MODELING THE
EXCHANGE RATE AND INTEREST RATE
INTERVENTION
OF
CENTRAL BANK OF THE REPUBLIC OF TURKEY

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Abstract

Financial crisis of 2008 has started a new era for world economics and financial markets. Results of the crisis changed the perceptions of the decision makers, policy makers, businessmen and every individual and created new definition for economics and markets. These perception changes directly affect the aims and priorities of the related institutions in world economy. Financial crisis of 2008 found warriors and announced them as a hero from its ashes. New responsibilities are given these heroes which are called as central banks. Price stability is not the premier aim of central banks anymore after the financial crisis of 2008. After the crisis central banks become crisis warriors which struggle with the crisis, intervene the markets in order to calm down the financial markets, have key roles for growth and decrease unemployment. Central Banks become independent institutions which carry the loads of many different ministries. As central banks become too officious it is important to know predict and analyze the time of the intervention for all decision making units. Central banks intervene to normalize or to balance the markets. It is crucial to know what makes central banks to intervene and timing of this intervention.The basic aims of this thesis to analyze the time of intervention and dynamics behind the direct intervention of Central Bank of The Republic of Turkey. Analysis of timing and conditions of the intervention is useful to understand the reasons of the past interventions and predict future interventions. Besides that findings of this thesis contribute to understand the perception of the Central Bank to define what disorder market is. In order to achieve this aims logit regressions are estimated and theory of reaction functions analyzed. A modified daily reaction function is suggested after analysis. Next this updated function applied to regression, VAR and M-Garch methods. By this way relations among variables analyzed in a detailed way. According to feedback of these analysis decision trees are used to analyze and model 26 direct exchange rate interventions and 54 interest rate interventions of Central Bank of The Republic of Turkey.

Özet

2008 küresel finans krizi dünya ekonomisi ve finans piyasaları için yeni bir dönemi başlatmıştır. Bu kriz karar vericilerin, politika yapıcıların, iş adamlarının, vergi ödeyenlerin, seçmenlerin ve her bir bireyin algısında yeni bir "ekonomi" ve "piyasa" olgusunun oluşmasına neden olmuştur. Bu algı kurumların amaçlarını ve önceliklerini genişletmiş ve değiştirmiştir.

2008 küresel finans krizi küllerinden eski bir oyuncuyu kahraman olarak ilan etmiş ve ona bir çok sorumluluk yüklemiştir. Kuşkusuz bu eski kahraman merkez bankalarıdır. Merkez bankalarının artık öncelikli ve tek amacı fiyat istikrarını sağlamak değildir. Bu amacın yanında, merkez bankaları krizle mücadele eden, piyasaya gün içinde dolaylı veya dolaysız müdahale ederek piyasanın ateşini söndüren, şirketlerin batmasını engelleyen, işsizlikle mücadele eden, büyüme için katkı veren, bir çok bakanlığın görevini üstlenmiş "bağımsız" bir kahraman haline dönüşmüştür. Merkez bankalarının piyasaya bu kadar müdahil olması ve müdahalesinin ne zaman gerçekleşeceği sorusu tüm karar vericiler için önemli hale gelmiştir. Çünkü merkez bankaları müdahaleyi piyasayı "normalleştirmek" veya "dengelemek" için yapmaktadır. Piyasaya bu kadar etkin müdahele edebilen bir oyuncunun müdahalenin yapma zamanını bilmek, öngörmek ve analiz etmek kuşkusuz piyasanın tüm paydaşları için çok önemlidir.

Bu tezin temal amacı Türkiye Cumhuriyet Merkez Bankası'nın döviz kuruna ve faize doğrudan müdahalesinin ne zaman ve hangi koşullarda olduğunu analiz etmektir. Bu zamanlamanın ve koşulların analizi hem geçmiş piyasa dinamiklerini anlamakta hem de gelecekteki müdahaleleri tahmin etmekte faydalı olacaktır. Bulgularımız, ayrıca Merkez Bankasının piyasayı okuma algısında, dengesizliğin ve anormalliğin tanımlanmasında yardımcı olacaktır. Bu tezde logit regresyonlar tahminlenmiş ve reaction fonksiyon teorisi incelenmiştir. Reaction fonksiyon teorisi incelendikten sonra günlük data ile temellenen bir model önerilmiş. Bu model regresyon, VAR ve M-Garch teknikleriyle analiz edilerek değişkenler arasındaki ilişkiler ayrıntılı olarak incelenmiştir. Bu analizlerden elde edilen sonuçlar karar ağaçları metoduna uygulanmıştır. Karar ağaçlarıyla kurduğumuz modeller ile TCMB'nin 2002-2012 yılların ararında döviz kuruna (26 kez) ve gösterge faize (54 kez) ne zaman doğrudan müdahale ettiği analiz edilmiştir.

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Dedicated to my family

and

to honor memory of miners who died in Soma/Turkey in 2014,

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CHAPTER 1

INTRODUCTION

“Time is money but also it has its own spirit”

Central Banks become the major actors of the economies. The interaction among countries and results of the globalization empower this role of Central Banks. After the last financial crisis in 2008, coordination among different Central Banks has increased and efficiency of central banks has become a dominant factor for the economies of the countries. In the economic literature, increasing attention has been recently devoted to the modeling of the monetary policy decision-making process in the form of simple monetary policy rules based on market indicators.

Intervention and especially intervention of central banks triggers curiosity as the subject of this thesis. Central banks do not only affect the monetary policy, but also their policies are the complementary of the fiscal policies. Central banks also directly affect the expectations of the investors and households in an economy. Since a long time, different schools of economics have discussed whether governments should or should not intervene the economy. Today after these filtered knowledge we have experienced mixed economies. However there are still questions need to search for such as, “When central banks should intervene the market? How much money should they spend for intervention? Should they intervene? Which firms should be saved or let to be bankrupted? What is the cost or benefit of saving a private firm or intervention of Central Bank?" The answers of these questions are linked to each other and attract attention of not only policy makers and investors but also tax payers.

Since 2008 and aftermath we have faced a global economic crisis. Both governments and central banks have intervened the financial markets. In the framework of this thesis it is intended to model the conditions that force the policy makers to intervene the markets regarding changing the interest rates, changing mandatory provision rates or buying/selling foreign currency. Empirical studies suggest that central banks intervene in foreign exchange markets mainly to slow or correct excessive trends in the exchange rate. Central banks also can decrease or increase the interest rates in order to affect the money supply and money demand. This thesis not only considers and model exchange rate interventions but also examines and model interest rate intervention.

It would be important to model timing, amount and effect of interventions of the central banks in the market or similar markets of different countries. In order to offer a common monetary policy which can create a faster collaboration for different central banks before or during a financial crisis may be useful for policy makers. To form a model and analyze the factors which force interventions of central banks would be important for this thesis. After detecting these variables it would be important to figure out to answer "When Central Banks should intervene the market?" According to answer of this question, it would be logical to understand the behavior of Central Bank. This answer is crucial for policy makers, academicians, market players, financial analyst, planners, manufacturing sector and every individual in the economy.

In this thesis a detailed literature review is considered. Many different papers which cover the subject of central bank interventions are analyzed. Literature of central banks interventions generally gives emphasis to foreign exchange interventions and especially effect of the interventions in this market. Different assumptions, different theories and different variables of the models are examined in this literature review chapter. Next chapter briefly mission of the central banks are underlined. This subject is linked to reasons of central banks for intervention. In this chapter answers of central banks are analyzed to understand why they intervene the market. Which factors trigger them to intervene? Do they find the interventions successful or not? The answers of the central banks let us form the variables that are used in the model of the thesis. Thus the model variables of this thesis both cover the related literature and the answers of the central banks which are collected by Bank for International Settlement. More over types of central bank interventions are also underlined in that chapter to have a better sight for the analysis.

Next chapter model of the thesis started to be drawn. This part is layered in itself and we continue to form the model of the thesis from the information that we gathered at the end of each layer. Related literature is also examined in order to estimate the interventions of central banks. Different models are analyzed. However it is crucial to state that definition of central bank intervention is extremely important in the scope of this thesis. Oral speeches and indirect regulations are also covered as interventions by many papers in the literature. Many of the papers in the literature also cover the auctions of central banks as an intervention. But time and amount of these auctions are already announced by central banks before the auction are held and known by the market players. Thus to consider the numbers of the auctions as an intervention might help to model efforts because by this way numbers of interventions increase. But it is not reasonable to estimate something which is already announced. Thus we only accept the interventions which are not announced, directly and secretly held. Thus we have only 26 foreign exchange interventions and 54 interest rate intervention in 2741 days. This creates econometrical problems because it is difficult to balance the interventions and non interventions days when there is an unbalanced condition. However this is one of the problems that thesis tries to solve. In the model chapter logit regression is the first step to start our estimation. For independent variables new independent variables are offered as a contribution. Results of the logit regression give insights us to have better results both to analyze the interventions and econometric problems.

As a next step we try to improve our theoretical background to get better results. In order to achieve this we analyze Taylor rule and theory of reaction functions. There are many different modified forms of reaction function for central banks in the literature. We analyze them and summarize the criticism for the reaction functions such as smoothing, not having daily data, calculation of inflation and output data. One of the contributions of this thesis is to use daily data for detecting interventions. Thus analyzing reaction functions and understanding the critics for this theory gives crucial feedbacks for progress of the thesis. We take the basic logic of reaction functions and adopt variables from reaction function in our model. We transform this adoption to use the logic and variable of the reaction function in our model by converting them into daily data which successfully represent them in our model. Reaction functions theory totally increases the credibility of the model and results of the model in this thesis.

Next we adopt and modify a daily reaction function. In order to accomplish this transformation we search for representative variables. To get a benchmark we apply OLS regression for new modified daily reaction function. To capture the effect of GDP growth, which is excluded, is also added to the function in this part and its effect is also analyzed.

After OLS regression we perform VAR and M-Garch analysis for new modified version of daily reaction function. Results of the analysis give crucial insights for the behavior of CBRT.

After the information we get from logit regression results, reaction functions, VAR and M-Garch analysis considering the data set, decision trees are chosen to create the model the interventions of Central Bank of The Republic of Turkey. Result of the model gives important analysis to understand what makes Central Bank of The Republic of Turkey intervene interest rate and exchange rate. A hypothetical scenario is also created and calculated for a market player considering what would be the amount that he/she has earned if he/she followed the model of this thesis. To use decision trees to model the intervention decision of the Central Bank of The Republic of Turkey is also another contribution of this thesis. This is one of the pioneering papers which use decision trees in order to model intervention of a central bank.

By referring the chapters outline which is mentioned above this thesis contributes to the literature in five dimensions. Firstly this thesis models both the interest rate and exchange rate interventions in Turkey for the years between 2002 and 2012. This thesis is one of the pioneering papers to model interest rate intervention of Central Bank of the Republic of Turkey (CBRT). Secondly it gathers information both from logit regression, reaction functions, OLS regression, VAR and M-Garch and uses these feedbacks in decision trees. Thirdly it suggests a way to handle unbalanced data for central bank intervention and apply decision trees to model CBRT. Fourthly in the literature one of the common reasons of central bank intervention is accepted as “to calm down the disorderly markets”, this thesis simply explains what this “disorder” means by the model results and analysis. Lastly the data set, which is gathered and improved by the literature and central bank surveys, covers the four moments of variables presents precise analysis for CBRT.

CHAPTER 2

LITERATURE REVIEW

"Shallow men believe in luck or in circumstance. Strong men believe in cause and effect"

Most of the literature about intervention focuses the efficiency of the intervention. These studies generally analyze the intervention result oriented and determine whether intervention of central banks decrease the volatility of exchange or not. However the dynamics of exchange market intervention and factors which affect the timing intervention needs more sophisticated analysis. In the literature exchange rate intervention generally is underlined. Amount of intervention and analysis of magnitude of volatility is calculated to understand the effect of the intervention. Thus generally effect of intervention becomes a major problem in the literature. This thesis covers this framework, however directs the spotlights another issue, which is less examined, when there central banks intervenes and which conditions stimulate central bank to intervene in the market.

Central Bank intervention is generally accepted as interventions in foreign exchange market. Dominguez (1998) explains foreign exchange market intervention as "any transaction or announcement by an official agent of a government that is intended to influence the value of an exchange rate". In most countries, intervention operations are implemented by the monetary authority, although the decision to intervene can often also be made by authorities in the finance ministry or treasury department depending on the country. In practice, central banks define intervention more narrowly as any official sale or purchase of foreign assets against domestic assets in the foreign exchange market. Although each central bank has its own particular set of practices, intervention operations generally take place in the dealer market. For instance the Federal Reserve of USA often chooses to deal directly with the foreign exchange desk of several large commercial banks simultaneously to achieve maximum visibility and results. As with any other foreign exchange transaction, trades are officially anonymous. However, most central banks have developed relationships with traders which allow them to inform the market of their presence within minutes of the original transaction, or to keep their intervention operations secret.

In this literature part, papers related to issue classified as the papers which underline effect of central bank intervention, different type and different central bank interventions and different models in order to analyze the central bank intervention.

In the first place papers which underline the effect of the interventions are clearly referred. As it is known interventions of central banks have been one of the most secretive activities of monetary policy makers in financial markets. They have been always a source of controversy, both in the academic literature and in practice. Some scholars or market players have believed that intervention cannot be effective based on a popular monetary model of determining the exchange rate. Besides that the size of intervention tends to be overwhelmed by the market size, especially for major currencies. People who disagree have argued that in some instances, interventions seemed to be effective by changing the sentiment of the market through signaling policy intentions.

Ito (2002) mentions some models that take into account the risk difference between domestic and foreign bonds would show some influences of intervention through portfolio shifts among the private sector. A dominant view on effectiveness of intervention has changed the side a few times in the past decades. The monetary authorities tended to intervene heavily in the foreign exchange market during the transition from the Bretton Woods system that collapsed in 1971 to the floating of major currencies in the beginning of 1973. Even after the floating exchange regime began, some of the monetary policy makers in among developed economies still believed to be intervene heavily in the foreign exchange market.

In the early 1980s studies concluded that interventions did not have much impact on the exchange rate. Non-sterilized interventions have some effects but these were temporarily. However success of concerted interventions following the Plaza Accord of September 1985 in driving down the overvalued US dollar renewed academic interest. Papers of Dominguez (1990 and 1993) display some effects of interventions on the level, volatility, and risk premium of exchange rates.

Dominguez in her papers emphasize the signaling effect of intervention that would work on expectation of institutional investors. Although effects of interventions have been debated extensively, no conclusive consensus has detected. Except for the United States, intervention data have not been disclosed publicly among the G7 countries. Although the authorities could exchange information for internal studies on intervention through G10 or Bank of International Settlements, outside researchers could not obtain intervention data freely.

Empirical studies of intervention have become a popular exercise as data on intervention have become available to researchers. The past empirical studies have some contradictions results on the effectiveness of foreign exchange interventions.

Moreover according to Karninsky and Lewis (1993) the potential effects of foreign exchange intervention in exchange rate behavior has been an important issue of debate in both academic and policy makers since the end of the Bretton Woods system. Thus a great deal of research has documented how exchange rates respond to foreign exchange intervention. But the results of the studies are also mixed. For instance depending upon the sample period, regressions of exchange rate movements on intervention have either found strong effects of intervention, no effects of intervention, or even movements of exchange rates in the opposite direction of that suggested by the intervention.

The second problem with related literature is to define what is intervention of Central Banks? In most of the study to increase the number of observations and interventions of Central Banks, studies also consider the auctions of exchange buying or selling. However timing and amount of these interventions are clearly known. On the other hand this thesis aims to find the direct and secret interventions of CBRT. Thus even the number of the interventions decrease the observation number we consider only direct interventions, which are not declared before the intervention of CBRT, it strengths the analysis of this thesis. Definition of Central Bank intervention in this thesis covers direct purchases or sales of foreign currency made by the central bank on the spot market with the explicit aim of influencing the dynamics of the exchange rate and direct change of interest rate. Thirdly another subject which is rarely underlined is interest rate intervention of Central Banks. In this thesis both exchange rate intervention and interest rate intervention are considered and analyzed.

If we re-highlight the literature which seeks the effect of intervention, the efficacy or effectiveness of foreign exchange intervention by central banks was studied especially after 1970s. Much of the early literature focused only on the longer term implications and objectives of intervention. Edison (1993) in his study models the effectiveness of central bank intervention. Kearns and Rigobon (2005) in their study, identify the efficacy of central bank interventions. In this paper they use a model incorporating the endogenous relationship between exchange rates and intervention. Fischer and Zurlinden (1999) examine exchange rate effects of central bank interventions.

Moreover Disyatat and Galati (2007) also study the effectiveness of foreign exchange intervention in emerging market countries. In the study of Disyatat and Galati they use official statistics on central bank intervention by the central bank in conjunction with options market data to study the impact of intervention during 2001 and 2002. They find that central bank intervention had some statistically significant impact on the spot rate and the risk reversal. Neely (2000) who is a leading scholar in this subject examines the foreign exchange reserve management departments of 22 central banks and ask questions about the mechanics of intervention. Most responders conduct intervention in spot markets, with domestic commercial banks, during domestic business hours. According to Neely (2000) misalignments and volatility motivate interventions while desire for market impact produces mixed effects on secrecy. In the same study Neely finds that central banks unanimously support the idea that intervention is effective in changing exchange rates. Six years later Lecourt and Raymond (2006) replicate Neely's study for the central banks of industrialized countries, exploring beliefs about the effectiveness of intervention through various channels. After emphasizing the importance of expectations and credibility to the effectiveness of intervention, Lecourt and

Raymond (2006) describe the quantity and frequency of G3 intervention from publicly released data. Mihaljek (2004) refers policy makers of developing countries. He finds that interventions are small relative to market size and that most authorities view intervention as effective in calming disorderly markets and finds that responders consider intervention to work through expectations of both future monetary policy and intervention. The study of Mihaljek states that intervention's effectiveness depends on the consistency of macro/monetary fundamentals with intervention.

Moreover Rangasamy and Mihaljek (2011) underline the relations among capital flows, commodity price movements and foreign exchange intervention. Kang (2000) offers an analysis on the effectiveness of foreign exchange interventions during pre-crisis period in Korea. Kang reviews how central bank intervention influence the path exchange rates can take during pre-crisis period many factors contributed on the excessive foreign exchange rate movements. Kim (2000) examines the key characteristics of foreign exchange intervention by the Reserve Bank of Australia in the period of 1983–1997. He classifies the period into five distinct phases regarding his analysis. Kim investigates the changing effectiveness of daily intervention on the exchange rate by decomposing the exchange rate response to the intervention into various separate components. Paper finds contemporaneous positive correlation between the direction of intervention and the conditional mean and variance of exchange rate returns. They show that sustained and large interventions have a stabilizing influence in the foreign exchange market in terms of direction and volatility.

Dominguez (2003), who dominates the literature, in her study examine the relationship between the efficacy of intervention operations and the state of the market at the moment that the operation is made public. In this study Dominguez answers how quickly do central bank intervention operations impact the foreign exchange and do intra-daily market conditions influence the effectiveness of central bank interventions. Baillie and Osterberg (1997) investigate the motivations for intervention policy and the evidence for its effectiveness. Ozlu (2006) examines the relation between the risk premium and central bank intervention.

Dominguez (1998) in his other study explores the effects of foreign exchange intervention by central banks on the behavior of exchange rates. Dominguez examines the effects of US, German and Japanese monetary and intervention policies on dollar-mark and dollar-yen exchange rate volatility over the 1977-1994 periods. The results indicate that intervention operations generally increase exchange rate volatility. This is particularly true of secret interventions, which are those undertaken by central banks without notification of the public. Interventions in the mid-1980s appear to have reduced exchange rate volatility, but in other periods, and for the 1977-1994 periods as a whole, central bank intervention is associated with greater exchange rate volatility.

Reitz and Taylor (2006) give another insight about the issue. They state that the coordination channel has been proposed as a means by which foreign exchange market intervention may be effective, in addition to the traditional portfolio balance and signaling channels. If strong and persistent misalignments of the exchange rate are caused by non-fundamental influences, such that a return to equilibrium is hampered by a coordination failure among fundamentals-based traders, then central bank intervention may act as a coordinating signal, encouraging stabilizing speculators to re-enter the market at the same time. They develop this idea in the framework of a simple microstructural model of exchange rate movements, then they estimate using daily data on the dollar-mark exchange rate and on Federal Reserve and Bundesbank intervention operations. The results are supportive of the existence of a coordination channel of intervention effectiveness.

Behera et al. (2006) empirically explores the relationship between central bank intervention and exchange rate behavior in the Indian foreign exchange market. This study investigates the effects of RBI intervention on exchange rate level and volatility. Using GARCH model, they find that the intervention of RBI is effective in reducing volatility in the Indian foreign exchange market. However, the result is not supporting the theoretical positive association between exchange rate return and RBI intervention because of this the Reserve Bank intervention has been reducing the extent of fluctuations of the exchange rate rather than changing the direction of the rupee movement against the US$.

Michel et al (2002) investigate the effects of official interventions on the evolution and volatility of exchange rates. To this aim paper offers a new measure of volatility implied by the FIGARCH model that outperforms the traditionally used GARCH one. In the study it is found that central bank interventions exert an incorrectly signed effect on the levels of exchange rates and tend to increase their volatility in the short run. In general, results also show that the traditional GARCH estimations tend to underestimate the effects in terms of volatility. Vitale (1999) states sterilized intervention can be used to influences agents' expectations and exchange rates, as the central bank possesses private information on these fundamentals. A surprising result of our analysis is that while announcements on the objective of intervention are not credible, they are not even desirable. In fact, the foreign exchange market is more efficient when this objective is secret than when it is common knowledge, because in the former case the central bank is more aggressive and reveals more of its private information. Saacke (2002) in his paper by using daily data on foreign exchange interventions of both the Bundesbank and the Fed provide further evidence that central banks earn profits with interventions and that technical trading rules are unusually profitable on days on which interventions take place. In this paper it is argued that what lies at the root of these seemingly contradictory results is that intervention profits and trading rule profitability are measured over different horizons and after interventions, exchange rates tend to move contrary to central banks' intentions in the short run, but in agreement with their intentions in the long run.

Cadenillas and Zapatero (1999) consider a currency with exchange rate dynamics modeled as a geometric Brownian motion. The objective of the Central Bank is to keep this exchange rate as close as possible to a given target, so there is a running cost associated to the difference between the exchange rate and the target. According to them there are also fixed and proportional costs associated with each intervention. The objective of this paper is to find the optimal level of intervention, and the optimal sizes of the interventions, so as to minimize the total cost. They solve this problem by applying the theory of stochastic impulse controls.

Szakmary and Ike (1997) in their paper state that Regression results demonstrate that central bank intervention is strongly associated with the profitability of trading returns for the three major currencies (Deutsche Mark, Yen and Pound), and partially explains returns for the SF and CD. Consistent with conjectures in previous studies that news concerning intervention tends to be revealed over weekends, they find that moving average trading rule returns are significantly positive on Fridays and Mondays, and not significantly different from zero in the middle of the week.

Neely and Weller (2001) extend genetic programming techniques to show that US foreign exchange intervention information improves technical trading rules' profitability for two of four Exchange rates over part of the out-of-sample period. Rules trade contrary to intervention and are unusually profitable on days prior to intervention, indicating that intervention is intended to halt predictable trends. Intervention seems to be more successful in checking such trends in the out-of-sample (1981–98) period than in the in-sample (1975–80) period. Any improvement in performance results from more precise estimation of the relationship between current and past exchange rates, rather than from information about contemporaneous intervention.

LeBaron (1999) states reliable evidence that simple rules used by traders have some predictive value over the future movement of foreign exchange prices. This paper reviews some of this evidence and discusses the economic magnitude of this predictability. The profitability of these trading rules analyzed in connection with central bank activity using intervention data from the Federal Reserve. The objective is to find out to what extent foreign exchange predictability can be confined to periods of central bank activity in the foreign exchange market. The results indicate that after removing periods in which the Federal Reserve is active, exchange rate predictability is dramatically reduced.

Payne and Vitale (2003) study the effects of sterilized intervention operations executed on behalf of the Swiss National Bank (SNB) using tick-by-tick transactions data between 1986 and 1995. They extend the preliminary analysis of by matching these data with indicative intra-day exchange rate quotes and news-wire reports of central bank activity. Using an event study approach they find that intervention has important short-run effects on exchange rate returns. In particular, among various results, they find that intervention has a stronger impact when the SNB moves with-the-market and when its activity is concerted with that of other central banks and exchange rate returns move in the 15 min interval prior to interventions.

Sjöö and Sweeney (2001) present evidence on risk-adjusted profits for the Swedish central bank. Estimated profits can be quite sensitive as to whether rates of return are risk-adjusted or not, and how the risk-adjustment is done. Various ways of adjusting for abnormal returns, and extracting buy–sell signals, are tried. Results, on daily data, support the view that Riksbank intervention did not make risk-adjusted losses over the period 1986–1990. The results might be challenged as arising from inappropriate risk adjustment.

Kohlscheen (2013) presents indirect evidence of the effectiveness of sterilized interventions in Brazil based on the complete records of daily customer order flow data reported by Brazilian dealers, as well as foreign exchange intervention data over a time span of 10 years (2002-2011). Paper finds that the effect of USD sales by end-users on the BRL/USD was much stronger on days in which the BCB did not intervene in the spot foreign exchange market.

Verdu and Zerecero (2013) assess the effectiveness of two specific interventions that occurred in periods of great stress for the Mexican economy. The aims of these two interventions were respectively to provide liquidty and promote orderly conditions in the foreign exchange market. They follow the framework of Dominguez (2003 and 2006). They use bid-ask spreads as a measure of liquidty and of orderly conditions. Their result display no indication of an effect in the opposite direction from the one intended for the first intervention and fairly conclusive regarding a significant reduction on the bid-ask spread for second intervention.

Allen et al (2009) develop a simple model of the interbank market where banks trade a long term, safe asset. When there is a lack of opportunities for banks to hedge idiosyncratic and aggregate liquidity shocks, the interbank market is characterized by excessive price volatility. In such a situation, a central bank can implement the constrained efficient allocation by using open market operations to fix the short term interest rate. It can be constrained efficient for banks to hoard liquidity and stop trading with each other if there is sufficient uncertainty about aggregate liquidity demand compared to idiosyncratic liquidity demand.

Sweeney (1986) filter rule profits found in foreign exchange markets in the early days of the current managed float persist in later periods, as shown by statistical tests developed and implemented here. The test is consistent with, but independent of, a wide variety of asset pricing models. The profits found cannot be explained by risk if risk premia are constant over time. Inclusion of the home-foreign interest rate differential in computing profits has little effect on the comparison of filter returns to those of buy-and-hold. Sweeney (1997) estimates of central bank intervention losses or profits vary widely; some estimates and substantial losses, others profits. In most cases, estimated profits are not risk adjusted, and risk adjustment can have large effects. Furthermore, profits estimates involve variables integrated of order one, and because of this test-statistics may have nonstandard distributions; few studies take this into account. Estimates of risk-adjusted profits for the US Fed and the Swedish Riskbank, with allowances for possible nonstandard distributions, suggest that neither made losses and might have made significant profits.

Fatum and Hutchison (2003) provide evidence supporting the effectiveness of sterilized foreign exchange market intervention by central banks using an event study approach. An event study framework is better suited to the study of sporadic and intense periods of official intervention, juxtaposed with continuously changing exchange rates, than standard time-series studies. Focusing on daily Bundesbank and US official intervention operations, they identify separate intervention episodes and analyze the subsequent effect on the exchange rate. Using the non-parametric sign test and matched-sample test, they find strong evidence that sterilized intervention systemically affects the exchange rate in the short run. This result is robust to changes in event window definitions over the short run and to controlling for central bank interest rate changes during events.

Spolander (1999) contributes to the measurement of exchange market pressure and central bank intervention policy in a system of floating currency and partly sterilized foreign exchange interventions. In the paper a model-consistent approach is used. The measures of exchange market pressure and degree of intervention in the foreign exchange market are derived in the context of an empirically oriented small open economy monetary model with rational expectations. Monetary and foreign exchange policies are explicitly defined and foreign exchange interventions are allowed to be partly sterilized. Finally, the model is applied to Finnish data in order to analyze the pressure on the markka, which was floating during the period 1992–1996 and the Bank of Finland’s reaction to that pressure. In contrast to most other empirical studies using various proxy variables, actual intervention data is used.

