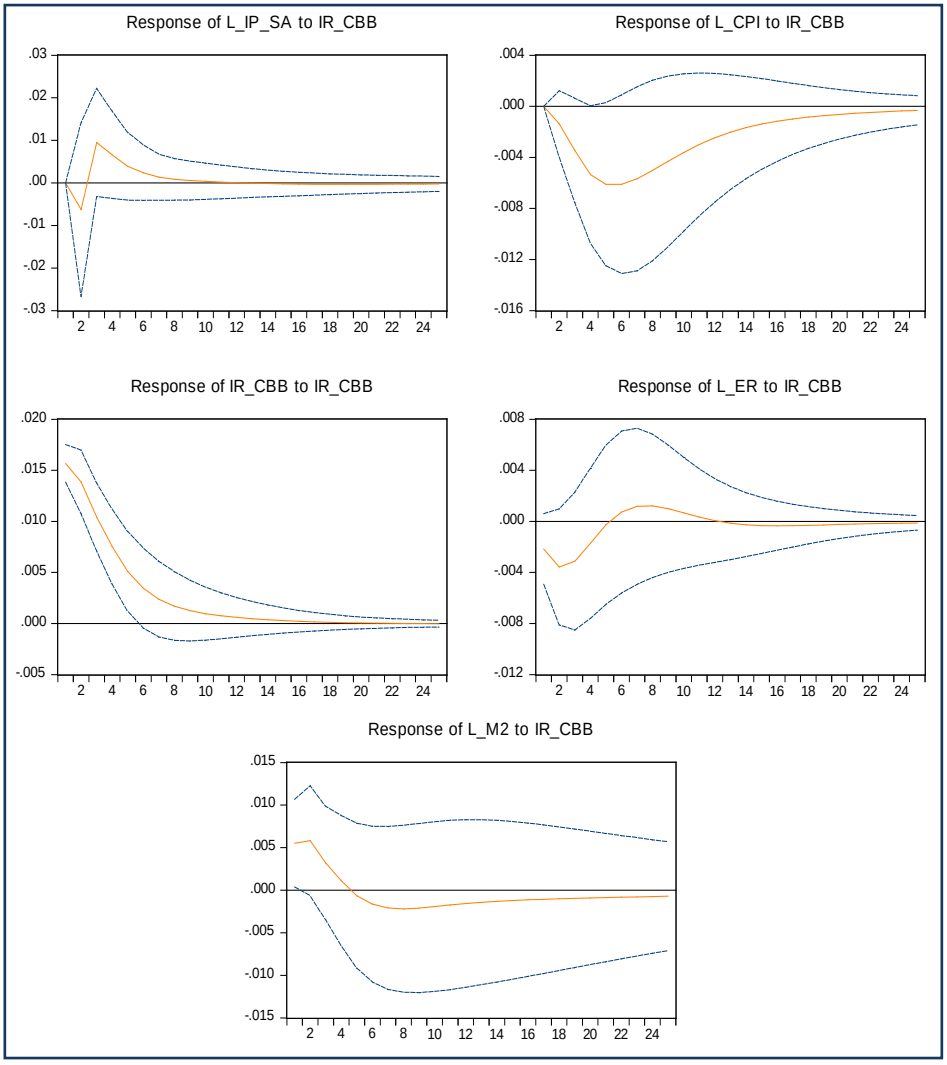
SVAR model with Broad Money

The dynamic effects of monetary policy shock and broad money shock on macroeconomic variables (industrial production, CPI, policy rate and exchange rate) are shown in Figures 5.2 and Figure 5.3. As we can see in Figure 5.2, the CPI decreases immediately, reaches it's the lowest level after 6 months and turns back its initial level after 2 years. The consistent with uncovered interest parity (UIP) condition, foreign exchange rate depreciates after unexpected monetary policy shock. The industrial production reacts to contrary monetary policy as decreasing almost right after, but back on track of increasing after 3 months. In addition, in response of tight monetary policy shock, the monetary aggregate increases, stays positive for 6 months and decreases afterwards. This result is the line with previous findings[5] of Mongolian monetary transmission mechanism which found that monetary policy has weak conventional

[4] In some sense, it may needless to show same thing every time, since we have very stable core model.
[5] This result is consistent with Batnyam.D, Gan-Ochir.D and Lyziak.T (2009).

interest rate channel and most of the monetary policy impacts go through exchange rate channel and bank lending channel.

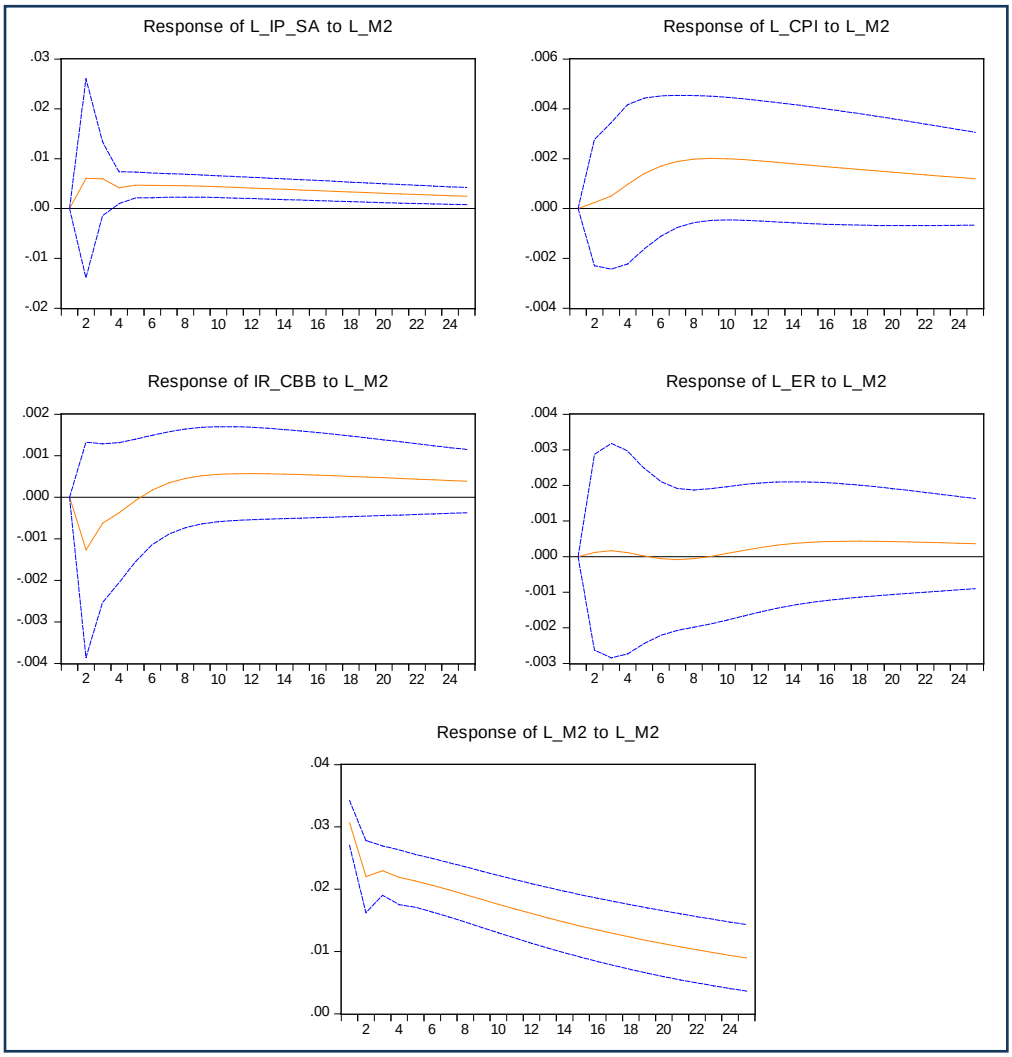
Figure 5.2: Impulse responses: Effect of Monetary policy rate shock on macro variables



As shown in Figure 5.3, Response of industrial production to broad money shock is positive and significant after 4 months. The positive shock for broad also causes inflation pressure in the economy, but has a lot of uncertainty around. Response of CPI is not significant at all. The monetary policy reacts to broad money shock negatively (loosening monetary policy), but becomes more tight 5-6 months after shock occurred. Impact of broad money shock on exchange rate is rather small. Initial response of exchange rate is appreciation, but has very big uncertain surrounded. Speaking in terms of magnitude of response of variables to shock, industrial production has the biggest response to shock. One percent of standard deviation shock (approximately 3%

percentage point increase) increases industrial production by 0.6 percentage points after 2 months at most.

Figure 5.3: Impulse responses: Effect of monetary aggregate (M2 money) shock on macro variables

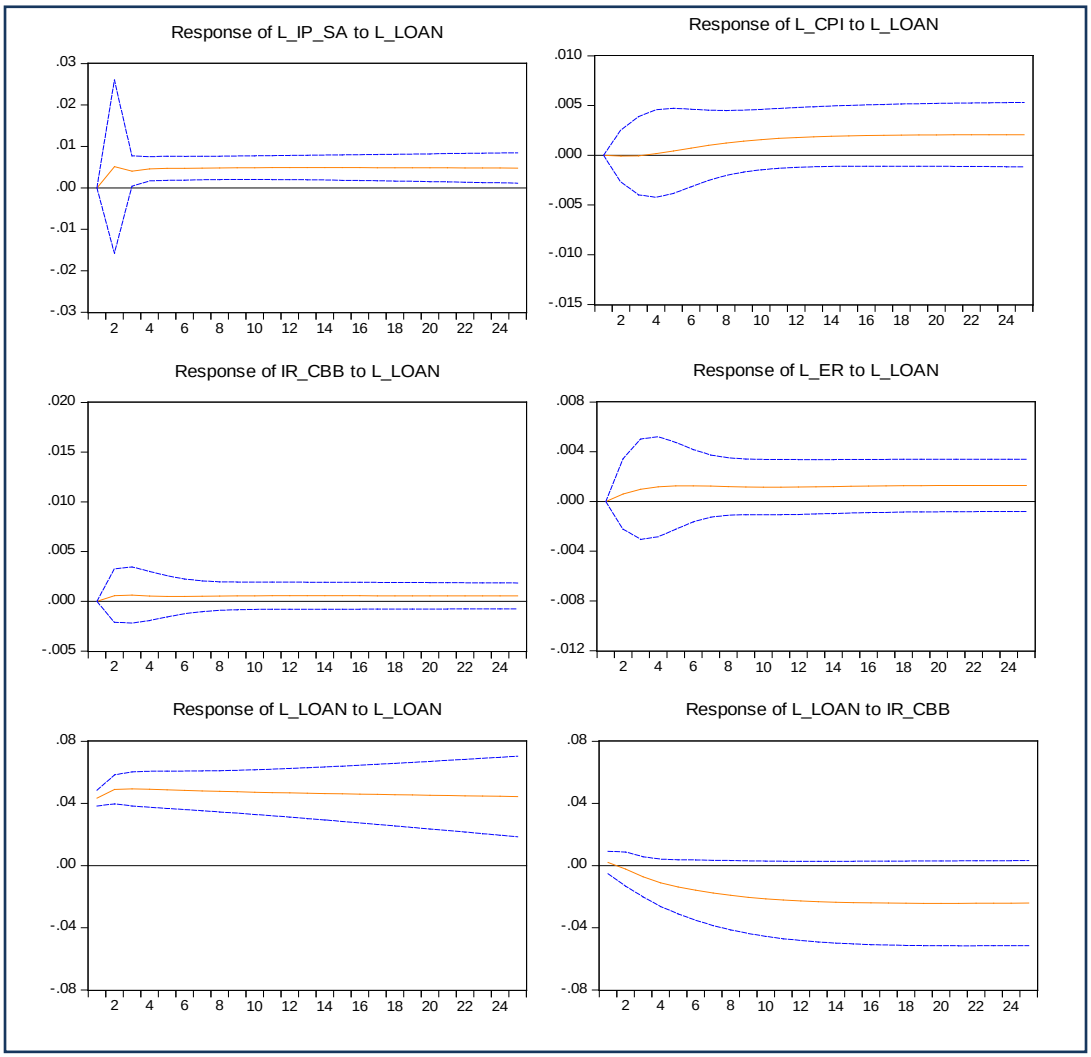


SVAR model with Credit

Unexpected positive shock of credit has significant positive effect on industrial production. The peak value comes after second month with 0.5 percentage point increase, and persists at level afterwards. Same as broad money shock, the credit expansion shock has also positive effect on CPI, but response comes later than broad money shock. The response of monetary policy to credit boost is tightening, unfortunately, response is not significant. Reaction of exchange rate to increasing credit

is appreciation. In addition to the credit shock, we also show response of credit to tighter monetary policy. Credit decreased right after monetary policy tightening occurs, and stays lower level further. It means tight monetary policy can slow down expansion of credit growth.

