Abstract

In this dissertation, we are interested in the relationships among monetary policy, stock prices and exchange rates. This thesis argues that on the one hand, monetary policy affects both stock prices and the exchange rate, on the other hand, stock prices and exchange rates affect monetary policy as well as each other. Therefore, the relationships between these variables are reciprocal, and it is highly probable that a shock to one variable will affect the other variables. This paper takes into account the endogenous relationship among the above mentioned variables, the conditional variances and conditional cross covariances among these variables . We examine the simultaneous relationship between monetary policy and stock prices, and between monetary policy and the exchange rate by employing the Identification Through Heteroscedasticity (ITH) method. We also examine the dynamic relationships among monetary policy and the financial variables(stock prices and the exchange rate) and the dynamic relationships among the volatilities of shocks to monetary policy and financial variables using the Vector Error Correction Model (VECM) , Multivariate VAR (p), Multivariate-VARX (p) and Multivariate VAR (p)-GARCH (q, p) models.

Our findings indicate that monetary policy reacts to the fluctuations in the stock market and the exchange rate and that monetary policy has significant effects on the stock and exchange rate. We also find that there are strong spillover effects of shocks and volatilities across interest rates, stock prices and the exchange rate.

THE RELATIONSHIPS AMONG MONETARY POLICY, STOCK PRICES AND THE EXCHANGE RATE

BY

MEHMET IVRENDI

A DISSERTATION SUBMITTED TO THE GRADUATE FACULTY OF

NORTH CAROLINA STATE UNIVERSITY

IN PARTIAL FULFILLMENT OF THE

REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

DEPARTMENT OF ECONOMICS

RALEIGH

DECEMBER 2004

APPROVED BY:

_____   _____

_____   _____
CHAIR OF ADVISORY COMMITTEE

Biography

Mehmet Ivrendi was born in 1967 to Kemal and Fecriye Ivrendi, in Batman, Turkey. After he graduated from Batman High School, He attended Uludag University and graduated with a Bachelor's degree in Economics from that university. He got his masters degree in Economics from Old Dominion University (ODU) in 1997. After spending the next year at Nigde University in Turkey as a Research Assistant, he entered North Carolina State University (NCSU) in 1999 to begin the PhD program in Economics. Upon the receipt of his PhD, he will begin his career at Nigde University, Turkey as an Assistant Professor of Economics.

Acknowledgements

I would like to acknowledge the members of my committee Dr. Douglas K. Pearce, Dr. John S. Lapp, Dr. Atsushi Inoue and Dr. John F. Monahan. Their helpful comments and guidance are greatly appreciated. I feel privileged to be able to work with Dr. Pearce. Thank you Dr. Pearce for your many hours of input and suggestions. I can hardly imagine that I could have chosen any four better individuals to have for my dissertation committee. Thank you all.

I would like to thanks my parents, especially my father who always believed in me and encouraged me to pursue a higher education. Thank you dad forever.

Special thanks go to my family: my wife Asiye and my daughter Seva Bilgesu Ivrendi. Without their love, support and smiling faces, this accomplishment would not have been possible. Thanks to my lovely wife and my lovely baby.

Table of Contents

List of Tables

List of Figures

Chapter 1

A GENERAL INTRODUCTION

This dissertation analyzes the relationships among monetary policy, stock prices and exchange rates. This analysis is developed through three essays. The first essay focuses on the simultaneous relationship between monetary policy and stock prices. The second essay looks at the simultaneous relationship between monetary policy and the exchange rate. The third essay examines multivariate relationships among monetary policy, stock prices and the exchange rate.

There is an abundant literature that looks at the relationship between monetary policy and either the stock or exchange market. The literature on measuring the reaction of monetary policy to macro economic variables or vice versa has focused either on a single equation of monetary response, which is subject to the simultaneity problem, or the Vector Auto Regression (VAR) analysis, which is subject to the heteroscedasticity problem (macroeconomic data exhibit heteroscedasticity).

In the first two essays of the dissertation, we employ the Identification Through Heteroscedasticity (ITH) method to overcome the aforementioned two problems (simultaneity and heteroscedasticity).

A single equation is subject to the simultaneity problem because monetary policy affects macro economic variables and macro economic variables affect monetary policy. Therefore, a single equation that tries to capture the reaction of monetary policy to

macro variables has simultaneity bias. The ITH method allows us to use simultaneous equations to estimate the simultaneous relationship between two variables of interest if there is heteroscedasticity in the data. We employ the ITH method, developed by Rigobon and Sack(2003), to estimate the reaction of monetary policy to stock prices and the reaction of monetary policy to the exchange rate.

The VAR analysis is likely subject to the heteroscedasticity problem because it is well known that macro economic data exhibit heteroscedasticity. Typical VAR studies do not take the heteroscedasticity of the data into account. Since the ITH method uses the heteroscedasticity of the data to estimate the parameters of interest, it has an advantage over the VAR model in measuring the reaction of monetary policy to macroeconomic variables.

When we estimate the system of simultaneous relationships either between monetary policy and stock prices (first essay, in chapter two) or between monetary policy and the exchange rate (second essay, in chapter three), we include five macroeconomic shocks and five lags of endogenous variables in the structural simultaneous equations. Including macroeconomic shocks and lags of endogenous variables into structural equations makes the models more realistic and overcomes the problem of excluding relevant variables, and leads to unbiased estimates of the system.

The macroeconomic shocks that we employ are Consumer Price Index(CPI), Producer Price Index(PPI), Durable Good and Services(DRGS), Unemployment(UNEMP) and Retail Sale (RTLS) shocks. Each of these shocks is measured by the difference between the released value and the expected value based on Money Market Services survey data.

In all the models that we employ in this dissertation, we use the three month Treasury bill rate in the secondary market(tc3m) as an indicator of monetary policy, following Rigobon and Sack (2003). We reason that the three-month Treasury bill rate is a good indicator of monetary policy assuming economic agents in the financial markets have rational expectations: If in reality, monetary policy reacts to fluctuations in the financial markets, then the economic agents in the financial markets

2

would know this fact from their experience and/or knowledge and would expect that the FED would change the interest rate at the next FOMC meeting. This market expectation would affect the interest rate on the three-month Treasury bill rate in the secondary market even before the FED changed the interest rate. In other words, the market expectations of monetary policy show up in daily trading of three-month Treasury bills: changes in expectations about monetary policy affect the daily interest rate in the secondary market of three-month Treasury bill.

In this dissertation, we use monetary policy, stock prices and the exchange rate interchangeably with interest rate(or return), stock returns and exchange rate returns ,respectively.

In the first essay(chapter two), we set up a simultaneous equations system which consists of two equations. In this system, monetary policy and stock prices are endogenous while the above mentioned macroeconomic shocks and the lag of endogenous variables are exogenous. There are strong theoretical reasons that we employ simultaneous equations to capture the relationship between monetary policy and stock prices: the monetary economics literature provides at least three channels that allow asset prices to affect the monetary policy and at least four channels by which monetary variables or policy can affect asset prices. The channels by which asset prices affect the monetary policy are Balance-Sheet Channel, Consumption Channel and Tobin's marginal Q Theory. The channels through which information about the monetary policy can affect asset prices are the Expected Inflation Hypothesis, The Keynesian Hypothesis, Real Activity Hypothesis and Risk Premium Hypothesis. We discuss these channels in detail in the first essay.

In the second essay(chapter three), we analyze the relationship between monetary policy and the exchange rate by again employing the ITH method. The method and variables that we employ are the same as that of the first essay except various exchange rates are used instead of stock prices and regime changes are determined exogenously beside endogenously determined regime changes.

The theoretical reasons why we use simultaneous equations to estimate the reaction of monetary policy to the exchange rate are both direct and indirect. There are at least three direct reasons why central banks may react to fluctuations in the exchange rate:

1. Exchange rate misalignments or volatility can reduce international financial investment flows. This leads to foreign capital outflows.

2. Uncertainty in exchange rates deters Foreign Direct Investment(FDI), that is, foreign investor may not feel safe from buying or building new plants in a country that does not have a stable currency. This leads to inefficiency in the allocation of resources in the domestic and the world economies.

3. Exchange rate misalignments, uncertainty, or volatility may have a negative effect on international trade. Unstable exchange rates force economic agents to add more risk to the cost of goods that they trade abroad.

There are at least two indirect reasons why monetary policy may react to fluctuation in exchange rates. Even if monetary policy makers restrict themselves by reacting only to fluctuations in output and inflation, an appreciation of the domestic currency will have two effects on the economy:

1. It will lower real GDP by expenditure switching. The appreciation of the domestic currency makes foreign goods and services cheaper than domestic goods and services, which leads an increase in imports and a decrease in exports, therefore reducing real GDP.

2. It will lower domestic inflation because the price of imported goods will not increase as much due to the appreciation of domestic currency.

These direct and indirect effects of the exchange rate on the domestic economy force many central banks to be sensitive to changes in exchange rates.

On the one hand, based on the Uncovered Interest Parity or the Portfolio Balance arguments, higher interest rates (tightening of monetary policy) lead to capital inflows, and therefore, lead to an appreciation of the domestic currency. We can interpret this as a market reaction to monetary policy. Thus tighter monetary policy leads to an appreciation of the domestic currency. On the other hand, monetary policy may react to a depreciation of the domestic currency by increasing the interest rate and to an appreciation of the domestic currency by decreasing the interest rate. Thus an appreciation of the domestic currency would lead to an easing of monetary policy. These relationships are the reasons that we employ simultaneous equations to measure the relationship between monetary policy and exchange rates in the second essay.

As mentioned above, this dissertation examines the relationships among monetary policy, stock prices and exchange rates. There is an abundant literature that looks at the relationship between monetary policy and either the stock or exchange market i.e. bi-Variate relationships(see the literature reviews of the first and second essays of this dissertation). But, to the best of our knowledge, there is no study that looks at the relationships among these three macroeconomic variables i.e. a Tri-Variate relationship. In the third essay of this dissertation we study Tri-Variate relationships among monetary policy, stock prices and the exchange rate by employing the Vector Error Correction Method(VECM), Vector Autoregressive(VAR), Vector Autoregressive with exogenous variables(VARX) and Vector Autoregressive with Generalized Auotoregresive Conditional Heteroskedasticity (VAR-GARCH) methods.

The argument that we make is that monetary policy affects the stock market: when stock prices (as an index) go up, many academicians as well as the FED policy advisors think that it is the time to cool the economy, i.e. impose a contractionary monetary policy. And when stock prices go down, they think that it is time to heat up the economy, i.e. impose an expansionary monetary policy. We can observe similar but opposite arguments about the reaction of monetary policy to the exchange rate. The overvaluation of domestic currency negatively affects exports and increases

5

the quantity of imports of the domestic country leading to spending switching from domestic goods to imported goods and to rising unemployment. The monetary authorities that try to stabilize price and/or employment will react to such overvaluation of domestic currency by either using direct buying/selling foreign currency or using a monetary policy tool such as the short-term interest rate.

It is well known that the main goals of central banks are to control inflation and/or the output gap. Most central banks try to reach these goals by using monetary policy tools such as Open Market Operations (OMO) and rarely bank reserve requirement ratio. Central banks try to reach their goals by setting some intermediate target. The short-term interest rate is the most widely used as an intermediate target. In this scenario, the Central Banks will try to stabilize aggregate demand by tuning the short-term interest rate. The effects of the short-term interest rate on aggregate demand are through two channels:

- Direct Channel Effect: Interest rate affects aggregate demand by affecting investment and consumption in an economy. Lowering the short term interest rate stimulates investment and consumption while raising the short-term interest rate has a reverse effect.

- Indirect Effect Channel: Short-term interest rate affects aggregate demand indirectly by affecting stock (equity) prices and the exchange rate. On the one hand, a high interest rate reduces the expected return from stock, i.e. lowers the present value of stocks (See the first essay of the dissertation), therefore, this high interest rate has a negative wealth effect on aggregate demand. On the other hand, a high interest rate attracts foreign capital into the domestic market, leading to higher demand for the domestic currency and this in turn appreciates the domestic currency. Appreciation of the domestic currency affects the exports and imports of the domestic country as well as expenditure switching from domestic goods to import goods.

6

The above mentioned indirect effects of monetary policy are based on the ideas that stock prices affect private consumption (wealth effect) and corporate investment (Tobin's Q- theory of investment), and that the exchange rate affect the exports and imports. These two effects of monetary policy together or individually affect aggregate demand.

Therefore, financial asset prices (or volatility) such as stock prices and exchange rates are very important parts of the monetary transmission mechanism. When a Central Bank reacts to an aggregate demand shock by fine tuning the short term interest rate, monetary policy will not only affect the real markets such as consumption and investment but also affect financial markets such as stock and exchange markets. Therefore, monetary policy makers need to take the effect of monetary policy on the stock and exchange markets into account before they adjust the interest rate to control aggregate demand, because stock prices and the exchange rate also affect aggregate demand.

The basic motivation for this third essay (fourth chapter of the dissertation) comes from the findings of the first and second essays (second and third chapter of the dissertation) in which we observe the following relationships:

- When we allow regime changes based on high and low variances of interest and stock market shocks, we find that in the high variance regimes, the covariance between interest rate shocks and stock market shocks is very high and vice versa when the variances are low.
- We observe the same relationship between interest rate shocks and exchange rate shocks in the second essay of this dissertation.

That is, we find that there is a strong covariance between interest rate shocks and stock market shocks as well as a strong covariance between interest rate shocks and exchange rate shocks.

These findings initially suggest we set up a multivariate ARCH or GARCH model to take the cross volatility of markets into account. Theoretically, we expect an

endogenous and lagged relationship between the conditional mean returns of interest rates, stock prices and the exchange rate. This would ultimately suggest we set up a simultaneous or a multivariate VAR model. In the empirical part, we employ various models based on these suggestions and compare the estimates of the models.

There is a lack of literature on the effect of monetary policy on both stock and exchange market simultaneously and likewise their effect on monetary policy. This is another motivation for this study. As Bauwens, Laurent and Rombouts (2003) stated, "... it is now widely accepted that financial volatilities move together over time across assets and markets." Based on this reality, a multi-variate modelling framework to capture the mean and volatility in a market or across markets may perform better than separate univariate models. From an economist or policy maker point of view, multivariate modelling draws a clearer picture for making decisions about how to use economic tools either for stabilizing aggregate demand or for knowing what would be the effect of monetary policy on the markets.

In the third essay (chapter four) of the dissertation, we examine three relationships:

1. Cross market influences on the returns to debt, equity and foreign exchange

2. Volatilities of these returns

3. Cross market influences in the volatility of these returns.

We are interested in the following:

1. Modelling lag/lead relationships among the returns of debt, equity and foreign currency ;

2. How rapidly an innovation originating in one of the markets is transmitted to the other markets

3. How the volatility of the innovations is transmitted to the other markets

The dissertation is organized as follows. The first essay(chapter two) discusses the relationship between monetary policy and stock market and introduces the ITH estimation and the bootstrap technique to get the asymptotic properties of the estimation method. The second essay(chapter three) analyzes the relationship between monetary policy and various exchange rates. Third essay(chapter four) hypothesizes and estimates the relationships among monetary policy, stock and exchange returns by employing various Multivariate models. Chapter five summarizes and concludes the dissertation.

Chapter 2

THE REACTION OF MONETARY POLICY TO THE STOCK MARKET

Abstract

In this essay we analyze the simultaneous relationship between monetary policy and stock prices by employing the Identification Through Heteroscedasticity (ITH) method. There are two big advantages of this method: First, it solves the heteroscedasticity problem that exists in most macroeconomic data. Second, it allows the use of a simultaneous relationship between variables in a bi-variate system to estimate the parameters of interest. We use the heteroscedasticity of the data to determine regime changes and use regime changes to estimate the reaction of monetary policy to stock prices.

2.0.1 Introduction

The effect of asset/stock booms and busts on the economy is well documented and well understood. There is a consensus that asset booms and busts can cause significant damage to the economy. There is no consensus, however, for the reason and direction of the relationship, or even if there is a relationship, between asset market fluctuations and monetary variables (or policy). There are at least three channels that allow the asset market to affect the economy and at least four channels by which monetary variables or policy can affect asset prices. The channels by which asset prices affect the economy are as follows:

1. Balance-Sheet Channel: A change in asset prices alters the borrowing capacity of firms and households by changing the value of collateral. An increase in asset prices creates additional available credit that can be used to purchase goods and services thereby stimulating the economy. The share of loans secured by real estate collateral is 66% in the USA, more than 61% in Sweden and 59% in UK (Goodhart & Hoffman, forthcoming p.6). These numbers in and of themselves show the importance of the balance sheet on the economy: an increase in asset prices creates available credit that can be used to stimulate the economy. That means an increase in stock prices reduces credit rationing problems, which in turn increases economic activity.

2. Consumption Channel: Changes in stock prices affect consumption spending via their effect on household wealth. Goodhart and Hoffman (forthcoming) estimate that the rate of private sector wealth held in equity to private sector wealth in property is 45% in the US, 52% in the UK and 45% in Japan. This estimate shows how changes in equity prices may affect consumption and thus the economy.

3. Tobin's Marginal Q - Theory: The value of a firm is the sum of the present value of sales of good services and services, and the value of capital stock. The

theory emphasizes that an investment decision is based on the following ratio

$$[(P_t y_k + P_t^I(1 - \delta))/(1 + r)]/P_{t-1}^I = 1 \qquad (2.1)$$

where

- $P_t y_k$ = the increase in sale of goods and services that the firm provides to markets (y_k is marginal productivity of capital).
- $P_t^I(1 - \delta$ = the increase in the value of firm's stock.
- P_{t-1}^I = the cost of acquiring an increment to the capital stock in period t-1.

If the LHS (Left Hand Side) of the equation (1) is bigger than one, then the firm will be better off by investing, and disinvesting if the LHS is smaller than 1. The economy is in equilibrium when the LHS of eq.(1) is equal to 1. An increase in the stock prices, $P_t^I(1 - \delta)$, makes the LHS bigger than 1 and therefore it increases investment and economic growth.

Cornell (1983) summarized four channels through which information about the money stock can affect asset prices. He starts by introducing the Fisher Equation

$$i_t = E_t(r_{t+1}|I_t) + E_t(\Pi_{t+1}|I_{t+1}) \qquad (2.2)$$

which states that the nominal interest rate equals the expected real interest rate plus expected inflation. In the Fisher equation, a money supply announcement affects the interest rate by changing the information set of economic agents and thereby their expectations. Cornell discusses four hypotheses that explain how money supply announcements affect the asset prices. Those hypotheses are as follows:

1. The Expected Inflation Hypothesis. According to this hypothesis, the announcement of an unanticipated increase in the money supply leads to an increase in expected inflation, which then causes an increase in the short-term interest rate, and an announcement of an unanticipated drop in the money

supply leads to a drop in expected inflation and thereby the interest rate. This hypothesis predicts that the response of stock prices to an unexpected increase in money supply depends on the role of taxes, nominal contracts by firms, and other market imperfections: If all markets are perfect and if there are no taxes, then changes in expected inflation will have little impact on stock prices because under these conditions anticipated cash flows and the discount rate will be adjusted by offsetting amounts. However, if there are taxes and if markets are imperfect, or there is money illusion in the market, then unanticipated increases in the money supply will have a significantly negative effect on stock prices.

2. The Keynesian Hypothesis. The relationship between money and asset prices is through the expected real rate. This link is based on an assumption that actual innovations in money affect the ex ante real rate. The Keynesian liquidity preference model with sticky prices can explain the channel. The money demand function is:

$$M/P = f(Y, i) \tag{2.3}$$

Since prices do not respond instantaneously to a monetary shock, the interest rate must adjust to clear the money market. A sudden increase in money supply causes real money balances to rise. Since prices are sticky and income constant in the short-run, the interest rate must fall to produce an offsetting increase in money demand. In the Keynesian approach, since actual changes in money affect the ex-ante real rate, announced changes have an impact if economic agents alter their expectations about Fed policy: an unexpected increase in the money stock is considered an indicator that the Fed will need to tighten credit to offset the rise. An increase in the ex-ante real rate leads to lower stock prices for two reasons:

(a) -The discount rate rises to adjust with the market real rate.

(b) Since agents expect that a high interest rate will depress economic activity, expected cash flows will decrease and thereby stock prices.

3. Real Activity Hypothesis. This hypothesis emphasizes that a money supply announcement provides information about future money demand. Money demand depends on both current output and expected future output. An unanticipated increase in the money stock means that money demand is greater than expected. Therefore, the unanticipated increase in money stock leads to higher expected future output. The real rate must rise to clear the market, and since a higher announcement in money stock leads to higher expected economic activity, it also increases stock prices. This argument is opposite to both the expected inflation and Keynesian arguments: This hypothesis foresees a positive relationship between unanticipated increases in the money supply and stock prices while the other two foresee a negative relationship between unanticipated increases in the money supply and stock prices .

4. Risk Premium Hypothesis. This hypothesis makes a connection between an increase in unanticipated money supply, risk and risk aversion. The money demand function is:

$$M/P = f(Y, i, \theta) \quad and \quad df/d\theta > 0 \tag{2.4}$$

where θ is a parameter which depends on aggregate risk aversion and aggregate expected future security returns .The announcements of an expected increase in the money stock is an indicator of either an increase in aggregate risk aversion or an increase in the risk of financial assets. In either case, the announcement of an unanticipated increase in the money stock leads to a rise in required returns on assets and hence asset prices fall. Since money is considered a more risk-free asset under this condition, the real interest rate also rises. Also the increase in money demand stemmed from an increase in θ raises the real interest rate.

Whenever asset booms and busts occur in the stock market, both monetarists and financial economists face the same question. What should, will or must the central bank do to offset the stock market? This issue is discussed in the next section.

2.0.2 Theoretical Arguments on Monetary Policy and Stock Market Fluctuations

One of the questions that monetary economists, as well as, financial economists face is how should central banks view the booms and busts in asset/stock markets?

It is well known that developments in the asset market can have a significant effect on both financial stability and macroeconomic stability. The Great Depression , the Tokyo housing and equity bubble in late 1980s, and the South-East Asian asset market crisis in 1997-1998 are examples of how regularities and misalignments in assets (or stock prices) can cause recessions. Even though there is no consensus on the cause and effect of asset/stock booms and busts, there is no doubt that they induce serious economic imbalances. This reality leads to the question of how, if at all, central banks should respond to misalignments (asset booms and busts) in asset prices? In other words, what kind of role do central banks play to stabilize the economy? These questions and the answers to these questions have been controversial issues among both monetarist and financial economists.

There are two sides of the argument. On the one side of the argument, Bernanke and Gentler (1999) claim that the inflation-targeting approach answers the question of how central bankers (or policy makers) or monetary policy should respond to asset price booms and busts. They suggest that monetary policy should react to the asset price booms and busts only to the extent that they affect the central bank's forecast of inflation. They claim that the best policy framework for obtaining both price and financial stability objectives is the flexible inflation targeting policy. Bernanke and Gentler believe that by focusing on inflationary or deflationary pressures, a central bank effectively eliminates the negative side effects of asset booms and busts. With

15

this policy, a central bank does not have to consider what are the fundamental or non-fundamental movements in the stock market. Bernanke and Gentler (2001), in their recent study, support their earlier claim that "inflation-targeting central banks' automatically accommodate productivity gains that lift stock prices, while offsetting purely speculative increases or decreases in stock values whose primary effects are through aggregate demand" (p. 253) On this side of the argument, many academicians as well as analysts think that central banks should set the interest rate in response to forecasts of actual inflation and the output gap, but that they should not react directly to asset or stock prices. The underlying reasons behind this argument are as follows:

1. Asset prices are too volatile to use in monetary policy.

2. It is almost impossible to determine the misalignments of asset prices. How can the real value of assets be determined?

3. Systematic response of central banks to the asset prices may destabilize the economy and cause "moral hazard" problems.

Spaventa (1998) also argues that it is difficult to form a reasonable short-term assessment of what the equilibrium asset prices should be, because they depend on current and expected developments in the market. It is also difficult to recognize, he argues, when bubbles begin and when they should be offset. Spaventa contends that even if economists provide some good models to analyze the bubbles and possible causes of misalignments, they may not provide reliable operational tools to analyze and respond to short-run movements of the asset markets.

On the other side of the argument, Cecchetti, Genberg, Lipsky, and Wadhwani(2000), henceforth denoted CGLW, argue that it is possible for central banks to achieve superior performance by giving consideration to asset booms and busts as well as forecasts of future inflation and the output gap. The authors contend that the policy makers should not ignore asset price misalignments. In fact there is a strong belief

that central banks are not neutral to asset (or stock) market fluctuations. Allan Greenspan (1999) in a symposium sponsored by the Federal Reserve Bank of Kansas City claimed "monetary policy tools are going to have to increasingly focus on changes in asset values and resulting balance sheet variation if we are to understand this important economic force. Central bankers, in particular, are going to have to be able to ascertain how changes in the balance sheet of economic actors influence real economic activity and, hence, affect appropriate macroeconomic policies" (p.1). He also emphasized that in a large part, valuation of assets or stocks are determined by the macroeconomic process itself. But he admits that history shows that the value of assets also reflect waves of optimism and pessimism that can be affected by a small exogenous event. Similarly "European Central Bank president, Willem Duisenberg ensured Europeans that neither price stability nor their personal wealth would be left at risk" CGLW (2000, p.1). Also a survey conducted by the Centre for Central Banking Studies (CCSB) of the Bank of England provides evidence that asset price volatility influences monetary policy in the majority of 77 Central Banks questioned (CGLW, 2000, p.1). CGLW (2000) argue that the Central Banks may achieve superior performance by giving serious consideration to asset price booms and busts as well as output and inflation gaps. The underlining reasons behind their arguments are as following.

1. A quick reaction by the central bank to asset prices would reduce the risk of boom and bust investment cycles and provide more stability to the economy.

2. The difficulties of measuring asset price misalignments should not be a reason to ignore them. The central banks should develop a policy framework that responds to asset price misalignments.

3. Asset prices that contain information about future inflation should be incorporated into inflation forecasts and used in monetary policy.

Goodfriend (1998) argues that even though neither McCallum's nor Taylor's rule puts asset prices in the central bank's reaction function, asset prices provide timely

and forward looking information. Therefore the involvement of the central bank to facilitate the functioning of the asset market may provide macroeconomic stability. He suggests, "central banks must consider the proper role of monetary policy vis-à-vis asset markets" (p.10).

Goodhart and Hofmann (Manuscript) study 17 developed countries to analyze the role of financial variables in the conduct of monetary policy. They find that if financial variables, especially property and share prices, are not included into the inflation targeting model, there is no significant effects of monetary policy. In the inflation targeting models future inflationary pressures are estimated by the output gap, which is in turn determined by the past short- term interest rate. But also financial variables ,such as real estate and equity prices, may affect future inflation via their effects on aggregate demand. They argue that if these variables, real estate and equity prices, do have a significant effect on the output gap, then the omission of these variables would lead to biases in the estimated effects of monetary policy. They provide an example to make their point: if the CB raises interest rates to offset the expansionary effects of a housing and property price boom, ignoring the latter leads the interest rate effect to be under estimated. But, if financial variables are included in the estimation it is possible to detect a significant effect of a monetary policy instrument (The omission of relevant variable problem). Therefore, they suggest that property and share prices be included in the information set of monetary policy.

In the literature, the effectiveness of monetary policy to stabilize asset or stock price fluctuations is tested by using simulation methods. That is, alternative policy rules are analyzed with the goal of seeing what type of policy rules are best at reducing the negative side effect of asset bubbles or busts in the market. However, this approach is criticized by Lucas (1976) and his critique is known as the Lucas critique. Most of the econometric models that aim to capture the effectiveness of monetary policy assume that the parameters of these models are invariant to the specification of the monetary policy rule or the choice of monetary policy. Lucas argued that the economic agents' decisions for investment /consumption and their expectations are not invariant

to changes in monetary policy.

2.0.3 Literature Review on Money and Stock Return

The relationship between money (monetary policy) and real stock returns has been an important issue for a long time in the economic literature. The existence of a strong relationship between the two has been supported by many studies: Friedman & Schwartz, 1963; Berkman, 1978; Lynge, 1981; Sorensen, E. H., 1982; Cornell, 1983; Thorbecke, 1997. Rigobon & Sack (2000, 2001). In general, the findings show there is a relationship between money (or monetary policy) and stock returns although there is no consensus for the mechanism and the direction of the relationship.

Friedman and Schwartz (1963) evaluate money as an asset that investors keep in their portfolios. Since investors' responses to monetary changes are lagged, money might help to predict future returns. This portfolio approach was supported by some empirical studies. However, the empirical studies were criticized because of the possibility of reverse causality, that is, stock returns may lead to changes in money (Sellin & Riksbank, 2001).

Because of the endogenity problem, economists have concentrated on the event-study methodology. They looked at the effect of money announcements on stock returns, monetary variables and other macroeconomic variables. In other words, money supply announcements were used as possible indicators of future monetary policy (Lynge, 1981; Sorense, 1982; Pearce & Roley, 1983).

Berkman (1978) found that stock prices only respond to unanticipated changes in money supply. If announced money supply is higher than expected, then stock prices go down. Lynge (1981) found the same negative effect of a money supply announcement on stock prices. Pearce and Roley (1983) looked at the very short-run relationship between stock prices and money supply announcements. They categorize money announcements as anticipated and unanticipated changes. They found that only an unexpected money supply announcement has significant effects on stock prices, and its coefficient is negative and significant in two of three sub-periods. That

is, an unanticipated increase in the announced money supply causes a decrease in stock prices, and an unanticipated decrease in the announced money supply leads to an increase in stock prices. They argue that there are at least two mechanisms that lead to the above relationship. First, when money supply rises more than expected, economic agents' expectations of future inflation would rise, this increase in inflation would reduce after-tax profits, which in return reduces stock prices. Second, when money supply rises more than expected and if the central bank is concerned with money supply growth, economic agents would think that the CB would increase short-term interest rates in the future, and these expectations depress stock prices. They conclude that their findings are consistent with the efficient market hypothesis.

Waud (1970) uses the discount rate as a monetary policy instrument to see the relationship between monetary policy and stock (and or equity) prices. He finds that the stock market reacts positively to discount rate decreases, and negatively to discount rate increases. Baker and Meyer (1980) show that discount rate changes provide announcement effects because they are indicators of the future course of monetary policy which significantly affect security prices. They analyze the effect of announcements of changes in the discount rate on Treasury bill yields. They find that the Treasury bill market adjusts repeatedly to changes in the discount rate and that the discount rate announcements are not anticipated. These findings are criticized by Santomero (1983). He argues that the discount rate responds to the market interest rate with a lag, which indicates that the market is inefficient and the discount rate cannot be used as an explanatory variable because it will create an endogenity problem.

To overcome the endogenity problem, Smirlock and Yawitz (1985) test whether announcement effects depend on Federal Reserve policy for the change. They define changes in the discount rate as technical and non-technical changes. They find that if the Fed adjusts the discount rate rate because of changes in the market rate (which is called a technical adjustment), then there is no significant announcement effect. But if the Fed adjusts the discount rate because of changes in monetary policy (which is

called a non-technical change), then there is a significant announcement effect. They conclude, "one cannot rule out the discount rate as a useful tool of monetary policy" (p.1157).

Pearce and Roley (1985) test whether the efficient market hypothesis (EMH) holds or not. The EMH states that economic agents process all available information efficiently and immediately incorporate it into stock prices. According to the EMH, since current and past information is immediately incorporated into current prices, only new information or news can cause price changes. By definition, news is unforecastable and therefore changes in stock prices are unforecastable as well too. The authors employ survey data on market participants expectations and the announcements about money supply, inflation, real economic activity, and the discount rate. They identify unexpected components of an announcement. They test whether these unexpected (surprise) components of announcements affect stock prices or not. Their findings support the efficient market hypothesis (EMH). Their evidence shows that surprises that come from monetary policy have a significant negative effect on stock prices.

Hafer (1986) examines how the stock market's reaction to the discount rate changes in three alternative periods. He find that stock returns had a direct relationship (although insignificant) with the discount rate changes before 1979 and after the 1982 period, but he demonstrates that changes in the discount rate had a negative effect on equity prices between 1979 and 1982. He concludes that before 1979 and after 1982 , changes in the Fed's policy objectives were conveyed directly by movements in the Federal Funds rate. Therefore, the discount rate changes do not contain information in these periods.

Hardouvelis (1987) analyzes the effect of monetary and nonmonetary announcements on the stock market. His findings show that the coefficients on M1, the discount rate and the surcharge rate were negative and statistically significant for the period 1979-1982. However, the relationship between the stock prices and the discount rate has a positive sign after 1982 and the discount rate coefficient is not significant.

Jensen and Johnson (1993) discuss whether discount rate changes lead to an announcement effect in the stock market between 1962 and 1990. They find 75 discount rate changes, 36 decreases and 39 increases during the period. Their findings show a strong negative correlation between discount rate and reaction by the stock market: as the discount rate decreases, there is a significant increase in stock prices, and as the discount rate increases, there is a significant decrease in the stock prices. They argue that their findings are consistent with the proposition that discount rate decreases are interpreted as good news, and increases are interpreted as bad news for the stock market. Their evidence shows that the Fed's motivation for changing the discount rate has an important effect on the strength of the signal: Changes in the discount rate that aim to adjust a problem identified by the Fed (non-technical change) lead to a larger response in the stock market than changes in the discount rate which aim to allign the discount rate with the market rate (technical change). In other words, the stock market response to a non-technical change is larger than that of technical change.

Jensen and Johnson (1995) look at long-term returns around a change in the discount rate. They find that before, at the time of, and after the announcement, there are a negative effect on stock returns for all periods, i.e. if the discount rate goes up, stock return does down and if the discount rate goes down, stock returns goes up.

Tarhan (1995) analyzes the effects of open market operations (OMO) on both short and long-term interest rates. He argues that monetary policy may affect stock prices via three channels:

1. Open Market Operations (say an increase in OMO purchases) may boost stock prices by lowering the interest rate and leading investors to reduce their previously expected discount rate and also increasing their expected cash flows.

2. A purchase of a security by the Fed from the market may reduce investor

uncertainty and therefore risk premiums. This also leads to an increase in stock prices.

3. A lower interest rate as a result of open market purchases is associated with higher expected corporate profits, and therefore higher stock prices.

Despite his theoretical argument, Tarhan found no evidence that the Fed influences stock prices.

Thorbecke (1997) uses innovations in the federal funds rate and non-borrowed reserves as indicators of monetary policy. He shows that either negative shocks to the federal funds rate or positive shocks to non-borrowed reserves have a large and significantly positive effect on stock returns. That is, both shocks increased stock returns significantly. He also demonstrates that an event study of changes by the Federal Reserve in its federal funds rate, provided evidence that a monetary expansion increases stock returns. His results support the hypothesis that monetary policy has a real and important effect on the economy, at least in the short-run.

Lobo (2000) examines the stock price adjustment activities around announcements of changes in the federal funds rate in the 1990s. He finds that changes in the federal funds rate target provide new information to the stock market: stock prices incorporate news that suggests overpricing (bad news) faster than news that suggests under-pricing (good news). This means that risk aversion increases before announcements of change. He concludes that monetary policy, measured by a change in the target announcement, has a significant impact on stock returns: changes in the interest rate are inversely related to changes in stock prices.

As Sellin and Riksbank (2001) argue that empirical evidence gives completely different results based on whether the money supply or the interest rate is used as a measure of monetary policy. Most of the event-studies that used M1 shocks as indicators of future policy found that monetary policy had a negative effect on stock returns. This is because the money supply announcements were for past changes in money and that an unexpected increase in money leads to expectation of future

decrease in money and increase in interest rate. Sellin and Riksbank (2001) argue that most of the studies employed interest rate as indicators of monetary policy found that monetary policy had a positive effect on stock prices.

2.0.4 Literature Review on Monetary Policy and The Predictability Of Stock Returns

Over the last two decades there has been a comprehensive literature that tries to forecast stock returns by using either monetary policy variables, financial variables or a combination of both. Fama and French (1988,1989) employed a long horizon-regression; Campbell and Shiller (1988a, 1988b) made use of a short -run vector autoregression to predict stock returns; Lapp, Pearce, and Laksanasut (2003) looked at the other way around: stock returns to predict monetary policy. They analyze the relationship between the Federal Open Market Committee (FOMC) decisions and macroeconomic variables to forecast FOMC decisions, which is considered monetary policy. They found no statistically significant relationship between FMOC decisions and stock price movements. That is, stock price movements do not help forecast monetary policy.

Rigobon and Sack (2002) analyzed the reaction of asset prices to changes in monetary policy. They employed the Identification Through Heteroscedasticity method. Their findings show that an increase in the short-term interest rate leads to a decline in stock prices.

Rigobon and Sack (2001) found a positive relationship between stock prices and the interest rate. That is, monetary policy reacts significantly to the stock market. Their results show that an unexpected increase in the SP500 index by 5% will increase the federal fund rate by about 14 basis points after the next FOMC meeting. They argue that their findings are consistent with Alan Greenspan's view, that policy makers should respond to stock prices according to their effect on the outlook for output and inflation. This means that the Federal Reserve responds to stock price

movements only if the movements have impact on the macro-economy. The mechanism for the positive relationship is that an increase in stock prices has a positive effect on aggregate demand.

Darrat (1990) combined the effect of monetary and fiscal policy on stock returns. He found that monetary policy does not Granger cause stock returns but that the budget deficit has a significantly negative effect on returns. Jensen, Mercer, and Johnson (1996) found that both monetary policy and business conditions can predict stock returns. Patelis (1997) using both a long-horizon regression and a short-horizon vector autoregression found that monetary policy variables are significant predictors of future returns. However, they cannot fully account for observed stock return predictability.These findings are inconsistent with market efficiency.

Thorbecke (1997) found that all of the 22-industry portfolio returns that he investigated responded negatively to the federal funds rate. He also analyzed whether monetary policy innovations can be used for forecasting error variance (FEV) of stock returns. His findings showed that innovations to monetary policy explain 4% of the FEV of stock returns and non-borrowed reserve innovations explain 16% of the FEV of stock returns.

2.0.5 A Summary of Methodology and Model

Whenever data are generated by simultaneous equations, the problem of identification occurs. The problem of identification is that the number of equations obtained from the reduced form is smaller than the number of parameters of interest (unknowns). In this case, the parameters of interest (unknowns) in a system of simultaneous equations cannot be directly estimated. Only the linear transformation of the system, which is called the reduced form, can be estimated.

In the macroeconomic literature, there are four common methods that are used to solve the reduced form of simultaneous equations. These are exclusion restrictions; instrumental variables; long-run restrictions and sign restrictions methods. Each of the methods is based on some assumptions that are imposed on the reduced form of the simultaneous equations. We will discuss these assumptions after we show the variance-covariance matrix of the reduced form of simultaneous equations.

As discussed in the theoretical part, monetary policy affects the stock market and fluctuations of the stock market can affect monetary policy. The relationship between these two macroeconomic variables can be written as follows:

$$I_t = \beta S_t + \phi X_t + \varepsilon_t \tag{2.5}$$

$$S_t = \alpha I_t + \theta X_t + \eta_t \tag{2.6}$$

where

S_t = the daily stock return

I_t = the interest rate

X_t = some lags of I_t and S_t plus macroeconomic shocks:

- $CPI \rightarrow$ consumer price index shock,

- $Unemp \rightarrow$ unemployment shock,
- $PPI \rightarrow$ producer price shock,
- Ret $\rightarrow$ retail sales shock,
- ε_t and $\eta_t =$ The monetary policy and the stock market shocks, respectively

Equations (2.5) and (2.6) cannot be directly estimated because of simultaneity bias. That is, if α and β are different from zero, the RHS variables are correlated with errors in both equations. In this case, the only solution that can be obtained to determine the parameters is the variance-covariance matrix of the reduced form: By substituting one equation into another in the original equations and solving the system, we obtain the following reduced forms:

$$I_t = \frac{1}{(1 - \alpha\beta)}[(\beta\theta + \phi)X_t + \beta\eta_t + \varepsilon_t] \tag{2.7}$$

$$S_t = \frac{1}{(1 - \alpha\beta)}[(\alpha\phi + \theta)X_t + \alpha\varepsilon_t + \eta_t] \tag{2.8}$$

The reduced form shocks are

$$\xi_t^i = \frac{1}{(1 - \alpha\beta)}[\beta\eta_t + \varepsilon_t] \tag{2.9}$$

$$\xi_t^s = \frac{1}{(1 - \alpha\beta)}[\alpha\varepsilon_t + \eta_t] \tag{2.10}$$

The above reduced form innovations have the following variance- covariance matrix

$$\Omega = \begin{bmatrix} \xi_t^{\,i} \\ \xi_t^{\,s} \end{bmatrix} \begin{bmatrix} \xi_t^{\,i} & \xi_t^{\,s} \end{bmatrix} = \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} \beta^2\sigma_\eta^2 + \sigma_\varepsilon^2 & \beta\sigma_\eta^2 + \alpha\sigma_\varepsilon^2 \\ & \sigma_\eta^2 + \alpha^2\sigma_\varepsilon^2 \end{bmatrix} \qquad (2.11)$$

The problem of identification is that this variance-covariance matrix provides 3 equations (two variances and one covariance) and 4 unknowns: α, β, σ_ε and σ_η.

In the macroeconomic literature, there are four methods that are used to identify the parameters of simultaneous equations:

Method 1: Exclusion restrictions. This method imposes a restriction which is either $\alpha = 0$ or $\beta = 0$. When the relation between the stock market and monetary policy is considered, neither of them is likely to be zero.

Method 2: Instrumental variables. This method requires an instrumental variable that affects the variable in one original equation but does not affect both. It is difficult to find an instrumental variable that would affect the interest rate I_t but would not affect the stock market S_t or vice versa.

Method 3: Long-run restrictions. It is difficult to identify whether the shock is coming from the stock market or from the interest rate unless one knows the long-run equilibrium of the variables. One variable returns to its previous equilibrium whereas the other will deviate. The one that deviates from its previous equilibrium is the source of the shock.

Method 4: Sign restriction. In the simultaneous equations, the partial identification can be obtained by imposition of the sign on the slope of structural equations. But this estimation gives a region of admissible parameters, not a unique estimate.

Method 5: Covariance constraint. This method imposes the assumption that the ratio of variances, $\sigma_\eta^2 / \sigma_\varepsilon^2$, is constant. In macroeconomic data, it is difficult to find a constant variance ratio because of heteroscedasticity.

The above shortcomings led to a new method developed by Rigobon (1999) and applied by Rigobon & Sack (2001) and (2002). The method is called Identification Through Heteroscedasticity (ITH). The solution of the ITH method is based on two assumptions if a common shock is not included in the original equations:

1. The parameters of interest (α) and (β) are stable across the regimes. This assumption is common in many estimation methods like VAR, OLS and ARCH.

2. There are at least two regimes where the ratio of variances $\sigma_\eta^2 / \sigma_\varepsilon^2$ is different.

If a common shock which affects the stock market and the interest rate is included in the original structural equations, (2.5) and (2.6), then more than two regimes and an additional assumption are needed to identify the parameters of the simultaneous equations. This issue will be discussed next.

Under the assumptions that the parameters of interest are stable and that it is known when the regime changes, the parameter β can be identified.

Define the regime $r \in \{1, 2\}$ and the variances of the structural shocks in regime r as $\sigma_{\varepsilon,r}^2$ and $\sigma_{\eta,r}^2$. In this case the variance -covariance matrix of the reduced form can be written as the following:

$$\Omega r = \begin{bmatrix} S_{11,r} & S_{12,r} \\ & S_{22,r} \end{bmatrix} = \frac{1}{(1 - \alpha\beta)^2} \begin{bmatrix} \beta^2\sigma_{\eta,r}^2 + \sigma_{\varepsilon,r}^2 & \beta\sigma_{\eta,r}^2 + \alpha\sigma_{\varepsilon,r}^2 \\ & \sigma_{\eta,r}^2 + \alpha^2\sigma_{\varepsilon,r}^2 \end{bmatrix} \tag{2.12}$$

where Ω_t = the variance -covariance of the regime r. Under two regimes there will be 6 unknowns, α, β, $\sigma_{\eta,1}^2$, $\sigma_{\varepsilon,1}^2$, $\sigma_{\eta,2}^2$, $\sigma_{\varepsilon,2}^2$, and six equations, therefore, it can be solved as a non-linear system with six unknowns and six equations. Two conditions that satisfy the solutions are the following:

1.

$$det|\Omega_1 - \Omega_2| \neq 0 \tag{2.13}$$

2.

$$det|\Omega_2 - \frac{S_{11,2}}{S_{11,1}}\Omega_1| \neq 0 \tag{2.14}$$

Solving equation (2.12) for the variances σ_η^2 and σ_ε^2, α and β have the following non-linear system of equations:

$$\beta = \frac{S_{12,r} - \alpha S_{11,r}}{S_{22,r} - \alpha S_{12,r}} \tag{2.15}$$

or

$$\beta = \frac{S_{12,1} - \alpha S_{11,1}}{S_{22,1} - \alpha S_{12,1}} \tag{2.16}$$

$$\beta = \frac{S_{12,2} - \alpha S_{11,2}}{S_{22,2} - \alpha S_{12,2}} \tag{2.17}$$

The system can be solved for α and β if we have two regimes ($r = 1, 2$).

The above two conditions (equation 2.13 and equation 2.14) that the ITH solution requires need to be tested before attempting the estimation of the structural equations (equations 2.5 and 2.6). That is, the model has to pass the heteroscedasticity test.

The coefficient of policy response, β, can be estimated by a bootstrap estimation technique, which allows us to use asymptotic properties of the variance-covariance matrix to estimate the parameter of interest.

If there are more than two regimes, the coefficient β can be estimated from different combinations of regime subsets, e.g. regime1 and 2; regime 1 and 3; regime 2 and

3 etc. The point estimates resulting from these different combinations should not be statistically different if the assumption of the model, which is the parameters of interest are constant across regimes, is true. The distribution of the estimate of β can be estimated by a bootstrap technique. By simulating hundreds of draws of the variance-covariance matrix, we can estimate the hundreds beta estimates and get a distribution of the point estimate of β.

The differences between estimated coefficients obtained under different combinations of the regimes would indicate whether the restriction imposed (stable parameters) on the model could be rejected or not. If the difference is normally distributed with mean zero, it means the assumption that parameters are constant across regimes is a valid assumption. If the difference is not normally distributed with mean zero, it means the parameter is not stable across regimes.

It can be argued that there might be a common domestic shock that affects both the stock market and the interest rate in the regimes that are defined above and this leads to a biased estimation. This argument can be taken into account by including a common domestic shock into the structural equations. In this case, the structural equations (2.5) and (2.6) become:

$$I_t = \beta S_t + \phi X_t + \varphi DS_t + \varepsilon_t \tag{2.18}$$

$$S_t = \alpha I_t + \theta X_t + DS_t + \eta_t \tag{2.19}$$

where DS_t = unobservable common domestic shock that is not captured by ε_t and η_t. DS_t is normalized in the stock market (equation 2.19). The reduced form is now:

$$\Omega_i = \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} (\alpha+\varphi)^2\sigma_{i,z}^2 + \beta^2\sigma_i^2\eta + \sigma_\varepsilon^2 & (1+\alpha\varphi)(\beta+\alpha)\sigma_{i,z}^2 + \beta^2\sigma_i^2\eta + \alpha\sigma_\varepsilon^2 \\ & (1+\alpha\varphi)^2\sigma_{i,z}^2 + \sigma_i^2\eta + \alpha\sigma_\varepsilon^2 \end{bmatrix} \tag{2.20}$$

where $i = 1, 2, 3$ refers to the regimes.

The solution of the system is still similar to the previous one (equation 2.12), but at least three regimes are required to solve this new system. Also, a new assumption which is the homogeneity of ε_t^{us} or η_t^{us} across the regimes is necessary to solve the new system. In the previous system (equations 2.5 and 2.6)we assumed that only a change in the σ_η^2 / σ_ε^2 ratio was required for a solution. In this new system (equations 2.18 - 2.19), it is necessary to assume that one of the variances, σ_η^2 and σ_ε^2, is homogenous across regimes for the solution. The solution is discussed next.

2.0.6 The Model and Identification Through Heteroscedasticity Solution

Determination of Regimes and their Variance-Covariance Matrices

The initial step in the estimation procedure of the ITH method that we apply here is to obtain the shocks (equations 2.9 - 2.10), ξ_t^i and ξ_t^s, of the reduced form of the structural equations. We get the reduced form shocks (residuals), ξ_t^i and ξ_t^s, by estimating equations (2.7) (reduced form of monetary policy equation) and (2.8) (reduced form of stock market equation). On the RHS of the equations (2.7 and 2.8), X_t includes 5 lags of the 3 month T-Bill and 5 lags of S&P 500 returns plus unemployment shocks ($Unemp\_shk$), consumer price shocks(cpi_shk), durable good and services shocks(dgs_shk), retail sale shocks($rtls\_shk$) and producer price shocks(ppi_shk). The reduced form shocks, ξ_t^i and ξ_t^s, are used to construct a matrix, which has a 2910 (number of observations) times 2 dimension. From now on, we call this matrix the "data matrix". The first column of the data matrix is the shocks to interest rate, ξ_t^i and the second column of the data matrix is the shocks to stock market, ξ_t^s.