Sarno and Taylor (2001) studies official intervention in the foreign exchange market and they examine intervention in the framework of effectiveness and they examine the process of intervention. Herrera and Özbay (2004) examine central bank intervention in foreign exchange markets using a dynamic censored regression model. They allow the amount of purchase and sale interventions to depend nonlinearly upon lagged values of intervention and on measures of disorderly foreign exchange markets. Using data for the CBRT, they find persistence in interventions, which suggests the presence of political costs and/or a signal of future monetary policy. They find strong evidence of non-normality and heteroskedasticity in the Tobit model of the reaction function.

In the first step, the papers which emphasize the effect of central bank intervention are considered. Secondly it is crucial to consider the papers related to different type, application and central bank interventions. Such as Kristen et al. (2012) state paper that the Japanese foreign exchange interventions in 2003/04 seem to have lowered long-term interest rates in a wide range of countries, including Japan. It seems that this decline was triggered by the investment of the intervention proceeds in US bonds and that a global portfolio balance effect spread the resulting decline in US yields to other bond markets, thus easing global monetary conditions. Moreno (2005) examines foreign exchange market intervention in emerging markets and implications for central banks. In this paper Moreno discusses recent trends in the balance sheets of central banks and the motives for accumulating foreign assets and issues raised by the use of alternative approaches to the sterilization of foreign exchange market interventions. Such as, Boehm (2005) provides comparative information on governance arrangements guiding foreign exchange interventions, on central banks' related communications policies, and on the accountability of central banks for their intervention decisions. The paper makes use of data from the BIS survey. Moreover Pincheira (2013) explores the role that exchange rate interventions may play in determining inflation expectations in Chile. In the paper he sets of nine deciles of inflation expectations coming from the survey of professional forecasters carried out by the Central Bank of Chile. It is considered two episodes of preannounced central bank interventions during the sample period 2007–2012. Results indicate, on the one hand, that the intervention program carried out in 2008 had a significant, but relatively short-lived, impact on the distribution of inflation expectations at long horizons. On the other hand, the intervention carried out in 2011 shows no relevant impact on the distribution of inflation expectations in Chile.

Echavarría et. al (2013) examine Colombian exchange rate interventions. According to the paper adoption of a managed regime assumes that interventions are relatively successful. In the paper they ask whether dirty interventions are more powerful than pre-announced constant ones or not. Paper compares the effects of day-to-day interventions with discretionary interventions by combining a Tobit-GARCH reaction function with an asymmetric power PGARCH impact function. Besides that Lahura and Vega (2013) underline asymmetric effects of Central Bank foreign exchange intervention, even though in practice Central Bank's motives for purchasing and for selling foreign currency may differ. Paper studies asymmetric effects of Central Bank interventions under the premise that policy authorities view depreciations and appreciations as having asymmetric implications. Using undisclosed intraday data for Peru from 2009 to 2011, paper displays that Central Bank interventions in the foreign exchange market have a significant and asymmetric effect on interbank exchange rates.

Adler and Tovar (2011) examine foreign exchange intervention practices and their effectiveness using a new qualitative and quantitative database for a panel of 15 economies covering 2004–10, with special focus on Latin America. Qualitatively, it examines institutional aspects such as declared motives, instruments employed, the use of rules versus discretion, and the degree of transparency. Quantitatively, it assesses the effectiveness of sterilized interventions in influencing the exchange rate using a two-stage IV-panel data approach to overcome endogeneity bias.

Thirdly, in a broad sense, in this literature review part, literature related to different models for central bank intervention is underlined. It is important to state that these models are generally formed in order to calculate the effect intervention or analyze the intervention. However closer models are also given to analyze to detect the time of central bank intervention. We take advantage of this specific literature when we try to choose and adopt the variables in our model. This part of the literature is also extended in the reaction functions part considering the structure of reaction functions.

Otero and Ramirez (2008) suggest a simple ordered probit model to analyse the monetary policy reaction function of the Colombian Central Bank. There is evidence that the reaction function is asymmetric, in the sense that the Bank increases the Bank rate when the gap between observed inflation and the inflation target is positive, but it does not reduce the Bank rate when the gap is negative. This behaviour suggests that the Bank is more interested in fulfilling the announced inflation target rather than in reducing inflation excessively. Moreover Perera et al. (2012) analyze a central bank intervention problem in the foreign exchange market when the market observes and reacts to the bank's interventions. Impulse control theory is used to solve the problem of finding the optimal times, types and amounts of interventions. They model an impulse control problem when the controller's action affects the state as well as the dynamics of the state process for a random amount of time. Then they apply our model to solve the central bank intervention problem. Results suggest that the central bank would intervene less frequently and the optimal policy is more expensive than its corresponding value without the market reactions if the market reactions increase the exchange rate volatility.

Dolado et. al. (2003) investigates the implications of a nonlinear Phillips curve for the derivation of optimal monetary policy rules. Combined with a quadratic loss function, the optimal policy is also nonlinear, with the policymaker increasing interest rates by a larger amount when inflation or output are above target than the amount it will reduce them when they are below target. Specifically, the main prediction of the model is that such a source of nonlinearity leads to the inclusion of the interaction between expected inflation and the output gap in an otherwise linear Taylor rule. They find empirical support for this type of asymmetries in the interest rate-setting behaviour of four European central banks but none for the US Fed. Next Agur and Demertzis (2013) underline the idea of financial stability objectives are shown to make monetary policy more aggressive: in reaction to negative shocks, cuts are deeper but shorter-lived than otherwise. By keeping cuts brief, monetary policy tightens as soon as bank risk appetite heats up. Within this shorter time span, cuts must then be deeper than otherwise to also achieve standard objectives

Beine and Lecourt (2004) calculate the proportion of secret interventions of central banks and conduct a different analysis. In the paper by using a new approach relying on news wire reports, they estimate the proportion of secret interventions in the foreign exchange markets thathave been conducted by the three major central banks since 1985. Thus they revisit the estimation of conditional probabilities of secret operations and compute them by both central bank and operation type. The proportion of secret interventions is found to be lower for concerted operations and to display a great deal of variability over time as well as across the three major central banks. In another paper of Beine et al. (2007) relationship between interventions and volatility at daily and intra-daily frequencies for the two major exchange rate markets are analyzed. By using recent econometric methods to estimate realized volatility, they employ bipower variation to decompose this volatility into continuously varying and jump component. Analysis of the timing and direction of jumps and interventions imply that coordinated interventions tend to cause few, but large jumps. Most coordinated operations explain, statistically, an increase in the persistent part of exchange rate volatility. Paper concludes that correlation is even stronger on days with jumps.

Ferre and Manzano (2010) in their paper develop a theoretical microstructure model of co-ordinated central bank intervention based on asymmetric information. In this paper they form a game where central banks will choose whether to intervene unilaterally or in a coordinated manner. At the end they study the economic implications of coordination on some measures of market quality and see that the model predicts higher volatility and more significant exchange rate changes when central banks coordinate compared to when they intervene unilaterally.

Mundaca (2001) in her paper explores an endogenous switching regression model for the exchange rate process where the switch is defined by the central bank criteria functions for intervening. In the study signal effect of interventions are analyzed on the exchange rate using Norwegian daily data on official interventions. Mundaca finds that interventions seemed to have been more effective in moving the exchange rate in the expected direction in the regime when the exchange rate was kept away from the edges of the band. Another finding of the paper is that type of intervention regime also reduces significantly the conditional volatility of the exchange rate.

In these different methodologies paper of Herrera and Özbay (2004) combines different model in their paper. They analyz central bank intervention in foreign exchange markets using a dynamic censored regression model. They let the amount of purchase and sale interventions to depend nonlinearly upon lagged values of intervention and on measures of disorderly foreign exchange markets. By ssing data for the CBRT, they find persistence in interventions, which may suggest the presence of political costs and/or a signal of future monetary policy. They also conclude thet strong evidence of non-normality and heteroskedasticity in the Tobit model of the reaction function. Estimation results using Powell's LAD, a robust estimator, reveal the importance of considering these specification issues when modeling central bank intervention.

After these filtered literature it can be summarized that, literature generally is interested in effect of central bank interventions in exchange rate market. Interest rate intervention is rarely discussed relatively to exchange rate intervention in the literature. Results and effect of central bank interventions differ even in the same country for different time with the same type of intervention. Next different central banks intervene the market in different and combined ways for different aims. Moreover currently the data used for analysis of intervention has become daily based. In the former literature because of the data type it is common to see some monthly data in functions and models. However need of transforming these data into daily based is crucial for the adoption of the variables especially in reaction functions. The common variable of central bank intervention is volatility. Volatility is taken as a base when effect of intervention is analyzed. Thus we capture this variable in different models in this thesis. Besides that the difference between target inflation and actual data is another dominant variable for the intervention analysis. We also capture this variable. As it is referred in the literature, intervention is exemption (in crisis time it sometimes become the rule itself) which is used for to calm down the disorder or failure in the markets. It is difficult to analyze a concept which is exemption in the financial markets. Because of this models in this literature tries to solve this difficulty. This thesis also tries to take a step to solve this difficulty by its suggestions and results.

CHAPTER 3

MISSION OF CENTRAL BANKS

"When you discover your mission, you will feel its demand. It will fill you with enthusiasm and a burning desire to get to work on it."

At the first and top of the web page of Central Bank of the Republic of Turkey, it is stated that “the primary objective of the Bank shall be achieve and maintain price stability”. According to article 4 of CBRT (As amended by Law No. 4651 of April 25, 2001) primary objective of the Bank shall be to achieve and maintain price stability. CBRT shall determine on its own discretion the monetary policy that it shall implement and the monetary policy instruments that it is going to use in order to achieve and maintain price stability.

The CBRT shall, provided that it shall not be in confliction with the objective of achieving and maintaining price stability, support the growth and employment policies of the Government. Price stability denotes a level of sustainable inflation low enough that economic agents may ignore it in their investment, consumption and saving decisions. The largest contribution that the Central Bank has made and can make to strong, stable and sustainable growth and increased employment is to achieve and maintain price stability.

Dominguez (2003) states the US Federal Reserve describes four different reasons to intervene in foreign exchange markets. These reasons are; to influence trend movements in exchange rates, to calm disorderly markets, to rebalance its foreign exchange reserve holdings and to support fellow central banks in their exchange rate operations. The global financial crises of 2008 extended the primary objectives of central banks in the world and intervention reasons. They started act as also ministries of finance, economics and growth. The missions of the central banks widen with last crisis. It is clear that power of central banks and efficiency depends on their independence. In discussing central bank independence it is useful to draw a distinction between goal independence and instrument independence. A central bank has goal independence when it is free to set the final goals of monetary policy. Thus a central bank with goal independence could determine that price stability was less important than output stability and act accordingly. Goal independence is related to the concept, which is underlined by Grilli (1991), concept of political independence. Grill states that independence is related to the central bank's ability to pursue the goal of low inflation free of political interference

However it is debatable subject to determine the framework of the mission of central banks. Mishkin (2000) in his paper answers what should central banks do? In this study Mishkin classifies the missions of central banks, discuss basic principles for central banks and then uses these principles to outline what the role of central banks should be. According to Mishkin (2000) in monetary policy there are seven basic principles that can serve as useful guides for central banks to help them achieve outcomes in their conduct of monetary policy which are price stability provides substantial benefits, fiscal policy should be aligned with monetary policy, time inconsistency is a serious problem to be avoided, monetary policy should be forward looking, accountability is a basic principle of democracy, monetary policy should be concerned about output as well as price fluctuations and the most serious economic downturns are associated with financial instability.

These are strong but important statements to understand the changing and extending mission of central banks. Price stability decreases the costs in financial sector and decrease risk perceptions. It also prevents overinvestment in the financial sector which in a high inflation environment expands to profitably act as a middleman to help individuals and businesses escape some of the costs of inflation. It is not a coincidence that CBRT announces price stability as a basic principle in the top of their web-site. Price stability lowers the uncertainty about relative prices and the future price level, making it easier for firms and individuals to make appropriate decisions. By the help of price stability economic efficiency is increased. Price stability also lowers the distortions from the interaction of the tax system and inflation. Large government deficits put risk on the monetary policy makers to monetize the debt and producing rapid money growth and inflation. Restraining the fiscal authorities from engaging in excessive deficit financing aligns fiscal policy with monetary policy and makes it easier for the monetary authorities to keep inflation under control. The time inconsistency problem exists because there are motives for a policymaker to try to exploit the short run tradeoff between employment and inflation to pursue short-run employment motive. The time inconsistency literature points out both why there will be pressures on central banks to pursue overly expansionary monetary policy and why central banks whose commitment to price stability is in doubt are more likely to experience higher inflation. In order to prevent high inflation and the pursuit of a suboptimal monetary policy, monetary policy institutions need to be designed in order to avoid the time inconsistency trap.

The existence of long lags from monetary policy actions to their intended effects on output and inflation suggests that monetary policy should be forward looking. If policymakers wait until undesirable outcomes on inflation and output fluctuations actually arise, their policy actions are likely to be counterproductive. To avoid these problems, monetary authorities must behave in a forward-looking fashion and act preemptively.

Clearly the public cares about Gross Domestic Product as well as inflation fluctuations. Thus the objectives for a central bank in the context of a long-run strategy should thus not only include minimizing inflation fluctuations. It also includes minimizing output fluctuations. Objective functions with these characteristics have now become standard in the monetary economics literature which focuses on the conduct of monetary policy.

Accountability is one the major principles of governance. Monetary policy makers should also responsible of their decisions or target accomplishments. If policymakers cannot be removed from office or punished in some other way, this basic principle of democracy is violated. In a democracy, government policymakers need to be held accountable to the public. A second reason why accountability of policymakers is vital is that it helps to promote efficiency in government. Making policymakers subject to punishment makes it more likely that incompetent policymakers will be replaced by competent policymakers and creates better incentives for policymakers to do their jobs well.

Financial instability is a key reason for the depth of these economic contractions. The financial crises and depressions in Mexico, Russia and East Asia also support this view Preventing financial instability is therefore crucial to promoting a healthy economy and reducing output fluctuations, an important objective for central banks.

According to principles listed above Mishkin (2000) suggests that role of a central bank covers; price stability should be the overriding, long-run goal of monetary policy; an explicit nominal anchor should be adopted; a central bank should be goal dependent; a central bank should be instrument independent; a central bank should be accountable; a central bank should stress transparency and communication; a central bank should also have the goal of financial stability

3.1 Central Bank of Republic of Turkey

Turkey operates a floating exchange rate regime with inflation targeting since 2002. (See Table 1) The data set of this thesis is also in line with this time horizon and adopts its variables according to this homegenous political perspective.

CBRT reserves the right to intervene to mitigate exchange rate volatility and manage foreign exchange reserves. As Özatay (2005) states a strong foreign exchange reserve position has been consistently stated as a prime CBRT objective, especially in the after the 2001 economic crisis when Turkey switched the lira's crawling peg to floating.

When accelerated reserve accumulation is needed, CBRT holds foreign exchange buying auctions under pre-announced terms and conditions. The program was first put in place in 2002 to build up the foreign exchange reserve position with minimum interference in exchange rate movements. Moreover CBRT holds foreign exchange selling auctions when it is needed to provide liquidity to the market. Auction programs may be complemented by discretionary intervention. The CBRT publishes the results of its daily foreign exchange auctions.

TABLE 1 Target Inflation of Central Bank of Republic Of Turkey

	Target Inflation	**Realized Inflation**
2002	35	29,7
2003	20	18,4
2004	12	9,3
2005	8	7,7
2006	5	9,7
2007	4	8,4
2008	4	10,1
2009	7,5	6,5
2010	6,5	6,4
2011	5,5	10,4
2012	5	6,2
2013	5	7,4

Source: Central Bank of Republic of Turkey

In September 2011, the CBRT introduced a new instrument, which is called as, the reserve option mechanism as a complementary tool to mitigate the impact of volatile capital flows on the exchange rate and the domestic supply of credit.

As Basu and Varoudakis (2013) mention the reserve option mechanism provides banks the option of holding up to a fraction of their required reserves in foreign exchange or gold. According to a reserve option coefficient that sets the amount of reserves in foreign exchange or gold needed per unit of Turkish lira (TL) of required reserves. Individual banks are expected to optimize the use of reserve option mechanism with reference to their relative funding costs in foreign exchange and TL. These costs vary with the size of net capital flows. This is realized when capital inflows are abundant; foreign exchange funding costs are low, while when capital outflows intensify shortages of foreign exchange raise foreign exchange funding costs.

The reserve option mechanism plays as a stabilizer of the foreign exchange market in the face of capital flow volatility. This is realized when capital inflows are high a fraction of foreign exchange liquidity is withdrawn by the banks from the foreign exchange market and converted into reserves with CBRT and containing exchange rate appreciation and when capital outflows increase a fraction of foreign exchange balances held by banks as reserves with CBRT is converted back into TL and released into the FX market. This result limits exchange rate depreciation. The reserve option mechanism has an effect similar to rules-based, un-sterilized foreign exchange interventions to the extent it withdraws foreign exchange liquidity when capital net inflows are high. It could limit the need for pre-announced or discretionary foreign exchange intervention to smooth exchange rate volatility. Foreign exchange intervention in Turkey was significant in the first half of the 2000s, approaching 0.5 percent of GDP in 2004 and 2006. The central bank intervened at a smaller scale before and after the global financial crisis in order to counter appreciation of the TL and again from mid-2011 to mid-2012 by selling foreign exchange in response to depreciation pressures on the TL. There is a significant positive correlation between foreign exchange interventions and the nominal effective exchange rate indicating a focus on mitigating exchange rate volatility.

CBRT has different options to intervene the markets as it is mentioned above. CBRT also intervenes the market in a direct and secret way. In Table 2 you may follow the direct foreign exchange rate interventions of CBRT.

TABLE 2 Direct FX Interventions of Central Banks of Turkey

Date	Buying Amounts (Million $)	Selling Amounts (Million $)
11.07.2002		3
02.12.2002	16	
24.12.2002		9
12.05.2003	62	
21.05.2003	517	
09.06.2003	566	
18.07.2003	938	
10.09.2003	704	
25.09.2003	1,442	
16.02.2004	1,283	
11.05.2004		9
27.01.2005	1,347	
09.03.2005	2,361	
03.06.2005	2,056	
22.07.2005	2,366	
04.10.2005	3,271	
18.11.2005	3,164	
15.02.2006	5,441	
13.06.2006		494
23.03.2006		763
26.06.2006		848
18.10.2011		525
30.12.2011		1,865
02.01.2012		525
03.01.2012		326
04.01.2012		155
23.01.2014*		3,151
*This intervention is not included in the analysis, data of the thesis covers the years 2002-2012 **Central Bank of Republic of Turkey announces the amount of intervention 15 days later.		

Source: Central Bank of Republic of Turkey

CHAPTER 4

INTERVENTION THEORY

"If you put the federal government in charge of the Sahara Desert, in 5 years there'd be a shortage of sand"

It is an ongoing debate whether central banks should or should not intervene the markets. Literature finds easily supportive answers for both situations. Dominguez (1998) defines intervention "as any official sale or purchase of foreign assets against domestic assets in the foreign exchange market". There has been a detailed literature about central bank interventions. Mostly these studies focus in foreign exchange markets and efficiency of central bank intervention in foreign exchange market which is mentioned at the beginning of this thesis. Because of this general tendency intervention definition of central banks generally finds a place in foreign exchange market. Indeed central banks also change the interest rate in order to intervene the markets. This is also important intervention. After 2008 central banks intensively changed the interest rate with a collaborative motive.

Kearns and Rigobon (2002) state empirical studies and statements by central banks suggest that central banks intervene in foreign exchange markets to slow or correct excessive trends in the exchange rate, they lean against the wind and to calm disorderly markets. The survey responses of central banks in Neely (2001) suggest that these factors continue to drive the decision to intervene. When central banks intervene they may trade in blocks throughout the day.

In 1977 as Dominguez (1988) underline IMF Executive Board provided its member countries three guiding principles for intervention policy and aims. First policy according to IMF, countries should not manipulate exchange rates in order to prevent balance of payments adjustment or to gain unfair competitive advantage over others. Secondly countries should intervene to counter disorderly market conditions. Thirdly countries should take into account the exchange rate interests of others. These principles implicitly assume that intervention policy can effectively influence exchange rates and explicitly state that countries should use intervention policy to decrease foreign exchange rate volatility.

As Neely (2001) mentions central banks subsequent trades are conditional on the response of the exchange rate to their earlier trade. The general objective for intervention is to prevent too much appreciation or depreciation both as a level and as a speed. Too much appreciation would harm exporters while too much depreciation would harm importers or people who are in short or carry foreign exchange debt and confidence of financial market in general. To maintain a stable exchange rate that is broadly consistent with fundamentals is an aim of the monetary authorities.

As Cukierman (1998) figures out a great portion of economists agree that monetary policy has important effects only when it is unanticipated. This proves that type, magnitude and persistence of private information available to policy makers affect their ability to stabilize the economy, the degree of activism and various macroeconomic variables. Despite the variety of ways in which private information interacts with the economy and policy outcomes, a small number of general principles emerge. Intervention efforts in the foreign exchange market do not have the same application of dominating power that government has at her usage for other political or economic problems.

Currently the volume of activity in international financial markets is so huge that governments cannot easily impose their political targets on this area. However central banks continue to intervene in the foreign exchange market and buying or selling foreign exchange. Moreover it is difficult to hope that the interventions of central bank will determine the trend of the exchange market.

In a broader sense Basu and Varoudakis (2013) reveal that central banks intervene in foreign exchange markets when they target particular levels of the exchange rate, through pegs, crawls, or bands with respect to other currencies or currency baskets. Even when they do not target a particular rate, they may intervene when there is excessive volatility in the exchange rate, which can be destabilizing for traders and ordinary consumers. Verdu and Zerecero (2013) underline another issue, whether an intervention should be public, rules-based, and transparent, or whether it should be discretionary and private. On the one hand Kenen (1988) state the rules of the foreign exchange market need to be as transparent as possible to maintain credibility. Thus, the authorities have an incentive to clearly convey their intentions for the expectations channel to be more effective.

On the other hand, Dominguez and Frankel (1993) have considered whether the authorities might have an incentive to keep the effects of an intervention to a minimum under some circumstances and in such cases, to make it private and discretionary. Cuckierman and Meltzer (1986) argue that a public intervention under an adverse macroeconomic environment, for example if the authority lacks a high degree of credibility, might be unfavorable.

Another case might be when a central bank wishes only to readjust its reserves portfolio and chooses a secret intervention. There is also question of whether coordinated interventions by authorities in two countries are more effective than an intervention implemented by just one country on its own. The main motive for such an approach is the potential for policy spillovers. Thus if two interventions are intended to have opposite effects, it is in the authorities' interests at least to share some information. In this sense Kenen (1995) states that coordinated interventions have tended to be more effective than unilateral ones. In the case of an unsterilized coordinated intervention, the effect on the exchange rate would be affected by the relative monetary policy stance. One of the important points of the theory is the study of the central bank's reaction function. It is challenging both to posit and estimate a reaction function because central banks take into consideration several elements when making a decision to intervene.

Interventions of central banks in countries of emerging markets have an important role especially for exchange rate interventions. Miyajima (2013) states also this issue and underline that exchange rate expectations are particularly important for the monetary policy decisions in emerging market economies. The exchange rate has been a policy tool in emerging markets to various degrees due to relatively large exchange rate pass-through to domestic inflation or currency mismatches.

In this context, BIS (2011) provides a rich discussion as, how external factors can influence monetary policy frameworks and operations in emerging markets. Ball (1999) also characterizes the monetary policy reaction function in emerging markets as an exchange rate-augmented Taylor-type rule, and finds that the exchange rate is an important policy tool in emerging markets. One important factor dictating exchange rate expectations is macroeconomic fundamentals. A favorable growth outlook or perception of lower macroeconomic vulnerabilities to external shocks can attract foreign capital inflows and strengthen the exchange rate. In addition, central bank foreign exchange intervention can potentially influence exchange rate expectations. The authorities in many emerging markets have intervened in foreign exchange markets, and often persistently. Since the onset of the global financial crisis in 2008, higher capital flow volatility in the low global interest rate environment has had important implications for their exchange rates, prompting central banks in emerging markets to increase their involvement in exchange rate management.

Pincheira (2013) states in practice small open economies implementing inflation targeting regimes do occasionally intervene in the exchange rate market. The effectiveness of these sterilized interventions is the subject of debate and the empirical evidence is mixed with positive and negative results as it is mentioned in this thesis above.

Another interesting topic associated with foreign exchange rate interventions is that these countries that have inflation targeting may potentially conflict with the conduct of monetary policy. This is important because, irrespective of their effectiveness, interventions could have side effects on other variables of the economy and they might run the risk of being perceived as inconsistent with monetary policy. In particular, they could have the collateral effect of an impact on the distribution of inflation. Recall that Turkey is in the same group of country which is in both emerging market and implementing inflation targeting.

Basu and Varoudakis (2013) mainly analyze that in emerging market economies the motives of foreign exchange intervention have evolved with a gradual change in their exchange rate regimes and content for monetary policy. An increasing number of emerging economies, especially after the East Asian financial crisis, moved away from pegged or tightly managed exchange rate regimes to flexible exchange rates.

Moreover emerging markets adopted inflation targeting after the crisis that they faced. Short-term interest rates are used as the main policy instrument to achieve the inflation targets. Under this monetary policy rules, the inflation target serves as a nominal policy anchor while the flexible exchange rate serves as a shock absorber to the economy and an information variable to the monetary authorities, rather than a policy variable. The motives of foreign exchange intervention have changed over time. At earlier the main aim is stabilizing the exchange rate, and then it moves to containing excessive exchange rate volatility and preventing movements that appear to be inconsistent with fundamentals. Despite the move toward inflation targeting and flexible exchange rates, there is evidence that inflation-targeting central banks in emerging market economies intervene actively in foreign exchange markets. The rationale for intervening in the foreign Exchange rate market is to contain volatility and misalignment is that the exchange rate may not only absorb shocks but also generate shocks. This may happen when the exchange rate fluctuates because of sudden capital flow swings, changes in market confidence, or contagion, unrelated to economic fundamentals.

4.1 Why Do Central Banks Intervene?

It is clear that missions and objectives of central banks expanded especially after the last financial crisis in the world in 2008. Markets started to expect central banks act as government because the power of monetary policy has shadowed the power of fiscal policies. In the last decade price stability is the main objective of the central banks but after 2008 crisis central banks started to support growth, decrease the unemployment and combat financial crisis. Thus this mission expansion changed the intervention motives of the central bank. Related literature and announcements by central banks state that central banks intervene in markets to slow or correct excessive trends in the exchange rate (or interest rate) they try to lean against the wind and to calm disorderly markets.

What does it mean that “disorder”? is one of the major answers of this thesis. In this part briefly an answer of this question regarding the literature is given. Then announcements of central banks and BIS survey depends on Central Banks answers are analyzed in order to answer the reasons of intervention for central banks.

Dominguez and Frankel (1993) classify different aims of interventions of central banks. According to them there are four main reasons for central bank interventions which are to influence trend movements in exchange rates, to calm disorderly markets, to rebalance its foreign exchange reserve holdings and to support fellow central banks in their exchange rate operations. According to Dominguez and Frankel (1993) interventions can be defined as any transaction or announcement by an official agent of a government that is intended to influence the value of an exchange rate.

Countries intervene in the foreign exchange market when they perceive that the exchange rate dynamics is not consistent with their objectives. However the objectives of central banks differ. Generally they intervene when the exchange rate level is not adequate or when the exchange rate volatility is excessive. Garcia and Zerecero (2003) extend the possible objectives of central bank intervention. According to Garcia and Zerecero the motive behind the intervention could be to try to reverse an exchange rate trend, for example if the domestic currency is felt to have weakened excessively so as to shake monetary policy targets, be it either an inflation target or a fixed exchange rate target.

Karninsky and Lewis (1993) mention that intervention can provide useful information about future monetary policy even if current interventions are systematically associated with changes in monetary policy in the opposite direction to the one suggested by the signaling effect. For instance laying domestic currency in the foreign exchange market today may be correlated with future expansionary monetary policy. In this case, interventions may provide a signal in the opposite direction to that suggested by the standard signaling effect. Moreover Basu and Varoudakis (2013) count specific aims of central banks to intervene when a floating exchange rate exist such as decreasing volatility, preventing exchange rate misalignment, leaning against the wind, countering disorderly foreign exchange markets and managing foreign exchange reserves.