Figure 5.4: Impulse responses: Effect of credit rate shock on macro variables and Effect of Monetary policy shock on credit

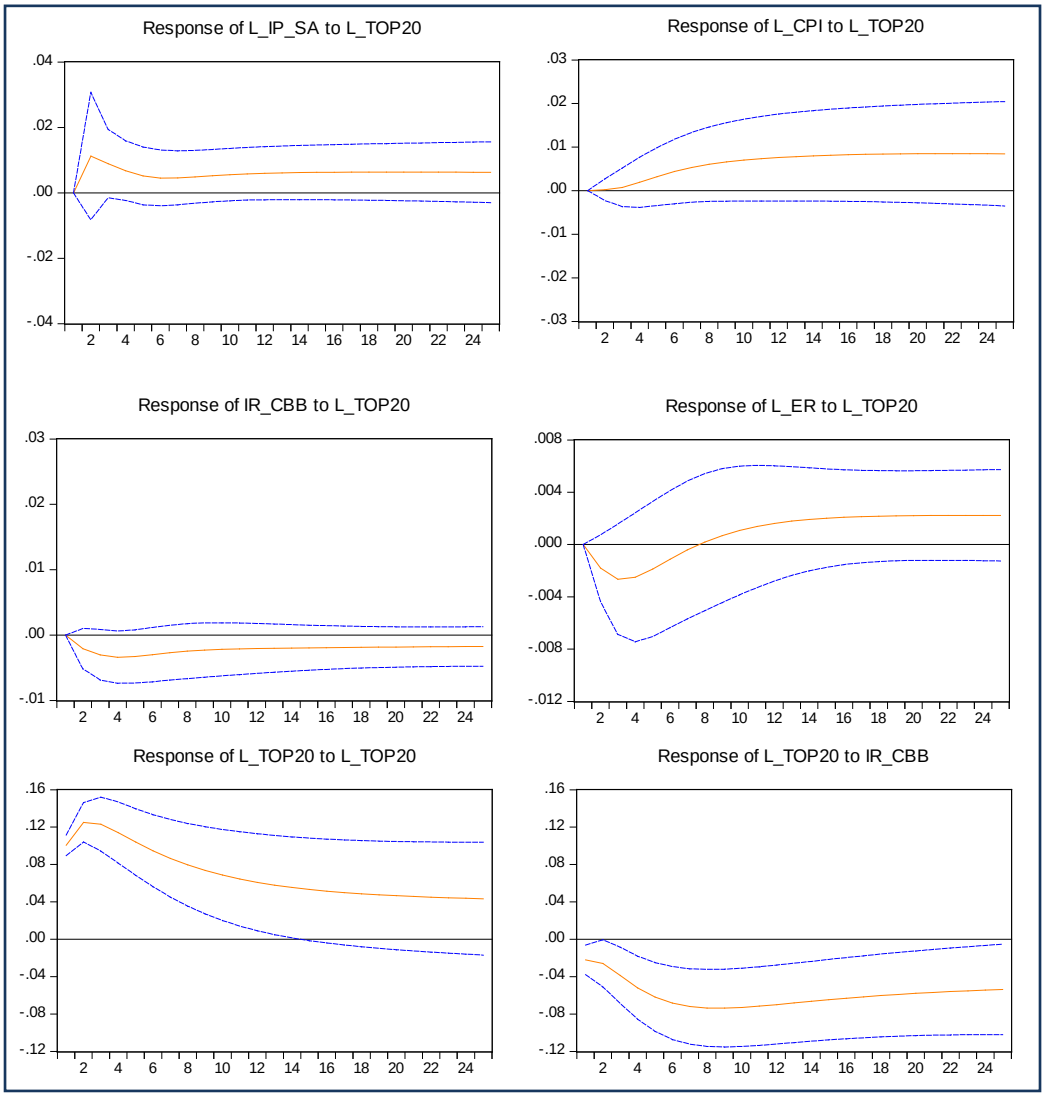


SVAR model with Top20 index

The effect of stock market index has initially positive impact on industrial production which is used as proxy for real activity. This finding is supporting our initial assumption regarding role of financial market that further increase of stock market can create economic growth. CPI reacts to positive shock of stock price index as increasing. It says that deepening stock market may increase demand for money in the market

which causes further inflation pressure. Line with the inflation pressure, policy rate responded to decrease for shock of increasing stock market index. The exchange rate depreciates in short run, but in long run, it appreciates. Moreover, tighter monetary policy has statistically significant negative impact on Top20 index.

Figure 5.5: Impulse responses: Effect of Top20 index shock on macro variables and Effect of Monetary policy shock on Top20 index

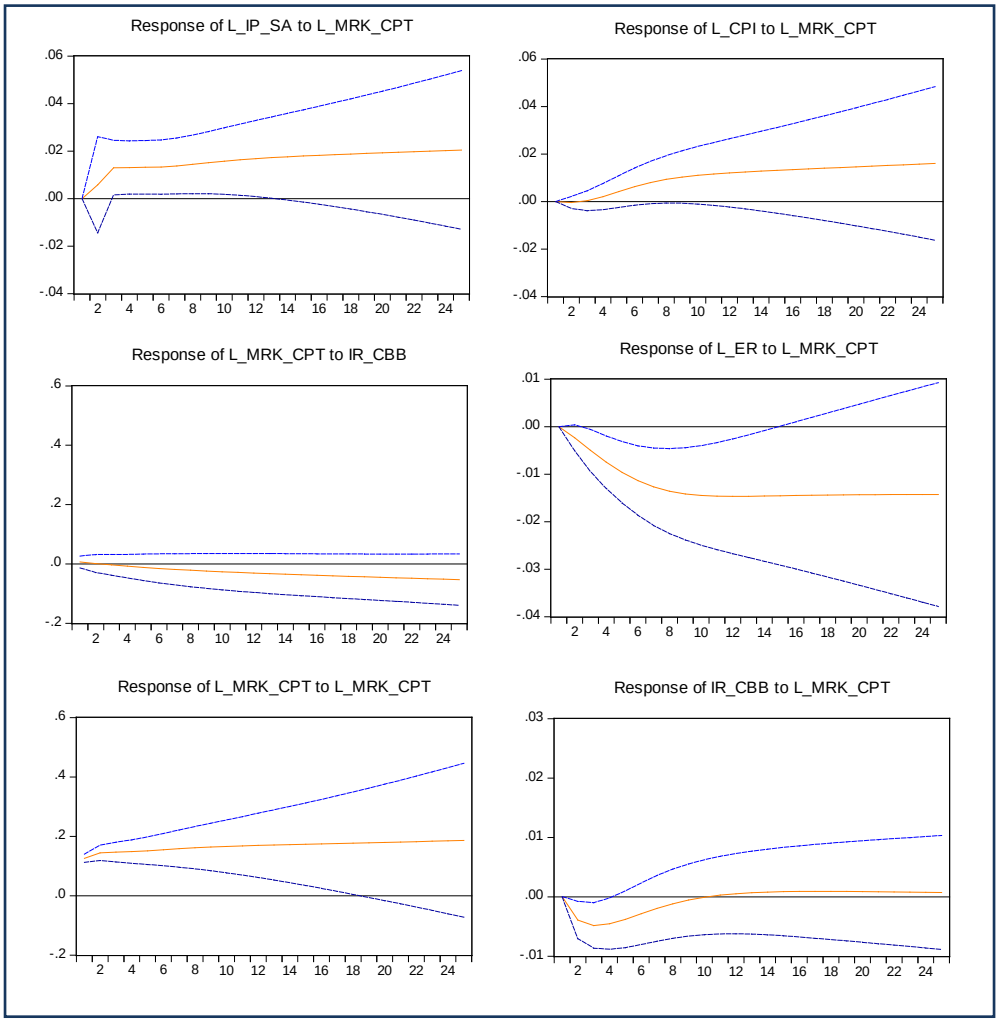


SVAR model with Market Capitalization

Impulse response result in Figure 5.6, exhibits that increase in stock market capitalization leads to permanent increase in industrial production. Impact of shock is statistically significant from 3rd month after shock. Same as Top20 index shock, market capitalization also has not significant positive impact on CPI. Boosting stock market has

permanent and significant impact exchange rate to depreciate. But market capitalization has significant and negative response to tight monetary policy shock. Last two impulse responses of stock market variables also confirm us that commercial banks are playing in main and active role in stock market. Since that, when policy rate moves any direction, commercial banks can easily trades its funds and converts to positions which have higher yields.

Figure 5.6: Impulse responses: Effect of Stock market capitalization index shock on macro variables and Effect of Monetary policy shock on market capitalization



5.2.2 Small Scale Macro Model (SSMM)

In this section we present estimation result of Small-Scale Macro Model (SSMM) which has 2 main bodies, namely, core SSMM and financial SSMM. The SSMM is reduced form of gap model of the monetary transmission which based on the "New Keynesian" paradigm. This kind of small-scale macro models have been employed in many central

banks since 1996 when the central banks started to adopt in inflation targeting (e.g. Bank of England, 1999; Batini and Haldane, 1999; Łyziak, 2002; Kłos et al., 2005). Since our model is not for forecasting propose, we construct very simple and highly aggregated model with 8 endogenous variables and 6 endogenous variables[6], excluding seasonal dummies and model is build only for propose of analyzing role of financial variables in that model.

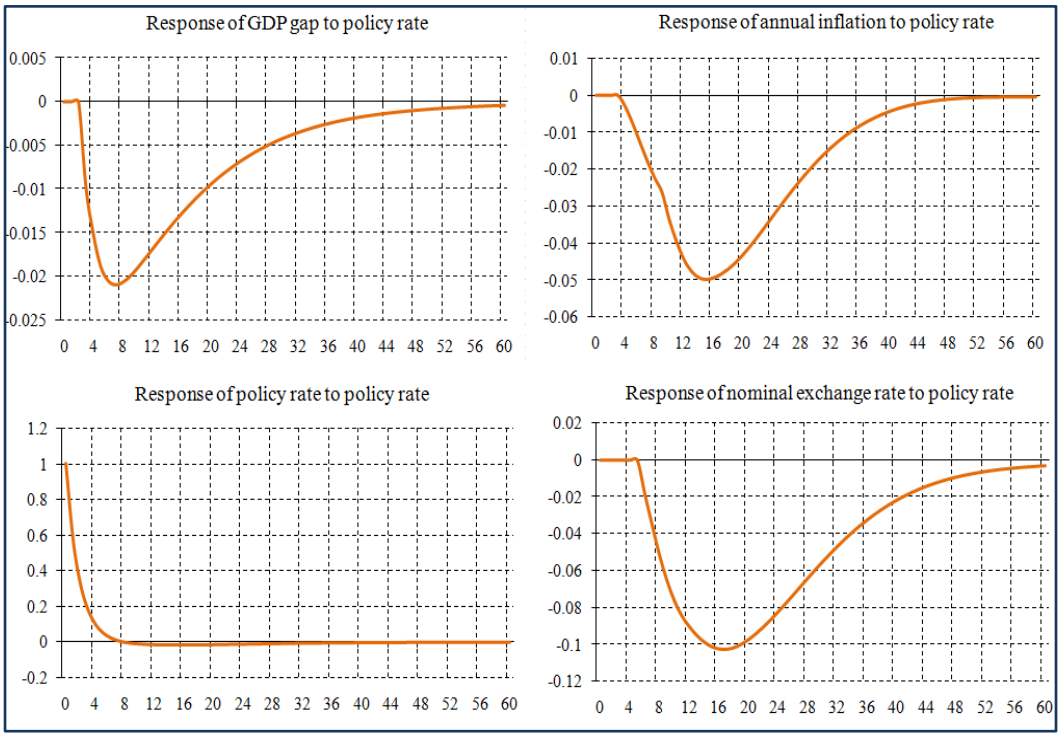
We estimated the model with OLS technique equation by equation using quarterly time series covering the period 1998Q1-2011Q4. Model variables are not subject to seasonal adjustment – the exception is the GDP series, which is used to determine the output gap. However, in some of the equations there is a need to include seasonal dummies in order to capture strong seasonality. The estimated coefficients are line with our expectation and theoretically and empirically consistent (Appendix 3) and diagnostic test results of equations are quite satisfactory. After estimating coefficients, we checked dynamic effect of monetary policy shock financial variables shocks, same as we did in previous section, and summarized in Figure 5.7 - Figure 5.8.

Core SSMModel

The shock of monetary policy is to increase monetary policy rate (7-days Central bank bill rate) by 1 percentage point for 1 quarter. The responses to the shock are consistent and line with result of similar researches. As depicted in Figure 5.7, unexpected increase in monetary policy rate leads to drop in GDP gap starting after 2 quarters and the biggest impact of monetary policy to economic activity comes after 7 quarters. Slowed economic activity is followed with inflation decline. Decrease of annual inflation occurs after 3 quarters and reaches the bottom level after 15 months. Compare with previous model, impulse response results of core SSM model are weak and delayed in terms of magnitude of shock. As response of monetary policy shock, the nominal exchange rate depreciates after 5 quarters and this is consistent with uncovered interest parity condition. So summarizes all impulse responses of variables, when monetary tightening takes place, inflation and real economic activity slow down and foreign exchange rate depreciates.

[6] Core model has 5 endogenous model and 3 exogenous variables.

Figure 5.7: Impulse responses: Effect of Monetary policy rate shock on macro variables

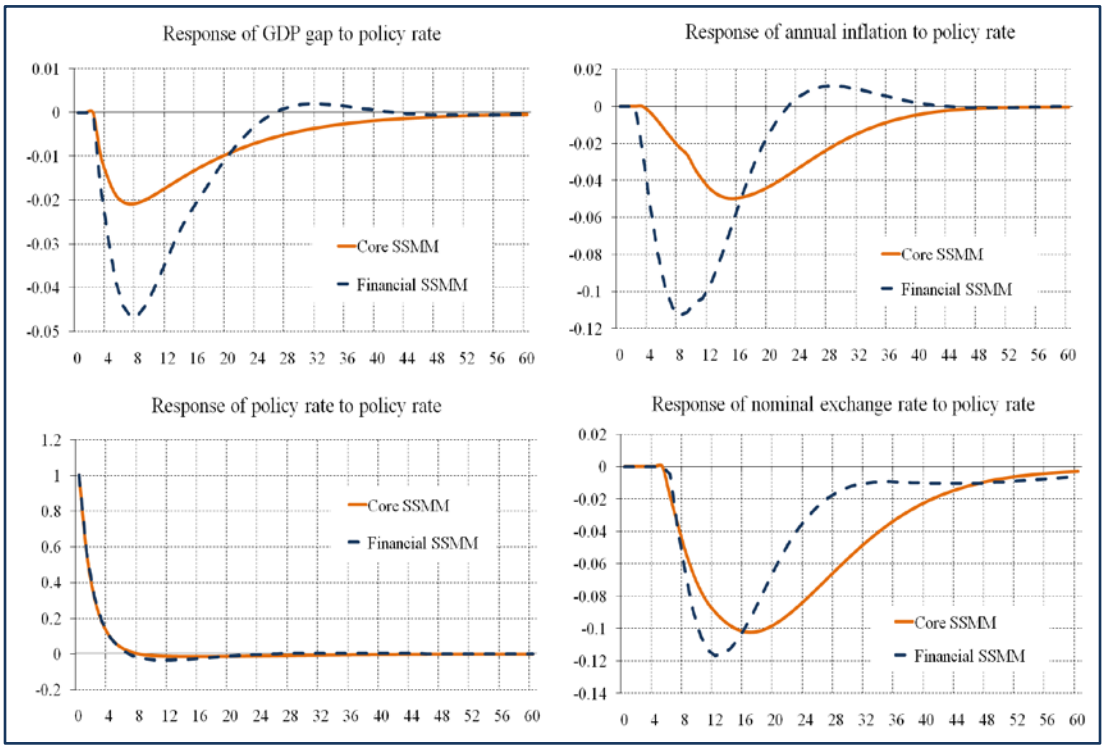


Financial SSMModel

Same as SVAR approach, after we estimate core SSMM, we re-estimated model extended with financial variables. We added 3 more equation into the system such as money demand equation, stock market index equation and market capitalization equation. Moreover, we introduced 3 more exogenous variables in the model, namely, loan loss provision in exchange rate equation, share of non-performing loan in money demand equation and annual credit growth in GDP gap equation. All the estimated coefficients in additional equations are performed statistically significant, theoretically consistent and line with our expectation. So we presented results of newly estimated financial SSMM with impulse response analysis. Here we compare the responses of macro variables to monetary policy shock, with core SSMM. Moreover, we show how the macro variables react to shock financial variables. Strategy for estimating financial SSMM is to introduce only selected financial variables into system and keep main structure of system as it is in core model. By doing this, it will make more sense to compare them.