After we estimated the reduced form of the structural equations and obtained the shocks, ξ_t^i and ξ_t^s, the next step is to determine regime changes using the data matrix. We use the variance of shocks to stock market returns, $var(\xi_t^s)$ and that of the short term interest rate, $var(\xi_t^i)$ to determine the regimes: There are times when the volatility(variance) of shocks to stock returns and that of interest rates coincide and there are times when they do not. Regimes are determined by using the different combinations of high and low variance (volatility) of shocks to stock returns and to interest rates. To define the high and low variance (volatility), we use 30 -day rolling variances of the shocks to stock returns and of the shocks to the interest rate. The 30-day rolling windows are noted as 1-30, 2-31, 3-32, 4-33 . . . 2881-2910. Whether the variances of the shocks would be called high or low in the 30 - day windows are

determined by comparing the variances of shocks in the 30-day rolling window to the variances of shocks in the long run ($\overline{LR}$:all days in the sample) according to the following four schemes:

1. **Regime 1**:

   If $\mathrm{var}(\xi_t^i)$ in 30 days rol. wind. $\ngtr$1 std.dev of $\overline{LR}+$ $\overline{LR}\mathrm{var}(\xi_t^i) \to$ (low variance)

   If $\mathrm{var}(\xi_t^s)$ in 30 days rol. wind.$\ngtr$1 std.dev.of $\overline{LR} + \overline{LR}\mathrm{var}(\xi_t^s) \to$ (low variance)

   That is, if the variance of the interest rate shock and the variance of stock market return shock in a 30- day rolling window are not one standard deviation above their long run average, they are classified as regime 1, where both variances are low.

2. **Regime 2**:

   If $\mathrm{var}(\xi_t^i)$ in 30 days rol. wind. $\ngtr$1 std.dev of $\overline{LR}+$ $\overline{LR}\mathrm{var}(\xi_t^i) \to$ (low variance)

   If $\mathrm{var}(\xi_t^s)$ in 30 days rol. wind.$>$1 std.dev.of $\overline{LR} + \overline{LR}\mathrm{var}(\xi_t^s) \to$ (high variance)

   That is, if the variance of the interest rate shock is not one standard deviation above its long run average but the variance of the stock market return shock is one standard deviation above its long run average in a 30 - day rolling window, they are classified as regime 2, where the variance of the interest rate shock is low while that of the stock market shock is high.

3. **Regime 3**:

   If $\mathrm{var}(\xi_t^i)$ in 30 days rol. wind. $>$1 std.dev of $\overline{LR}+$ $\overline{LR}\mathrm{var}(\xi_t^i) \to$ (high variance)

   If $\mathrm{var}(\xi_t^s)$ in 30 days rol. wind.$>$1 std.dev.of $\overline{LR} + \overline{LR}\mathrm{var}(\xi_t^s) \to$ (low variance)

   That is, if both the variance of the interest rate shock and the variance of the stock market return shock are one standard deviation above their long run

average in a 30 - day rolling window, they are classified as regime 3, where both variances are high.

4. **Regime 4**:

   If $\text{var}(\xi_t^i)$ in 30 days rol. wind. >1 std.dev of $\overline{LR}+\overline{LR}\text{var}(\xi_t^i) \rightarrow$ (high variance)

   If $\text{var}(\xi_t^s)$ in 30 days rol. wind. $\ngtr 1$ std.dev.of $\overline{LR}+\overline{LR}\text{var}(\xi_t^s) \rightarrow$ (low variance)

   That is, if the variance of the interest rate shock is one standard deviation above its long run average but the variance of stock market return shock is not one standard deviation above its long run average in a 30 - day rolling window, they are classified as regime 4, where the variance of the interest rate shock is high while that of the stock market shock is low.

Thus by using our data matrix, the shocks of the reduced form of the simultaneous equations(2.5 and 2.6), we are going to obtain up to four possible regimes. Each regime has a matrix, dimension equal to the number of shocks falling into the regime classification above times two columns, in which the first column is the shocks to the interest rate and the second column is the shocks to the stock market.

We take the transpose of each regime's matrix and multiply by itself to obtain the variance -covariance matrix of each regime, which is always a 2x2 matrix.

After we obtain the variance-covariance matrix of each regime, we vectorize the matrix by retaining only the lower triangular portion of the matrix as a column vector. By doing vectorization , we obtain a 3x1 column vector where the first element is the variance of the interest shock, the second element is the covariance between the interest shock and the stock market shock and the third element is the variance of the stock market shock. The vectorization technique allows us to do mathematical operations easily. By taking the transpose of the column vector, we obtain a 1x3 row vector where the first element is the variance of monetary policy shock, the second element is the covariance between interest shock and shock market shock and the third element the variance of the stock market shock for a regime. We do the above

procedure for all regimes and obtain a 1x3 row vector for each regime. By putting all four row regime's matrices into a matrix, we create a 4X3 matrix, in which each row refers to a regime's variance of the shocks to interest rate $(S_{11,r})$, a regime's covariance between interest rate shock and stock market shock $(S_{12,r})$ and a regime's variance of the shocks to stock market $(S_{22,r})$ respectively, where r is the regime number. The 4X3 matrix is,

$$
\Omega_r = \begin{bmatrix} S_{11,1} & S_{12,1} & S_{22,1} \\ S_{11,2} & S_{12,2} & S_{22,2} \\ S_{11,3} & S_{12,3} & S_{22,3} \\ S_{11,4} & S_{12,4} & S_{22,4} \end{bmatrix}
$$

Notice that each row in the above matrix has all of the information of a regime's variance -covariance matrix.

The ITH Solution without a Common Shock

The following equations represent the simultaneous relationship between stock market and monetary policy

$$I_t = \beta S_t + \phi X_t + \varepsilon_t \tag{2.21}$$

$$S_t = \alpha I_t + \theta X_t + \eta_t \tag{2.22}$$

From above simultaneous equations, we obtain the following reduced forms:

$$I_t = \frac{1}{(1 - \alpha\beta)}[(\beta\theta + \phi)X_t + \beta\eta_t + \varepsilon_t] \tag{2.23}$$

$$S_t = \frac{1}{(1 - \alpha\beta)}[(\alpha\phi + \theta)X_t + \alpha\varepsilon_t + \eta_t] \tag{2.24}$$

The reduced form shocks, that is, shocks to monetary policy and the stock market are:

$$\xi_t^i = \frac{1}{(1 - \alpha\beta)}[\beta\eta_t + \varepsilon_t] \tag{2.25}$$

$$\xi_t^s = \frac{1}{(1 - \alpha\beta)}[\alpha\varepsilon_t + \eta_t] \tag{2.26}$$

The above reduced form shocks, ξ_t^i and ξ_t^s, have the following variance - covariance matrix

$$\Omega = \begin{bmatrix} \xi_t^i \\ \xi_t^s \end{bmatrix} \begin{bmatrix} \xi_t^i & \xi_t^s \end{bmatrix} = \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} \beta^2\sigma_\eta^2 + \sigma_\varepsilon^2 & \beta\sigma_\eta^2 + \alpha\sigma_\varepsilon^2 \\ & \sigma_\eta^2 + \alpha^2\sigma_\varepsilon^2 \end{bmatrix} \tag{2.27}$$

The Identification Through Heteroscedasticity (ITH) method uses the heteroscedasticity of the data and the variance-covariance matrix of shocks from the reduced form of simultaneous equations to estimate parameters of interest. If the data exhibit heteroscedasticity, we can identify different regimes (r) and therefore different variance-covariance matrices from the reduced form shocks. If we have two different regimes for example $r =1$ and $r =2$, we can use the variance-covariance matrices of regimes to obtain the estimates of α and β :

$$\Omega_r = \begin{bmatrix} S_{11,r} & S_{12,r} \\ S_{21,r} & S_{22,r} \end{bmatrix} \tag{2.28}$$

which is

$$= \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} \beta^2\sigma_{\eta,r}^2 + \sigma_{\varepsilon,r}^2 & \beta\sigma_{\eta,r}^2 + \alpha\sigma_{\varepsilon,r}^2 \\ & \sigma_{\eta,r}^2 + \alpha^2\sigma_{\varepsilon,r}^2 \end{bmatrix} \tag{2.29}$$

where $r \in \{1,2\}$ and $\Omega_r =$ The variance-covariance matrix of the regime 1 and 2. We have six unknowns α, β, $\sigma_{\eta,1}^2$, $\sigma_{\eta,2}^2$, $\sigma_{\varepsilon,1}^2$, $\sigma_{\varepsilon,2}^2$, and 6 equations under two regimes. Setting the RHS of equation (2.28) and equation (2.29) against to each other, we obtain the following six equations:

$$S_{11,1} = \beta^2\sigma_{\eta,1}^2 + \sigma_{\varepsilon,1}^2 \tag{2.30}$$

$$S_{12,1} = \beta\sigma_{\eta,1}^2 + \alpha\sigma_{\varepsilon,1}^2 \tag{2.31}$$

$$S_{22,1} = \sigma_{\eta,1}^2 + \alpha^2\sigma_{\varepsilon,1}^2 \tag{2.32}$$

$$S_{11,2} = \beta^2\sigma_{\eta,2}^2 + \sigma_{\varepsilon,2}^2 \tag{2.33}$$

$$S_{12,2} = \beta\sigma_{\eta,2}^2 + \alpha\sigma_{\varepsilon,2}^2 \tag{2.34}$$

$$S_{22,2} = \sigma_{\eta,2}^2 + \alpha^2\sigma_{\varepsilon,2}^2 \tag{2.35}$$

We know the LHS of the above equations $(2.30 - 2.35)$. The RHS side of the six equations have a total of six unknowns so we can solve for α and β. Notice that α and β are constant across regimes. The solution of the six equations gives the following non-linear system of equations:

$$\beta = \frac{S_{12,1} - \alpha S_{11,1}}{S_{22,1} - \alpha S_{12,1}} \tag{2.36}$$

$$\beta = \frac{S_{12,2} - \alpha S_{11,2}}{S_{22,2} - \alpha S_{12,2}} \tag{2.37}$$

Setting these two equations against each other and solving for α , we obtain

$$\alpha^2(S_{11,1}S_{12,2} - S_{12,1}S_{11,2}) - \alpha(S_{22,2}S_{11,1} - S_{11,2}S_{22,2}) + (S_{12,1}S_{22,2} - S_{22,1}S_{12,2}) = 0$$

that is similar in structure to

$$\mathbf{a}\alpha^2 - \mathbf{b}\alpha + \mathbf{c} = \mathbf{0} \tag{2.38}$$

where

$$\mathbf{a} = S_{11,1}S_{12,2} - S_{12,1}S_{11,2}$$

$$\mathbf{b} = S_{22,2}S_{11,1} - S_{11,2}S_{22,2}$$

$$\mathbf{c} = S_{12,1}S_{22,2} - S_{22,1}S_{12,2}$$

There are two solutions to this quadratic equation (2.38):

$$\alpha_1 = \frac{b + \sqrt{b^2 - 4ac}}{2a}$$

$$\alpha_2 = \frac{b - \sqrt{b^2 - 4ac}}{2a}$$

It can be shown that if α , β is one solution set to the system of the structural equations (see equations 2.21 and 2.22), then $\alpha = 1/\beta$ and $\beta = 1/\alpha$ is the other solution set, which is the other way of writing the structural equations. Starting with the structural equations:

$$I_t = \beta S_t + \phi X_t + \varepsilon_t \tag{2.39}$$

40

$$S_t = \alpha I_t + \theta X_t + \eta_t \tag{2.40}$$

we can rearrange the above equations to obtain equation (2.41)

$$\frac{1}{\alpha} S_t = I_t + \frac{\theta}{\alpha} X_t \frac{1}{\alpha} \eta_t$$

$$I_t = \frac{1}{\alpha} S_t - \frac{\theta}{\alpha} X_t - \frac{\eta_t}{\alpha} \tag{2.41}$$

and equation (2.42)

$$\frac{1}{\beta} I_t = S_t + \frac{\phi}{\beta} X_t + \frac{\varepsilon_t}{\beta}$$

$$S_t = \frac{1}{\beta} I_t - \frac{\phi}{\beta} X_t - \frac{\varepsilon_t}{\beta} \tag{2.42}$$

Equation (2.38) has two solutions and we know the expected signs of the parameters in the structural equations, $\beta > 0$ and $\alpha < 0$. Therefore, we can identify the α that corresponds to the solution to the structural equations: one α is negative which corresponds to the structural equations (equations 2.39 and 2.40 or our original equations 2.21 and 2.22) and the other is positive which corresponds to the other way of arranging the structural equations (equations 2.41 and 2.42). We will choose the negative α value which corresponds to the structural equations (equations 2.39 and 2.40), and solve for β using an expanded form of equations (2.36) and (2.37):

$$\beta, r = \frac{S_{12,r} - \alpha S_{11,r}}{S_{22,r} - \alpha S_{12,r}} = \frac{c\hat{o}v(I\_shock\&S\_shock), r - \alpha(v\hat{a}r(I\_shock)), r}{v\hat{a}r(S\_shock), r - \alpha(c\hat{o}v(I\_shock\&S\_shock)), r} \quad (2.43)$$

Where lowercase r refers to regimes. Notice that if one variance in equation (2.43) goes up or down, it is expected that the covariance will go up or down to keep β constant across regimes.

If we have more than two regimes, the model is overidentified. Whether the overidentification is a problem or not is tested by taking the differences of the bootstrap estimations obtained from different subset of regimes combinations in the empirical part. If the differences are normally distributed with mean zero, then the overidentification is not a problem. If the differences are not normally distributed with mean zero, then the overidentification is a problem.

β is the point estimate that we obtain from two regimes, such as regime1 and regime2. We can obtain other estimates of β from the other combinations of the regimes, such as regime1 and regime3, regime1 and regime4. We assume that the βs that we will get from different combinations of the regimes are the same. In the empirical part, we test this assumption by comparing the bootstrap distributions of βs that we obtain form the different combinations of regimes. If the difference between two distributions of βs that we obtain by employing a bootstrap estimation method and different combinations of regimes is normally distributed with a mean zero, it means that our assumption of β being constant across regimes is supported by the data. If the difference between two distributions of βs that we obtain by employing bootstrap estimation is not normally distributed, the reason could be the exclusion of a common shock from the structural equations (see equations 2.21 and 2.22). In the next section, we discuss the ITH solution with a common shock.

The ITH Solution with a Common Shock

The inclusion of a common shock into the structural equations is important because there are times that some factors affect both stock market and interest rate in the same direction. For example a flight to safety would affect both stock market returns and interest rates, leading to a positive correlation between changes in stock prices and interest rates. Another example could be pessimistic expectations about a whole economy leading investors to withdraw their investment from the stock market and put it into interest rate investments, pushing both interest rate and stock prices down. Exclusion of such factors from the structural equations may lead to a biased estimation. If we introduce a common shock (DS) into the structural equations (see equations 2.21 and 2.22), we will have:

$$I_t = \beta S_t + \phi X_t + \gamma DS_t + \varepsilon_t \tag{2.44}$$

$$S_t = \alpha \beta I_t + \theta X_t + DS_t + \eta_t \tag{2.45}$$

And the variance-covariance matrix that we obtain from the reduced form of the simultaneous equations changes from equation (2.21) to the following:

$$\Omega_r = \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} (\beta+\gamma)^2\sigma_{r,z}^2 + \beta^2\sigma_{r,\eta}^2 + \sigma_\varepsilon^2 & (1+\alpha\gamma)(\beta+\gamma)\sigma_{r,z}^2 + \beta\sigma_{r,\eta}^2 + \alpha\sigma_\varepsilon^2 \\ & (1+\alpha\gamma)^2\sigma_{r,z}^2 + \sigma_{r,\eta}^2 + \alpha^2\sigma_\varepsilon^2 \end{bmatrix}$$
$$\tag{2.46}$$

r refers to three different regimes, such as 1,2 and 3. The parameter β can be identified if we have at least three different regimes. The only new assumption that we need is that one of the error variance terms, σ_ε^2 or σ_η^2, must be homoscedastic, for example a change in the variance - covariance matrix is not a result of changes in the variance of monetary policy shock, i.e. $\sigma_{\varepsilon 1}^2 = \sigma_{\varepsilon 2}^2 = \sigma_{\varepsilon 3}^2$. In this case, the ITH

solution to the structural equations with a common shock follows.

Define

$$\Delta\Omega_2 1 = \Omega_2 - \Omega_1$$

$$\Delta\Omega_3 1 = \Omega_3 - \Omega_1$$

and

$$\Delta\sigma_{j1,z}^2 = \sigma_{j,z}^2 - \sigma_{1,z}^2$$

$$\Delta\sigma_{j1,\eta}^2 = \sigma_{j,\eta}^2 - \sigma_{1,\eta}^2$$

where $j=$ 2, 3. From the differences between the variance-covariance of matrices of the regimes, Ω_{31} and Ω_{21} we can obtain

$$\Delta\Omega_{ji} = \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} (\beta+\gamma)^2\Delta\sigma_{j1,z}^2 + \beta^2\Delta\sigma_{j1,\eta} & (1+\alpha\gamma)(\beta+\gamma)\Delta\sigma_{j1,z}^2 + \beta\Delta\sigma_{j1,\eta}^2 \\ & (1+\alpha\beta)^2\Delta\sigma_{j1,z}^2 + \Delta\sigma_{j1,\eta}^2 \end{bmatrix}$$

(2.47)

This matrix provides 6 non-linear equations with seven unknowns. Even though the number of unknowns is bigger than that of equations, β can be identified. The solution to the above variance - covariance matrix (equation 2.47) to obtain β is as follows:

If we let

$$\theta = \frac{1+\alpha\gamma}{\beta+\gamma}$$

and

$$w_{z,j} = (\beta + \gamma)^2 \Delta\sigma_{j1,z}^2$$

then equation (2.47) becomes

$$\Delta\Omega_{j1} = \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} w_{z,j} + \beta^2\Delta\sigma_{j1,\eta}^2 & \theta w_{z,2} + \beta\Delta\sigma_{j1,\eta}^2 \\ & \theta^2 w_{z,2} + \Delta\sigma_{j1,\eta}^2 \end{bmatrix} \quad (2.48)$$

Now, we subtract one regime from the rest of the regimes, for example we subtract regime1 from regime2 and regime3 and obtain the following:

$$\Delta\Omega_{21} = \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} w_{z,2} + \beta^2\Delta\sigma_{21,\eta} & \theta w_{z,2} + \beta\Delta\sigma_{21,\eta}^2 \\ & \theta^2 w_{z,2} + \Delta\sigma_{21,\eta}^2 \end{bmatrix} \quad (2.49)$$

which is the difference between the variance-covariance matrices of regime2 and regime1,

$$\begin{bmatrix} \Delta\Omega_{21,11} & \Delta\Omega_{21,12} \\ & \Delta\Omega_{21,22} \end{bmatrix} \quad (2.50)$$

and

$$\Delta\Omega_{31} = \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} w_{z,3} + \beta^2\Delta\sigma_{31,\eta}^2 & \theta w_{z,3} + \beta\Delta\sigma_{31,\eta}^2 \\ & \theta^2 w_{z,3} + \Delta\sigma_{31,\eta}^2 \end{bmatrix} \quad (2.51)$$

45

which is the difference between the variance-covariance matrices of regimes3 and regime1,

$$\begin{bmatrix} \Delta\Omega_{31,11} & \Delta\Omega_{31,12} \\ & \Delta\Omega_{31,22} \end{bmatrix} \qquad (2.52)$$

Setting the RHS of equation (2.49) against to equation (2.50) and the RHS of equation (2.51) against to equation (2.52), we obtain the following six equations (see equations 2.53 - 2.58)

$$w_{z,2} + \beta^2 \Delta\sigma_{21,\eta}^2 = (1 - \alpha\beta)^2 \Delta\Omega_{21,11} \qquad (2.53)$$

$$\theta w_{z,2} + \beta \Delta\sigma_{21,\eta}^2 = (1 - \alpha\beta)^2 \Delta\Omega_{21,12} \qquad (2.54)$$

$$\theta^2 w_{z,2} + \beta^2 \Delta\sigma_{21,\eta}^2 = (1 - \alpha\beta)^2 \Delta\Omega_{21,22} \qquad (2.55)$$

$$w_{z,3} + \beta^2 \Delta\sigma_{31,\eta}^2 = (1 - \alpha\beta)^2 \Delta\Omega_{31,11} \qquad (2.56)$$

$$\theta w_{z,3} + \beta \Delta\sigma_{31,\eta}^2 = (1 - \alpha\beta)^2 \Delta\Omega_{31,12} \qquad (2.57)$$

$$\theta^2 w_{z,3} + \beta^2 \Delta\sigma_{31,\eta}^2 = (1 - \alpha\beta)^2 \Delta\Omega_{21,22} \qquad (2.58)$$

If $\alpha\beta \neq 0$, then we can solve the above 6 equations to obtain β. The two possible solutions have the following equations:

$$\theta = \frac{\Delta\Omega_{21,12} - \beta\Delta\Omega_{21,22}}{\Delta\Omega_{21,11} - \beta\Delta\Omega_{21,12}} \qquad (2.59)$$

$$\theta = \frac{\Delta\Omega_{31,12} - \beta\Delta\Omega_{31,22}}{\Delta\Omega_{31,11} - \beta\Delta\Omega_{31,12}} \tag{2.60}$$

Setting the RHS (Right Hand Side) of the equations (2.59 and 2.60) against to each other and solving for β , we obtain a partial solution. That is, we can obtain a solution for β but not for α. The reason that we obtain a partial solution is that we have two equation (2.59 and 2.60) and two unknowns β and θ above, therefore we can obtain a solution for β and θ. But, θ is a function of three variables β, α and γ, therefore, we can not get a solution for α by manipulating θ. Since in this essay we are interested in the reaction of monetary policy to the stock market, the estimation of β is sufficient for our purpose

Setting the RHS (Right Hand Side) of the equations (2.59 and 2.60) against to each other and solving for β, we obtain a quadratic equation

$$\mathbf{a}\ \beta^2 - \mathbf{b}\beta + \mathbf{c} = \mathbf{0} \tag{2.61}$$

where

$$\mathbf{a} = \Delta\Omega_{31,22}\Delta\Omega_{21,12} - \Delta\Omega_{21,22}\Delta\Omega_{31,12} \tag{2.62}$$

$$\mathbf{b} = \Delta\Omega_{31,22}\Delta\Omega_{21,11} - \Delta\Omega_{21,22}\Delta\Omega_{31,11} \tag{2.63}$$

$$\mathbf{c} = \Delta\Omega_{31,12}\Delta\Omega_{21,11} - \Delta\Omega_{21,12}\Delta\Omega_{31,11} \tag{2.64}$$

If equation (2.61) has a real solution, then we can solve for β. Here again we obtain two solutions for the quadratic equation. We apply the previous criteria, i.e. $\beta > 0$, to choose the root that corresponds to the structural equations. That is, the root of β that is positive.

In the above example solution we use regime1, regime2 and regime3 to estimate β. We do the same thing for the other possible subsets of the regimes such as regime1, regime3, regime4; and for regime2, regime3, regime 4 to estimate β. By a basic assumption of ITH method, the point estimates, β, that we obtain from the different subsets of the regimes will be the same.

In the empirical part we test this assumption again by taking the differences in the bootstrap distribution of estimates of β from different subsets of regimes and checking whether the difference is normally distributed with a mean of zero.

GMM/Minimum Distance Solution using all Regimes

The ITH assumptions and solution technique also allow us to use all regimes (in our case, regime1, 2, 3, 4) together to estimate the parameter of interest by employing the GMM/Minimum Distance Method. We would consider the variance-covariance matrix of the reduced form (equation 2.29) as moment conditions and solve for the monetary policy coefficient using GMM/Minimum Distance Estimation Method. We would consider equation (2.47) if we use the structural equations with a common shock to demonstrate the GMM solution of the ITH method. Since it is easier to use the structural equations without a common shock to demonstrate the GMM solution of the ITH method, we consider equation (2.29) as moment conditions. The following GMM solution is based on this choice.

For the GMM solution, the variance -covariance matrix of the reduced form (equation 2.29) that we are using as moment conditions is the following

$$\Omega_r = \frac{1}{(1 - \alpha\beta)^2} \begin{bmatrix} \beta^2\sigma_{\eta,r}^2 + \sigma_{\varepsilon,r}^2 & \beta\sigma_{\eta,r}^2 + \alpha\sigma_{\varepsilon,r}^2 \\ & \sigma_{\eta,r}^2 + \alpha^2\sigma_{\varepsilon,r}^2 \end{bmatrix} \tag{2.65}$$

We have four regimes, therefore four variance-covariance matrices. Each regime has its own 2x2 variance-covariance matrix, corresponding to the above reduced form matrix (59).

For the GMM solution, we start with vectorizing each regime's variance-covariance matrix. This gives a 3x1 vector, where the first element is the variance of the interest rate shock (S11) in the regime, the second element is the covariance between the interest rate shock and the stock market shock (S_{12}) in the regime and the third element is the variance of the stock market shock (S_{22}) in the regime. By taking the transpose of

this vector, we obtain a 1x3 row vector, where the first element is the variance of the interest rate shock (S_{11}) in the regime, the second element is the covariance between the interest rate shock and the stock market shock (S_{12}) in the regime and the third element is the variance of stock market shock (S_{22}) in the regime. We do vectorization and take the transpose of the variance-covariance matrix of all regimes (1,2,3 and 4) and obtain the following 4X3 matrix in which each row refers to a regime's variance of the shocks to the interest rate ($S_{11,r}$), a regime's covariance between the interest rate shock and stock market shock ($S_{12,r}$), and a regime's variance of the shocks to the stock market ($S_{22,r}$) respectively.

$$
\Omega_r = \begin{bmatrix}
S_{11,1} & S_{12,1} & S_{22,1} \\
S_{11,2} & S_{12,2} & S_{22,2} \\
S_{11,3} & S_{12,3} & S_{22,3} \\
S_{11,4} & S_{12,4} & S_{22,4}
\end{bmatrix}
\tag{2.66}
$$

We use the ITH solution without a common shock to estimate β. For each regime, β is determined using the following in the ITH solution without a common shock (See equations 2.36 and 2.37).

$$
\beta, r = \frac{S_{12,r} - \alpha S_{11,r}}{S_{22,r} - \alpha S_{12,r}} = \frac{cov(I\_shock \& S\_shock), r - \alpha(var(I\_shock)), r}{var(S\_shock), r - \alpha(cov(I\_shock \& S\_shock)), r}
\tag{2.67}
$$

For the numerator and dominator in equation (2.67), we do the following to obtain a β for each regime:

$$
Nums = \begin{bmatrix} S_{12,1} \\ S_{12,2} \\ S_{12,3} \\ S_{12,4} \end{bmatrix} - \alpha \begin{bmatrix} S_{11,1} \\ S_{11,2} \\ S_{11,3} \\ S_{11,4} \end{bmatrix} = \begin{bmatrix} S_{12,1} - \alpha S_{11,1} \\ S_{12,2} - \alpha S_{11,2} \\ S_{12,3} - \alpha S_{11,3} \\ S_{12,4} - \alpha S_{11,4} \end{bmatrix} \tag{2.68}
$$

$$
Doms = \begin{bmatrix} S_{22,1} \\ S_{22,2} \\ S_{22,3} \\ S_{22,4} \end{bmatrix} - \alpha \begin{bmatrix} S_{12,1} \\ S_{12,2} \\ S_{12,3} \\ S_{12,4} \end{bmatrix} = \begin{bmatrix} S_{22,1} - \alpha S_{12,1} \\ S_{22,2} - \alpha S_{12,2} \\ S_{22,3} - \alpha S_{12,3} \\ S_{22,4} - \alpha S_{12,4} \end{bmatrix} \tag{2.69}
$$

Now, we can get β for each regime.

$$
\beta_r = \begin{bmatrix} (S_{12,1} - \alpha S_{11,1})/(S_{22,1} - \alpha S_{12,1}) \\ (S_{12,2} - \alpha S_{11,2})/(S_{22,2} - \alpha S_{12,2}) \\ (S_{12,3} - \alpha S_{11,3})/(S_{22,3} - \alpha S_{12,3}) \\ (S_{12,4} - \alpha S_{11,4})/(S_{22,4} - \alpha S_{12,4}) \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{bmatrix} \tag{2.70}
$$

For the GMM minimum distance solution, we subtract the first row of equation (2.70) from itself and the rest of rows in the vectors (in both the LHS and RHS vectors). Notice that we can subtract any row from itself and the rest of rows in equation (2.70). By the ITH assumption, we should get the same result since the RHS will be a vector of zeros. The result of subtracting the first row from itself and the rest of the vector is the following,

$$
\begin{bmatrix} 0 \\ \Omega_{21,2} \\ \Omega_{31,3} \\ \Omega_{41,4} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{2.71}
$$

when

$$
\Omega_{21,2} = [(S_{12,2} - \alpha S_{11,2})/(S_{22,2} - \alpha S_{12,2})] - [(S_{12,1} - \alpha S_{11,1})/(S_{22,1} - \alpha S_{12,1})]
$$

$$
\Omega_{31,3} = [(S_{12,3} - \alpha S_{11,3})/(S_{22,3} - \alpha S_{12,3})] - [(S_{12,1} - \alpha S_{11,1})/(S_{22,1} - \alpha S_{12,1})]
$$

$$
\Omega_{41,4} = [(S_{12,4} - \alpha S_{11,4})/(S_{22,4} - \alpha S_{12,4})] - [(S_{12,1} - \alpha S_{11,1})/(S_{22,1} - \alpha S_{12,1})]
$$

To get the minimum distance estimation, we search for the α that will give the minimum distance between the RHS and LHS of equation (2.71), which means the α that minimizes the LHS of equation (2.71). We arbitrarily set up lower and upper bounds for α: lower bound = -2 and upper bound = +2. Starting at -2, we increment by 0.000099998 until we reach +2. This set up of creates 40001 different values of from -2 to +2. These will be used to obtain the value that minimizes the distance between above two vectors (equation 2.71).

Distance by definition is the transpose of a vector times the vector itself. We take the transpose of the LHS of equation (2.71) and multiply by itself to get the distance for our GMM/minimum distance solution:

$$DIST = \begin{bmatrix} 0 & \Omega_{21,2} & \Omega_{31,3} & \Omega_{41,4} \end{bmatrix} \begin{bmatrix} 0 \\ \Omega_{21,2} \\ \Omega_{31,3} \\ \Omega_{41,4} \end{bmatrix} \qquad (2.72)$$

Notice we get a numerical value for distance for each value of α and the $DIST$ is a vector:

$$DIST = \begin{bmatrix} \alpha\_value \\ \alpha\_value \\ \alpha\_value \\ . \\ . \\ . \\ . \\ \alpha\_value \end{bmatrix} \qquad (2.73)$$

$DIST$ (distance vector) is a 40001 by 1 vector. We determine the minimum value in the distance vector and determine the corresponding value of α that gives this minimum distance. We estimate β by substituting this minimum α into equation (2.67).

As an alternative, if we subtract the second row (or third or fourth row) of equation (2.67) from itself and the rest of the vector, we should get equal or close β values.

In the empirical part, we test whether subtraction of different rows in equation

(2.70) gives different estimate of β . We subtract two different bootstrap estimations obtained by different row subtractions in equation (2.70). If the distribution of the difference between two bootstrap estimations is normally distributed with mean zero, it means subtracting different rows does not make a difference and the ITH assumption that parameters are constant across regimes is a valid assumption (to be performed).

Bootstrap Estimation of Variance -Covariance Matrices

Once we obtain a variance-covariance matrix for each regime, we can bootstrap them and obtain many variance-covariance matrices that can be repeatedly used to estimate the parameter of interest, in our case, the reaction of monetary policy to the stock market, β . The distribution of β values that we obtain by employing the bootstrap will show us whether we consistently estimate the reaction of monetary policy by using the variance-covariance matrices of regimes. A normal distribution of β with a non-zero mean shows that we consistently estimate the reaction of monetary policy by using the bootstrap of the variance-covariance matrices of any subset of regimes. Also we use bootstrap estimation of parameters to test whether the parameter is constant across regimes as the ITH estimation method requires.We explain further how to compute a bootstrap variance - covariance matrix in the appendix

   To compute the bootstrap variance-covariance matrices for each regime, we do the following:

1. We take the Cholesky decomposition of the variance -covariance matrix of each regime(W. H Greene, Econometric Analsis,2000 pg.169) .Notice that for each regime (1,2,3,4) we have a 2x2 variance-covariance matrix, in which the first element is the variance of the interest shock, the second element (same as the third) is the covariance between the interest shock and the stock market shock, and the fourth element is the variance of the stock market shock. The Cholesky decomposition is a square root of an original variance-covariance matrix, that is, it is an upper triangular matrix. Notice that the transpose of the Cholesky decomposition matrix times itself is equal to the original variance-covariance matrix.

2. By using simulation techniques, we also create a simulation matrix for each regime, where the dimension is equal to the number of shocks in the regime

and two columns. Then, we randomly generate the elements of this matrix. Thus, for each regime, we create a randomly generated matrix from normal distribution , which has the same dimensions as the regime matrix.

3. Then, for each regime, we multiply its "Cholesky decomposition matrix" from step 1 by its "randomly generated matrix" from step 2, which has the same numbers of rows as the number of the regime's shocks and two columns. We do this for each regime. By doing this procedure, that is, multiplying the Cholesky decomposition matrix with the randomly generated matrices for each regime, we obtain new interest and stock market shocks, that is, **bootstrap estimation of shocks**, for each regime.

4. By using the above new generated shocks (bootstrap estimation of shocks) for each regime, we create a new variance-covariance matrix, that is, **bootstrap estimation of variance-covariance matrix**, for each regime.

We repeat the above process and create 1000 bootstrap variance -covariance matrices for each regime.

We use the above bootstrap variance -covariance matrices to get the parameter estimates by different subsets of regimes such as regime1 and regime2, regime1 and regime3, regime1 and regime4; regime1, regime 2 and regime 3; regime1, regime 2 and regime4; regime2, regime3 and regime4 and so on.

In the empirical part, we get 1000 bootstrap variance-covariance matrices for each regime and we create vectors of zeros, which are 1000x1, for each subset of regimes. We perform a simulation (using the bootstrap variance-covariance matrices to get parameter estimates) and fill these vectors by estimated parameters for each subset of regimes. Notice, we use 1000 bootstrap variance-covariance matrices to obtain 1000 estimates of β and α for each subset of regimes. Then we use these 1000 estimated parameters to get their distribution, mean, standard deviation and mass

below zero. Also we use these bootstrap estimated parameters to test whether the stable parameter assumption is valid and the estimation is significant.

2.0.7 Empirical Results of The ITH Estimation

Introduction of VAR and Endogenity Problem

To show how ignoring the simultaneous response of the stock market to monetary pol-
icy creates a biased estimation of the effect of the stock market on monetary policy,
we estimate a policy reaction function (equation 2.5) directly by using a Vector Auto
Regression (VAR). In the VAR, we ignore the common shock (DS_t) and estimate
the policy reaction function (equation 2.5) directly. This means we assume that the
stock market has no contemporaneous response to the interest rate ($\alpha = 0$). The
variable X_t in the structural equations (equations 2.5 and 2.6) represent the lags of
the dependent variables (I_t and S_t) as well as the macroeconomic shocks that might
affect I_t and S_t.

We employ daily data that run from 03/04/1985 to 12/31/1999. Macroeconomic
shocks data are obtained from Money Market Services survey. We do not have data
for weekends and holidays when markets are closed. We treat holidays like weekends.
Therefore, we end up with 3707 observations for the above period.

In the VAR, X_t includes five lags of the 3-month T-bill rate and five lags of the
stock market return as well as an unemployment shock ($UNEMP\_SK$); a producer
price index shock (PPI_SK); a durable good and services shock ($DRGS\_SK$); a
retail sales shock ($RTLS\_SK$) and a consumer price index shock (CPI_SK). Each
of these shocks is measured by the difference between the released value and the ex-
pected value. Equation (2.5) , which is a VAR can be perceived as a high frequency
monetary policy reaction function. The high frequency of the data helps to determine
the heteroscedasticity of shocks, which in turn would be used in the ITH method to
estimate the monetary policy reaction, β .

The results from the VAR estimation are shown in Table 2.1. It can be seen that
the three-month Treasury bill rate reacts significantly to the macro economic news

releases and the estimation reaction function does suggest the Fed tightens when the economy is strengthening or inflation is increasing . However, the reaction of monetary policy to the stock market is negative, which is inconsistent with the theory and practices of monetary policy, although it is statistically insignificant. The reason for this inconsistent estimation of the policy reaction parameter, β , might be the endogenity of the stock market response to monetary policy. Ignoring the endogenity of the stock market response creates a strongly biased estimation of the parameter, in our case a biased estimation of the monetary policy coefficient, β.

To overcome the endogenity problem between monetary policy and the stock market, in the next section, we employ the ITH method to estimate the monetary policy response coefficient. The advantage of the ITH method is that it takes both the simultaneous relationship between dependent variables in the simultaneous equations (endogenity problem) and the heteroscedasticity of the data into account to estimate the parameter of interest. In our case, The ITH method allows us to set up a simultaneous relationship between monetary policy and the stock market and it also overcomes the heteroscedasticity problem that most of macroeconomic data have.

Estimation of Monetary Policy Coefficient with a Common Shock

By using the steps and classification criteria of section 2.6.1, we obtain the regimes' shocks (ξ_t^i and ξ_t^s). Using regimes' shocks, we create the variance-covariance matrices of regimes. Table 2.2 shows the variance-covariance of the reduced form shocks for each regime. In regime 1, the variance of the interest rate shock and that of the stock market are low. In regime 2, the variance of the interest rate shock is low while that of the stock market is high. In regime 3, both the variance of the interest rate shock and that of the stock market are high. In regime 4, the variance of the interest rate shock is high while that of the stock market is low. The last column in Table 2.2 shows how many of both shocks (interest rate and stock market shocks) fall into a regime based on a 30-day rolling window and the criteria described in the section 2.6.1

As is shown in Table 2.2, the covariance between the shocks to the interest rate and shocks to the stocks market return fluctuates with the movements in their variances. As the variance of the interest rate shocks and variance of the stock returns shock increase, from regime1 to regime4, the covariance between the two residuals changes from negative to positive (The third column in the Table 2.2). This is a strong indicator of the relationship between these two shocks. As the variances of both shocks rise (regime3), the covariance between them reaches the highest level among

Table 2.1: **Short-Term Interest Rate Equation (Ignoring Endogenity)**

Number of obs.:	2905
Mis.cases:	0
Total SS:	0.677
R-squared	0.998
Res. SS:	0.001
F(16,2888)	100473
D-W:	1.989

Variable	Estimate	Standard Error	t-value	Prob > |t|	Standirezed Estimate	Cor with Dep Var
CONSTANT	0.000073	0.000046	1.592116	0.111	—	—
sp500	-0.000941	0.001344	-0.700216	0.484	-0.000558	0.013281
unemp_sk	-0.001497	0.000328	-4.561347	0	-0.003599	0.016591
ppi_sk	0.00043	0.000194	2.211608	0.027	0.00175	0.009983
drgs_sk	0.000018	0.000019	0.980829	0.327	0.000775	0.004118
rtls_sk	0.000249	0.0001	2.490841	0.013	0.001973	-0.028261
cpi_sk	0.000802	0.000498	1.610241	0.107	0.001272	0.022659
l1_3mtb	1.086737	0.018415	59.014626	0	1.087494	0.999069
l2_3mtb	-0.126925	0.027076	-4.687775	0	-0.127123	0.99797
l3_3mtb	-0.060049	0.027198	-2.207869	0.027	-0.06019	0.996962
l4_3mtb	0.160713	0.02716	5.91727	0	0.161212	0.99615
l5_3mtb	-0.062022	0.018449	-3.361736	0.001	-0.062259	0.995256
l1_sp500	0.000602	0.00134	0.44899	0.653	0.000357	0.012912
l2_sp500	0.000877	0.00134	0.654424	0.513	0.00052	0.013654
l3_sp500	0.001747	0.001339	1.304434	0.192	0.001036	0.013887
l4_sp500	0.000533	0.001337	0.398368	0.69	0.000316	0.014516
l5_sp500	0.001333	0.001336	0.997551	0.319	0.000791	0.015064

Table 2.2: **Regimes For Variance-Covariance of Reduced Form Shocks**

		Variance of Int. rate shock	Variance of stock mrk. shock	Covariance	Frequency of obs.	Percentage of obs.
Regime	1	0.3312	63.3476	-0.3569	2594	89.30%
Regime	2	0.3856	**282.9302**	2.4498	126	4.30%
Regime	3	**1.4793**	**417.2105**	3.3504	58	2%
Regime	4	**1.7152**	58.0353	1.4802	127	4.40%

High Variance in bold. Variables in percentage points

the four regimes. Finally, the covariance goes down as the variance of the stock market return goes down (regime 4). As can be noticed the covariance is very low and negative when the variance of shocks are low (regime1).

It was discussed previously that the monetary policy reaction to the stock market, β in equation (2.5), can be identified if there are at least three regimes in the presence of a common shock in the structural equations (equations 2.5 and 2.6).

We start with structural equations that have a common shock (equations 2.43 and 2.44). We will show that the exclusion of a common shock from the structural equations does not yield consistent estimates of the parameters. (Figure V and VI are not normally distributed).

We estimate the monetary policy coefficient by using regimes 1, 2 and 3 listed in Table II. By using this subset of regimes, we estimate the coefficient of the monetary policy reaction, β, to the stock market, which is a positive coefficient and $\cong 0.013$.

The distribution of the coefficient, β is obtained by the bootstrap estimation technique with replacement of sample (variance-covariance matrices of regimes) in 1000 draws.

Figure I shows the distribution of the bootstrap estimations of the monetary policy response coefficient, β by using regime1, 2 and 3. The bootstrap estimations of the monetary policy response coefficient are normally distributed in Figure I. The mean , standard deviation, median and mess below zero of this distribution are also shown in Table III. As shown in Table III, the mean of the distribution is 0.013 and none of estimates of the parameter fall below zero.

Figure II shows the distribution of the bootstrap estimations of the monetary policy response coefficient β by using regime1, 2 and 4. These bootstrap estimations of monetary response coefficients are also normally distributed with mean 0.014. The most important result of this empirical study is that the estimated parameter, β is positive and none of the calculated bootstrap estimates of β fall below zero.

Taking into account both the simultaneous relationship between monetary policy and the stock market return and the heteroscedasticity of the data, we find a significant positive reaction of monetary policy to the stock market fluctuation.

The point estimate of the response coefficient, β , indicates that a 5 % rise in the $S \& P$ index will increase the three month interest rate by ($0.013 x 0.05 = 0.00065$) 6.5 basis points. We can translate this estimate into the probability of policy tightening or easing. Since the $FOMC$ meets every six weeks, on average, the next $FOMC$ meeting will be about three weeks away. The 3-month T-Bill rate reflects the average expected rate for the next thirteen weeks (or 91 days). Therefore, the estimated coefficient corresponds roughly to an increase in the expected federal funds rate of (6.5 times 13/9) 9.39 basis points. The results suggest that an unexpected increase in the $S \& P$ 500 index by 5 % increases the federal fund rate expected after the next $FOMC$ meeting by 9.39 basis points. If we translate this into discrete policy actions, a 5 % rise in the $S \& P$ 500 index increases the probability of a 25 basis point tightening by about (9.39/25) 38 %. And a 5 % decline in the stock prices has similar effects for policy easing.

These findings do not necessarily mean that the Federal Reserve is targeting stock

prices or reacts to perceived misalignments in stock prices. This issue is still controversial among academics as well as policy makers. While some academics as well as policy makers argue that the monetary policy should react to the stock market only to the extend that stock prices affect aggregate demand, some argue that monetary policy makers should react to misalignments in stock markets to prevent stock market booms and busts (Cecchetti, Genberg, Lipsky and Wadhwani, (2000).

We employed different combinations of regimes to estimate the monetary policy coefficient, β. The estimates under alternative subsets of regimes are shown in Table 2.3.

Table 2.3: **Estimates Under Alternative Subsets of Regimes with a Common Shock**

	Regimes 1,2 ,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4	Regimes All
Mean of distribution	0.0133	0.0142	0.2604	0.2809	0.0126
Std.dev. of distribution	0.0177	0.0513	1.1654	0.5737	0.0043
Median of distribution	0.0127	0.0126	0.0122	0.0119	0.0126
Mass below zero	0.00%	0%	0.4%	0.7%	0.1%

The estimates obtained under four possible combinations of regimes are very close to each other. Two subsets of the regimes (1, 3, 4 and 2, 3, 4) yield estimates that are the least precise compared to the other combinations of regimes (like regime1,2,3 or 1,2,4 or All) i.e., their standard deviations are significantly higher. Rigobon and Sack claim that "The standard deviation of these estimates blows up considerably, primarily because of some realizations with very high values in regime3 and regime 4". Based on this evaluation, subsets of regimes 1, 3, 4 and 2, 3, 4 will not be considered

for future comparison.

As we discussed in section 2.6.4, we can use all regimes (1, 2, 3, 4) together to estimate the coefficient of monetary response function by using GMM/Minimum Distance Estimation. The GMM estimation of the parameter, All regimes, in Table III is very close to the estimations that are obtained by using regimes 1, 2, 3 and regimes 1, 2, 4. As can be seen in Table 2.3, the medians of distributions of all five subsets of regimes are very close to each other and range from 0.0119 to 0.0127.

As shown in Table 2.3, One of the most powerful points in this study is that even under bad subsets of regimes such as regime1,3,4 and 2,3,4 only a small mass of observations falls below zero . This is a strong indication that stock returns affect monetary policy.

As discussed in the theoretical part of the paper, we can test whether the restriction imposed on the model to get the ITH solution, that is, that the estimates are constant across regimes is valid. To do the test, we subtract the estimates that are obtained by bootstrap using regimes 1,2,3 and 1,2,4. The distribution of the difference in estimates that are obtained by the bootstrap is shown in Figure III. The mean of the distribution is -0.00095 and 54.9 percent of observations are positive and 45.1 percentage of observations are either zero or negative, which imply that we can not reject the hypothesis that the estimates are the same across regimes. It also implies that over identification is not a problem.

To evaluate the robustness of previous regime specifications, we employ some alternative regime specifications to see whether the ITH solution is sensitive to a misspecification of heteroscedasticity. We first create new specifications of rolling windows, such as 3-months and 6-months instead of the former 30-day window. We keep the same definition of high and low variance of shocks (in section II.a) to determine the regimes. The results are shown in Table 2.4

As can be seen, the mean of the β estimates under the alternative definitions of regimes falls within the range of what we previously estimated. Also there is an improvement in the standard deviation of distributions. The Table 2.4 shows that

Table 2.4: Estimates under Alternative Definition of Regimes.

	3- Month Regimes	6-Month Regimes
Mean of distribution	0.0149	0.0161
Standard deviation of distribution	0.0042	0.0042
Median of distribution	0.0148	0.0161
Mass below zero	0.00%	0.00%

Estimates based on all regimes with a common shock

the reaction of monetary policy to stock market is positive and strongly significant.

We also compute the estimates with different criteria for determining high variance and low variance regimes. One scenario is to reduce the high variance criteria to half of one standard deviation above its long run average and another scenario is to increase it to 2-standard deviation above its long run average. The point estimates under above two scenarios are shown in Table V.

Table 2.5: Estimates Under Alternative Definitions of Regimes

	One-half std.dev. Regimes	Two std. Dev. Regimes
Mean of distribution	0.016	0.0143
Standard deviation of the distribution	0.2106	0.0075
Median of distribution	0.221	0.0142
Mass below zero	0.02%	2.20%

Even though we changed the criteria for determining the regimes, the estimates are very close to the estimates in Table 2.4, which is consistent with the argument that the ITH method is not very sensitive to misspecification of regime unless the regimes are very poorly specified.

Estimation of Monetary Policy Coefficient without a Common Shock

In the absence of a common shock, we use equations (2.5) and (2.6), that is, the structural equations that do not include a common shock. We use four different possible subsets of regimes to estimate the monetary policy response coefficient. The distribution of the bootstrap estimation of the monetary policy response coefficient using regime 1 and regime 2 is shown in Figure IV. The monetary policy response coefficients that are obtained by employing bootstrap estimation of the variance-covariance matrices are normally distributed with mean 0.01298. This is an indicator that when using regime 1 and 2 we can consistently estimate the reaction of monetary policy. However, when we estimate the monetary policy coefficients using regime1 and 3 or regime 1 and 4 , the estimated coefficients are not normally distributed as shown in figure V and figure VI. These graphical results imply that the exclusion of a common shock in the structural equations leads to an inconsistent estimation. Furthermore, to show that the monetary policy coefficient, β can not be consistently estimated, we take the differences between the bootstrap estimation of β values that we obtained by using regime1, 3 and regime1, 4. We obtain the results shown in figure VII. As we expected, the distribution of the differences is not normally distributed with mean zero. This implies the over identification is a problem if we estimate the monetary policy coefficient without a common shock. It also implies that the parameter is not constant across regimes: a violation of the ITH assumption that we imposed on the solution.