Another motive could be to support an exchange rate trend, for example if the central bank identifies an opportunity to expedite or consolidate an upward or downward exchange rate trend in the market. Preserving financial stability could be another motive. For example, the bank wants to dampen excessive short-term volatility which reflects uncertainty in the market or to try to decrease or resolve some market failure in the foreign exchange market. The central bank could regard new information or changes in the interest rate differential with abroad as causing an overshoot in the exchange rate which would lead to excessive volatility due to herd behaviour by market participants. An appropriate move for the central bank could then be to intervene in order to prevent such herd behaviour from becoming entrenched. Another objective behind an intervention could be to profit from trading. For example, if a central bank manages to reverse a downward domestic exchange rate trend it could later buy back the currency it had used for the intervention, at a more favorable price. Even though the survey by Neely (2001) which covers 22 central banks in various parts of the world indicates that the profit motive plays no part in their intervention decisions, bad experience of previous interventions could be one reason for reluctance on behalf of the central bank to enter the market again.

Central banks would not be expected to intervene in the market in order to reverse an exchange rate trend or dampen volatility if they see little likelihood of success but feel they would probably sustain considerable losses from it. Kim and Sheen (2002) find evidence of such behavior by the Reserve Bank of Australia.

Finally, central banks could enter the foreign exchange market in order to adjust their foreign reserve position if they consider reserves too small or too large. They could take advantage of the opportunity to do so in periods of market tranquillity, so that their intervention would be unlikely to have much impact on the domestic exchange rate. Research has shown that the most common reasons for interventions seem to be to attempt to reverse exchange rate trends and dampen volatility.

It is also obvious that the motivation behind interventions is determined by the monetary policy framework of the central bank in question. If the central bank follows some form of fixed exchange rate policy the main reason for interventions will clearly be to contribute towards maintaining the exchange rate of the domestic currency as closely aligned to the target as possible. However, as experience from many countries shows, a central bank has extremely limited ability to maintain an exchange rate target which is inconsistent with underlying economic fundamentals or views of market participants. Interventions could also remain an option even if the central bank has an inflation target and the exchange rate floats. Although the central bank's main instrument for attaining its inflation target is its policy interest rate, cases may arise where it can be useful to use interventions as well. The central bank's ability to bring down the real inflation rate and attain its inflation target solely by cutting interest rates would then be very restricted. In such a case the bank could use interventions in order to try to depreciate the exchange rate, in order to get the economy moving again and turn the disinflation process around Interventions can also be an attractive option for reducing exchange rate volatility which may threaten financial stability, and for contributing towards achieving the inflation target. If the bank regards the domestic exchange rate development to be in obvious contradiction to the assumption on which it bases its inflation forecast, and thereby the prevailing monetary stance, it can use interventions along with a change in the policy rate to achieve the inflation target. The chief argument would then be that, by also using interventions, the bank would need a smaller interest rate change than would otherwise be the case to attain the inflation target, so that the negative effects on the real economy would be smaller as Heikensten and Borg (2002) states.

Central banks with inflation targets have, however, in general not used interventions to attain the target since it is difficult to exert a permanent effect on the exchange rate with interventions. Furthermore, the exchange rate pass-through to domestic prices varies from one time to another, and the impact of short lived exchange rate changes on inflation is only temporary.

Bernanke and Gertler (1999) ask that whether fluctuations in asset prices should concern policy makers or not for intervention. According their comment for benchmark case, this assumes that capital markets are efficient without regulatory distortions, policy makers should not concern of fluctuations. According to them there are two conditions to concern the policy makers for interventions. The first condition is that non-fundamental factors sometime underlie asset market volatility. The second factor is that changes in asset prices unrelated to fundamental factors have significant impacts on the rest of the economy. If these two conditions are met then policy makers should start to think about intervention.

It would be supportive to understand the central banks’ intervention motives. The announcements and surveys answered by monetary policy makers can fill the blanks of related literature. In this sense Boehm (2005) asks primary objectives of the central banks. Table 3 which is formed by Boehm (2005) shows that the central bank laws of industrialized countries, often stipulate price stability as the principal objective, or set out a broader or more complex objective that combines the value of money, economic growth and overall public welfare. By contrast the central bank laws of many emerging market economies are in between the two situations. First they do not specify the broad objectives that are typical of relatively old central bank laws and they are also not so specific as to demand price stability. Instead, many ask the central bank to maintain the value of the currency without distinguishing between its external and internal value.

TABLE 3 Primary Objective of the Central Banks

	Preserve *internal* value of currency	Preserve *external* value of currency	Preserve value of currency	Broader or more complex objective
25 central banks in BIS survey	32%[1]	4%	32%	32%
53 emerging market economies	21%	4%	38%	38%
12 industrialised countries	42%	0%	0%	58%
Total	27%	3%	31%	39%

[1] Colombia, the Czech Republic, Hungary, Korea, New Zealand, the Philippines, Poland and Turkey.

This raises the question whether the choice of broader central bank mandates in emerging market economies is linked to their higher propensity than industrialized countries to engage in foreign exchange intervention. The link could be direct or indirect. There does indeed seem to be widespread agreement that emerging market economies display greater aversion to exchange rate volatility than the typical floating exchange rate developed economy, as encapsulated by the fear of floating idea.

In thesis we try to seek what makes Central Bank of Turkey to intervene to the market. In order to see an overall picture Mohanty and Berger[1] (2013) in their paper review central banks' views on the objectives, methods and effectiveness of foreign exchange intervention, according to their

[1] Data and tables between pages 43-50 are gathered from the paper of Mohanty and Berger (2013)

responses to a survey questionnaire. In the paper of Mohanty and Berger (2013) reasons and effect of interventions asked to leading central banks. Table 4 below summarizes central bank responses regarding the motives of intervention. The motives are ranked according to their importance by the central banks. Although the broad objectives of intervention have remained similar over the past decade, changes are significant in several directions. Curbing excessive exchange rate speculation – the prime motive for intervention – has gained further prominence in the aftermath of the 2007–09 global financial crises. Of the 19 central banks that responded to this question, 15 (or 79%) considered this to be either highly or moderately important in 2011–12 compared with 12 (or 63%) in 2005–06.

TABLE 4 Motives of Intervention

	Importance[1] in 2005–06			Importance[1] in 2011–12		
	High[2]	Moderate[3]	Low[4]	High[2]	Moderate[3]	Low[4]
To curb excessive exchange market speculation	8	4	0	11	4	0
To maintain monetary stability	7	2	2	10	2	2
To discourage sharp capital inflows or outflows	4	3	1	5	5	1
To build or reduce foreign exchange reserves	7	0	2	6	2	2
To smooth the impact of commodity price fluctuations	3	1	3	4	1	3
To maintain or enhance competitiveness	2	2	3	4	1	3
To alleviate FX funding shortages of banks and corporations	4	2	0	5	2	0

[1] On a scale of 1 to 7, where 1 is most important and 7 is least important. [2] 1 or 2. [3] 3 to 5. [4] 6 or 7.

*Source: BIS questionnaire 2013/February- Based on the responses of 19 central banks

To achieve its final objective, the central bank needs to set an intermediate one in terms of either the level or the volatility of the exchange rate, or both. Table 5 given below summarizes what central banks consider as their exchange rate objectives. Most consider limiting volatility and smoothing the trend path of the exchange rate as more important than influencing the level of the exchange rate. Going by the number of responses, it is interesting to note that the relative position of the three objectives has not changed since the mid-2000s. As shown by the last two columns of Table 5 below, the number of central banks intervening for these two purposes increased dramatically in 2008 and 2009 but fell in the following years as market conditions improved gradually.

TABLE 5 Immediate Objectives and Success of Foreign Exchange Intervention

	Influence the level of the exchange rate	Smooth trend path of the exchange rate	Limit exchange rate volatility	Limit upward or downward pressure caused by international investors	Provide liquidity to a thin exchange market
2005	4	7	11	8	2
2006	4	8	12	7	2
2007	5	8	12	7	2
2008	5	8	12	12	10
2009	4	8	13	10	8
2010	3	9	12	7	6
2011	3	8	12	8	4
2012	4	7	11	8	4

*Source: BIS questionnaire 2013/February- Based on the responses of 19 central banks

Regarding timing, the results suggest an overwhelming preference for intervening only after the market has moved in a certain direction, and very little appetite for pre-emptive intervention. Of 21 respondents, 17 stated that they regularly time their interventions according to market developments (that’s why daily financial indicators data is included the data set of this thesis) and three said that they do so only occasionally. By contrast, only eight central banks reported that they regularly or occasionally conduct pre-emptive interventions. This is not surprising result as preemptive intervention may increase market uncertainty and cause unwarranted volatility. To the extent that pre-emptive intervention is more difficult to justify than reactive intervention, it also exposes the central bank to political criticism. In contrast, timing intervention relative to a certain positioning of market participants can lead to faster and more concrete results.

TABLE 6 Intervention Tactics

Based on the responses of 21 central banks

	Regularly	Occasionally	Never
Monitoring activity for FX intervention			
Monitoring of cross-border bank lending	12	2	5
Monitoring of cross-border security purchases/sales	13	2	4
Monitoring of equity/corporate bond market developments in the US or Europe	11	2	6
Monitoring of risk indicators in industrial countries (VIX, sovereign spreads, etc)	15	2	3
Timing			
Timing of intervention based on observed developments in FX markets	17	3	0
Intervention is pre-emptive, in response to other news	2	6	11
Market-based instruments			
Direct or indirect intervention in spot markets	19	2	0
Intervention in forward markets	2	8	11
Use of derivatives (futures, swaps, volatility options, others)	3	7	11

*Source: BIS questionnaire 2013/February- Based on the responses of 21 central banks

As Archer (2005) mentions some of the central banks prefer secrecy to transparency, especially when intervention is inconsistent with the goals of monetary policy. Others have argued that transparent intervention is preferable because it increases the power of the signaling and coordination channels, thereby enhancing the efficacy of intervention. It is clear that few central banks conduct preannounced interventions. A majority of emerging countries central banks (15 out of 22) keep intervention secret. Only four central banks reported that they announce their interventions on a regular basis before carrying them out, while two said that they rarely do so.

It is again not surprising that central banks conducting a preannounced intervention provide full details of timing, size and types of instrument used. Behind many of these interventions, the objective may simply be to accumulate reserves rather than affect the exchange rate. In addition, the survey results show that post-intervention transparency is quite limited. Only a few countries (those conducting preannounced interventions) publish intervention-related data on either a daily or a real-time basis. CBRT announces secret interventions fifteen days later the intervention.

TABLE 7 Information Frequencies

<table>
<tr><th></th><th colspan="2">Regularly</th><th>Rarely</th><th colspan="2">Never</th></tr>
<tr><td>Does the central bank preannounce FX intervention?</td><td colspan="2">4</td><td>2</td><td colspan="2">15</td></tr>
<tr><td colspan="6">Accompanied by information on which of the following aspects?</td></tr>
<tr><td>Size</td><td colspan="2">5</td><td></td><td colspan="2">1</td></tr>
<tr><td>Time span</td><td colspan="2">5</td><td></td><td colspan="2">1</td></tr>
<tr><td>Instrument(s) used</td><td colspan="2">5</td><td>1</td><td colspan="2"></td></tr>
<tr><td>Are intervention-related data made public ex post</td><td colspan="2">13</td><td></td><td colspan="2">7</td></tr>
<tr><td>If so, what is the frequency of the data published?</td><td>Real time / hourly
3</td><td>Daily
5</td><td>Weekly
1</td><td>Monthly
6</td><td>Annually
1</td></tr>
</table>

*Source: BIS questionnaire 2013/February- Based on the responses of 22 central banks

Table 8 reports the results of the survey with reference to the traditional channels. According to the central banks questioned, intervention is effective mainly through the signaling channel, a finding which confirms the results of previous surveys reported by Lecourt and Raymond (2006) and Neely (2008). Importantly, this channel works primarily by changing the expectations of the future exchange rate rather than the interest rate. Taking the post-crisis period as a whole, nine out of 16 respondents (56%) reported that intervention was often accompanied by a change in expectations regarding the future exchange rate. This is a significantly higher percentage than that reported for the pre-crisis period (37%). Two central banks reported that the signaling channel was sometimes important for the impact of intervention, while three said that it was rarely important (the same number as in the pre-crisis period). By contrast, only two central banks reported that intervention changed expectations regarding the future stance of monetary policy.

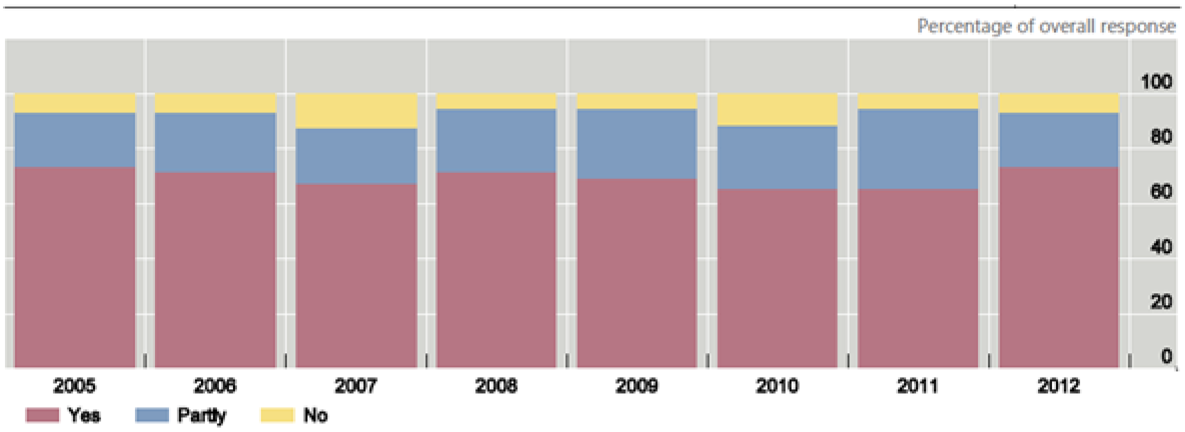
TABLE 8 Effectiveness of Different Types Intervention

	Unsterilised intervention		Sterilised intervention							
	Monetary policy[1]		Portfolio balance[2]		Expectations about:				Other[4]	
					future monetary policy stance[3]		future exchange rate and interventions			
	Up to 2007	After 2008	Up to 2007	After 2008	Up to 2007	After 2008	Up to 2007	After 2008	Up to 2007	After 2008
Often	2	2	1	2	1	2	6	9	2	3
Some-times	1	1	3	4	3	2	2	2	1	2
Rarely	4	5	4	3	2	4	3	3	2	2

*Source: BIS questionnaire 2013/February- Based on the responses of 16 central banks

As Neely (2000) and Mihaljek (2005) mention most central banks regarded their interventions as successful in moving the exchange rate in the desired direction. This contrasts with some empirical literature which finds that intervention has had very little or no effect on the exchange rate. The results, shown in Figure 1 are important in at least two respects. First, they confirm the findings of the previous surveys about the effectiveness of intervention: of the 19 central banks, around 70% reported that interventions were successful in achieving the exchange rate objective, while roughly 20% reported that they were only partly successful. In the remaining cases, intervention was seen to have had no effect on the exchange rate.

FIGURE 1 Success of Intervention

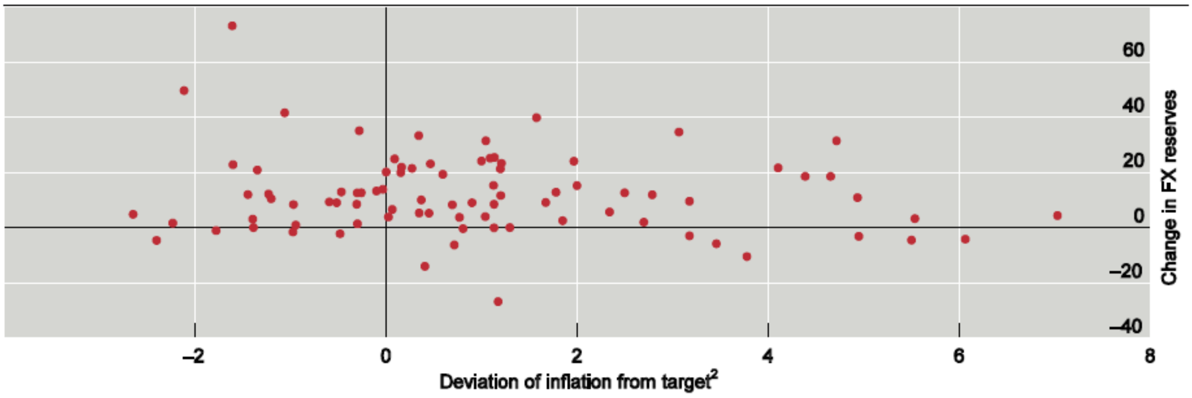


*Source: BIS questionnaire 2013/February

Figure 2 demonstrates a generalized illustration of policy consistency for inflation targeting countries. The figure shows the deviations of inflation from the target and the change in the foreign exchange reserve in the same year. Policy consistency implies that when intervention is motivated by inflation concerns, and inflation is above target, foreign exchange reserves should not increase, as the central bank should allow for more rapid appreciation.

In the same way, efforts to resist appreciation by increasing reserves should be accompanied by a decline in inflation below the target. When there is no conflict between the policies for one particular year, the observation for that year should be in quadrants 2 or 4. Figure 2 below shows that there have been cases where above-target inflation was accompanied by an increase in foreign exchange reserves (observations falling in quadrant 1), suggesting that intervention possibly came into conflict with the objective of domestic monetary policy. Interestingly, however, when inflation has been below target, foreign exchange intervention has mostly been consistent with inflation targets (observation falling in quadrant 2).

FIGURE 2 Inflation Targeting and Foreign Exchange Intervention



[1] Year-on-year percentage changes over the period 2001–11; for Turkey, 2003–11. [2] Deviation of inflation is expressed as the difference between actual inflation and the inflation target (point target, or lower or upper bound of target range), based on annual data. Economies included: Brazil, Chile, Colombia, the Czech Republic, Hungary, Indonesia, Israel, Korea, Mexico, Peru, Poland, the Philippines, South Africa, Thailand and Turkey.

In Table 9 central banks rank each sterilization instrument on a scale of 1 to 3 according to its effectiveness, cost affordability and impact on market development. The responses, shown in Table 9 below, highlight the perceived benefits of using market-based methods, in particular central bank securities, for sterilization. Of the 21 central banks that responded, 15 said that issuing their own securities is the most effective way to sterilize intervention and that method is generally seen as conducive to financial sector development. But it is costly as central banks have to pay the market rate of interest, which could rise given an increased supply of securities. Next in order of importance are foreign exchange swaps, although they are not perceived as being as effective as central bank securities. It is not surprising that reserve requirements are viewed by central banks as one of the most cost-effective tools for sterilization, but at the same time this relatively blunt instrument is not regarded as beneficial for market development.

TABLE 9 Central Bank Instruments

Ranked by 21 central banks, with 1 being the highest score and 3 the lowest

Instrument	Number of central banks using instrument	Assessment								
		Highly effective			Low-cost			Beneficial to overall market development		
		1	2	3	1	2	3	1	2	3
Market instrument										
Central bank securities	15	14	1	0	4	7	3	11	4	0
FX swaps	7	2	4	0	4	2	0	3	3	0
Government bonds	6	1	3	1	2	1	2	5	0	0
Other[1]	6	2	4	0	0	5	0	2	4	0
Non-market instruments										
Reserve requirements	8	3	1	3	4	2	1	0	1	6
Government deposits	7	4	1	1	3	3	0	3	0	3
Special deposit facilities	2	0	0	1	1	0	0	0	0	1
Other[2]	4	3	1	0	3	1	0	1	2	1
No sterilisation using monetary instruments	3									

Source: BIS questionnaire 2013/February / 1) Repos and uncollateralized borrowing 2*) Banks Deposits

Many countries attempt to achieve these objectives by limiting exchange rate volatility rather than by setting a path for the exchange rate level. The basic intervention strategy has remained unchanged, that is: monitoring of information about international investors' positions; a focus on the most liquid segments of the market; and a preference for less transparent intervention practices to maximize results. Most central banks believe that their interventions have been successful in achieving the desired exchange rate objective, although differences of opinion exist as to the size and the duration of impacts. As regards the channels of influence, many central banks think that intervention works primarily through the signaling channel, that is, by changing expectations about the future exchange rate as well as signaling forthcoming interventions. The recent success could also be due to the fact that many countries used macro prudential and capital control measures as a complementary tool to intervention.

4.2 Types Of Intervention

There are many types of central bank interventions in the literature and as the expansion of the mission of central banks continue new types of interventions will be invented. Central bank interventions are classified into different classifications such as; sterilized or non-sterilized intervention, direct or indirect interventions, oral interventions, public versus secret (they are also called as discreet or stealth) intervention, joint or unilateral intervention, leaning against the wind or with the wind. In this chapter these classifications are shortly discussed and markets which are intervened will be analyzed.

Direct intervention, can be defined as the purchase and sale of foreign exchange assets by monetary authorities as we mentioned above. The purchase of monetary authority that leads to an increase in the monetary base is non-sterilized intervention. When the authority simultaneously or with a very short time lag take the necessary steps to offset the effects of the change in official foreign asset holdings on the domestic monetary base, it is called sterilized intervention. Non-sterilized intervention affects exchange rate by stimulating changes in the stock of the monetary base. The effect of sterilized intervention on exchange rate is a matter of debate as it leaves the monetary base unchanged. At the time when the central bank takes the operational steps to offset the effects of the change in official foreign asset holdings on the domestic monetary base we call it as sterilized intervention.

As Isberg and Petursson (2003) underline sterilized intervention, generally can be classified into three channels, these are portfolio balance channel, signaling channel and noise-trading channel. In the portfolio balance channel, domestic and foreign assets are assumed imperfect substitutes. Investors allocate their portfolios to balance exchange rate risk against expected rate of return so intervention could lead to a change in the value of the exchange rate. When the central bank sells foreign currency assets for domestic currency assets this creates an excess supply of foreign currency assets. This creates excess demand for domestic currency assets. In order to provide the equilibrium again economic agents need to be compensated by a higher expected return on foreign currency assets. This may take the form of a widening interest-rate differential or in other words an appreciation of the domestic currency.

On the other hand the portfolio balance model cannot work if the assets are perfect substitutes. Sterilized intervention could still be effective in influencing the exchange rate through the signaling channel. This way of thinking assumes asymmetric information is realized between market participants and the central bank. Sterilized intervention operates through the signaling channel by causing private agents to change or shift their exchange rate expectations.

The next channel is the noise trading channel. The noise trading channel can operate even when intervention is carried out discreetly and hence does not provide a signal to market participants. When it is not large enough to change the relative supply of assets denominated in domestic and foreign currencies in a significant way. A central bank can use sterilized interventions to dominate noise traders to buy or sell currency. The idea underlying in noise trading channel is that a central bank can affect the exchange rate by entering in a weaker market and on a minute-by minute basis; the exchange rate is determined by marginal demand and supply flow in the foreign exchange market.

It is possible to find different classifications for Central Bank Interventions. Bernal and Gnabo (2006) give another insight about classification of central bank intervention and they state that "actual interventions" involve central bank's transactions designed to appropriately influence the exchange rate dynamics. They are generally leaning against the wind procedures and operations.

These operations try to reverse the exchange rate trend. Another type of intervention mentioned in the study is so-called oral interventions. They are pure announcements that do not involve any currency transaction. These interventions are official speeches, answers or communications that are intended to influence the exchange rate by providing the market with explicit relevant information. A third type of intervention corresponds to confirmed interventions. They are actual interventions accompanied by an announcement directly related to it.

Beine and Bernal (2005) underline the secret interventions. The literature covers many insights about the usual practice of central banks but has still not been able to rationalize the use of secret interventions as Sarno and Taylor (2001) also mentions. Secret interventions are defined as foreign exchange operations that are not disclosed to market participants. Depending on the central bank's communication policy and the way the order is transmitted to the commercial banks these operations can be hidden from foreign exchange traders and can be mistakenly viewed as purely private trades by the market.

Types of the intervention differs the effect of the interventions. Moreover there is another subject which also affects the power of intervention. This is related to type of the market where the intervention is performed.

As Neely (2000) mentions most of the papers which underline foreign exchange intervention generally distinguish between intervention that does or does not change the monetary base. We learnt that classification above. The former type is called unsterilized intervention while the latter is referred to as sterilized intervention. The crucial distinction between sterilized and unsterilized intervention is that the former constitutes a potentially useful independent policy tool while the latter is simply another way of conducting monetary policy. Fully sterilized intervention doesn't directly affect prices or interest rates and so does not influence the exchange rate through these variables like ordinary monetary policy. Rather, sterilized intervention might affect the foreign exchange market through two routes: the portfolio balance channel and the signaling channel.

Sterilized interventions affect the composition of domestic and foreign assets held by the central bank and the public. By purchasing foreign securities the central bank increases its foreign reserves and its domestic securities holdings are reduced by the same amount. Since the volume of securities has not increased, and as asset markets must clear, this change is reflected in the fact that the public has increased its holdings of domestic securities and reduced its holdings of foreign ones. According to the portfolio-balance effect, the public will only be willing to hold relatively more domestic assets if the price of these assets falls, i.e. if the domestic currency depreciates. A precondition for the portfolio-balance effect to be present is that investors must not regard domestic and foreign securities as perfect substitutes. If domestic and foreign assets are perfect substitutes, agents will be indifferent as to the relative amounts of domestic and foreign assets they are holding, all that matters is their total amount, which remains unchanged. Hence, no change in market clearing prices or quantities is required. Sterilized interventions can affect the exchange rate if it is observed as signaling future monetary policy decisions which are not yet reflected in exchange rates assuming that the central bank has better information than private agents. In this way the central bank would possibly be relaying information about future monetary policy decisions which would impact the exchange rate immediately because of the effect on exchange rate expectations.

Credibility of the central banks also affects the intervention power. It is important to realize that, in order for this signaling effect to work, the signal must be credible. It should follow up by the response that it implies. Thus a sterilized intervention is not really an independent monetary policy instrument, as it might seem on first impression, but rather serves the sole purpose of signaling future monetary policy decisions. In effect the message about future monetary policy decisions which influences the current exchange rate, and not the intervention in its own right.

A sterilized intervention might also have an effect on exchange rates through the impact of the central bank’s order on the foreign exchange market. In a perfectly functioning foreign exchange market where the exchange rate reflects all relevant and publicly available information, the impact of individual currency orders should not have any effect on price formation. If this assumption is relaxed the market structure and response of market participants to order flows can cause a sterilized intervention to influence the exchange rate, especially in a thinly traded market. This order flow effect can prove particularly important when the foreign exchange market is characterized by a hot potato problem.

As we mentioned above type of the market where interventions is held is also important as the type of the intervention. Intervention should not be carried out only in the spot market. It might also be carried out in the forward or future market. This is not so common in financial market of Turkey. However derivatives market in Turkey is developing and monetary policy makers might also think to intervene derivatives markets to accomplish the intervention aim. Derivatives market covers forward, future, option and swap markets. This idea is not implemented in Turkey but it has ground in the financial markets of the developed countries.

Forward-Future markets are those in which currencies are sold for delivery in more than two days. Because the forward or future price is linked to the spot price through covered interest parity, intervention in the forward market can influence the spot exchange rate. Forward-Future market interventions, the purchase or sale of foreign exchange for delivery at a future date, have the advantage that they do not require immediate cash outlay. If a central bank expects that the need for intervention will be short-lived and will be reversed, then a forward market intervention may be conducted discreetly with no effect on foreign exchange reserves data.

The options market has also been used by central banks for intervention. A European style call option confers the right, but not the obligation to purchase a given quantity of the underlying asset on a given date. Usually, the option contract specifies the prices for which the asset may be bought or sold, called the strike or exercise price. Monetary authorities seeking to prevent depreciation or devaluation of their currency may sell put options on the domestic currency or call options on the foreign currency. While the price of options has no direct effect on spot exchange rates, speculators often purchase put options instead of shorting a weak currency. The writers of these put options attempt to hedge their position by taking a long position in the weak currency, adding to the downward pressure on its price. By writing put options on the weak currency, adding liquidity to the options market, the central bank provides dealers with a synthetic hedge; dealers need not go into the spot market to take short positions in the weak currency. This arrangement creates the same type of financial risk for the central bank, if the currency is devalued as would the direct purchase of the weak currency in spot or forward markets. Like forward market intervention, it does not, however, require the monetary authority to immediately expend foreign exchange reserves. In fact, the strategy generates revenues upon the sales of the options.