Magnitude of shock is exactly same as core model in case of monetary policy shock. But for financial variable shocks, there is unexpected increase in each financial variable by 1 percentage point from baseline level for 4 quarters. Impulse responses of variables are shown in percentage points.

Figure 5.8: Impulse responses: Effect of Monetary policy rate shock on macro variables

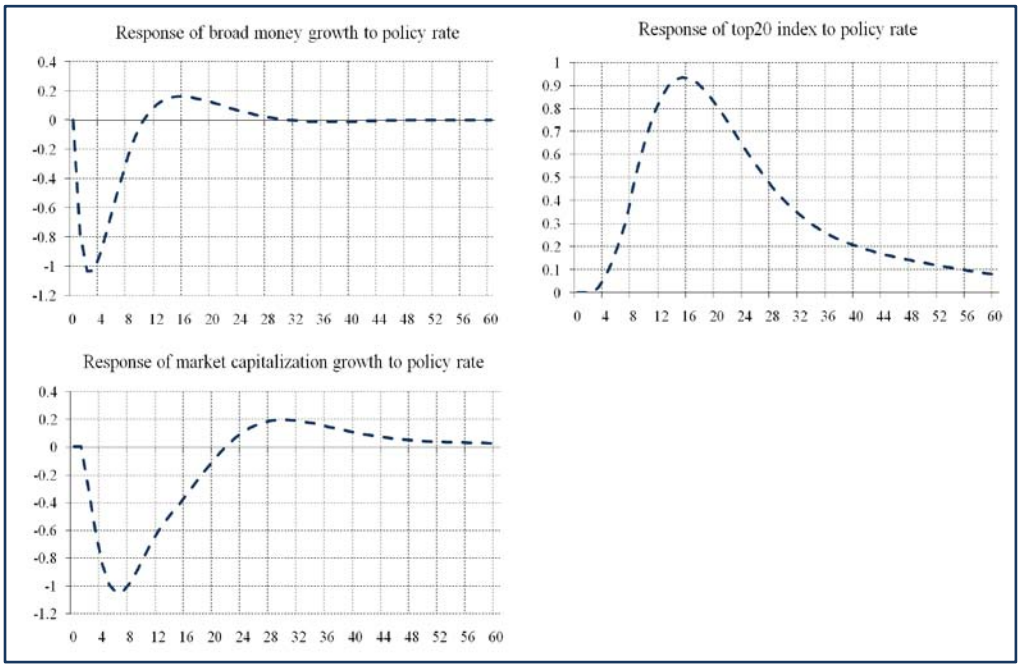


As depicted in Figure 5.8, signs of all responses to the monetary policy shock in financial SSMM are same with core SSMM. Saying in terms of magnitude and time horizon of responses, financial SSMM is more improved than core model for all macro variables. First picture from Figure 5.8 illustrates impulse response of real GDP gap to unexpected increase of monetary policy rate. Real GDP gap responds to decrease 3 quarters after shock occurs, and the biggest drop comes after 8 quarters. Magnitude of response of real GDP gap in financial model is almost 2.5 times greater than response in core model. Annual inflation responds to decrease for shock of tighter monetary policy. The first response comes 3 quarters after shock occurs and reaches its peak bottom level after 8 quarters. Compare with core SSMM, inflation response to monetary policy shock comes earlier and stronger which makes it more realistic. Magnitude of response

increased from 0.04 percentage points to 0.12 percentage points and time of response shortened to 8 quarters from 16 quarters after shock. Exchange rate impulse response is more similar with core SSMM, depreciates after shock.

In addition to that, we show the response of financial variables in model to monetary policy shock in Figure 5.9. Broad money growth reacted to decrease to shock. Compare with other macro variables, broad money responded strong (more than initial shock) in short time. As similar to the broad money, market capitalization also decreases after shock. Most interesting result here is response of stock market index. Our initial expectation was decreasing reaction of stock market index to monetary policy shock, but result was vice versa. When we are tracking result, we find that increasing response of stock market shock is mainly due to exchange rate movement. So from this result, we conclude that market players mainly play in two markets, exchange rate and stock market. When exchange rate depreciates, they go to stock market, and when exchange rate appreciates, they tend to buy foreign currency.

Figure 5.9: Impulse responses: Effect of Monetary policy rate shock on financial variables



Next figures illustrate how macro variables (real GDP gap, annual inflation and nominal exchange rate) react to financial variable shocks. As we mention before, shocks

are to increase each financial variable[7] by 1 percentage point from baseline level for 4 quarters.

Figure 5.10: Impulse responses of nominal exchange rate, annual inflation and real GDP gap to shock of financial variables

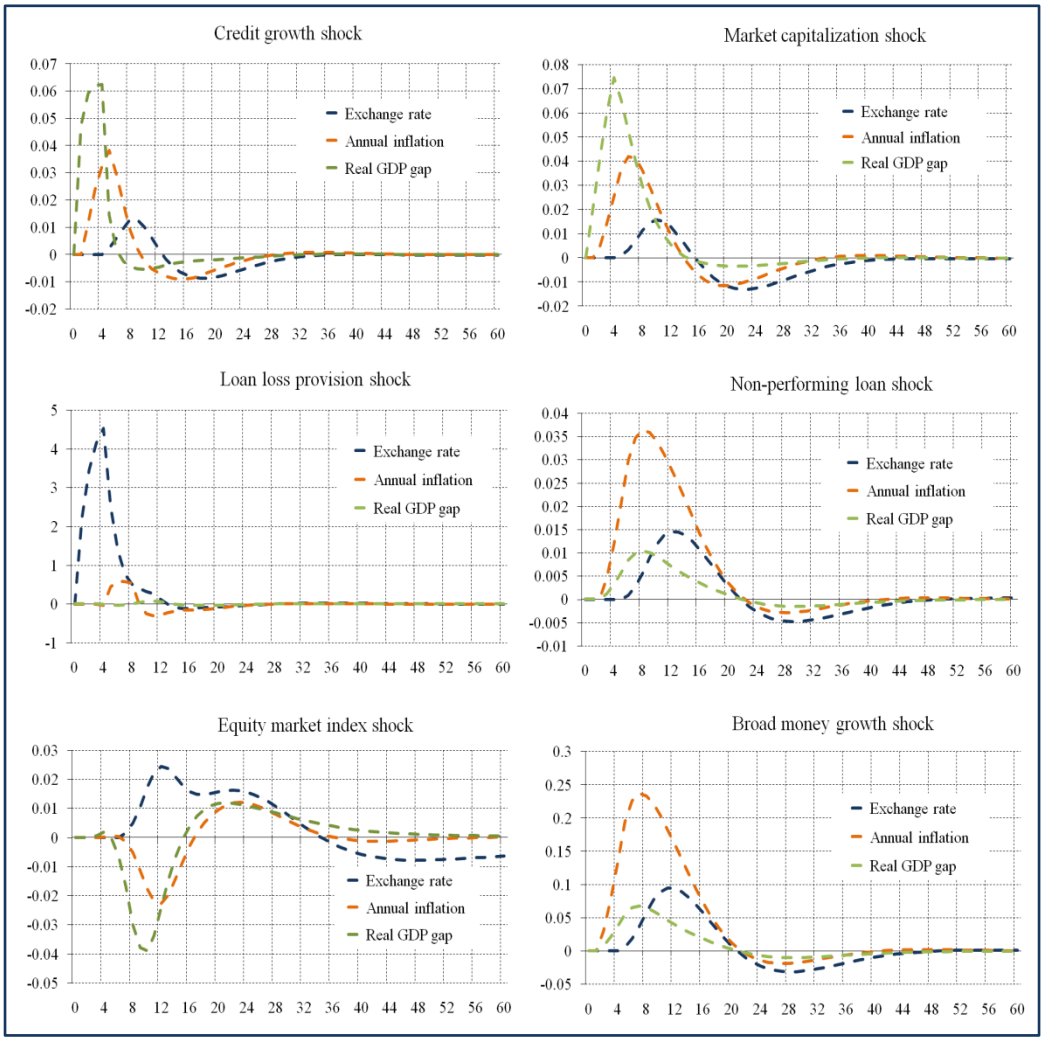


Figure 5.10 shows comparison analysis of how macro variables react to unexpected shock of financial variables. Responses of selected macro variables are quite similar in every case except exchange rate response in stock market index shock. In credit growth, market capitalization and stock market index shock, real GDP gap leads all response, and annual inflation follows in terms of time and magnitude. But inflation responses the strongest and leads in case of non-performing loan and broad money growth shock. Exchange rate leads only in loan loss provision shock.

[7] As a source of shock, we choose credit growth, broad money growth, share of loan-loss provision rate in total asset, share of non-performing loan in total loan, market capitalization and stock market index.

5.2.3 Evaluating Models Based on Forecasting Performance

One of the ways to assess the models can be evaluating model forecasting performance, since most of the macro models are used for forecasting purpose. As mentioned in Clements et al (2003), number of views and dichotomies can be employed in assess forecasting performance such as ex ante versus ex post and 1 step versus multi horizon forecast etc. But we use only a conditional multi horizon, out of sample forecast as comparing models in our study.

Procedure of forecast comparison as follows: first we make from one to twelve months ahead forecasts for SVAR model and from one to twelve quarters ahead forecasts for SSMM in quarterly basis starting from 2005Q1. Then we calculate errors of the forecast for each forecasting horizon by comparing forecast results with actual values. Lastly, we estimate average mean absolute errors of forecast for financial models relative to core models for each quarter. We perform forecasting error analysis for variables such as real industrial production, real GDP gap, annual inflation and nominal exchange rate forecasts and show in Table 5.4 – Table 5.5. For illustration of model forecasting, we also show forecasting accuracy in Figure 5.11 – Figure 5.14 as an example in case of inflation.

Figure 5.11: Annual Inflation Forecast: Core SVAR model

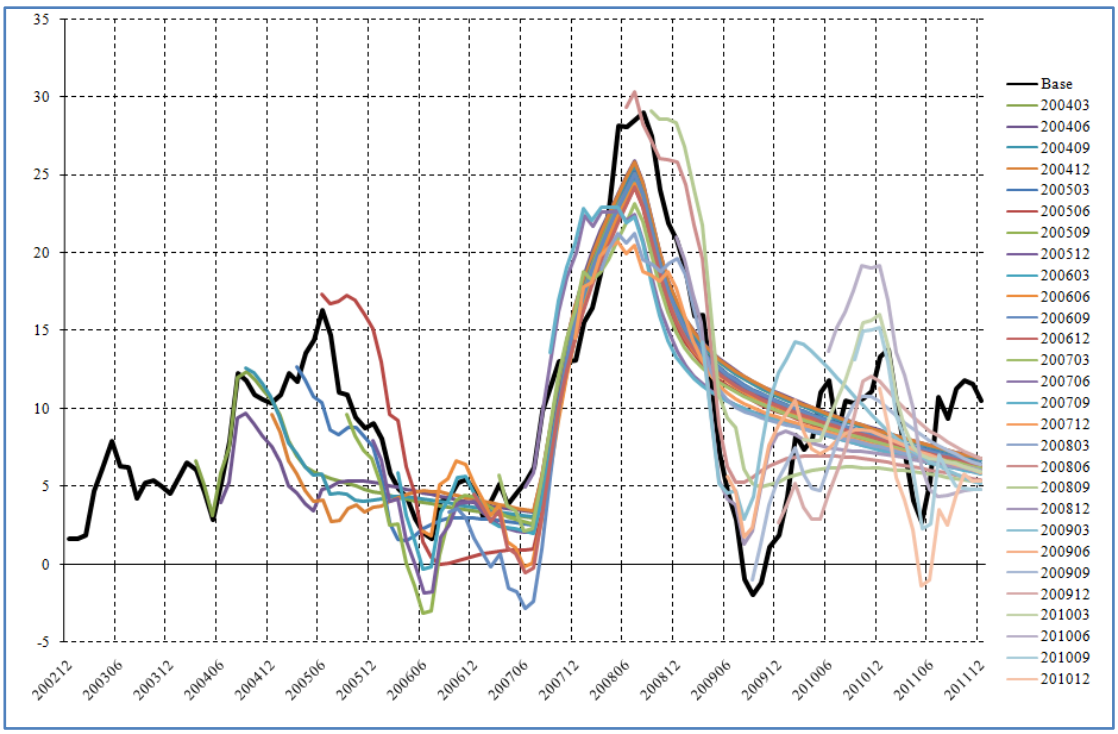
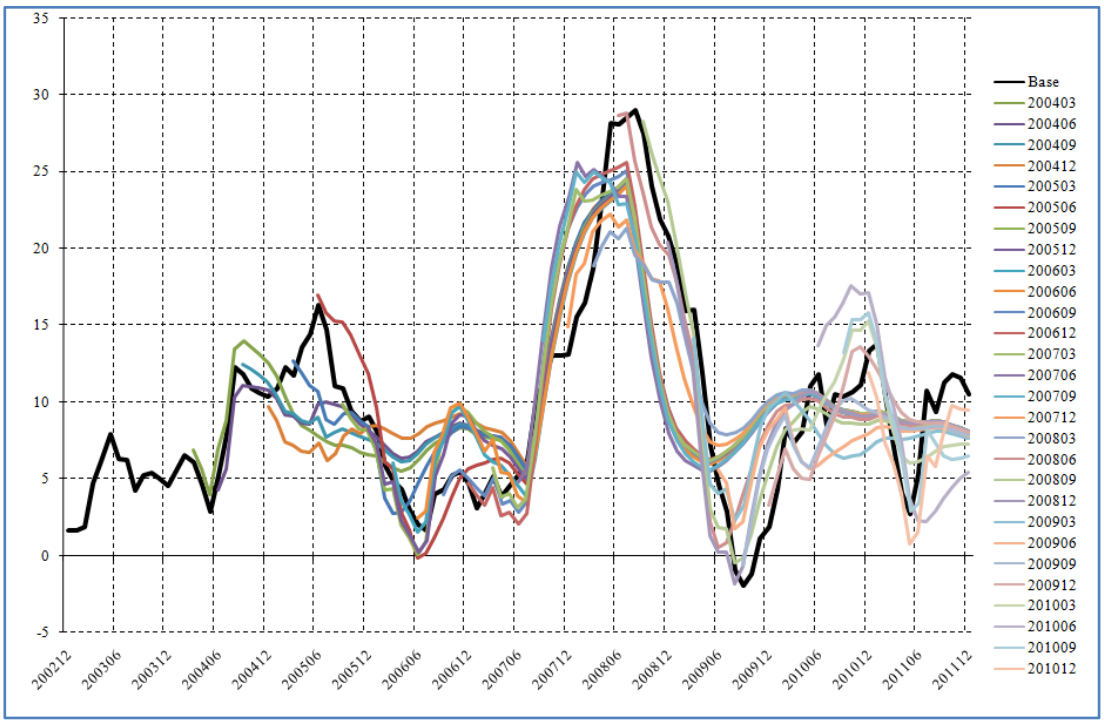