Table 2.6 shows the different subsets of regimes that are used in the bootstrap estimation of monetary policy coefficients without a common shock. Unexpected β values are obtained if we use All regimes. As shown in Table 2.6, the estimated β values of this regime are 99.9 percent negative. This is another reason to not estimate the monetary policy coefficient without a common shock.

68

Table 2.6: **Estimates Under Alternative Subsets of Regimes**

	Regimes 1, 2	Regimes 1, 3	Regimes 1, 4	Regimes All
Mean of distribution	0.01298	0.08445	2.50362	-0.01147
Standard deviation of distribution	0.00422	0.46657	30.66186	0.00318
Median of distribution	0.01289	0.03132	0.74218	-0.01162
Mass below zero	0.01%	0.02%	0.018%	99.90%

2.0.8 Conclusion

By employing the Identification Through Heteroscedasticity method, we estimated the reaction of monetary policy to the stock market. There are two big advantages of this method: First, it solves the heteroscedasticity problem that exits in most of macroeconomic data. It uses the heteroscedasticity of data to determine regime change and uses regime change to estimate the parameter of interest, in our case, the reaction of monetary policy, β. Second, it allows the use of simultaneous relationships between the variables of interest, in our case the relationship between the interest rate and stock prices.

The estimated results indicate that a 5 % increase in stock price would raise the Treasury bill rate by 6.5 basis point, implying that 5 % increase in stock price raises the probability of a 25% basis point tightening by 38%. And, a 5 % decline in stock price has similar effect for policy easing.

These findings do not necessarily mean that the Federal Reserve is targeting stock prices or reacts to perceived misalignments in stock prices. There is some debate about whether targeting stock prices would be effective: while some academics as well as policy makers argue that the monetary policy should react to the stock market only to the extend that stock prices affect aggregate demand, some argue that monetary

policy makers should react to perceived misalignments in stock markets to reduce asset price bubbles and boost (Cecchetti, Genberg, Lipsky and Wadhwani,2000).

Our finding is consistent with the Federal Reserve's model of the U.S economy as described in Reifschneider, Tetlow and Williams (1999). According to that model, under a stabilizing policy, a 5% permanent shock to stock market would suggest 12.5 basis points increase in federal fund rate (Rigobon & Sack 2003), which is very close to our finding of 9.4 basis point increase in federal fund rate if $S \& P$ index goes up by 5%.
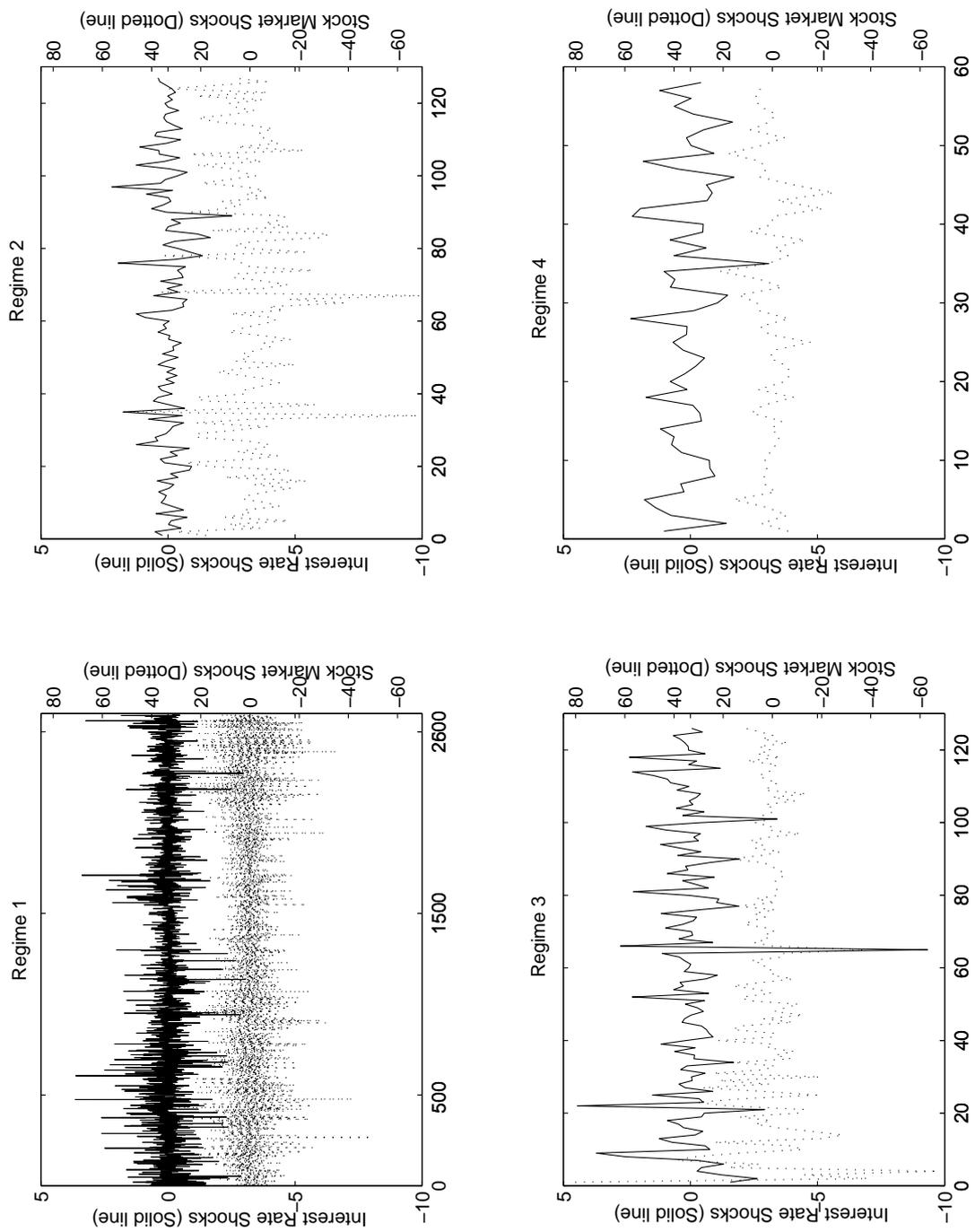
Figure 2.1: All Regimes:shocks multiplied by 10000

FIGURE I.

Distribution of Estimated Monetary Policy Response Coefficient
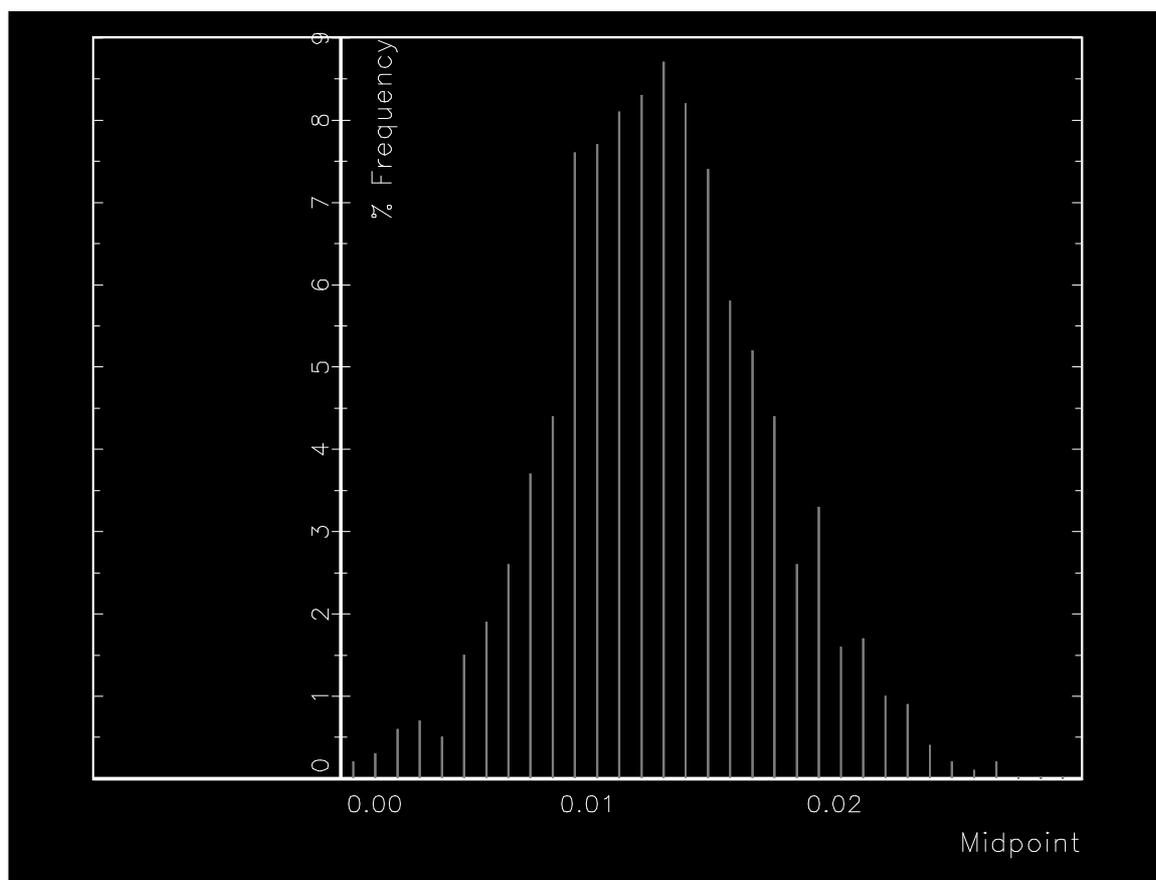
Figure 2.2: Using Regimes 1, 2 and 3

Distribution of Estimated Monetary Policy Response Coefficient
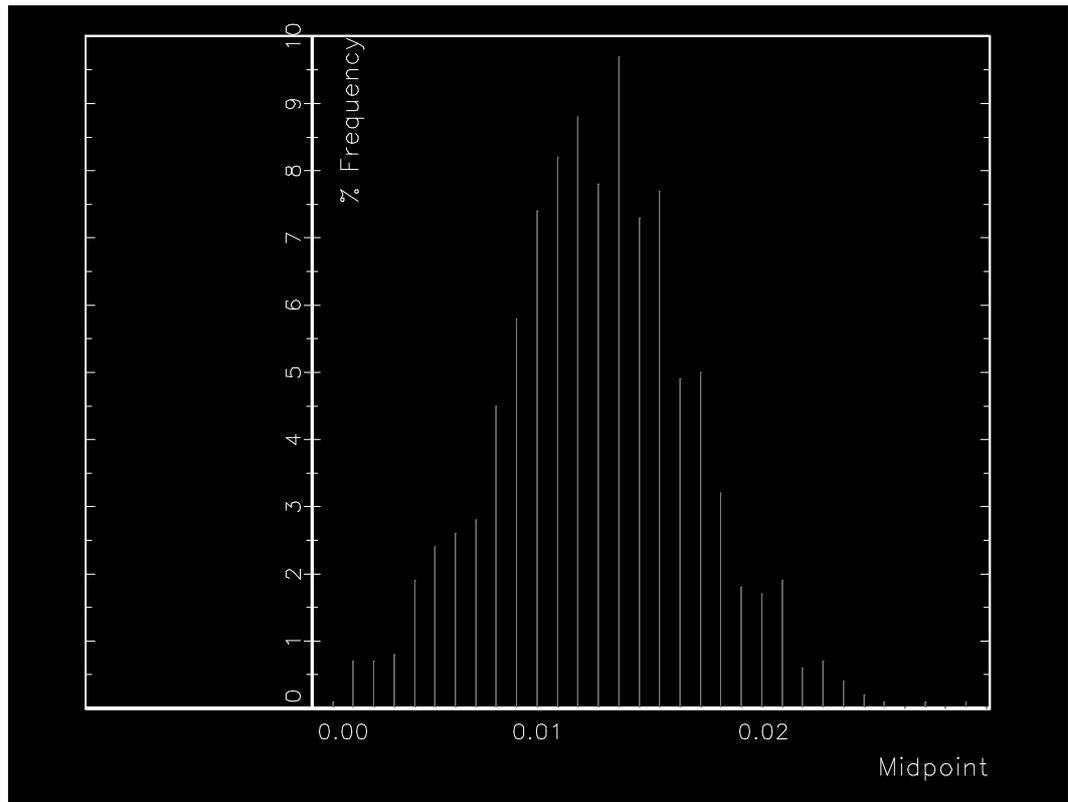
Figure 2.3: Using Regimes 1, 2 and 4

Difference between Estimated Coefficients
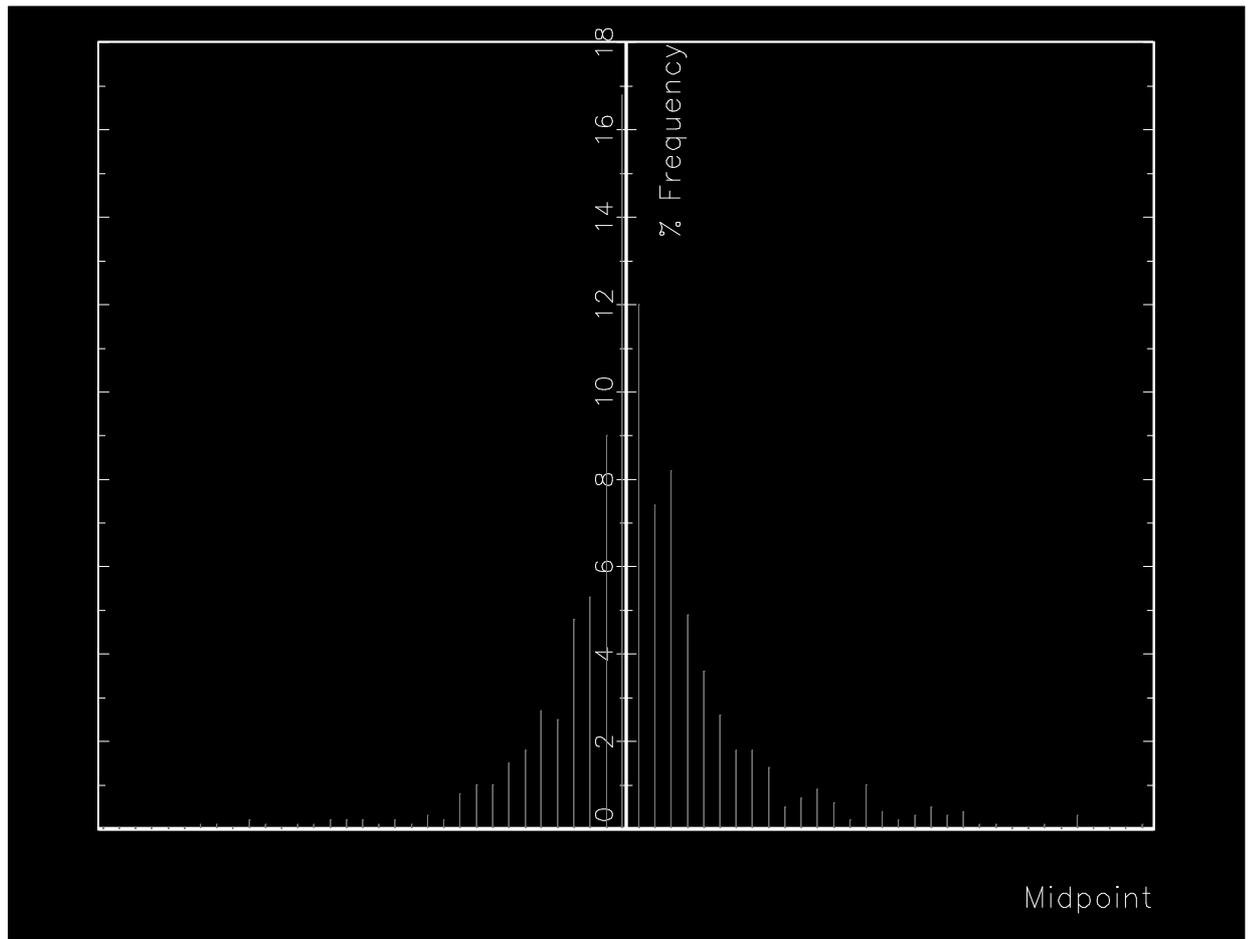
Figure 2.4: Test of Over identifying Restrictions (Regime 1,2,3 versus Regimes 1,2,4)

Distribution of Estimated Monetary Policy Response Coefficient
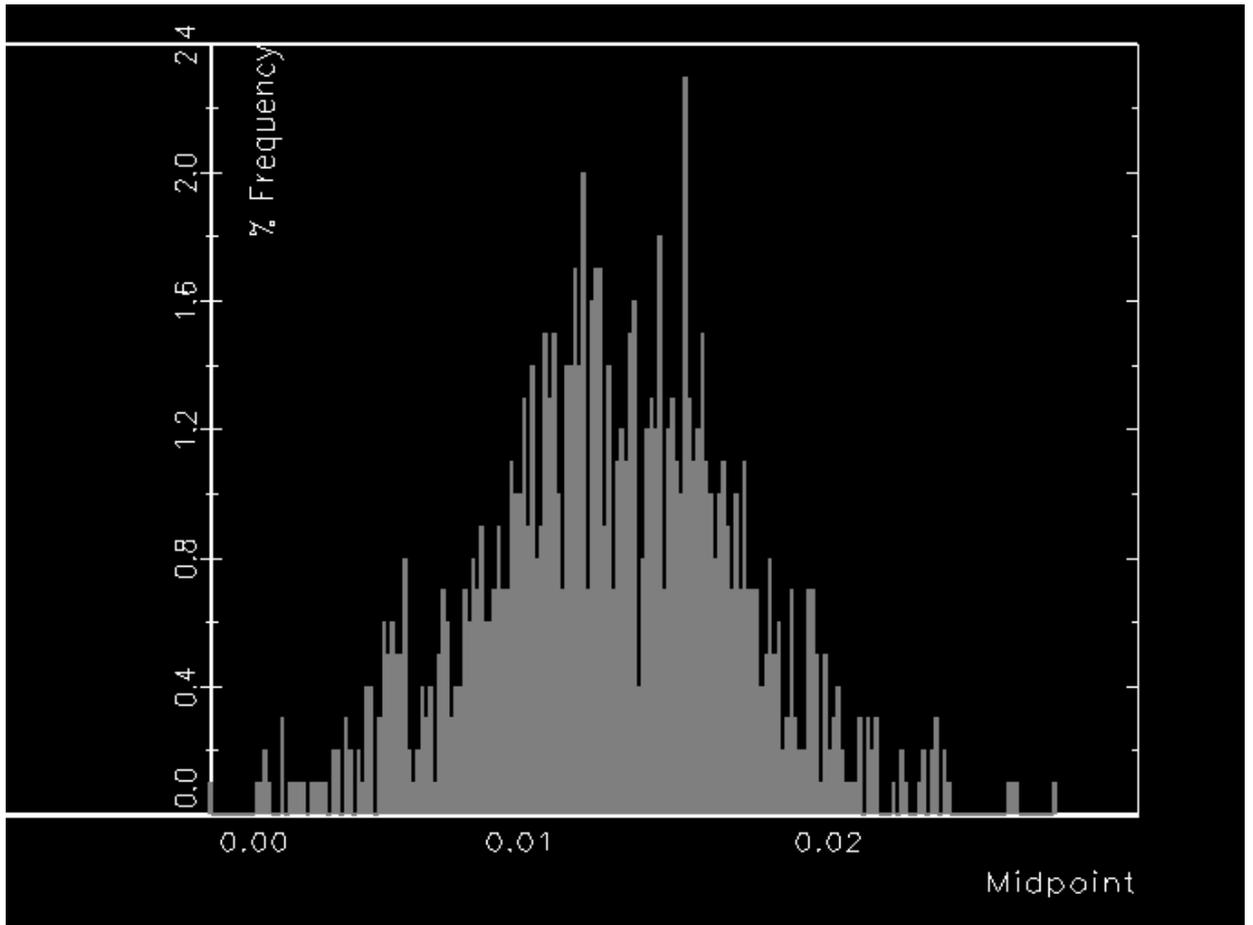
Figure 2.5: Using Regime 1 and 2

Distribution of Estimated Monetary Policy Response Coefficient
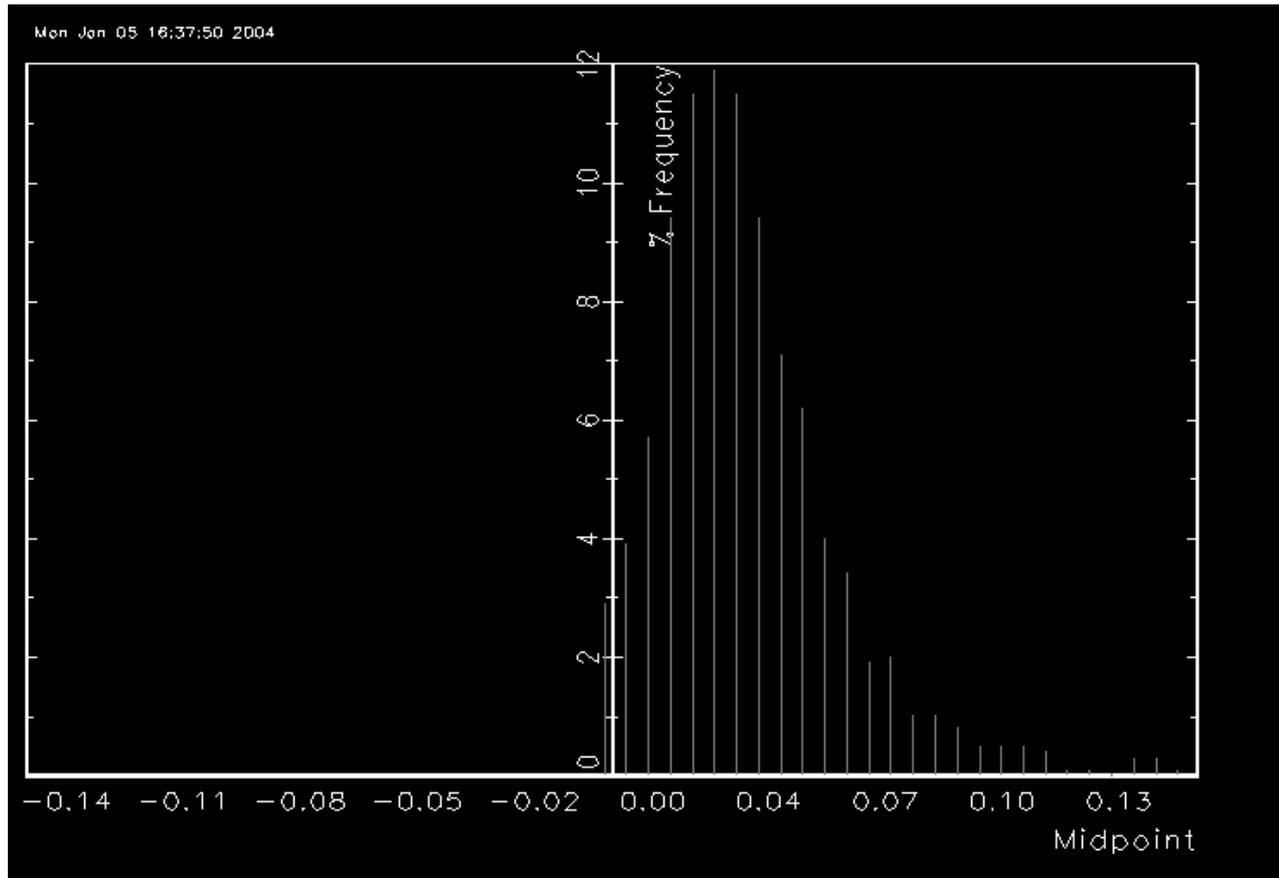
Figure 2.6: Using Regime 1 and 3

Distribution of Estimated Monetary Policy Response Coefficient
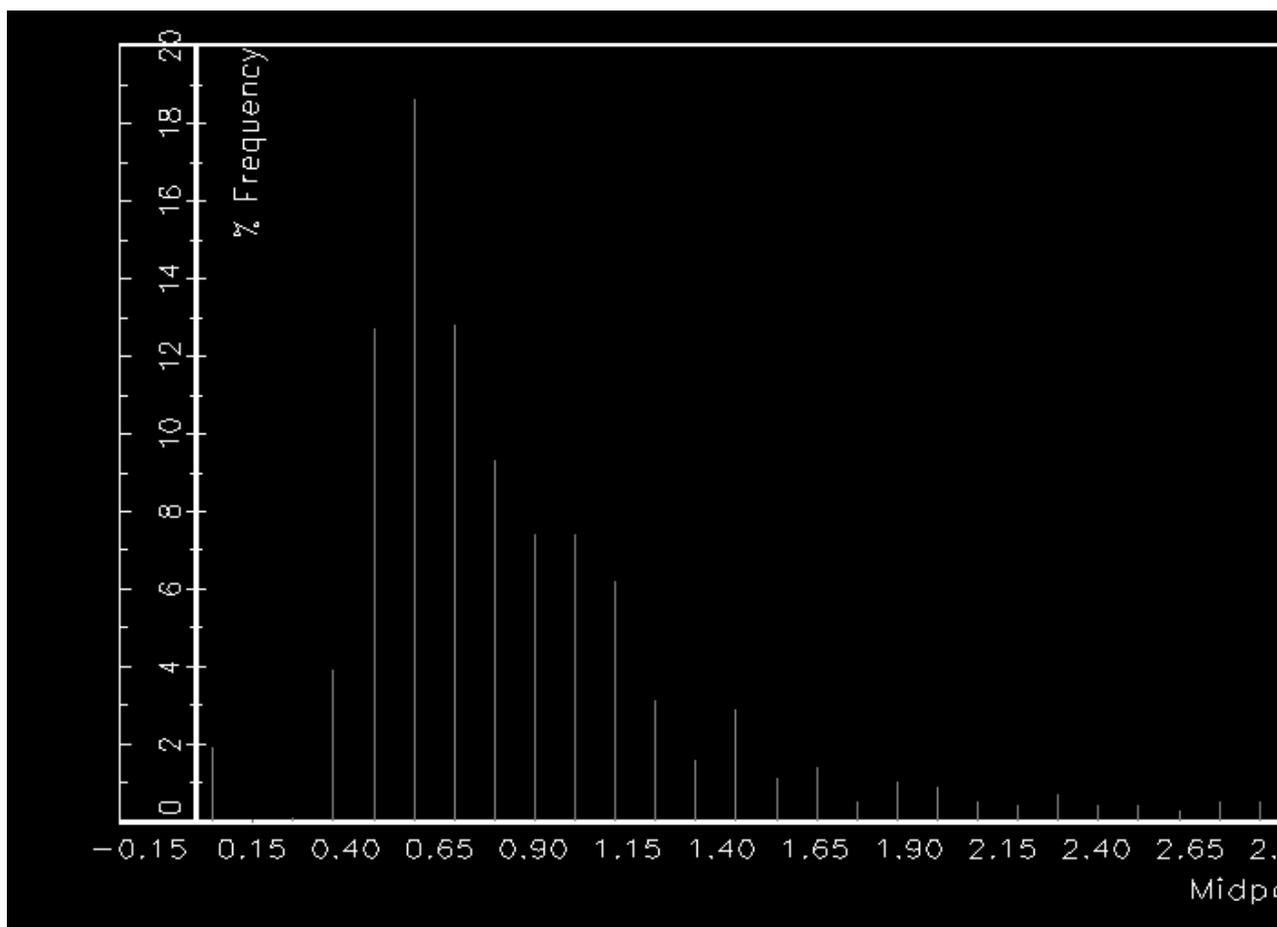
Figure 2.7: Using Regime 1 and 4

Difference between Estimated Coefficients
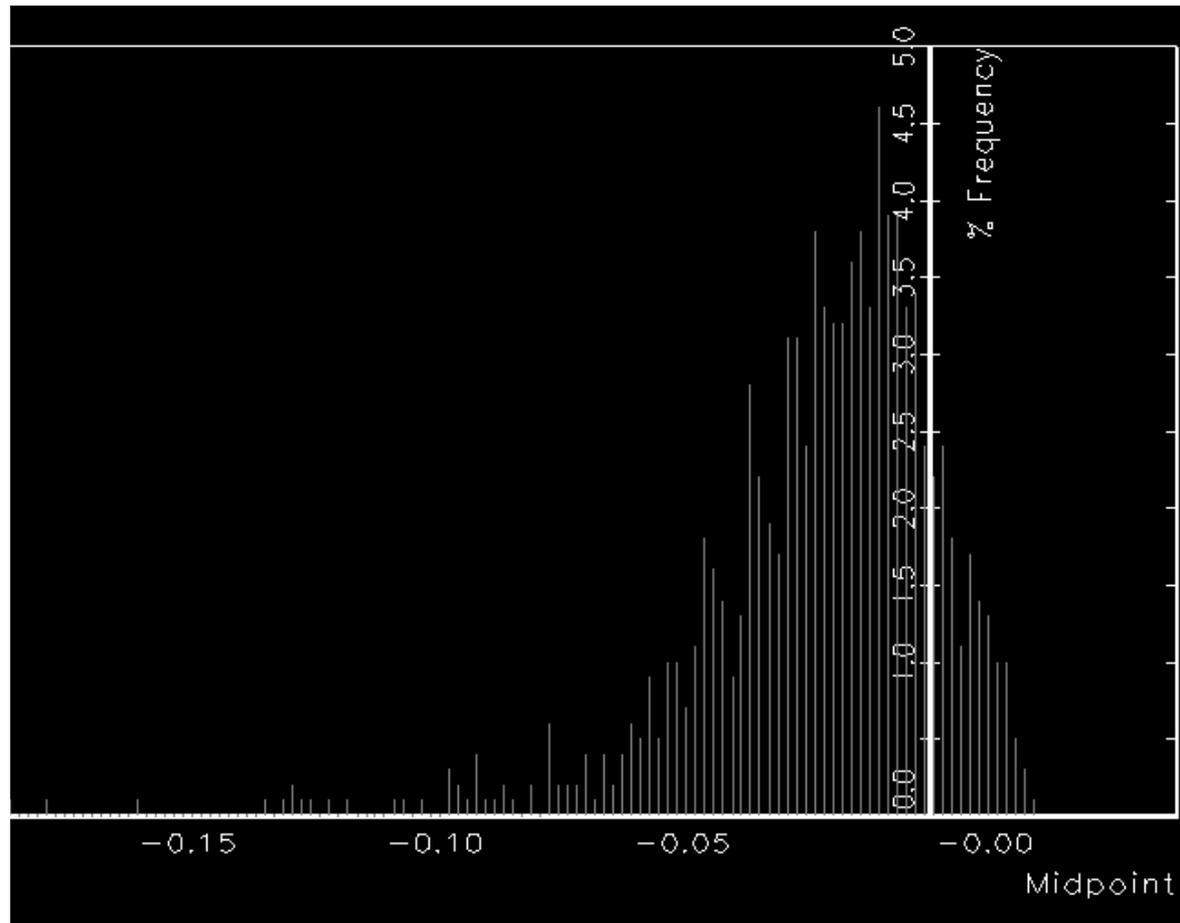
Figure 2.8: Test of Over Identification Restrictions (Regime 1,2 versus regime 1,3)

Chapter 3

THE REACTION OF MONETARY POLICY TO EXCHANGE RATE

Abstract

In this second essay we analyze the relationship between monetary policy and the exchange rate using the ITH method. In this essay we define regime changes based on two different methods: First, we allow the data to determine the regime changes and estimate the reaction of monetary policy to different exchange rates such as Yen/\$, Index/\$ and Pound/\$. Second, we determine regime changes exogenously, based on the historical exchange rate policies in the United States and estimate the reaction of monetary policy to exchange rates.

3.0.9 Introduction

Both the theoretical and the empirical literature on the relationship between monetary policy and exchange rate are ambiguous. This issue can be represented by the Uncovered Interest Parity (UIP) equation:

$$i_t - i_t^* = S_t - E(S_{t+1}) + \rho_t + \phi_t \tag{3.1}$$

The traditional view suggests that the relationship between the interest rate and the exchange rate is positive, holding foreign policies (i_t^*), the expectation of future exchange rate $E(S_{t+1})$, the exchange rate risk premium (ρ_t) and the default risk on domestic bond (ϕ_t) constant. However, it is argued that these assumptions are unrealistic. The expectations about the exchange rate and the exchange rate risk premium are sensitive to stages of the economy. In times of economic crisis, expectations and risk premiums are volatile. Also, the default risk on domestic bonds can be positively correlated with interest rates during bad times. If this correlation is high, then it is possible to have a perverse relationship between the interest rate and the exchange rate. That is, a rise in the interest rate may lead to a depreciation in the exchange rate. As we discuss in the next section there is a huge amount of literature that shows that a rise in the interest rate leads a depreciation of the domestic currency and vice versa.

The conflicting results of empirical studies on the relationship between monetary policy and exchange rate are still a controversial issue among both academicians and policy makers. Sims (1992) looked at five major industrial countries and analyzed their monetary shocks. He found that there was a positive relationship between positive interest rate innovations and domestic prices that he labelled the "Price Puzzle." He also found that a positive interest rate innovation causes a depreciation of the home currency that he labelled the "exchange rate puzzle."

Despite the controversial evidence of the relationship between monetary policy and exchange rates, there are at least four direct reasons why a central bank may

react to fluctuations in the exchange market

- Fluctuations in the exchange rate or misalignments can reduce international investment flows. That is, an unstable exchange rate increases the risk on the rate of return on foreign assets. This leads to foreign capital outflows.
- Fluctuation or uncertainty in exchange rates negatively affect Foreign Direct Investment i.e. investors may not feel safe buying or building new plants in a country that does not have a stable currency. This leads to inefficiency in the allocation of resources in a domestic and global economy
- Exchange rate misalignments, uncertainty, or volatility have a negative effect on international trade. Unstable exchange rates affect the profitability on traded goods and services . Economic agents have to add a risk premium to the cost of goods that they trade abroad, which reduces overall trade.
- Exchange rate fluctuations and uncertainty may affect financial markets. If exchange rate fluctuations affect the riskiness of domestic assets, then the price of these assets will be more volatile. One goal of policy is to stabilize financial markets.

There are at least two indirect reasons why monetary policy may react to fluctuation in exchange rate. Regardless of whether monetary policy makers react to only fluctuations in output and inflation, an appreciation of the domestic currency will have two effects on the economy that will force monetary policy makers to react to exchange markets:

- An appreciation of domestic currency will lower real GDP by expenditure switching. The appreciation of domestic currency makes foreign goods and services cheaper than domestic goods and services, which leads to an increase in imports and a decrease in exports,

therefore reducing real GDP.

- An appreciation of domestic currency will lower domestic inflation because the price of imported goods will not increase as much as the appreciation of the domestic currency.

These direct and indirect effects of the exchange rate on the domestic economy force many central banks to be sensitive to changes in exchange rates.

On the one hand, based on the Uncovered Interest Parity or the Portfolio Balance arguments, a higher interest rate (tightening monetary policy) leads to capital inflows, and therefore, to an appreciation of domestic currency. We can interpret this as a market reaction to monetary policy. This is a positive relationship between monetary policy and the exchange rate. On the other hand, monetary policy reacts to a depreciation of domestic currency by the increasing the interest rate and to appreciation of the domestic currency by decreasing the interest rate. Therefore, the relationship between monetary policy and the exchange rate is negative. These relationships are the reasons that we employ simultaneous equations to measure the reaction of monetary policy to exchange rates in this essay.

We employ Identification the Through Heteroscedasticity (ITH) method to measure the reaction of monetary policy to fluctuations in the exchange market. We define two different regime changes: First, we allow data determine regimes changes based on the heteroscedasticity in the data and use regime changes to measure the reaction of monetary policy to fluctuations in exchange market. Second, we determine regime changes based on exchange rate policies applied during the time period that we are interested in. As we discussed in the first section of this dissertation there are two big advantages of the ITH method. It allows us to estimate the reaction of monetary policy to fluctuation in exchange market simultaneously and it overcomes the heteroscedasticity problem. We analyze the relationship between monetary policy and exchange rate based on Yen/Dollar, Index/Dollar and Pound/Dollar

3.0.10 Literature

The theoretical literature on the "Asset-Market" view of the exchange market can be classified into two broad approaches:

1. The Monetary Approach

2. The Portfolio-Balance Approach.

The common theoretical assumptions of asset market models are the following:

a)There are no capital controls or other barriers to the flow of capital among countries.

b) There are no transaction costs.

The above two assumptions guarantee "perfect capital mobility" across borders. If capital is perfectly mobile across countries, then the exchange rates respond instantly to changes in the demand for national assets in order to equilibrate the international demand for those national assets. In the traditional view of the exchange rate, the exchange rate adjusts in order to equilibrate the international demand for the flow of national goods. While in the asset market view, the exchange rate adjusts to equilibrate the international demand for the flow of capital.

The basic difference between the Monetary Approach and the Portfolio-Balance Approach comes from assuming whether domestic and foreign bonds are perfect substitutes for each other in economic agents' portfolios. We begin with a brief review of the literature on how the Monetary Approach and the Portfolio-Balance Approach relate to monetary policy and exchange rates.

3.0.11 The Monetary Approaches

The Monetary Approach assumes that national and foreign bonds as well as national and foreign goods are perfect substitutes across borders. This will be referred to as "the one bond and one good assumption".

There are two very different models of the Monetary Approach to the exchange rate: The first one is called the "Chicago Theory" since it assumes that prices are perfectly flexible. The second one is called the "Keynesian Theory" since it assumes that prices are sticky at least in the short-run (Frankel, 1997, pp.77-78).

Chicago Theory (Or The Flexible-Price Monetary Models)

Since prices are assumed to be perfectly flexible, changes in expected inflation drive the domestic interest rate up and lead to a depreciation in the domestic currency. As the expected inflation rate rises, the demand for the domestic currency falls and the demand for the foreign currency rises. Therefore, the domestic currency depreciates immediately. If we define the "exchange rate" as the dollar price of the foreign currency, then the above process means a rise in the exchange rate. Thus, according to the Chicago Theory, there is a positive relationship between the exchange rate and the nominal interest rate differential. We can see that the Chicago Theory implies purchasing power parity which means that the domestic price (p^d) level is equal to the foreign price level (p^f) times the exchange rate (S=\$/foreign currency):

$$P^d = SP^f \tag{3.2}$$

The flexible price monetary model has been developed by Frankel (1977 and 1980), Mussa (1976), Bilson (1978), and Barro (1998). The money demand function for the domestic country is

$$M = P + \gamma Y - \alpha I \tag{3.3}$$

and for the foreign country is

$$M^* = P^* + \gamma Y^* - \alpha I^* \tag{3.4}$$

where M, P, and Y are the domestic money supply, price level and real income respectively, in log form. I is the domestic short-run interest rate. γ is the money demand elasticity with respect to income and α is the money demand semi-elasticity with respect to the interest rate. Asterisks denote the foreign variables. By taking

the differences between domestic and the foreign demand functions, we can obtain a relative demand function:

$$M - M^* = (P - P^*) + \gamma(Y - Y^*) - \alpha(I - I^*) \tag{3.5}$$

The one-bond assumption yields the "uncovered interest parity" relationship

$$E(\Delta S) = I - I^* \tag{3.6}$$

where $E(\Delta S)$ is the expected depreciation of domestic currency. The one-good assumption yields the purchasing power parity relationship:

$$S = P - P^* \tag{3.7}$$

where S is log of the spot exchange rate. Therefore, expected depreciation can be written as

$$E(\Delta S) = E(\Delta P) - E(\Delta P^*) \tag{3.8}$$

where $E(\Delta P)$ is expected domestic inflation and $E(\Delta P^*)$ is expected foreign inflation. Now by combining eqs. (3.5), (3.7), and (3.8), we can obtain the monetary approach of exchange rate:

$$S = (M - M^*) - \gamma(Y - Y^*) + \alpha[E(\Delta P) - E(\Delta P^*)] \tag{3.9}$$

This equation reveals that an increase in the domestic money supply or in the expected domestic price level leads to a proportional rise in the exchange rate (depreciation in the domestic currency) while an increase in domestic income leads to an increase in the demand for domestic money and therefore leads to a fall in the exchange rate (appreciation of domestic currency).

Mussa (1976) expanded this kind of monetary model to give consideration to permanent and transitory monetary disturbances. Barro (1978) added consideration to anticipated and unanticipated disturbances.

85

Keynesian Theory (Sticky Prices or Overshooting Monetary Model)

Since prices are often assumed to be sticky, an increase in the domestic money supply relative to money demand leads to the domestic interest rate going down, therefore causing capital outflows which in turn causes the domestic currency to depreciate instantaneously. In this case, the theory states that there will be a negative relationship between the exchange rate and nominal interest differential.

Mundell (1963) is known as the pioneer of this kind of model. He assumes perfect capital mobility. He argues that a monetary expansion causes a large instant depreciation in the domestic currency, due to the domestic interest rate falling as the money supply increases. The falling domestic interest rate causes a capital outflow and depreciation of the domestic currency.

Dornbusch (1976) developed this kind of model by including sticky prices in the short-run and rational expectations. In the Dornbusch model, Purchasing Power Parity holds in the long run. He states that an increase in the money supply increases the exchange rate proportionally. In the short-run since prices are sticky, an increasing money supply reduces the domestic interest rate. This causes a capital outflow, which leads to a depreciation of the domestic currency below its long-run equilibrium. This is where the "overshooting" name comes from. The overshooting model has the same demand function and uncovered interest parity condition as the flexible price monetary model but it replaces the short-run PPP (Purchasing Power Parity) condition with long-run PPP (indicated by bar):

$$\bar{S} = \bar{P} - \bar{P}^* \tag{3.10}$$

Therefore the long-run version of the monetary exchange rate is

$$\bar{S} = (\bar{M} - \bar{M}^*) - \gamma(\bar{Y} - \bar{Y}^*) + \alpha[E(\Delta\bar{P}) - E(\Delta\bar{P}^*)] \tag{3.11}$$

(see eq. 3.5 for reference). Under rational expectation assumptions, relative price levels and the exchange rate all grow at the current rate of monetary growth . Therefore

eq.(3.11) becomes

$$\bar{S} = (\bar{M} - \bar{M}^*) - \gamma(\bar{Y} - \bar{Y}^*) + \alpha(\Pi - \Pi^*) \tag{3.12}$$

In the short-run, the exchange rate deviates from its equilibrium level because prices are sticky. This deviation will disappear in the long-run. The length of time depends on the speed of adjustment. In the long-run, the exchange rate increases at a rate equal to $\Pi - \Pi^*$. Therefore, the expected exchange rate becomes:

$$E(\Delta S) = -\beta(S - \bar{S}) + \Pi - \Pi^* \tag{3.13}$$

Where β is the speed of the adjustment. Combining (3.13) with uncovered interest parity

$$E(\Delta S) = I - I^* \tag{3.14}$$

, and we obtain:

$$S - \bar{S} = -(\frac{1}{\beta})[(I - \Pi) - (I^* - \Pi^*)] \tag{3.15}$$

Eq.(3.15) shows that the deviation of the exchange rate from its equilibrium value is proportional to the real interest rate differential. This means that expansionary monetary policy causes the nominal interest differential to fall below its equilibrium level, which leads to capital outflows and depreciation of the domestic currency. By combining eq. (3.12), a long-run equilibrium equation, and eq.(3.15) , a short-run equilibrium equation, we obtain the sticky price (overshooting) monetary equation for the exchange rate:

$$S = (\bar{M} - \bar{M}^*) - \gamma(\bar{Y} - \bar{Y}^*) + \alpha(\Pi - \Pi^*) - (\frac{1}{\beta})[(I - \Pi) - (I^* - \Pi^*)] \tag{3.16}$$

This equation is the same as that of the flexible monetary model, eq.(3.9), except for the real interest rate differential. If the flexible price model is correct, then (adjustment speed) is very fast, the coefficient of the real interest differential is essentially zero and eq.(3.16) becomes eq.(3.9). This means both the flexible and sticky

price models end up with the same equation. But if prices are sticky, which means β is small, then a monetary expansion reduces the domestic interest rate due to the liquidity effect and causes outflows of capital. This leads to a large depreciation of the domestic currency in the short-run than in the long run.

Wilson's (1979) model gave consideration to transitory and permanent disturbances. Gray and Turnosky (1979) extended this model by giving consideration to anticipated and unanticipated monetary disturbances.

3.0.12 The Portfolio-Balance Approach

In this class of asset market models, domestic and foreign bonds are not perfect substitutes.

The portfolio-balance approach assumes that domestic investors allocate a proportion (α_d) of their wealth (W_d) to domestic assets (A_d) and the rest of their wealth to foreign currency (F_d). Thus,

$$A_d = \alpha_d W_d, \qquad where \quad W_d = A_d + SF_d \qquad (3.17)$$

If we define a "partner country" as a country that domestic investors keep a part of their wealth in its currency, then the partner country's investors would have another portfolio-balance formula:

$$A_p = \alpha_p W_p, \qquad where \quad W_p = A_P + SF_P \qquad (3.18)$$

The investors of the rest of the world have:

$$A_r = \alpha_r W_r, \qquad where \quad W_r = A_d + SF_r \qquad (3.19)$$

Frankel(1997) argues that data on A_d, A_P, A_R, and on F_d, F_P, F_r are not normally available. But he set up the totals for the assets and foreign currency as follows:

$$A = A_d + A_p + A_r \qquad (3.20)$$

$$F = F_d + F_p + F_r \qquad (3.21)$$

where A is the cumulation in each country of government deficits and F is the cumulation of past current account surpluses. He admitted that it is not clear how to formulate S as a function of A, F, W_d and W_p but he argued that the relationships are:

a- An increase in the supply of foreign assets (Fd) lowers their prices causing an appreciation of domestic currency (decrease in S).

b- An increase in the domestic asset supply (A_d) depreciates the domestic currency (an increase in S)

c- An increase in partner's wealth (W_p) raises the demand for the foreign assets leading to a depreciation of domestic currency. The assumption that leads to this result is that the ratio of foreign assets to partner assets in foreigners' portfolio is bigger than one

d- -An increase in domestic wealth (W_d) increases the demand for the domestic assets. Therefore, it appreciates the domestic currency (decrease in S).

Branson, Hannu, Masson (1979) and Frankel (1997) looked at the relationship between the exchange rate and aforementioned variables, but found little evidence supporting the model.

3.0.13 Empirical Research about the Relationship between Monetary Policy and Exchange Rate

The empirical literature of the exchange rate models showed that most of the popular models were of no use whatsoever in predicting the behavior of the exchange rate during the 1980s. For example, Meese and Rogoff (1983) wrote that the well-known models of the exchange rate, like Frankel (1976), Bilson (1978), Dornbusch (1976) and Hooper and Morton (1982) did not predict as well as a simple random walk model (Frankel, 1997). Therefore, since the early 1990s, the empirical research on

the reaction of monetary policy to exchange rate shocks focused on the VAR analysis (Sims, 1992), Baglino and Favora (1999), Clarida and Gertler (1997), Faust and Rogers (1998), Anker (2001) and Kim (2002). The empirical results of the papers that used VAR and other methods to estimate the reaction of the monetary policy to the exchange rate or vice versa are mixed. The direction and significance of exchange rate responses to monetary policy or vice versa are still controversial.

Aghion, Bacehetta, and Banerjee (2000) developed a two- period, small- open economy monetary model. They argue that a higher interest rate policy in response to a currency crisis may not work especially in emerging market economies. Their argument is that you have on the one hand, a higher interest rate affecting the appreciation of the domestic currency and therefore improving the finances of the domestic firms that have debts in the foreign currency. On the other hand, you have higher interest rates also affecting an increase in the current debt burden of the domestic firms (due to depreciation of the domestic currency) and therefore reducing their ability to avoid bankruptcy or their ability to resist short-run fluctuations in the economy. If the firms are credit constrained, the second effect of high interest rates is bigger, and the higher interest rate depreciates the exchange rate. The argument states that the reason for depreciation is that there would be a huge capital outflow, either because of the high probability of bankruptcy or the reality of bankruptcy .

Anker (2001) found that neither real shocks nor the actual monetary policy reaction to shocks can explain exchange rate movements. Sims (1992) looked at five major industrial countries and analyzed their monetary shocks. He found that there was a positive relationship between interest rate innovations and domestic prices that he labelled the "Price Puzzle." He also found that a positive interest rate innovation causes a depreciation of the home currency that he labelled the "exchange rate puzzle."

Faust and Rogers (1999) conclude that monetary policy shocks account for a small portion of the variance of the exchange rate and they doubt that the monetary policy shocks are the main source of exchange rate volatility. Clarida and Gali (1994) found

that monetary shocks explain only 2.8 % of the variance of the real exchange rate.