While official intervention is generally defined as foreign exchange transactions of monetary authorities designed to influence exchange rates, it can also refer to indirect policies for that purpose. Dooley, Mathieson and Rojas Suarez (1993) underline innumerable methods of indirectly influencing the exchange that do not fit in the narrow definition of intervention as foreign exchange transactions of monetary authorities designed to influence exchange rates. These methods involve capital controls, taxes or restrictions on international transactions in assets like stocks or bonds or exchange controls, the restriction of trade in currencies rather than transactions. Sometimes such methods are substituted for more direct foreign exchange intervention, especially by the monetary authorities of countries without a long history of free capital movements. For example, Spain, Ireland and Portugal introduced capital controls, including mandatory deposits against the holding of foreign currencies, in the ERM crises of 1992-93, in response to speculation against their currencies.

CHAPTER 5

THESIS MODEL

"Statistics is the grammar of science"

The market specific features directly affect the analysis content and model set up. Today market dynamics and financial indicators find place for themselves most of the conversations in daily life. Generally the volatility of exchange rates or interest rate changes is accepted as risk indicators in the financial markets. Volatility of exchange rates referred in most of the studies such as Dominguez (1993,1997 and 1998), Baillie and Humpage (1992), Almekinders and Eijffinger (1994), Kim (2000), Michel et al (2002), Behera et al. (2006), Basu and Varoudakis (2013). In order to catch this volatility effect we use the volatility of financial indicators in our model.

The foreign exchange market is decentralized and open 24 hours a day in a week. Even though foreign exchange trading occurs at all hours there appear to be three distinct geographical markets defined by daylight hours in Tokyo, London and New York. There is a small overlap between Asian and European trading, substantial overlap between European and American trading, and no overlap between American and Asian trading. It is during the overlap in European and American trading that volume is typically highest in the foreign exchange market Empirical literature has found proofs for disorderly foreign exchange markets motivate central bank intervention. The costs of smoothing out these fluctuations may exceed the benefits; the optimal level of intervention can take on zero values. Thus generally recent literature has underlined on specifying and estimating a reaction function that allows for regions of zero intervention in the presence of small variations in the measures of disorderly markets. Central banks generally exercise discretion in the timing and amount of their foreign exchange interventions. But some central banks also use rules when they intervene to increase visibility the signaling channel of their policy.

If you deal with a market which is 24 hours open in week time, it is not reasonable to use the lagged data about inflation or output. Foreign exchange market is a dynamic market and distortions in this market can sometimes cause severe results. Thus in order to detect these interventions daily data should be used to capture the effects. Thus the variables which are not used as daily should be adapted to daily data by using financial market indicators. What we did is to accomplish to create a link between reaction function and the model of the thesis is realized by this type of adoption.

According to Ito and Yabu (2004) the model of reaction function can be seen as a prediction of intervention. The literature on the prediction has been developed in the financial crisis literature. One strand of the early warning model of currency crises, such as Kaminsky and Reinhart (1999), uses a model to predict a crisis and evaluate alternative model specifications by calculating the noise-to-signal ratio. Ito and Yabu (2004) apply the noise-to-signal ratio method to evaluation of various specifications of the intervention reaction function. For instance Almekinders and Eijffinger (1994) and Humpage (1999) use a Tobit model to study purchase and sale interventions separately; Almekinders and Eijffinger (1996) and Kim and Sheen (2002) estimate a friction model to explain both types of intervention simultaneously. Alternatively, Baillie and Osterberg (1997), Dominguez (1998), Kim and Sheen (2002); McKenzie (2004), Frenkel and Stadtmann (2001), Frenkel et al. (2003), and Ito and Yabu (2004) estimate discrete choice models for cases when the object of interest is the probability of intervention.

Boeckx (2011) analyzes probit models in a detailed way and offer modifications of probit model for central bank interventions. Many studies are devoted to trying to describe the way monetary policy is set by central banks, the most prominent by Taylor (1993). Most subsequent research is related to this seminal article by Taylor since they specify the interest rate as a continuous variable that is linearly related to a set of macroeconomic variables. Clarida, Gali and Gertler (1997) present estimates of this type of monetary policy rule for a range of countries, while Gerdesmeier and Roffia (2004) and Gorter, Jacobs and de Haan (2008) focus on the euro area. Policy interest rates are not set in a continuous way. Decisions on monetary policy are taken during meetings at pre-specified dates where rates are adjusted in small increments, mostly multiples of 25 basis points. These considerations led authors to employing discrete choice models where the dependent variable is not the policy rate but rather the decision to increase, decrease or keep the policy rate constant. Gascoine and Turner (2004) estimate ordered discrete choice models for the Bank of England's interest rate decisions over the period 1997-2003. They find a significant effect of output while inflation is not found to be significant. However, the predictive power of their model is very low and they cannot interpret the obtained estimates as coefficients in an interest rate rule because only the marginal effects on the probabilities of every outcome are identified in standard ordered probit models.

Gerlach (2007) tries to improve the forecasting performance of an ordered probit model for the European Central Banks's (ECB) decision-making process during the period February 1999-June 2006 by including indicator variables on macroeconomic variables constructed using the editorials in the ECB's Monthly Bulletin. He finds economic sentiment and indicator variables on output to be important, while infation is not significant. He relates the latter to the fact that the high inflation rates were mainly seen as the result of relative price shocks which can in principle be accommodated by a central bank. Money enters his model in a significant way given the importance the ECB assigns to monetary aggregates. Using press articles during the short period from January 1999 to May 2002, Jansen and de Haan (2009) construct variables on the direction a macro-economic variable or the policy rate is likely to develop according to ECB officials. They include these variables in an ordered probit model. Using only macro-economic variables, expected inflation and economic sentiment are both significant while in a backward-looking model neither is significant. Adding the communication variables does not generally add information although they enter significantly in some specifications. Yet, this does not yield a very successful predictive model for the monetary policy moves by the ECB.

In order to get a sound model we take benefit of all literature, theory and application. On the left side of the model we have 1 for interventions and 0 for non-intervention days. As it is mentioned above among 2741 days there are only 26 foreign exchange rate interventions and 54 interest rate interventions which are directly and secretly held. Because of this binary and situation we first apply logit regression.

5.1 Logit Regression

Comparing logit and probit model, we decided to start our analysis with logit regression. In statistics, logit or logistic regression is a type of probabilistic statistical classification model which has similarities with probit model. It is also used to predict a binary response from a binary predictor, used for predicting the outcome of a categorical dependent variable based on one or more predictor variables which is proper in our case and date profile in our thesis. That is, it is used in estimating empirical values of the parameters in a qualitative response model. The probabilities describing the possible outcomes of a single trial are modeled, as a function of the explanatory (predictor) variables, using a logistic function.

Logit regression is used to refer specifically to the problem in which the dependent variable is binary while problems with more than two categories are referred to as multinomial logit regression or if the multiple categories are ordered, as ordered logit regression. Logit regression measures the relationship between a categorical dependent variable and one or more independent variables by using probability scores as the predicted values of the dependent variable. As such it treats the same set of problems as probit regression using similar techniques. Variables used in the regression are given in Table A-1. (See Appendix A)

There are four significant logit regression model is found for exchange rate intervention and one significant logit regression model is found for interest rate intervention. However all models have problems with the cut value because of unbalanced data and the models only estimate around seventy percentage of the interventions.   Results of the logit regressions are given in appendix. (See Appendix B, Tables in B-1, B-2, B-3,B-4,B-5)

The best models estimate only 72 % of exchange rate interventions and 61,5 % of interest rate interventions. Moreover logit regression can not handle the problem with unbalanced data. Because there are few numbers of 1 (around 26-54) but a lot of (more than 2733) 0 in the data. Thus statistical problems occurred because unbalanced data. The best model in logit regression finds the following variables significant to model the exchange rate interventions such as, volatility of Borsa İstanbul 100 index, volatility of benchmark interest rates, skewness of benchmark interest rate, volatility of EURO/TL exchange rate and kurtosis of EURO/TL exchange rate. The best model in logit regression finds the following variables significant to model the interest rate interventions such as daily change in Borsa İstanbul 100 index, daily change in benchmark interest rate and volatility of USD/TL exchange rate. In this point there are two problems we have encountered. First the rate of intervention detection is not satisfactory and statistical problems affect the result in a negative way. Because of this we review the theory and analyze reaction functions in order to increase success of our model.

5.2 Reaction Functions

Monetary policy is one the central tool and framework for providing price stability and it has become the key tool in managing the business cycle especially the last financial crisis in the world in 2008.

Monetary policy changes and has its own objectives for different central banks. In order to analyze and understand this behavior we seek for some patterns to put the behavior of central banks in a framework. A monetary policy rule defines the systematic relationship between the central bank's policy rate and macroeconomic developments. As Rosa (2009) states estimating a reaction function is important for two main reasons. Firstly it is a useful tool to forecast future policy rates or policy framework. For central bank purposes, the reaction function displays how, given economic conditions, interest rates would have been set in the past, which may supply background information for future policy decisions. Secondly, by providing explicitly one equation of the macroeconomic system, the monetary policy rule closes the general equilibrium macro-econometric model of the economy and thus it allows simulating policy experiments. These simulations would provide a quantitative assessment of the economy's dynamic behavior under alternative policy experiments.

Central Banks' reaction function, which summarizes how the Central Banks alter monetary policy in response to economic developments, plays an important role in macroeconomic and policy analyses. As Mehra (1999) states, it can be helpful in predicting actual policy actions, thereby serving as a benchmark for assessing the current stance and the future direction of monetary policy. Beine and Bernal (2005) state that reaction functions have been estimated for the major central banks and suggest that monetary authorities react to reverse undesirable trends and to a lesser extent, to smooth exchange rate volatility. Also, in macro models, the reaction function is central in evaluating CB policy and determining effects of other macro policies or economic shocks, implying macroeconomic performance may itself depend upon the conduct of monetary policy. Consequently, there is considerable interest in identifying the nature of actual policy pursued by the CB and determining whether the estimated reaction function fostered or hindered macroeconomic stability.

The monetary policy reaction function (MPRF) is the upward-sloping relationship between the inflation rate and the unemployment rate. When the inflation rate rises, a central bank wishing to fight inflation will raise interest rates to reduce output and thus increase the unemployment rate. The MPRF is a function of the Taylor rule, the IS curve, and Okun's law

The MPRF has the equation:

u = $u_0 + \Phi (\pi - \pi_t)$

Where a Φ parameter that tells us how much unemployment is rises when the central bank raises the real interest rate because it thinks that inflation is too high and needs to be reduced.

In economics, a Taylor rule is a monetary-policy rule that stipulates how much the central bank should change the nominal interest rate in response to changes in inflation, output, or other economic conditions. In particular, the rule stipulates that for each one-percent increase in inflation, the central bank should raise the nominal interest rate by more than one percentage point. This aspect of the rule is often called the Taylor principle.

According to Taylor's original version of the rule, the nominal interest rate should respond to divergences of actual inflation rates from target inflation rates and of actual Gross Domestic Product (GDP) from potential GDP:

$$i_t = \pi_t + r_t^* + a_\pi(\pi - \pi_t) + a_y(y_t - \overline{y_t})$$

In this equation, i_t is the target short-term nominal interest rate, π_t is the rate of inflation as measured by the GDP deflator, π_t^* is the desired rate of inflation, π_t^* is the assumed equilibrium real interest rate, y_t is the logarithm of real GDP, y_t hat and is the logarithm of potential output, as determined by a linear trend.

Nelson (2007) states that the Taylor-rule approach predicts that the exchange rate is determined by relative expected inflation gaps and relative output or unemployment gaps which is in sharp contrast to the standard fundamentals typically used in empirical work on exchange rates.

As Kristen (2003) also mentions since the publication of Taylor’s seminal paper (1993) on the interest rate setting by the Federal Reserve, it has become common practice to describe monetary policy using reaction functions which link the level of the nominal short-term interest rate to inflation and economic activity. Such Taylor rules (TRs) are of interest both from a central bank and an academic perspective. For central bank purposes, TRs illustrate how, given economic conditions, interest rates would have been set in the past, which may provide background information for policy decisions. From an academic perspective, TRs are attractive because they provide an extremely simple model that captures the main considerations underlying central banks’ interest rate setting

Rosa (2009) in her paper gives the general Taylor rule (Taylor, 1993),i.e. a linear static interest-rate rule of the following form:

$$i_t^{TR} = \alpha + \emptyset_\pi(\pi - \pi^*) + \emptyset_x (x_t - x^*)$$

where i_t^{TR} denotes the central bank desired policy rate implied by a static Taylor rule, π_t is the inflation rate, x_t is the output gap (i.e. the difference between actual and potential output), α stands the intercept, and $\pi^*$and x^* are constant target values for the inflation rate and the output gap.

Woodford (2001 and 2003) among others shows that the Taylor rule specification is consistent with the optimal monetary policy rule that stabilizes the price level and the output gap as long as Φ_π and Φ_x are large enough to ensure that the rational-expectation equilibrium paths of prices and interest rates are locally determinate. In this respect, a sufficient condition is that $\Phi\pi > 1$, also known as Taylor Principle: the policy rate should adjust more than one for one with respect to inflation in order to rule out sunspot equilibrium.

Rosa (2009) explains the reasons of smoothing motives for interest rates and she offers the modified version of Taylor rule which is usually estimated by including on its right-hand side a gradual adjustment of the optimal policy rate i_t^* (i.e. including an element of inertia represented by the lagged policy rate):

$$i_t^* = \rho i_{t-1}^* + (1 - \rho)\, i_t^{TR}$$

Rosa (2009) criticizes the formula above some aspects. In a framework of optimizing models with nominal price stickiness, where the central bank has only partial information about the state of the economy and macroeconomic variables are determined in a forward-looking fashion, the optimal rule can only depend on observable variables. In particular, as proved by Aoki (2003) and Svensson and Woodford (2003), when the central bank's measures of current inflation and output are subject to measurement errors, the monetary authority has to solve an optimal filtering problem, i.e. it needs to put the appropriate weights on different information and draw the most efficient inference of potential output and inflation. Therefore, these noisy indicators models imply that any variable can enter in the reaction function as long as it is correlated with inflation and output.

Alternatively, in Bernanke and Frank (2012) the MPRF is a model of the Fed's interest rate behavior. In its most simple form, the MPRF is an upward-sloping relationship between the real interest rate and the inflation rate.

$r = r^* + g\ (\pi - \pi^*)$

where r is target real interest rate (or actual real interest rate), r^* is long-run target for the real interest rate, g is constant term, π is actual inflation rate and π^* is long-run target for the inflation rate.

Indeed there are many different and modified reaction functions are offered to analyze the intervention of central banks, which are based on Taylor Rule. In this part it is useful to analyze these different and modified reaction functions.

By remembering Taylor Rule it might be possible to describe monetary policy by a rule depending upon both inflation and output gap developments. Sauer and Sturm (2003) give a simple brief of this idea. They start by a common reaction function in their study which is the rule as advocated by Taylor (1993) to describe the monetary policy of the Federal Reserve in the US.

$$i_t = r^* + \pi_t + 0.5(\pi_t - \pi^*) + 0.5y_t = (r^* - 0.5\pi^*) + 1.5\pi_t + 0.5y_t$$

where i_t is the policy interest rate, r * the equilibrium real rate, π_t the rate of inflation (as a proxy for expected inflation), π * the inflation target and yt the output gap. From a theoretical point of view, Svensson (1999) shows that such a rule is the optimal reaction function for a central bank pursuing inflation target in a simple backward-looking model.

Brouwer and Gilbert (2003) in their paper use the basic formulation of the simple reaction function (Bryant-Hooper-Mann rule) used in the monetary policy literature as:

$$i_t = \bar{\iota} + \beta\,(\pi - \pi^*) + \gamma\,(y - y^*)$$

which states that the monetary authorities move the nominal interest rate (i) above (below) neutral when inflation (π) is above (below) the target and/or output (y) is above (below) potential. The general case can be particularized by specifying or estimating the reaction parameters, and by specifying whether policy responds to past, current or future expected values of the reaction variables.

According to Brouwer and Gilbert (2003) reaction functions or interest rate rules have a sound intuitive appeal since they maintain a simple organizing principle for assessing monetary policy and second-guessing how central banks will set their instrument. But they need to be used and interpreted with considerable caution. In contrast to this opinion as Kohn (1999) states central bankers say that they do not follow rules because the economy and decision making are much more complex. Simple rules are only ever approximations to reality; other factors, like dealing with financial instability and economic uncertainty, impinge on decision making.

Brouwer and Gilbert (2003) also criticize the reaction functions in different aspects. Estimated rules are also subject to considerable uncertainty because the output gap and neutral interest rate are not independently observable variables. The standard errors of the estimate from econometric estimations can be important. The structure of Bryant-Hooper-Mann rules may be too compact; more accurate rules may be obtained by including more variables and longer lag structures on the right hand side of the equation. Because reaction functions are a reduced form of the objective function of the central bank and the set of equations that describe the economy, changes in reaction functions may reflect either changes in central bank preferences or structural changes in the economy. It is best to estimate the central bank's objective function directly if the focus is on stability or otherwise of central bankers' preferences. Lastly even if estimated reaction functions show that policymakers have acted in a consistent manner, this does not necessarily mean that policymakers have acted in an optimal manner.

Girardin, Lunven and Ma (2012) examine China's reaction function. Firstly they define the Taylor rule as:

$$i_t^* = r^* + \delta_1 y_t + \delta_2(\pi_t - \pi^*)$$

This rule models the desired or targeted nominal short-term interest rate i^* as a function of the output gap y_t , π_t inflation, and its target level π^* and $r*$ the equilibrium level of the real interest rate. Accordingly, since the real interest rate actually drives private decisions, the size of the inflation coefficient, δ_2, needs to ensure that the nominal interest rate is raised enough to increase the real interest rate as a response to a rise in inflation. According to Girardin, Lunven and Ma (2012) Taylor rule to better correspond to the practical uses of central banks, for instance, extending the specification from a contemporary (π_t) model, as in above function, (or backward-looking by replacing (π_t) by (π_{t-1})) to a forward-looking specification as:

$$i_t^* = r^* + \delta_1 y_t + \delta_3 \left(E_t \pi_{t+1} - \pi^*\right)$$

where $E_t\pi_{t+1}$ stands for expected future inflation. Indeed, if economic agents view the central bank as credible, inflation expectations are more likely to be well anchored, further enhancing the effectiveness of monetary policy. Moreover, inflation expectations are one of the main drivers of current inflation, because expected inflation influences current wage negotiations, price setting and financial contracting for investment.

Girardin, Lunven and Ma (2012) also explain interest rate smoothing aspect in the specification and offer the function below:

$$i_t = \rho\,(L) i_{t-1} + (1-\rho) i_t^*$$

where $p\ (L) = p_1+p_2L+\ldots..+p_nL^{n-1}$ and $p \equiv p(1)$. Equation above postulates partial adjustment of the interest rate to the target i_t^*. Specifically, the interest rate i_t is adjusted each period to eliminate a fraction (1-p) of the gap between its current target level and some linear combination of its past values.

Goodhart (2004) starts his paper by criticizing Taylor-type Central Bank reaction functions. According to Goodhart (2004) these functions indicate how Central Banks might adjust interest rates in response to deviations of current inflation and current output from some desired level, so that,

$$i_t^* = a + b(\pi_t - \pi^*)b_2 y_t + b_3 i_{t-1}$$

where i is the nominal interest rate, π the current rate of inflation, y is the estimated output gap, and the final term ($b_3 i_{t-1}$) is usually included to account for the empirical evidence of auto-correlation in the time path of interest rates. Goodhart (2004) criticizes this framework and state that formulation is above distinctly odd. In particular, all the main empirical studies suggest that interest rates do not affect output significantly until after a lag of a few quarters, then building up into a hump-shaped response; and similarly do not affect inflation until a further delay, with a humped shape response following after that of output.

Goodhart (2004) expands his critiques with a question why the Central Bank decision makers should vary interest rates in reaction to current movements in variables which are unaffected by the Central Bank instrument, in the sense that they are believed to be almost totally unresponsive to such interest rate changes. Central Bank decision-makers in practice relate their interest decisions, not to current (and from the monetary policy view-point predetermined) variables, but to forecast values for future inflation and output, with a forward-looking interest rate reaction function of the form

$$i_t^* = a + b_1 E_t(\pi_t - \pi^*) b_2 E_t(Y_{t+j})$$

Goodhart (2004) underlines that a problem facing those wishing to do applied empirical research is that data on the forecasts which formed an input into the interest rate decision are generally not available, or, if available, often without any indication of the prospective future interest rate path that was assumed for the purpose of completing that forecast. There are only a few examples of Central Banks releasing both an official authorized forecast, and a complementary projected path for interest rates.

Gerdesmeier and Barbara (2004) use a different modification of the model which is given below:

$$i_t = (1-\rho)\alpha + (1-\rho)\beta\pi_t + (1-\rho)\gamma(y_t - \bar{y}) + \rho i_{t-1} + \varepsilon_t$$

where i_t represents the policy rate of the central bank, π_t is the inflation rate and (y_t-y) represents the output gap. This specification of the Taylor rule also contains an interest rate smoothing term. They claim that its inclusion can be justified on the basis that central banks appear to adjust interest rates in a gradual fashion, being adverse to large interest rate movements, thus slowly bringing the interest rate towards its desired setting or “target” level. This smoothing of the interest rate is based on the hypothesis that the current interest rate is determined by weighting the interest rate target of the Taylor rule and the lagged interest rate according to the following:

$$i_t = \rho i_{t-1} + (1-\rho) i_t^* + \varepsilon_t$$

where the target interest rate is derived from the standard Taylor rule

$$i_t^* = \alpha + \beta\pi_t + \gamma(y_t - \bar{y})$$

and p represents the smoothing parameter. It should be noted that, with an inflation parameter β larger than unity, the rule indicates that the real interest rate would be increased whenever inflation rises, thus exerting a stabilizing effect on inflation (the so called "Taylor principle").

The use of this simple specification allows for a direct comparability of our results with those presented by Orphanides, who considered a specification which did not take into account the possibility that the central bank might have reacted to other additional economic variables not contained in the original specification proposed by Taylor. Along the same lines, in order to check for the robustness of the results obtained with the specification in their first equation, they also consider some slightly modified alternative specifications. On the basis that central banks can only affect inflation with some lags, a forward-looking specification of the following form is estimated

$$i_t = (1-\rho)\alpha + (1-\rho)\beta E_t\pi_{t+n} + (1-\rho)\gamma(y_t - \bar{y}) + \rho i_{t-1} + \varepsilon_t$$

where π_{t+n} represents the inflation rate forecast (E denotes the expected value) at time (t+n) given the available information at current time t.

By referring inflation forecasts in this estimation Salgoda (2001) underlines a basic reaction function based on Taylor which the Central Bank uses the nominal interest rate to minimize the total variance of inflation and output. It has the following representation

$$i_t = \mathrm{a} + \mathrm{g}\overline{y_t}(\pi_t - \pi^*)$$

where i_t is the short-run nominal interest rate, π_t is the rate of inflation, π_t^* is the inflation target, y_t hat is the output gap and a, g and h are parameters.

Other reaction functions are forward looking, as they depend on the expectation of future inflation rates and output. For example, Clarida, Gali, and Gertler (2000) propose the following rule:

$$r_t^* = \alpha + \beta\left[E(\pi_{t,k} \mid \Omega t) - \pi^*\right] + \gamma\, E(\pi_{t,k} \mid \Omega t)$$

where r_t* is the nominal interest rate target determined by the Central Bank, $\pi_{t,k}$ is the inflation rate between t and t + k, π^* is the inflation target, $x_{t,k}$ is a measure of the output gap between t and t + k, E(.) is the conditional expectations operator and Ω_t is the information set available in t, when the interest rate is determined. The scalars α, β, and ϒ are parameters. The constant represents the desired nominal interest rate when inflation and output are equal to the targets. The authors argue, however, that there is a tendency for Central Banks to smooth changes in interest rates, so that they do not always achieve r_t*. Therefore, the effective nominal interest rate would be:

$$i_t = (1 - \rho)\, r_t^* + \rho i_{t-1} + v_t$$

where p ϵ [0; 1] indicates the degree of smoothing of interest rates, v_t is a zero mean external shock, and r_t* is the interest rate target determined by.

Monetary policy rules can have many different instruments and objectives. McCallum (2000), for example, suggests the following:

$$\Delta b_t = \Delta x^* - \Delta v_t^a + 0{,}5\,(\Delta x^* - \Delta x_{t-1})$$

where Δbt is the change in the log of the monetary base, Δx^* is the target for nominal GDP growthand Δv_t^a is the average growth rate of the monetary base velocity over the last sixteen quarters. The term (Δx^*- Δx_{t-1}) reflects long-run changes in the demand for monetary base

Salgoda (2001) argues that the Brazilian Central Bank has used the nominal interest rate as a monetary policy instrument since the implementation of the Real Plan in July 1994. Its main objectives, aside from controlling inflation and output, are to prevent large changes in international reserves without, however, promoting drastic changes in the interest rate as in Clarida, Gali, and Gertler (2000). Therefore they offer the following rule:

$$i_t = \alpha + \beta i_{t-1} + \delta\pi_t + ky_t + \theta\Delta R_t$$

where ΔRt is the change in international reserves and α, δ, κ, , and Θ are parameters. A similar rule is estimated for Brazil by Carneiro and Wu (2001) and is clearly supported by the Central Bank´s actions which are documented in the reports made during the meetings of the Central Bank´s Committee of Monetary Policy in which the nominal interest rate is determined.

Bernal and Gnabo (2006) also modify their own reaction functions. They state that traditional reaction functions are designed to explain when actual interventions occur. They are generally derived from a standard loss minimization program. In such a framework, interventions occur because of the losses caused by an inadequate exchange rate level, an excessive volatility or a bad economic conjuncture. They formulate the equation below and form a generic reaction function.

$$I_t^* = f(\beta_1 X_t, \beta_2 Z_t, \beta_3 W_t)$$

It denotes optimal interventions. Xt, Zt and Wt respectively capture the exchange rate level and volatility, and the economic conjuncture. The work proposes an extended reaction function. It incorporates the different types of interventions and provides some elements valuable to understand their occurrence. From the theoretical discussion interventions can be classified in a discreet way according to the strength of the signal they convey.

Faust, Rogers, and Wright (2001) also use a different reaction function. The reaction function that they build depends on the following equation:

$i_t = \rho i_{t-1} + (1-\rho)\, i_t^* + \varepsilon_t$

where ϵ_t is an i.id. zero mean error term. Smoothing interest rate changes might be rational for a central bank in a leading model, or might result from a fear that abrupt changes in interest rates would be too disruptive to bond and equity markets. According to Faust, Rogers, and Wright (2001) calculates the interest rate satisfies the equation below:

$$i_t^* = \alpha + \beta E_t(\pi_{t+n}) + \gamma E_t(y_t)$$

Where π_t is the year-on-year inflation y_t is the output gap (a positive gap implying output above potential). The inflation rate being targeted is n periods in the future, so the monetary policy rule is forward-looking.

We reviewed the different reaction functions and analyze the critics of these functions. After this filtered information we detect that the common variable is the difference between actual and expected (or target inflation) inflation which is denoted by (π - π*). This distortion triggers central bank monetary policy in order to change the interest rate or intervene the foreign exchange market.

In order to increase the success of the model and establish a theoretical background for our model we should create a link between reaction function and our model. In this phase we have to adapt (π - π*) into our model and transform it into a daily data. Here we decide to use difference of benchmark interest rate and target inflation of CBRT. As it is mentioned above Turkey operates a floating exchange rate regime with inflation targeting since 2002 (See Table 1). We think that daily benchmark interest rate covers most of the concerns and expaectations with inflation (π) and can represent it in our model in daily based. The distortion between benchmark interest rate and target inflation of CBRT can represent (π - π*) in our model. By this way we capture the basic principle of reaction functions in our model. In a broader sense we also create a second variable which is difference of benchmark interest rate and interest rate of CBRT. We also think that the distortion between these two rates also can trigger CBRT by referring the theory of reaction functions.

5.3 Theoretical Model and Reaction Function of Interventions

"For economist the real world is often a special case."

After detecting which determinants affect the intervention and when CBRT intervenes the interest end exchange rate market, we can design a model and find the reaction functions of these two interventions. In order to set up a model we will refer the papers of Gali and Monacelli (2005) and Lubik and Schorfheide (2007).