Figure 5.12: Annual Inflation Forecast: Financial SVAR model with M2 money



As shown in Figure 5.11 and Figure 5.12, annual inflation forecast in SVAR model improved in crisis period (2008M7 – 2009M6) and pre-crisis periods (2004M9 – 2005M12) when we introduce broad money into system.

Figure 5.13 Annual Inflation Forecast: Core SSMM

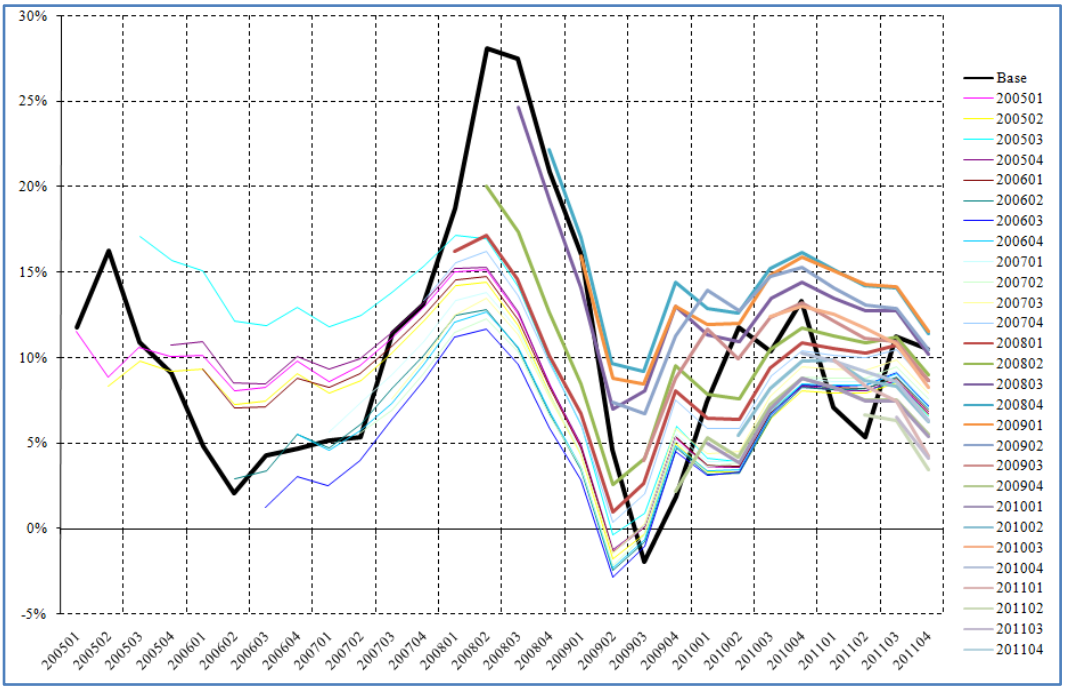
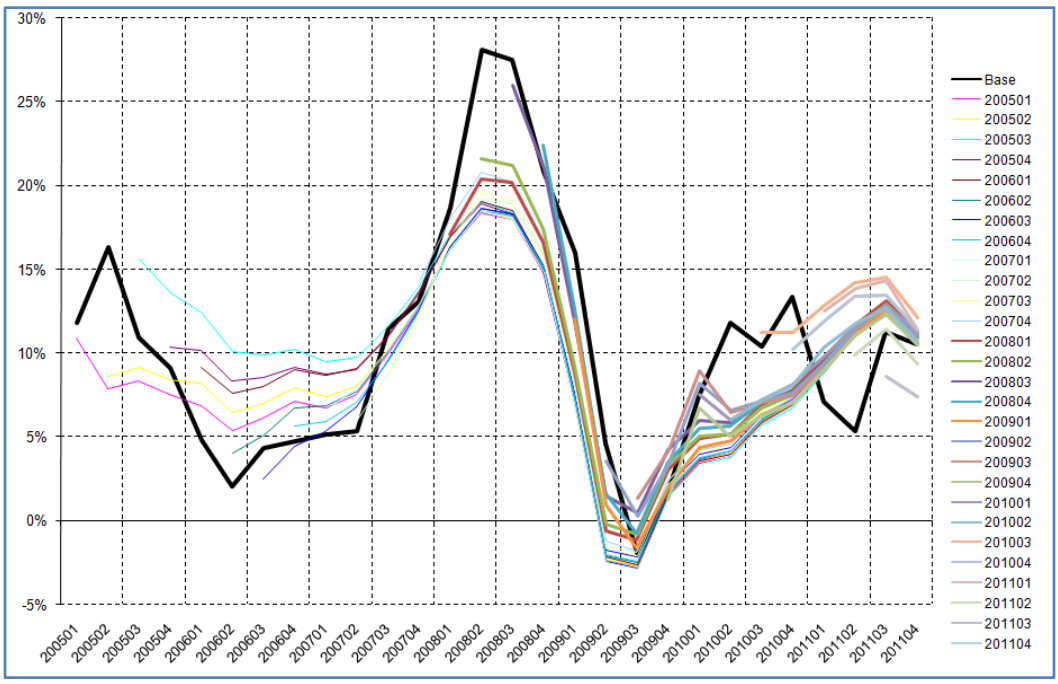


Figure 5.14 Annual Inflation Forecast: Financial SSMM



Very similar with result of SVAR model, inclusion of financial variables in structural model is help to capture annual inflation movements. The financial SSMM forecast annual inflation narrow and with correct trends and break points in most cases. In next few tables, we draw average mean absolute error of forecast in different models. For SVAR model, we could only show forecast errors for separate financial models with different financial variables.

As reported in Table 5.4, all the financial variables are found to improve forecast of macro variables, but with different magnitude. For example, contributions of broad money in forecasting CPI and Industrial production are found the best among the financial variables. Broad money can decrease mean absolute error of CPI forecasting up to 40 percent, and up to 20 percent for industrial production (highlighted in table). The most models are struggling to forecast exchange rate and but size of contribution of credit in forecasting exchange rate is found the biggest in terms of relative mean absolute error. The stock market variables found to have higher contribution in shorter time, for instance, market capitalization performed better in first 4 months to forecast exchange rate, and Top20 index has biggest contribution in last 3 months for exchange rate and first 2 months in industrial production forecast.

Table 5.4 Comparison of out-of-sample forecasts of financial SVAR models with core SVAR models in terms of MAE ratio ($\frac{MAE_{fin\ .SVAR}}{MAE_{core\ .SVAR}}$)

Financial SVAR with Top20 index

	1M	2M	3M	4M	5M	6M	7M	8M	9M	10M	11M	12M
Exchange rate	0.99	1.08	1.19	1.16	1.10	1.08	0.99	0.91	0.88	0.81	0.80	0.77
CPI	1.02	0.99	0.98	0.99	0.93	0.94	0.94	0.91	0.89	0.93	1.02	1.04
Industrial output	0.93	0.90	1.06	0.96	0.92	1.01	0.97	0.96	1.05	0.96	0.98	1.06

Financial SVAR with Credit

	1M	2M	3M	4M	5M	6M	7M	8M	9M	10M	11M	12M
Exchange rate	0.97	0.98	1.02	0.96	0.92	0.97	0.93	0.80	0.84	0.87	0.83	0.87
CPI	0.93	0.88	0.88	0.88	0.80	0.73	0.73	0.74	0.70	0.68	0.73	0.73
Industrial output	1.02	0.89	0.97	0.96	0.93	0.88	0.91	0.91	0.86	0.90	0.95	0.85

Financial SVAR with Broad money

	1M	2M	3M	4M	5M	6M	7M	8M	9M	10M	11M	12M
Exchange rate	1.09	1.06	1.18	1.12	1.08	1.07	0.99	0.91	0.87	0.83	0.80	0.79
CPI	0.93	0.89	0.87	0.86	0.77	0.72	0.68	0.65	0.60	0.60	0.59	0.60
Industrial output	0.97	0.92	0.84	0.93	0.83	0.84	0.87	0.82	0.80	0.84	0.83	0.78

Financial SVAR with Market capitalization

	1M	2M	3M	4M	5M	6M	7M	8M	9M	10M	11M	12M
Exchange rate	0.91	0.92	0.97	0.88	0.94	0.99	0.91	0.93	0.97	0.97	1.01	1.06
CPI	0.98	1.01	0.95	0.95	0.95	0.94	0.94	0.92	0.92	0.92	1.02	1.05
Industrial output	0.96	0.93	1.15	1.00	0.96	1.05	1.00	1.04	1.07	0.99	1.03	1.11

In next table, we have same results with previous table but in SSMM. For SSMM, we calculated mean absolute of forecasting from financial SSMM which is combination of macro and financial variables. As we have seen in Table 5.5, forecasting of real GDP gap is the most improved after introducing financial variables into system, even in some periods, forecasting accuracy increased by more than 40 percent compare with core model. Contribution of financial variables to forecast annual inflation is also visible. Since forecasting period covers recent crisis, inclusion of financial variable brings useful information of crisis into system. Annual inflation forecast improved by approximately 30 percent compare with core model. Even in this model, we can see that exchange rate is most difficult variable to forecast. But financial SSMM could improve forecasting accuracy of exchange rate in every time horizon somehow.

Table 5.5 Comparison of out-of-sample forecasts of financial SSMM with core SSMM in terms of MAE ratio ($\frac{MAE_{fin\ .SSMM}}{MAE_{core\ .SSMM}}$)

	1Q	2Q	3Q	4Q	5Q	6Q	7Q	8Q	9Q	10Q	11Q	12Q
Exchange Rate	0.89	0.79	0.72	0.77	0.83	0.79	0.77	0.76	0.76	0.79	0.80	0.81
Annual Inflation	0.93	0.76	0.67	0.63	0.69	0.69	0.63	0.63	0.62	0.69	0.74	0.74
Real GDP gap	0.63	0.66	0.65	0.65	0.68	0.63	0.63	0.62	0.58	0.61	0.60	0.58

6. Conclusion

In this study, we evaluated role of financial variables in macro modeling and their performance in case of Mongolia. We employed two different models for assessing performance of financial variables in macro modeling. The one is SVAR model which is employed for short-term forecasting in most Central banks, and another one is small scale macro model which is used to be employed for mid-range forecast. Selection of financial variables is straightforward. Mongolian economy has heavily bank-based financial system and role of stock market and other markets are growing very rapid in recent years. So we use broad set of financial variables mostly from banking sector, such as total loan of banking sector, broad money, non-performing loan ratio and loan loss provision share of liquidity assets of banks, together with stock market variables, market capitalization and stock market index. For exploring role of financial variables, we perform different analysis such as impulse response for seeing how financial variables fit into system and forecasting performance for how accurate model performs after introducing financial variables.

The impulse responses analysis performed in way of drawing monetary transmission mechanism through policy rate shock and financial variable shock to other macro variables. The impulse responses to monetary policy shock are consistent with standard open macro economy models. Monetary policy has significant effect on inflation, real demand and nominal exchange rate in short and long run, for instance, inflation reaches its lowest level after 10 months in SVAR model and 8 quarters after SSMM. At the same time all those macro variables also have significant and consistent responses to financial variable shocks. For example, all positive shocks of financial variables have significant effect to increase industrial production and then it follows by increase of inflation in SVAR models. But in case of SSMM, responses of selected macro variables are quite similar in every case except exchange rate response in stock market index shock.