On the other hand, some other recent VAR models provide evidence of the relationship between monetary policy and exchange rates. Rogers (1999) used annual observations from 1889 to 1992 and found that the contribution of monetary shocks to the exchange rate variation ranges from 18.7 % to 60.2 % with a median contribution of 40.6 %. Kim (2002) employed a structural VAR model for three European countries (France, Denmark, and Germany) during the exchange rate management (ERM) period to analyze the monetary policy reaction to the exchange rate. By using monthly data from 1979 to 1997, he found that the exchange rate shock and the interest rate shock together explain 45-60 % of the interest rate variation in France and 35-42 % in Denmark. The exchange rate shock explains 10-12 % of the interest rate variations in Germany. He argued that if the variations in the interest rate represent the variations in the policy instrument, then France and Denmark changed their monetary policy in order to eliminate the negative side effects of the exchange rate destabilization. He concluded that in response to the exchange rate shocks (depreciation), the monetary authorities of each of these countries increased the interest rate to stabilize (or appreciate) the exchange rate. In response to German interest rate shocks, France and Denmark also increased their interest rates to stabilize their exchange rates.

Dekle, Hsiao, Wang (2002) classified the literature on high interest rates and exchange rates into two categories:

a- Traditional View

b- Revisionist View

The traditional view emphasizes that a higher interest rate attracts foreign capital and increases the return that foreign investors obtain by investing in the country, assuming no offsetting expected depreciation. This leads to an appreciation of the domestic currency. The revisionist view accentuates that during financial turmoil an increase in interest rates may lead to a depreciation of the domestic currency. The reason

for this contrary effect is that a high interest rate can have a negative effect on the ability of firms to pay back their loans and increase default probabilities. This leads to huge capital outflows and in turn depreciates the domestic currency. They found that during the Asian financial crisis, raising the interest rate has had the traditional impact of appreciation of the domestic currency. In all three countries (Korean, Malaysia, and Thailand), the coefficients on the interest rate were negative, indicating that raising the interest rate would have the traditional impact of appreciating of the exchange rate in the short-run.

Caporale, Cipollini and Demetriades (2003) employ the Identification Through Heteroscedasticity (ITH) method to analyze the relationship between monetary policy and the exchange rate before and during the Asian Crisis. Their findings support the "traditional view": a higher interest rate leads to an appreciation in nominal exchange rate during tranquil periods. However, their findings also support the "revisionist view": tightening monetary policy during the Asian Crisis was excessive and has contributed to the further depreciation of the exchange rates.

Cushman and Zha (1997) analyzed the impact of monetary policy shocks on the exchange rate. By employing a VAR with "Block Exogenity", they found in the short-run following a contractionary monetary policy shock that the values of the nominal and real Canadian interest rates rise and that the nominal and real values of the Canadian currency also rise.

Zettelmeyer (2000) studied the impact of monetary policy shocks on the exchange rate in Australia, Canada, and New Zealand. He used regular regression to analyze the response of the exchange rate to the three-month interest rate on the day of the announcement. He found that there is a significant response of the exchange rate to policy shocks. That is, a contractionary policy leads to an appreciation of the domestic currency. He found that even in times of financial turmoil, monetary policy shocks affect the exchange rate, which contradicts the revisionist approach of the exchange rate. He admitted that even though central banks were capable of stabilizing the exchange rate, they often end up partly accommodating exchange rate

pressures.

As we mentioned above the empirical results are mixed on whether monetary policies and money affect exchange markets. The next question we discuss is whether a monetary policy should react to exchange markets.

3.0.14 Should Central Banks React (Intervene) to Exchange Market?

Literature

After the collapse of the fixed exchange rate system (Bretton Woods) in 1973, most of the central banks adopted a flexible exchange rate system, but they have continued to intervene in foreign exchange markets. Most of the central banks try to keep the exchange rate within a band around a target exchange rate and they intervene in the foreign exchange market when they think it is necessary. Even though some central banks, e.g. the US and Japan, do not explicitly commit themselves to stabilizing their exchange rates, they have intervened in foreign exchange markets (Bonser-Neal, 1996).

As we discussed in the introduction section of this essay, there are at least three reasons why the central banks may want to intervene in the exchange markets:

1. Volatility in exchange rate can reduce international investment flows. Uncertainty in domestic currency increases the risk on the rate of return on a foreign asset. This leads to foreign capital outflows. Also, uncertainty in exchange rates deters foreign investors from buying or building new plants in a country that does not have a stable currency. This leads to inefficiency in the allocation of resources in the domestic and the world economies.

2. Exchange rate misalignments, uncertainty, or volatility may have a negative effect on international trade. Unstable exchange rates force economic agents to add a risk premium to the cost of goods that they trade abroad.

3. An exchange rate misalignment may affect the profitability of intervention. Most of central banks make profit by intervening financial markets.

The empirical evidence for the last reason is mixed. Taylor's (1982) estimates shows that nine industrial countries all together lost between 11 and 12 billion dollars over

1973-1979 while Jacob(1983) shows that for the same period US made $ 289 million profit. Leahy (1989) estimates that US monetary authorities have earned profits during the 1973-1989 period. Neely and Weller (1997) find that the intervention improves the profitability of Federal Reserve Bank

In the literature concerning intervention, there is a distinction between "**sterilized**" and "**non-sterilized** " interventions. Sterilized intervention in the exchange market means that the central banks would buy or sell enough bonds (or other domestic assets) to leave the monetary base unchanged while non-sterilized intervention means that the intervention does change the monetary base (or money supply) in the economy. Non-sterilized intervention is like open market operations (OMO) except that central banks buy or sell foreign assets rather than domestic assets. Regardless of whether the intervention is sterilized or not, there are at least two channels through which interventions affect the exchange rate: the Portfolio- Balance Channel and the Signaling Channel (or expectation channel).

1. **The Portfolio-Balance Channel**

   According to this approach, economic agents hold their wealth in the form of domestic currency and interest bearing assets (denominated in domestic and foreign currency). Assets that are denominated in different currencies are not perfect substitutes. When a central bank sterilizes an intervention, the relative supply of domestic and foreign assets are changed. Changes in the relative asset stocks will affect the exchange rate. The mechanism can be shown by a typical risk-premium equation (Edison, 1993):

$$\phi = r^d - r^f + E(S_{t+1}) - S = f(B^d/B^f) \tag{3.22}$$

   where

$$\phi \quad = \quad \text{risk premium}$$

$$
\begin{aligned}
S_t &= \text{exchange rate,} \\
r^d - r^f &= \ \text{domestic and foreign interest rate,} \\
E(S_{t+1}) &= \text{expected exchange rate,} \\
B^d and B^f &= \text{domestic and foreign bonds in the economic agent's portfolio.}
\end{aligned}
$$

A change in B^d because of sterilized intervention will require a change in either the interest rate or exchange rate or both to restore equilibrium. If we assume the interest rate is determined in the money market, then the exchange rate will change as a consequence of sterilized interventions. If domestic and foreign assets are perfect substitutes, then there will be no risk premium between domestic and foreign assets, that is, $\phi = 0$ which means uncovered interest parity (UIP) holds.

2. **The Signaling Channel (Or Expectation Channel)**

According to this approach, sterilized intervention affects the exchange rate through expectations. The effect of intervention does not depend on whether domestic or foreign bonds are perfect or imperfect substitutes. Sterilized intervention causes economic agents to change their exchange rate expectations. For example, if the central bank sells foreign bonds, economic agents may be induced to change their expectations about monetary policy - they may expect tighter future monetary policy. Thus, the expected tighter monetary policy would make the domestic currency appreciate, regardless of whether the monetary effects of interventions are sterilized or not.

The Role of Exchange Rate in Monetary Policy Rules

Most recently Laurence Ball (1999), John Taylor (1999) and Lars Svensson (2000) and Taylor (Manuscript) studied the role of exchange rates in monetary policy rules.

Their monetary policy rules can be summarized in the following form

$$i_t = a\Pi + by_t + c_0e_t + c_1e_{t-1} \tag{3.23}$$

where

$$
\begin{aligned}
i_t &= \text{the short term interest rate,} \\
\Pi &= \text{the rate of inflation,} \\
y_t &= \text{the deviation of GDP from the potential GDP.} \\
e_t &= \text{the real exchange rate, an increase in } e_t \text{ is an appreciation}
\end{aligned}
$$

There is no intercept in the above equation which means that the central bank targets zero inflation. In the above equation, a , b, c_0 and c_1 are policy parameters. If c_0 and c_1 are zero and $a > 1$, $b > 0$ then the equation above(3.23)is the monetary policy rule that Taylor (1993) proposed with no reaction to the exchange rate. The role of the exchange rate in monetary policy rules is determined by whether c_o and c_1 parameters are nonzero and their signs and numerical values. If c_0 is negative and c_1 is positive, then the exchange rate is higher than the real exchange rate and this would mean that the central bank would lower the short- term interest rate i.e. easing the monetary policy. The lagged exchange rate allows a dynamic reaction to the exchange rate: if c_1 is positive, and c_0 is negative but greater in absolute value than c_1, then the initial interest rate reaction is partially offset in the next period.

Ball (1999) found that the optimal value for c_0 is -.37 and for c_1 is .17 by using a simple open economy model with sticky prices (in Taylor, Manuscript). Thus, according to this policy rule, an appreciation of the exchange rate of 5 percent would call for a cut in the interest rate of 1.85 percentage points, followed by a partial offset of 0.85 percentage point, implying a net 1 percentage point cut in the interest rate. The coefficient, c_0, of exchange rate is negative because the appreciation of domestic

97

currency has a contractionary effect on aggregate demand: foreign goods become cheaper and domestic goods become expensive, causing a reduction in net exports.

Taylor (manuscript) argues that even if we find c_0 and c_1 are zero, which means there is no direct reaction of monetary policy to the exchange rate, there is an indirect reaction of monetary policy to the exchange rate. Suppose monetary policy reacts only to inflation and to real output. An appreciation of the domestic currency has two effects:

1. it will lower real GDP by expenditure switching, and

2. it will lower domestic inflation because the price of imported goods will not increase as much as the appreciation of the domestic currency. Also, inflation may go down because of the decline in output

The above effects of the exchange rate on inflation and output will occur with lags. That is, an appreciation of the exchange rate today will decrease the level of output and inflation that is expected in the future and therefore it will lower the interest rate in the future. According to the expectation theory of the term structure of interest rates, the expectation of a lower future short-term interest rate leads to a lower long-term interest rate today. Thus, the appreciation of the exchange rate lowers the interest today even though the exchange rate is not directly in the monetary policy rule. If the monetary policy rule is based on forecasts of future inflation and output, then the effect of appreciation of the exchange rate on the interest rate will be even stronger.

Another reason that the reaction of monetary policy to the exchange rate might be weak or empirically insignificant is that there may be some deviations of the exchange rate from purchasing power parity that should not be offset by changes in interest rate. For example, it may reflect changes in productivity. In this case, monetary policy should not react to the changes in the exchange rate.

In short, the indirect effect of the exchange rate exists even though the central bank follows a policy rule without a direct exchange rate effect.

Empirical Evidence about Central Banks Intervention and Exchange Rates

Existing empirical evidence on the impact of intervention on exchange rates is mixed. Dominguez and Frankel (1993) found that the effect of FED and Bundesbank interventions on exchange rates is statistically significant. Evans and Lyons (2001) using portfolio analysis showed that $1 billion of net dollar purchases increases the DM price of dollars by 0.44 % and that approximately 80% of this effect persists. That is, they found strong evidence of intervention effects on exchange rates. They also found that the effect of intervention is stronger when the flow of macroeconomic announcements is strong. On the other hand, Bonser-Neal and Taner (1996) provide empirical evidence that shows that central bank intervention does not have any significant effects on exchange rate volatility.

Ramchander and Sant (2002) argue that "theory is equally ambiguous on the direction of the relationship between volatility and intervention." They continue by stating that "in other words, the question of whether central banks intervene in order to influence currency volatility, or on the other hand, increased volatility draws central bank intervention in foreign exchange market has been hitherto left unanswered. Thus, the ultimate impact of central bank intervention policy on currency volatility is an empirical question" (p.233).

As stated in the beginning of this section, there are strong theoretical reasons as to why intervention may affect the exchange rate. There can be cases where central bank intervention causes volatility in the exchange market. Dominguez (1998) demonstrated that intervention at different time periods may have different effects: In the mid-1980s, intervention reduced the exchange rate volatility, however, for the 1977-1994 period, central bank intervention is connected to higher exchange rate volatility.

Because of the simultaneous responses of intervention and exchange rates and the heteroskedasticity of data, the ITH method is a useful technique to employ to measure the reaction of monetary policy (intervention) to the fluctuations in the foreign exchange market.

3.0.15 Empirical Results of the ITH Estimation

Introduction of Model and ITH Estimation

As discussed in the introduction , the literature on the relationship between the exchange rate and monetary policy has focused either on a single equation of the monetary response, which is subject to the simultaneous equations problem, or VAR analysis, which is subject to a heteroscedasticity problem. A newly developed method, identification through heteroscedasticity, allows us to overcome the aforementioned two problems. We employ the identification through heteroscedasticity method to measure the reaction of the monetary policy to the exchange rate in the United States. The simultaneous model that we employ to identify the reaction of monetary policy to the exchange market is the following,

$$I_t = \beta E_t + \phi X_t + \epsilon_t \tag{3.24}$$

$$E_t = \alpha I_t + \theta X_t + \eta_t \tag{3.25}$$

where

$$
\begin{aligned}
E_t &= \text{the daily exchange measured as return} \\
I_t &= \text{3-month treasury bill rate,} \\
X_t &= \text{5 lags of } I_t \text{ and 5 lags of } E_t \text{ plus macroeconomic shocks:} \\
CPI &= \text{consumer price index shock,} \\
UNP &= \text{unemployment shock,} \\
DGS &= \text{durable good and services shock,} \\
PPI &= \text{producer price shock,} \\
RET &= \text{retail sale shock.}
\end{aligned}
$$

ϵ_t and η_t = The monetary policy and the exchange market shocks, respectively

Equations (3.24) and (3.25) should not be estimated by OLS because of simultaneity bias. That is, α if β and are different from zero, the RHS variables are correlated with errors in both equations and each is not identified if X_t is common.

We employ the identification and estimation technique that we discuss in chapter two, subsections 2.5 and 2.6 . That is, we use "Identification Through Heteroscedasticity" method to estimate β in eq. (3.24).

In this chapter, we determine two different sets of regimes. the first set of regime is based on the same as definition of regime changes that we discussed in chapter two. That is, we allow the data to determine regime changes. The second set of regimes is based on exogenous regime changes. We determine regimes based on historical exchange rate policies:

- Plaza Period (jan.1,1985- Feb.21,1987)
- Louvre Period (Feb.22,1987-Dec.31,1987)
- Post-Louvre Period (Jan.1,1990-Jul.1,1997)
- During and after Asian Crisis (Jul.2,1997-Dec.31,199)period

Equations (3.24 and 3.25) are extended by including a common shock into the equations. The inclusion of a common shock into the structural equations is important because there are times when some factors affect both exchange market and interest rate in the same direction. For example, an increase in expected inflation, affect both exchange market returns and interest rates, leading to a positive correlation between changes in exchange rate (foreign currency/domestic currency) and interest rates. Another example could be the loss of a big trading partner. This reduces the export of domestic country and leads to a depression in domestic economy, pushing both the interest rate and the exchange rate down. Exclusion of such factors from the structural equations may lead to a biased estimation if they are correlated with X_t. When we introduce a common shock (DS) into the structural equations (eqs.3.24 and 3.25), we have:

$$I_t = \beta E_t + \phi X_t + \varphi DS_t + \epsilon_t \tag{3.26}$$

$$E_t = \alpha I_t + \theta X_t + DS_t + \eta_t \tag{3.27}$$

And the variance-covariance matrix that we obtain from the reduced form of the simultaneous equations changes as we discussed in the second section of this dissertation.

The parameter of interest, β, in this extended version of the structural equations can be identified if we have at least three different regimes. The only new assumption that we need is that one of the error variance terms must be homoscedastic, for example a change in the variance - covariance matrix is not a result of changes in the variance of monetary policy shock, i.e. $\sigma_{\epsilon 1}^2 = \sigma_{\epsilon 2}^2 = \sigma_{\epsilon 3}^2$. In this case, the ITH solution to the structural equations with a common shock exists.

Estimation of Monetary Policy Coefficient with a Common Shock

Because of the above discussed reasons, we start with structural equations that have a common shock (eqs. 3.26 and 3.27). We then show that the exclusion of a common shock from the structural equations (3.24, 3.25) does not yield a consistent estimate of parameters compared to the one with a common shock. We estimate the above structural equations, using both data determined regime changes and exogenous regime changes.

By using the steps and classification criteria of chapter two, we obtain the regimes' shocks (ϵ_t and η_t). Using these regimes' shocks, we create the variance-covariance matrices of the regimes. Table 3.1 shows the variance -covariance of the reduced form shocks for each regime. In regime 1, the variance of the interest rate shock and that of the exchange rate shock are relatively low. In regime 2, the variance of the interest rate shock is low while that of the exchange rate is high. In regime 3, both the variance of the interest rate shock and that of the exchange rate are high. In regime 4, the variance of the interest rate shock is high while that of the exchange

rate is low. The last column in Table 3.1 shows how many of both shocks (interest rate and exchange rate shocks) fall into a regime based on a 30-day rolling window and based on the criteria described in chapter two.

Table 3.1: **Regimes For Variance-Covariance of Reduced Form Shocks (Yen/Dollar 30-Day Rolling Window**

		Variance of Int. rate shock	Variance of Exchange return shock	Covariance	Frequency of obs.	Percentage of obs.
Regime	1	0.3344	37.1371	0.3163	2388	82.%
Regime	2	0.3038	**118.8384**	0.1127	344	11%
Regime	3	**0.9446**	**108.3732**	-5.4418	10	0.3%
Regime	4	**1.6625**	45.6561	-.2671	176	7%

High Variance in bold. Variables in percentage points

As is shown in Table 3.1, the covariance between the shocks to the interest rate and shocks to the exchange market fluctuates with the movements in their variances. As the variance of the interest rate shocks and variance of the exchange returns shock changes, from regime 1 to regime 4, the covariance between the two residuals changes from positive to negative (The third column in the table I). This is a strong indicator of the relationship between these two shocks. As the variances of both shocks rise (regime 3), the covariance between them reaches the highest level in absolute value among the four regimes. And at high variances the sign of the covariance changes from positive to negative. Finally, the covariance goes down as the variance of the exchange returns goes down (regime 4). As can be noticed the covariance is positive when the variances of shocks to the interest rate are low (regime 1 and regime 2).

Theoretically we expect a shock to the exchange rate to be negatively correlated

with a shock to monetary policy if it is measuring the reaction of monetary policy to the exchange rate. The reason for our theoretical expectation is the following: A negative shock to exchange market means a depreciation of the domestic currency. If the market expects the monetary authority will react to the devaluation of domestic currency by tightening monetary policy , the interest rate goes up, leading to a negative covariance between the exchange rate shock and the monetary policy shock (See:figure 7 for the relationship between shocks)

It was discussed previously that the monetary policy reaction to the exchange market, in equation (3.24) can be identified if there are at least three regimes in the presence of a common shock in the structural equations (eqs.3.24 and 3.25).

We start with structural equations that have a common shock (eqs. 3.26, 3.27). We then show that the exclusion of a common shock from the structural equations does not yield a consistent estimate of parameters compared to the one with a common shock.

We estimate the reaction of monetary policy to exchange rate using yen/\$ as the exchange rate. The point estimates that we obtain by using the ITH method are shown in the first row of Table 3.2. The point estimates of three out of five regime combinations are close to each other: - 0.11 from regime 1, 2, 3; -0.079 from regime 1, 3, 4 and- 0.059 from regime 2, 3, 4. And also, all of the point estimates that we obtain from different combination of regimes are negative. This can be considered as an indicator that monetary policy reacts to fluctuations in the exchange rate. To test the significance of the point estimates, we employ the bootstrap method. The bootstrap estimation of the reaction of monetary policy to exchange rate, using a 1000 bootstrap variance-covariance matrices of different regime subset combinations, are shown in the second row of Table 3.2. By using these subsets of regimes, we estimate the bootstrap coefficients of the monetary policy reaction, β , to the exchange market, which is negative in all possible combinations of regimes. This negative sign is consistent with our theoretical expectations.

The ITH estimations of monetary policy reaction to exchange rate, using regime

1, 2, 3 and regime 2, 3, 4 , give very close means of bootstrap estimators (-0.2057 and -0.2626) and their standard deviations are considerably lower compared to the other three subsets of regimes combinations. Also, the bootstrap estimations of the parameters using the combination of regime 1, 2, 3 and regime 2, 3, 4 have very low mass above zero ratios: 2 % for regime 1, 2, 3 and 0.0 % for regime 2, 3, 4. The 1, 2, 4 combination omits the high variance for both shocks and gets the strongest results. The point estimates and means of bootstrap estimation of monetary policy coefficient in Table 3.2 are indicators of the negative relationship between the monetary policy and exchange rate. That is, a depreciation of domestic currency is associated with an increase in the interest rate by the market.

One point to note is that GMM estimation (all regimes) of the reaction of monetary policy to exchange rate gives a negative coefficient that is numerically very different from the other regime combinations. Also, the mass above zero is 48 % in GMM estimation of the ITH method. This means, by using GMM and bootstrap estimation, we cannot even determine the sign of the reaction of monetary policy: figure 3.2 shows that almost half of the bootstrap estimates are negative and the other half are positive, which means we can not determine the sign of the parameter.

To see whether the differences between the point estimates and the mean of bootstrap estimates comes from the outliers of the bootstrap estimates, we plot the bootstrap estimates of the monetary policy coefficient. Figures 9 through 13 show the distributions of bootstrap estimations of the monetary policy coefficient. We were expecting that the distribution of estimates from different combination of regimes would be symmetrical around a negative mean. Figures 9 and 10 show that some of the bootstrap estimates are positive even though the majority are negative. This implies that we can not consistently estimate the monetary policy coefficient by using our data. Figure 11 and 12 are skewed to the right and they do not look like symmetric distributions. They have some outliers that push the mean of bootstrap estimates up and their standard deviations are high.

One of the ITH assumptions is that parameters are constant across regimes. That

Table 3.2: **Point and Bootstrap Estimates Under Alternative Subsets of Regimes with a Common Shock**

	Regimes 1,2 ,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4	Regimes All
Point estimates	-0.111	-3.320	-0.079	-0.059	-0.0004
Mean of distribution	-0.2057	-5.1771	-4.5499	-0.2626	-0.0003
Std.dev. of distribution	1.6332	51.9361	43.5023	2.0344	0.004
Median of distribution	-0.1008	-1.4675	-0.1575	-0.06807	-0.0002
Mass above zero	1.8%	11%	0.0%	0.0%	48%

is, the parameters that are obtained from different combinations of regimes would have similar distributions. The plots of distributions (Figure 9 through figure 13) show that this assumption is not valid

To evaluate the robustness of previous regime specifications, we employ some alternative regime specifications to see whether the ITH solution is sensitive to a misspecification of heteroscedasticity. We first create new specifications of rolling windows, such as a 90 day instead of the former 30-day window. We keep the same definitions of high and low variance of shocks (in chapter two) to determine the regimes. The results are shown in Table 3.3.

As we can see, the results are very close to the previous regime specification (30 -day rolling window in Table 3.2). The covariance between the shocks to monetary policy and the shocks to the exchange market return is positive when the variances of shocks are relatively low and it reaches the highest point in absolute terms in regime 3, in which the variances of both shocks are high. Finally, the covariance goes down

Table 3.3: **Regimes For Variance-Covariance of Reduced Form Shocks (Yen/Dollar 90-day Rolling Window)**

		Variance of Int. rate shock	Variance of exc. market shock	Covariance	Frequency of obs.	Percentage of obs.
Regime	1	0.3370	39.6000	0.1480	2308	79%
Regime	2	0.2621	**100.1261**	0.0408	314	11%
Regime	3	**0.8736**	**72.7804**	-2.3157	27	1%
Regime	4	**1.2035**	52.3560	-0.0017	269	9%

High Variance in bold. Variables in percentage points

as the variance of exchange returns goes down as in the regime 4. Compared to the previous regime definitions, which were 30-day rolling window, there is an increase in the number of observations that fall in regime 3: from 10 to 27 observations. Table 3.4 shows the bootstrap estimation of monetary policy reaction from 1000 draws. The results of this new specification (90- day rolling window) are very close to our previous specification (30-day rolling- window). As previously, the different combinations of regimes give different results. But, again the bootstrap estimates of regime 1, 2, 3 and regime 2, 3, 4 are close to each other and the mass above zero ratios are very low: 2.2 % for regime 1, 2, 3 and 0.0 % for regime 2, 3, 4. The GMM estimation of the monetary policy reaction (All regimes) different from other regime combinations and the mass above zero ratio is very high (34 %) compare to the other regime combinations.

From the tables 3.2 and3.4, we conclude that even though we consistently estimate the negative sign of the relationship between the monetary policy and exchange rate and find the bootstrap estimation of two out of five regime combinations (regime 1,2,3

Table 3.4: **Point and Bootstrap Estimates Under Alternative Subsets of Regimes with a Common Shock**

	Regimes 1,2 ,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4	Regimes All
Point estimates	-0.233	-6.942	-0.085	-0.057	-0.0022
Mean of distribution	-0.460	-3.139	-1.29	-0.333	-0.0023
Std.dev. of distribution	3.819	24.599	17.524	2.138	0.005
Median of distribution	-0.205	-1.181	-0.112	-0.065	-0.002
Mass above zero	2.2%	12%	0.1%	0.0%	34%

and regime 2,3,4) are very close to each other, -0.2056 and -0.2626, respectively for 30 day rolling window. And, -0.460 and -0.333 respectively for 90 day rolling window, it would be difficult to argue that the restriction of constant parameters across regimes that we impose on the solution of the ITH method is valid. Since the restriction that we impose on the parameters is not valid, the means of the bootstrap estimation of GMM parameters are quite different for different windows: -0.0003 for 30 day window and -0.0023 for 90 day window.

Exogenously Determined Regime Change

We also exogenously determine regime changes and look at the reaction of monetary policy to the exchange market using the same yen/$ ratio. Exchange regime changes are defined as changes in the FED policy on exchange rates. We define four different exchange regimes. In two of them(regime 1 and 2 in the following) the FED committed itself to react if the of exchange rate falls below or above certain boundary values: Plaza period and Louvre period. In other two regimes(3 and 4) the FED did not commit to react to exchange rate volatility: Post Louvre period and After Asian Financial Crisis. The above regimes have the following name and time periods:

Regime 1: Plaza Period, from January 1, 1985 to February 21, 1987

Regime 2: Louvre Period, from February 22, 1987 to December 31, 1989

Regime 3: Post - Louvre Period, from January 1, 1990 to July 1, 1997

Regime 4: During and after Asian Financial Crisis, from July 2, 1997 to December 31, 1999

We are aware that the reaction of monetary policy may be different in these regimes. But, it is possible that market participants think that monetary policy makers will react to fluctuations in the exchange market regardless of whether monetary policy makers commit to react or not.

The variances and covariances of monetary policy and exchange rate shocks in each regime are shown in table VI. As can be seen in the table, the covariance between monetary policy shock and exchange market shock is very high, 0.572, in Plaza Period compared to the other regimes. Also, the covariance, in absolute terms, between interest rate shocks and exchange rate shocks goes down as time passes: from 0.572 to 0.063. This result is consistent with the direction of monetary policy on exchange rates. That is, monetary policy makers are more unwilling to react to the shocks in the exchange market compared to the Plaza and Louvre Period. Interestingly, even though the variance of exchange return shocks in the Asian Financial Crisis regime is the highest among all other periods, the covariance, in absolute terms, between exchange rate shocks and interest rate shocks is the lowest compared to all other

periods.

Table 3.5: **Regimes For Variance-Covariance of Reduced Form Shocks(Yen/Dollar 30-day Rolling Window)**

	Variance of int. shock	Variance of exc. shock	Covariance	Frequency of obs.	Percentage of obs.
Plaza Period	0.494	39.341	0.572	367	13%
The Louvre Period	0.885	41.160	-0.219	572	20%
Post Louvre Period	0.255	40.958	0.105	1482	50%
Asian Financial Crisis	0.280	80.408	0.063	496	17%

High Variance in bold. Variables in percentage points

The point and bootstrap estimates of the ITH method, using exogenously determined regime changes, are shown in Table 3.6. As can be seen, all point estimates that are obtained from different subsets of regimes are negative and four out of five means of bootstrap estimates that obtained from different subsets of regimes are also negative. The point estimates that obtained from regime 1,3,4 and regime 2, 3, 4 are close to each other(-0.0023 and -0.0015) and the point estimates that obtained from regime 1, 2, 4 and GMM (all regimes) are close to each other(-0.499 and -0.412). This can be considered as an indicator of the reaction of monetary policy to exchange rate since all point estimates and four out of five bootstrap estimates are negative. But, both point estimates and bootstrap estimates do not support the restriction that ITH method imposes on the model to estimate the coefficient: the parameter of interest is fixed across the regimes. These results lead to over identification problem. We cannot determine which regime combination estimates better represents the reaction of monetary policy to the exchange market.

Table 3.6: **Estimates Under Alternative Subsets of Regimes with a Common Shock**

	Regimes 1,2 ,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4	Regimes All
Point estimates	-2.064	-0.499	-0.0023	-0.0015	-0.412
Mean of distribution	-4.003	-0.838	0.167	-1.143	-0.213
Std.dev. of distribution	33.096	4.047	0.250	11.731	0.212
Median of distribution	-0.444	-0.546	-0.002	-0.008	-0.210
Mass above zero	0.009	0.000	0.340	0.126	0.099

Index - Dollar Rate

We employ different exchange rates to see whether monetary policy in the US reacts to changes in exchange rates. There is an Index/$ ratio which consists of a trade-weighted average of different countries' currencies. We use this index as an exchange rate and estimate the reaction of monetary policy to the index. As previously, we define different regimes based on the heteroscedasticity of the data: whether the variance of a shock is one standard deviation bigger than its long run mean. The variance of shocks to the exchange rate and to monetary policy and the covariance between these shocks in each regime are shown in Table 3.7. In a regime that has high variances in both exchange rate and monetary policy shocks (regime 3), we expect the covariance to be higher in absolute terms compared to the other regimes that have lower variances. The table shows that the covariance in regime 3 in which both variances are high is lower than the covariance of regime 2 in which the variance of monetary policy is low and the variance of exchange rate is high.

111

Table 3.7: **Regimes For Variance-Covariance of Reduced Form Shocks (Index/Dollar 30-day rolling window)**

		Variance of Int. rate shock	Variance of exc. market shock	Covariance	Frequency of obs.	Percentage of obs.
Regime	1	0.3078	13.500	0.0759	2318	80%
Regime	2	0.4616	**32.0643**	0.4839	405	14%
Regime	3	**0.6868**	**35.1441**	0.1924	34	1.2%
Regime	4	**1.8241**	18.6836	-0.103	154	5.3%

High Variance in bold. Variables in percentage points

The bootstrap estimates of the reaction of monetary policy to the exchange rate index, which is based on the ITH method, are shown in the second row of Table 3.8. Except for the GMM estimates, the means of bootstrap estimates (1000) are negative which means there is a negative relationship between monetary policy and exchange rate index. This result is consistent with our previous finding of the relationship between monetary policy and exchange rate using Yen/$ relationship. However, the relationship is not statistically significant: the mass above zero in 1000 bootstrap estimates is high in each of regime combinations. The GMM estimates of the reaction of monetary policy to the exchange rate, denoted by all regimes, have a perverse sign (positive) and ninety nine percent of them are above zero. From Table 3.8, we can conclude that the restriction that we impose to estimate the reaction of monetary policy by the ITH method is not valid. That is, the parameter of interest, in our case, reaction of monetary policy is not constant across regimes. As shown in Table 3.8, the bootstrap estimates of different regime combinations give completely different means of bootstrap distribution.

Table 3.8: **Bootstrap Estimates Under Alternative Subsets of Regimes with a Common Shock**

	Regimes 1,2 ,3	Regimes 1,2,4	Regimes 1,3,4	Regimes 2,3,4	Regimes All
Mean of distribution	-0.7221	-3.307	-4.604	-3.356	0.02407
Std.dev. of distribution	17.027	89.234	29.701	34.434	0.0108
Median of distribution	-0.151	-2.231	-1.7443	-1.337	0.0240
Mass above zero	17.7%	27%	12%	9%	99%

Pound-Dollar Rate

We also estimated the reaction of monetary policy to the exchange rate by using pound/$ ratio. The results are not significant (we do not report the results)

3.0.16   The Intuition for the Empirical Findings

What do we expect about the relationship between exchange rate and monetary policy? A reasonable answer comes from the Uncovered Interest Parity Equation, which shows the relationship between domestic and foreign interest rates and the expected future appreciation of domestic currency. The equation is the following.

$$i_d = i_f - \frac{\Delta EX^e}{EX} \tag{3.28}$$

where i_d is domestic interest rate, i_f is foreign interest rate , ΔEX^e is expected future appreciation of domestic currency and EX is nominal exchange rate in foreign currency per domestic currency (yen per dollar or yen/$). According to the Uncovered Interest Parity Equation, an increase in the foreign interest rate or in expected future

depreciation of the domestic currency reduces the rate of return on domestic assets compared to foreign assets. This leads to a capital outflow and in turn an increase in the domestic interest rate, holding everything else constant.

Consider Figure 3.1. MP_RF represents the monetary policy response function and MRK_RF represents the market response function. Monetary Policy response function is downward sloping which means monetary authority increases the interest rate if domestic currency depreciates and reduces the interest rate if domestic currency appreciates. Market response function is upward sloping which means a higher interest rate is associated with appreciation of domestic currency and a lower interest rate is associated with depreciation of domestic currency. Now, assume that the market is in equilibrium at E_0. I_0 and EX_0 represent the equilibrium values of interest rate and of exchange rate respectively. The exchange rate is the ratio of foreign currency to the domestic currency. That is , EXi = Foreign currency/ Domestic currency, which means the amount of the foreign currency that can be bought by one unit of domestic currency. Therefore, a reduction in EXi (i=0,1,2) refers to a depreciation of domestic currency and an increase in EXi refers to an appreciation in domestic currency.

We want to analyze the relationship between the monetary policy and the exchange rate. To do so on the graph, we assume that the foreign interest rate goes up. Holding everything else constant, this means that the rate of return on domestic assets is lower than that of foreign assets. Therefore, this is a negative shock to the exchange market. The savings in the economy shift from domestic assets to foreign assets causing capital outflows. As a result, the market response function will shift to the left from MRK_RF to MRK_RF*: if monetary policy does not react to fluctuations in the exchange rate, the exchange rate will go down (depreciation of domestic currency) from E_0 to E_1 and the interest rate will stay the same, assuming agents believe the exchange rate will return to EX_0; If monetary policy reacts to the exchange rate, then, the exchange rate will fall to EX_2 and the interest rate will rise from I_0 to I_1. And, if monetary authorities fix the exchange rate at E_0, then the interest rate
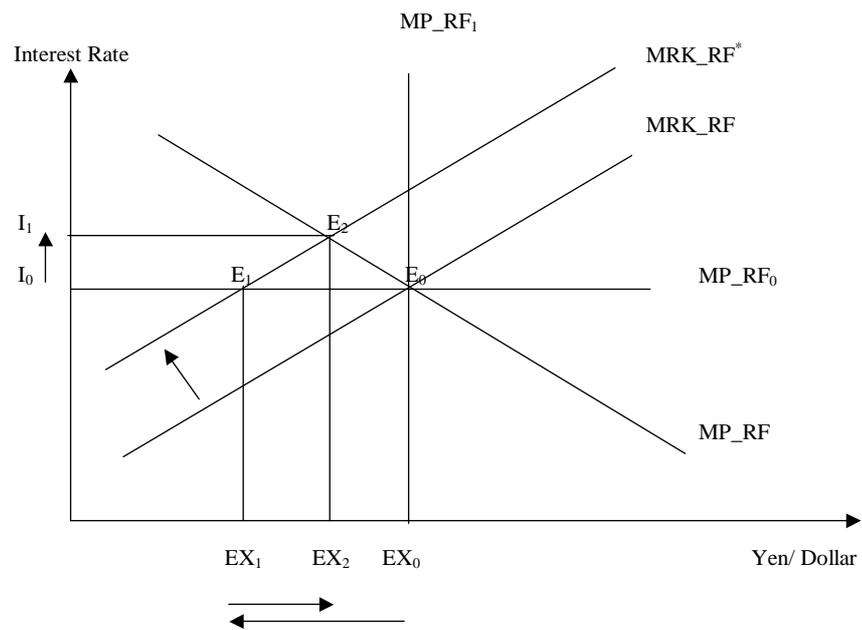
Figure 3.1: Relationship between Monetary Policy and Exchange Rate

will be higher than I_1. Therefore we expect a negative relationship between monetary policy and the exchange rate. Our empirical result is consistent with our theoretical expectation.

We also find that there are negative relationships between exchange rates and monetary policy shocks using different exchange rates (yen/$, Pound/$ and Index/$). In Table 3.1, we can see that the covariance between the exchange rate (yen/$) shock and interest rate shocks is positive and low when the variance of the exchange rate shock and the variance of the interest rate shock are low, and the covariance between them is negative and very high when the variances of both shocks are high. We observe the same pattern in pound/$ rate (not reported): The covariance between the exchange rate (pound/$) shock and monetary policy shock is positive and very low when the variances of shocks are low and it becomes positive and high when the variances of both shocks are high.

Our empirical results, by analyzing Tables 3.1 and 3.4 suggest that a VAR model with GARCH may lead to an improvement in the estimation of monetary policy reaction to exchange market. Notice that a VAR model with GARCH will take both past shocks and their variances into account to estimate the parameters of interest. This extension will be done in the fourth chapter of the dissertation.

3.0.17 Conclusion

We employ the newly developed Identification Through Heteroscedasticity Estimation Method to estimate the reaction of monetary policy to the exchange market. The advantages of this method are that it allows us to estimate the simultaneous relationship between dependent variables in a system of structural equations and use the heteroscedasticity of the data to estimate the parameter of interest. We use different exchange rates (Yen/$; Index/$ and Pound/$) to estimate the reaction of monetary policy to exchange rate in the United States. Our findings show that even though we find consistent negative estimates of the relationship between monetary policy and exchange rate, the results are not statistically significant so we cannot substantiate

116

the claim that monetary policy reacts to the fluctuations in the exchange market. The means of bootstrap estimates show that the parameter, the reaction of monetary policy to the exchange market, is not constant across regime combinations (Table 3.3, 3.5 and 3.6, 3.8). We report the asymptotic properties of our ITH estimates by plotting the distribution of bootstrap estimates (Figure 9 through 13) but we do not report the differences between bootstrap estimates that are obtained by combining different regimes. That is, plotting the distribution of bootstrap estimates that we obtain from different regimes combinations and taking their differences to see if the difference gives a mean zero and a symmetric distribution . From Figure I through Figure V, it is clear that the difference would not give a zero mean and a symmetric distribution. Also, the empirical results of structural equations without a common shock give wider means and some positive means in both point and bootstrap estimations. Therefore we do not report the empirical result of the structural equations without a common shock.

There are several reasons why we might not find a statistically significant reaction of monetary policy to exchange rate by using the method that we employed:

1. The FED may not react to the fluctuation of any foreign currency because of the size of the US economy. Therefore, no foreign country's currency has a significant effect on the US economy that would force the FED to change monetary policy. This argument is based on a big country theory of exchange rates. To see if the insignificant reaction of monetary policy comes from big country argument, we employ the index/\$ rate which represents the fluctuation of the US \$ against the weighted average of US trade partner currencies. Our findings show that even though we consistently estimate a negative relationship between monetary policy and index/\$ rate, the relationship is not statistically significant.

2. The monetary policy makers may believe that a floating exchange rate performs better than intervention in the exchange market so that they may

Distribution of Estimated Monetary Policy Response Coefficient
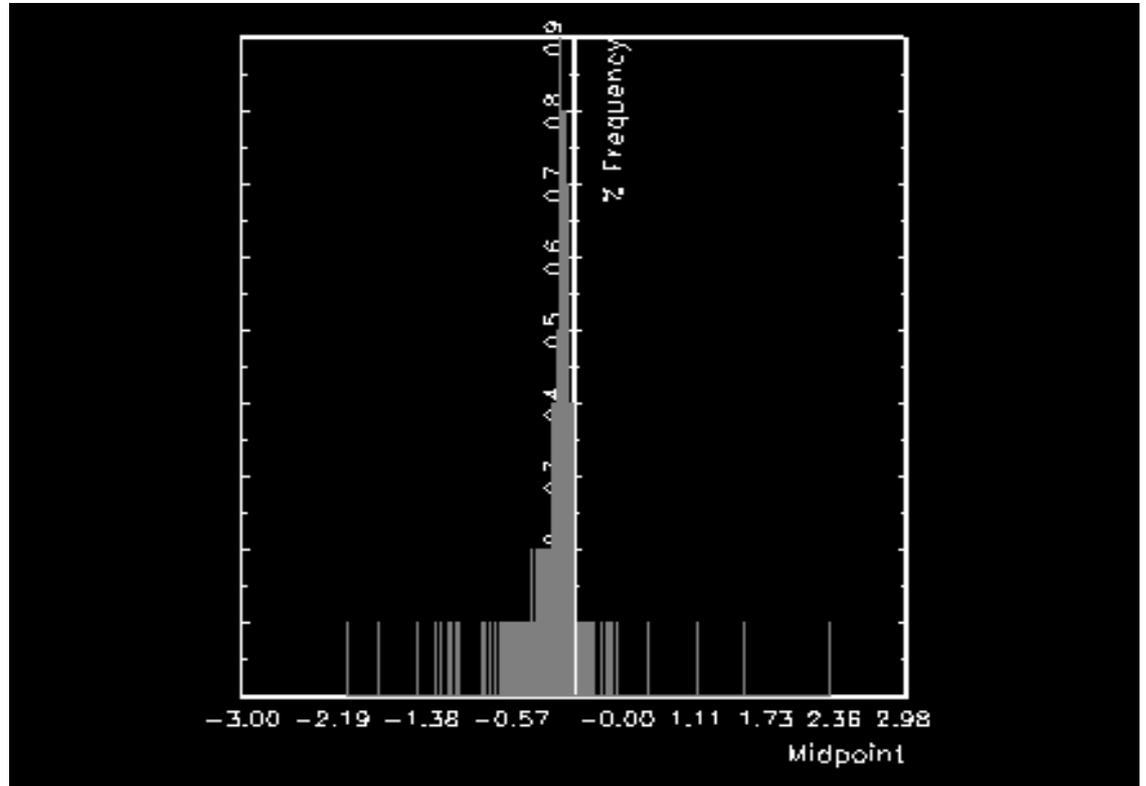
Figure 3.2: **Using Regimes 1, 2 and 3**

intentionally not react to the fluctuations in exchange rates. Our exogenously determined regime changes findings (table VI) support this argument. The covariance between monetary policy and exchange rate goes down as time passes(during 1985 and 1999).

3. The relationship between monetary policy and the exchange rate may not be linear as many exchange models as well as our model assume. The reaction of monetary policy may depend on the stage of economy.