Firstly we follow the model Gali and Monacelli (2005) in order to model a small open economy. Then we extend this model the basics of Lubik and Schorfheide (2007) in order to get a reaction function. Finally we modify the reaction function of Lubik and Schorfheide (2007) and transform it in a daily based reaction function for interest rate and exchange rate.

It would be reasonable to start with assumptions of the model. Since each economy is of measure zero, its domestic policy decisions do not have any impact on the rest of the world. While different economies are subject to imperfectly correlated productivity shocks, it is assumed that they share identical preferences, technology, and market structure. Since the focus of the model is on the behaviour of a single economy and its interaction with the world economy, and in order to lighten the notation, variables are used without an i-index to refer to the small open economy being modelled. Variables with an i ϵ [0, 1] subscript refer to economy i , one among the continuum of economies making up the world economy. Finally, variables with a star superscript correspond to the world economy as a whole.

In the model of Gali and Monacelli (2005) households seek to maximize

$$E_0 \sum_{t=0}^{\infty} \beta t \; U \; (Ct \, , Nt) \qquad (1)$$

where *Nt* denotes hours of labour, and *Ct* is a composite consumption index defined by

$$C_t \equiv \left[(1-\alpha)^{\frac{1}{n}} \; (C_{H,t})^{\frac{n-1}{n}} + \alpha^{\frac{1}{n}}(C_{F,t})^{\frac{n-1}{n}} \right]^{\frac{n}{n-1}} \quad (2)$$

where $C_{H,t}$ is an index of consumption of domestic goods given by the CES function.

$$C_{H,t} \equiv \left(\int_0^1 C_{H,t}(j)^{\frac{\varepsilon-1}{\varepsilon}} \; dj \right)^{\frac{\varepsilon-1}{\varepsilon}} \quad (3)$$

where j ϵ [0, 1] denotes the good variety. $C_{F,t}$ is an index of imported goods given by

$$C_{F,t} \equiv \left(\int_0^1 C_{i,t}(j)^{\frac{\gamma-1}{\gamma}} \; di \right)^{\frac{\gamma-1}{\gamma}} \quad (4)$$

where $C_{i,t}$ is, in turn, an index of the quantity of goods imported from country i and consumed by domestic households. It is given by an analogous CES function

$$C_{i,t} \equiv \left(\int_0^1 C_{i,t}(j)^{\frac{\varepsilon-1}{\varepsilon}} \; dj \right)^{\frac{\varepsilon-1}{\varepsilon}} \quad (5)$$

The maximization of (1) is subject to a sequence of budget constraints of the form

$$\int_0^1 P_{H,t}(j)C_{H,t}(j)dj + \int_1^1 \int_0^1 P_{i,t}(j)C_{i,t}(j)djdi + E\{Q_{t,t+1} + D_{t+1}\} \leq D_t + W_t N_t + T_t \quad (6)$$

for t = 0, 1, 2, . . ., where $P_{i,t}(j)$ is the price of variety j imported from country i (expressed in domestic currency, i.e. the currency of the importing country whose economy is being modelled). D_{t+1} is the nominal pay-off in period t +1 of the portfolio held at the end of period t (and which includes shares in firms), W_t is the nominal wage, and Tt denotes lump-sum transfers/taxes. All the previous variables are expressed in units of domestic currency. $Q_{t,t+1}$ is the stochastic discount factor for one-period ahead nominal pay-offs relevant to the domestic household

The optimal allocation of any given expenditure within each category of goods yields the demand functions

$$C_{H,t}(j) = \left(\frac{P_{H,t}(j)}{P_{H,t}}\right)^{-\varepsilon} C_{H,t}; \quad C_{i,t}(j) = \left(\frac{P_{i,t}(j)}{P_{i,t}}\right)^{-\varepsilon} C_{i,t} \quad (7)$$

Furthermore, the optimal allocation of expenditures on imported goods by country of origin implies

$$C_{i,t}(j) = \left(\frac{P_{i,t}(j)}{P_{F,t}}\right)^{-\gamma} C_{F,t} \quad (8)$$

The optimal allocation of expenditures between domestic and imported goods is given by

$$C_{H,t}(j) = (1-\alpha)\left(\frac{P_{H,t}}{P_t}\right)^{-n} C_t\,; \; C_{F,t}(j) = \alpha\left(\frac{P_{F,t}}{P_t}\right)^{-n} C_t \quad (9)$$

Accordingly, total consumption expenditures by domestic households are given by

PH,t CH,t + PF,tCF,t = PtCt . Thus, the period budget constraint can be rewritten as

Pt Ct + Et {*Qt,t*+1 *Dt*+1} ≤ *Dt + Wt Nt + Tt* *(10)*

In what follows in order to specialize the period utility function to take the form

U(C,N)≡ $\frac{C^{1-\sigma}}{1-\sigma}$ -$\frac{N^{1+\varphi}}{1+\varphi}$ (11)

Then it can be rewritten as the remaining optimality conditions for the household's problem as follows:

$C_t^{\sigma} N_t^{\varphi} \ = \frac{W_t}{P_t}$ (12)

which is a standard intra-temporal optimality condition, and

$\beta \left(\frac{C_{t+1}}{C_t}\right)^{-\sigma} \left(\frac{P_t}{P_{t+1}}\right) = Q_{t,t+1}$ (13)

Taking conditional expectations on both sides of (13) and rearranging terms a conventional stochastic Euler equation is obtained:

$\beta R_t \ E_t \ \left\{\left(\frac{C_{t+1}}{C_t}\right)^{-\sigma} \left(\frac{P_t}{P_{t+1}}\right)\right\} = 1$ (14)

For future reference it is useful to note that (12) and (14) can be respectively written in log-linearized form as:

$w_t - p_t = \sigma C_t \ +\varphi n_t$

$c_t = E_t\{c_{t+1}\}$ -$\frac{1}{\sigma}$$(r_t$-$E_t\{\pi_{t+1}\} - p)$

where lower case letters denote the logs of the respective variables

p≡ $\beta^{-1} - 1$ is the time discount rate, and $\pi_t \equiv p_t$- p_{t-1} is CPI inflation (with $p_t \equiv \log P_t$).

Lubika and Schorfheide (2007) simplify the small open economy model of Gali and Monacelli (2005) they refer for details on the derivation of the reduced form equations. Like its closed-economy counterpart, the model consists of a forward-looking (open economy) IS-equation and a Phillips curve. Monetary policy is described by an interest rate rule, while the exchange rate is introduced via the definition of the CPI and under the assumption of PPP. Specifically, the evolution of the small open economy is determined by the following equations

The consumption Euler equation can be rewritten as an open economy IS-curve:

$$y_t = E_t y_{t+1} - [\tau + \alpha(2-\alpha)(1-\tau)]\,(R_t - E_t\pi_{t+1}) - p_z z_t$$

$$-\alpha[\tau + \alpha(2-\alpha)(1-\tau)]E_t\Delta q_{t+1} + \alpha(2-\alpha)\frac{1-\tau}{\tau}\,E_t\Delta {y^*}_{t+1} \quad (15)$$

where 0< $\alpha < 1$ is the import share, and t the intertemporal substitution elasticity. Notice that the equation reduces to its closed economy variant when $\alpha = 0$. Endogenous variables are aggregate output y_t and the CPI inflation rate $\pi_t . q_t$ are the terms of trade, defined as the relative price of exports in terms of imports.

The terms of trade enter in first difference form since it is changes in (relative) prices that affect inflation (and ultimately the real rate) via the definition of the consumption based price index. ${y^*}_t$ is exogenous world output, while z_t is the growth rate of an underlying non-stationary world technology process A_t. Inorder to guarantee stationary of the model, all real variables are therefore expressed in terms of percentage deviations from A_t.

Optimal price setting of domestic firms leads to the open economy Phillips curve:

$$\pi_t = \beta E_t\pi_{t+1} + \alpha\beta E_t\Delta q_{t+1} - \alpha\Delta q_t + \frac{K}{\tau+\alpha(2-\alpha)(1-\tau)}(y - \bar{y}_t) \quad (16)$$

In order to study exchange rate policies we introduce the nominal exchange rate et via

the definition of the CPI. Assuming that relative PPP holds and

$$\pi_t = \Delta e_t + (1-\alpha)\Delta q_t + \pi^*{}_t \quad (17)$$

where $\pi^*{}_t$ is a world inflation shock which we treat as an unobservable. It is assumed that monetary policy is described by an interest rate rule, where the central bank adjusts its instrument in response to movements in CPI inflation and output. Moreover, we allow for the possibility of including nominal exchange rate depreciation Δe_t in the policy rule:

$$R_t = \rho_R R_{t-1} + (1-\rho_R)[\psi_1\pi_{t+}\psi_2 y_{t+}\psi_3\Delta e_t] + \varepsilon_t^R \quad (18)$$

It is assumed that the policy coefficients $\psi_1, \psi_2, \psi_3 \geq 0$. In order to match the persistence in nominal interest rates, it is included a smoothing term in the rule with 0< ρ_R <1. ε_t^R is an exogenous policy shock which can be interpreted as the non-systematic component of monetary policy. The primary interest is whether monetary authorities include exchange rate terms in their reaction functions. It is evaluated this hypothesis by estimating the model separately under the restrictions $\varphi_3 > 0$ and φ_3 =0 and computing a posterior odds ratio for the two specifications.

Instead of solving endogenously for the terms of trade, we add a law of motion for their growth rate to the system

$$\Delta q_t = \rho_q \Delta q_{t-1} + \varepsilon_q \quad (19)$$

This specification is not fully consistent with the underlying structural model. Since firms do have a certain modicum of market power, the prices of internationally traded products are not exogenous to the economy even if its size relative to the rest of the world goes to zero. The terms of trade are thus determined endogenously as the relative price that clears international goods markets. In terms of growth rates this relationship can be written as

$$[\tau + \alpha(2-\alpha)(1-\tau)]\Delta q_t = \Delta y_t^* - \bar{y}_t \quad (20)$$

5.3.1 Econometric Methodology

On the estimation of the monetary policy rule (18) and in particular the magnitude of ψ_3 which determines the extent to which central banks respond to exchange rate movements. The policy rule cannot be consistently estimated by ordinary least squares because the regressors are endogenous, that is, $\mathrm{E}[\varepsilon_t^R | \pi_t, y_t, \Delta e_t] \neq 0$. System-based estimation methods correct for the endogeneity by adjusting for the non-zero conditional expectation of the monetary policy shock. The monetary policy rule is implicitly replaced by the following equation:

$$R_t = \mathrm{E}[\varepsilon_t^R | \pi_t, y_t, \Delta e_t] + \rho_r R_{t-1} + (1-\rho_r)[\psi_1 \pi_{t+} \psi_2 y_{t+} \psi_3 \Delta e_t] + (\varepsilon_t^R - \mathrm{E}[\varepsilon_t^R | \pi_t, y_t, \Delta e_t]) \quad (21)$$

5.3.2 Modified Version of Daily Reaction Function

Recall that, we find the answer of when CBRT interventions are performed in the exchange rate market and interest rate market by the help of decision trees. This process is the first stage analysis of the thesis. Next we follow the model Gali and Monacelli (2005) in order to form a small open economy. Then we extend this model by the help of the model in the paper of Lubik and Schorfheide (2007) in order to get a reaction function (See equation 21). These reaction functions improve the analysis of the thesis one stage forward.

In this we analyzed different modified versions of reaction functions such as Rosa (2009), Bernanke and Frank (2012), Goodhart (2004), Gerdesmeier and Barbara (2004), Bernal and Gnabo, Faust, Rogers, and Wright (2001) and Clarida, Gali, and Gertler (2000). In order to find the time of interventions daily data used and advantages of using daily date are underlined in related section.

In this part of the thesis we suggest reaction functions which cover specific daily data of our data set which is in line with the models in the study of Gali and Monacelli (2005) and Lubik and Schorfheide (2007). According to model that we refer above, reaction function theory and applicable data set we suggest two reaction functions for interest rate market and exchange rate market, as follows:

$$\mathrm{CBO} = a + b(\pi - \pi^*) + b_2\Delta er_t + b_3\Delta i_t$$

Where CBO is the overnight interest rate of CBRT, a is constant, $(\pi - \pi^*)$ is the difference between benchmark interest rate (in order to represent inflation) and target inflation of CBRT, Δer_t is the volatility of USD/TL exchange rate and and Δi_t is the volatility of interest rate.

$$er_t = a + b(\pi - \pi^*) + b_2\ \Delta er_t + b_3\Delta i_t$$

where is er_t is the interest rate, a is constant, $(\pi - \pi^*)$ is the difference between benchmark interest rate (in order to represent inflation) and target inflation of CBRT, Δer_t is the volatility of USD/TL exchange rate and Δi_t is the volatility of interest rate.

5.4 Ordinary Least Square (OLS) Regression for Modified Daily Reaction Functions

In this thesis in each step we analyze it is aimed to apply what we learn in these processes. For this aim we take benefit of related literature, results of the analysis above and theory of reaction function In order to analyze and forecast the dynamic structure of the modified daily reaction function and to see their effect on each other we will perform Vector-Auto Regression (VAR) and Multivariate-Garch (M-Garch) respectively. These two methods are commonly used in Central Bank intervention literature such as Dominguez (1998), Caskurlu et al. (2007), Seerattan (2012), Baillie and Osterberg (1997), Song (2009), Beine (2007) and Echavarría (2013). Before applying VAR and M-Garch, to get a benchmark and capture another variable in reaction function theory a standard OLS is applied to modified daily reaction function. All applications are handled by using E-views 6.

Ordinary least square is a way of estimating the unknown parameters in a linear regression model. This method simply minimizes the sum of squared vertical distances between observed responses in the dataset and the responses predicted by the linear approximation. Because simplicity of the model we try to add a new variable to this function. As it is mentioned above we have to adopt the data into daily form by using proper variables. However we disregard growth variable considering the early reaction function theory. There are two basic reasons. First it is difficult to find a variable which can represent GDP growth in daily based form. Second when aim of central bank is underlined effect of central banks' effect on growth is a debatable issue. Generally the prior aim of central bank is defined as price stability. Because of this we disregard the effect of growth on central bank intervention in modified daily reaction function. But in order to not to leave any missing variable behind we add a dummy variable to analyze the effect of GDP growth on central bank interventions both for interest rate and exchange rate interventions. In order to get a dummy variable average GDP growth rate of Turkey is taken during the years 2002-201 and found as % 5,1. This ratio is compared to each year's own GDP and if existing GDP growth rate is more than % 5,1 everyday of that year is accepted as 1 and if it is less than % 5,1 everyday of that year is accepted as 0 and added as a dummy variable representing GDP effect on central bank intervention. Thus we run a standard OLS regression considering modified daily reaction function and add a dummy variable which help us to analyze the effect of GDP.

The new version of interest rate reaction function for OLS can be rewritten as:

$$\text{CBO} = a + b(\pi - \pi^{*}) + b_2\Delta er_t + \ b_3\Delta i_t + dummy$$

Where CBO is the overnight interest rate of CBRT, a is constant, $(\pi - \pi^{*})$ is the difference between benchmark interest rate (in order to represent inflation) and target inflation of CBRT, Δer_t is the volatility of USD/TL exchange rate, Δi_t is the volatility of interest rate and dummy is the dummy variable for GDP.

And the second reaction for exchange rate intervention for OLS can be rewritten as:

$$er_t = a + b(\pi - \pi^{*}) + b_2\ \Delta er_t + b_3\Delta i_t + dummy$$

where is er_t is the interest rate, a is constant, $(\pi - \pi^{*})$ is the difference between benchmark interest rate (in order to represent inflation) and target inflation of CBRT, Δer_t is the volatility of USD/TL exchange rate, Δi_t is the volatility of interest rate and dummy is the dummy variable for GDP.

Before running a standard OLS, unit root tests are performed regarding different techniques. Result of unit root tests let us analyze whether the variables are stationary or not. This is crucial to model long term variables. Result of these test are also used for VAR and M-Garch analyses. Results of the unit root tests are given in Table C-1 at Appendix C.Acccording to Augmented Dickey-Fuller, Phillips-Perron and Kwiatkowski-Phillips-Schmidt-Shin test statistics, it is concluded that interest rate of CBRT (CMB_IR) and volatility of USD/TL (USD/TL) exchange rate are stationary. On the other hand the difference between benchmark interest rate and target inflation, USD/TL exchange rate and volatility of benchmark interest rate are non-stationary. In order to come over this problem we will use the first difference of these variables which are stationary as it is shown in the Table C-1 at Appendix C. First differences of these variables are represented as DBNCH_TARGET_INFLATION, DBRATE_VOL and DLUSDTL. In this part we have two OLS regressions which cover interest rate and exchange rate modified daily reaction functions.

TABLE 10 Regression results For Modified Daily Reaction Function of Interest Rate of CBRT

Constant	0.035 (0.009)
Dbnch_Target_Inflation	-0.092 (0.597)
Dbrate_Vol	3.487 (26.021)
Usdtl_Vol	7.399*** (1.175)
Dummy	0.106*** (0.009)
R-squared Adjusted R-squared	0.188 0.187
2740 Observations HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 9.0000)	

Standard errors are reported in parentheses,

*,**, *** indicates significance at the 90%, 95 % and 99 % level respectively

As it is seen in the Table 10, USD/TL and Dummy variable (covers GDP effect) are significant to explain the changes in interest rate of CBRT. This is in line with related literature. However as it is seen R-square and Adjusted R-square ratios the variables can only explain a small portion of changes in interest rate of CBRT. Next we re-run the OLS regression for exchange rate of DLUSD/TL.

TABLE 11 Regression results For Modified Daily Reaction Function Exchange Rate

Constant	0.000 (0.000)
Dbnch_Target_Inflation	0.055** (0.027)
Dbrate_Vol	0.805 (0.822)
USDTL_Vol	0.005 (0.073)
Dummy	-0.000 (0.000)
R-squared Adjusted R-squared	0.002366 0.000907
2740 Observations HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 9.0000)	

Standard errors are reported in parentheses,

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

As it is seen in the table 11 the only significant variable is the difference between benchmark interest rate and target inflation in order to explain USD/TL. However again, as it is seen R-square and adjusted R-square ratios the variables can only explain a small portion of changes in USD/TL exchange rate. More ever when two regressions is compared GDP based dummy is significant for interest rate of CBRT however the same dummy is not significant for USD/TL. Next in OLS regression the difference between benchmark and target inflation is the only variable which is significant for USD/TL. On the other hand, dummy and USD/TL volatility are significant variables for interest of CBRT. These feedbacks are important however we should gather more detailed information to get better insights. Thus in order to see the relations among these variables we need a more sophisticated and sensitive analysis.

5.5 Vector Auto Regression for Modified Daily Reaction Function of Interest of CBRT and Exchange Rate

This thesis has a progressive way and tries to fill the gaps and shortages of the previous chapter to get a better insights and analysis to understand the relations among variables considering modified daily reaction function. Vector Auto Regression (VAR) models analyze dynamic behaviours of variables. Litterman (1979), Sims (1980) and Doan et al. (1984) in their pioneering papers developed this methodology. This model treats all variables as priori endogenous. VAR models are useful for also forecasting. Their formation capture current values a set of variables are explained by past values of the variables in the model. VAR models are also useful for economic analysis. Because VAR models explain the joint generation mechanism of the variables involved. Granger causality tests, impulse response analysis and variance decomposition tests complete the other analysis related to VAR specifications. In VAR models each variable estimated with its own lagged variables and lagged variables of other variables. In OLS Regression part, unit root tests are already performed. We have again two different VAR models considering modified daily reaction functions and interest rate of CBRT and exchange rate (USD/TL) as:

$$\mathrm{CBO} = a + b(\pi - \pi^{*}) + b_2 \Delta er_t + b_3 \Delta i_t$$

and

$er_t = a + b(\pi - \pi^*) + b_2\ \Delta er_t + b_3 \Delta i_t$

In this VAR model CMB_IR stands for interest rate of CBRT (CBO), DBNCH_TARGET_INFLATION stands for (first difference of) difference of benchmark interest rate target inflation$(\pi - \pi^*)$, DBRATE_VOL stands for first difference of benchmark interest rate volatility (Δi_t), USDTL_VOL stands for USD/TL exchange rate volatility (Δer_t) and DLUSDTL stands for first difference of USD/TL exchange rate (er_t). In VAR model proper lag length for variable is determined by Akaike information criterion Schwarz information criterion and Hannan-Quinn information criterion. Both Akaike information criterion and Hannan-Quinn information criterion supported seventh lags of variables should be considered. Related VAR Lag Order Selection Criteria Table is given at Appendix C in Table C-2.

5.5.1 Vector Auto Regression for Modified Daily Reaction Function for Interest of CBRT

VAR results for interest rate of CBRT are given below in Table 12. Results give important insights for the variables. In the first phase our priority is to analyze relation between interest rate of CBRT and other variables. As it is observed in the Table 12 first lagged of interest rate of CBRT, first, second, third, fourth, fifth and seventh lagged of difference of benchmark interest rate and target inflation and fourth lagged of volatility of benchmark interest rate significantly affect the interest rate of CBRT. This finding is crucial for the thesis progress. Because we adopt difference of benchmark interest rate and target inflation variable based on reaction function theory and modify it regarding daily based data. According to results of

VAR analysis we understand that this adoption and modification is proper and significant. Another important result of VAR results R-square and Adjusted R-Square ratio increased when these results compared to OLS regression.

TABLE 12 VAR Results for Modified Daily Reaction Function for Interest Rate of CBRT

Vector Autoregression Estimates
Included observations: 2733 after adjustments

	CMB_IR	DBNCH_TARGET_INFLATION	DBRATE_VOL	USDTL_VOL
CMB_IR(-1)	0.968643	-0.031641	0.000507	1.68E-05
	(0.01933)	(0.06697)	(0.00188)	(0.00236)
	[50.1123]* **	[-0.47248]	[0.26979]	[0.00713]
CMB_IR(-2)	-0.000332	0.132037	-0.001774	-0.000864
	(0.02690)	(0.09321)	(0.00261)	(0.00328)
	[-0.01235]	[1.41650]	[-0.67881]	[-0.26349]
CMB_IR(-3)	-0.002251	-0.099479	0.003192	-0.001867
	(0.02689)	(0.09316)	(0.00261)	(0.00328)
	[-0.08371]	[-1.06783]	[1.22205]	[-0.56991]
CMB_IR(-4)	0.007693	0.003416	-0.002393	0.005353
	(0.02686)	(0.09307)	(0.00261)	(0.00327)
	[0.28636]	[0.03671]	[-0.91692]	[1.63535]
CMB_IR(-5)	-0.000583	0.028168	-0.000160	-0.000218
	(0.02685)	(0.09303)	(0.00261)	(0.00327)
	[-0.02171]	[0.30279]	[-0.06129]	[-0.06665]
CMB_IR(-6)	0.004140	-0.111536	0.000712	-0.004558
	(0.02633)	(0.09122)	(0.00256)	(0.00321)
	[0.15723]	[-1.22271]	[0.27851]	[-1.42080]
CMB_IR(-7)	0.020991	0.079256	-8.39E-05	0.002170
	(0.01844)	(0.06388)	(0.00179)	(0.00225)
	[1.13852]	[1.24075]	[-0.04685]	[0.96603]
DBNCH_TARGET_INFLATION(-1)	0.010066	0.032885	0.000801	0.001567
	(0.00558)	(0.01934)	(0.00054)	(0.00068)
	[1.80322]*	**[1.70026]***	[1.47695]	**[2.30296]** **
DBNCH_TARGET_INFLATION(-2)	0.019418	-0.059130	0.002274	-0.000565
	(0.00559)	(0.01938)	(0.00054)	(0.00068)
	[3.47188]* **	**[-3.05146]*** **	**[4.18507]*** **	[-0.82860]
DBNCH_TARGET_INFLATION(-3)	0.023180	0.067289	0.000613	0.000861
	(0.00560)	(0.01941)	(0.00054)	(0.00068)
	[4.13796]* **	**[3.46709]*** **	[1.12622]	[1.26114]
DBNCH_TARGET_INFLATION(-4)	0.012341	-0.064023	0.000468	0.000621
	(0.00561)	(0.01944)	(0.00055)	(0.00068)

	[2.19891]**	**[-3.29253]*****	[0.85846]	[0.90737]
DBNCH_TARGET_INFLATION(-5)	0.016206	-0.031492	0.000261	0.000801
	(0.00561)	(0.01944)	(0.00054)	(0.00068)
	[2.88870]***	[-1.62022]	[0.47876]	[1.17203]
DBNCH_TARGET_INFLATION(-6)	-0.000955	-0.015178	-0.000956	-0.000882
	(0.00560)	(0.01940)	(0.00054)	(0.00068)
	[-0.17062]	[-0.78246]	**[-1.75736]***	[-1.29299]
DBNCH_TARGET_INFLATION(-7)	0.015454	0.022894	0.001663	0.000398
	(0.00556)	(0.01925)	(0.00054)	(0.00068)
	[2.78093]***	[1.18905]	**[3.08068]*****	[0.58822]
DBRATE_VOL(-1)	0.032407	1.762914	0.093494	0.284258
	(0.19592)	(0.67878)	(0.01903)	(0.02387)
	[0.16541]	**[2.59720]****	**[4.91244]*****	**[11.9069]*****
DBRATE_VOL(-2)	0.329348	0.540816	0.115743	-0.002084
	(0.20146)	(0.69797)	(0.01957)	(0.02455)
	[1.63483]	[0.77484]	**[5.91422]*****	[-0.08488]
DBRATE_VOL(-3)	-0.033822	-2.277298	-0.010405	0.004230
	(0.20160)	(0.69846)	(0.01958)	(0.02457)
	[-0.16777]	**[-3.26046]*****	[-0.53129]	[0.17220]
DBRATE_VOL(-4)	-0.705619	0.071659	-0.001237	-0.015337
	(0.20194)	(0.69965)	(0.01962)	(0.02461)
	[-3.49414]***	[0.10242]	[-0.06305]	[-0.62325]
DBRATE_VOL(-5)	0.124881	2.030639	0.070436	-0.003259
	(0.20240)	(0.70123)	(0.01966)	(0.02466)
	[0.61700]	**[2.89582]*****	**[3.58238]*****	[-0.13216]
DBRATE_VOL(-6)	0.302451	-0.190112	0.047574	-0.043070
	(0.20112)	(0.69681)	(0.01954)	(0.02451)
	[1.50380]	[-0.27283]	**[2.43495]****	**[-1.75739]***
DBRATE_VOL(-7)	-0.243132	-1.892209	0.136051	-0.005324
	(0.20040)	(0.69432)	(0.01947)	(0.02442)
	[-1.21321]	**[-2.72529]****	**[6.98849]*****	[-0.21803]
USDTL_VOL(-1)	0.058261	-0.684477	0.031096	1.082374
	(0.15794)	(0.54719)	(0.01534)	(0.01925)
	[0.36888]	[-1.25089]	**[2.02680]****	**[56.2407]*****
USDTL_VOL(-2)	-0.001897	1.182864	-0.013388	-0.064934
	(0.23162)	(0.80248)	(0.02250)	(0.02822)
	[-0.00819]	[1.47401]	[-0.59498]	**[-2.30063]***
USDTL_VOL(-3)	0.003110	-0.872527	-0.018553	0.056502
	(0.23133)	(0.80146)	(0.02247)	(0.02819)
	[0.01344]	[-1.08868]	[-0.82561]	**[2.00446]****
USDTL_VOL(-4)	0.026369	0.380466	0.018976	-0.004817
	(0.23148)	(0.80199)	(0.02249)	(0.02821)
	[0.11391]	[0.47440]	[0.84388]	[-0.17078]
USDTL_VOL(-5)	0.011064	0.353568	-0.027661	0.094460
	(0.23133)	(0.80145)	(0.02247)	(0.02819)
	[0.04783]	[0.44116]	[-1.23091]	**[3.35108]*****

USDTL_VOL(-6)	-0.213575	-0.144293	0.013198	-0.144790
	(0.23147)	(0.80193)	(0.02249)	(0.02821)
	[-0.92271]	[-0.17993]	[0.58697]	**[-5.13349]*** **
USDTL_VOL(-7)	0.117018	-0.256634	-0.003955	-0.023098
	(0.15771)	(0.54641)	(0.01532)	(0.01922)
	[0.74196]	[-0.46967]	[-0.25813]	[-1.20187]
C	9.79E-05	0.000218	6.82E-07	2.86E-05
	(0.00010)	(0.00035)	(9.7E-06)	(1.2E-05)
	[0.97799]	[0.62821]	[0.07019]	[2.34787]
R-squared	0.999719	0.027623	0.089404	0.995773
Adj. R-squared	0.999716	0.017554	0.079975	0.995729
F-statistic	343518.2	2.743377	9.481543	22749.30

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

Standard errors in displayed in ( ) and t-statistics displayed in [ ]

Graph of Residuals, Serial Correlation of LM test results, Normality test of Jarque-Bera is given in Tables C-3, C-4 and C-5 respectively at Appendix C.