In addition, forecasting performance indicate that financial variables have substantial role on macro modeling and inclusion of financial variable is performing very good result in terms of forecasting in both SVAR and SSMM. Financial model with broad money performs the best among the SVAR type models. This model could

decrease forecasting errors by 40 percent in inflation forecast, and 20 percent for industrial output. The financial SSMM decreased forecasting errors measurably. The annual inflation forecast is improved a lot and decreased by almost 40 percent.

The most interesting result and definitely should be taken into consideration is that core models in SVAR and SSMM, were struggling with forecasting macro variables from recent crisis period. So when we put financial variables into system, there helped not only in overall period, but also and most importantly they carried more information about crisis and helped to forecast macro variables in crisis period. So policy implication from this study can be defined as inclusion of financial variables, more importantly broad money and loan growth rate, can improve aggregate macroeconomic model in predictive perspective in Mongolia economy.

Bibliography

Adrian, T and Shin, H, S (2008): "Liquidity and Financial Contagion", *Banque de France Financial Stability Review*, no 11, pp 1–8.

Antony, J and Broer, P (2010): "Linkages between the Financial and the Real Sector of the Economy", *CPB Netherlands Bureau for Economic Policy Analysis*, No 216.

Atanasova, C (2003): "Credit Market Imperfections and Business Cycle Dynamics: A Nonlinear Approach", *Studies in Nonlinear Dynamics and Econometrics*, Vol. 7, no 4, pp 1–20.

Bagliano, F C and Favero, C A (1997): "Measuring Monetary Policy with VAR Models: An Evaluation", *European Economic Review*, vol.42, 6, 1998, p.1069-1112.

Batnyam.D, Gan-Ochir.D and Lyziak.T (2009): "Small Inflation Model of Mongolia (SIMOM)", *Bank of Mongolia Working Paper Series*, Vol. 6.

Berg, A, Karam, P and Laxton, D (2006): "A Practical Model Based Approach to Monetary Policy Analysis - Overview", , WP.06.80.

Bernanke, B, S (1983): "Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression", *American Economic Review* 73, 257-76.

Bernanke, B, S and Blinder, A S (1988): "Credit, Money, and Aggregate Demand", *American Economic Review*, vol 78, no 2, pp 435–9.

Bernanke, B, S and Gertler, M (1989): "Agency Costs, Net Worth, and Business Fluctuations", *American Economic Review*, vol 79, no 1, pp 14–31.

BIS (2010): "The Transmission Channels between the Financial and Real Sectors: Critical Survey of the Literature", *Basel Committee on Banking Supervision Working Paper*, No.18.

Borio, C and Zhu, H (2009): "Capital Regulation, Risk-taking and Monetary Policy: A Missing Link in the Transmission Mechanism?" *BIS Working Papers*, no 268, Basel.

Brunnermeier, M, K and Pedersen, L, H (2007): "Market Liquidity and Funding Liquidity", *NBER Working Papers*, no 12939.

Brunnermeier, M K and Sannikov, Y (2011): "A Macroeconomic Model with a Financial Sector".

Calderon-Rossell, R Jorge (1990): "The Structure and Evolution of World Stock Markets," in *S.Ghon Rhee and Rosita P. Chang (eds.), Pacific Basin Capital Markets*

Research Proceeding of the First Annual Pacific Basin Finance Conference, Taipei, China, 13-15 March 1989.

Calderon-Rossell, R Jorge (1991): "The Determinants of Stock Market Growth," *in S. Ghon Rhee and Rosita P. Chang (eds.), Pacific Basin Capital Markets Research Proceeding of the Second Annual Pacific Basin Finance Conference*, Vol. II, Bangkok, Thailand, 4–6 June.

Carlstrom, C, T and Fuerst, T, S (1997): "Agency Costs, Net Worth, and Business Fluctuations: A Computable General Equilibrium Analysis", *American Economic Review*, vol 87, no 5, pp 893–910.

Cecchetti, S G, Disyatat, P and Kohler, M (2009): "Integrating Financial Stability: New Models for a New Challenge", *Joint BIS-ECB Workshop*.

Drehmann, M and Nikolaou, K (2009): "Funding Liquidity Risk: Definition and Measurement", *European Central Bank Working Paper Series*, no 1024.

Ediz, T, I and Perraudin, W (1998): "The Impact of Capital Requirements on U.K. Bank Behavior", *Federal Reserve Bank of New York Economic Policy Review*, Vol. 4, no 3, pp 15–22.

Esponza, R, Fornari, F and Lombardi, M, J (2009): "The Role of Financial Variables in Predicting Economic Activity", *ECB Working Paper Series*, No.1108.

Fisher, I (1933): "The Debt-Deflation Theory of Great Depressions", *Econometrica*, vol. 1, no. 4, pp. 337–357.

Friedman, M and Schwartz, A, J (1963): "A Monetary History of the United States", 1867-1960, *Princeton University Press*.

Gertler, M and Gilchrist, S (1994): "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms", *Quarterly Journal of Economics*, vol 109, no 2, pp 309–40.

Gilchrist, S, Yankov, V and Zakrajšek, E (2009): "Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bond and Stock Markets", *Journal of Monetary Economics*, vol 56, no 4, pp 471–93.

Goodhart, C, A, Hofmann, B and Segoviano, M (2006): "Default, Credit Growth, and Asset Prices", *IMF Working Paper*, no 06/223.

Guichard, S, Haugh, D and Turner, D (2009): "Quantifying the Effects of Financial Conditions in the Euro Area, Japan, United Kingdom and United States", *OECD Economics Department Working Papers*, No. 677, OECD Publishing.

Havranek, T, Horvath, R and Mateju, J (2010): “Do Financial Variables Help Predict Macroeconomic Environment? The Case of the Czech Republic”, *CNB Working Paper Series*, Vol.6.

Hernando I. (1998): “The Credit Channel in the Transmission of Monetary Policy: The Case of Spain, Topics in Monetary Policy Modeling”, *BIS Conference Papers*,Vol. 6.

Horváth. R and Rusnák. M (2008): “How Important Are Foreign Shocks in Small Open Economy? The Case of Slovakia”, *William Davidson Institute Working Paper*, № 933.

Hulswig, O, Winker, P and Worms, A (2002): “Bank Lending in the Transmission of Monetary Policy: A VECM Analysis for Germany”

Jacobson, T, Linde, J and Roszbach, K (2005): “Exploring interactions between Real Activity and the Financial Stance”, *Journal of Financial Stability*, Vol. 1, no 3, pp 308–41.

Jakubík, P and Schmieder, C (2008): “Stress Testing Credit Risk: Is the Czech Republic Different from Germany?” *Czech National Bank Working Paper Series*, no 9

Kashyap, A K, Stein, J C and Wilcox, D W (1993): “Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance”, *American Economic Review*, vol 83, no 1, pp 78–98.

Kashyap, A K and Stein, J C (2000): “What do a Million Observations on Banks Say about the Transmission of Monetary Policy?”, *American Economic Review*, vol 90, no 3, pp 407–28.

Keynes, J.M. (1936): “The General Theory of Employment, Interest and Money”, *Macmillan.*

Kiyotaki, N and Moore, J (1997): “Credit Cycles”, *Journal of Political Economy*, vol 105, no 2, pp 211–48.

Laeven, L and Majnoni, G (2003): “Loan loss Provisioning and Economic Slowdowns: Too much, Too late?”, *Journal of Financial Intermediation*, vol 12, no 2, pp 178–97.

Kakes J, Sturm J, and Maier P. (1999): “Monetary Transmission and Bank Lending in Germany”, *CCSO Working Paper* 199906, University of Groningen, Netherlands.

Li, Y D, Iscan, T B and Xu, K (2009): “The Impact of Monetary Policy Shocks on Stock Prices: Evidence from Canada and the United States”.

Leu, S.C.Y (2011): “A new Keynesian SVAR model of the Australian economy”, *Economic Modeling*, Vol. 28, pp. 157-168.

Liew, J. and Vassalou, M (2000): “Can Book-to-Market Size and Momentum be Risk Factors that Predict Economic Growth?” *Journal of Financial Economics* 57.

Mahmood, W and Dinniah, N (2009): “Stock Returns and Macroeconomics Variables: Evidence from the Six Asian-Pacific Countries”, International Research Journal of Finance and Economics, ISSN 1450-2887 Issue 30 (2009)

Mishkin, F S (1977): “What Depressed the Consumer? The Household balance sheet and the 1973–75 recessions”, *Brookings Papers on Economic Activity*, Vol. 1977; no 1, pp 123–64.

Pesaran, M H, Schuermann, T, Treutler, B, J and Weiner, S, M (2006): “Macroeconomic Dynamics and Credit Risk: A Global Perspective”, *Journal of Money, Credit, and Banking*, vol 38, no 5, pp 1211–61.

Rudebusch, G, D (2010): “Macro-Finance Models of Interest Rates and the Economy”, *Federal Reserve Bank of San Francisco, Working Paper* 2010-01.

Qi, M and Yang, X (2009): “Loss given Default of High Loan-to-value Residential Mortgages”, *Journal of Banking and Finance*, Vol. 33, no 5, pp 788–99.

Stock, J H and Watson, M W (2003): “Forecasting Output and Inflation: The Role of Asset Prices”, *Journal of Economic Literature*, Vol. 41, no 3, pp 788–829.

Appendix 1 – Data descriptions

Names in equation	Variable name	Definition	Unit	Currency	Source	Frequency
cpi	CPI overall in Ulaanbaatar	Overall consumer price index in Ulaanbaatar, Seasonally adjusted, base year December 2010 = 100, in logarithm	index	MNT	National Statistical Office	monthly
ip	Real gross industrial output	Total industrial output at constant prices 2005, in logarithm	millions	MNT	National Statistical Office	monthly
ir_cbb	Central bank policy rate	Annual interest rate on Central Bank 7 day bills, since July 2007, 7 day CB bill rate has been named as policy rate	percent p.a.	MNT	Bank of Mongolia	monthly
er	Nominal exchange rate USD/MNT	Cross exchange rate MNT per 1USD, monthly average, in logarithm	MNT per 1 USD	MNT	Bank of Mongolia	monthly
gdp	Real GDP	Gross domestic product level at constant 2005 prices in MNT, in logarithm	millions	MNT	National Statistical Office	quarterly
M2	Broad money (M2)	Broad money as a part of monetary survey, end of period, in logarithm	millions	MNT	Bank of Mongolia	monthly
loan	Total loan outstanding	Total loan outstanding of banking sector, end of period, in logarithm	millions	MNT	Bank of Mongolia	monthly
top20	MSE Top 20 Index	Mongolian stock exchange Top 20 securities Index calculated based on the market capitalization, end of period, in logarithm	index	MNT	National Statistical Office	monthly
mrk_cpt	Market capitalization	Market capitalization, end of period, in logarithm	millions	MNT	National Statistical Office	monthly
lo_prov	Loan loss provision	Ratio of loan loss provision to total asset, end of period	percent	MNT	Bank of Mongolia	monthly
shr_fcyloan	Foreign currency deposit in total deposit	Share of foreign currency denominated loan in total loan, end of period	percent	MNT	Bank of Mongolia	monthly
shr_nploan	Share of non-performing loan	Share of non-performing loan in total loan, end of period.	percent	MNT	Bank of Mongolia	monthly
shr_liqasst	Total bank liquidity assets	Share of liquid assets in total assets, end of period	percent	MNT	Bank of Mongolia	monthly
chi_ind	China value added of industry	Total value of industrial production in China at current prices	billions	CNY	Bloomberg	monthly
w_food	World food price index	World food price index calculated as a average of 55 agricultural commodity prices, base year 2002-2004=100, in logarithm	index	USD	Food Agriculture Organization	monthly

Appendix 2 – Long run restrictions on SVAR models

A.2.1: Estimation of contemporaneous coefficients: Core SVAR model

Structural VAR Estimates
Sample (adjusted): 1998M03 2011M12
Included observations: 166 after adjustments
Estimation method: method of scoring (analytic derivatives)
Convergence achieved after 7 iterations
Structural VAR is just-identified

Model: Ae = Bu where E[uu']=I
Restriction Type: short-run text form
@e1 = C(1)*@u1
@e2 = C(2)*@e1 + C(3)*@u2
@e3 = C(4)*@e1 + C(5)*@e2 + C(6)*@u3
@e4 = C(7)*@e1 + C(8)*@e2 + C(9)*@e3 + C(10)*@u4
where
@e1 represents L_IP_SA residuals
@e2 represents L_CPI residuals
@e3 represents IR_CBB residuals
@e4 represents L_ER residuals

	Coefficient	Std. Error	z-Statistic	Prob.
C(2)	0.019643	0.009728	2.019286	0.0435
C(4)	-0.016268	0.012143	-1.339717	0.1803
C(5)	-0.110191	0.095717	-1.151219	0.2496
C(7)	-0.006398	0.010668	-0.599789	0.5486
C(8)	-0.091288	0.083970	-1.087146	0.2770
C(9)	-0.097159	0.067820	-1.432601	0.1520
C(1)	0.126429	0.006939	18.22087	0.0000
C(3)	0.015846	0.000870	18.22087	0.0000
C(6)	0.019541	0.001072	18.22087	0.0000
C(10)	0.017075	0.000937	18.22087	0.0000

Log likelihood 1418.061

Estimated A matrix:

1.000000	0.000000	0.000000	0.000000
-0.019643	1.000000	0.000000	0.000000
0.016268	0.110191	1.000000	0.000000
0.006398	0.091288	0.097159	1.000000

Estimated B matrix:

0.126429	0.000000	0.000000	0.000000
0.000000	0.015846	0.000000	0.000000
0.000000	0.000000	0.019541	0.000000
0.000000	0.000000	0.000000	0.017075

A.2.2: Estimation of contemporaneous coefficients: Financial SVAR model with broad money

Structural VAR Estimates
Sample (adjusted): 1999M12 2011M12
Included observations: 145 after adjustments
Estimation method: method of scoring (analytic derivatives)
Convergence achieved after 7 iterations
Structural VAR is just-identified