Distribution of Estimated Monetary Policy Response Coefficient
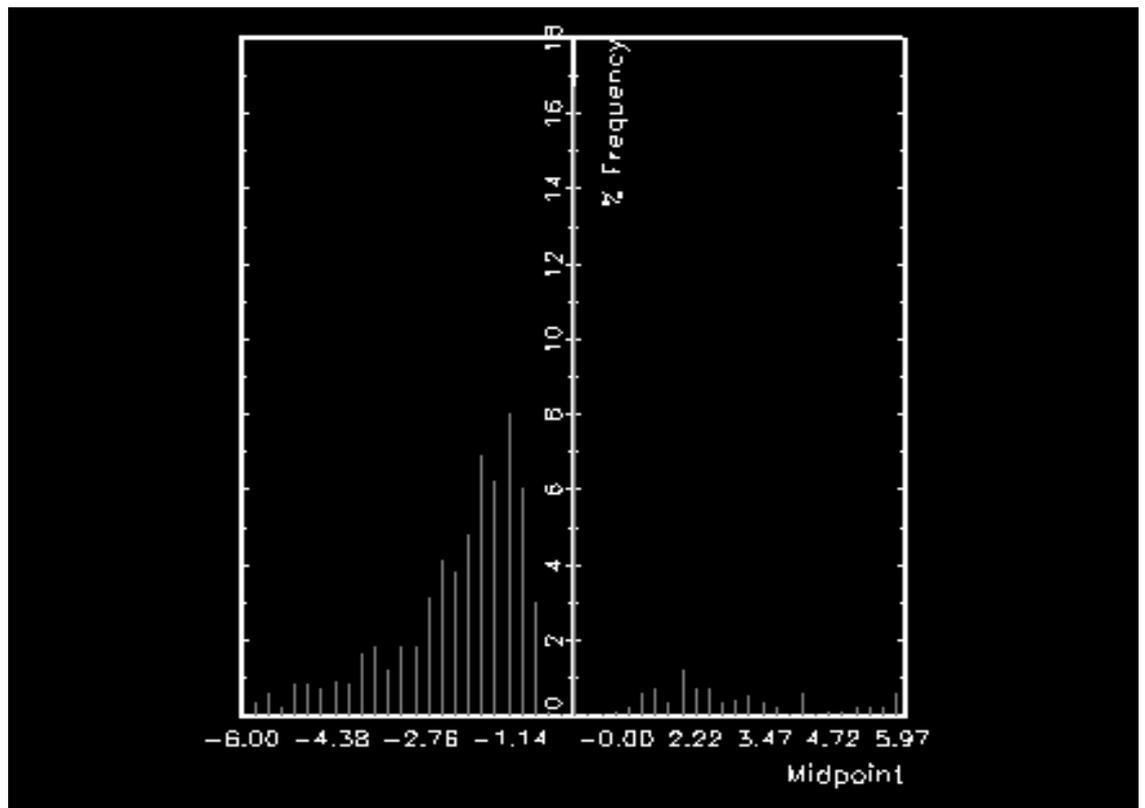
Figure 3.3: Using Regimes 1, 2 and 4

Distribution of Estimated Monetary Policy Response Coefficient
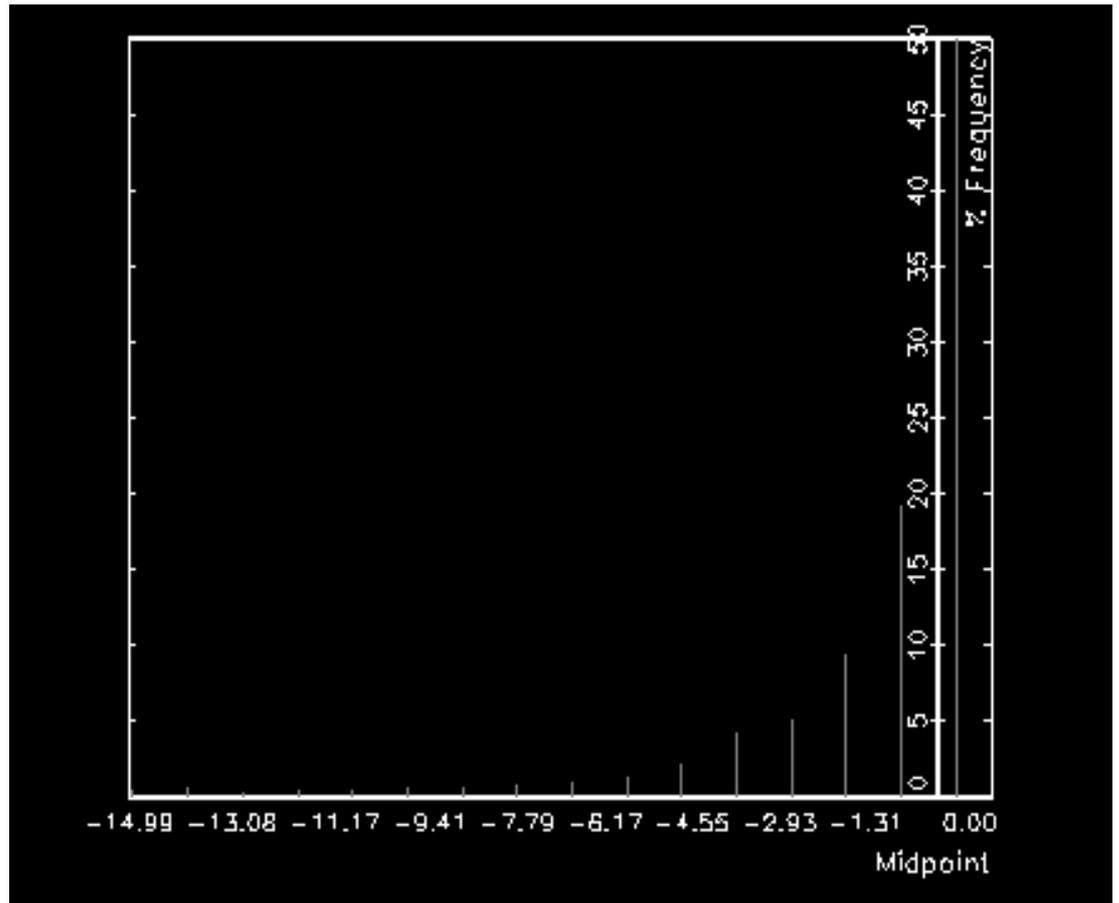
Figure 3.4: Using Regimes 1, 3 and 4

Distribution of Estimated Monetary Policy Response Coefficient
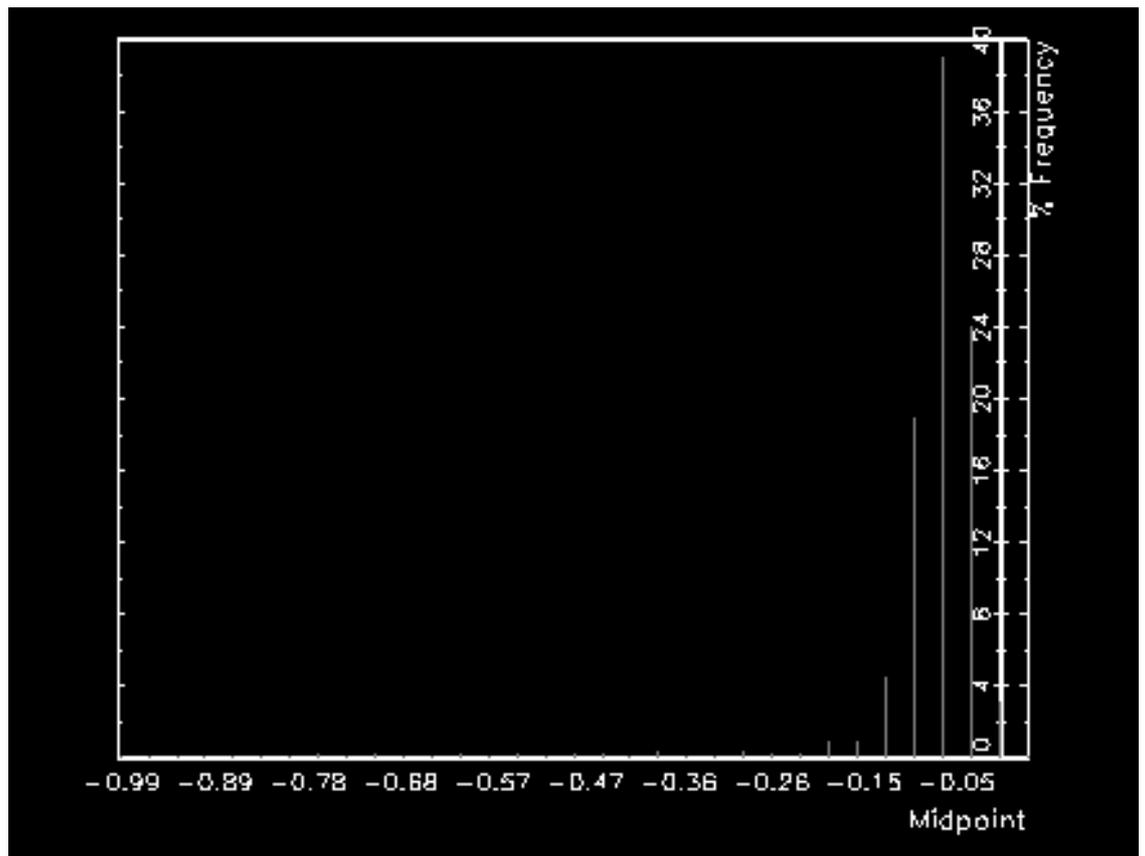
Figure 3.5: Using Regimes 2, 3 and 4

Distribution of Estimated Monetary Policy Response Coefficient
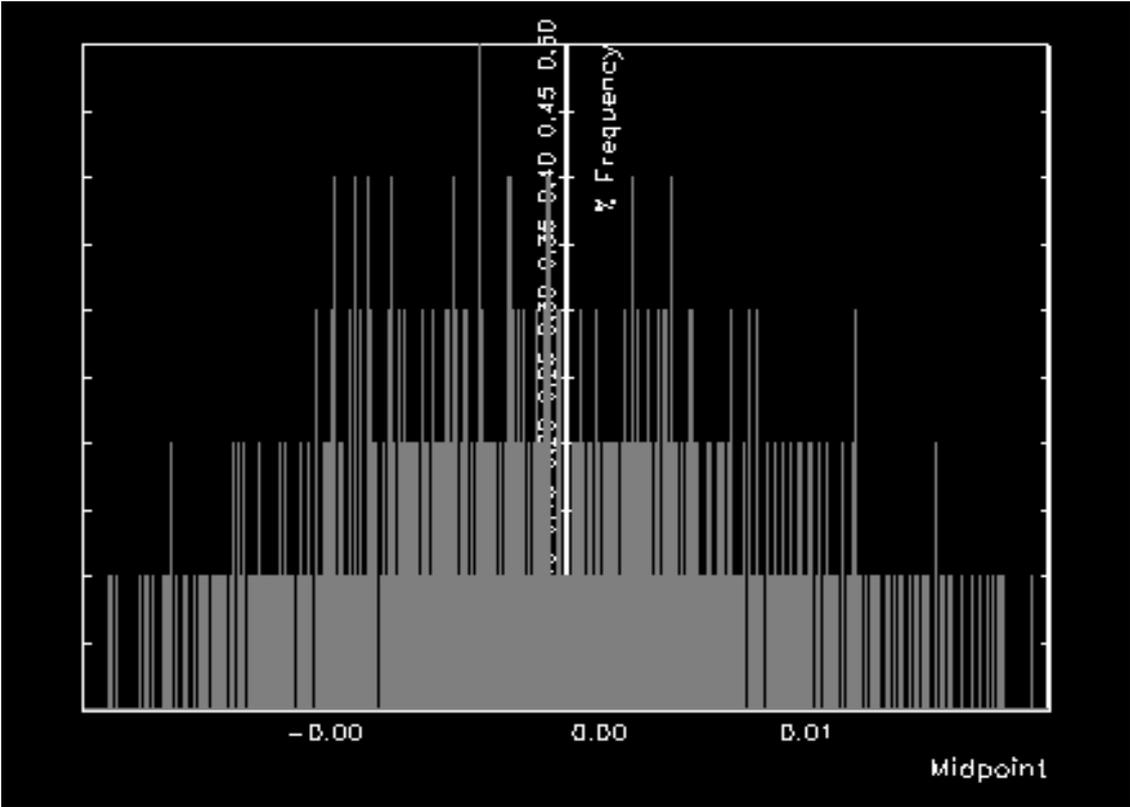
Figure 3.6: **Using ITH assumptions and GMM Method (All Regimes**

Chapter 4

THE RELATIONSHIPS AMONG MONETARY POLICY, STOCK RETURN AND EXCHANGE RATES: A MULTIVARIATE VAR(P)-GARCH(Q, P) APPROACH

Abstract

In this essay, we are interested in the relationship among monetary policy, stock prices and exchange rates. The argument that we make is that on the one hand, monetary policy affects both stock prices and the exchange rate, on the other hand, stock and exchange rates affect monetary policy as well as each other. Therefore, the relationships between these variables are reciprocal, and it is highly probably a shock to one variable will affect the other variables. This paper takes into account the endogenous relationship among the above mentioned variables and the conditional variances as

well as conditional cross covariances among them . We examine the dynamic relationships among monetary policy and the financial variables as well as the dynamic relationships among their volatilities using Vector Error Correction Model(VECM) , Multivariate VAR (p), multivariate-VARX (p) and Multivariate VAR (p)-GARCH (q, p) models.

4.0.18 Introduction

This paper examines the relationships among monetary policy, stock prices and exchange rates. There is an abundant literature that looks at the relationship between monetary policy and either the stock or exchange market i.e. bivariate relationship(references: the literature review of the first and second chapter of the dissertation). But, to the best of our knowledge, there is no study that looks at the relationships among these three macroeconomic variables i.e. a tri-variate relationship.

The argument that we make is that monetary policy affects the stock market: when stock prices (as an index) goes up, many academicians as well as the FED policy advisors think that it is the time to cool the economy, i.e. impose a contractionary monetary policy. And when the stock price goes down, they think that it is time to heat up the economy, i.e. impose an expansionary monetary policy. This pattern can be observed in the briefing of the chairman of the FED to the congress and his talks (see:Greenspan, A. 1999 talk). Also, this kind of pattern exists in the Geneva Report on the World Economy (see: CGLW (2000)). We can observe similar but opposite arguments about the reaction of monetary policy to the exchange rate. The overvaluation of domestic currency negatively affects exports and increases the quantity of imports of the domestic country, leading to spending switching from domestic goods to imported goods and to rising unemployment. The monetary authorities that try to stabilize price and/or employment will react to such overvaluation of domestic currency by either using direct buying/selling foreign currency or using a monetary policy tool such as the short-term interest rate.

It is well known that the main goals of central banks are to control inflation and/or the output gap. Most central banks try to reach these targets by using monetary policy tools such as open market operations and rarely bank reserve requirement ratio. Central banks try to reach their targets by setting some intermediate target. The short-term interest rate is the most widely used intermediate target. In this scenario, the Central Banks will try to stabilize aggregate demand by tuning the

short-term interest rate. The effects of the short-term interest rate on aggregate demand are through two channels:

1. Direct Channel Effect: Interest rate affects aggregate demand by affecting investment and consumption in an economy. Lowering the short term interest rate stimulates investment and consumption while raising the short-term interest rate has a reverse effect.

2. Indirect Effect Channel: Short-term interest rate affects aggregate demand indirectly by affecting stock (equity) prices and the exchange rate: On the one hand, a high interest rate reduces the expected return from stock, i.e. lowers the present value of stocks (See chapter 1 of the dissertation). Therefore, it has a negative wealth effect on aggregate demand. On the other hand, a high interest rate attracts foreign capital into the domestic market, leading to higher demand for the domestic currency and that in turn appreciates the domestic currency. Appreciation of the domestic currency affects the exports and imports of the domestic country as well as expenditure switching from domestic goods to import goods.

These indirect effects of monetary policy are based on the ideas that stock prices affect private consumption (wealth effect) and corporate investment (Tobin's Q- theory of investment). And, the exchange rate affects the export/import as well as expenditure switching of the domestic country. These two effects of monetary policy together or individually affect aggregate demand.

Therefore, financial asset prices (or volatility) such as stock prices and exchange rates are very important parts of the monetary transmission mechanism. When a Central Bank reacts to an aggregate demand shock by tuning the short term interest rate, monetary policy will not only affect the real markets such as consumption and investment but also affect financial markets such as stock and exchange markets. Therefore, monetary policy makers need to take the effect of monetary policy on the stock and exchange markets into account before they tune the interest rate to control

126

aggregate demand, because stock prices and the exchange rate also affect aggregate demand.

The basic motivation for this study comes from the findings of the first two chapters of the dissertation in which we observe the following relationships:

1. When we allow regime changes based on high and low variances of interest and stock market shocks, we find that in the high variance regimes, the covariance between interest rate shocks and stock market shocks is very high and vice versa when the variances are low.

2. We observe the same relationship between interest rate shocks and exchange rate shocks in the second chapter of the dissertation.

That is, we find that there is a strong covariance between interest rate shocks and stocks market shocks as well as a strong covariance between interest rate shocks and exchange rate shocks.

On the one hand, these findings suggest we set up a multivariate ARCH/GARCH model to take the cross volatility of markets into account. On the other hand, theoretically, we expect a endogenous and lagged relationship between the conditional mean returns of interest rates, stock prices and the exchange rate. This would suggest we set up a simultaneous or a multivariate VAR (p) model. We combine these two suggestions into one model and analyze the relationship among them and their volatility. Notice that theoretically, the combined model must be at least as efficient as multivariate VAR (p) and GARCH (q,p) models alone. In the empirical part, we test whether there is an efficiency gain by combining multivariate VAR (p) and VAR (p)-GARCH (q, p) models.

The literature on the transmission of movements in financial markets has been focused on whether returns in one country at a time t are useful for predicting returns in other markets at a time t+1. Examples of studies looking at the co-movement and volatility spillover across markets for **stock markets** include: Koch and Koch(1991) who looked at the relationship among daily returns of eight stock indexes. They find

the market interdependence grows over three different years 1972, 1980 and 1987; Malliaris and Urrutia (1992) who studied the Crash of October 1987 and its influences on international (six major) stock markets provide statistical evidence regarding the international propagation of the October 1987 stock market crush; Peiro, Quesada and Uriel (1998) who analyzed the relationships between New York, Tokyo and Frankfurt stock markets illustrate strong relationships among these markets; Copeland and Copeland (1998) who investigated lead/lag relationships among major stock markets around world find a significant market effect from America to Europe and to the pacific but not in the opposite direction; Booth, Martikainen and Tse (1997) who looked at the price and spillovers in Scandinavian stock markets show that there are significant price and volatility spillovers among Scandinavian stock markets; Karolyi (1995) who analyzed the transmission of stock returns and volatilities in the case of the US and Canada by using a multivariate GARCH model finds a significant relationship between the SP500 and TSE 300; Gannon and Choi (1998) who examined intra/inter-day volatility transmission and spillover persistence of Hong Kong Hang Seng Stock Index (HSI), Hang Song index futures (HSIF) and $S\&P500$ futures find significant spillover effects from the SP500 to the other markets. Some of the studies that look at the **exchange rate market** and volatilities are the following: Bollerslew (1990) who looked at the coherence in short-run nominal exchange rates for five major currencies and developed the Constant Conditional Correlation(CCC) model to allow time-varying conditional variances find a significant comovements among the currencies; Engle, Ito and Lin (1990)who analyzed the effect of shocks or news on the exchange markets by taking the variance of exchange rates into consideration find that the volatility is not a country specific, it is a phenomenon of spillover from one market to the another; MacDonald and Marsh (2004) who looked currency spillovers between US dollar, Germany mark and Japanese yen find significant spillovers effect among currencies ; Jumah and Kunst (2003) who analyzed the effect of exchange rate volatility in New York and London on coffee and cocoa markets find significant spillover from exchange rate volatility to commodity price volatility but not visa-versa.

The only paper that is close to our paper is Dor and Purre (2000) who discuss in theory how monetary policy, stock and exchange markets can be related.

In this essay, we examine three relationships :

1. Cross market influences in the mean of interest rate, stock returns and exchange rate returns

2. Volatilities of returns in interest rate, stock price and exchange rate

3. Cross market influences in the volatility of returns.

We are interested in :

1. Modelling lag/lead relationships among the means of interest, stock and exchange returns (Multivariate VAR (p) model),

2. How rapidly an innovation originating in one of the markets is transmitted to the other markets (impulse responses of the models)

3. How the volatility of the innovations transmits to the other markets(GARCH(q, p) part of our model).

The paper is organized in the following way: In section 4.2, 4.3 and 4.4, we discuss possible econometric models (multivariate VAR (p) and a multivariate VARX (p, s) models) to capture the mean relationships among monetary policy, stock and exchange market. In section 4.5, we introduces univariate and multivariate ARCH/GARCH models. In section 4.6, 4.7 and 4.8 , we present tri-variate VAR(p) model with GARCH(q,p) to capture both mean and volatility relationships among monetary policy, stock and exchange markets. In section 4.9 through 9.14, we do empirical analyzes of the relationships. A general summary and conclusion is provided in the last section.

4.0.19 The Econometric Models for Monetary Policy, Stock Price and Exchange Rate Relationships

We develop a tri-variate VAR (p)-GARCH (q, p) model to capture the relationship between monetary policy and two financial variables(stock index and exchange rate). We divide our discussion about the models into two sections: section 7.3-7.4 and section 7.5-7.8 In section 7.3-7.4, we introduce a tri-variate VAR (p) and a tri-variate VARX (p, s) models to capture the dynamic and lag/lead relationships among monetary policy, stock price and exchange rate. In section 7.5-7.8, we discuss the possible GARCH part of the models to capture the volatilities and the spilovers of volatilities across monetary policy, stock price and exchange rate.

There are three bodies of literature that look at the relationships:

1. between monetary policy and stock market (see chapter 1 of the dissertation),

2. between monetary policy and exchange rate (see chapter 2 of the dissertation),

3. among international markets such as spillover effects of a market shock to the international markets.

But, to the best of our knowledge, there is no empirical as well theoretical literature that analyzes the means and volatilities among interest rate, stock price and exchange rate returns. We discuss the possible theoretical and examine the empirical relationship among the above mentioned variables in this chapter of the dissertation.

4.0.20 Multivariate VAR(P) Model

A model that aims to capture the effect of monetary policy on stock price and exchange rates requires accounting for the reciprocal and cross market relationship among these variables. On one hand, monetary policy affects both stock prices and exchange rates: the relationship is negative between the interest rate and stock prices, assuming stock prices are the present values of expected dividends; and it is positive

between the interest rate and the exchange rate, due to foreign capital mobility from one market to another, as investors search for high returns in the short-run. On the other hand, the stock price and exchange rate affect monetary policy because of their effects on aggregate demand and because of their effects on each other. The existence of a relationship between stock price and exchange rates can be explained by considering them to be two alternative investments in a portfolio. The expected high return on one of them leads to switching assets from one market to another market. That is, expectations of exchange rate changes affect the decision to hold domestic or foreign assets.

One way of looking at the relationships among monetary policy, stock prices and exchange rates is to model the relationship as a Tri-Variate Vector Auto Regression (VAR) model. The reason to model the relationship as a Tri-Variate VAR(p) rather than a simultaneous model is Sims' Criticism(1980). Identification in a simultaneous system is achieved by assuming that some of the predetermined variables are present in some equations but not in others. What variables should be in the each equation in the system is subjective and criticized by Sims (1980). He argues that if there is a true simultaneity among a set of variables, they all should be treated on an equal footing; there should not be any prior distinction between endogenous and exogenous variables in the equations; and all endogenous and exogenous variables should appear in the all equations. This argument leads him to develop what is called in the literature as the Vector Auto Regression (VAR) model. In the VAR(p) set up, the lags of all dependent variables appear on the right side of equations with exogenous variables (if there are exogenous variables in the model).

To analyze the relationship among monetary policy, stock return and exchange rate return, we set up a Multivariate-VAR(p) model in which stock return, exchange rate return and monetary policy are endogenous. The set up of a Multivariate-VAR(p) model is discussed below.

Let $y_t = \{(y_{1t}, y_{2t} \ ... \ y_{kt})'$ $t = 0, 1, 2$, denote a k-dimensional time series vector of

random variables of interest. The pth-order VAR process is written as

$$y_t = c + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t \qquad (4.1)$$

where ε_t is a vector white noise process with $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}...\varepsilon_{kt})$ such that

1. $E(\varepsilon_t) = 0$,

2. $E(\varepsilon_t \varepsilon_t') = \Sigma$,

3. $E(\varepsilon_t \varepsilon_s') \neq 0$ for $t \neq s$

Analyzing and modelling the series jointly help us understand the dynamic relationship over time among the series and provide the additional information available from other related series.

The length of p on the summations is determined by model selection methods such as AIC, SIC and Final Prediction Error Criteia (FPE).

4.0.21   Multivariate-VARX(P, S) Model

Another way of looking at the relationships among monetary policy, stock returns and exchange rate returns is to model the relationship as a Multivariate- VARX(p, s) model. The reason to model the relationship as Multivariate- VARX(p, s) after modelling the relationship Multivariate- VAR(p) is the following. One can argue that the Multivariate-VAR(p) model may have some other exogenous variables that affect the endogenous variables. If this is true, then the estimated parameters are biased if the excluded variables are correlated with the included endogenous variables. In other words, the Multivariate VAR (p) model may have the problem of excluding some relevant variables (underspecifying the model).

To test this possibility, we set up a Multivariate VAR (p) model with some exogenous macroeconomic shock variables. This kind of modelling is called a Vector Autoregressive Process with Exogenous Variables or VARX (p, s), where p refers to lags of endogenous variables and s refers to lags of exogenous variables.

A Multivariate-VAR (p) model is a represented in reduced form of our simultaneous model, and it may include the lags of exogenous variables, depending on model selection criteria such as AIC, SIC, and Final Prediction Error(FPI).

Since we assumed that there are macroeconomic shocks such as inflation and income shocks affecting monetary policy, stock prices and exchange rates, we employ a Multivariate VARX (p, s) model in the empirical part of this study. Each of the returns (interest, stock and exchange) depends on its past as well as the past of other returns and macroeconomic shocks. The benefits of the VARX(p, s) model are that it allows us to forecast endogenous variables and to detect the effect of a shock to any equation in the system on the other endogenous variables for some period after the shock occurs.

The effects of shocks are traced by what is called the Impulse Response Function (IRF) in the literature. If we want to see what happens in a stock market when a shock hits the stock market and how long the effect of that shock persists on the stock market as well as on the other markets such as interest rate, exchange rate in a multivariate VAR (p, s) system , then VAR/VARX(p, s) models are useful to capture these effects.

The VARX (p, s) model that we employ in the empirical part to capture the relationship between monetary policy, stock returns and exchange rate returns is as follows:

$$y_t = c + \sum_{i=1}^{p} A_i y_{t-i} + \sum_{i=0}^{s} B_i x_{t-i} + \varepsilon_t \tag{4.2}$$

where $y_t = (y_{1t}, y_{2t}, y_{3t})'$ and $x_t = (x_{1t}, x_{2t}, x_{3t}, x_{4t}, x_{5t})'$.

The length of p and s on the summations are determined by model selection methods such as AIC, SIC and Final Prediction Error Criteia (FPE). In the VARX (p, s) model, we still assume the errors are normally distributed with mean zero, and do not correlate with their past as well as across equations. We test this assumption by introducing GARCH into the error terms of VAR model in the empirical part to see whether the assumptions about the errors term are valid. If the GARCH parameters are significant, it means the assumption that we impose on the VARX(p,s), that is,

constant variance and non-correlated errors assumption, are not valid.

In the VARX (p, s) set up, we estimate the parameters of interest as well as the Impulse Response Function. The impulse response function traces out the response of the dependent variables in the system to shocks in the error terms. It allows us to see how long the effect of a shock, such as a monetary policy shock lasts on the stock market and exchange rate returns, or how long the financial market shocks (stock and exchange) affect monetary policy as well as each other.

The VARX(p, s) set up of the model also allows us to test group causality between monetary policy and financial variables. We are interested in testing whether monetary policy causes fluctuation in financial markets (stock and exchange market) and in testing if the fluctuation in the stock and exchange market causes changes in monetary policy. That is, we are interested in whether there is a lead/lag relationship between monetary policy and financial variables.

So far, we assumed that ε_t has mean zero and constant variances. Also, we assume that the errors are not correlated both with their past and across equations. But, in the introduction section, we argued that variances of errors are not constant for most macroeconomic series and they are closely related with their past variances as well as covariances across other macroeconomic series. This issue leads us to consider adjusting our model.

There are two ways that the literature takes the above argument into account.

1. Seemingly Unrelated Regression: If the errors in different equations with different exogenous variables are correlated, Seemingly Unrelated Regressors(SUR), which takes cross correlation into account, gives a better estimate compared to conventional estimation. This method requires different exogenous variables and no correlation among dependent variables in a system of equations. Based on what we have argued so far, we can not employ this method because of a simultaneous and/or lagged relationship among the return of interest rate, stock price and exchange rate.

2. ARCH or GARCH model: Some of ARCH and GARCH models take not only the conditional variance and past errors into account but also take the cross correlation across equations' shocks into account. We discuss the GARCH model in detail in the next section. But here we should emphasize that the BEKK (Baba, Engle, Kraft and Kroner) representation of ARCH/GARCH is a model that allows us to use cross equation relationships in the estimation process. The Diagonal Vector (DVEC) presentation ignores the cross correlation and Constant Conditional Correlation (CCC) presentation assumes a constant correlation across the error terms of a system. For the relationship that we are interested in, we believe that the BEKK presentation is best. In the empirical part, we employ the BEKK presentation to use the information in the cross equation errors in the estimation procedure, but we also employ the DVEC presentation to see the difference between the BEKK and the DVEC. This will allow us to see if taking cross correlation across markets into account improves the power of our models.

Since we assumed that a shock to monetary policy affects the financial markets and a shock to financial markets affects monetary policy, in the empirical part, we do not employ a SUR model but employ a GARCH model. These allow us to estimate the contemporaneous as well as lagged relationship among the monetary policy, stock price and exchange market. GARCH allows us to use the information in the variance of errors as well as the previous errors to estimate the model that we are interested in. Next we discuss the GARCH part of the model.

4.0.22 Overview of ARCH and GARCH Models

An econometric model consists of two components: one is predictable and the other is unpredictable. The predictable component (or conditional mean) of a dependent variable is a function of some exogenous variables and/or some lags of dependent variables based on an available information set i.e.,

$$y_t = E(y_t|\Psi_{t-1}) + \epsilon_t \tag{4.3}$$

and

$$E(y_t|\psi_{t-1}) = a_0 + \sum_{i=0}^{p} a_i y_{t-i} + \sum_{j=0}^{k} x_{jt} \tag{4.4}$$

where, y_{t-i} are some lags of dependent variables and x_{jt} are some exogenous variables. The unpredictable component, ϵ_t , which is called the error or innovation in the model, cannot be observed, but it can be estimated and its statistical properties can be tested. What is observed in many monetary/financial models is that the unpredictable component of the models, even though normally distributed, does not have constant variances as conventional estimation methods assume. It is possible to get more efficient estimates by taking the non-constant variance into account. Engle (1982) argues that the unobservable second moment of a model can be taken into account by specifying a functional form for it. He specifies that the conditional variance depends on the elements in the information set in an autoregressive manner. His specification leads to what is called in the literature "Autoregressive Conditional Heteroscedasticity" or ARCH model. It is widely used in time series models. The univariate ARCH model is

$$\epsilon_t|\Psi_{t-1} \sim \mathrm{N}(0, \sigma_t^2) \tag{4.5}$$

and

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 \epsilon_{t-2}^2 + \ldots + \alpha_p \epsilon_{t-p}^2. \tag{4.6}$$

This model is called ARCH of order p and represented by ARCH(p).

Bollerslev (1986) extends the ARCH model by introducing the past conditional variances as explanatory variables in the current conditional variance;

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 \epsilon_{t-2}^2 + \ldots + \alpha_p \epsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \ldots + \beta_q \sigma_{t-q}^2 \quad (4.7)$$

This model is called Generalized ARCH of order (p,q) or GARCH (p,q). The above representations are for univariate ARCH (p) and GARCH (p,q).

To extend them to a multivariate models, we have to change the presentation of the conditional variance-covariance matrix to the N- dimensional zero mean residual, ϵ_t which depends on elements of information set. This can be shown as follows

$$\epsilon_t | \Psi_{t-1} \sim N(0, \Sigma_t) \quad (4.8)$$

where

$$\epsilon_t = (\epsilon_{1t}, \epsilon_{2t}, \epsilon_{3t} \ldots \epsilon_{nt})' \quad (4.9)$$

and denotes a N-dimensional error process. In the literature, it is written as

$$\epsilon_t = \Sigma_t^{1/2} Z_t \quad (4.10)$$

where $\Sigma_t^{1/2}$ is a NxN positive definite matrix; Z_t is assumed to be i.i.d. and $Nx1$ random vector with the following first two moments,

$$E(Z_t) = 0$$

$$Var(Z_t) = I_N \quad (4.11)$$

Here I_N is a NxN identity matrix. The conditional variance of y_t is,

$$\begin{aligned} Var(y_t | \Psi_{t-1}) = Var_{t-1}(y_t) &= Var_{t-1}(\epsilon_t) \\ &= \Sigma_t^{1/2} Var_{t-1}(Z_t)(\Sigma_t^{1/2})' \\ &= \Sigma_t. \end{aligned} \quad (4.12)$$

or, in another way,

$$\Sigma_t = E([\epsilon_t \epsilon_t']|\psi_{t-1}). \tag{4.13}$$

The elements of Σ_t are σ_{ii} and σ_{ij} where i,j $= 1, 2...N$; σ_{ii} denotes the conditional variances and σ_{ij} denotes the conditional covariances.

In a multivariate setting, dependencies of conditional variances in Σ_t , which are based on Ψ_{t-1}, get computationally intractable as the number of lags in the conditional variances increases or the number of equations in the multivariate setting increases. We will make these points clearer below.

In the past decade, many models have been proposed in the GARCH literature to estimate the conditional variance-covariance matrix: VEC (Vector); DVEC(Diagonal Vector); BEEK (Baba, Engle, Kraff and Kroner); CCC (Constant Conditional Correlation); DCC(Dynamic Conditional Correlation); O (Ortogonal); F (Factor,); GDC (General Dynamic Covariance Models (See Bauwens et.al (2003) for the detail). We discuss below the most famous four of above mentioned models i.e., VEC, DVEC, BEKK and CCC.

Let vech(.) denotes a half vectorization operator. It stacks a lower half of a matrix including its diagonal elements into a column vector. If A is an NxN matrix, vech(A) will be a column vector which has $1/2(N(N+1))$ elements rather than NxN elements. A GARCH (p,q) model is as follows

$$vech(\Sigma_t) = C + \sum_{i=1}^{q} A_i vech(\epsilon_{t-i}\epsilon_{t-i}') + \sum_{i=1}^{p} G_i vech(\Sigma_{t-i}) \tag{4.14}$$

Now, A_i and G_i contain $(N(N+1)/2)^2$ elements and C is an $N(N+1)/2$ column vector. This is called VEC-representation of a GARCH (p,q) model.

This presentation allows for a very general dynamic structure of the multivariate volatility process. But it suffers from two problems:

1. High dimensionality of the relevant parameters space, and

2. Σ_t has to be positive. This requires some restrictions to be imposed on it.

If we employ the above VEC-model to estimate our tri-Variate GARCH(1,1), we have to estimate 72 parameters excluding 6 constants in the C vector. Notice that if we have a tri-variate model, A_i and G_i each will be a $6x6$ matrix.

To reduce this dimensionality problem in parameter space, Bollerslev, Engle and Wooldridge (1988) suggest a diagonal vector (DVEC) model; Bollerslev (1990) suggests a constant correlation covariance (CCC) model; Baba, Engle, Kraff and Kroner (1990) suggest the BEKK model.

In a DVEC- model A_i and G_i are assumed to be diagonal. Imposing this assumption on the GARCH (p,q) model(eq.40) reduces the number of parameters to be estimated from 72 to 12 parameters (we discuss this issue further in our GARCH model specification, section 4). The DVEC model assumes the absence of cross equation dynamics while the CCC model assumes a constant correlation across the equation ,i.e., the only dynamics are

$$\sigma_{ii,t} = c_{ii} + a_i \epsilon_{i,t-1}^2 + g_i \sigma_{ii,t-1} \qquad i = 1, 2 \ldots, N \qquad (4.15)$$

where N is the number of equations. For off diagonal elements of Σ_t Bollerslev et.al (1988) suggest an ARMA-type dynamic structure such as

$$\sigma_{ij,t} = c_{ij} + a_{ij} \epsilon_{i,t-1} \epsilon_{j,t-1} + g_{ij} \sigma_{ij,t-1} \qquad i = 1, 2 \ldots, N \qquad (4.16)$$

and Bollerslev(1990) proposes a constant contemporaneous correlation. In his proposal the conditional covariance is:

$$\sigma_{ij,t} = \rho_{ij} \sqrt{\sigma_{ii} \sigma_{jj}} \qquad i, j = 1, 2 \ldots, N \qquad (4.17)$$

where ρ_{ij} is a constant (time invariant) correlation between i and j equations.

Note that for a Bi-Variate case, $N = 2$, with $p = q = 1$, the CCC model has to estimate 7 parameters while in the general VEC model (eq.40) has to estimate 21 parameters and the DVEC model has to estimate 9 parameters. The disadvantage of CCC and DVEC models are that they rule out cross equation dynamics while the general VEC model allows the cross equation dynamics.

Baba, Engle, Kraff and Kroner (1990) suggest a model that allows a dynamic structure compared to DVEC and CCC models. It is called BEKK model (named after Baba, Engle, Kraff and Kroner). They define A_i and G_i in (eq.40) as NxN matrices and C as an upper triangular matrix. The BEKK model is as follows;

$$\Sigma_t = c'c + \sum_{k=1}^{K}\sum_{i=1}^{q} A'_{ik}\epsilon_{t-i}\epsilon'_{t-1}A_{ik} + \sum_{k=1}^{K}\sum_{i=1}^{p} G'_{ik}\Sigma_{t-i}G_{ik} \qquad (4.18)$$

Summation K denotes the generality of model. In the BEKK model A_i and G_i have N^2 elements while in VEC and CCC they have $(N(N+1)/2)^2$ elements. Since A_{ik} and G_{ik} are not required be diagonal, the BEKK model allows for cross dynamics of conditional covariances. This property of BEKK leads us to employ it to capture the relationship between monetary policy, stock market and exchange markets volatilities that is the empirical part of this study.

4.0.23 Tri-Variate VAR(P) Model with GARCH(Q, P)

In our tri-variate VAR and tri-variate VARX models, we made three assumptions about the error terms of equations in order to estimate the parameters of interest:

1. The expected value of errors are zero,

2. The variance of errors are constant, and

3. The errors across equations are not correlated.

But, it is known that macroeconomic and financial series do not behave as assumed above. Their behavior generally depends on economic fluctuations. For example, in a expansionary or turbulent period, a high variance follows a high variance and in a sluggish or tranquil period, a low variance follows a low variance. This behavior of economic series is known as heteroscedasticity. Now, if the error terms $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$ in the VAR and VARX system that we discussed are correlated or not zero mean or their variances change by over time , then we can take this information and use it as regressors in the system to estimate the parameters of interest. Using this information would increase the efficiency of estimation. By knowing the previous variance given today's information set, we can estimate the current variance and make better estimates and forecasts for endogenous variables of interest in the system.

In this section, we relax the constant variance assumption in our Tri-variate VAR system, that is, we allow the variances of errors $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$ to be correlated with their error square and with their past conditional variances as well as with their covariances across errors as a special presentation (BEKK). There are different methods that allow variances to vary over time. They are different versions of Generalized ARCH (GARCH) models. We discuss below how GARCH modelling of the error terms in our tri-variate VAR model, and our tri-variate VARX model helps to improve the estimation of the models. But first we have to emphasize a few practical steps before we employ a GARCH model.

In the empirical part, before we remodel the errors term (ε_t) of the structural VAR model with GARCH , we must test whether the errors that we obtain from the structural VAR or VARX model are normally distributed. If they are normally distributed, are uncorrelated across equations and have constant variances, then there is no efficiency gain to include GARCH into the error terms. But, if they have time varying variances, autocorrelated, or across correlated, then inclusion of GARCH as a new part of the models would provide a better estimation. There are tests that can be used to see the behavior of the errors of VAR or VARX models. These tests include Skewness, Kurtosis, and the Engle ARCH(p) tests. These tests are employed and discussed in the empirical part before a GARCH specification is added to the models. These tests let us decide whether inclusion of GARCH is reasonable or not. If these tests indicate the non normality of the error term and large kurtosis, then we employ a GARCH specification of errors to improve the estimation of the model. Another test of normality is the Jarque-Bera (1980) test which is a combination of skewness and kurtosis. All these tests are employed before we include the GARCH into the models.

If the series of ε_t in equations (4.1, 4.2 and 4.3) are correlated with their past squares and past conditional variance, then we have a GARCH in the errors. It is presented as follows:

$$\varepsilon_t|\Psi_{t-1} \sim N(0, H_t). \tag{4.19}$$

Now, errors are still normally distributed with mean zero, but the variances are not constant. Each elements of H_t, that is, h_{it}, depends on q lagged values of ε squares and cross products of ε_t as well as p lagged value of the element of H_t. To illustrate the process let

$$h_t = vech(H_t) \tag{4.20}$$

$$\eta_t = vech(H_t) \tag{4.21}$$

Here, vech(.) is the vector operator that stacks the lower element of a matrix including the diagonal elements as a column vector. Since we have a tri-variate model, the

142

conditional variance-covariance matrix is

$$h_t = c_0 + A_1\eta_{t-1} + \vdots + A_q + G_1 h_{t-1} \vdots + G_p h_{t-p} \tag{4.22}$$

where

$c_0 = n^2$ parameter vector of constants,

$A_i = n^2 x n^2$ parameter matrix of var-cov of cross equation shocks, and

$G_i = n^2 x n^2$ parameter matrix of past conditional variances.

In tri-variate case, if we let GARCH(p,q)=GARCH(1,1), that is, the current variance-covariance matrix is a function of one period previous shocks and one period previous conditional variances, then for GARCH(1,1) specification, the VEC model is

$$h_t = \begin{bmatrix} h_{11} \\ h_{21} \\ h_{22} \\ h_{31} \\ h_{32} \\ h_{33} \end{bmatrix} = \begin{bmatrix} c_{01} \\ c_{02} \\ c_{03} \\ c_{04} \\ c_{05} \\ c_{06} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} & a_{26} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} & a_{46} \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & a_{56} \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{3,t-1}^2 \end{bmatrix}$$

$$+ \begin{bmatrix} g_{11} & g_{12} & g_{13} & g_{14} & g_{15} & g_{16} \\ g_{21} & g_{22} & g_{23} & g_{24} & g_{25} & g_{26} \\ g_{31} & g_{32} & g_{33} & g_{34} & g_{35} & g_{36} \\ g_{41} & g_{42} & g_{43} & g_{44} & g_{45} & g_{46} \\ g_{51} & g_{52} & g_{53} & g_{54} & g_{55} & g_{56} \\ g_{61} & g_{62} & g_{63} & g_{64} & g_{65} & g_{66} \end{bmatrix} \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \\ h_{31,t-1} \\ h_{32,t-1} \\ h_{33,t-1} \end{bmatrix} \tag{4.23}$$

Notice that we eliminate redundant terms, h_{21}, h_{13}, h_{23} and $\varepsilon_{2,t-1}$, $\varepsilon_{3,t-1}$ $\varepsilon_{1,t-1}$, $\varepsilon_{3,t-1}$, $\varepsilon_{2,t-1}$. This elimination of redundant terms leaves 36 free parameters in A_1 and G_1 matrices. In general for n equations in the VEC presentation (as above), we will have $(n(n+1)/2)^2$ unique parameters in each of A_1 and G_1 matrices rather

than $n^2 x n^2$ and $n(n + 1)/2$ terms in the constant vector c_0 rather than n^2. Even though this VEC presentation eliminates the redundant terms, the dimensionality of the relevant parameters spaces is very high. In this representation of the tri-variate model, we have to estimate 78 parameters which is not tractable empirically.

To deal with the high dimensionality problem, there are methods that impose some restrictions on the parameter space to reduce the number of parameters to be estimated. As we discuss in the introduction , Bollerslew et al.(1988) present a diagonal vector (DVEC) model; Bollerslew (1990) suggests a Constant Correlation Covariance (CCC) model to restrict the above VEC Model parameters ; Baba, Engle, Kraft and Kroner (1990) introduce the BEKK model.

We discuss the DVEC and BEKK models respectively in the following subsections and ignore the CCC model since we employ DVEC and BEKK models in the empirical section. Another reason not to discuss the CCC model besides the space problem is that it is too restrictive for the relationships that we are interested in. It assumes that the correlations among the errors are constant. Both theoretically and empirically, it is difficult to argue that the correlations among shocks of returns of interest, stock and exchange rate return are constant. Additionally, the first two chapters of the dissertation demonstrate that the correlations are not constant across variables that we are interested: interest, stock and exchange returns.

4.0.24   DVEC Presentation of GARCH (1,1) Model

A DVEC presentation is obtained from a VEC presentation if the matrices A_i and G_i are assumed to be diagonal. Imposing this diagonal assumption on A_i and G_i means that the volatilities of interest, stock and exchange rate returns are not affected by their cross covariances. The illustration of our tri-variate model in the DVEC

presentation is as follow,

$$
h_t = \begin{bmatrix} h_{11} \\ h_{21} \\ h_{22} \\ h_{31} \\ h_{32} \\ h_{33} \end{bmatrix} = \begin{bmatrix} c_{01} \\ c_{02} \\ c_{03} \\ c_{04} \\ c_{05} \\ c_{06} \end{bmatrix} + \begin{bmatrix} a_{11} & 0 & \cdot & \cdot & \cdot & 0 \\ 0 & a_{22} & \cdot & \cdot & \cdot & 0 \\ \cdot & \cdot & a_{33} & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & a_{44} & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & a_{55} & \cdot \\ 0 & 0 & \cdot & \cdot & \cdot & a_{66} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{3,t-1}^2 \end{bmatrix}
$$

$$
+ \begin{bmatrix} g_{11} & 0 & \cdot & \cdot & \cdot & 0 \\ 0 & g_{22} & \cdot & \cdot & \cdot & 0 \\ \cdot & \cdot & g_{33} & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & g_{44} & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & g_{55} & \cdot \\ 0 & 0 & \cdot & \cdot & \cdot & g_{66} \end{bmatrix} \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \\ h_{31,t-1} \\ h_{32,t-1} \\ h_{33,t-1} \end{bmatrix} \quad (4.24)
$$

Notice that the conditional variances,$h_{11,t}, h_{22,t}$ and $h_{33,t}$ do not include the cross covariances. This means that in our model the conditional variances of interest rate, stock index and exchange rate depend only on their previous square shocks and their previous conditional variance. In other words, the conditional variances depend on only their market specific information. Notice that in the DVEC specification, we do not take the cross covariance among variables into account in the conditional variance. That is, the conditional variance of the stock market does not depend on the relationship between stock market shock and interest rate shock or exchange market shock. It depends on the square of the shocks of the previous period and the previous conditional variance. In other words, there is no spillover of the shock from one market to the other markets according to DVEC specification. This is at odds with our arguments in this study.

4.0.25   BEKK Representation of GARCH(1,1)Model

The DVEC model in the previous section does not allow the potential interaction in the variances of variables. The restriction that the DVEC model imposes may not be consistent with the behavior of the variables of interest. That is, the variance of a variable in the system may affect the variance of other variables. A high variance of interest rate series may be related with the high variance in the stock or exchange markets and so on for others.

The BEKK kind of multivariate GARCH model allows these kind of interactions. Therefore, the BEKK is a very useful model to capture the volatility transfer from one market to the others in a system. In other words, the BEKK model allows us to see if the volatilities of the variables are correlated in our system. If the high variance of the stock market is correlated with a high variance of interest and exchange rate, then we can get a better estimate of the conditional variance of the stock market if we include this information into our information set. The same thing is true for interest and exchange returns.

The illustration of the BEKK kind of multivariate GARCH(1,1) is the following for our tri-variate model;

$$H_t = C_0' C_0 + A_{11}' \varepsilon_{T-1} \varepsilon_{T-1}' A_{11} + G_{11}' H_{T-1} G_{11} \tag{4.25}$$

where C_0 is a triangular matrix, A_{11} and G_{11} are nxn parameter matrices. The extension of equation (4.25) is the following for tri-variate GARCH(1,1) model:

$$H_t = C_0' C_0 + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 & \varepsilon_{2,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{3,t-1}\varepsilon_{1,t-1} & \varepsilon_{3,t-1}\varepsilon_{2,t-1} & \varepsilon_{3,t-1}^2 \end{bmatrix}$$

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \end{bmatrix} \tag{4.26}$$

Notice that in the BEKK GARCH presentation, the variance of a shock in our simultaneous system (2.1) and VARX (2.2) models depends on the squared past error

of itself, on the cross covariances among shocks, on the past variance and on the past covariance of other shocks. To demonstrate spillovers effects across markets, we ignore the conditional variance, G_i and the constant C_0 parts in equation (4.26). Consider the second part of equation (4.26), A_i, ignoring the time subscripts. The conditional variance (or volatilities) of interest, stock return and exchange rate returns are $h_{11,t}$, $h_{22,t}$ and $h_{33,t}$, respectively. Notice that $h_{11,t}$, $h_{22,t}$ and $h_{33,t}$ are the diagonal elements of H_t in the LHS of equation (4.26). They are as follows;

$$h_{11,t} = a_{11}^2(e_1^2) + a_{11}a_{21}(e_2e_1) + a_{11}a_{31}(e_3e_1) + a_{21}a_{11}(e_1e_2) + a_{21}^2(e_2^2) +$$
$$a_{21}a_{31}(e_3e_2) + a_{31}a_{11}(e_1e_3) + a_{31}a_{21}(e_2e_3) + a_{31}^2(e_3^2) \quad (4.27)$$

$$h_{22,t} = a_{12}^2(e_1^2) + a_{12}a_{22}(e_2e_1) + a_{12}a_{32}(e_3e_1) + a_{22}a_{12}(e_1e_2) + a_{22}^2(e_2^2) +$$
$$a_{22}a_{32}(e_3e_2) + a_{32}a_{12}(e_1e_3) + a_{32}a_{22}(e_2e_3) + a_{32}^2(e_3^2) \quad (4.28)$$

$$h_{33,t} = a_{13}^2(e_1^2) + a_{13}a_{23}(e_2e_1) + a_{13}a_{33}(e_3e_1) + a_{23}a_{13}(e_1e_2) + a_{23}^2(e_2^2) +$$
$$a_{23}a_{33}(e_3e_2) + a_{33}a_{13}(e_1e_3) + a_{33}a_{23}(e_2e_3) + a_{33}^2(e_3^2) \quad (4.29)$$

The conditional variances (or volatilities) such as $h_{11,t}$ would also include $h_{11,t-1}$, $h_{22,t-1}$, $h_{33,t-1}$, $h_{1,t-1}h_{2,t-1}$, $h_{1,t-1}h_{3,t-1}$, $h_{2,t-1}h_{1,t-1}$, $h_{2,t-1}h_{3,t-1}$, $h_{3,t-1}h_{1,t-1}$ and $h_{3,t-1}h_{2,t-1}$ from the third part of equation(4.26). But these conditional variance-covariances do not change very fast (Zahnd, 2002). Therefore, the main influences on the conditional variances(or volatilities),h_{11}^2, h_{22}^2 and h_{33}^2 depend on e_{11}^2, e_{22}^2 and e_{33}^2. i.e. the second part of equation (4.25).

We want to see how the volatility transfers occur in the BEKK representation. In our model, h_{11}, h_{22}, h_{33} are the volatilities of interest, stock and exchange returns, respectively, and they are shown by eqs. (4.27, 4.28 and (4.29).

Consider equation (4.27). It represents the volatility of interest return. The effect of a shock to the stock market on the volatility of interest return,h_{11} is given by the coefficient of e_{22}^2. That is, a_{21}^2 in equation (4.27) captures the spillover effect of a

shock to the stock market on the interest rate (monetary policy) volatility. In the same equation (4.27), the effect of a shock to the exchange return on the volatility of interest return is given by the coefficient of e_{33}^2. That is, a_{31}^2 in equation (4.27) captures the spillover effect of a shock to exchange market on the monetary policy.

The same analysis can be done to see other spillovers across markets in equations (4.28 and 4.29). For example, the coefficients a_{12}^2 and a_{32}^2 in equation (4.28) capture the effect of interest and exchange shocks on the volatility of stock market, respectively.

One benefit of the our VAR(1)-GARCH(1,1) BEKK model compared to CCC and DEV models is that it allows asymmetry in the A_i matrix. For example, in our model the effect of interest rate on the stock market is not the same as the effect of stock market on interest rate. Therefore, the coefficient a_{31} captures the spillovers effect of exchange market on the monetary policy in the equation (4.27) while the coefficient a_{13} in equation (4.29) captures the volatility spilovers effect of monetary policy shock on exchange market.

4.0.26 Empirical Results and Diagnostic Tests

Diagnostic Tests and Data

In this section, we discuss the various models used to capture the relationships, if exist, among monetary policy, stock return and exchange rate return based on our diagnostic tests, economic theory and econometric reasoning. After each model is discussed, we will explain why we need to extend the Multivariate VAR (p) model to such as a VECM (p), a Multivariate VARX (p, s), or a Multivariate VAR(p)-GARCH (p, q) model. The first model used to capture the relationship is based on our diagnostic test of cointegration among the variables of interest, that is, a Vector Error Correction model (VECM). The second model is a Multivariate-VAR (p)model. The third model is Multivariate VARX (p, s) model. The fourth model is a Multivariate VAR (p)-GARCH (q, p,) using BEKK representation.

We report and analyze the empirical results of VECM (p), Multivariate VAR (p), Multivariate VARX (p, s), Multivariate VAR (p)-GARCH (q, p) models' identifications and estimations using the methodology discussed in the previous theoretical part.

In this study, we use the three-month treasury bill rate in the secondary market as an indicator of monetary policy following Rigobon and Sack (2003). We reason that the three-month treasury bill rate is a good indicator of monetary policy because economic agents in the financial markets have rational expectations. If in reality, monetary policy reacts to fluctuations in the financial markets, then the economic agents in the financial markets would know that fact and would expect that the FED would change the interest rate in the next FOMC meeting. This market expectation, which is based on rational expectations, would affect the interest rate on the three month treasury bill rate in the secondary market even before the FED changes the interest rate.

The data and macroeconomic shocks that we employ in this chapter are the same as that of the previous chapters.