In this thesis we mention that some additional test complete VAR analysis. Next analysis is Granger Causality test which provides extra information that we gather from VAR analysis. Granger (1963) in his paper introduces this methodology. These tests are statistical hypothesis test to decide whether one time series is proper to forecast another or not. Result of Granger Causality tests are given below in Table 13.

TABLE 13 Pairwise Granger Causality Tests for Modified Daily Recation Function for Interest Rate of CBRT

Cause → Result	F-Test	Prob.
DBNCH_TARGET_INFLATION → CMB_IR	7.55205	5.E-09***
DBRATE_VOL→ CMB_IR	2.67463	0.0093***
DBRATE_VOL → DBNCH_TARGET_INFLATION	3.86094	0.0003***
DBNCH_TARGET_INFLATION→ DBRATE_VOL	5.25332	6.E-06***
DBNCH_TARGET_INFLATION→ USDTL_VOL	1.96809	0.0557*
DBRATE_VOL → USDTL_VOL	21.4849	2.E-28***

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

As it is observed in Table 13, Granger Causality Tests imply that there exists one-way causality from the variable of difference of benchmark interest rate and target inflation to interest rate of CBRT. This is in line with the findings of VAR. More over there is another one-way causality is also founded from volatility of benchmark interest rate to interest rate of CBRT. This finding is also in line with VAR analysis and our expectations from the reaction function theory. Other significant causalities are also given in the table. There is a reciprocal causality relation among volatility of benchmark interest rate and difference of benchmark interest rate and target inflation. Finally there exists one-way causality from difference of benchmark interest rate and target inflation and volatility of benchmark interest rate to volatility of USD/TL exchange rate.

Another analysis which completes VAR analysis is impulse response functions. These functions display the effects of shocks on the adjustment path of the variables. Impulse response function is a dynamic system it presents its output with a input signal which is called as impulse. This impulse response indicates a reaction of any dynamic system in response to some external change or shock. Figure of these functions regarding variable couples are given in Figure C-1 at Appendix C.

In this figure we basically underline the variable couples which involve interest rate of CBRT. As it is displayed in the first figure, reaction of interest rate of CBRT to difference of benchmark interest rate and target inflation is considerable. A change in difference of benchmark interest rate and target inflation affects the interest rate of CBRT from the first day of the change and creates a new equilibrium in following days. After eleven days a new equilibrium is set. A change or shock can be derived from two reasons. This might be caused by the change or shock in the benchmark interest rate or target inflation. This is crucial finding because in this finding implicitly if the expectations change regarding the difference of benchmark interest rate and target inflation interest rate of CBRT adopts itself to new expectations and stay in this new equilibrium for a long time as it is observed from the figure.

In the second figure reaction of interest rate of CBRT to volatility of benchmark is displayed. This figure does not look like the previous figure. When a change or shock happens in volatility of benchmark interest rate, interest rate of CBRT gives a response in the third day of the change and starts to fluctuate around its own path. We do not observe this fluctuation in the previous shock which is derived by difference of benchmark interest rate and target inflation. Thus the content of the variable which is based on volatility cause a fluctuation in interest rate of CBRT. Even the effect of this change is not significant when it is compared to change in difference of benchmark interest rate and target inflation, it is clear that time of adjustment takes more time.

In the third figure reaction of interest rate of CBRT to volatility of USD/TL is shown. When we compare this figure with two previous ones we again face a new picture. The reaction of interest rate of CBRT is also limited when it is compared to change in difference of benchmark interest rate and target inflation. However in this figure again CBRT gives a response in the third day of the change and starts to fluctuate around its own path which looks like its reaction we observed in volatility of benchmark. Moreover interest rate of CBRT finds its new equilibrium in the eight day of change and do not turn back its previous path. Thus a change or shock in volatility of USD/TL exchange rate creates a combined effect of difference of benchmark interest rate and target inflation and volatility of benchmark on interest rate of CBRT. These results are also in line with VAR results of interest rate of CBRT. It is clear that CBRT is more sensitive to changes in difference of benchmark interest rate and target inflation rather than volatility of benchmark and volatility of USD/TL exchange rate.

Finally considering VAR analysis our last test which is related to interest rate of CBRT is variance decomposition test. Variance decomposition is aimed to help in the comment of a VAR model once it has been fitted. This test display that the amount of information each variable contributes to other variables in the auto regression. It determines how much of the forecast error variance of each of the variables can be explained by exogenous shocks to other variables.

Results of the variance decomposition test results are given in Table C-6 at Appendix C. As it is observed in Table C-6 at Appendix C, change in interest rate of CBRT is mostly sensitive to itself but as the time proceeds its sensitivity to change is started to affected by difference of benchmark interest rate and target inflation (up to 6 %). This result is also in line with the analysis we referred above.

5.5.2 Vector Auto Regression for Modified Daily Reaction Function for Exchange Rate

In this part we will apply the same VAR analysis procedure for USD/TL exchange rate. Finding of the results contribute to understanding of the CBRT intervention behavior. Up to this part we apply what we learnt in previous sections. In the first phase our priority is to analyze relation between USD/TL exchange rate and other variables. DLUSD/TL is the first difference of USD/TL exchange rate. We realized that transformation after unit root tests were handled. Firstly as it is observed in Table 14, fifth lagged of USD/TL exchange rate, first and second lagged of difference of benchmark interest rate and target inflation, first and second lagged of volatility of benchmark interest rate, first, second, third and fifth lagged of volatility of USD/TL significantly affect the USD/TL exchange rate. Secondly R-Square and

Adjusted R-Square ratios increased significantly when these ratios are compared to OLS regressions. However R-Square and Adjusted R-Square ratios of exchange rate are considerably less than the ratios for interest rate of CBRT.

TABLE 14 VAR Results For Modified Daily Reaction Function For Exchange Rate

Vector Autoregression Estimates
Sample (adjusted): 4/16/2002 2/28/2013
Included observations: 2733 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	DLUSDTL	DBNCH_TARGET_INFLATION	DBRATE_VOL	USDTL_VOL
DLUSDTL(-1)	0.027104	-0.007547	5.63E-05	0.001110
	(0.01927)	(0.01647)	(0.00046)	(0.00057)
	[1.40629]	[-0.45813]	[0.12184]	**[1.93874]****
DLUSDTL(-2)	0.006521	-0.006216	0.000665	-0.000210
	(0.01926)	(0.01646)	(0.00046)	(0.00057)
	[0.33858]	[-0.37759]	[1.44178]	[-0.36628]
DLUSDTL(-3)	0.021618	0.014844	0.000155	0.001365
	(0.01923)	(0.01644)	(0.00046)	(0.00057)
	[1.12402]	[0.90302]	[0.33587]	[2.38882]
DLUSDTL(-4)	0.025501	-0.002367	0.000199	0.002701
	(0.01925)	(0.01645)	(0.00046)	(0.00057)
	[1.32466]	[-0.14386]	[0.43196]	**[4.72182]*****
DLUSDTL(-5)	-0.040426	0.020487	0.000198	0.002938
	(0.01926)	(0.01646)	(0.00046)	(0.00057)
	[-2.09904]**	[1.24461]	[0.42886]	**[5.13344]*****
DLUSDTL(-6)	-0.026684	0.008528	0.000333	0.000517
	(0.01935)	(0.01653)	(0.00046)	(0.00057)
	[-1.37933]	[0.51580]	[0.71803]	[0.89966]
DLUSDTL(-7)	0.013220	0.017483	9.82E-05	-0.001507
	(0.01790)	(0.01530)	(0.00043)	(0.00053)
	[0.73867]	[1.14294]	[0.22899]	**[-2.83345]*****
DBNCH_TARGET_INFLATION(-1)	0.479370	0.031171	0.000833	0.001499
	(0.02249)	(0.01922)	(0.00054)	(0.00067)
	[21.3174]***	[1.62186]	[1.54648]	**[2.24328]****
DBNCH_TARGET_INFLATION(-2)	-0.054151	-0.052363	0.002175	-0.001041
	(0.02431)	(0.02078)	(0.00058)	(0.00072)
	[-2.22776]**	**[-2.52043]****	**[3.73470]*****	[-1.44129]
DBNCH_TARGET_INFLATION(-3)	0.007050	0.069617	0.000358	0.000859
	(0.02427)	(0.02075)	(0.00058)	(0.00072)
	[0.29044]	**[3.35549]*****	[0.61568]	[1.19137]

DBNCH_TARGET_INFLATION(-4)	0.006820	-0.069633	0.000406	-7.94E-05
	(0.02429)	(0.02076)	(0.00058)	(0.00072)
	[0.28076]	**[-3.35427]***	[0.69716]	[-0.11000]
DBNCH_TARGET_INFLATION(-5)	-0.023869	-0.027633	0.000164	-0.000461
	(0.02424)	(0.02072)	(0.00058)	(0.00072)
	[-0.98467]	[-1.33375]	[0.28274]	[-0.64005]
DBNCH_TARGET_INFLATION(-6)	0.004626	-0.025778	-0.001049	-0.002301
	(0.02422)	(0.02070)	(0.00058)	(0.00072)
	[0.19099]	[-1.24523]	**[-1.80807]***	**[-3.19694]***
DBNCH_TARGET_INFLATION(-7)	-0.007356	0.019532	0.001500	0.000313
	(0.02421)	(0.02069)	(0.00058)	(0.00072)
	[-0.30387]	[0.94401]	**[2.58707]**	[0.43520]
DBRATE_VOL(-1)	1.331300	1.719534	0.092733	0.284049
	(0.79485)	(0.67934)	(0.01904)	(0.02362)
	[1.67491]*	**[2.53117]**	**[4.86970]***	**[12.0265]***
DBRATE_VOL(-2)	-1.714053	0.596872	0.116238	-0.004487
	(0.81708)	(0.69834)	(0.01958)	(0.02428)
	[-2.09779]	[0.85470]	**[5.93792]***	[-0.18482]
DBRATE_VOL(-3)	0.238403	-2.270499	-0.010207	0.003947
	(0.81803)	(0.69916)	(0.01960)	(0.02431)
	[0.29144]	**[-3.24749]**	[-0.52080]	[0.16240]
DBRATE_VOL(-4)	0.703728	0.084973	-0.000696	-0.016264
	(0.81922)	(0.70017)	(0.01963)	(0.02434)
	[0.85903]	[0.12136]	[-0.03547]	[-0.66812]
DBRATE_VOL(-5)	-0.339400	2.089852	0.070307	-0.002072
	(0.81931)	(0.70025)	(0.01963)	(0.02435)
	[-0.41425]	**[2.98442]***	**[3.58179]***	[-0.08510]
DBRATE_VOL(-6)	0.558605	-0.311994	0.048338	-0.038250
	(0.81432)	(0.69599)	(0.01951)	(0.02420)
	[0.68597]	[-0.44827]	**[2.47764]**	[-1.58074]
DBRATE_VOL(-7)	0.080237	-1.868467	0.134813	-0.001396
	(0.81120)	(0.69332)	(0.01943)	(0.02410)
	[0.09891]	**[-2.69496]***	**[6.93675]***	[-0.05793]
USDTL_VOL(-1)	2.516698	-0.759589	0.027773	1.066872
	(0.64762)	(0.55351)	(0.01552)	(0.01924)
	[3.88605]*	[-1.37231]	**[1.79003]***	**[55.4398]***
USDTL_VOL(-2)	-4.722917	1.124796	-0.012401	-0.053569
	(0.94103)	(0.80428)	(0.02255)	(0.02796)
	[-5.01888]*	[1.39851]	[-0.55005]	**[-1.91576]***
USDTL_VOL(-3)	2.817623	-0.801368	-0.018999	0.064082
	(0.94294)	(0.80591)	(0.02259)	(0.02802)
	[2.98813]*	[-0.99436]	[-0.84099]	**[2.28709]**
USDTL_VOL(-4)	0.781519	0.369007	0.022781	-0.017929
	(0.94559)	(0.80818)	(0.02265)	(0.02810)

	[0.82649]	[0.45659]	[1.00558]	[-0.63809]
USDTL_VOL(-5)	-2.574361	0.455822	-0.029436	0.095680
	(0.94444)	(0.80719)	(0.02263)	(0.02806)
	[-2.72581]*	[0.56470]	[-1.30095]	**[3.40940]***
USDTL_VOL(-6)	1.436980	-0.222926	0.013281	-0.131200
	(0.94639)	(0.80886)	(0.02267)	(0.02812)
	[1.51838]	[-0.27560]	[0.58575]	**[-4.66546]***
USDTL_VOL(-7)	-0.248424	-0.207689	-0.003334	-0.028247
	(0.64300)	(0.54956)	(0.01540)	(0.01911)
	[-0.38635]	[-0.37792]	[-0.21645]	[-1.47842]
C	9.82E-05	0.000253	8.19E-07	3.32E-05
	(0.00037)	(0.00032)	(8.9E-06)	(1.1E-05)
	[0.26516]	[0.79858]	[0.09233]	[3.02025]
R-squared	0.165000	0.027618	0.089884	0.995870
Adj. R-squared	0.156353	0.017549	0.080459	0.995827
F-statistic	19.08296	2.742846	9.537437	23283.95

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

Standard errors in displayed in ( ) and t-statistics displayed in [ ]

Graph of Residuals, Serial Correlation of LM test results, Normality test of Jarque-Bera is given in Table C-7, C-8 and C-9 respectively at Appendix C.

As a second step of VAR analysis Granger Causality tests are performed for the pairs of variables. Result of Granger Causality tests are given below. According to Table 15, Granger Causality Tests imply that there exists one-way causality from the variable of difference of benchmark interest rate and target inflation to USD/TL exchange rate. This finding is also ratifies the adoption and modification of daily reaction function of this thesis. Next there is one-way causality from USD/TL exchange rate to volatility of benchmark interest rate. Moreover it is clear that there is reciprocal causality between volatility of USD/TL exchange rate and USD/TL exchange rate. Besides that there is also reciprocal causality between volatility of benchmark and difference of benchmark interest rate and target inflation. Finally there is one- way causality from difference of benchmark interest rate and target inflation and volatility of benchmark interest rate to volatility of USD/TL exchange rate.

TABLE 15 Pairwise Granger Causality Tests for Modified Daily Recation for Exchange Rate

Cause → Result	F-Test	Prob.
DBNCH_TARGET_INFLATION → DLUSDTL	67.5094	4.E-90***
DLUSDTL → DBRATE_VOL	1.93412	0.0605*
USDTL_VOL → DLUSDTL	5.32707	5.E-06***
DLUSDTL → USDTL_VOL	8.83093	9.E-11***
DBRATE_VOL→ DBNCH_TARGET_INFLATION	3.86094	0.0003***
DBNCH_TARGET_INFLATION→ DBRATE_VOL	5.25332	6.E-06***
DBNCH_TARGET_INFLATION → USDTL_VOL	1.96809	0.0557*
DBRATE_VOL→ USDTL_VOL	21.4849	2.E-28***

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

Thirdly impulse response functions are considered for USD/TL exchange rate. It is mentioned above that impulse reactions functions display the effects of shocks on the adjustment path of the variables. Figure of these functions regarding variable couples are given in Figure C-2 at Appendix C.

In the first figure USD/TL exchange rate gives a response in the first day of a change or shock in difference of benchmark interest rate and target inflation. The response of USD/TL is strong in this phase.Then USD/TL fluctuates on its own path and normalizes in the ninth day. This response behavior is also in line with VAR results.

In the second figure USD/TL exchange rate gives a response in the first day of a change or shock in volatility of benchmark interest rate. However response power of this behavior is less than the reaction that is observed to change in difference of benchmark interest rate and target inflation. Then USD/TL fluctuates on its own path and normalizes in the ninth day again. However fluctuation distance is also less than fluctuation is observed to the change in difference of benchmark interest rate and target inflation.

In the third figure USD/TL exchange rate gives a response in the first day of a change or shock in volatility of USD/TL exchange rate. The fluctuation distance is relatively higher when it is compared to response given to volatility of benchmark interest rate. Besides that normalization process takes longer time and it takes eleven day to catch its own way of USD/TL exchange rate.

Finally considering VAR analysis last test which is related to interest rate of CBRT is variance decomposition test. Results of the variance decomposition test results are given in Table C-10 at Appendix C. As it is observed in Table C-10 change in interest rate of USD/TL is mostly sensitive to itself but as the time proceeds its sensitivity to change is started to affected by difference of benchmark interest rate and target inflation (up to % 14). This result is also in line with the analysis we referred above.

5.6 M-GARCH Analysis of Modified Daily Reaction Function

Observation values of time series may change as the time proceeds. This change may occur as an increase or decrease. Economic, social and physiological affects are prominent reasons of the intensity and way differences on data patterns. These data patterns are classified into four groups as trend, cyclical, seasonal and irregular. Time series may be under the effect of one or more components of these four dimensions. Cyclical fluctuations which are observed around trend is generally called as volatility. There are many different reasons of volatility such as economic, cultural, seasonal, unexpected events, crisis or shocks. Volatilities and correlations are important factors of economic and financial analysis. The leading paper of Engel (1982) introduces autoregressive conditional heteroskedasticity (ARCH) model and analyzes univariate volatility modeling. Paper of Bollerslov (1986) generalizes ARCH (GARCH) model. Since the introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) ARCH and later GARCH family models have become the most widely used tool for modeling volatility in financial time series. Multivariate GARCH models have been broadly used to investigate volatility transmission and spillover effects.

As Song (2009) mentions univariate ARCH/GARCH models are proved to be very powerful in explaining the stylized facts of univariate time series. However researchers find them unsatisfactorily incapable to examine the characteristics of multivariate time series simultaneously. Scholars are more concerned about the relationships between volatilities of several markets or assets and variance–covariance matrices of various portfolios, univariate ARCH/GARCH models seem to be not applicable and therefore their multivariate generalization stands out to be the better solution. There are mainly two ways for modeling the multivariate time series, modeling the variance–covariance matrix directly and modeling the correlation between the time series indirectly. Bollerslev et al. (1988) propose the first multivariate GARCH model for the conditional variance–covariance matrix, namely the VEC model which is a very general model but difficult to apply. Bollerslev et al. (1988) introduce simple version of the VEC model, the Diagonal–VEC model. This model decreases the number of parameters and is relatively easier to detect the conditions to guarantee the positive definiteness of variance–covariance matrix.

On the other hand since the variance or covariance in the model is only the function of its past observations, it can not capture the interactions between different variance and covariance. Engle and Kroner (1995) propose the BEKK (Abbrevation of initials of the founders of the model) model which can be viewed as a restricted version of VEC model. BEKK model let conditional variance–covariance matrix is positive definite by construction. But the number of parameters in BEKK model increases rapidly with the dimension of the model. Another problem is that it is hard to interpret the coefficients of the model. As a next step the Diagonal–BEKK model and the Scalar–BEKK model are proposed. Diagonal–BEKK model has the same problem of Diagonal–VEC model, although it decreases the number of parameters greatly. After this brief information about M-garch model, we both apply and analyze the results for modified daily reaction function for interest rate of CBRT and USD/TL exchange rate.

5.6.1 M-GARCH Analysis of Modified Daily Reaction Function for Interest of CBRT

In order to analyze modified daily reaction function for interest rate of CBRT, Diagonal-BEKK specification of M-garch, underlined above, is performed. Results are given in Table C-11 and Table C-12 at Appendix C. Normality test is also given in this part in Table C-13. Average, variance and covariance equations are also given in Table C-14. Interest rate of CBRT is sensitive to both volatility spread of itself and volatility spread of other variables. In the model both conditional variance and covariance of variables affect each other. Conditional covariance, conditional correlation and conditional variance graphs are given in Table C-15, Table C-16 and Table C-17 at Appendix C. When these tables are examined, especially for interest rate of CBRT, it is clear that variance of interest rate of CBRT increases in 2002, 2003, 2006 and 2008. It is another result that conditional covariance and conditional correlation of interest rate of CBRT and difference of benchmark interest rate and target inflation also increases in 2002, 2003, 2006 and 2008. These two results also support the economic indicators because in those years in Turkey both interest rate and inflation have decreased. Moreover conditional covariance and conditional correlation of interest rate of

CBRT and volatility of Benchmark fluctuates. Both indicators have positive and negative relations in different years or even in the same year. This finding also supports the same pattern when conditional covariance of interest of CBRT and volatility of CBRT is analyzed. The sign of conditional covariance and conditional correlation of interest rate of CBRT and volatility of USD/TL exchange rate fluctuates and changes quickly when it is compared to volatility of benchmark interest rate.

In M-Garch Results C coefficients represent the constant terms, for the period of t, models of average, conditional variance and conditional covariance. A1 coefficients represent effect of previous period's volatility shocks to current period. B1 coefficients represent the effect of permanence of previous period's volatility.

All A coefficients are significant in the %99 level. Thus it implies that all variables involved in the function, is affected by their own previous volatility shocks. Their previous volatility shocks affect current volatility of the all variables. In other words all variables in the function are sensitive to their past volatility shocks. Volatility of USD/TL exchange rate and volatility of benchmark interest rate are most sensitive to their previous volatility shocks respectively. (A4=0.396288 for USD/TL and A3=0.392547). Thus if it is need to calculated if in t-1 period volatility of USD/TL exchange rate increases % 1 then, this creates or transposes 3.9 % change in t period of volatility USD/TL exchange rate. Interest rate of CBRT has the lowest coefficient and less sensitive to its previous volatility shocks. (A1=0,064160). Coefficient of difference of benchmark interest rate and target inflation A3 equals to 0.109618.

Secondly B coefficients are analyzed. As it is mentioned above B1 coefficients display the permanence of previous volatility shocks. All B coefficients are significant in % 99 level except for interest of CBRT. This is important finding. Because all variables are sensitive to and their previous volatility has a permanent effect on them. However this invalid for interest rate of CBRT. This finding is also in line with the result that is found for A coefficients. The highest B coefficient belongs to difference of benchmark interest rate and target inflation (B2=0.993478). Volatility of USD/TL exchange rate and volatility of benchmark interest rate follow it respectively.

Finally when we compare B coefficients to A coefficients, it is observed that B coefficients have higher values. Thus we can conclude that volatility shocks have permanent effect on variables in the function.

5.6.2 M-GARCH Analysis of Modified Daily Reaction Function for Exchange Rate

A similar M-GarcH analysis is also performed for USD/TL exchange rate. Tables of M-Garch analysis given in Table C-18 and Table C-19 .in Appendix C. Average, variance and covariance equations are also given in Table C-20. Residual Normality Test is also given in Table C-21.Dioganal VEC specifiation is used in this phase. The VEC model proposed by Bollerslev et al (1988) is a generalized version of the univariate GARCH model to the multivariate case. Every conditional variance and covariance is a function of all lagged conditional variances and covariances, as well as lagged squared returns and cross–products of returns. BEKK model is in fact a restricted version of the VEC model which is applied for daily reaction function of interest rate.

USD/TL exchange rate is sensitive to both volatility spread of itself and volatility spread of other variables. In the model both conditional variance and covariance of variables affect each other. Conditional covariance, conditional correlation and conditional variance graphs are given in Table C-22, Table C-23 and Table C-24 at Appendix C. When these tables are examined, especially for interest rate of USD/TL exchange rate, it is clear that variance of USD/TL exchange rate increases in 2002, 2006, 2007 and 2008. However we should underline that increase in 2008 is severe. This finding has an economic background considering the financial crisis in the world in 2008.

Secondly conditional covariance between USD/TL exchange rate and difference of benchmark interest rate and target inflation fluctuate frequantley and the picture they form can be generalized as volatile. Moreover conditional covariance of USD/TL exchange rate and volatility of benchmark interst rate have a high observation value. Especially after 2008 this ratio sharply increases. Next conditional covariance between USD/TL exchange rate and volaitility of USD/TL exchange rate acts in the same channel. However this tendency is disturbed in 2008 the relation among them becames volatile for 2008.

Thirdly when conditional correlations are analyzed, the conditional correlation between USD/TL exchange rate and difference of benchmark interest rate and target inflation is very volatile. This relation has reached its highest value in 2006, 2008 and 2011. Next conditional correlation between USD/TL exchange rate and volatility of benchmark interest graph looks like the same relation between two variables considering the conditional covariance. Conditional correlation of USD/TL exchange rate and volatility of benchmark fluctuates in a certain channel up to 2008. After 2008 this relation increases sharply. Finally conditional correlation of USD/TL exchange rate and volaitility of USD/TL exchange rate acts very volatile in a certain channel however this pattern is also disturbed in 2008 sharply.

As it is mentined above in M-Garch Results C coefficients represent the constant terms, for the period of t, models of average, conditional variance and conditional covariance. A1 coefficients represent effect of previous period's volatility shocks to current period. B1 coefficients represent the effect of permanence of previous period's volatility. When Table C-19 is analyzed 16 of 20 of coefficients A and B are significant. 16 coefficients which are significant are significant in % 99 level.

Here we will examine A1(1,1), A1(2,2), A1(3,3), A1(4,4) and B1(1,1), B1(2,2),B1(3,3) and B1(4,4). All A coefficients are significant in the %99 level. Thus it implies that all variables involved in the function, is affected by their own previous volatility shocks. Their previous volatility shocks affect current volatility of the all variables. In other words all variables in the function are sensitive to their past volatility shocks. Volatility of benchmark interest rate and volatility of USD/TL exchange rate are most sensitive to their previous volatility shocks respectively (A3=0411433, A4=0.188812). USD/TL exchange rate has the third rank when four variables are considered among coefficients (A1=0.117423). Difference of benchmark interest rate and target inflation has the lowest coefficient and less sensitive to its previous volatility shocks (A2=0.011658)

Secondly B coefficients are analyzed. As it is mentioned above B1 coefficients display the permanence of previous volatility shocks. All B coefficients are significant in % 99 level. This is important finding. Because all variables are sensitive to and their previous volatility has a permanent effect on them. The highest B coefficient belongs to difference of benchmark interest rate and target inflation (B2=0.985871). USD/TL exchange rate and volatility of USD/TL exchange rate follow it respectively (B1=0.842214, B4=0.771681). Volatility of benchmark interest rate has the lowest coefficient and less sensitive permanence of previous volatility shocks.Finally when we compare B coefficients to A coefficients, it is observed that

B coefficients have higher values. Thus we can conclude that volatility shocks have permanent effect on variables in the function.

CHAPTER6

MODEL FOR TIME OF INTERVENTION BY USING DECISION TREES

In the above equations we can observe very different modifications of reaction functions. Indeed these equations both cover general theory and country specific features. The fragile part of these equations they bear the load of output data which is lagged variable such as inflation data. It is crucial that Central Banks interventions cover many different specific aims. In this thesis we take the general reaction equation as a base to develop and strengthen the framework of this thesis. Secondly we realize that we need to integrate daily data with this theory. Central Banks react and intervene the market by considering many financial and economic indicators.

Taylor rules and reaction functions teach us a basic lesson. If there is a divergence appears or a possibility of divergence appears in the market central banks intervene to fix this divergence. However it is very difficult to guess and detect this divergence by using lagged variables. What motivates us in this thesis is to use market data to follow the theoretical background of reaction functions. Thus we try to detect the divergence by calculating two differences. The first difference which we underline is between bench mark interest rate (daily market data) and target inflation (which is announced by Central Bank of Turkey). Secondly we also calculate the difference bench mark interest (daily market data) and interest rate of Central bank for overnight. By using these two differences we try to detect the divergence which can be replaced on behalf of the inflation variable in reaction functions ($\pi_t^- \pi_t^*$) or

$r = r^* + g(\pi - \pi^*)$.