Model: Ae = Bu where E[uu']=I
Restriction Type: short-run text form
@e1 = C(1)*@u1
@e2 = C(2)*@e1 + C(3)*@u2
@e3 = C(4)*@e1 + C(5)*@e2 + C(6)*@u3
@e4 = C(7)*@e1 + C(8)*@e2 + C(9)*@e3 + C(10)*@u4
@e5 = C(11)*@e1 + C(12)*@e2 + C(13)*@e3 + C(14)*@e4 +C(15)*@u5
where
@e1 represents L_IP_SA residuals
@e2 represents L_CPI residuals
@e3 represents IR_CBB residuals
@e4 represents L_ER residuals
@e5 represents L_M2 residuals

	Coefficient	Std. Error	z-Statistic	Prob.
C(2)	0.020265	0.010404	1.947716	0.0514
C(4)	-0.014231	0.010827	-1.314486	0.1887
C(5)	0.040982	0.085307	0.480409	0.6309
C(7)	-0.004656	0.011538	-0.403561	0.6865
C(8)	-0.063956	0.090444	-0.707138	0.4795
C(9)	-0.138224	0.087976	-1.571153	0.1161
C(11)	-0.025567	0.021322	-1.199084	0.2305
C(12)	0.173858	0.167337	1.038969	0.2988
C(13)	0.378110	0.163869	2.307390	0.0210
C(14)	0.184505	0.153385	1.202893	0.2290
C(1)	0.121734	0.007148	17.02939	0.0000
C(3)	0.015251	0.000896	17.02939	0.0000
C(6)	0.015667	0.000920	17.02939	0.0000
C(10)	0.016597	0.000975	17.02939	0.0000
C(15)	0.030655	0.001800	17.02939	0.0000
Log likelihood	1585.434			

Estimated A matrix:

1.000000	0.000000	0.000000	0.000000	0.000000
-0.020265	1.000000	0.000000	0.000000	0.000000
0.014231	-0.040982	1.000000	0.000000	0.000000
0.004656	0.063956	0.138224	1.000000	0.000000
0.025567	-0.173858	-0.378110	-0.184505	1.000000

Estimated B matrix:

0.121734	0.000000	0.000000	0.000000	0.000000
0.000000	0.015251	0.000000	0.000000	0.000000
0.000000	0.000000	0.015667	0.000000	0.000000
0.000000	0.000000	0.000000	0.016597	0.000000
0.000000	0.000000	0.000000	0.000000	0.030655

A.2.3: Estimation of contemporaneous coefficients: Financial SVAR model with credit

Structural VAR Estimates
Sample (adjusted): 1999M12 2011M12
Included observations: 145 after adjustments
Estimation method: method of scoring (analytic derivatives)
Convergence achieved after 8 iterations
Structural VAR is just-identified

Model: Ae = Bu where E[uu']=I
Restriction Type: short-run text form
@e1 = C(1)*@u1
@e2 = C(2)*@e1 + C(3)*@u2
@e3 = C(4)*@e1 + C(5)*@e2 + C(6)*@u3
@e4 = C(7)*@e1 + C(8)*@e2 + C(9)*@e3 + C(10)*@u4
@e5 = C(11)*@e1 + C(12)*@e2 + C(13)*@e3 + C(14)*@e4 +C(15)*@u5
where
@e1 represents L_IP_SA residuals
@e2 represents L_CPI residuals
@e3 represents IR_CBB residuals
@e4 represents L_ER residuals
@e5 represents L_LOAN residuals

	Coefficient	Std. Error	z-Statistic	Prob.
C(2)	0.020423	0.010280	1.986646	0.0470
C(4)	-0.012771	0.010761	-1.186872	0.2353
C(5)	0.039459	0.085769	0.460067	0.6455
C(7)	-0.008908	0.011337	-0.785711	0.4320
C(8)	-0.059429	0.089996	-0.660352	0.5090
C(9)	-0.143864	0.087074	-1.652202	0.0985
C(11)	0.004246	0.029839	0.142294	0.8868
C(12)	0.083546	0.236716	0.352938	0.7241
C(13)	0.115267	0.230831	0.499355	0.6175
C(14)	-0.071145	0.218107	-0.326192	0.7443
C(1)	0.123182	0.007233	17.02939	0.0000
C(3)	0.015248	0.000895	17.02939	0.0000
C(6)	0.015748	0.000925	17.02939	0.0000
C(10)	0.016512	0.000970	17.02939	0.0000
C(15)	0.043367	0.002547	17.02939	0.0000
Log likelihood	1533.432			

Estimated A matrix:

1.000000	0.000000	0.000000	0.000000	0.000000
-0.020423	1.000000	0.000000	0.000000	0.000000
0.012771	-0.039459	1.000000	0.000000	0.000000
0.008908	0.059429	0.143864	1.000000	0.000000
-0.004246	-0.083546	-0.115267	0.071145	1.000000

Estimated B matrix:

0.123182	0.000000	0.000000	0.000000	0.000000
0.000000	0.015248	0.000000	0.000000	0.000000
0.000000	0.000000	0.015748	0.000000	0.000000
0.000000	0.000000	0.000000	0.016512	0.000000
0.000000	0.000000	0.000000	0.000000	0.043367

A.2.4: Estimation of contemporaneous coefficients: Financial SVAR model with stock market index

Structural VAR Estimates
Sample (adjusted): 1998M03 2011M12
Included observations: 166 after adjustments
Estimation method: method of scoring (analytic derivatives)
Convergence achieved after 8 iterations
Structural VAR is just-identified

Model: Ae = Bu where E[uu']=I
Restriction Type: short-run text form
@e1 = C(1)*@u1
@e2 = C(2)*@e1 + C(3)*@u2
@e3 = C(4)*@e1 + C(5)*@e2 + C(6)*@u3
@e4 = C(7)*@e1 + C(8)*@e2 + C(9)*@e3 + C(10)*@u4
@e5 = C(11)*@e1 + C(12)*@e2 + C(13)*@e3 + C(14)*@e4 +C(15)*@u5
where
@e1 represents L_IP_SA residuals
@e2 represents L_CPI residuals
@e3 represents IR_CBB residuals
@e4 represents L_ER residuals
@e5 represents L_TOP20 residuals

	Coefficient	Std. Error	z-Statistic	Prob.
C(2)	0.019564	0.009946	1.966901	0.0492
C(4)	-0.015643	0.012282	-1.273675	0.2028
C(5)	-0.104554	0.094741	-1.103573	0.2698
C(7)	0.003201	0.010217	0.313329	0.7540
C(8)	-0.096062	0.078716	-1.220361	0.2223
C(9)	-0.087507	0.064251	-1.361952	0.1732
C(11)	-0.048201	0.063606	-0.757812	0.4486
C(12)	-0.043403	0.492108	-0.088198	0.9297
C(13)	-1.148347	0.402118	-2.855744	0.0043
C(14)	-0.180660	0.483065	-0.373988	0.7084
C(1)	0.124736	0.006846	18.22087	0.0000
C(3)	0.015985	0.000877	18.22087	0.0000
C(6)	0.019512	0.001071	18.22087	0.0000
C(10)	0.016153	0.000886	18.22087	0.0000
C(15)	0.100531	0.005517	18.22087	0.0000
Log likelihood	1574.117			

Estimated A matrix:

1.000000	0.000000	0.000000	0.000000	0.000000
-0.019564	1.000000	0.000000	0.000000	0.000000
0.015643	0.104554	1.000000	0.000000	0.000000
-0.003201	0.096062	0.087507	1.000000	0.000000
0.048201	0.043403	1.148347	0.180660	1.000000

Estimated B matrix:

0.124736	0.000000	0.000000	0.000000	0.000000
0.000000	0.015985	0.000000	0.000000	0.000000
0.000000	0.000000	0.019512	0.000000	0.000000
0.000000	0.000000	0.000000	0.016153	0.000000
0.000000	0.000000	0.000000	0.000000	0.100531

A.2.5: Estimation of contemporaneous coefficients: Financial SVAR model with market capitalization

Structural VAR Estimates
Sample (adjusted): 1998M06 2011M12
Included observations: 163 after adjustments
Estimation method: method of scoring (analytic derivatives)
Convergence achieved after 8 iterations
Structural VAR is just-identified

Model: Ae = Bu where E[uu']=I
Restriction Type: short-run text form
@e1 = C(1)*@u1
@e2 = C(2)*@e1 + C(3)*@u2
@e3 = C(4)*@e1 + C(5)*@e2 + C(6)*@u3
@e4 = C(7)*@e1 + C(8)*@e2 + C(9)*@e3 + C(10)*@u4
@e5 = C(11)*@e1 + C(12)*@e2 + C(13)*@e3 + C(14)*@e4 +C(15)*@u5
where
@e1 represents L_IP_SA residuals
@e2 represents L_CPI residuals
@e3 represents IR_CBB residuals
@e4 represents L_ER residuals
@e5 represents L_MRK_CPT residuals

	Coefficient	Std. Error	z-Statistic	Prob.
C(2)	0.017432	0.009609	1.814101	0.0697
C(4)	-0.014317	0.012095	-1.183705	0.2365
C(5)	-0.095269	0.097609	-0.976036	0.3290
C(7)	-0.002306	0.010367	-0.222467	0.8240
C(8)	-0.043865	0.083550	-0.525014	0.5996
C(9)	-0.142495	0.066850	-2.131566	0.0330
C(11)	0.034454	0.079097	0.435595	0.6631
C(12)	-0.959390	0.637897	-1.503988	0.1326
C(13)	0.373184	0.517020	0.721798	0.4704
C(14)	0.327389	0.597505	0.547927	0.5837
C(1)	0.126725	0.007019	18.05547	0.0000
C(3)	0.015547	0.000861	18.05547	0.0000
C(6)	0.019374	0.001073	18.05547	0.0000
C(10)	0.016536	0.000916	18.05547	0.0000
C(15)	0.126140	0.006986	18.05547	0.0000
Log likelihood	1507.972			

Estimated A matrix:

1.000000	0.000000	0.000000	0.000000	0.000000
-0.017432	1.000000	0.000000	0.000000	0.000000
0.014317	0.095269	1.000000	0.000000	0.000000
0.002306	0.043865	0.142495	1.000000	0.000000
-0.034454	0.959390	-0.373184	-0.327389	1.000000

Estimated B matrix:

0.126725	0.000000	0.000000	0.000000	0.000000
0.000000	0.015547	0.000000	0.000000	0.000000
0.000000	0.000000	0.019374	0.000000	0.000000
0.000000	0.000000	0.000000	0.016536	0.000000
0.000000	0.000000	0.000000	0.000000	0.126140

Appendix 3 – Coefficients estimations of SSMM

A.3.1: Estimation of coefficients: Core SSM Model

a. IS curve equation

Dependent Variable: GAP
Method: Least Squares
Sample: 2001Q1 2011Q4
Included observations: 44
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)
GAP=C(2)*GAP(-1)+C(3)*LR(-2)+C(4)*CHI_IND(-2)

	Coefficient	Std. Error	t-Statistic	Prob.
C(2)	0.383915	0.108772	3.529547	0.0010
C(3)	-0.096419	0.056613	-1.703139	0.0961
C(4)	0.175726	0.107573	1.633551	0.1100

R-squared	0.247109	Mean dependent var	-0.001339
Adjusted R-squared	0.210382	S.D. dependent var	0.038245
S.E. of regression	0.033985	Akaike info criterion	-3.860078
Sum squared resid	0.047353	Schwarz criterion	-3.738429
Log likelihood	87.92172	Hannan-Quinn criter.	-3.814965
Durbin-Watson stat	1.735909		

b. Phillips curve equation

Dependent Variable: AINF
Method: Least Squares
Sample (adjusted): 1999Q3 2011Q4
Included observations: 50 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)
AINF=C(2)*AINF(-1)+C(3)*GAP(-1)+C(4)*D4L_M2(-2)+C(5)*D(ER_MEAN_L(-4))+C(6)*D(P_OIL_L(-2))+C(7)*(W_FOOD_L-W_FOOD_L(-4))

	Coefficient	Std. Error	t-Statistic	Prob.
C(2)	0.783466	0.069065	11.34382	0.0000
C(3)	0.245109	0.133160	1.840707	0.0724
C(4)	0.029515	0.020802	1.418847	0.1630
C(5)	0.226815	0.064295	3.527713	0.0010
C(6)	0.054429	0.022821	2.385087	0.0214
C(7)	0.090031	0.036379	2.474778	0.0173

R-squared	0.743003	Mean dependent var	0.086928
Adjusted R-squared	0.713798	S.D. dependent var	0.063000
S.E. of regression	0.033704	Akaike info criterion	-3.830259
Sum squared resid	0.049981	Schwarz criterion	-3.600816
Log likelihood	101.7565	Hannan-Quinn criter.	-3.742885
Durbin-Watson stat	2.238789		

c. Exchange rate equation

Dependent Variable: ER_MEAN_L
Method: Least Squares
Sample (adjusted): 1999Q3 2009Q4
Included observations: 42 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)
ER_MEAN_L=C(1)+C(2)*ER_MEAN_L(-1)+C(3)*I(-3)+C(4)*SEAS2+C(5)*AINF(-2)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.759310	0.388273	1.955605	0.0581
C(2)	0.889271	0.056146	15.83867	0.0000
C(3)	0.139042	0.069648	1.996363	0.0533
C(4)	-0.028169	0.009314	-3.024414	0.0045
C(5)	0.246147	0.147692	1.666624	0.1040

R-squared	0.854154	Mean dependent var	7.060096
Adjusted R-squared	0.838387	S.D. dependent var	0.083937
S.E. of regression	0.033744	Akaike info criterion	-3.828698
Sum squared resid	0.042130	Schwarz criterion	-3.621833
Log likelihood	85.40266	Hannan-Quinn criter.	-3.752874
F-statistic	54.17306	Durbin-Watson stat	2.331400
Prob(F-statistic)	0.000000		

d. Policy rate equation

Dependent Variable: I
Method: Least Squares
Sample: 2001Q1 2011Q4
Included observations: 44
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)
I=C(1)+C(2)*I(-1)+C(3)*GAP(-1)+C(4)*AINF(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.040333	0.018493	2.181034	0.0351
C(2)	0.565878	0.169653	3.335503	0.0018
C(3)	0.212027	0.094665	2.239751	0.0307
C(4)	0.073399	0.050153	1.463518	0.1511