In section 4.9.1 through section 4.9.10, we report and discuss diagnostic tests such as the Dickey-Fuller and Phillips-Perron tests for stationary time series data; Minimum Information Criterion for Order and Model Selection in a Multivariate VAR system; Granger Causality test for the direction of causality; Johanson and Stock-Watson tests for cointegration. in section 4.10 we deal with cointegration and discusse the Vector Error Correction Model (VECM) model and report the estimates of the VECM (p). In section 4.11 we employ the Multivariate VAR (p) model to analyze the relationship among the returns of interest rate, SP500, and the exchange rate and to report the impulse response of variables to a shock to a market in the system. In section 4.12 we extend the Multivariate- VAR (p) model by including exogenous (macroeconomic shocks) variables in the system, i.e. it is a Multivariate VARX (p, s) model. In section 4.13 we discuss the need to extend the model to a Multivariate VAR (p)- GARCH (q, p) model based on the findings of sections 4.11, 4.12 and other diagnostic tests and report and the estimates and impulse response of the Multivariate VAR (2)- GARCH (q, p) model based on BEKK representations. We discuss summary and conclusion of this essay in section 4.14.

We employ daily data that runs from 03/4/1985 to 12/31/99. We do not have data for weekends and holidays when markets are closed. We treat holidays like weekends. Therefore, we end up with 3707 observations for the above period.

Stationary Tests

We test the stationarity of interest rate, stock price and exchange rate by employing Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF) and Phillips -Perron (PP) tests. We do employ both the Dickey-Fuller and Phillips-Perron tests because in the literature there is some discussion and there are cases when one test rejects the non-stationary hypothesis of one series while the other does not reject the non-stationary hypothesis of the same series.

West (1988) discusses that when there is a high order of autocorrelation, the DF and ADF tests are unable to discriminate well between non-stationarity and

stationary series: since we are using daily data, this might well be the case.

Culver and Papell(1997) shows that the DF and ADF tests are sensitive to structural breaks. In general, when the series has a persistent autocorrelation and/or structural break , the Philips-Perron (PP) test gives more robust estimates of stationarity than either the DF or the ADF test. Therefore, we employed both the DF/ADF and PP tests.

The Dickey-Fuller, the Augmented Dickey-Fuller and the Phillips-Perron tests are based on the autoregressive models, eqs. (4.30, 4.31 and 4.32). Both the DF and the ADF test assume that the errors are statistically independent and have a constant variance. The Phillips -Perron test for unit roots allows for serial correlation in the series and take this into account when it does stationary test.

The critical values for the PP test are the same as for the DF test. That is, the distribution of both tests is the same. The Dickey-Fuller and Phillips-Perron tests employ the Dickey -Fuller test's critical values to see if $\alpha_1 = 0$ in the following equations.

Zero Mean:
$$\Delta y_t = \alpha_1 y_{t-1} + \sum_{j=1}^{P} \gamma_j \Delta y_{t-j} + \epsilon_t \tag{4.30}$$

Single Mean:
$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \sum_{j=1}^{P} \gamma_j \Delta y_{t-j} + \epsilon_t \tag{4.31}$$

Trend Mean:
$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 t + \sum_{j=1}^{P} \gamma_j \Delta y_{t-j} + \epsilon_t \tag{4.32}$$

For the Augmented DF test we employ 20 lags i.e. p=20 for the above equations. Both ADF and PP- tests check whether α_1 in the above equations are zero. We report the results of DF and PP tests based on the estimates of eqs. (4.30, 4.31 and 4.32)

Dickey-Fuller Test

To check whether the variables that we are interested in are stationary or not, we employ the Dickey -Fuller test for three different means of each variable: Zero Mean,

Single Mean and Trend Mean autoregressive models. In Dickey-Fuller test, the null hypothesis is that the each variable is non-stationary, i.e. not rejecting $\alpha_1=0$ means that the series is non stationary.

<div align="center">

Table 4.1: **Descriptive Statistics**

</div>

Variable	Type	NoMissN	Mean	StdDev	Min	Max	Label
Logtc3m	DEP	3707	1.69081	0.28546	0.98208	2.24601	log of tc3m
Logsp500	DEP	3707	6.1083	0.54368	5.17349	7.29251	log of sp500
Logexcyd	DEP	3707	4.86075	0.21285	4.39593	5.56693	log of excyd

Table 4.1 shows the descriptive statistics of the variables while Table 4.2 reports the results of the DF unit root test.

<div align="center">

Table 4.2: **Dickey-Fuller Unit Root Tests**

</div>

Variable	Type	Rho	Prob<Rho	Tau	Prob<Tau
Logtc3m	Zero Mean	-0.43802	0.5838	-1.03	0.2712
	Single Mean	-4.84674	0.4507	-1.91	0.3294
	Trend	-4.43783	0.8596	-1.52	0.8239
Logsp500	Zero Mean	0.341597	0.7667	3.29	0.9998
	Single Mean	0.30444	0.9708	0.26	0.9763
	Trend	-9.29758	0.4868	-1.95	0.6299
Logexcyd	Zero Mean	-0.20568	0.6363	-2.15	0.0304
	Single Mean	-7.21234	0.2625	-3.3	0.0153
	Trend	-8.9528	0.5121	-2.92	0.1555

The data in Table 4.2 indicate that we do not reject the null hypothesis that the log of three month Treasury bill rate(logtc3m) is non-stationary in each of above three (zero mean, single mean and Trend) auto-regressive models at any statistical

significance levels such as 1 , 5 and 10 percent. Also, Table 4.2 shows that we do not reject the hypothesis that logSP500 index is non-stationary in each of the three auto-regressive models. And the hypothesis that log of exchange price (yen/$) is non- stationary in the zero mean and single mean of above models is rejected but the null hypothesis is not rejected in the trend mean model at any statistical significance level. We test the non-stationarity of the log exchange rate with less observations and find that series is non-stationary. We treat exchange rate as a non-stationary series and do cointegration test among three variables. The plots of logtc3m, logsp500 and logexcyd are shown in Figure 14.

For the above variables we also employ the Augmented Dickey -Fuller test with lag length 20. The results are the similar to Table 4.2. Therefore, we do not report these results. The Phillips -Perron test results are discussed next.

Phillips-Perron Test

As we discussed in the introduction to this section, the Phillips-Perron test gives robust estimates in data series that have persistent autocorrelation and/or structural breaks. The Phillips-Perron test results are reported in Table 4.3.

The result of the Philips-Perron unit test shown in Table 4.3 is consistent with that of Dickey -Fuller test: we reject the hypothesis that the logs of three month Treasury bill rate and sp500 index are stationary and we do reject the hypothesis that the log of exchange rate is stationary in zero mean and single mean but do not reject in trend mean.

Order and Model Selection in a VAR System

There are several approaches to determine order selection in VAR (p) models: The cross-correlation matrix of endogenous variables in the VAR; Partial Autoregression Matrices; Partial Correlation Matrix and Minimum Information Criteria. We employ all the above approaches but report only Information Criteria to check significance of different lags.

<div align="center">**Table 4.3**: Phillips-Perron Unit Root Tests</div>

Variable	Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau
logtc3m	Zero Mean	12	-0.4286	0.586	-1.1171	0.241
	Single Mean	12	-4.333	0.504	-1.8755	0.344
	Trend	12	-3.7234	0.903	-1.4039	0.86
logSP500	Zero Mean	12	0.3444	0.768	3.6616	0.999
	Single Mean	12	0.378	0.974	0.3557	0.982
	Trend	12	-7.4286	0.631	-1.7046	0.75
logexcyd	Zero Mean	12	-0.2066	0.637	-2.1372	0.032
	Single Mean	12	-7.3711	0.253	-3.3412	0.014
	Trend	12	-9.1886	0.495	-2.9669	0.143

Multivariate Model Diagnostic

In the literature there are several model selection criteria that are used to choose the appropriate model. All of them are normalized by the number of observations(T). We employ the Akaike Information Criterion (AIC), the Corrected Akaike Information Criterion (AICC), the Final Prediction Error criterion (FPE), the Hannan-Quinn Criterion (HQC) , the Schwarz Bayesian Criterion (SBC). Lutkepohl discusses the properties of these testing criteria in his book "Introduction To Multiple Time Series Analysis" pp. 128)

The testing criteria that we employ and report for our model selection are shown in equations 4.33 through 4.37.

$$\textbf{AIC} = \log(|\tilde{\Sigma}|) + \frac{2r}{T} \tag{4.33}$$

$$\textbf{AICC} = \log(|\tilde{\Sigma}|) + \frac{2r}{T - (\frac{r}{k})} \tag{4.34}$$

$$\textbf{FPE} = (\frac{T + \frac{r}{k}}{T - (\frac{r}{k})})^k |\tilde{\Sigma}| \tag{4.35}$$

$$\mathbf{HQC} = \log(|\tilde{\Sigma}|) + \frac{2r \log(\log(T))}{T} \qquad (4.36)$$

$$\mathbf{SBC} = \log(|\tilde{\Sigma}|) + \frac{r(\log(T))}{T} \qquad (4.37)$$

where r denotes the number of parameters estimated and $\tilde{\Sigma}$ is the maximum likelihood estimate of Σ. The smaller value of information criteria fits the data better when it is compared to other models. We estimate our VAR model with different lags and compare their information criteria and we make our model choice (lag order) based on above information criteria.

Portmanteau Statistic

In the information criteria section, we determine the model selection based on the minimum sum of errors in the VAR. We may be interested in choosing the model where the VAR errors are white noise. If we are interested in obtaining a forecast, we may not be interested in whether residuals are white noise or not. But if the VAR order is chosen, say, on the basis of some economic theories, it may be useful to check the properties of residuals. Also, since different criteria emphasize different aspects of the data generation process, we may get a better idea of how to choose the model order by comparing different Information Criteria. Also, checking whether the residual in a multivariate model are correlated will help us to see whether we need to add more lags to our VAR model. We employ the Portmanteau test to check whether our VAR residuals are correlated. Notice that in a VAR system errors are cross correlated until lags in the VAR system. The Portmanteau test checks whether the VAR residuals are correlated after the length of VAR lags.

Diagnostic Test Results

We initially estimate our VAR model with sixteen lags, VAR(16). Since we do not know the "right" order and there is no economic theory that can be used for order selection, we use statistical tools to find a reasonable one.

155

Table 4.4 shows the information criteria that we employ. Criteria suggestions for appropriate VAR order are in bold . The information criteria in Table 4.4 shows that the SBC suggests a VAR model order of 1 while the HQC suggests 2 and the AICC, AIC and FPEC criteria suggest VAR order of 11. Lutkepohl (1993) discusses this issue. He argues that AIC and FPEC will be about equivalent for large data series(p.130) and they are equivalent in our VAR order 11.

The estimated criteria values are partly based on the assumption that the errors are not cross correlated. Whether this condition holds or not is tested in this subsection. Here we will consider the residual analysis and a test for non correlated residuals. We employ the Portmanteau test for checking cross-correlations across residuals. The null hypothesis is that residuals in the VAR system are not correlated with their past. That is, $\epsilon_t = (\epsilon_{1t}, \epsilon_{2t}, \epsilon_{3t})'$ is independent of $\epsilon_{t-1}, \epsilon_{t-2}...\epsilon_{t-s}$.

The result of the Portmanteau Test in Table 4.5 shows that we reject the hypothesis that residuals are not correlated with their past at any significant level through lags 2-12 by using VAR lags 1, 2 and 3.

The Portmanteau Test in Table 4.5 suggests that either we set up a VAR(p) model with many lags(large p) or we set up a VAR (p) -ARCH (p, q) or VAR(p)-GARCH(p, q) model to increase the efficiency of model since the residuals are not independent. We report the portmanteau test results at lag 11 in Table 4.15. The result shows we do not reject the hypothesis that residuals are not correlated at lag 11. These portmanteau results support the Information Criteria that we should set up VAR with 11 lags.

Granger Causality Test

In the literature, economists often disagree on the direction of causality for macroeconomic variables. The relationship among monetary policy, stock and exchange rate returns certainly requires a test of causality. There are two common ways of testing causality in a multivariate VAR model: Granger Causality Test and Test of Weak Exogeneity. These tests do not depend on any prior economic theory. The Granger

156

Table 4.4: **VAR(p) Order Selection : Information Criteria Variables at Log level**

	lag=1	lag=2	lag=3	lag=4
AICC(Corrected AIC)	-28.0497	-28.0585	-28.0608	-28.069
HQC(Hannan-Quinn Criterion)	-28.0425	**-28.0459**	-28.0429	-28.0458
AIC(Akaike Information Criterion)	-28.0497	-28.0585	-28.0608	-28.0691
SBC(Schwarz Bayesian Criterion)	**-28.0295**	-28.0232	-28.0105	-28.0036
FPEC(Final Prediction Error Criterion)	6.58E-13	6.52E-13	6.51E-13	6.45E-13
	lag=5	lag=6	lag=7	lag=8
	-28.0704	-28.0694	-28.0711	-28.0679
	-28.0419	-28.0355	-28.0318	-28.0233
	-28.0705	-28.0696	-28.0713	-28.0682
	-27.9899	-27.9739	-27.9604	-27.9422
	6.44E-13	6.45E-13	6.44E-13	6.46E-13
	lag=9	lag=10	lag=11	lag=12
	-28.0699	-28.0703	**-28.0731**	-28.0718
	-28.02	-28.0151	-28.0126	-28.006
	-28.0703	-28.0707	**-28.0736**	-28.0725
	-27.9291	-27.9144	-27.9021	-27.8858
	6.45E-13	6.44E-13	**6.42E-13**	6.43E-13
	lag=13	lag=14	lag=15	lag=16
	-28.0719	-28.0701	-28.0692	-28.0702
	-28.0007	-27.9936	-27.9874	-27.9832
	-28.0726	-28.0709	-28.0701	-28.0712
	-27.8707	-27.8538	-27.8378	-27.8238
	6.43E-13	6.44E-13	6.45E-13	6.44E-13

Table 4.5: Portmanteau Test of Residual Cross Correlations

				lag=1			lag=2			lag=3
To Lag	Chi-Square	DF	Prob > ChiSq	Chi-Square	DF	Prob > ChiSq	Chi-Square	DF	Prob > ChiSq	
2	79.12	9	<.001							
3	131.57	18	<.001	81.66	9	<.001				
4	151.86	27	<.0001	102.46	18	<.0001	69.62	9	<.0001	
5	170.11	36	<.0001	120.57	27	<.0001	84.68	18	<.0001	
6	193.07	45	<.0001	143	36	<.0001	109.36	27	<.0001	
7	209.53	54	<.0001	156.05	45	<.0001	118.91	36	<.0001	
8	237.59	63	<.0001	184.52	54	<.0001	147.81	45	<.0001	
9	258.78	72	<.0001	207.36	63	<.0001	168.75	54	<.0001	
10	286.06	81	<.0001	234.17	72	<.0001	191.68	63	<.0001	
11	298.58	90	<.0001	246.63	81	<.0001	203.95	72	<.0001	
12	323.37	99	<.0001	268.97	90	<.0001	221.49	81	<.0001	
13	338.03	108	<.0001	283.89	99	<.0001	236.44	90	<.0001	
14	365.92	117	<.0001	309.84	108	<.0001	258.87	99	<.0001	
15	393.95	126	<.0001	337.96	117	<.0001	284.05	108	<.0001	
16	407.71	135	<.0001	352.06	126	<.0001	296.88	117	<.0001	

Test is based on the assumption that the future cannot cause the present or the past. Therefore, it tests whether the past of other variables explains the variation in the variable of interest. If they do, we say that they are Granger Causes and if they do not we say there is no Granger causality.

We report various Granger Causality test results among the variables. Table 4.6 shows the null hypothesis of None Granger-Causality(Non G-C) among variables.

Table 4.6: Granger Causality Wald Test

	Test	Chi-Square	DF	Prob> Chisq
logsp500 Non G-C logtc3m	**1**	**9.56**	**2**	**0.0084**
logexcyd Non G-C logtc3m	**2**	**5.25**	**2**	**0.0725**
logexcyd Non G-C logtc3m	3	2.46	2	0.2916
logexcyd Non G-C logsp500	4	0.40	2	0.8206
logtc3m Non G-C logexcyd	**5**	**8.14**	**2**	**0.0171**
logsp500 Non G-C logexcyd	6	2.25	2	0.3253
logsp500 & logexcyd Non G-C logtc3m	**7**	**14.96**	**4**	**0.0048**
logtc3m & logexcyd None G-C logsp500	8	3.06	4	0.5483
logtc3m & logsp500 None G-C logexcyd	**9**	**10.27**	**4**	**0.0361**
logtc3m None G-C logsp500 & logexcyd	**10**	**10.92**	**4**	**0.0275**
logsp500 None G-C logtc3m & logexcyd	**11**	**11.66**	**4**	**0.0201**
logexcyd None G-C logtc3m & logsp500	12	5.965	4	0.2031

Each row in boldface in Table 4.6 indicates that we reject the null hypothesis of Non -Granger Causality (Non-G-C). That is, there is Granger Causality between variables when we reject the null hypothesis.

According to Granger Causality test, both the SP500 price and the exchange rate Garnger -Causes the monetary policy variable(Test 1 and 2)in the Table 4.6. Also in the Table, Test 5 indicates that monetary policy Granger causes the exchange rate.

We employ and report "group Non-Granger- Causality Test" results. These test are cross -equation tests. Table 4.6 shows that we reject the hypothesis that stock

and exchange rate returns do not Granger cause interest rate (Test 7). This means that monetary policy reacts to fluctuations in stock and exchange markets. We also tested whether the monetary policy affects the stock price and exchange rate(Test 10). The result is shown in the Table (Test 10), which indicates that monetary policy Granger causes the stock and exchange rate returns. The results of Test 9 and Test 11 in Table 4.6 indicate that monetary policy and stock returns Granger cause exchange rate returns and stock returns Granger cause monetary policy and exchange rates, respectively.

These diagnostic results suggest that a multivariate VAR(p) or a system of equations is a reasonable specification (model) to estimate the data generation process. Therefore, we base our research on a Multivariate VAR(p) and other Multivariate models such as Vector Error Correction Model(VECM), Multivariate VARX(p, s) and Multivariate VAR-GARCH(q, p) model specifications.

4.0.27 Vector Error Correction Model (VECM): Monetary Policy, Stock Price and Exchange Rate

Since the logs of three month Treasury bill and SP500 index and exchange rate(stationary with trend but we treat it as non stationary here) are not stationary, we test the possibility of cointegration among the three variables. If the variables are cointegrated, then the VECM(p) model performs better than Multivariate VAR(p) model. It is known that if variables of interest in a system of equations or in a single model are not stationary but cointegrated, then the model can be estimated in levels, even though the variables are not stationary, by employing a Vector Error Correction Model (VECM). In other words, if in a system of equations or in a single equation variables are cointegrated , then a VECM(p) or ECM(p) performs better than Multivariate VAR(p) or a VAR(p) model.

In the literature when the variables are not stationary, they are usually transformed to stationary by taking their first differences. But, this transformation of

160

variables may distort the original relationship between the variables of interest. When we take the first difference of the series, we lose the long-run relationship among the variables of interest because the first difference just allow us to analyze the relationship among the changes in variables. This is different than the long -run relationship, i.e. the relationship at the level.

In our case, we are trying to capture the relationship between monetary policy and financial variables (stock index and exchange rate). Taking the first difference of variables and setting up a model means that we can only test the relationship between the changes in monetary policy and changes in financial variables, which is a short-run relationship. But, we are also interested in whether there is a long run relationship between monetary policy and the financial variables.

Some important questions that we want to answer in this study concern the relationship between monetary policy and financial markets:

- Does a high interest rate mean lower stock price as we theoretically expect,holding expected cash flows constant ?
- Does a high interest rate attract capital inflows and therefore appreciate the domestic currency as we theoretically expect?

If the interest rate, stock market index and exchange rate are cointegrated in a system of equations, then we can answer these questions by employing a Vector Error Correction Model (VECM), which performs better than a VAR model with first difference variables. Additionally, the VECM allows us to see if there is a long run relationship among the variables of interest.

There are a few ways of checking the existence of cointegration in a multivariate system. We employ Johanson (1995, 1995b) and Stock-Watson (1988) tests to check if the logs of three month Treasury bill rate, stock index and exchange rate are cointegrated. On the one hand, the Johanson cointegration tests and Stock-Watson cointegration test results do not reject the null hypothesis that rank is zero when we do

not include a drift in the long-run relationship among variables. But, they accept the null hypothesis that rank is one when we include a drift in the long-run relationship among the variables. On the other hand, Stock-Watson tests do not reject that the rank is two and three(full rank). Despite these problems, we employ VECM(11) and estimate both long-run and short-run relationships among the variables of interest. The normalized long-run relationship based on log of interest rate is the following:

$$logtc = -15.231 + 0.062(logsp500) + 3.507(logexc) \tag{4.38}$$

The magnitude of log exchange rate coefficient does not make sense because it shows that one unit increase in the log of exchange rate increases the log of interest rate by 3.57 units. Therefore, we do not report the VECM(11) results.

The normality (Jarque-Bera), Portmantaeu test and Heteroscedasticity (LM test) tests show that the errors in the VECM(11) are not normally distributed, they are correlated and there is a heteroscedasticity in the data. This implies that employing VAR(p)-ARCH(q) (or GARCH(p,q) may increase the performance of the model. Next we discuss these models.

4.0.28 Multivariate VAR (P) Model:The Relationship among Monetary Policy, Stock Price and Exchange Rate

In this section, we discuss the relationship between the first differences of interest rate (tc3m), stock price (sp500) and exchange rate(yen/\$). We call it returns but it is not really returns

$$(y_t) = log(y_t/y_{t-1}) = log(y_t) - log(y_{t-1}) \tag{4.39}$$

where y_t is a 3x1 vector that represents the returns of three month Treasury bill rate, sp500 index and exchange rate. Analyzing the relationship among the returns of variables rather than their log levels helps us to overcome the non-stationarity problems that exist in the data. Additionally, this analysis shows how monetary policy may affect the stock and exchange markets in the short run.

As we said before in study, we use monetary policy, stock price and exchange rate interchangeable with interest rate (or return), stock return and exchange rate return, respectively.

First, we report some diagnostic checks on the returns of the three month Treasury bill rate, sp500 stock index and exchange rate (yen/\$). We test whether the returns of

Table 4.7: **Descriptive Statistics**

Variable	Type	Mean	StdDev	Min	Max
fdlogtc3m	DEP	-0.00014	0.011	-0.12838	0.07645
fdlogsp500	DEP	0.000562	0.01026	-0.229	0.08709
fdlogexcyd	DEP	-0.00025	0.0072	-0.0563	0.03366

variables are stationary by employing Dickey-Fuller and Perron-Phillips tests. Both tests show that the variables are stationary. The D-F test results are reported in Table 4.8.

Table 4.8: **Dickey-Fuller Test**

Variable	Type	Rho	Prob<Rho	Tau	Prob<Tau
fdlogtc3m	Zero Mean	-3903.25	0.0001	-44.15	<.0001
	Single Mean	-3905.14	0.0001	-44.15	<0001
	Trend	-3909.73	0.0001	-44.17	<.0001
fdlogsp500	Zero Mean	-3931.67	0.0001	-44.33	<.0001
	Single Mean	-3967.28	0.0001	-44.52	<.0001
	Trend	-3969.25	0.0001	-44.53	<.0001
fdlogexcyd	Zero Mean	-3396.35	0.0001	-41.2	<.0001
	Single Mean	-3407.91	0.0001	-41.26	<.0001
	Trend	-3416.63	0.0001	-41.31	<.0001

The Granger Causality test 1 in Table 4.9 shows that we reject the null hypothesis that the monetary policy variable (three month Treasury bill return) does not Granger cause financial market variables (stock and exchange returns). That is, monetary policy Granger causes sp500 and exchange returns. The Granger Causality test 2 in the Table shows that we reject the null hypothesis that financial market variables (stock and exchange returns) do not Granger cause the monetary policy variable (three month Treasury bill return). The Granger Causality tests (1 and 2) in Table 4.9 show that monetary policy reacts to the fluctuations in the financial markets and also financial fluctuations Granger cause monetary policy. This results of Granger Causality test are consistent with our theoretical expectations. That is, monetary policy makers react to the fluctuations in the financial markets and monetary policy has effects on the financial markets.

The Information Criteria tests are shown below for further comparison of multivariate VAR (11) models. The multivariate VAR (11) estimates are reported in Table 4.11, 4.12 and 4.13.

The most important coefficients are the first lags in the system because the financial markets react very fast to the news and they are generally close to efficient.

164

Table 4.9: Granger Causality Wald Test

	Test	Chi Square	DF	Prob> ChiSq
fdlogtc3m N-G-C fdlogsp500 &fdlogexcyd	1	44.97	22	0.027
fdlogsp500 & fdlogexcyd N-G-C fdlogtc3m	2	44.97	22	0.031

Table 4.10: Information Criteria

AICC(Corrected AIC)	-28.0707
HQC(Hannan-Quinn Criterion)	-28.0101
AIC(Akaike Information Criterion)	-28.0712
SBC(Schwarz Bayesian Criterion)	-27.8996
FPEC(Final Prediction Error Criterion)	6.44E-13

Therefore, our interpretation is mainly based on the coefficients of first lags. All reported t-statistics in VAR (11) are heteroscedasticity corrected t-statistics.

The monetary policy equation (fdltc) in Table 4.11 shows the positive and highly significant relationship between the lag return of SP500 and return of Treasury bill rate. The coefficient of SP500 in monetary policy equation is 0.055 which indicate that a 5% rise in SP500 index return will increase the three month Treasury bill rate by (0.055x0.05= 0.00275) 27.5 basis point. This is what we expect: High stock returns cause the secondary market for the three month Treasury bill rate to react today by predicting the future increase of the interest rate at the next FOMC meeting. This market expectation drives the interest rate on the three month Treasury bill rate to higher levels and therefore a positive relationship between monetary policy and fluctuations in the stock market as shown by the positive coefficient of stock return in monetary policy equation (eq.1) in Table 4.11. Table 4.11 also shows that the monetary policy reacts to sp500 returns at lags 3 and 6 beside lag 1 and the signs

165

Table 4.11: Multivariate VAR (11) Estimates of Returns with Heteroscedasticity Corrected t-Statistics

Model Parameter Estimates

Equation	Parameter	Estimate	Std Error	T Value	Pr.> $|T|$	Variable
fdltc(t)	CONST1	-0.00025	0.000181	-1.381	0.1673	
	AR1_1_1	**0.08254**	**0.0164204**	**5.027**	**0.0000**	**fdltc(t-1)**
	AR1_1_2	**0.05509**	**0.0173183**	**3.181**	**0.0015**	**fdlsp(t-1)**
	AR1_1_3	0.02186	0.0246669	0.886	0.3755	fdlex(t-1)
	AR2_1_1	**-0.0532**	**0.0164339**	**-3.237**	**0.0012**	**fdltc(t-2)**
	AR2_1_2	0.02255	0.0173389	1.301	0.1934	fdlsp(t-2)
	AR2_1_3	-0.02823	0.0246834	-1.144	0.2528	fdlex(t-2)
	AR3_1_1	**-0.0558**	**0.0164416**	**-3.394**	**0.0007**	**fdltc(t-3)**
	AR3_1_2	**0.07428**	**0.0173573**	**4.279**	**0.0000**	**fdlsp(t-3)**
	AR3_1_3	-0.00645	0.024675	-0.261	0.7938	fdlex(t-3)
	AR4_1_1	**0.0542**	**0.0164502**	**3.295**	**0.0010**	**fdltc(t-4)**
	AR4_1_2	0.01051	0.0174085	0.604	0.5460	fdlsp(t-4)
	AR4_1_3	0.01281	0.024659	0.519	0.6034	fdlex(t-4)
	AR5_1_1	0.0249	0.0164786	1.511	0.1308	fdltc(t-5)
	AR5_1_2	0.01079	0.0174084	0.620	0.5354	fdlsp(t-5)
	AR5_1_3	0.01532	0.024667	0.621	0.5346	fdlex(t-5)
	AR6_1_1	**-0.05412**	**0.0164643**	**-3.287**	**0.0010**	**fdltc(t-6)**
	AR6_1_2	**0.03161**	**0.0174075**	**1.816**	**0.0694**	**fdlsp(t-6)**
	AR6_1_3	0.00887	0.0246533	0.360	0.7190	fdlex(t-6)
	AR7_1_1	-0.01676	0.0164804	-1.017	0.3092	fdltc(t-7)
	AR7_1_2	0.01069	0.0174081	0.614	0.5392	fdlsp(t-7)
	AR7_1_3	-0.01328	0.0246604	-0.539	0.5902	fdlex(t-7)
	AR8_1_1	**-0.07004**	**0.0164605**	**-4.255**	**0.0000**	**fdltc(t-8)**
	AR8_1_2	0.02328	0.0173959	1.338	0.1808	fdlsp(t-8)
	AR8_1_3	-0.00187	0.0246596	-0.076	0.9396	fdlex(t-8)
	AR9_1_1	**0.05629**	**0.0164772**	**3.416**	**0.0006**	**fdltc(t-9)**
	AR9_1_2	-0.00699	0.0173526	-0.403	0.6871	fdlsp(t-9)
	AR9_1_3	-0.02884	0.0246524	-1.170	0.2421	fdlex(t-9)
	AR10_1_1	**0.05453**	**0.0164813**	**3.309**	**0.0009**	**fdltc(t-10)**
	AR10_1_2	-0.02126	0.0173385	-1.226	0.2201	fdlsp(t-10)
	AR10_1_3	0.00749	0.0246548	0.304	0.7613	fdlex(t-10)
	AR11_1_1	**-0.0374**	**0.0164386**	**-2.275**	**0.0229**	**fdltc(t-11)**
	AR11_1_2	-0.02752	0.0173427	-1.587	0.1126	fdlsp(t-11)
	AR11_1_3	-0.02109	0.0246039	-0.857	0.3913	fdlex(t-11)

Table 4.12:   **Multivariate VAR (11) Estimates of Returns (Cont'd)**

Equation	Parameter	Estimate	Std Error	T Value	Pr.> $|T|$	Variable
fdlsp(t)	**CONST2**	**0.000602**	**0.0001722**	**3.496**	**0.0005**	
	AR1_2_1	-0.01953	0.015619	-1.250	0.2112	fdltc(t-1)
	AR1_2_2	0.01648	0.016473	1.000	0.3171	fdlsp(t-1)
	AR1_2_3	0.00465	0.023463	0.198	0.8429	fdlex(t-1)
	AR2_2_1	0.00355	0.0156318	0.227	0.8203	fdltc(t-2)
	AR2_2_2	**-0.04235**	**0.0164926**	**-2.568**	**0.0102**	**fdlsp(t-2)**
	AR2_2_3	0.00776	0.0234786	0.331	0.7410	fdlex(t-2)
	AR3_2_1	**-0.05092**	**0.0156391**	**-3.256**	**0.0011**	**fdltc(t-3)**
	AR3_2_2	**-0.03949**	**0.0165101**	**-2.392**	**0.0168**	**fdlsp(t-3)**
	AR3_2_3	-0.02646	0.0234706	-1.127	0.2596	fdlex(t-3)
	AR4_2_1	0.01837	0.0156473	1.174	0.2404	fdltc(t-4)
	AR4_2_2	**-0.02775**	**0.0165588**	**-1.676**	**0.0938**	**fdlsp(t-4)**
	AR4_2_3	-0.03649	0.0234554	-1.556	0.1198	fdlex(t-4)
	AR5_2_1	0.02374	0.0156743	1.515	0.1299	fdltc(t-5)
	AR5_2_2	0.02289	0.0165587	1.382	0.1669	fdlsp(t-5)
	AR5_2_3	-0.02472	0.023463	-1.054	0.2921	fdlex(t-5)
	AR6_2_1	-0.02498	0.0156607	-1.595	0.1107	fdltc(t-6)
	AR6_2_2	-0.01006	0.0165579	-0.608	0.5435	fdlsp(t-6)
	AR6_2_3	-0.0276	0.02345	-1.177	0.2392	fdlex(t-6)
	AR7_2_1	-0.01663	0.015676	-1.061	0.2888	fdltc(t-7)
	AR7_2_2	-0.01475	0.0165585	-0.891	0.3730	fdlsp(t-7)
	AR7_2_3	0.02582	0.0234568	1.101	0.2710	fdlex(t-7)
	AR8_2_1	-0.01	0.0156571	-0.639	0.5230	fdltc(t-8)
	AR8_2_2	0.00793	0.0165468	0.479	0.6318	fdlsp(t-8)
	AR8_2_3	0.000966	0.023456	0.041	0.9671	fdlex(t-8)
	AR9_2_1	0.01244	0.015673	0.794	0.4274	fdltc(t-9)
	AR9_2_2	-0.018	0.0165057	-1.091	0.2755	fdlsp(t-9)
	AR9_2_3	0.022	0.0234491	0.938	0.3481	fdlex(t-9)
	AR10_2_1	**-0.0285**	**0.0156768**	**-1.818**	**0.0691**	**fdltc(t-10)**
	AR10_2_2	-0.01073	0.0164922	-0.651	0.5153	fdlsp(t-10)
	AR10_2_3	0.0159	0.0234514	0.678	0.4978	fdlex(t-10)
	AR11_2_1	0.00185	0.0156363	0.118	0.9058	fdltc(t-11)
	AR11_2_2	0.01022	0.0164963	0.620	0.5356	fdlsp(t-11)
	AR11_2_3	-0.03346	0.023403	-1.430	0.1528	fdlex(t-11)

Table 4.13: Multivariate VAR (11) Estimates of Returns (Cont'd)

Equation	Parameter	Estimate	Std Error	T Value	Pr.> $\|T\|$	Variable
fdlexc(t)	**CONST3**	**-0.00024**	**0.0001209**	**-1.985**	**0.0471**	
	AR1_3_1	**0.02099**	**0.0109683**	**1.914**	**0.0557**	**fdltc(t-1)**
	AR1_3_2	0.01839	0.011568	1.590	0.1119	fdlsp(t-1)
	AR1_3_3	**0.05556**	**0.0164767**	**3.372**	**0.0007**	**fdlex(t-1)**
	AR2_3_1	0.000577	0.0109773	0.053	0.9581	fdltc(t-2)
	AR2_3_2	-0.01272	0.0115818	-1.098	0.2721	fdlsp(t-2)
	AR2_3_3	0.00802	0.0164877	0.486	0.6267	fdlex(t-2)
	AR3_3_1	0.01545	0.0109824	1.407	0.1595	fdltc(t-3)
	AR3_3_2	0.00518	0.0115941	0.447	0.6550	fdlsp(t-3)
	AR3_3_3	-0.01842	0.0164821	-1.118	0.2637	fdlex(t-3)
	AR4_3_1	**0.01914**	**0.0109882**	**1.742**	**0.0815**	**fdltc(t-4)**
	AR4_3_2	0.0018	0.0116283	0.155	0.8770	fdlsp(t-4)
	AR4_3_3	0.00235	0.0164714	0.143	0.8865	fdlex(t-4)
	AR5_3_1	0.00644	0.0110072	0.585	0.5585	fdltc(t-5)
	AR5_3_2	0.00501	0.0116282	0.431	0.6666	fdlsp(t-5)
	AR5_3_3	0.0039	0.0164767	0.237	0.8129	fdlex(t-5)
	AR6_3_1	0.01699	0.0109976	1.545	0.1224	fdltc(t-6)
	AR6_3_2	0.01732	0.0116277	1.490	0.1363	fdlsp(t-6)
	AR6_3_3	-0.01733	0.0164676	-1.052	0.2926	fdlex(t-6)
	AR7_3_1	-0.00543	0.0110084	-0.493	0.6218	fdltc(t-7)
	AR7_3_2	-0.00225	0.011628	-0.193	0.8466	fdlsp(t-7)
	AR7_3_3	0.00331	0.0164723	0.201	0.8407	fdlex(t-7)
	AR8_3_1	**0.02317**	**0.0109951**	**2.107**	**0.0351**	**fdltc(t-8)**
	AR8_3_2	0.01671	0.0116199	1.438	0.1504	fdlsp(t-8)
	AR8_3_3	0.01591	0.0164718	0.966	0.3341	fdlex(t-8)
	AR9_3_1	0.01529	0.0110062	1.389	0.1648	fdltc(t-9)
	AR9_3_2	-0.01402	0.011591	-1.210	0.2264	fdlsp(t-9)
	AR9_3_3	0.0146	0.0164669	0.887	0.3753	fdlex(t-9)
	AR10_3_1	0.01383	0.0110089	1.256	0.2090	fdltc(t-10)
	AR10_3_2	**0.02259**	**0.0115815**	**1.951**	**0.0511**	**fdlsp(t-10)**
	AR10_3_3	0.01781	0.0164686	1.081	0.2795	fdlex(t-10)
	AR11_3_1	-0.00176	0.0109805	-0.160	0.8727	fdltc(t-11)
	AR11_3_2	-0.01357	0.0115844	-1.171	0.2414	fdlsp(t-11)
	AR11_3_3	0.00544	0.0164346	0.331	0.7406	fdlex(t-11)

of coefficients are positive and highly significant. Additionally, eq.(1) in Table 4.11 shows that monetary policy are affected by its lags at lag 2, 3, 6, 8, 9, 10 and 11. Eq.(1) in Table 4.11 also shows that monetary policy does not react the fluctuations in the exchange market. The coefficients of exchange rate are not significant up to lag 11 at any statistically significant level.

The stock market equation (eq.2) in Table 4.12 shows that the return on SP500 index reacts to monetary policy at lags 3 and 10. The relationship is negative as we expected: if monetary policy has an effect on the stock prices, then its effect should be negative. Monetary policy makers increase the interest rate to reduce stock prices. The stock market eq.(2) also shows that SP500 return is affected by its past at lags 2, 3 and 4 and there is no effect of exchange rate return in eq.2 at any lag. We find some effects of monetary policy and some lags of SP500 on SP500 return in (eq.2), but, the first two lags of interest rate are not significant in stock market equation. Therefore, we believe that our finding is consistent with the Efficiency of Market Hypothesis (EMH), which states that we cannot predict the stock price by employing all past and current publicly available information, i.e. one cannot consistently earn excess returns by using past prices or returns information. This includes all firm specific information as well as other economic, financial and political news. We can argue that our multivariate VAR (11) findings are consistent with the EMH since the first lags are not significant.

The exchange market equation (eq.3) shows that the exchange rate reacts to changes in monetary policy . The sign of the monetary policy coefficient is positive as expected and its coefficient is significant at lag 1. the monetary policy coefficient is 0.021 which means one percent increase in the interest rate appreciates the dollar by 0.02 percent against yen. Also, monetary policy coefficients are significant at lags 3 and 8. This is an indicator that international capital inflows are sensitive to changes in the monetary policy of the USA. A high interest rate in the United State attracts the foreign capital inflows and appreciates the value of the dollar.

One assumption of VAR(p) estimation is that the residuals are normally distributed. Therefore, we need to check whether the residuals are normally distributed. We employ various tests to analyze the behavior of residuals: Jargue-Bera Normality Test to check if the residuals are normally distributed; ARCH(LM) Test to see if there is heteroscedasticity in the residuals and Pormanteau Test to analyze the cross correlation in the residuals. Portmanteau Test shows that we do not reject the null hypothesis that errors are not correlated by lags 12 in VAR (at lags 1, 2 and 3) models in Table 4.5 but Portmantaeu test in Table 4.15 shows that we do not reject the null hypothesis that errors are not correlated to lags 12 in Table 4.15. This is another justification (beside, Information criteria) to use lag 11 in our VAR model. Jarque-Bera Test in Table 4.14 rejects the null hypothesis that residuals are normally distributed in all three models . The F-test for Autoregressive Conditional Heteroscedasticity (ARCH or LM) in Table 4.14 shows that there is heteroscedasticity in all three models . Therefore, a Multivariate VAR(p)-ARCH (or GARCH) model may perform better than a Multivariate VAR (p) model.

Table 4.14: **Univariate Model Diagnostic Tests**

Variable	ChiSq (Jarque-Bera)	Prob> ChiSq	F Value (LM test)	Prob>F
fdlogtc3m	9999.99	<.0001	243.60	<.0001
fdlogsp500	9999.99	<.0001	44.06	<.0001
fdlogexcyd	2332.85	<.0001	104.32	<.0001

Table 4.14 shows that the normality of residuals (Jarque-Bera, Normality Chisq in the table) is strongly rejected. That is, the errors are not normally distributed. This is a violation of one of the VAR (p) estimation techniques. The Heteroscedasticity test (or homogeneity of variance test, LM in Table 4.14 shows that the variances of errors are not constant and homogeneity of residual hypothesis is strongly rejected. Overall, the results suggest an ARCH (or GARCH) presentation in the Multivariate

Table 4.15: Portmanteau Test for Residual Cross Correlations

To Lag	Chi-Square	DF	Prob> ChiSq
12	11.69	9	<.2313

VAR (11) model.

The impulse responses of the Multivariate VAR (11) model show that on average the effect of a shock to one variable on the other variables lasts between 11 and 13 days. The impulse responses of the VAR(11) are shown through Figures 18-26. Almost all figures indicate that the innovation in one of variables are rapidly transmitted across markets with the most dramatic responses usually on day 1 through day 11 and latter responses tapering off very fast. The figures shows that almost there is no permanent effect of shocks. The impulse responses generally die after lags 13 very fast. This is what we expect in the financial markets: we cannot have a permanent higher returns after some shocks.

By analyzing Multivariate VAR (11) model above, we determine that the residuals are not normally distributed, and there is heteroscedasticity in the data set. These problems may occur because of excluding some relevant variables that should have been included into the Multivariate VAR (11) model. Therefore, we include some macroeconomic shocks to see if we can overcome the above problems. In the next section, we discuss a Multivariate VAR(p) model with some exogenous macroeconomic variables such as Unemployment(UNEMP),Durable Good and Services (DRGS), Retail Sale(RTLS), Consumer Price Index (CPI) and Producer Price Index (PPI). This kind of modified Multivariate VAR (p) model is called Multivariate VARX (p, s) model. This model is discussed in the next section.

4.0.29 Multivariate VARX (P, S) Model: The Relationship among Monetary Policy, Stock Index and Exchange Rate

In this section, we extend our previous Multivariate VAR (11) model. By analyzing the residuals of our Multivariate VAR (11) model, we found that the residuals are not normally distributed and there is heteroscedasticity in the data set. One can argue that the model omits some other exogenous variables that affect the endogenous variables. If this is true and these exogenous variables are correlated with included variables, then the estimated parameters are biased. In other words, the Multivariate VAR (2) model may suffer the problem of excluding some relevant variables (under-specifying the model), which causes biased estimations of parameters. To test this possibility, we set up a Multivariate VAR (11) model with some exogenous macroeconomic shock variables. This kind of modelling is called Vector Autoregressive Process with Exogenous Variables or VARX (p, s), where p refers to lags of endogenous variables and s refers to lags of exogenous variables. The macroeconomic shocks variables are defined as the difference between actual(released) values of variables and the expected (Money Market Survey) values, i.e. a shock is actual (released) value minus expected (survey) value of a variable. We include five macroeconomics shocks as exogenous variables into our VAR (11) system. The shocks are unemployment (UNEMP), producer price index (PPI), durable good and services (DRGS), retail sale (RTLS) and consumer price index (CPI) shocks. The multivariate VARX (p, s) has the following representation:

$$Y_t = \delta + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=0}^{s} \beta_i X_{t-i} + \epsilon_t \qquad (4.40)$$

where $Y_t = (y_{1,t}, y_{2,t}, y_{3,t})$ and $X_t = (x_{1,t}, x_{2,t}, x_{3,t}, x_{4,t}, x_{5,t}$. That is, Y_t refers to endogenous (the tree month Treasury bill rate, SP500 index and exchange rate) variables in the Multivariate VAR (11) system and X_t refers to exogenous (UNEMP, PPI, DRGS, RTLS and CPI shocks) variables in the system.

The estimates of Multivariate VARX (11, 0) are shown in Table 4.16. All reported t-statistics in VARX (11, 0) are heteroscedasticity corrected t-statistics. We test whether lags of exogenous variables are significant. Since none of lag of shocks is significant, we employ just the contemporaneous shocks.

The results show that the monetary policy (the first equation in the table) reacts to all exogenous macroeconomic shocks(announced-expected) except DRGS shock. The coefficients of UNEMP, PPI, RTLS and CPI macroeconomic shocks are significant at 1% level. The negative sign of unemployment coefficient means that a positive unemployment shock(increase) leads monetary policy makers to reduce interest rate. One unit unexpected increase in unemployment is expected to reduce the interest rate by 0.031 unit. This is consistent with the theory of monetary policy. The coefficients of PPI, RTLS and CPI shocks are positive and the coefficient of CPI is bigger than that of PPI. One unit increase in CPI shock is expected to increase the interest rate by 0.01 unit as we expected : monetary policy reacts to higher inflation and overheated economy by increasing the interest rate. This is an indicator that the market perceives and expects very active monetary policy toward macroeconomic shocks. If a shock hits a macroeconomic variable such as unemployment, general price level and retail sales, the FED will react to this shock by changing the interest rate in the next FOMC meeting or at least the market expects so and therefore the interest rate goes up before the next FOMC meeting. This finding supports the argument that FED is active and reacts to shocks by changing short run interest rates and the market knows this fact and reacts to shocks before the next FOMC meeting.

The Monetary policy equation (eq.1)in Table 4.16 also shows that the market expects that monetary policy will react to fluctuations in the stock market. The coefficient of stock market in the first lag is 0.057 and significant in monetary policy equation at 1% level.

The coefficient of stock returns in Multivariate VARX (11, 0) is almost the same as that of Multivariate VAR (11) model. This has the same interpretation: the market

173

expects that the monetary policy reacts to the fluctuation in the stock market therefore an increase in stock price is followed by an increase in three month Treasury bill rate in the secondary market. The coefficients of sp500 in VAR(11)and VARX(11,0) have the same sign, significance and magnitude.

Since the variables are in log differences, we can interpret the coefficient of endogenous variables in the Multivariate VAR and Multivariate VARX models as the elasticity of dependent variable with respect to other endogenous variables. For example, in the monetary policy equation, the elasticity of interest rate return with respect to stock market return is 0.05.

The stock market equation (eq.2) in Table 4.17 shows that the stock return responds to the producer price index (PPI) shock and durable good and services (DRGS) shock. It also responds to monetary policy at the lags 3 and 10. Additionally, it responds 2nd ,3th and 4th lags of itself. The efficiency of market hypothesis (EMH) is weaker in the Multivariate VARX (11, 0) model than in the Multivariate VAR(11) model. This result is not surprising if the shocks are really unexpected then we expect to find significant coefficients of shocks in the stock equation. The elasticity of SP500 return to a shock in PPI index is -0.006. It looks like the expected inflation is negatively related with SP500 return.

The exchange market equation (eq.3) in Table 4.18 and 4.19 shows that the exchange return responds to changes in the monetary policy variable at the first lag. The coefficient of the three month Treasury bill rate return is significant and has a positive sign as we expected. Additionally, exchange returns responds to monetary policy at lags 4 and 8 with positive coefficients. This is an indicator that high interest rate returns attract foreign capital inflows. This in turn appreciates the value of dollar. The exchange rate return also reacts to unemployment(UNEMP) shocks at 5% level but not other macroeconomic shocks. The sign of unemployment coefficient in exchange return equation is negative as we expected: high unemployment is an indicator of weak economic conditions, therefore it leads capital outflows and in turn depreciates domestic currency.