By using these differences as variables in the data set, we try to capture the most highlighted variable of reaction functions. It should be noted that the model that we use and the data set we form are based on daily market data. Thus we follow the theoretical background of reaction functions by using daily data. The adoption and transformation of this process is provided by these differences which is reasonable and strong enough to represent (π_t- π_t^*) in the daily data set of the thesis. This thesis strongly underlines that by referring daily market indicators and following the basic idea of reaction functions; intervention of Central Bank of Turkey can be estimated. Difference of benchmark interest rate and target inflation of the Central Bank of Turkey (mean and volatility of this difference are also put into the data set). Difference benchmark interest rate and policy interest rate of Central Bank of Turkey (mean and volatility of this difference are also put into the data set). USDTL and EURTL exchange rate, Borsa Istanbul 100 Stock Index (XU100), Benchmark Interest Rate (BRATE), daily log return values are used as the leading indicators of the model. The outputs corresponding to these indicators of the entity are defined with four moments: average, volatility, skewness and kurtosis. This huge market data set enables us to analyze refractions of Central Bank of the Republic of Turkey's interventions in both interest rate market and exchange market.

Using daily data empowers the result of this thesis. As Menkhoff (2008) states that the analysis of central bank interventions in foreign exchange has entered new phase during the last few years by making use of high-frequency data and such intraday data is crucial to disentangle the impact of interventions from other determinants of exchange rates. Due to this new approach it has gained a much more precise understanding about the effect of interventions, which is also helpful for policy-makers.

In the above chapters as it mentioned by many scholars reaction functions carry the problems of lagged variables and calculation of two important variables of it which is about inflation and output calculation. In today's market structure it is difficult to analyze and decide to intervene the market considering the data which belong to three months or one month ago. By adding target inflation of the Central Bank of Turkey into data set and putting it in a form (difference of benchmark interest rate and target inflation of the Central Bank of Turkey) that which represent the reaction function is a contemporary market evaluation enables us to take a detailed and smooth picture of the conditions that trigger Central Bank of Rebuclic of Turkey to intervene or not. Thus daily data of the market/financial indicators are used in this thesis data set. Because volatility and other statistical behaviour of the variables affect the objective of the central bank and perception of the market players such as exchange rate, benchmark interest rate and exchange indices (Borsa Istanbul 100). Moreover moments of the variables are also added into data set which gives us a better insight to understand the decision behaviour of Central Bank of Turkey whether to intervene or not.

6.1. Data Set and Statistics of Data

As the Data Set, reliable official records of two sources Central Bank of Turkish Republic (CBRT) and Foreks Data Provider used. Data consists of the daily based leading indicator values between Jan 2, 2002 and Feb 28, 2013 used to predict currency and interest rate intervention of CBRT. In this data set the CBRT's currency and interest rate interventions are indicated with 1 in a separate intervention labeled column and non-intervention days were indicated with 0 of the same column. The distribution of data among its position in the 0-1 range that is used to indicate interventions, non- interventions and early warning segments are as follow. Each time series in the data set has 2741 days. There are 54 days with CBRT's intervention and 2687 days with non-intervention for interest rate and 26 days with CBRT's intervention for exchange rate and 2716 days with non-intervention for exchange rate market. Data preview is given appendix part D in Table D-1.

The data set is unbalanced and if we use the unbalanced data set, generated model has over fitted and overlearning problem. Thus, we use random sampling for non-intervention days to be balanced with intervention days. For example, we select all of intervention days (54 days) and almost 54 of non-intervention days are chosen randomly. For processing the data, the IBM SPSS Modeler 16 software have been used.

In the model DIFF_IR_INF displays the difference of benchmark interest rate and target inflation of the Central Bank of Turkey (mean and volatility of this difference are also put into the data set). DIFF_IR_CMB_IR displays the difference benchmark interest rate and policy interest rate of Central Bank of Turkey (mean and volatility of this difference are also put into the data set). USDTL and EURTL exchange rate, Borsa Istanbul 100 Stock Index (XU100), Benchmark Interest Rate (BRATE), daily log return values are used as the leading indicators of the model. The outputs corresponding to these indicators of the entity are defined with four moments: average, volatility, skewness and kurtosis. Each moment's estimate is calculated with a rolling window of the last three months (63-days rolling window). The model is consist of the six leading indicators' four moments with a moving 63-days window and these moments' one month (21-days) lags. In addition, we also use the level of daily log return values.

6.2. Decision Trees

Data mining can be defined as the process of extracting hidden patterns from large loads of data. The ambition of data mining can be knowledge discovery, prediction or forecasting. While knowledge discovery provides us explicit information about the characteristics of the data set predictive modeling provides predictions of future events. According to Simoudis (1996), data mining is the process of extracting valid, previously unknown, comprehensible and actionable information from large databases and using it to make business decisions.

The usage of decision tree analysis is relatively new. This analysis is substitute for multiple regression, discriminant analysis and logit regressions. The best advantage of the decision tree analysis, it does not involve any assumptions such multiple techniques do. Besides that decision tree methodology easily displays the relation and significance level between dependent and independent variables.

Decision analysis is a logical and systematic way to address a wide variety of problems involving decision-making in an uncertain environment. Rokach and Maimon (2009) defines decision tree as "a classifier expressed as a recursive partition of the instance space". The decision tree consists of nodes that form a rooted tree, meaning it is a directed tree with a node called "root" that has no incoming edges. All other nodes have exactly one incoming edge. A node with outgoing edges is called an internal or test node. All other nodes are called leaves, also known as terminal or decision nodes. In a decision tree, each internal node splits the instance space into two or more sub-spaces according to a certain discrete function of the input attributes values. In the simplest and most frequent case, each test considers a single attribute, such that the instance space is partitioned according to the attribute's value. In the case of numeric attributes, the condition refers to a range. Each leaf is assigned to one class representing the most appropriate target value. Alternatively, the leaf may hold a probability vector indicating the probability of the target attribute having a certain value. Instances are classified by navigating them from the root of the tree down to a leaf, according to the outcome of the tests along the path.

Decision trees are one of the methods of data classification. Under the name of the machine learning a lot of decision tree algorithms are developed. These algorithms are classified as entropy based, classification and regression trees and memory based classifications algorithms.

Rokach and Maimon (2009) summarizes the advantages of decision trees as the table below

TABLE 16 Advantages of Decision Trees

1. Decision trees are self–explanatory and when compacted they are also easy to follow. If the decision tree has a reasonable number of leaves, it can be grasped by non–professional users. Furthermore decision trees can be converted to a set of rules. Thus, this representation is considered as comprehensible.
2. Decision trees can handle both nominal and numeric input attributes.
3. Decision tree representation is rich enough to represent any discrete– value classifier.
4. Decision trees are capable of handling datasets that may have errors.
5. Decision trees are capable of handling datasets that may have missing values.
6. Decision trees are considered to be a nonparametric method. This means that decision trees have no assumptions about the space distribution and the classifier structure.

In case of numeric attributes, decision trees can be geometrically interpreted as a collection of hyper planes, each orthogonal to one of the axes. Naturally, decision-makers prefer less complex decision trees, since they may be considered more comprehensible. Furthermore, according to Breiman et al. (1984) the tree complexity has a crucial effect on its accuracy. The tree complexity is explicitly controlled by the stopping criteria used and the pruning method employed. Usually the tree complexity is measured by one of the following metrics: the total number of nodes, total number of leaves, tree depth and number of attributes used. Decision tree induction is closely related to rule induction. Each path from the root of a decision tree to one of its leaves can be transformed into a rule simply by conjoining the tests along the path to form the antecedent part, and taking the leaf's class prediction as the class value.

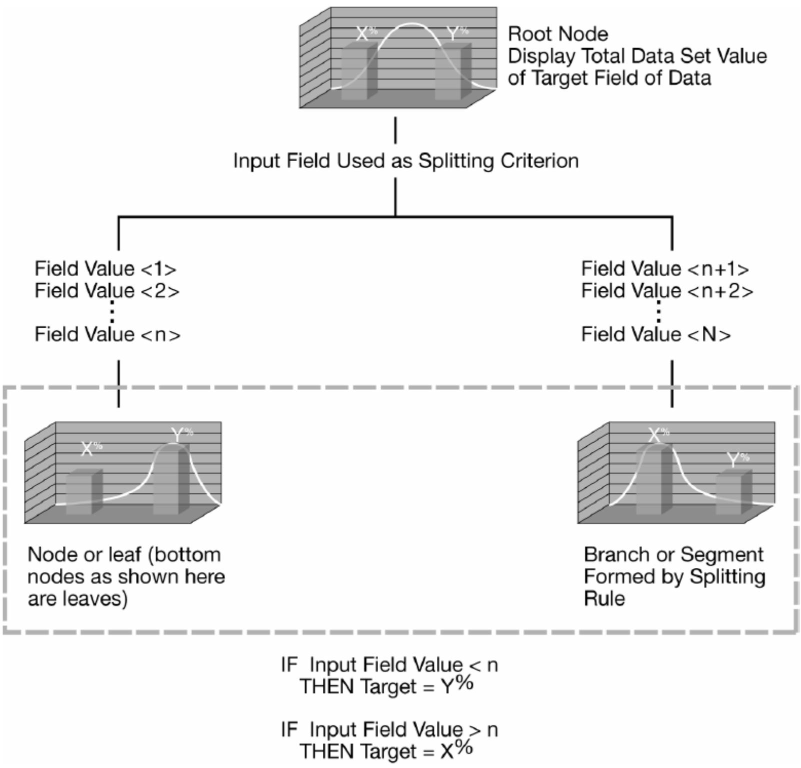
Decision tree inducers are algorithms that automatically construct a decision tree from a given dataset. Typically the goal is to find the optimal decision tree by minimizing the generalization error. However, other target functions can be also defined, for instance, minimizing the number of nodes or minimizing the average depth.

Decision trees are a simple, but powerful form of multiple variable analyses. They provide unique capabilities to supplement, complement, and substitute for traditional statistical forms of analysis (such as multiple linear regression) a variety of data mining tools and techniques (such as neural networks) and recently developed multidimensional forms of reporting and analysis found in the field of business intelligence Decision trees are produced by algorithms that identify various ways of splitting a data set into branch-like segments. These segments form an inverted decision tree that originates with a root node at the top of the tree. The object of analysis is reflected in this root node as a simple, one-dimensional display in the decision tree interface. The name of the field of data that is the object of analysis is usually displayed, along with the spread or distribution of the values that are contained in that field.

A sample decision tree is illustrated in Figure 3 which shows that the decision tree can reflect both a continuous and categorical object of analysis. The display of this node reflects all the data set records, fields, and field values that are found in the object of analysis. The discovery of the decision rule to form the branches or segments underneath the root node is based on a method that extracts the relationship between the object of analysis and one or more fields that serve as input fields to create the branches or segments. The values in the input field are used to estimate the likely value in the target field. The target field is also called an outcome, response, or dependent field or variable. The general form of this modeling approach is illustrated in Figure below.

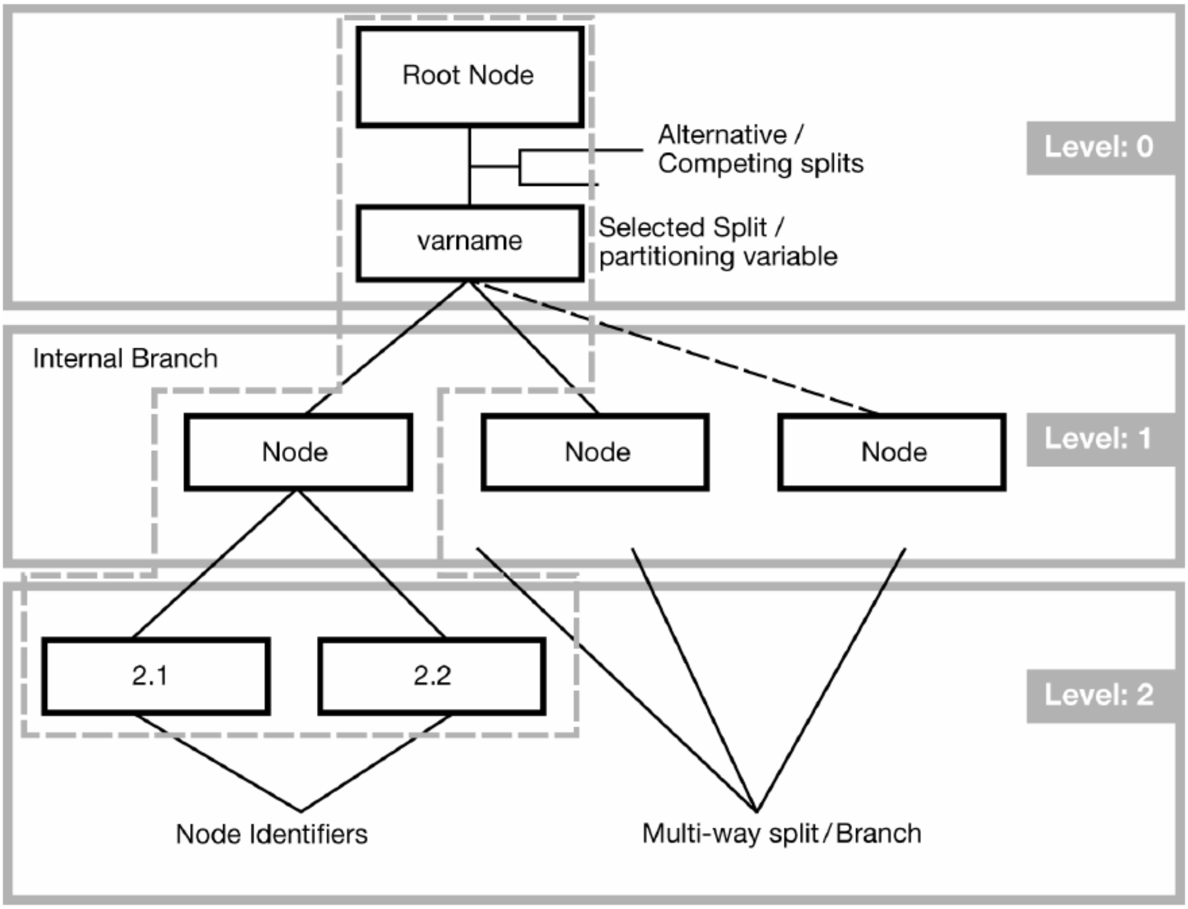
Once the relationship is extracted, then one or more decision rules can be derived that describe the relationships between inputs and targets. Rules can be selected and used to display the decision tree, which provides a means to visually examine and describe the tree-like network of relationships that characterize the input and target values. Decision rules can predict the values of new or unseen observations that contain values for the inputs, but might not contain values for the targets.

FIGURE 3 Decision Tree Nodes



Each rule assigns a record or observation from the data set to a node in a branch or segment based on the value of one of the fields or columns in the data set. Fields or columns that are used to create the rule are called inputs. Splitting rules are applied one after another, resulting in a hierarchy of branches within branches that produces the characteristic inverted decision tree form. The nested hierarchy of branches is called a decision tree, and each segment or branch is called a node. A node with all its descendent segments forms an additional segment or a branch of that node. The bottom nodes of the decision tree are called leaves or terminal nodes. For each leaf, the decision rule provides a unique path for data to enter the class that is defined as the leaf. All nodes, including the bottom leaf nodes, have mutually exclusive assignment rules; as a result, records or observations from the parent data set can be found in one node only. Once the decision rules have been determined, it is possible to use the rules to predict new node values based on new or unseen data. In predictive modeling, the decision rule yields the predicted value.

FIGURE 4 Illustration of Decision Tree



Decision trees are a form of multiple variable analyses. All forms of multiple variable analyses allow us to predict, explain, describe, or classify an outcome. An example of a multiple variable analysis is a probability of sale or the likelihood to respond to a marketing campaign as a result of the combined effects of multiple input variables, factors, or dimensions. This multiple variable analysis capability of decision trees enables you to go beyond simple one-cause, one-effect relationships and to discover and describe things in the context of multiple influences. Multiple variable analyses are particularly important in current problem-solving because almost all critical outcomes that determine success are based on multiple factors. Further, it is becoming increasingly clear that while it is easy to set up one-cause, one-effect relationships in the form of tables or graphs, this approach can lead to costly and misleading outcomes. According to research in cognitive psychology the ability to conceptually grasp and manipulate multiple chunks of knowledge is limited by the physical and cognitive processing limitations of the short term memory portion of the brain. This places a premium on the utilization of dimensional manipulation and presentation techniques that are capable of preserving and reflecting high-dimensionality relationships in a readily comprehensible form so that the relationships can be more easily consumed and applied by humans.

There are many multiple variable techniques available. The appeal of decision trees lies in their relative power, ease of use, robustness with a variety of data and levels of measurement, and ease of interpretability. Decision trees are developed and presented incrementally; thus, the combined set of multiple influences (which are necessary to fully explain the relationship of interest) is a collection of one-cause, one-effect relationships presented in the recursive form of a decision tree. This means that decision trees deal with human short-term memory limitations quite effectively and are easier to understand than more complex, multiple variable techniques. Decision trees turn raw data into an increased knowledge and awareness of business, engineering, and scientific issues, and they enable you to deploy that knowledge in a simple, but powerful set of human readable rules.

6.3. Decision Tree Algorithms

According to Mitchell (1997) algorithms[2] were developed for learning decision trees are variations on a core algorithm that employs a top down, greedy search through the space of possible decision tress. The proper quantitative measure of the worth of an attribute is defined as information gain as a statistical property which measures how well a given attribute separates the training examples

[2] Algorithms used in pages between 121-125 are gathered from the study of Mitchell (1997)

according to their target classification. In order to draw a framework for information gain, concept of entropy should be defined. Entropy is the uncertainty of a system.

Entropy characterizes the (im)purity of an arbitrary collection of examples. Given a collection S, containing positive and negative examples of some target concept, the entropy of S relative to this Boolean classification is

Entropy (S)≡ $-p_{\oplus} \log 2\, p_{\oplus} - p_{\ominus} \log 2\, p_{\ominus}$ (5.1)

Let's assume that S is a source which can produce n messages $\{m_1, m_2 \ldots m_n\}$. All messages are independently produced and possibility of production of m_i is p_i .

Source S which has the probability distribution of P= $\{p_1, p_2 \ldots pn\}$ and entropy (S) is calculated as:

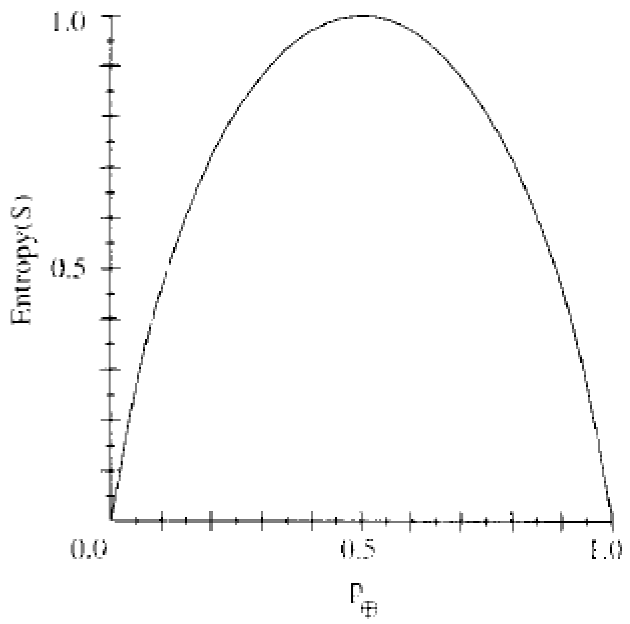
Entropy (S) = $-\sum_{i=1}^{n} p_i \log 2\, (p_i)$ (5.2)

If all members of S belong to same class then entropy is 0 If all members are positive

$(p_{\oplus} = 1)$, then $p_{\ominus}$ is 0 and Entropy (S) = -1.log 2 (-1)-0.log 2 0 = -1.0- 0.log 2 0 $= 0$

When entropy is 1, the collection contains an equal number of positive and negative examples. If the collection contains unequal numbers of positive and negative examples, the entropy is between 0 and 1.

FIGURE 5 Entropy Function



As it is seen in the figure 5 entropy function relative to a boolean classification, as $p_{\oplus}$, varies between 0 and 1.

When entropy is a measure of impurtiy in a collection, it is important to define the effectiveness condition of an attribute in classifying the training data. The measure of this effectiveness is called information gain, which is expected reduction in entropy caused by partitioning the examples according to this attribute. The information gain, Gain (S, A) of an attribute A, relative to a collection

Gain (S, A) ≡ Entropy (S) - $\sum_{v \epsilon Values\ (A)} \frac{|S_v|}{|S|}$ Entropy (S_v) (5.3)

Where Values (A) is the set of all possible values for attribute A, and S_v is the subset of S for which attribute A has value v (i,e., $S_v = \{s \ \epsilon \ S|A(s) = v\}$). The first term in Equation 5.3 is just entropy of the original collection S and the second term is the expected value of the entropy after S is partitioned using attribute A.

The expected entropy described by this second term is simply the sum of entropies of each subsetS_v, weighted by the fraction of examples $\frac{|S_v|}{|S|}$ that belong to S_v. Gain(S,A) is therefore the expected reduction in entropy caused by knowing the value of attribute A. In other words, gain (S,A) is the information provided about the target function value, given the value of some other attribute A. The value of Gain (S,A) is the number of bits saved when encoding the target value of an arbitrary member of S, by knowing the value of attribute A.

6.4 Mathematics of Decision Tree

It is important to underline the mathematical background of decision trees. Given training vectors $x_i \epsilon R^n, i =$
$1, \ldots\ldots, l$ and a label vector y ϵ R^l, a decision tree recursively partitions the space such that the Samples with the same labels are grouped together.

If the data at node m be represented by Q. For each candidate split $\theta = (j, t_m)$ consisting a feature j and threshold t_m partition the data into $Q_{left(\theta)}$ and $Q_{right(\theta)}$ subsets.

$$Q_{left(\theta)} = (x, y)\big|x_j \leq\ t_m$$

$$Q_{right(\theta)} = \frac{Q}{Q_{left(\theta)}}$$

The impurity at m is computed using an impurity function $H()$, the choice of which depends on the task being solved (classification or regression)

$$G(Q,\theta) = \frac{n_{left}}{N_m} H(Q_{left(\theta)}) + \frac{n_{right}}{N_m} H(Q_{right(\theta)})$$

Select the parameters that minimizes the impurity

$\theta^*= argmin_\theta G(Q,\theta)$

Recurse for subsets $Q_{left(\theta^*)}$ and $Q_{right(\theta^*)}$ until the maximum allowable depth is reached $N_m < min_{samples}$ OR $N_m = 1$

6.5 How Do Decision Tree Classify The Data?

If a target is a classification outcome taking on values 0,1,...,K-1, for node m, representing a region R_m with N_m observation, let

$$p_{mk}= \frac{1}{N_m} \sum_{x_i \epsilon R_m} I(y_i = k)$$

be the proportion of class k observations in node m

Common measures of impurity are Gini

$$H(X_m) = \sum_k p_{mk} (1 - p_{mk})$$

Cross-Entropy

$$H(X_m) = \sum_k p_{mk} \, log(p_{mk})$$

Misclassification

$$H(X_m) = 1 - max(p_{mk})$$

6.6. Regression Criteria

If the target is a continuous value, then for node m, representing a region $R_m$with $N_m$observations, a common criterion to minimise is the Mean Squared Error

$$c_m = \frac{1}{N_m} \sum_{i \epsilon N_m} y_i$$

$$\mathrm{H}(X_m) = \frac{1}{N_m} \sum\nolimits_{i \epsilon N_m} (y_i - c_m)^2$$

6.7 Decision Trees Applications

There are different types of decision tree application. They differ according to data type and content of the data. In this part we think that it is useful to summarize these applications for getting a better idea in order to understand the decision trees.

6.7.1 ID3

The ID3 algorithm is considered as a very simple decision tree algorithm (Quinlan, 1986). ID3 uses information gain as splitting criteria. The growing stops when all instances belong to a single value of target feature or when best information gain is not greater than zero. ID3 does not apply any pruning procedures nor does it handle numeric attributes or missing values.

6.7.2 C4.5

C4.5 is an evolution of ID3, presented by the same author (Quinlan, 1993). It uses gain ratio as splitting criteria. The splitting ceases when the number of instances to be split is below a certain threshold. Error–based pruning is performed after the growing phase. C4.5 can handle numeric attributes. It can induce from a training set that incorporates missing values by using corrected gain ratio criteria as presented above. C4.5 is the successor to ID3 and removed the restriction that features must be categorical by dynamically defining a discrete attribute (based on numerical variables) that partitions the continuous attribute value into a discrete set of intervals. C4.5 converts the trained trees (i.e. the output of the ID3 algorithm) into sets of if-then rules. These accuracy of each rule is then evaluated to determine the order in which they should be applied. Pruning is done by removing a rule's precondition if the accuracy of the rule improves without it.

6.7.3. C5

It uses less memory and builds smaller rulesets than C4.5 while being more accurate. C5.0 incorporates several new facilities such as variable misclassification costs. In C4.5, all errors are treated as equal, but in practical applications some classification errors are more serious than others. C5.0 allows a separate cost to be defined for each predicted/actual class pair; if this option is used, C5.0 then constructs classifiers to minimize expected misclassification costs rather than error rates.

The cases themselves may also be of unequal importance. In an application that classifies individuals as likely or not likely to "churn," for example, the importance of each case may vary with the size of the account. C5.0 has provision for a case weight attribute that quantifies the importance of each case; if this appears, C5.0 attempts to minimize the weighted predictive error rate.

C5.0 has several new data types in addition to those available in C4.5, including dates, times, timestamps, ordered discrete attributes, and case labels. In addition to missing values, C5.0 allows values to be noted as not applicable. Further, C5.0 provides facilities for defining new attributes as functions of other attributes.

Some recent data mining applications are characterized by very high dimensionality, with hundreds or even thousands of attributes. C5.0 can automatically winnow the attributes before a classifier is constructed, discarding those that appear to be only marginally relevant. For high-dimensional applications, winnowing can lead to smaller classifiers and higher predictive accuracy, and can often reduce the time required to generate rulesets.

6.7.4 CART (Classification and Regression Trees)

CART (Classification and Regression Trees) is very similar to C4.5, but it differs in that it supports numerical target variables (regression) and does not compute rule sets. CART constructs binary trees using the feature and threshold that yield the largest information gain at each node**.** Breiman et al (1984) give basic framework of CART which stands for Classification and Regression Trees. CART partitions the data into two subsets so that the records within each subset are more homogeneous than in the previous subset. It is a recursive process, each of those two subsets is then split again, and the process repeats until the homogeneity criterion is reached or until some other stopping criterion is satisfied. The same predictor field may be used several times at different levels in the tree. It uses surrogate splitting to make the best use of data with missing values. CART is quite flexible. It allows unequal misclassification costs to be considered in the tree growing process. It also allows you to specify the prior probability distribution in a classification problem. You can apply automatic cost-complexity pruning to a CART tree to obtain a more generalizable tree.

6.7.5 Chi-Squared Automatic Interaction Detector (CHAID)

CHAID stands for Chi-squared Automatic Interaction Detector. It is a highly efficient statistical technique for segmentation, or tree growing, developed by Kass (1980). CHAID is used for the decision tree applications in this thesis.

Using the significance of a statistical test as a criterion, CHAID evaluates all of the values of a potential predictor field. It merges values that are judged to be statistically homogeneous (similar) with respect to the target variable and maintains all other values that are heterogeneous (dissimilar). It then selects the best predictor to form the first branch in the decision tree, such that each child node is made of a group of homogeneous values of the selected field. This process continues recursively until the tree is fully grown. The statistical test used depends upon the measurement level of the target field. If the target field is continuous, an F test is used. If the target field is categorical, a chi-squared test is used. CHAID is not a binary tree method; that is, it can produce more than two categories at any particular level in the tree. Therefore, it tends to create a wider tree than do the binary growing methods. It works for all types of variables, and it accepts both case weights and frequency variables. It handles missing values by treating them all as a single valid category.

Starting from the early seventies, researchers in applied statistics developed procedures for generating decision trees, such as: AID (Sonquist et al., 1971), MAID (Gillo, 1972), THAID (Morgan and Messenger, 1973) and CHAID (Kass, 1980). CHAID (Chisquare–Automatic–Interaction–Detection) was originally designed to handle nominal attributes only.