R-squared	0.447410	Mean dependent var	0.105193
Adjusted R-squared	0.405965	S.D. dependent var	0.034896
S.E. of regression	0.026895	Akaike info criterion	-4.307210
Sum squared resid	0.028935	Schwarz criterion	-4.145011
Log likelihood	98.75861	Hannan-Quinn criter.	-4.247058
F-statistic	10.79545	Durbin-Watson stat	2.128119
Prob(F-statistic)	0.000025		

e. Interest rate equation (statistical equation as a connection of monetary transmission)

Dependent Variable: D(LR)
Method: Least Squares
Sample: 2002Q1 2011Q4
Included observations: 40
Convergence achieved after 4 iterations
D(LR)=C(2)*(LR(-1)+C(4)*I(-1))+C(3)*D(LR(-1))+C(5)*QINF(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(2)	-0.077968	0.022016	-3.541380	0.0011
C(4)	-1.284840	0.407949	-3.149512	0.0033
C(3)	-0.314880	0.129010	-2.440734	0.0197
C(5)	0.088372	0.062595	1.411808	0.1666

R-squared	0.280955	Mean dependent var	-0.006475
Adjusted R-squared	0.221035	S.D. dependent var	0.017117
S.E. of regression	0.015107	Akaike info criterion	-5.452693
Sum squared resid	0.008216	Schwarz criterion	-5.283805
Log likelihood	113.0539	Hannan-Quinn criter.	-5.391628
Durbin-Watson stat	2.240619		

A.3.2: Estimation of coefficients: Financial SSM Model

a. IS curve equation

Dependent Variable: GAP
Method: Least Squares
Sample: 2001Q1 2011Q4
Included observations: 44
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)
GAP=C(2)*GAP(-1)+C(3)*LR(-2)+0*D4L_P_COP(-1)+C(5)*LOAN_G(-1) +C(6)*D4L_MRK_CPT(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(2)	0.246798	0.088020	2.803886	0.0078
C(3)	-0.116338	0.026779	-4.344427	0.0001
C(5)	0.047365	0.015281	3.099518	0.0035
C(6)	0.020538	0.004831	4.251241	0.0001

R-squared	0.437126	Mean dependent var	-0.001339
Adjusted R-squared	0.394911	S.D. dependent var	0.038245
S.E. of regression	0.029750	Akaike info criterion	-4.105489
Sum squared resid	0.035402	Schwarz criterion	-3.943290
Log likelihood	94.32075	Hannan-Quinn criter.	-4.045338
Durbin-Watson stat	1.985854		

b. Phillips curve equation

Dependent Variable: AINF
Method: Least Squares
Sample (adjusted): 1999Q3 2011Q4
Included observations: 50 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)
AINF=C(2)*AINF(-1)+C(3)*GAP(-1)+C(4)*D4L_M2(-2)+C(5)*D(ER_MEAN_L(-4))+C(6)*D(P_OIL_L(-2))+C(7)*(W_FOOD_L-W_FOOD_L(-4))

	Coefficient	Std. Error	t-Statistic	Prob.
C(2)	0.783466	0.069065	11.34382	0.0000
C(3)	0.245109	0.133160	1.840707	0.0724
C(4)	0.029515	0.020802	1.418847	0.1630
C(5)	0.226815	0.064295	3.527713	0.0010
C(6)	0.054429	0.022821	2.385087	0.0214
C(7)	0.090031	0.036379	2.474778	0.0173

R-squared	0.743003	Mean dependent var	0.086928
Adjusted R-squared	0.713798	S.D. dependent var	0.063000
S.E. of regression	0.033704	Akaike info criterion	-3.830259
Sum squared resid	0.049981	Schwarz criterion	-3.600816
Log likelihood	101.7565	Hannan-Quinn criter.	-3.742885
Durbin-Watson stat	2.238789		

c. Exchange rate equation

Dependent Variable: ER_MEAN_L
Method: Least Squares
Sample (adjusted): 2000Q3 2011Q4
Included observations: 46 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)
ER_MEAN_L=C(1)+C(2)*ER_MEAN_L(-1)+C(3)*I(-3)+C(4)*SEAS2+C(5)*AINF(-2)+C(6)*LO_PROV(-3)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.756479	0.444086	1.703453	0.0962
C(2)	0.888459	0.064629	13.74705	0.0000
C(3)	0.344796	0.164291	2.098689	0.0422
C(4)	-0.024950	0.009192	-2.714374	0.0098
C(5)	0.171591	0.118963	1.442383	0.1570
C(6)	-0.919298	0.812341	-1.131665	0.2645

R-squared	0.861115	Mean dependent var	7.089313
Adjusted R-squared	0.843755	S.D. dependent var	0.086424
S.E. of regression	0.034162	Akaike info criterion	-3.794322
Sum squared resid	0.046681	Schwarz criterion	-3.555804
Log likelihood	93.26941	Hannan-Quinn criter.	-3.704972
F-statistic	49.60170	Durbin-Watson stat	2.183913
Prob(F-statistic)	0.000000		

d. Policy rate equation

Dependent Variable: I
Method: Least Squares
Sample: 2001Q1 2011Q4
Included observations: 44
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)
I=C(1)+C(2)*I(-1)+C(3)*GAP(-1)+C(4)*AINF(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.040333	0.018493	2.181034	0.0351
C(2)	0.565878	0.169653	3.335503	0.0018
C(3)	0.212027	0.094665	2.239751	0.0307
C(4)	0.073399	0.050153	1.463518	0.1511

R-squared	0.447410	Mean dependent var	0.105193
Adjusted R-squared	0.405965	S.D. dependent var	0.034896
S.E. of regression	0.026895	Akaike info criterion	-4.307210
Sum squared resid	0.028935	Schwarz criterion	-4.145011
Log likelihood	98.75861	Hannan-Quinn criter.	-4.247058
F-statistic	10.79545	Durbin-Watson stat	2.128119
Prob(F-statistic)	0.000025		

e. Interest rate equation (statistical equation as a connection of monetary transmission)

Dependent Variable: D(LR)
Method: Least Squares
Date: 03/27/12 Time: 00:12
Sample: 2002Q1 2011Q4
Included observations: 40
Convergence achieved after 3 iterations
D(LR)=C(2)*(LR(-1)+C(4)*I(-1))+C(3)*D(LR(-1))+C(5)*QINF(-1)+C(6)*D4L_TOP_20(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(2)	-0.072224	0.021811	-3.311354	0.0022
C(4)	-1.269947	0.433327	-2.930690	0.0059
C(3)	-0.358905	0.128986	-2.782514	0.0086
C(5)	0.126685	0.065549	1.932680	0.0614
C(6)	-0.005964	0.003656	-1.631538	0.1117

R-squared	0.331777	Mean dependent var	-0.006475
Adjusted R-squared	0.255408	S.D. dependent var	0.017117
S.E. of regression	0.014770	Akaike info criterion	-5.475994
Sum squared resid	0.007635	Schwarz criterion	-5.264884
Log likelihood	114.5199	Hannan-Quinn criter.	-5.399664
Durbin-Watson stat	2.325558		

f. LM curve equation

Dependent Variable: D4L_M2
Method: Least Squares
Sample: 2000Q1 2011Q4
Included observations: 48
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)
D4L_M2=C(1)+C(2)*GAP(-1)+C(3)*I(-1)+C(4)*D4L_M2(-1)+C(5)*DLOG(ER_MEAN(-1))+C(6)*SHR_NPLOAN(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.140804	0.031490	4.471403	0.0001
C(2)	-0.834157	0.261729	-3.187097	0.0027
C(3)	-0.784798	0.275753	-2.846014	0.0068
C(4)	0.752343	0.061368	12.25957	0.0000
C(5)	-0.384825	0.113876	-3.379338	0.0016
C(6)	0.153442	0.080504	1.906020	0.0635

R-squared	0.810688	Mean dependent var	0.285475
Adjusted R-squared	0.788151	S.D. dependent var	0.128626
S.E. of regression	0.059203	Akaike info criterion	-2.699222
Sum squared resid	0.147210	Schwarz criterion	-2.465322
Log likelihood	70.78134	Hannan-Quinn criter.	-2.610831
F-statistic	35.97121	Durbin-Watson stat	2.317531
Prob(F-statistic)	0.000000		

g. Stock market index equation

Dependent Variable: L_TOP_20
Method: Least Squares
Sample (adjusted): 1999Q1 2011Q4
Included observations: 52 after adjustments
(L_TOP_20)=C(1)*(L_TOP_20(-1))+0*L_TOP_20(-2)+C(3)*M2_L(-1)+C(4)*D(ER_MEAN_L(-1))+C(5)*AINF+C(6)*DUM0703

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.954717	0.031267	30.53410	0.0000
C(3)	0.035908	0.016751	2.143636	0.0373
C(4)	-1.564082	0.671488	-2.329277	0.0242
C(5)	-0.918666	0.452114	-2.031935	0.0478
C(6)	1.088325	0.191947	5.669938	0.0000

R-squared	0.983591	Mean dependent var	7.516869
Adjusted R-squared	0.982194	S.D. dependent var	1.418907
S.E. of regression	0.189337	Akaike info criterion	-0.399363
Sum squared resid	1.684883	Schwarz criterion	-0.211743
Log likelihood	15.38343	Hannan-Quinn criter.	-0.327434
Durbin-Watson stat	1.877842		

h. Stock market capitalization equation

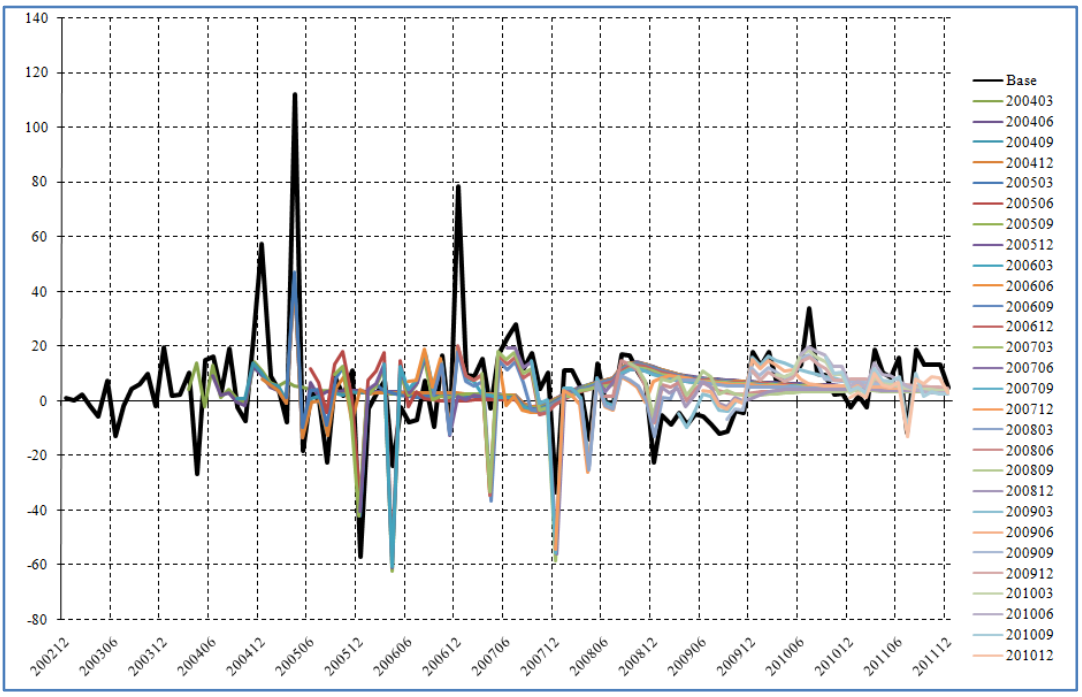
Dependent Variable: D4L_MRK_CPT
Method: Least Squares
Sample (adjusted): 2000Q1 2011Q4
Included observations: 48 after adjustments
D4L_MRK_CPT=C(2)*D4L_MRK_CPT(-1)+C(3)*DUM0703+0*GAP(-3)
+C(5)*D4L_M2(-1)+C(6)*D4L_TOP_20(-4)

	Coefficient	Std. Error	t-Statistic	Prob.
C(2)	0.792523	0.084132	9.420041	0.0000
C(3)	1.145058	0.295737	3.871877	0.0004
C(5)	0.359699	0.174132	2.065668	0.0448
C(6)	-0.203453	0.067339	-3.021309	0.0042