174

Table 4.16: **VARX (11,0) Parameter Estimates with Heteroscedasticity Corrected t-Statistics**

<div align="center">

Model Parameter Estimates

</div>

Equation	Parameter	Estimate	Std Error	T Value	Pr.$> |T|$	Variables
fdLtc(t)	**CONST1**	**-0.00028**	**0.0001801**	**-1.555**	**0.1200**	
	XL0_1_1	**-0.03156**	**0.0048615**	**-6.492**	**0.0000**	**unemp(t)**
	XL0_1_2	**0.00812**	**0.0028431**	**2.856**	**0.0043**	**ppi_s(t)**
	XL0_1_3	0.000145	0.0002913	0.498	0.6186	drgs_(t)
	XL0_1_4	**0.00456**	**0.0014117**	**3.230**	**0.0012**	**rtls_(t)**
	XL0_1_5	**0.01841**	**0.00704**	**2.615**	**0.0089**	**cpi_s(t)**
	AR1_1_1	**0.08425**	**0.0162879**	**5.173**	**0.0000**	**fdLtc(t-1)**
	AR1_1_2	**0.0565**	**0.0171648**	**3.292**	**0.0010**	**fdLsp(t-1)**
	AR1_1_3	0.01929	0.0244637	0.789	0.4304	fdLex(t-1)
	AR2_1_1	**-0.05021**	**0.0162959**	**-3.081**	**0.0021**	**fdLtc(t-2)**
	AR2_1_2	0.02117	0.017201	1.231	0.2184	fdLsp(t-2)
	AR2_1_3	-0.02906	0.0244663	-1.188	0.2349	fdLex(t-2)
	AR3_1_1	**-0.05968**	**0.0163001**	**-3.661**	**0.0003**	**fdLtc(t-3)**
	AR3_1_2	**0.07545**	**0.0172068**	**4.385**	**0.0000**	**fdLsp(t-3)**
	AR3_1_3	-0.00966	0.0244729	-0.395	0.6930	fdLex(t-3)
	AR4_1_1	**0.05335**	**0.0163303**	**3.267**	**0.0011**	**fdLtc(t-4)**
	AR4_1_2	0.00618	0.0172915	0.357	0.7208	fdLsp(t-4)
	AR4_1_3	0.0161	0.0244421	0.659	0.5101	fdLex(t-4)
	AR5_1_1	0.0244	0.0163327	1.494	0.1352	fdLtc(t-5)
	AR5_1_2	0.00745	0.0172603	0.432	0.6660	fdLsp(t-5)
	AR5_1_3	0.01837	0.0244551	0.751	0.4525	fdLex(t-5)
	AR6_1_1	**-0.05117**	**0.0163259**	**-3.134**	**0.0017**	**fdLtc(t-6)**
	AR6_1_2	**0.0324**	**0.0172536**	**1.878**	**0.0604**	**fdLsp(t-6)**
	AR6_1_3	0.01005	0.0244341	0.411	0.6808	fdLex(t-6)
	AR7_1_1	-0.01476	0.0163399	-0.903	0.3664	fdLtc(t-7)
	AR7_1_2	0.00992	0.017255	0.575	0.5654	fdLsp(t-7)
	AR7_1_3	-0.01382	0.0244397	-0.565	0.5718	fdLex(t-7)
	AR8_1_1	**-0.07107**	**0.0163128**	**-4.357**	**0.0000**	**fdLtc(t-8)**
	AR8_1_2	0.02261	0.0172424	1.311	0.1898	fdLsp(t-8)
	AR8_1_3	-0.00576	0.0244572	-0.236	0.8138	fdLex(t-8)
	AR9_1_1	**0.05539**	**0.0163539**	**3.387**	**0.0007**	**fdLtc(t-9)**
	AR9_1_2	-0.00619	0.0172044	-0.360	0.7190	fdLsp(t-9)
	AR9_1_3	-0.02627	0.0244462	-1.075	0.2826	fdLex(t-9)

Table 4.17: **VARX (11,0) Parameter Estimates (con't**

Equation	Parameter	Estimate	Std Error	T Value	Pr.> |T|	Variable
	AR10_1_1	**0.05078**	**0.0163534**	**3.105**	**0.0019**	**fdLtc(t-10)**
	AR10_1_2	-0.02231	0.0171866	-1.298	0.1943	fdLsp(t-10)
	AR10_1_3	0.00967	0.0244473	0.396	0.6924	fdLex(t-10)
	AR11_1_1	**-0.0402**	**0.0163148**	**-2.464**	**0.0137**	**fdLtc(t-11)**
	AR11_1_2	-0.02599	0.0172087	-1.510	0.1310	fdLsp(t-11)
	AR11_1_3	-0.01889	0.0244004	-0.774	0.4388	fdLex(t-11)
fdLsp(t)	**CONST2**	**0.000587**	**0.0001725**	**3.403**	**0.0007**	
	XL0_2_1	0.0026	0.0046588	0.558	0.5768	unemp(t)
	XL0_2_2	**-0.00641**	**0.0027246**	**-2.353**	**0.0186**	**ppi_s(t)**
	XL0_2_3	**-0.00052**	**0.0002791**	**-1.863**	**0.0624**	**drgs_(t)**
	XL0_2_4	-0.00057	0.0013529	-0.421	0.6735	rtls_(t)
	XL0_2_5	-0.00745	0.0067465	-1.104	0.2695	cpi_s(t)
	AR1_2_1	-0.02023	0.015609	-1.296	0.1950	fdLtc(t-1)
	AR1_2_2	0.01572	0.0164493	0.956	0.3392	fdLsp(t-1)
	AR1_2_3	0.00636	0.023444	0.271	0.7862	fdLex(t-1)
	AR2_2_1	0.00293	0.0156166	0.188	0.8512	fdLtc(t-2)
	AR2_2_2	**-0.04111**	**0.016484**	**-2.494**	**0.0126**	**fdLsp(t-2)**
	AR2_2_3	0.00731	0.0234464	0.312	0.7552	fdLex(t-2)
	AR3_2_1	**-0.05004**	**0.0156206**	**-3.203**	**0.0014**	**fdLtc(t-3)**
	AR3_2_2	**-0.03989**	**0.0164895**	**-2.419**	**0.0156**	**fdLsp(t-3)**
	AR3_2_3	-0.02536	0.0234527	-1.081	0.2796	fdLex(t-3)
	AR4_2_1	0.01736	0.0156496	1.109	0.2673	fdLtc(t-4)
	AR4_2_2	**-0.02745**	**0.0165707**	**-1.657**	**0.0976**	**fdLsp(t-4)**
	AR4_2_3	-0.03776	0.0234232	-1.612	0.1069	fdLex(t-4)
	AR5_2_1	0.02457	0.0156519	1.570	0.1165	fdLtc(t-5)
	AR5_2_2	0.02343	0.0165408	1.416	0.1566	fdLsp(t-5)
	AR5_2_3	-0.02696	0.0234357	-1.150	0.2500	fdLex(t-5)
	AR6_2_1	-0.0248	0.0156454	-1.585	0.1129	fdLtc(t-6)
	AR6_2_2	-0.00965	0.0165344	-0.584	0.5595	fdLsp(t-6)
	AR6_2_3	-0.02799	0.0234156	-1.195	0.2319	fdLex(t-6)
	AR7_2_1	-0.01782	0.0156587	-1.138	0.2551	fdLtc(t-7)
	AR7_2_2	-0.01438	0.0165357	-0.870	0.3845	fdLsp(t-7)
	AR7_2_3	0.02578	0.023421	1.101	0.2710	fdLex(t-7)
	AR8_2_1	-0.00978	0.0156328	-0.626	0.5316	fdLtc(t-8)

176

Table 4.18: VARX (11,0) Parameter Estimates (con't

Equation	Parameter	Estimate	Std Error	T Value	Pr.$> \vert T \vert$	Variable
	AR8_2_2	0.00771	0.0165236	0.467	0.6408	fdLsp(t-8)
	AR8_2_3	0.00285	0.0234377	0.122	0.9032	fdLex(t-8)
	AR9_2_1	0.01252	0.0156722	0.799	0.4244	fdLtc(t-9)
	AR9_2_2	-0.01808	0.0164872	-1.097	0.2728	fdLsp(t-9)
	AR9_2_3	0.02205	0.0234271	0.941	0.3466	fdLex(t-9)
	AR10_2_1	**-0.0281**	**0.0156717**	**-1.793**	**0.0730**	**fdLtc(t-10)**
	AR10_2_2	-0.01066	0.0164702	-0.647	0.5175	fdLsp(t-10)
	AR10_2_3	0.01622	0.0234282	0.692	0.4887	fdLex(t-10)
	AR11_2_1	0.0034	0.0156347	0.217	0.8278	fdLtc(t-11)
	AR11_2_2	0.00802	0.0164914	0.486	0.6267	fdLsp(t-11)
	AR11_2_3	-0.03174	0.0233833	-1.357	0.1747	fdLex(t-11)
fdLex(t)	**CONST3**	**-0.00025**	**0.0001213**	**-2.061**	**0.0393**	
	XL0_3_1	**-0.00694**	**0.0032753**	**-2.119**	**0.0341**	**unemp(t)**
	XL0_3_2	0.0022	0.0019154	1.149	0.2507	ppi_s(t)
	XL0_3_3	0.000172	0.0001962	0.877	0.3807	drgs_(t)
	XL0_3_4	-0.00049	0.0009511	-0.515	0.6064	rtls_(t)
	XL0_3_5	-0.00135	0.0047429	-0.285	0.7759	cpi_s(t)
	AR1_3_1	**0.02144**	**0.0109735**	**1.954**	**0.0507**	**fdLtc(t-1)**
	AR1_3_2	0.01868	0.0115642	1.615	0.1062	fdLsp(t-1)
	AR1_3_3	**0.05518**	**0.0164817**	**3.348**	**0.0008**	**fdLex(t-1)**
	AR2_3_1	0.00123	0.0109788	0.112	0.9108	fdLtc(t-2)
	AR2_3_2	-0.01357	0.0115886	-1.171	0.2416	fdLsp(t-2)
	AR2_3_3	0.00799	0.0164834	0.485	0.6279	fdLex(t-2)
	AR3_3_1	0.01474	0.0109817	1.342	0.1795	fdLtc(t-3)
	AR3_3_2	0.00503	0.0115925	0.434	0.6644	fdLsp(t-3)
	AR3_3_3	-0.01821	0.0164878	-1.104	0.2694	fdLex(t-3)
	AR4_3_1	**0.01875**	**0.011002**	**1.704**	**0.0883**	**fdLtc(t-4)**
	AR4_3_2	0.0021	0.0116496	0.180	0.8569	fdLsp(t-4)
	AR4_3_3	0.0032	0.0164671	0.194	0.8459	fdLex(t-4)
	AR5_3_1	0.00638	0.0110036	0.580	0.5620	fdLtc(t-5)
	AR5_3_2	0.00504	0.0116286	0.433	0.6647	fdLsp(t-5)
	AR5_3_3	0.00475	0.0164759	0.288	0.7731	fdLex(t-5)
	AR6_3_1	0.0172	0.0109991	1.564	0.1179	fdLtc(t-6)
	AR6_3_2	0.01727	0.0116241	1.486	0.1374	fdLsp(t-6)

Table 4.19: **VARX (11,0) Parameter Estimates (con't**

Equation	Parameter	Estimate	Std Error	T Value	Pr.$> |T|$	Variable
	AR6_3_3	-0.0174	0.0164617	-1.057	0.2905	fdLex(t-6)
	AR7_3_1	-0.00542	0.0110085	-0.492	0.6225	fdLtc(t-7)
	AR7_3_2	-0.00218	0.011625	-0.188	0.8512	fdLsp(t-7)
	AR7_3_3	0.00289	0.0164655	0.176	0.8607	fdLex(t-7)
	AR8_3_1	**0.02312**	**0.0109902**	**2.104**	**0.0354**	**fdLtc(t-8)**
	AR8_3_2	0.01632	0.0116165	1.405	0.1601	fdLsp(t-8)
	AR8_3_3	0.01603	0.0164772	0.973	0.3306	fdLex(t-8)
	AR9_3_1	0.01506	0.0110179	1.367	0.1717	fdLtc(t-9)
	AR9_3_2	-0.0133	0.0115909	-1.147	0.2512	fdLsp(t-9)
	AR9_3_3	0.01423	0.0164698	0.864	0.3876	fdLex(t-9)
	AR10_3_1	0.01317	0.0110176	1.195	0.2319	fdLtc(t-10)
	AR10_3_2	**0.02294**	**0.0115789**	**1.981**	**0.0476**	**fdLsp(t-10)**
	AR10_3_3	0.01806	0.0164706	1.096	0.2729	fdLex(t-10)
	AR11_3_1	-0.00157	0.0109916	-0.143	0.8864	fdLtc(t-11)
	AR11_3_2	-0.01362	0.0115938	-1.175	0.2401	fdLsp(t-11)
	AR11_3_3	0.00513	0.016439	0.312	0.7550	fdLex(t-11)

There is no significant changes in the Jarque -Bera normality test and in heteroscedasticity tests. Notice the result of these tests do not mean that the estimated parameters are biased, they are unbiased. But, the results still suggest an ARCH (or GARCH) presentation in the Multivariate VAR (11) or VARX (11) model. In the next section following the suggestions of our analysis of residuals and the above tests, we set up Multivariate VAR (p)-GARCH(q, p) models for searching the relationship among monetary policy, stock price and exchange rate returns.

4.0.30 Multivariate VAR (P)- GARCH (Q, P) Model: The Relationships among Monetary Policy, Stock Index and Exchange Rate

In our previous Multivariate VAR (p) and Multivariate VARX (p, s) models, we tested whether the residuals of the Multivariate VAR (p) and Multivariate VARX (p, s) models were normally distributed as we assumed in the VAR estimation procedure. The findings of the Jarque-Bera and ARCH (LM)tests show that the residuals are not normally distributed and the variances are not homogenous as assumed in the estimation procedure. Therefore, the t-test is not reliable.

To get a reliable t-test and more efficient estimates of variables, we extend our multivariate VAR (p) model to a Multivariate VAR(p)-GARCH (p, q) model. As we discussed in the theoretical part, there are a few different ways of estimating the conditional variances such as using BEKK, DIAG and BEW presentations. Here we employ and report BEKK presentations to estimate the GARCH(q, p) part of the VAR (p) model.

Another reason that we want to estimate the GARCH part of the Multivariate VAR(p) model, besides getting more efficient estimates is to analyze the spillover effects of shocks across markets. We are interested in whether a shock in stock returns affects the other returns such as interest and exchange rate returns, i.e. we are interested in how a volatility in one market affects the volatility in another market of interest.

In our Multivariate VAR (11)-GARCH (2, 1) model:

- The VAR part of the model captures the relationship among the interest rate, stock and exchange rate returns.
- The GARCH part of the model captures the relationship among the volatility of interest rate, stock and exchange rate returns, i.e. the spillover effect across the markets

.

We estimate the VAR (11) -GARCH (2, 1) model based on BEKK representation. Tables 4.20 through 4.23 show the estimates of Multivariate VAR (11)-GARCH (2, 1) model. Tables 4.20 through 4.22 show the estimates of VAR (11) part of the model and Table 4.23 shows the GARCH (2, 1) estimates of the model.

Overall there is a huge increase in the number of significant coefficients in the VAR part of the model when we add the GARCH part into the VAR system. Here we compare VAR (11) estimates with the estimates of VAR (11)part of VAR (11)-GARCH (2, 1) That is, we compare Tables 4.11- 4.13 with Tables 4.20-4.22: the number of significant parameters in the monetary policy equation rises from 12 to 22; the number of significant parameters in the sp500 rises from 7 to 17 and that of exchange rate rises from 7 to 15 when we add GARCH (2, 1) part to the VAR (11) model. We interpret these increase in significance of VAR (11) estimates as an indicator that VAR (11)-GARCH(2, 1) model outperforms VAR (11) model.

The monetary policy equation (in Table 4.20) shows that even though the first lag of sp500 return is not significant, the second, sixth and ninth lags are both positive and significant. The coefficients of lags eight and eleven are significant and negative. We interpret these coefficients in the monetary policy equation (Table 4.20) as an indicator that monetary policy reacts to stock market, which is consistent with VAR(11) and VARX(11) models' findings. This is consistent with the assumption that financial markets expect that an increase in SP500 index will be followed by an increase in three month Treasury bill rate. This positive relationship between these two returns is an indicator that markets expect that monetary policy reacts to fluctuations in the stock market.

The first equation in Table 4.20 also shows there is a significant positive relationship between the interest rate and the exchange rate, contrary to our expectations. The first lag of exchange rate is positive and highly significant in the monetary policy equation. This is an indicator that monetary policy reacts to fluctuations in the exchange rate. The positive and significant coefficients of exchange rate exists at lags two, four and and five. The negative and significant coefficients are at lags three,

six and eight in the monetary policy equation. we expected the negative relationship between monetary policy and exchange rate in the monetary policy equation.This finding can be interpreted as exchange rate puzzle

Additionally, the first equation in Table 4.20 shows that the monetary policy is highly affected by its past: the coefficients of monetary policy are significant at lags one through eleven except lag seven.

The monetary policy (first)equation in Table 4.20 captures the highly significant relationship between monetary policy and financial markets variables such as sp500 and exchange rate returns. This means that monetary policy reacts to the fluctuations in stock and exchange markets.

The second equation in the VAR-GARCH model shown in Table 4.21 represents sp500 returns. sp500 return is not significantly affected by interest rate return and lag of itself at lag one but it is significantly affected by the second lags of interest return and itself. The second and fifth lags of monetary policy coefficients are positive while the third, eight are negative. The exchange return in the sp500 equation has a positive and significant effect on the sp500 return at lags one, second and seventh but it has negative effect on sp500 return at lags three, four, five, six and eleven. Also, sp500 return is negatively affected by its second, third, seventh and eighth lags.

The third equation in Table 4.22 is the exchange rate (yen/\$) equation. It shows that the exchange rate is positively affected by the interest rate return at lags one, two, five and six. The positive relationship between interest rate and exchange rate indicate that a higher interest rate appreciates the dollar. This is an indicator that the US monetary policy has a significant effect on the exchange rate. A higher interest rate in the US attracts foreign capital inflows and appreciates the dollar. Also, exchange rate return is affected by its past at lags one, two, three, four, five, six, seven and eleven.

We estimate VARX(11)-GARCH(2, 1) model. We find some very small standard errors of some coefficients therefore very high t-values. We interpret the estimates of VARX-GARCH model as a local maximum and therefore we do not report them,

basing our interpretation on the VAR(11)-GARCH(2, 1) model. We think that the Multivariate VAR part of VAR(11)-GARCH(2, 1) model captures the significant relationships between monetary policy, stock index and exchange markets as shown in Tables 4.20- 4.22.

Table 4.20: Multivariate VAR (11)-GARCH (q=2 p=1) Estimates Based on the BEKK Representation

Equation	Parameter	Estimate	Std Error	T Ratio	Prob> $|T|$	Variable
		Model	**Parameter**	**Estimates**		
fdltc(t)	**CONST1**	**0.00319**	**6.69E-05**	**47.63**	**0.0001**	
	AR1_1_1	**0.2397**	**0.00076**	**315.55**	**0.0001**	**fdltc(t-1)**
	AR1_1_2	0.0017	0.02348	0.07	0.9423	fdlsp(t-1)
	AR1_1_3	**0.08781**	**0.0237**	**3.71**	**0.0002**	**fdlex(t-1)**
	AR2_1_1	**-0.20944**	**0.0235**	**-8.91**	**0.0001**	**fdltc(t-2)**
	AR2_1_2	**0.04848**	**0.02356**	**2.06**	**0.0397**	**fdlsp(t-2)**
	AR2_1_3	0.0162	0.02371	0.68	0.4946	fdlex(t-2)
	AR3_1_1	**-0.08744**	**0.02364**	**-3.7**	**0.0002**	**fdltc(t-3)**
	AR3_1_2	0.0333	0.02359	1.41	0.1581	fdlsp(t-3)
	AR3_1_3	**-0.04146**	**0.02371**	**-1.75**	**0.0804**	**fdlex(t-3)**
	AR4_1_1	**0.20032**	**0.02346**	**8.54**	**0.0001**	**fdltc(t-4)**
	AR4_1_2	-0.02013	0.02367	-0.85	0.3952	fdlsp(t-4)
	AR4_1_3	**0.11561**	**0.01566**	**7.38**	**0.0001**	**fdlex(t-4)**
	AR5_1_1	**0.18187**	**0.02326**	**7.82**	**0.0001**	**fdltc(t-5)**
	AR5_1_2	0.00311	0.02364	0.13	0.8952	fdlsp(t-5)
	AR5_1_3	**0.06081**	**0.02369**	**2.57**	**0.0103**	**fdlex(t-5)**
	AR6_1_1	**-0.0498**	**0.02369**	**-2.1**	**0.0356**	**fdltc(t-6)**
	AR6_1_2	**0.0891**	**0.02351**	**3.79**	**0.0002**	**fdlsp(t-6)**
	AR6_1_3	**-0.04084**	**0.02369**	**-1.72**	**0.0848**	**fdlex(t-6)**
	AR7_1_1	-0.03398	0.02362	-1.44	0.1503	fdltc(t-7)
	AR7_1_2	-0.01819	0.02365	-0.77	0.4418	fdlsp(t-7)
	AR7_1_3	-0.0303	0.02371	-1.28	0.2014	fdlex(t-7)
	AR8_1_1	**-0.14534**	**0.02329**	**-6.24**	**0.0001**	**fdltc(t-8)**
	AR8_1_2	**-0.13877**	**0.02362**	**-5.88**	**0.0001**	**fdlsp(t-8)**
	AR8_1_3	**-0.05513**	**0.02371**	**-2.33**	**0.0201**	**fdlex(t-8)**
	AR9_1_1	**0.15123**	**0.02361**	**6.41**	**0.0001**	**fdltc(t-9)**
	AR9_1_2	**0.0685**	**0.02364**	**2.9**	**0.0038**	**fdlsp(t-9)**
	AR9_1_3	-0.03602	0.02371	-1.52	0.1288	fdlex(t-9)
	AR10_1_1	**0.11547**	**0.02346**	**4.92**	**0.0001**	**fdltc(t-10)**
	AR10_1_2	-0.0329	0.02368	-1.39	0.1648	fdlsp(t-10)
	AR10_1_3	-0.01897	0.02372	-0.8	0.4238	fdlex(t-10)
	AR11_1_1	**-0.05527**	**0.02372**	**-2.33**	**0.0199**	**fdltc(t-11)**
	AR11_1_2	**-0.06793**	**0.02366**	**-2.87**	**0.0041**	**fdlsp(t-11)**
	AR11_1_3	-0.02032	0.02372	-0.86	0.3916	fdlex(t-11)

Table 4.21: Multivariate VAR (11)-GARCH (q=2 p=1) Estimates Based on the BEKK Representation (Cont'd)

Equation	Parameter	Estimate	Std Error	T Ratio	Prob> $|T|$	Variable
fdlsp(t)	**CONST2**	**0.00316**	**9.38E-05**	**33.71**	**0.0001**	
	AR1_2_1	0.00514	0.02351	0.22	0.8271	fdltc(t-1)
	AR1_2_2	0.01021	0.0233	0.44	0.6612	fdlsp(t-1)
	AR1_2_3	**0.09995**	**0.02363**	**4.23**	**0.0001**	**fdlex(t-1)**
	AR2_2_1	**0.10487**	**0.02324**	**4.51**	**0.0001**	**fdltc(t-2)**
	AR2_2_2	**-0.08013**	**0.02324**	**-3.45**	**0.0006**	**fdlsp(t-2)**
	AR2_2_3	**0.04397**	**0.02372**	**1.85**	**0.0638**	**fdlex(t-2)**
	AR3_2_1	**-0.0487**	**0.02297**	**-2.12**	**0.034**	**fdltc(t-3)**
	AR3_2_2	**-0.08707**	**0.02323**	**-3.75**	**0.0002**	**fdlsp(t-3)**
	AR3_2_3	**-0.07546**	**0.0236**	**-3.2**	**0.0014**	**fdlex(t-3)**
	AR4_2_1	0.01565	0.02363	0.66	0.5077	fdltc(t-4)
	AR4_2_2	-0.02656	0.02284	-1.16	0.245	fdlsp(t-4)
	AR4_2_3	**-0.16043**	**0.02338**	**-6.86**	**0.0001**	**fdlex(t-4)**
	AR5_2_1	**0.09175**	**0.02301**	**3.99**	**0.0001**	**fdltc(t-5)**
	AR5_2_2	0.01193	0.02364	0.5	0.614	fdlsp(t-5)
	AR5_2_3	**-0.07045**	**0.02369**	**-2.97**	**0.003**	**fdlex(t-5)**
	AR6_2_1	0.01746	0.02353	0.74	0.4582	fdltc(t-6)
	AR6_2_2	-0.02138	0.02367	-0.9	0.3664	fdlsp(t-6)
	AR6_2_3	**-0.0516**	**0.0237**	**-2.18**	**0.0295**	**fdlex(t-6)**
	AR7_2_1	-0.0227	0.02369	-0.96	0.338	fdltc(t-7)
	AR7_2_2	**-0.07331**	**0.02368**	**-3.1**	**0.002**	**fdlsp(t-7)**
	AR7_2_3	**0.06207**	**0.02372**	**2.62**	**0.0089**	**fdlex(t-7)**
	AR8_2_1	**-0.04607**	**0.02362**	**-1.95**	**0.0512**	**fdltc(t-8)**
	AR8_2_2	**-0.03919**	**0.0234**	**-1.67**	**0.0941**	**fdlsp(t-8)**
	AR8_2_3	-0.00747	0.02371	-0.31	0.7528	fdlex(t-8)
	AR9_2_1	-0.00902	0.02354	-0.38	0.7015	fdltc(t-9)
	AR9_2_2	-0.02573	0.02367	-1.09	0.277	fdlsp(t-9)
	AR9_2_3	0.01258	0.02372	0.53	0.5958	fdlex(t-9)
	AR10_2_1	-0.00158	0.02368	-0.07	0.947	fdltc(t-10)
	AR10_2_2	0.00282	0.02364	0.12	0.9052	fdlsp(t-10)
	AR10_2_3	-0.00496	0.0237	-0.21	0.8343	fdlex(t-10)
	AR11_2_1	0.00546	0.02369	0.23	0.8178	fdltc(t-11)
	AR11_2_2	-0.00818	0.0237	-0.35	0.73	fdlsp(t-11)
	AR11_2_3	**-0.06876**	**0.02365**	**-2.91**	**0.0037**	**fdlex(t-11)**

Table 4.22: Multivariate VAR (11)-GARCH (q=2 p=1) Estimates Based on the BEKK Representation (Cont'd)

fdlexc(t)	CONST3	0.00192	0.000143	13.46	0.0001	
	AR1_3_1	**0.1199**	**0.02371**	**5.06**	**0.0001**	**fdltc(t-1)**
	AR1_3_2	0.01903	0.02346	0.81	0.4173	fdlsp(t-1)
	AR1_3_3	**0.17153**	**0.02363**	**7.26**	**0.0001**	**fdlex(t-1)**
	AR2_3_1	**0.05232**	**0.02362**	**2.21**	**0.0268**	**fdltc(t-2)**
	AR2_3_2	-0.01017	0.02358	-0.43	0.6663	fdlsp(t-2)
	AR2_3_3	**0.05252**	**0.02371**	**2.21**	**0.0268**	**fdlex(t-2)**
	AR3_3_1	0.00759	0.02339	0.32	0.7457	fdltc(t-3)
	AR3_3_2	-0.02442	0.02342	-1.04	0.2972	fdlsp(t-3)
	AR3_3_3	**-0.07087**	**0.02368**	**-2.99**	**0.0028**	**fdlex(t-3)**
	AR4_3_1	-0.00493	0.02363	-0.21	0.8346	fdltc(t-4)
	AR4_3_2	0.03782	0.02359	1.6	0.109	fdlsp(t-4)
	AR4_3_3	**-0.09396**	**0.02361**	**-3.98**	**0.0001**	**fdlex(t-4)**
	AR5_3_1	**0.06616**	**0.02298**	**2.88**	**0.004**	**fdltc(t-5)**
	AR5_3_2	-0.00142	0.0237	-0.06	0.9521	fdlsp(t-5)
	AR5_3_3	**-0.05716**	**0.0237**	**-2.41**	**0.0159**	**fdlex(t-5)**
	AR6_3_1	**0.06067**	**0.02354**	**2.58**	**0.01**	**fdltc(t-6)**
	AR6_3_2	**0.04013**	**0.0237**	**1.69**	**0.0905**	**fdlsp(t-6)**
	AR6_3_3	**-0.04398**	**0.02371**	**-1.86**	**0.0637**	**fdlex(t-6)**
	AR7_3_1	0.01725	0.02364	0.73	0.4655	fdltc(t-7)
	AR7_3_2	-0.03225	0.02368	-1.36	0.1733	fdlsp(t-7)
	AR7_3_3	**0.04035**	**0.02372**	**1.7**	**0.089**	**fdlex(t-7)**
	AR8_3_1	-0.02229	0.02357	-0.95	0.3444	fdltc(t-8)
	AR8_3_2	0.0047	0.02359	0.2	0.8419	fdlsp(t-8)
	AR8_3_3	-0.00604	0.02371	-0.25	0.7991	fdlex(t-8)
	AR9_3_1	0.03626	0.02343	1.55	0.1219	fdltc(t-9)
	AR9_3_2	-0.028	0.02368	-1.18	0.2372	fdlsp(t-9)
	AR9_3_3	0.00944	0.02372	0.4	0.6906	fdlex(t-9)
	AR10_3_1	0.03643	0.02364	1.54	0.1235	fdltc(t-10)
	AR10_3_2	0.03356	0.02368	1.42	0.1566	fdlsp(t-10)
	AR10_3_3	0.01764	0.02371	0.74	0.457	fdlex(t-10)
	AR11_3_1	0.01519	0.02366	0.64	0.5208	fdltc(t-11)
	AR11_3_2	**-0.04207**	**0.02367**	**-1.78**	**0.0755**	**fdlsp(t-11)**
	AR11_3_3	**-0.0539**	**0.02368**	**-2.28**	**0.0229**	**fdlex(t-11)**

186

Table 4.23: GARCH Parameter Estimates Based on the BEKK Representation (q=2 p=1)

GARCH Model	Parameter	Estimates		
Parameter	**Estimate**	**Std Error**	**T Ratio**	**Prob> $|T|$**
GCHC1_1	0.000744	0.02255	0.03	0.9737
GCHC1_2	**0.0021**	**0.000136**	**15.49**	**0.0001**
GCHC2_2	**0.00753**	**0.00307**	**2.45**	**0.0143**
GCHC1_3	**0.00443**	**0.000156**	**28.32**	**0.0001**
GCHC2_3	**0.000858**	**0.000142**	**6.02**	**0.0001**
GCHC3_3	0.00806	0.01129	0.71	0.4757
ACH1_1_1	**0.21524**	**0.02071**	**10.39**	**0.0001**
ACH1_2_1	**0.0232**	**0.01273**	**1.82**	**0.0685**
ACH1_3_1	**0.21862**	**0.00794**	**27.54**	**0.0001**
ACH1_1_2	0.01853	0.02281	0.81	0.4168
ACH1_2_2	**-0.60283**	**0.02395**	**-25.17**	**0.0001**
ACH1_3_2	**-0.11614**	**0.02252**	**-5.16**	**0.0001**
ACH1_1_3	**0.42959**	**0.0204**	**21.06**	**0.0001**
ACH1_2_3	**-0.13692**	**0.02123**	**-6.45**	**0.0001**
ACH1_3_3	**0.14953**	**0.02187**	**6.84**	**0.0001**
ACH2_1_1	0.00028	0.02372	0.01	0.9906
ACH2_2_1	0.00116	0.02372	0.05	0.961
ACH2_3_1	0.000159	0.02372	0.01	0.9947
ACH2_1_2	-0.00203	0.02373	-0.09	0.9317
ACH2_2_2	-0.00528	0.02373	-0.22	0.8239
ACH2_3_2	-5E-05	0.02372	0	0.9983
ACH2_1_3	0.000303	0.02372	0.01	0.9898
ACH2_2_3	0.000309	0.02373	0.01	0.9896
ACH2_3_3	0.000158	0.02372	0.01	0.9947
GCH1_1_1	**0.90117**	**0.000564**	**999**	**0.0001**
GCH1_2_1	**0.17432**	**0.01338**	**13.03**	**0.0001**
GCH1_3_1	**0.14235**	**0.01273**	**11.18**	**0.0001**
GCH1_1_2	**-0.25931**	**0.02213**	**-11.72**	**0.0001**
GCH1_2_2	**-0.08319**	**0.0242**	**-3.44**	**0.0006**
GCH1_3_2	**-0.32568**	**0.02308**	**-14.11**	**0.0001**
GCH1_1_3	**0.26623**	**0.02317**	**11.49**	**0.0001**
GCH1_2_3	**0.04717**	**0.02359**	**2**	**0.0456**
GCH1_3_3	**-0.15146**	**0.02378**	**-6.37**	**0.0001**

The GARCH part of the model aims to capture the relationships among the volatilities of interest rate ($h_{11,t}$), stock market($h_{22,t}$) and exchange market($h_{33,t}$) in equations 4.41 , 4.42 and 4.43 and the squared shocks (residuals)e_{11}^2, e_{22}^2, e_{33}^2 in markets. In the GARCH part of the model, we are interested in how a shock in one market such as stock market(e_{22}^2) affects the volatilities in the three month treasury bill rate ($h_{11,t}$) and exchange rate ($h_{33,t}$). The volatility is represented by conditional variance of a market(a variable). In the BEKK representation of GARCH, the conditional variance ($h_{ii,t}$) is a function of lags of the squared shocks in variables, the lags of conditional variances and cross covariances as we discuss in the theoretical part(equation 4.26).

In this model, the volatility analysis is based on the presentation in eqs.4.41 , 4.42, and 4.43. The Second Lags of Shocks term in the equations 4.41 , 4.42, and 4.43 represents the second lags of the first nine variables in the right hand side of each equation in the same variable order.

$$h_{11,t} = cc_{11} + a_{11}^2(e_1^2) + a_{11}a_{21}(e_2e_1) + a_{11}a_{31}(e_3e_1) + a_{21}a_{11}(e_1e_2) + a_{21}^2(e_2^2) +$$
$$a_{21}a_{31}(e_3e_2) + a_{31}a_{11}(e_1e_3) + a_{31}a_{21}(e_2e_3) + a_{31}^2(e_3^2)$$
$$+The\ Second\ Lags\ of\ Shocks$$
$$+g_{11}^2(h_1^2) + g_{11}g_{21}(h_2h_1) + g_{11}g_{31}(h_3h_1) + g_{21}g_{11}(h_1h_2) + g_{21}^2(h_2^2) +$$
$$g_{21}g_{31}(h_3h_2) + g_{31}g_{11}(h_1h_3) + g_{31}g_{21}(h_2h_3) + g_{31}^2(h_3^2) \qquad (4.41)$$
$$h_{22,t} = cc_{22} + a_{12}^2(e_1^2) + a_{12}a_{22}(e_2e_1) + a_{12}a_{32}(e_3e_1) + a_{22}a_{12}(e_1e_2) + a_{22}^2(e_2^2) +$$
$$a_{22}a_{32}(e_3e_2) + a_{32}a_{12}(e_1e_3) + a_{32}a_{22}(e_2e_3) + a_{32}^2(e_3^2)$$
$$+The\ Second\ Lags\ of\ Shocks$$
$$+g_{11}^2(h_1^2) + g_{11}g_{21}(h_2h_1) + g_{11}g_{31}(h_3h_1) + g_{21}g_{11}(h_1h_2) + g_{21}^2(h_2^2) +$$
$$g_{21}g_{31}(h_3h_2) + g_{31}g_{11}(h_1h_3) + g_{31}g_{21}(h_2h_3) + g_{31}^2(h_3^2) \qquad (4.42)$$
$$h_{33,t} = cc_{33} + a_{13}^2(e_1^2) + a_{13}a_{23}(e_2e_1) + a_{13}a_{33}(e_3e_1) + a_{23}a_{13}(e_1e_2) + a_{23}^2(e_2^2) +$$
$$a_{23}a_{33}(e_3e_2) + a_{33}a_{13}(e_1e_3) + a_{33}a_{23}(e_2e_3) + a_{33}^2(e_3^2)$$

$$+g_{11}^2(h_1^2) + g_{11}g_{21}(h_2h_1) + g_{11}g_{31}(h_3h_1) + g_{21}g_{11}(h_1h_2) + g_{21}^2(h_2^2) +$$

$$g_{21}g_{31}(h_3h_2) + g_{31}g_{11}(h_1h_3) + g_{31}g_{21}(h_2h_3) + g_{31}^2(h_3^2) \qquad (4.43)$$

The argument that we make is that the coefficients a_{11}, a_{21} and a_{31} capture the spillover effect of the previous day shocks to the first, the second and the third markets, respectively on the volatility of the first market. In eqs. 4.41, 4.42 and 4.43, the coefficients a_{ji} refer to the effects of j*th* market shock on the volatility of the i*th* market.

GCHC*i_j* and ACH*l,i,j* in Table 4.23, refer to the effect of j*th* market on the i*th* market. That is, i refers to the row of the coefficient matrix A in eq. 4.26.

In Table 4.23, the GARCH estimates are based on VAR (11)-GARCH (q=2 p=1). GCHC*i_j* represents the constant terms (cc_{ii}) in the conditional variances (volatilities, ($h_{ii,t}$) equations 4.41, 4.42 and 4.43 . ACH*l,i,j* represents the previous lag ,l, value of the j*th* shock on the i*th* volatility. In other words, i stands for row and j stands for column. Therefore, ACH1_1_2 in our model refers to the effect of lag one shock in the sp500 market on the three month treasury bill rate volatility and ACH2_1_2 has the same interpretation except now it represents the second lag.

This BEKK representation of GARCH (q, p) model allows us to include the previous volatilities (conditional variances, ($h_{ii,t-p}$) into the volatility equations (conditional variances,$h_{ii,t}$). That is, in this presentation, the volatility is not only a function of shocks to the markets (first nine variables in the RHS of equations and their lags) but also a function of previous cross covariance among the volatility of the variables ($h_{ij,t-p}$)and the previous volatilities of the variables ($h_{ii,t-p}$).

The interpretation of the coefficients of volatility, g_{ji} in eqs. 4.41, 4.42 and 4.43 has the same interpretation of a_{ji} except it represent the effect of the volatility of the previous period rather than the effect of shocks of the previous period. In this presentation, g_{11}, g_{21} and g_{31} represent the impact of the previous days volatility in

189

the first, second and third markets,respectively on the volatility of the first market in the present day. The same interpretation is valid for other g_{ji} coefficients in other equations.

Table 4.23 shows the estimates of GARCH (2, 1) part of VAR (11)-GARCH (2, 1) model. We are only interested in the volatility in the markets even though from table 4.23 we can analyze the covariances among the markets by using the information in the table. That is, we analyze the volatility in interest $(h_{11,t})$, stock $(h_{22,t})$ and exchange $(h_{33,t})$ markets.

All constant terms (GCHCi_i) in the volatility equations are positive as we expected because negative constant terms in the conditional variance equation do not make sense. The coefficient ACHl_i_j represents the effect of j*th* market's shock on the i*th* market and the coefficient GHCl_i_j represents the effect of volatility of the j*th* market on the i*th* market. Notice that the coefficients ACHl_i_j refer to a_{ji} coefficients in the volatility eqs. 4.41, 4.42 and 4.43 and GHCl_i_j refers to g_{ji} coefficient in the volatility eqs. 4.41, 4.42 and 4.43

We analyze the volatilities in the markets by using the information in Table 4.23:

The volatility of interest return $(h_{11,t})$ is highly significantly affected by its previous squared shock(ACH1_1_1) and shocks to (exchange market)ACH1_1_3 as well as its previous volatility GHC1_1_1 $(h_{11,t-1})$ and the volatility of the other markets such as the volatility of stock market $h_{22,t-1}$ (since GHC1_1_2 is highly significant and the volatility of exchange market since GHC1_1_3 is highly significant). This means that there is a volatility transfer from stock and exchange market to interest market. That is, there is spillover effects from stock and exchange markets to interest market. In other words, there is spillover effect across markets. One interesting result is that the spillover effect lasts just one day: none of the second day coefficients of shocks(ACHC2_i_j) in Table 4.23 is statistically significant, indicating that the volatility effect from one market to the other is not significant in the second day but as we discussed above both shocks and volatilities are very highly significant in the first day.

In Table 4.23, the volatility of stock market $(h_{22,t})$ is positively and highly significantly affected by both the shocks and the volatility of the interest market: both ACH1_2_1 and GHC1_2_1, representing the effect of the shock and the volatility from the interest market to the stock market respectively are positive and highly significant. At the same time, the volatility of the stock market $(h_{22,t})$ is negatively and highly significantly affected by its previous shock$(e_{22,t-1})$, shock to exchange market $(e_{32,t-1})$ and the volatility of exchange $(h_{33,t-1})$ market: both ACH1_2_3 and GHC1_2_3, representing the effect of shock and the volatility from the exchange market to stock market, respectively are negative and highly significant. Also, the volatility in stock market is affected by its previous day's volatility. In short, our findings strongly show that there is a spillover effect from the interest and exchange market to stock market. This is a strong indicator that there is a spillover effect among monetary policy, stock index and exchange rates.

The volatility of exchange rate return $(h_{33,t})$ is positively and highly significantly affected by both the shock $(e_{12,t-1}^2)$ and the volatility of interest $(h_{11,t-1})$ market: both ACH1_3_1 and GHC1_3_1, representing the effect of shock and the volatility from interest market to exchange market respectively in Table 4.23 are positive and highly significant. At the same time, the volatility of exchange market $(h_{33,t})$ is negatively and highly significantly affected by both the shock $(e_{22,t-1})$ and the volatility of stock $(h_{22,t-1})$ market: both ACH1_3_2 and GHC1_3_2, representing the effect of shock and the volatility from the exchange market to stock market, respectively, are highly significant and negative. This is another indicator that there is a spillover effect among monetary policy and financial variables such as stock and exchange returns.

Our analyze of the GARCH (2,1) part of our Multivariate VAR (2)-GARCH (2, 1) model strongly indicate that there is a strong spillover effect across markets. A high shock and/or a high volatility in one market transfer the next day to other markets. We show that it does not matter whether a shock hits financial markets such as stock and exchange markets or monetary policy such as interest rate, it will be transfer to other markets that we analyzed in this study. We report the impulse response

191

function of VAR(11)-GARCH(2, 1) in the end of dissertation through Figure 14-20. The impulse response function of the VAR-GARCH model indicate that they are more volatile compare to that of VAR(11) model and they tape off slower than that of VAR model. The VAR-GARCH model did not pass the homogeneity test, that is, we could not overcome the heteroscedasticity problem by adding GARCH part to our VAR model. even though we employ GARCH part to our VAR model. Maybe more lags in GARCH part are needed but it will be difficult to interpret the coefficients in the GARCH part if there are many lags.

4.0.31   A Summary and Conclusion of the Third Essay

In this study we are interested in the relationship among monetary policy, stock price and exchange rate and in the relationship across the volatility of these variables, i.e. in how a shock and volatility that hits one variable (or market) affects the other variables' (markets) volatility. To see what are the relationships among the variables of our interest and how the shocks and volatilities spillover across markets, we utilize models such as VECM (p), Multivariate VAR (p), Multivariate VARX (p, s) and Multivariate VAR (p)-GARCH (q,p) models.

Initially, we employ VECM (11), Multivariate VAR (11) and Multivariate VARX (11, 0) to see:

- the relationship between monetary policy and financial markets - stock price and exchange rate

We later employ Multivariate VAR (2)-GARCH (q=2,p=1,) model using BEKK presentation to see:

- the relationship among monetary policy, stock price and exchange rate and
- the relationship among the volatility of monetary policy, stock price and exchange rate.

We use the three month Treasury bill rate in the secondary market as an indicator of monetary policy following Rigobon and Sack (2003).

Our findings in VECM (11) do not provide any acceptable information in the long-run the relationship between interest rate, stock price and exchange rate. Therefore,we do not report the results.

The findings of Multivariate VAR (11) show that the monetary policy reacts positively and significantly to the fluctuations in the stock market. That is, as stock prices goes up, the market expects that the FED will increase the interest rate in the next FOMC, therefore, the interest rate on the three month treasury bill rate goes up today. The findings of Multivariate VAR (11) model also show that even though the monetary policy does not react to the fluctuations in the exchange market, it has a highly significant effect on the exchange rate: as interest rate goes up, the dollar appreciates. This is probably because of foreign capital inflows. Again, the stock prices cannot be predicted by using monetary policy, exchange rate and past information about the stock prices . Again, the EMH is valid according to our Multivariate VAR (11) model.

We extend our Multivariate VAR(11) model to Multivariate VARX(11,0) model by including macroeconomic shocks such as unemployment (Unemp), retail sale (rtsl), durable good and services (drgs), consumer price index (CPI) and producer price index(PPI) shocks. Our Multivariate VARX (11,0) model also captures a positive and statistically significant relationship between monetary policy and the stock market. That is,the monetary policy reacts to fluctuations in the stock market: as stock price goes up, the financial markets expect that in the next FOMC meeting, the monetary authorities will increase the interest rate to cool the stock market down. Additionally, our Multivariate VARX (11,0) model captures the same relationship between monetary policy and exchange rate that the Multivariate VAR (11) model captured: even though the monetary policy does not react to the fluctuations in the exchange market in the first lag, it has a very statistically significant positive effect on the exchange rate. The Multivariate VARX (11, 0) findings show that as interest

rate goes up (tight monetary policy), the dollar appreciates. This result is consistent with the Uncovered Interest Parity (UIP) argument.

We extend our Multivariate VAR (p) model to Multivariate VAR (p)-GARCH (q, p) model. The results of Multivariate VAR (11)-GARCH (q=2,p=1,) model show that there is a substantial increase in the significance of VAR(11) parameters after the GARCH(q,p) part is included into the model. Most of insignificant parameters of Multivariate VAR(11) model become highly significant. The Monetary policy reacts significantly to the fluctuation in the stock and exchange markets . Also, the GARCH (q=2,p=1,) part of VAR (11) model strongly indicates that there are very significant spillover effects of multivariate shocks and volatility across the markets: knowing a shock to a market can help predict the volatility in other markets. For example, a shock to the stock market can help us predict the volatilities in the exchange and three month Treasury bill rate returns. Most of the GARCH(q, p) parameters are highly significant as shown in Table 4.23

The estimates of the Multivariate VAR(2)-GARCH(q=2,p=1) model in Tables 4.20- 4.23 indicate that the there is a significant relationship among monetary policy (Three month treasury bill rate), stock price and exchange rate . The reaction of monetary policy to stock prices is positive at the second lag and the monetary policy has a significant negative effect on the stock price. These findings are consistent with our theoretical expectations: as stock price goes up , the FED will react to this increase in the stock price by raising the the interest rate. Since the economic agents in the financial markets have rational expectations, they will know that the FED is going to increase the interest rate in the next FOMC meeting, and they will react according to these expectations, i.e. the interest rate on the three month treasury bill rate will go up before the FED increase it in the next FOMC meeting. If the monetary policy is effective, we expect that there will be negative effect of interest rate on the stock price, i.e. as interest rate goes up, the stock prices go down. These are what our Multivariate VAR(11)-GARCH(2,1) model captures in the interest and stock return equations.

The estimates of the GARCH(2, 1) part of VAR(11) model can be used to explain the volatility in the markets. Most of constant terms($GCHC_{i,j}$) are significant and can be used to explain the the volatilities of three month treasury bill rate, stock price and exchange rate return equations as shown in Table 4.23. Additionally, the estimates that capture the cross market effect of shocks (ACHl_i_j) and the cross market effects of volatility ($GCHl\_i\_j$) are highly significant, which strongly indicate spillover effects across markets.

An important note is none of the second lags of shocks in the GARCH (q=2,p=1) part is significant ,indicating that the spilover effects of shocks last just one day.

We find positive and significant relationships between monetary policy, stock returns and exchange rate returns in Multivariate VAR (11) and Multivariate VARX (11) models as we find in Multivariate VAR (11)-GARCH (2, 1) model. Our findings support Rigobon and Sack (2003) approach. That is, as the stock prices goes up, the markets expect the monetary authorities will react to the high price of stocks by increasing the interest rate in the next FOMC meeting. Our estimates of Multivariate VAR (11), Multivariate VARX (11, 0) and Multivariate VAR(11)- GARCH (2, 1) models indicate that monetary policy reacts to the fluctuations in the stock and exchange rate and it has a significant effect on the stock and exchange rate. Our Multivariate VAR (11)-GARCH (2, 1) model also indicates that there are strong spillover effects of shocks and volatilities cross markets.

We believe that our Multivariate VAR (11)-GARCH (q=2, q=1) fits best to our theoretical expectation.

Chapter 5

A GENERAL SUMMARY AND CONCLUSION

In this dissertation we examine the simultaneous and dynamic lead/lag relationships among monetary policy and stock and exchange rate markets in three essays. We argue that on the one hand, monetary policy affects both stock prices and the exchange rate and on the other hand, stock prices and exchange rates affect monetary policy as well as each other. Therefore, the relationships between these variables are reciprocal. We examine the simultaneous relationships between monetary policy and stock prices, simultaneous relationship between monetary policy and exchange rate by employing the Identification Through Heteroscedasticity (ITH) method. We also examine the dynamic relationships among monetary policy and the financial variables (stock returns and exchange rate returns) and the dynamic relationships among the volatilities of shocks to monetary policy and financial variables using Vector Error Correction Model (VECM), Multivariate-VAR (p), Multivariate-VARX (p) and Multivariate VAR (p)-GARCH (q, p) models.

In the second chapter, we examine the simultaneous relationship between monetary policy and stock returns by employing Identification Through Heteroscedasticity (ITH) method. By employing the ITH, we estimate the reaction of monetary policy

196

to the stock market. There are two big advantages to this method: First, it solves the heteroscedasticity problem that exists in most macroeconomic data. It uses the heteroscedasticity of the data to determine regime changes and uses regime changes to estimate the parameter of interest, in our case, the reaction of monetary policy, β. Second, it allows the use of simultaneous relationships between the variables of interest, in our case the relationship between the interest rate and stock prices.

We estimate that the monetary policy response coefficient, β, is 0.013, which indicates that a 5 % rise in the SP500 index will increase the three month interest rate by (0.013x0.05= 0.00065) 6.5 basis points. We can translate this estimate into the probability of policy tightening or easing. Since the $FOMC$ meets every six weeks, on average the next $FOMC$ meeting will be about three weeks away. The 3-month T-Bill rate reflects the expected rate to prevail next thirteen weeks. Therefore, the estimated coefficient corresponds roughly to an increase in the expected federal funds rate of (6.5 times 13/9) 9.4 basis points. Notice that 6.5 basis points increase that shows up in the 3-month T-bill is the 9/13 of the expected increase in the federal fund rate. Therefore, the results suggest that an unexpected increase in the $SP500$ index of 5% increases the federal fund rate expected after the next $FOMC$ meeting by 9.4 basis points. If we translate this into discrete policy actions, a 5 % rise in the $SP500$ index increases the probability of a 25 basis point tightening by about (9.4/25) 38 %. And a 5 % decline in the $SP500$ index has a similar effect for policy easing.

In the third chapter, we analyze the relationship between monetary policy and exchange rates by employing the ITH method. In this essay we define regime changes based on two different methods: First, we allow the data to determine the regime changes and estimate the reaction of monetary policy to different exchange rates. Second, we determine regime changes exogenously, based on the historical exchange rate policies and estimate the reaction of monetary policy to exchange rates. We use different exchange rates such as Yen/$, Index/$ and Pound/$ to estimate the reaction of monetary policy to exchange rates in the United States. The results indicate that there is not a statistically significant reaction of monetary policy to fluctuation in the

exchange rate.

In the fourth chapter we extend our interest from bi-variate relationships between monetary policy and stock market and/or monetary policy and exchange market to the tri-variate relationship among monetary policy, stock returns and exchange rates by employing various models. We analyze the relationships among monetary policy, stock and exchange rate returns by employing VECM, VAR(p), VARX(p, s), VAR(p)-GARCH(q, p) models.

Our findings in the fourth chapter indicate the existence of positive and significant relationships among monetary policy, stock returns and exchange rate returns in Multivariate VAR (11) and Multivariate VARX (11) models as well as in Multivariate VAR (11)-GARCH (2, 1) model. That is, as the financial assets (stock and exchange) prices goes up, the markets expect the monetary authorities will react to the high price of finacial assets by increasing the interest rate in the next FOCM meeting. Our estimates of Multivariate VAR (11), Multivariate VARX (11, 0) and Multivariate VAR(11)- GARCH (2, 1) models indicate that monetary policy reacts to the fluctuations in the stock and exchange rate and monetary policy has a significant effect on the stock and exchange rate. In the fourth chapter, our Multivariate VAR (11)-GARCH (2, 1) model also indicates that there are strong spillover effects of shocks and volatilities cross markets.

A further study of the relationship between monetary policy, stock price and exchange rate can be analyzed by using Simultaneous-Multivariate VAR(p)-GARCH(q, p) modelling with BEKK presentation for the GARCH part of the model. To the best of our knowledge, the asymptotic properties of the Simultaneous Multivariate VAR (p)-GARCH (q, p) model has not been studied. We plan to do this in further studies.
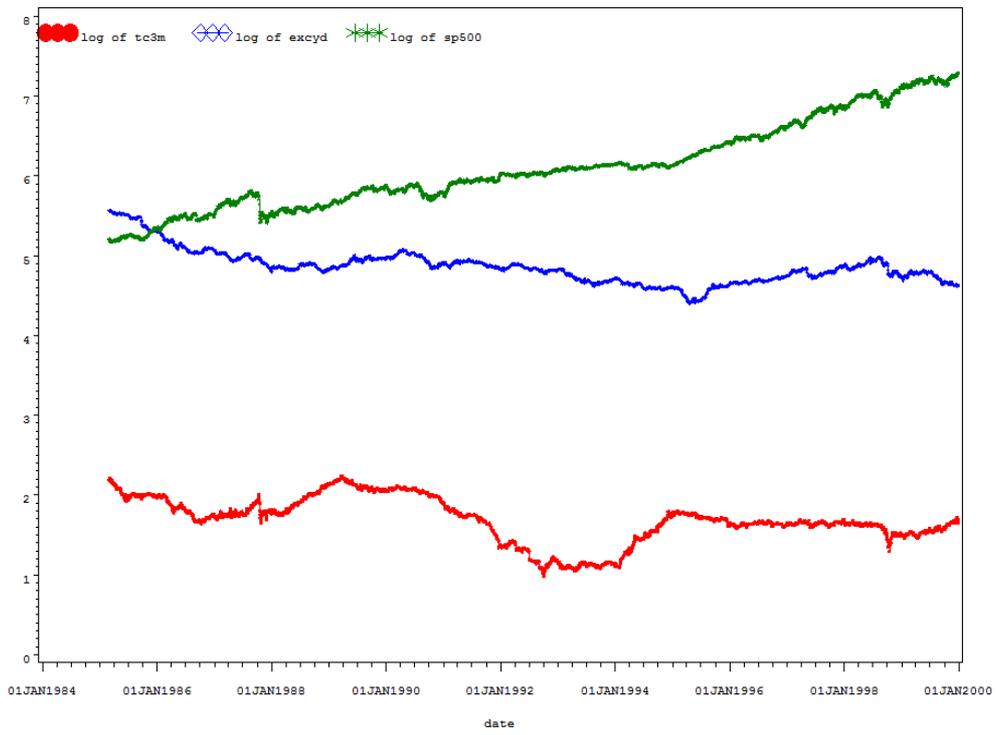
Figure 5.1: Variables at Log Level
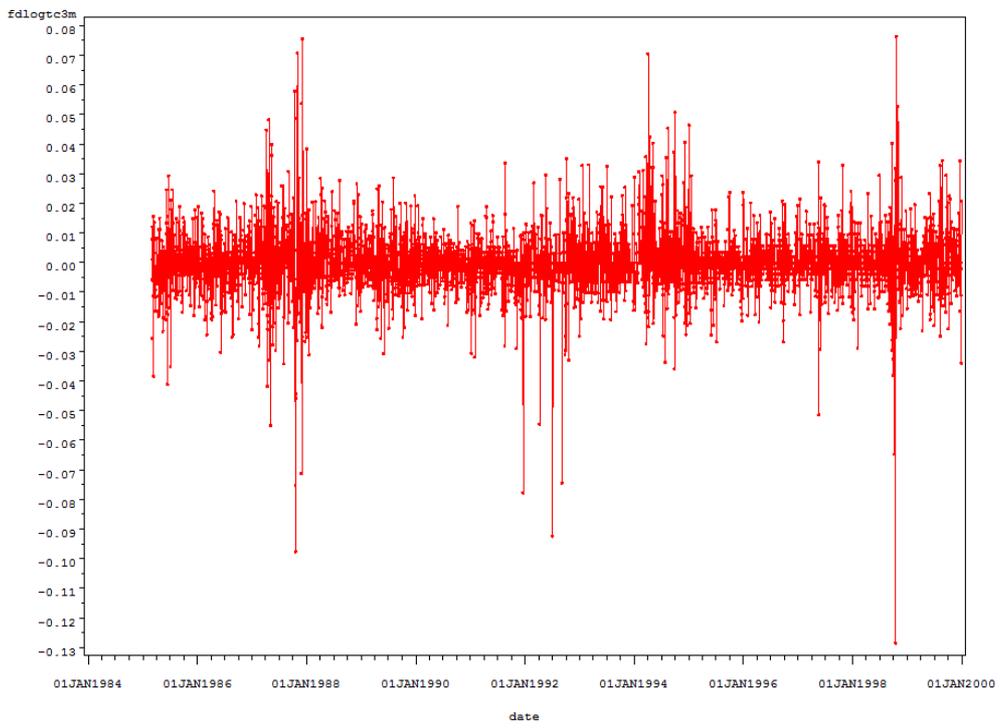
Figure 5.2: TC3M at First Difference
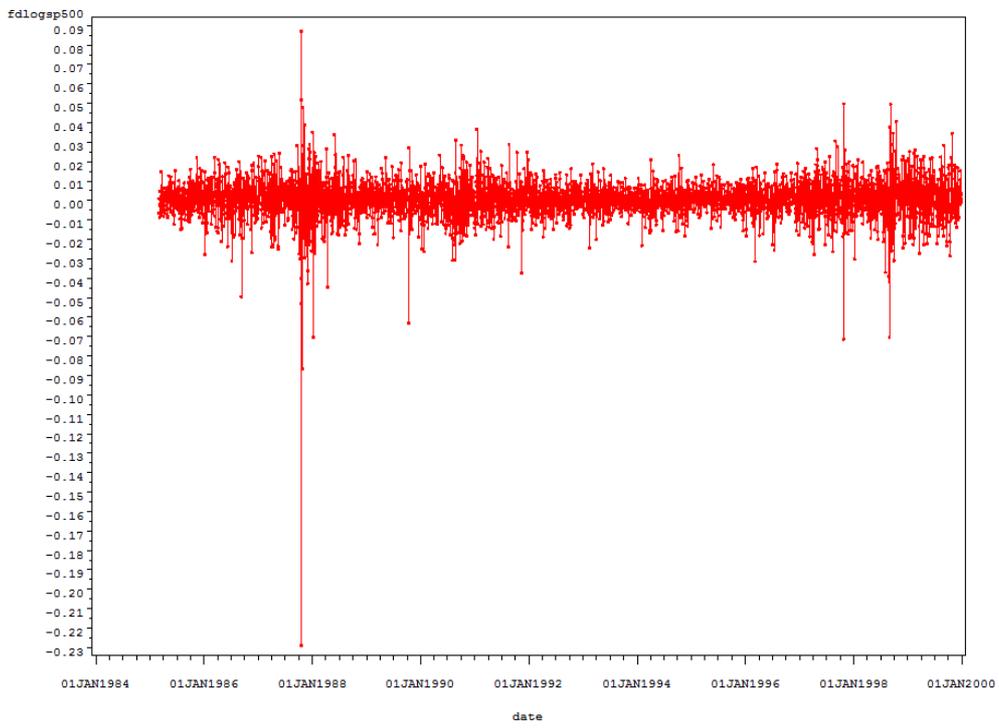
Figure 5.3: SP500 at First Difference
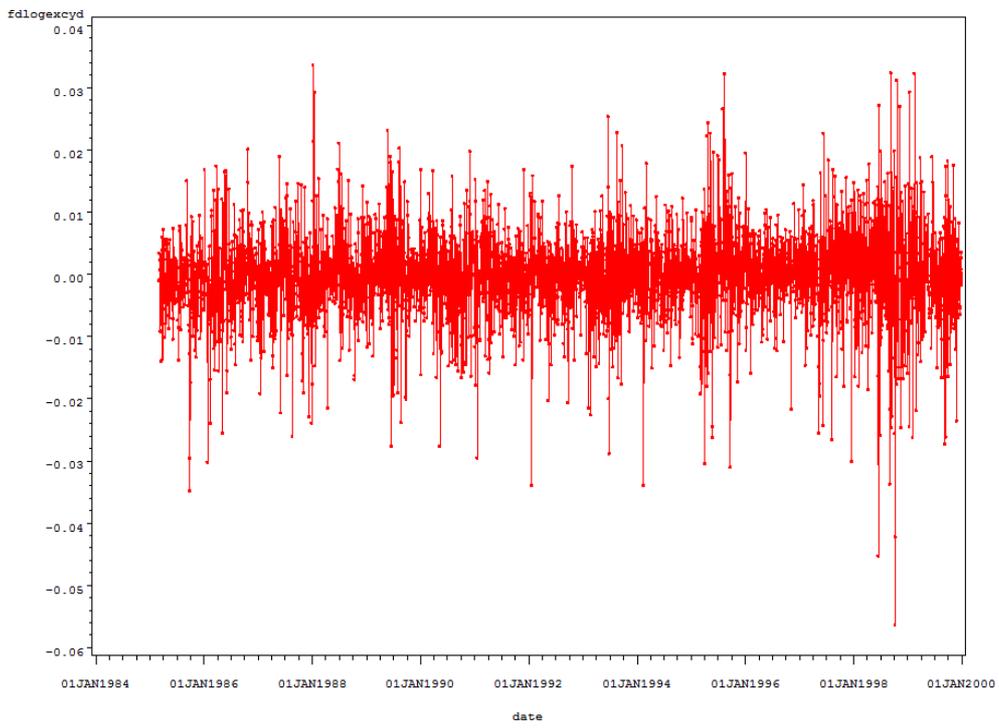
Figure 5.4: EXCYD at First Difference
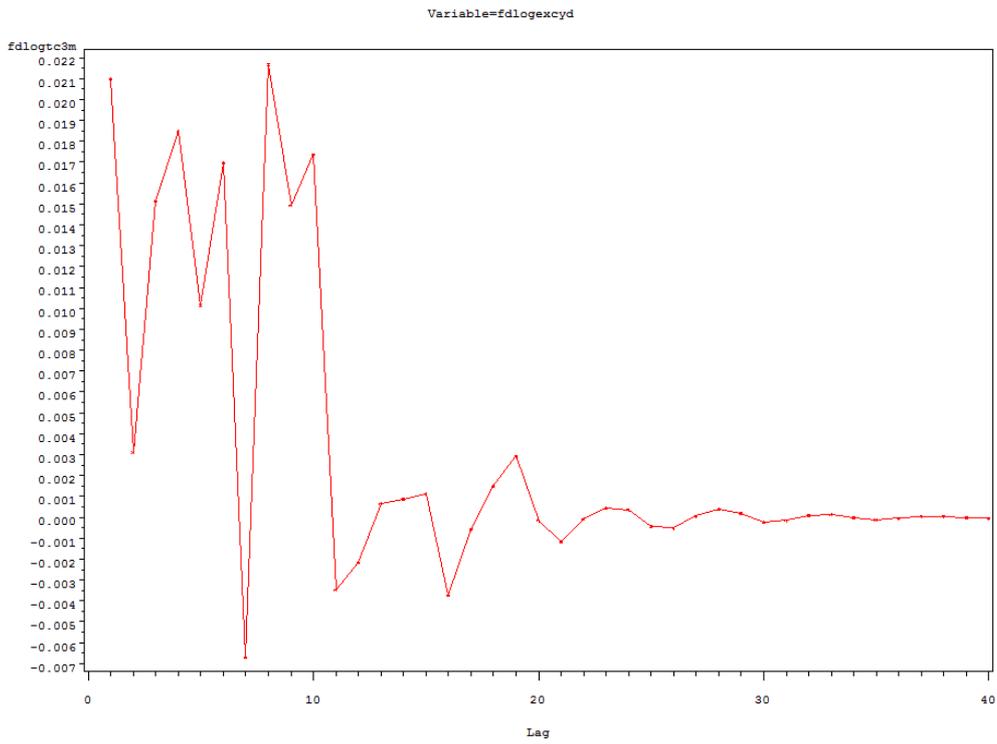
Figure 5.5: impulse from fdlogexc to fdlogtc3m
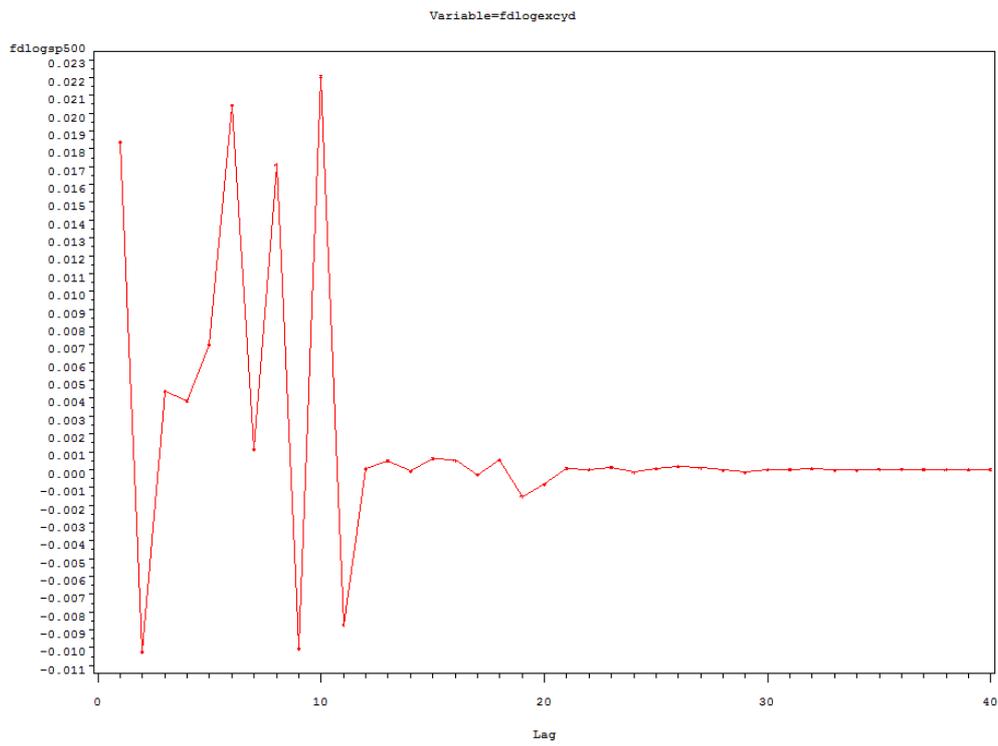
Figure 5.6: impulse from fdlogexcyd to fdlogsp500
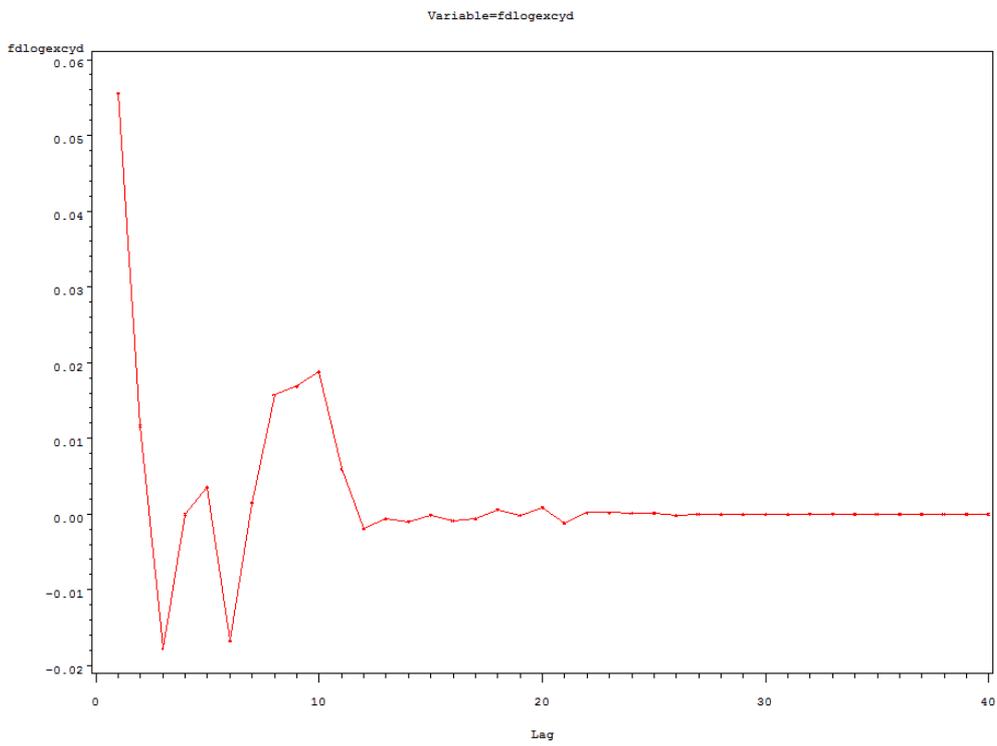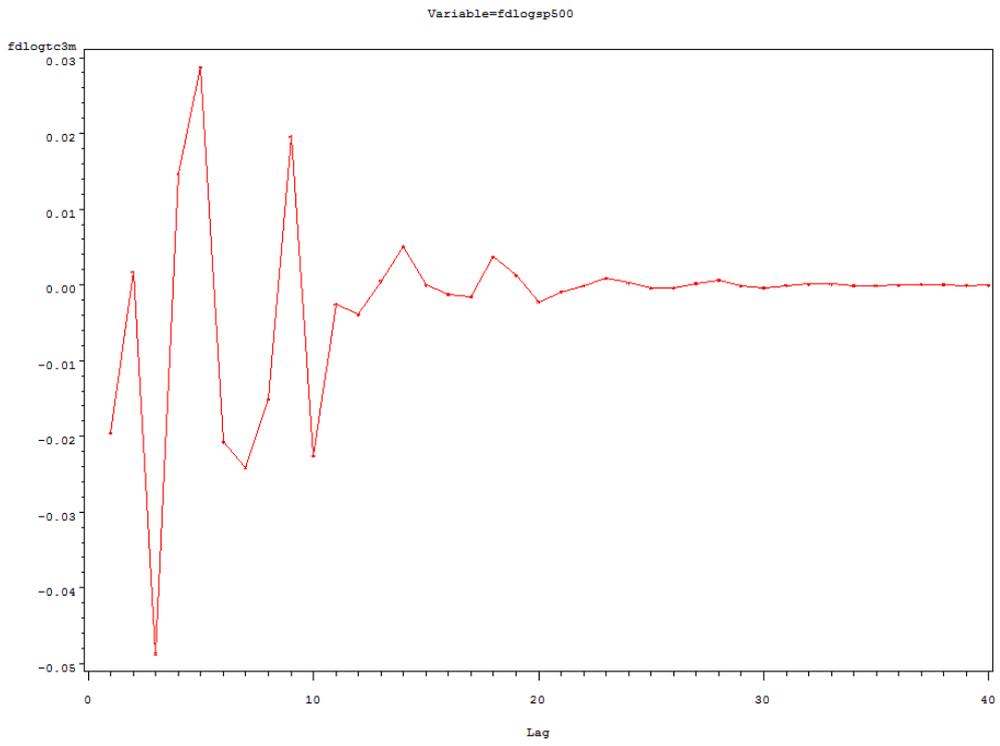
Figure 5.7: impulse from fdlogexcyd to fdlogexcyd

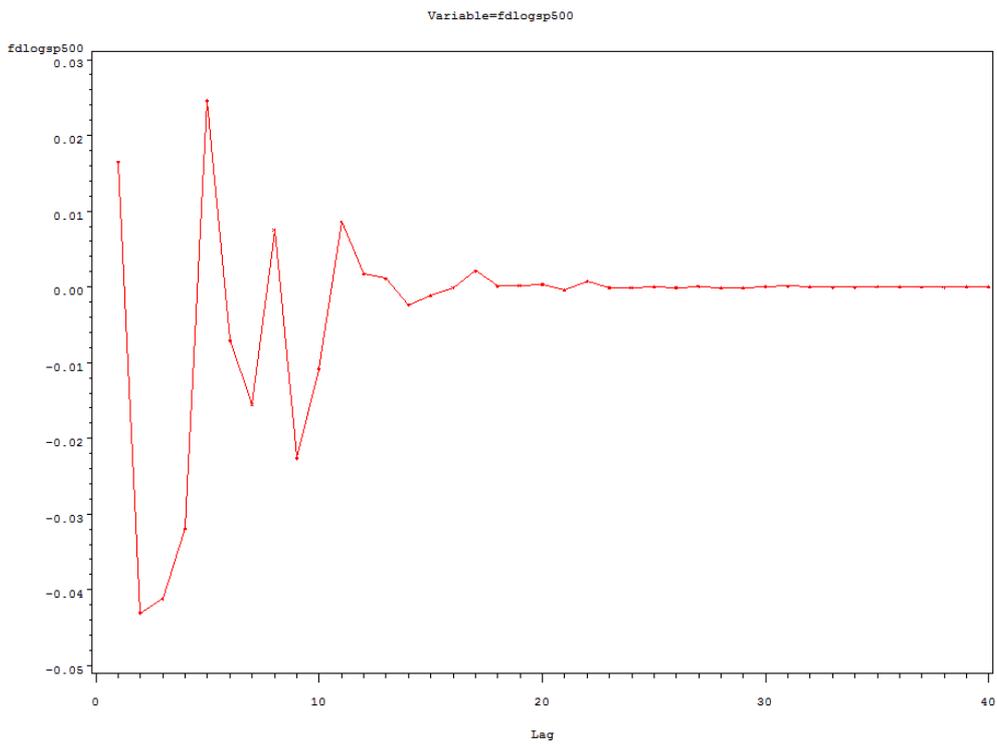Figure 5.8: impulse from fdlogsp500 to fdlogtc3m

206

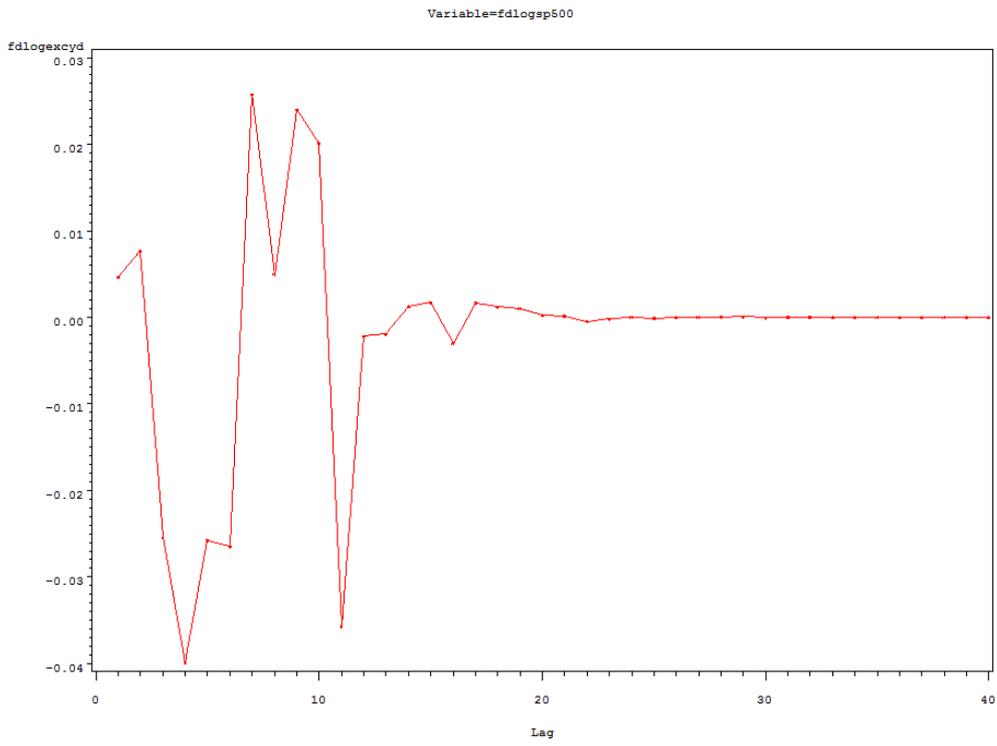**Figure 5.9**: impulse from fdlogsp500 to fdlogsp500
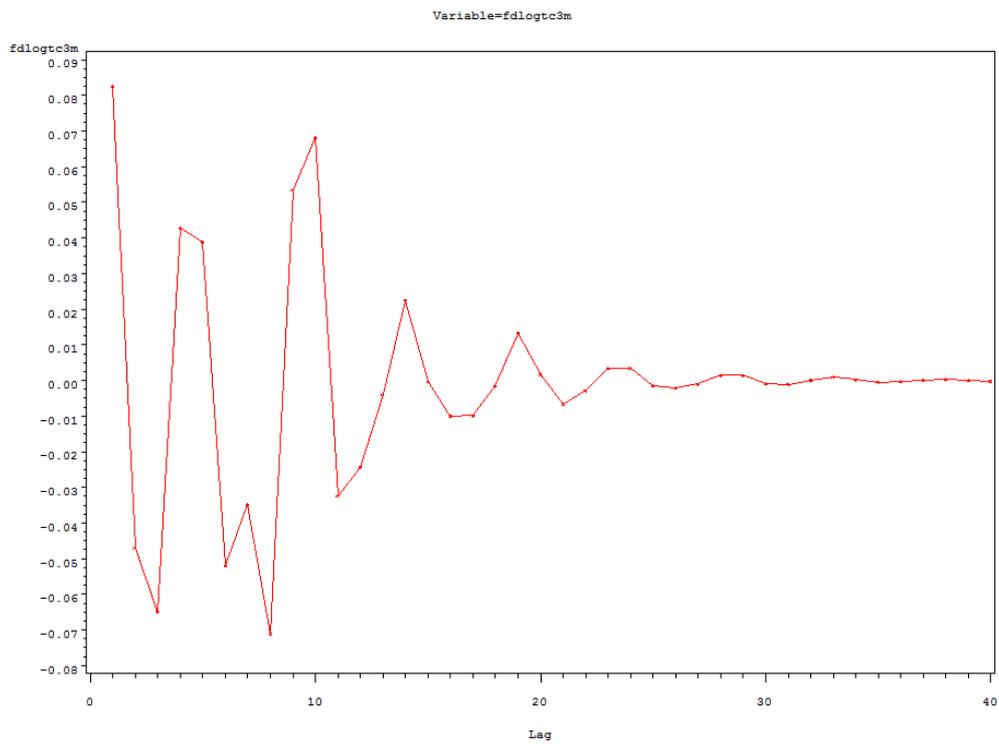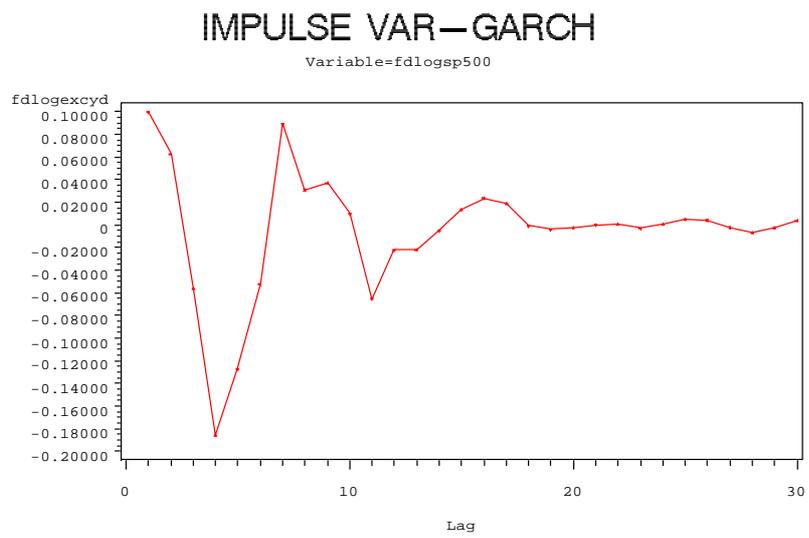
Figure 5.10: impulse from fdlogsp500 to fdlogexcyd

Figure 5.11: impulse from fdlogtc3m to fdlogtc3m

209
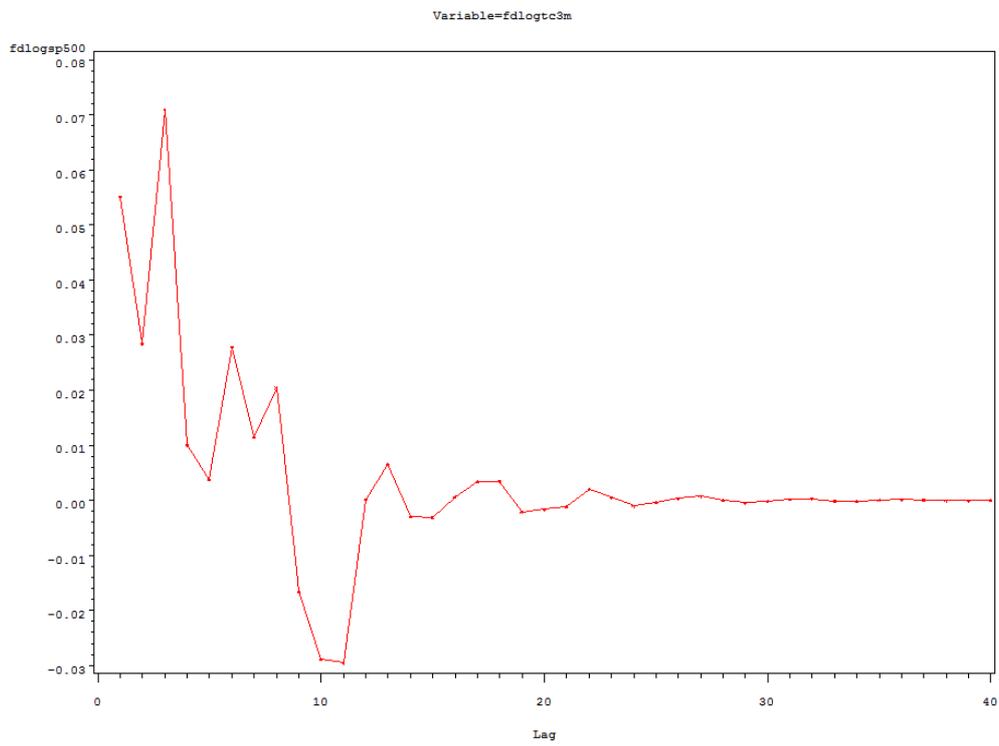
Figure 5.12: impulse from fdlogtc3m to fdlogsp500
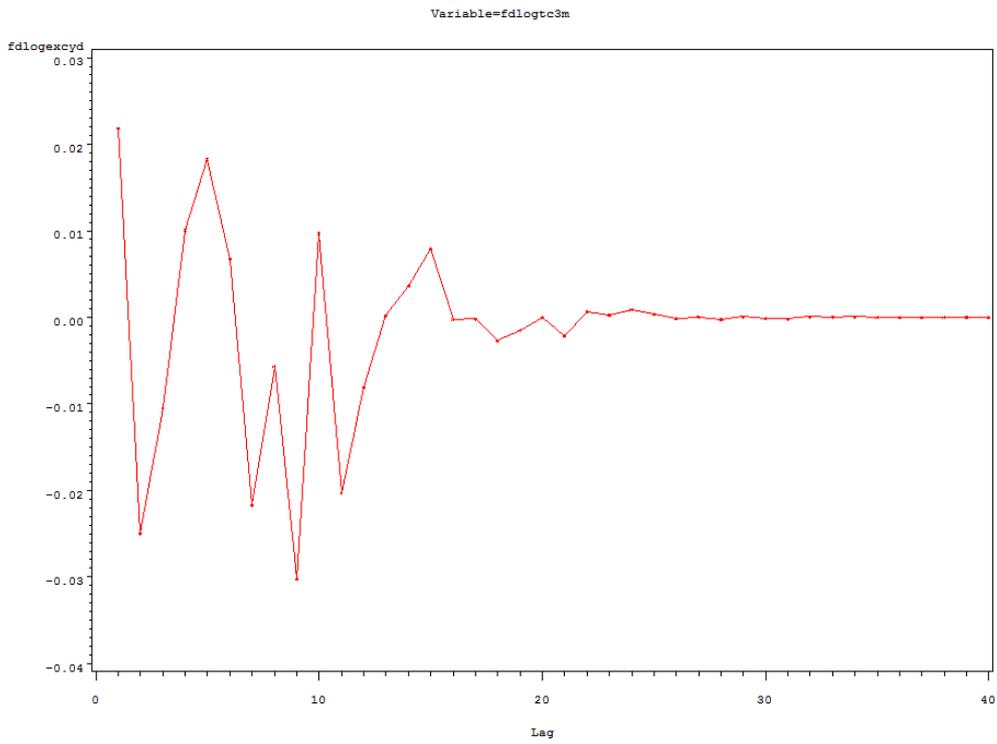
Figure 5.13: impulse from fdlogtc3m to fdlogexcyd
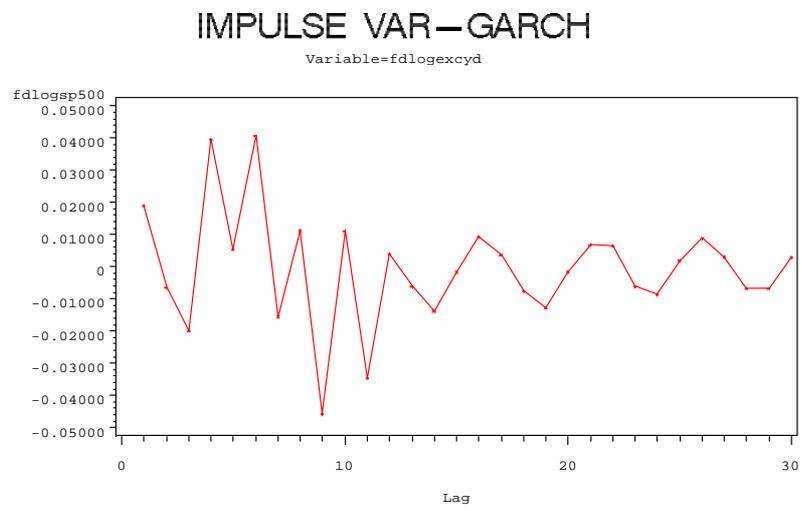
Figure 5.14: VARGARCH:impulse from fdlogexc to fdlogsp500
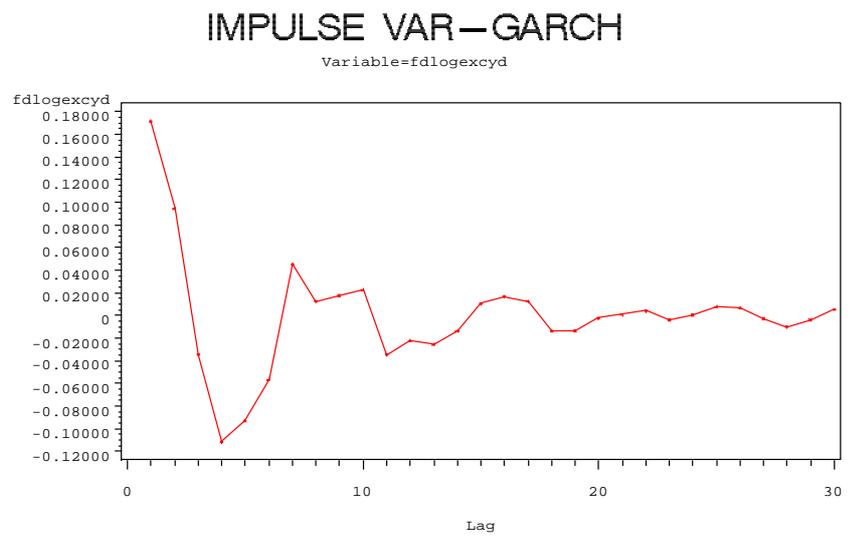
Figure 5.15: VARGARCH:impulse from fdlogexc to fdlogexc
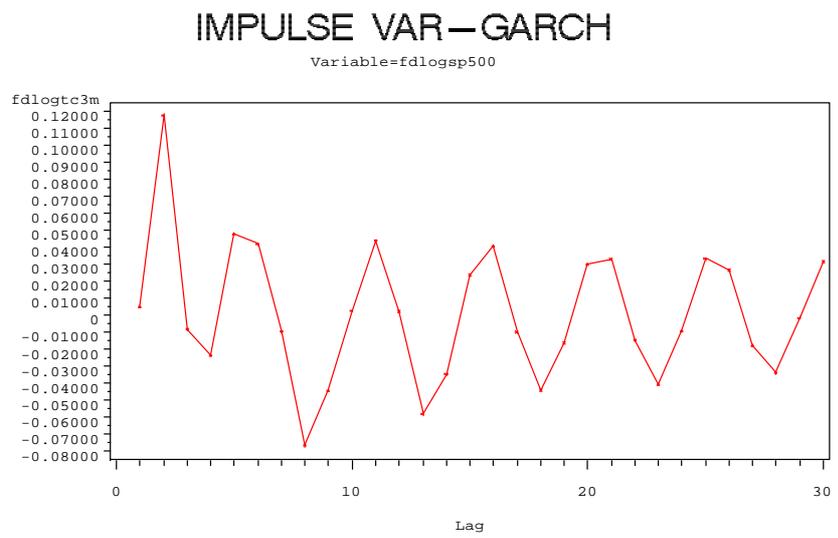
Figure 5.16: VARGARCH:impulse from fdlogsp500 to fdlogtc3m

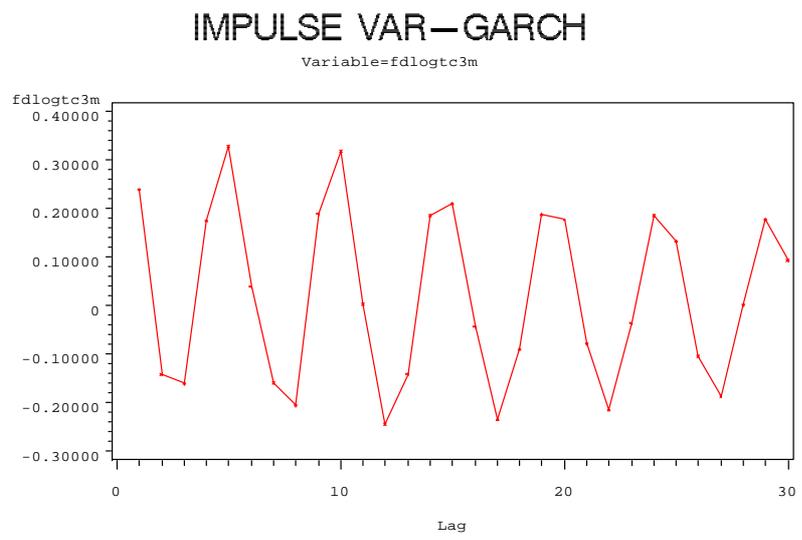**Figure 5.17**: VARGARCH:impulse from fdlogsp500 to fdlogexc

Figure 5.18: VARGARCH:impulse from fdlogtc3m to fdlogtc3m

Appendix A

Bootstrap estimation of a variance-covariance matrix

As Greene(2000) notes, the bootstrap of variance-covariance matrix in practice is done by the Cholesky decomposition of the original variance-covariance matrix. We follow the same practice here.

1. For each regime we have 2x2 variance-covariance matrix that we estimate from the reduced form of structural model. In the first step we take the Cholesky decomposition of the variance-covariance matrix of each regime. Let's define the variance-covariance of regime 1 and show how to bootstrap it:

$$V_1 = \begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix} \tag{A.1}$$

is the variance-covariance of regime 1. We take the Cholesky decomposition of the variance covariance of regime 1, which is

$$CD_1 = Cholesky \quad decomposition \quad of \quad \begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} \\ 0 & b_{22} \end{bmatrix} \tag{A.2}$$

CD_1 refers to the Chelosky decomposition the original variance-covariance of regime 1 , which is equal to the square root of V_1 and

$CD'_1 CD_1 = V_1$.

2. In second step, we simulate (create) a matrix of "standard normal" numbers with mean "0" and standard deviation "1" for each regime. The rows of the simulated matrix are determined by the number of shocks in the regime. The column of the matrix is two. The simulated matrix for regime 1 is

$$R_1 = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \\ c_{31} & c_{32} \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ c_{N1} & c_{N2} \end{bmatrix} \tag{A.3}$$

where c_{ij} are random draws from a standard normal distribution.

3. In third step, we multiply above simulated matrix(R_1) by Cholesky decomposition of the regime. For regime 1 we will have

$BES_1 = R_1 x CD_1 =$

$$\begin{bmatrix} bes_{11} & bes_{12} \\ bes_{21} & bes_{22} \\ bes_{31} & bes_{32} \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ bes_{N1} & bes_{N2} \end{bmatrix} \tag{A.4}$$

BES_1 refers to "bootstrap estimation of shocks" for regime 1. The number of rows in each of BES regime are determined by the number of shocks in each original regime.

4. By using BES, we create a bootstrap estimation of variance-covariance matrix by taking the transpose of BES and multiply by itself:

$BEV_1 = BES_1' BES_1 =$

$$
\begin{bmatrix} . & . & . & & & . \\ . & . & . & & & . \end{bmatrix}
\begin{bmatrix} . & . \\ . & . \\ . & . \\ \\ \\ . & . \end{bmatrix}
=
\begin{bmatrix} . & . \\ . & . \end{bmatrix}
\tag{A.5}
$$

5. Using BEV_1 and the ITH method we get a new β estimate. This procedure is repeated 1000 times for each regime.

6. Finally, using the 1000 simulated β values of each regime we access the statistical properties of β and whether we can estimate it consistently or not.

List of References

Bauwens, L., Laurent, S., & Rombouts, J. V. K. (2003). "Multivariate GARCH models: A survey." *Core Discussion Paper* 200331

Bollerslev, T (1986) ." Generilized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics,* 31 (June), pp 116-131

Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). " A capital asset pricing model with time-varying Covariances," *Journal of Political Economy,* 96(1), pp.116-131.

Booth, G. G., Martikainen, T., & Tse, Y. (1997)."Price and volatility spillovers in Scandinavian stock markets," *Journal of Banking and Finance,* 21, pp. 811-823.

Bollersev, T. (1990). Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model. *The Review of Economics and Statistics,* 72, pp.498-505

Brocklebank, J. C., & Dickey, D. A.(2003)"SAS for Forecasting Time Series" (2 edition)JohnWilley&sons, Inc. ISBN 0-471-39566-8

Copeland, M. & Copeland, T. (1998).Leads, lags, and trading in global markets. *Financial Analysts Journal,* 54(4), pp. 70-79.

Culver, S.E & Papell, D. H. (1997). "Is there a Unit Root in the Inflation Rate? Evidence from Sequential Break and Panel Data Models," *Jornal of Applied Econometrics,* 12, 4 (Jul.-Aug.,) pp 435-444

Dor, E. & Durre, A. (2000). Stock prices, exchange rates and monetary policy. , " *Universit catholique de Louvain, Institut de Recherches Economiques et Sociales (IRES) Discussion Paper 2000001, Universit catholique de Louvain, Institut de Recherches Economiques et Sociales (IRES)* *http:\\ideas.repec.org epdu52.html#works*

Engle, R. F. (1982). "Autoregrssive Conditional Heteroskedasticity with Estimates of the Variance of UK inflation," *Econometrica* 50 (july), pp.987-1008

Engle, R. F., Ito, T., & Lin, W. (1990). "Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market," *Econometrica,* 58(3), pp.525-542.

Engle, R. F. & Kroner, K. F. (1995) . " Multivariate simultaneous generalized ARCH," *Econometric Theory,* 11, pp.122-150.

Gannon, G. L. & Choi, D. F. S. (1998). "Structural models: Intra/Inter-day volatility transmission and spillover Persistence of the HIS, HSIF and S& P500 futures," *International Review of Financial Analysis,* 7(1), pp.19-36.

Greene, W. H. (2000). Econometric Analysis (4th Edition). *Prentice-Hall, Inc.*

Gujarati, D. N. (2003). Basic Econometric (4th Edition). *The McGraw-Hill Companies, Inc.*

Hausman, J. A (1978)." Specification Test in Econometrics, *Econometrica,* 46, pp.1251-1271

Judge, G. G., Carter Hill, R., Griffiths, W. E., Lutkepahl, H., & Lee, T. C. (1988). Introduction to the Theory and Practice of Econometrics (2nd Edition). *John Willey & Sons, Inc.*

Jarque, C. M., & Bera, A. K., (1987) ." A Test of Normality of Observations and Regression Residuals," *International Statistical Review,* vol.55, 1987, pp.163-172

Johansen, S.(1988). "Statistical Analysis of Cointegration Vectors," *Jornal of Economic Dynamics and Control,* 12(Jun-sept.,), pp. 231-254

Johansen, S. (1991). "Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models," *Econometrica,* 59 (Now.,), pp-1551-1580

Jumah, A. & Kunst, R. M. (2003). "Trivariate ARCH estimation of exchange rate volatility spillovers in commodity markets". *European Review of Agricultural Economics,* 28(3), pp. 307-328

Karolyi, G. A. (1995). "A multivariate GARCH model of international transmissions of stock returns and volatility: The case of the United States and Canada," *Journal of Business and Economic Statistics,* 13(1), pp. 11-25.

Koch, P. D. & Koch, T. W. (1991). "Evolution in dynamic linkages across daily

national stock indexes," *Journal of International Money and Finance,* 10, 231-251.

Ljung, G. M., & Box, G. E. P(1979). " The likelihood Function of Stationary Autoregressive- Moving Average Models," *Biometrika,* 66, 2 (Aug.,) pp.265-270

MacDonald, R. & Marsh, I. W. (2004). "Currency spillovers and tri-polarity: A simultaneous model of the US dollar, German mark and Japanese yen," *Journal of International Money and Finance,* 23, 99-111.

Maliaris , A. G. & Urrutia, J. L., (1992). " The international Crash of October 1987: Causality tests," *The Journal of financial and Quantiative Analysis,* 27, 3(sep.,) pp.353-364

Peiro, A., Quesada, J. & Uriel, E. (1998). " Transmission of movements in stock markets," *The European Journal of Finance,* 4, 331-343.

Phillips, P. C. P. & Perron, P.(1988). "Testing for a Unit Root in Time Seies Regression," *Biometrika,* 75, 2 (Jun.,) pp.335-346

Rigobon, R. & Sack, B(2003). " Measuring the Reaction of Monetary Policy to the Stock Market,"*The Quarterly Journal of Economics* May., pp.639-669

Stock, F. H. & Watson, M. W., (1988) "Testing for Common Trends," *Journal of American Statistical Assosiation,* 83(404), pp. 1097-1107

Sims, C. A (1980). " Macroeconomics and Reality", *Econometrica,* 48, 1 (jan.,) 1-48

West, K. D.(1988). "On the Interpretation of Near Random-Walk Behavior in GNP,"

The American Economic Review, 78. 1 (Mar.,), pp 202-209.

Zahnd, Edy (2002) . " The application of Multivariate GARCH models to Turbulent Financial Markets. http:\\www.dissertation.de