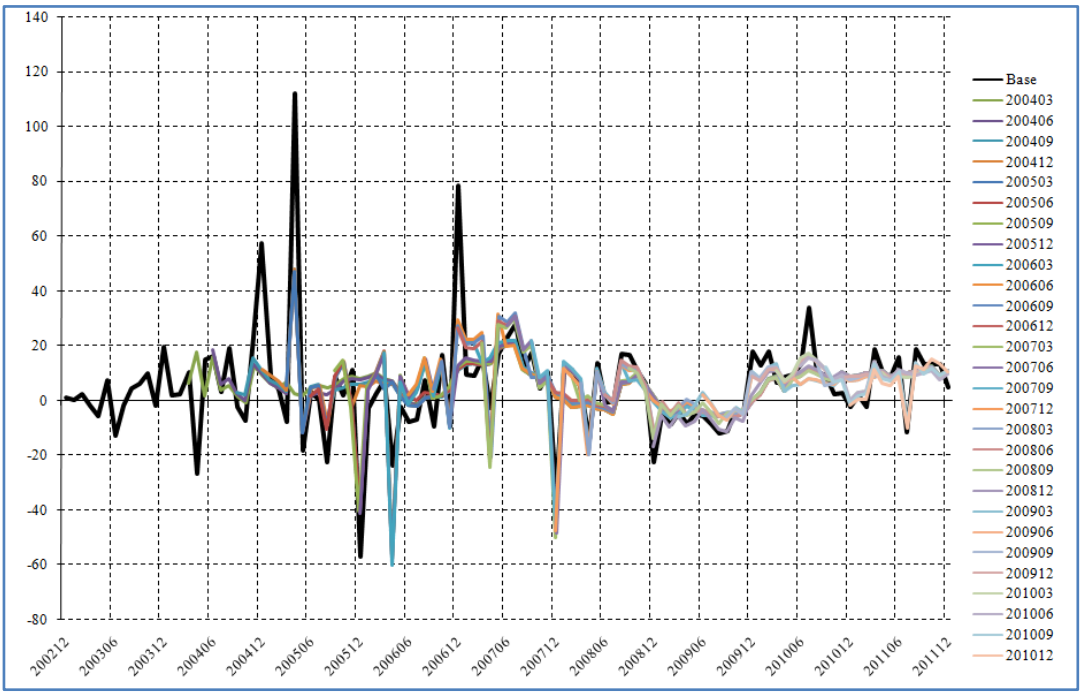
R-squared	0.775415	Mean dependent var	0.348163
Adjusted R-squared	0.760102	S.D. dependent var	0.587301
S.E. of regression	0.287656	Akaike info criterion	0.425552
Sum squared resid	3.640822	Schwarz criterion	0.581486
Log likelihood	-6.213251	Hannan-Quinn criter.	0.484480
Durbin-Watson stat	2.100493		

Appendix 4 – Forecasting Performances

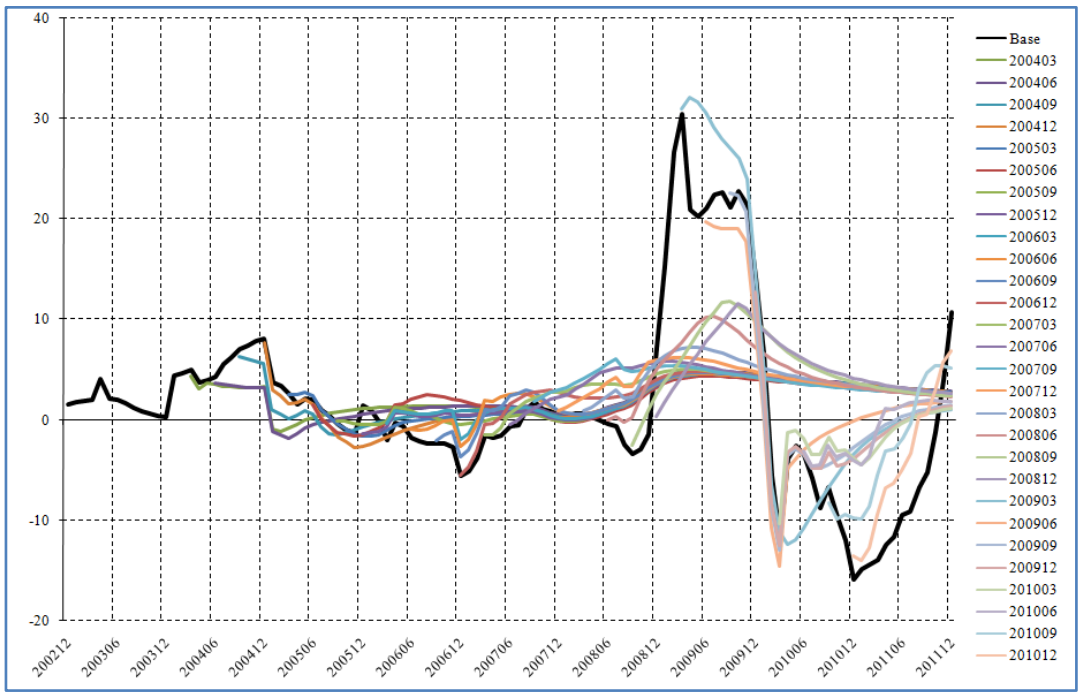
A.4.1: Forecasting performance of Real Economic Activity: Core SVAR



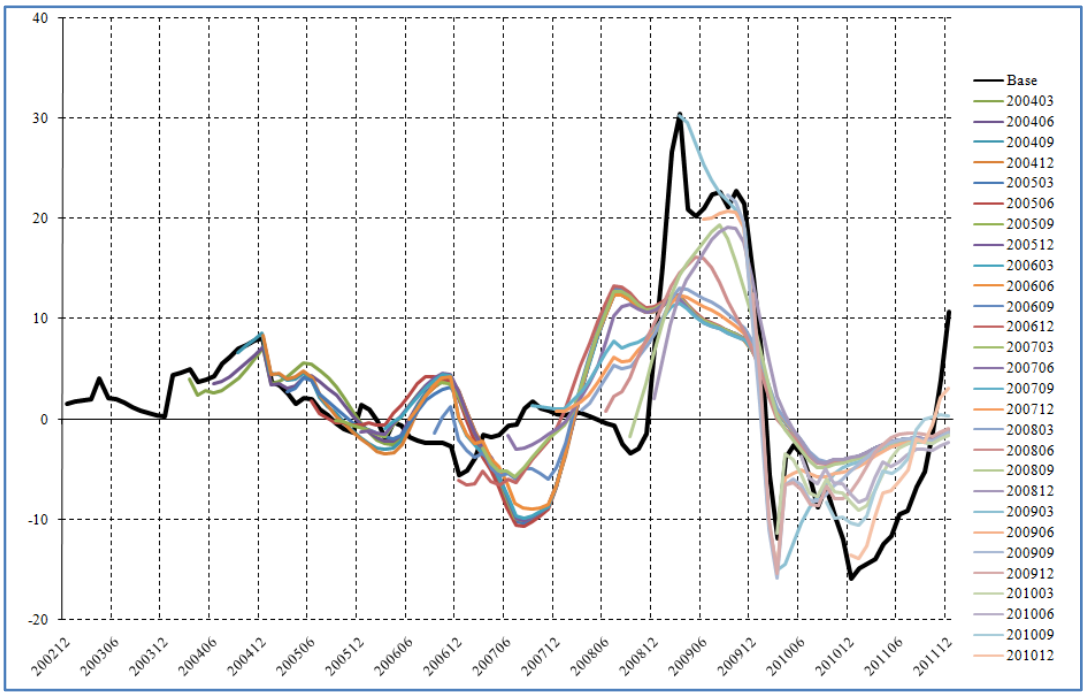
A.4.2: Forecasting performance of Real Economic Activity: Financial SVAR



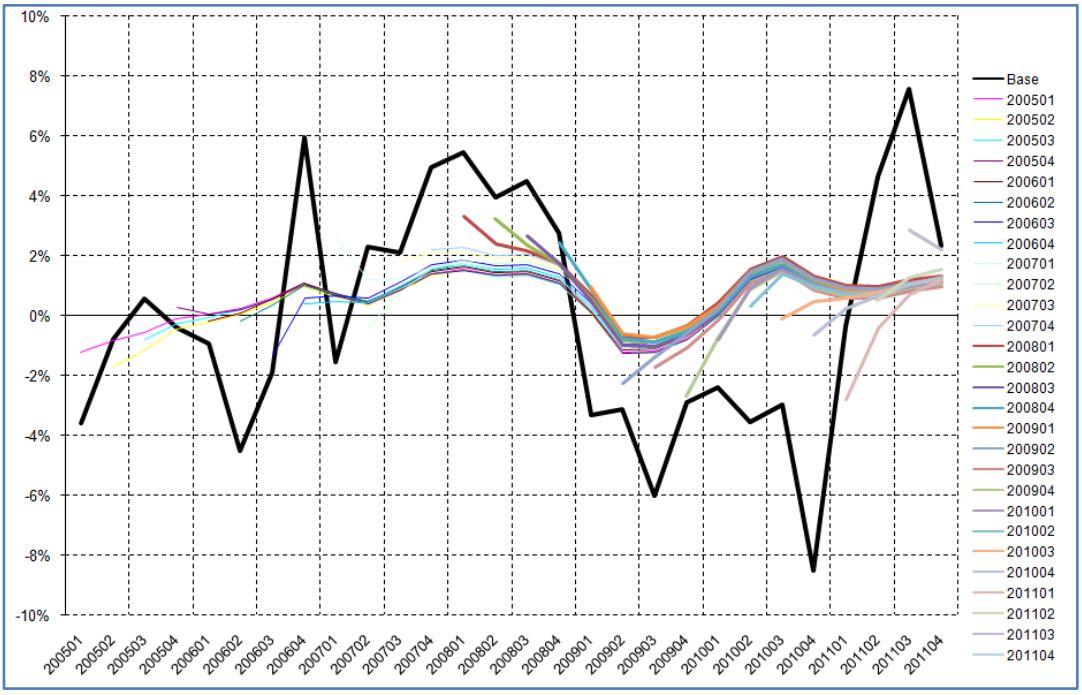
A.4.3: Forecasting performance of Exchange rate: Core SVAR



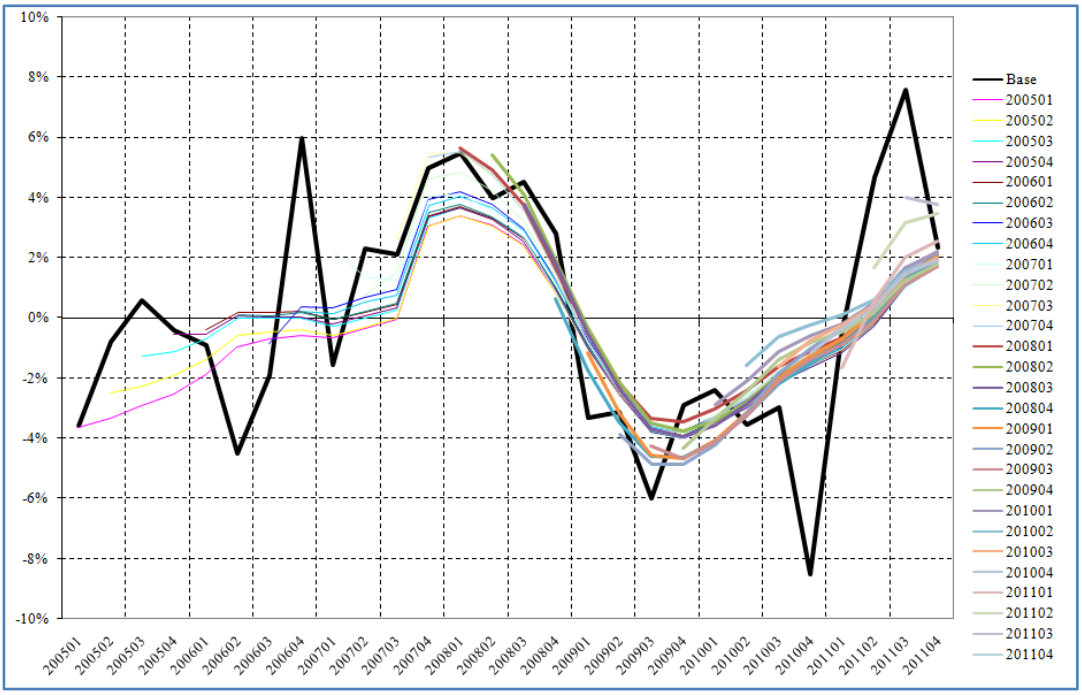
A.4.4: Forecasting performance of Exchange rate: Financial SVAR



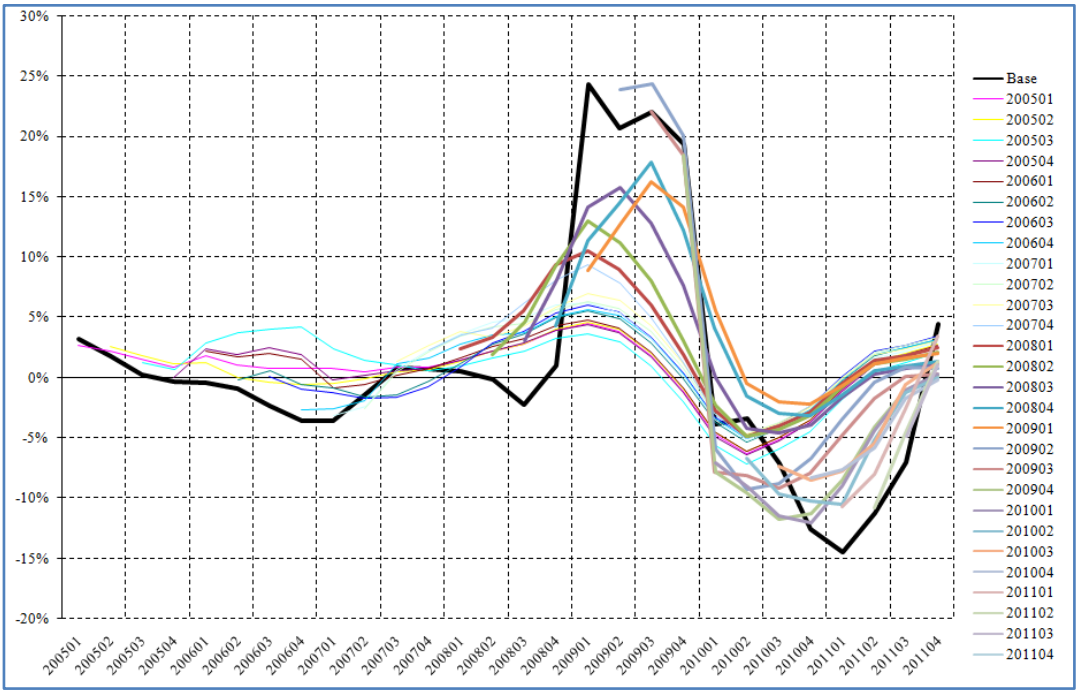
A.4.5: Forecasting performance of Output gap: Core SSMM



A.4.6: Forecasting performance of Output gap: Financial SSMM



A.4.7: Forecasting performance of Exchange rate: Core SSMM



A.4.8: Forecasting performance of Exchange rate: Financial SSMM