TABLE 17 Basic Tree Growing Algorithms

	Local	Dependent variable		Splitting criterion		
Algorithm	split	quantitative	categorical	association	purity	p-value
Belson	binary		x	x		
AID	binary	x		x		
MAID	binary	x		x		
THAID	binary		x	x	x	
Hunt et al.	n-ary		x	x		
ELISEE	binary		x	x		
IDEA	n-ary	x	x	x		x
CHAID	n-ary	x	x	x		x

Ritschard[3] (2010) states that, AID (Automatic Interac-tion Detector) the dependent variable is quantitative and the splitting criterion proposed in Morgan and Sonquist (1963) is the largest reduction in unexplained sum of squares. The latter is commonly known as the residual or *within sum of squares*, WSS, in analysis of variance. It reads

WSS= $\sum_{J=1}^{g}\sum_{\mathrm{i}=1}^{n_j}(y_{ij}-\bar{y}_j)^2$

where $\bar{y}_j$ is the mean value of the y_{ij}'s in node j. In this part WSS for the g=2 groups that would be produced by the split. Maximizing this reduction is equivalent to maximize the η^2 coefficient, i.e. the ratio BSS/TSS, where TSS is the *total sum of squares* (before the split)

TSS =$\sum_{J=1}^{g}\sum_{\mathrm{i}=1}^{n_j}(y_{ij}-\bar{y}_j)^2$

which is independent of the split variable, and BSS = TSS - WSS the resulting between sum of squares. Hence, it is some sort of R^2 association measure. MAID (Gillo and Shelly, 1974) uses a generalized version of this criterion applicable in the multivariate case. The proposed generalization is indeed a variant of Wilks' Λ, namely

[3] Table 17 is taken from the paper of Ritschard (2010)

$$\frac{1-K}{tr\,(TW^{-1})} = \frac{tr\,(BW^{-1})}{tr(TW^{-1})}$$

where T, W and B = T – W are respectively the total, within and between cross product matrices among the k dependent variables. Kass (1975) introduces statistical significance criteria for AID, namely the p-value of the BSS/TSS ratio that he evaluates through a distribution free permutation test. A Chi-square approximation of this test is proposed in Scott and Knott (1976).

For each input attribute a_i , CHAID finds the pair of values in V_i that is least significantly different with respect to the target attribute. The significant difference is measured by the p value obtained from a statistical test. The statistical test used depends on the type of target attribute. If the target attribute is continuous, an F test is used. If it is nominal, then a Pearson chi–squared test is used. If it is ordinal, then a likelihood–ratio test is used. For each selected pair, CHAID checks if the p value obtained is greater than a certain merge threshold. If the answer is positive, it merges the values and searches for an additional potential pair to be merged. The process is repeated until no significant pairs are found. The best input attribute to be used for splitting the current node is then selected, such that each child node is made of a group of homogeneous values of the selected attribute. Note that no split is performed if the adjusted p value of the best input attribute is not less than a certain split threshold. This procedure also stops when one of the following conditions is fulfilled as it is stated in Table 18.

TABLE 18 CHAID Algorithms 1

1. Maximum tree depth is reached.
2. Minimum number of cases in node for being a parent is reached, so it can not be split any further.
3. Minimum number of cases in node for being a child node is reached.

Ritschard (2010) mentions CHAID uses a Chi-square splitting criterion. More specially, it uses the p-value of the Chi-square. In his 1980 paper in Applied Statistics, Kass discusses only the case of a categorical dependent variable. The method is, nevertheless, most often implemented with an option for handling also quantitative dependent variables. The criteria are in that case the p-value of the F statistic for the difference in mean values between the g nodes generated by the split:

$$F = \frac{\mathrm{BSS}/(g-1)}{\mathrm{WSS}/(n-g)} \sim F_{(g-1),(n-g)}$$

An alternative could be using the Kass (1975)'s permutation test or its x^2 approximation (Scott and Knott, 1976). The main characteristics of CHAID that contributed to its popularity are stated in Table 46.

TABLE 19 CHAID ALGORITHMS 2

1. At each node, CHAID determines for each potential predictor the optimal n-ary split it would produce, and selects the predictor on the basis of these optimal splits.
2. CHAID uses p-values with a Bonferroni correction as splitting criteria. Resorting to p-values as growing criteria provides stopping rules that automatically account for statistical significance. Thresholds are naturally set to usual critical values considered for statistical significance, namely 1%, 5% or 10%. Such p-value criteria are sensitive to the number of cases involved in the split and tend to avoid splitting into too small groups.

CHAPTER 7

MODEL SPECIFICATIONS

"The book of nature is written in the language of mathematics."

Decision trees algorithms are realized with two different variables as dependent variables and independent variables. In the model dependent variables are classified as intervention (1) and non-intervention (0). Besides twenty six independent variables are formed regarding the results of the logit regression, related literature, reaction function theory and central bank surveys. Difference of benchmark interest rate and target inflation and difference of benchmark interest rate and interest rate of central bank are derived from reaction function to represent (π_t- π_t^*) by using daily market data. Besides that mean and volatility of these differences are also included in independent variables. Other independent variables are chosen to represent daily market indicators of Turkey such as EURO/TL exchange rate, USD/TL exchange rate, Borsa İstanbul 100 index and benchmark interest rate. Daily changes of these variables are included in independent variables. More over four moments of these four variables (mean, volatility, skewness and kurtosis) are also calculated and included in independent variables. This structure includes the moments of the variables strength the power of the model in order to analyze the behaviour of the Central Bank of Turkey. All variables for exchange rate intervention is displayed in Table 20.

TABLE 20 Model Variables for Exchange Rate Intervention

DEPENDENT VARIABLES	SYMBOLS	DEFINITION OF THE INDEPENDENT VARIABLES
Intervention (1)	DIFF_IR_INF	Difference of benchmark interest rate and target inflation
Non-Intervention (0)	DIFF_IR_CMB_IR	Difference of benchmark interest rate and interest rate of central bank
	DIFF_IR_INF_MEAN	Mean of difference of benchmark interest rate and target inflation
	DIFF_IR_CMB_IR_MEAN	Mean of benchmark interest rate and interest rate of central bank
	DIFF_IR_INF_VOL	Volatility of Difference of benchmark interest rate and target inflation
	DIFF_IR_CMB_IR_VOL	Volatility of Difference of benchmark interest rate and interest rate of central bank
	EURTL_CHG	Daily change of EURO/Turkish Lira
	EURTL_MEAN	Mean of EURO/Turkish Lira
	EURTL_VOL	Volatility of EURO/Turkish Lira
	EURTL_SKW	Skewness of EURO/Turkish Lira
	EURTL_KURT	Kurtosis of EURO/Turkish Lira
	USDTL_CHG	Daily change of USD/Turkish Lira

	USDTL_MEAN	Mean of USD/Turkish Lira
	USDTL_VOL	Volatility of USD/Turkish Lira
	USDTL_SKW	Skewness of USD/Turkish Lira
	USDTL_KURT	Kurtosis of USD/Turkish Lira
	XU100_MEAN	Mean of Borsa İstanbul 100 index
	XU100_CHG	Daily change of Borsa İstanbul 100 index
	XU100_MEAN	Mean of Borsa İstanbul 100 index
	XU100_VOL	Volatility of Borsa İstanbul 100 index
	XU100_SKW	Skewness of Borsa İstanbul 100 index
	XU100_KURT	Kurtosis of Borsa İstanbul 100 index
	BRATE_CHG	Daily change of benchmark interest rate
	BRATE_MEAN	Mean of benchmark interest rate
	BRATE_VOL	Volatility of benchmark interest rate
	BRATE_SKW	Skewness of benchmark interest rate
	BRATE_KURT	Kurtosis of benchmark interest rate

7.1 Model Results for Exchange Rate Intervention

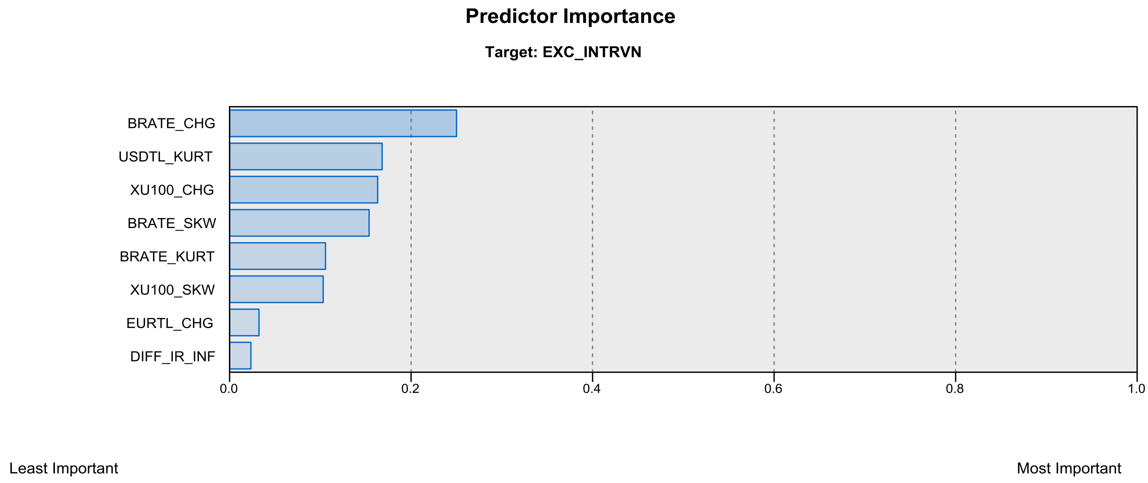
Since here logit regression results and reaction functions theory support to set up a model regarding the unbalanced data which depends on to analyze the intervention decision of Central Bank of Republic Of Turkey by the help of decision trees by using C5. The model in order to estimate the intervention and non intervention days has significant results to analyze. According to model results, as given in Table 21 below, 96% percentages of the interventions are detected by the model. This rate comparatively significant than the results which is found in logit regression. Secondly model has less significant results to model non-intervention days. However model detects 79,92 % percentages of non-intervention days. These results imply that model suggests in the 545 days intervention should be realized by Central Bank of Republic Of Turkey but she did not perform these interventions. Over all when 2741 days are considered model detects 79,20 % percentage of the days in a precise way. This is a crucial finding for the result the models because there is a certain success of the model to detect the interventions. However 545 days are also suggested by the model to have the possibility of intervention. But Central Bank of Republic Of Turkey did not choose to intervene in those days although she followed the same decision with the same data set and the same model in 25 days of 26. Thus it is one the main findings of this paper that Central Bank of Republic Of Turkey is too conservative to intervene the market. Thirdly even there is an unbalanced data by the help of the logit regression, reaction function and choice of successful independent variables model which are interpreted by the literature and central banks surveys. We also tried to figure out the interventions by using CHAID algorithm of decision trees (See table E-1 and Figure 13 at Appendix E). By using CHAID we find 23 of 26 interventions however in that model decision trees detect 473 days to intervene and over all model detects 81,90 % percentage of the days in a precise way. However our primary objective is to figure out the interventions. Because of this we decide to analyze the results of C5 but also share the CHAID results in Table E-1 and Table E-2, and Figure E-1 and Figure E-2 at Appendix E.

TABLE 21 Model Results for Exchange Rate Intervention

C5	EXC_INTRVN		Intervention	None	Total
	Intervention	Count	25	1	26
		Row %	96.15	3.85	100
	None	Count	545	2170	2715
		Row %	20.07	79.93	100
	Total	Count	570	2171	2741
		Row %	20.80	79.20	100

As it is seen in the Figure 6, according to results of the decision tree (C5) analysis daily change of benchmark interest rate has the highest predictor importance in order to model exchange rate intervention. Kurtosis of USD/TL exchange rate, daily change of Borsa İstanbul 100 index, skewness of benchmark interest rate, kurtosis of benchmark interest rate, skewness of Borsa İstanbul 100 index , daily change of EUR/TL exchange rate and difference of benchmark interest rate and target inflation and index follow the regarding predictor importance in the model.

FIGURE 6 Predictor Importance For Exchange Rate Intervention



Predictor importance is determined by computing the reduction in variance of the target attributable to each predictor, via a sensitivity analysis. This method of computing predictor importance is used for Neural Networks C5.0, CART, QUEST, CHAID, Regression, Logistic, Discriminant, Gen-Lin, SVM and Bayesian Networks.

In order to understand the predictor importance analysis, it is important to give a brief summary algorithm of predictor importance.

Firstly let's define the notation; If

Y = target

$$X_j = Predictor, where \;\; j = 1, \ldots\ldots, k$$

k= number of the predictors

Y= f $(X_1, X_2, \ldots, X_k)$ Model for Y based on predictors X_1 through X_k

Predictors are ranked according to the sensitivity measure defined as follows (which can be named as variance based model)

$$S_i = \frac{V_i}{V(Y)} = \frac{V(E(Y|X_i)}{V(Y)}$$

where $V(Y)$ is the unconditional output variance. In the numerator, the expectation operator E calls for an integral over X_{-i} , that is, over all factors but X_i , then the variance operator V implies a further integral over X_i. Predictor importance is then computed as the normalized sensitivity.

$$\mathrm{V}I_i = \frac{S_i}{\sum_{j=1}^{k} S_i}$$

S_i is the proper measure of sensitivity to rank the predictors in order of importance for any combination of interaction and non-orthogonality among predictors. The importance measure S_i is the first-order sensitivity measure, which is accurate if the set of the input factors $(X_1, X_2, \dots, X_k)$ is orthogonal/independent (a property of the factors), and the model is additive; that is, the model does not include interactions (a property of the model) between the input factors. For any combination of interaction and non-orthogonality among factors that S_i is still the proper measure of sensitivity to rank the input factors in order of importance, but there is a risk of inaccuracy due to the presence of interactions or/and non-orthogonality.

7.2 Analysis of Decision Tree for Exchange Rate Intervention

As it is mentioned above the data set is unbalanced and if we use the unbalanced data set, generated model has over fitted and overlearning problem. Thus, we use random sampling for non-intervention days to be balanced with intervention days. We select all of intervention days for foreign exchange rate interventions (26 days) and almost 47 of non-intervention days are chosen randomly. Then the model is extended to 2741 days and model is formed by the significant independent variables. Decision tree is formed according the predictor importance. For processing the data, decision tree C5 algorithm, the IBM SPSS Modeler 16 software have been used.

As it is observed in the Figure 7 below the first profile divides the interventions into two main nodes (node 1 and node 18) according to skewness of benchmark interest rate. Models indicates that seven (seven of twenty six) of the interventions are performed when the skewness of benchmark interest rate exceeds 2,025. In order to detect rest of the nineteen interventions model indicates the data set rule where skewness of benchmark interest rate is less than 2,025.

Following the model rules the second profile is divided into two nodes (node 2 and node 9) according to daily change of benchmark interest rate. Model indicates that twelve interventions are performed daily change of benchmark interest is less than -0,002. Model indicates that rests of the seven interventions are performed when daily change of benchmark interest rate is more than -0,002.

The third profile is divided into four nodes by two different variables which are daily change of Borsa İstanbul 100 index and kurtosis of USD/TL exchange rate respectively. Node 3 and Node 4 is divided by daily change of Borsa İstanbul 100 index. Node 10 and Node 11 is divided by kurtosis of USD/TL exchange. Twelve interventions are performed when the daily change of Borsa İstanbul 100 index is more than -0,008. Rest of the seven interventions is performed when kurtosis of USD/TL exchange rate is more than 0,436.

In the fourth profile Node 4 is divided into Node 5 and Node 8 by kurtosis of USD/TL exchange rate and Node 11 is divided into Node 12 and Node 13 by daily change of EURO/TL exchange rate. Following the model rules two interventions are carried out when kurtosis of USD/TL exchange rate is less than 0,123 and rest of the ten interventions are performed when kurtosis of USD/TL exchange rate is more than 0,123. Next seven interventions which are divided from node 11, follows the rule such that seven interventions are performed when daily change of EURO/TL exchange rate is more than -0,001.

In the fifth profile Node 5 is divided into Node 6 and Node 7 by difference of benchmark interest rate and target inflation and node 13 is divided into Node 14 and Node 15 by skewness of Borsa İstanbul 100 index. Following the model rules two interventions are carried out when difference of benchmark interest rate and target inflation is less than 7,910. Rests of the seven interventions are divided into to two nodes. These three of the seven interventions are performed when skewness of Borsa İstanbul 100 index is less than -0,755 and four of the seven interventions are performed when skewness of Borsa İstanbul 100 index is more than -0,755.

The last and six profile is divided into two nodes (node 16 and node 17) according to kurtosis of benchmark interest rate. Model rule indicates that one intervention is performed when kurtosis of bench mark interest rate is less than 5,181 and rests of the three interventions are performed when kurtosis of benchmark interest rate is more than 5,181.

The result of the model is crucial to answer, “What is the answer of disorder markets?” for central bank of Republic of Turkey and “What makes the Central Bank of Republic of Turkey to intervene the exchange rate market?” Thus all the significant predictors and cut value of them are important to understand the intervention behaviour of Central Bank of Republic of Turkey. Model rules indicate every step and possible outcome for interventions. The result of the model rules are easy to follow and compare with the market movements. Moreover investors in this market can follow the rule set of the model and can decide the way of their investment in a broad sense. Next by analyzing the behavior of CBRT, market players, academicians and researchers can shape their expectations about the interventions in this market. By this way the behavior of CBRT can transform into numbers instead of some vague concepts.

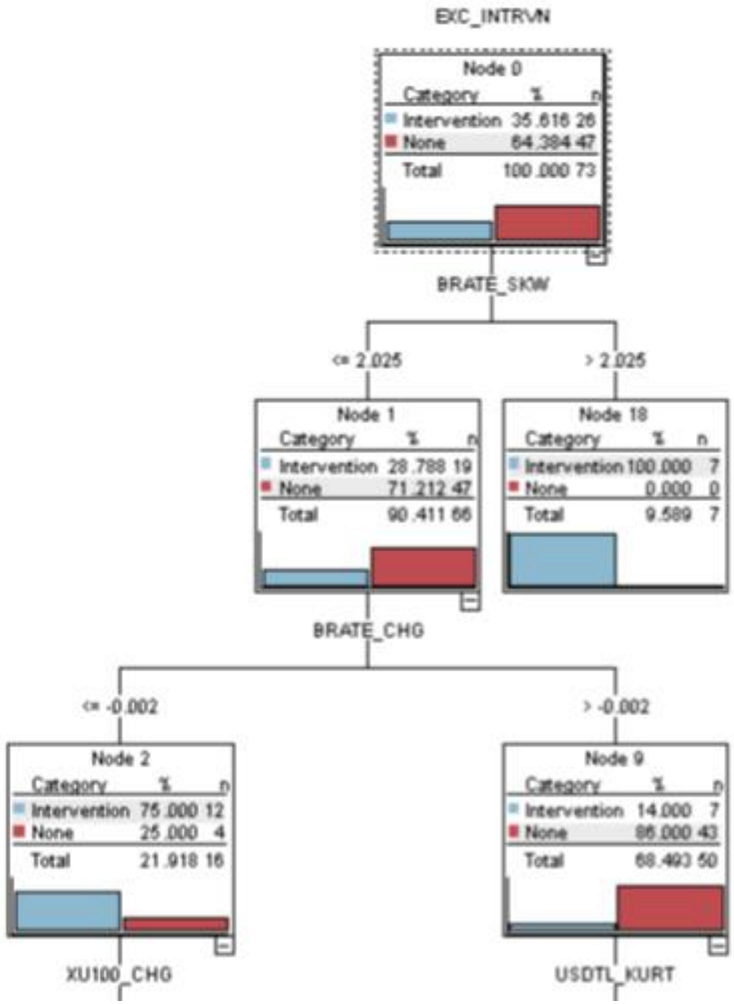
It can be summarized as the rules set which are modeled by decision tree and C5 algorithm captures 96,15 % of the interventions (25 of 26). The rule set model captures the 79,20 % of the whole intervention and non-intervention days. The model involves skewness of benchmark interest, daily change of benchmark interest rate, daily change of Borsa İstanbul 100 index, kurtosis of USD/TL exchange rate, daily change of EUR/TL exchange rate, difference of benchmark interest rate and target inflation and skewness of Borsa İstanbul 100 index as an significant predictors. The rule set of the model which covers these predictors let us analyze every intervention possibility in a very sensitive way considering the cut values of every sub nodes in a decision tree.

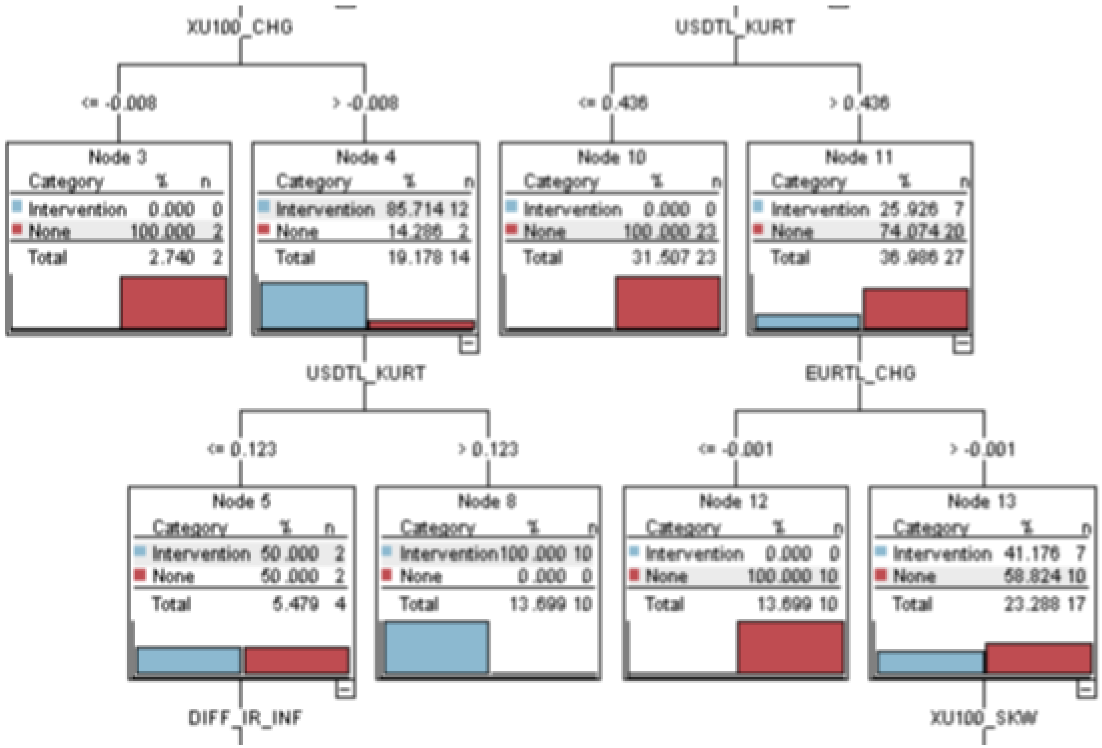
7.3 A Hypothetical Market Player Calculation by Using the Thesis Model in Foreign Exchange Market

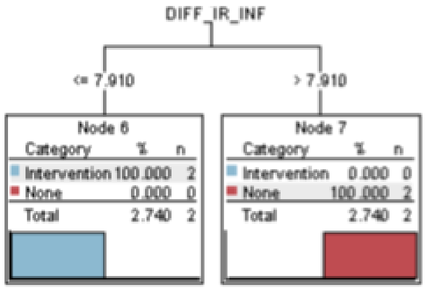
In the introduction part result of this thesis is said to be beneficial for policy makers, analysts, academicians and market players. This thesis involves academic results regarding the content of the results and formation process of methodology. Moreover result of the models let the market players to get profit from the model results.

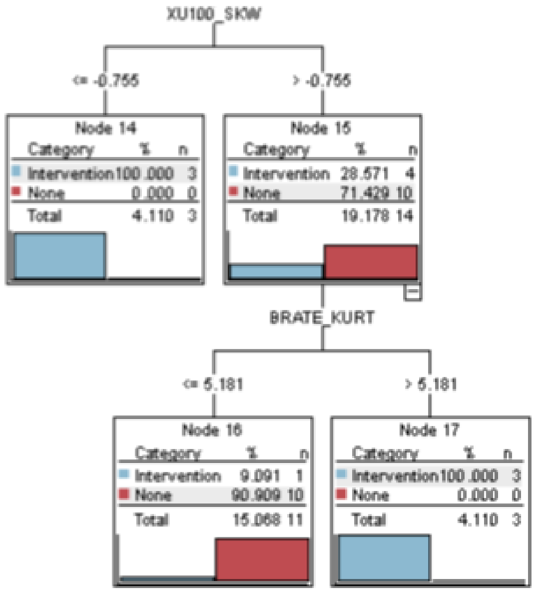
If a hypothetical investor would obey and follow the rules of the model for each market day and put money which brings him/her to get 1000 Turkish Lira at the end of the day for exchange rate movements regarding the intervention or non intervention movements for 2741 days he or she would gain 2.195.000 Turkish Lira and he or she would loose 546.000 Turkish Lira. However, totally he or she would gain 1.649.000 Turkish Lira profit.

FIGURE 7 Decision Tree for Exchange Rate Intervention


EXC_INTRVN
Node 0
Category % n
Intervention 35.616 26
None 64.384 47
Total 100.000 73
BRATE_SKW
<= 2.025
> 2.025
Node 1
Category % n
Intervention 28.788 19
None 71.212 47
Total 90.411 66
Node 18
Category % n
Intervention 100.000 7
None 0.000 0
Total 9.589 7
BRATE_CHG
<= -0.002
> -0.002
Node 2
Category % n
Intervention 75.000 12
None 25.000 4
Total 21.918 16
Node 9
Category % n
Intervention 14.000 7
None 86.000 43
Total 68.493 50
XU100_CHG
USDTL_KURT


XU100_CHG
<= -0.008
> -0.008
Node 3
Category % n
Intervention 0.000 0
None 100.000 2
Total 2.740 2
Node 4
Category % n
Intervention 85.714 12
None 14.286 2
Total 19.178 14
USDTL_KURT
<= 0.436
> 0.436
Node 10
Category % n
Intervention 0.000 0
None 100.000 23
Total 31.507 23
Node 11
Category % n
Intervention 25.926 7
None 74.074 20
Total 36.986 27
USDTL_KURT
<= 0.123
> 0.123
EURTL_CHG
<= -0.001
> -0.001
Node 5
Category % n
Intervention 50.000 2
None 50.000 2
Total 5.479 4
Node 8
Category % n
Intervention 100.000 10
None 0.000 0
Total 13.699 10
Node 12
Category % n
Intervention 0.000 0
None 100.000 10
Total 13.699 10
Node 13
Category % n
Intervention 41.176 7
None 58.824 10
Total 23.288 17
DIFF_IR_INF
XU100_SKW


DIFF_IR_INF
<= 7.910
> 7.910
Node 6
Category % n
Intervention 100.000 2
None 0.000 0
Total 2.740 2
Node 7
Category % n
Intervention 0.000 0
None 100.000 2
Total 2.740 2


XU100_SKW
<= -0.755
> -0.755
Node 14
Category % n
Intervention 100.000 3
None 0.000 0
Total 4.110 3
Node 15
Category % n
Intervention 28.571 4
None 71.429 10
Total 19.178 14
BRATE_KURT
<= 5.181
> 5.181
Node 16
Category % n
Intervention 9.091 1
None 90.909 10
Total 15.068 11
Node 17
Category % n
Intervention 100.000 3
None 0.000 0
Total 4.110 3

Model path for exchange rate intervention is given in Table 22.

TABLE 22 Model Path For Exchange Rate Intervention -C5

BRATE_SKW <= 2.025 [Mode: None]
BRATE_CHG <= -0.002 [Mode: Intervention]
XU100_CHG <= -0.008 [Mode: None] => None
XU100_CHG > -0.008 [Mode: Intervention]
USDTL_KURT <= 0.123 [Mode: Intervention]
DIFF_IR_INF <= 7.910 [Mode: Intervention] => Intervention
DIFF_IR_INF > 7.910 [Mode: None] => None
USDTL_KURT > 0.123 [Mode: Intervention] => Intervention
BRATE_CHG > -0.002 [Mode: None]
USDTL_KURT <= 0.436 [Mode: None] => None
USDTL_KURT > 0.436 [Mode: None]
EURTL_CHG <= -0.001 [Mode: None] => None
EURTL_CHG > -0.001 [Mode: None]
XU100_SKW <= -0.755 [Mode: Intervention] => Intervention
XU100_SKW > -0.755 [Mode: None]
BRATE_KURT <= 5.181 [Mode: None] => None

BRATE_KURT > 5.181 [Mode: Intervention] => Intervention
BRATE_SKW > 2.025 [Mode: Intervention] => Intervention

7.4 Model Results for Interest Rate Intervention

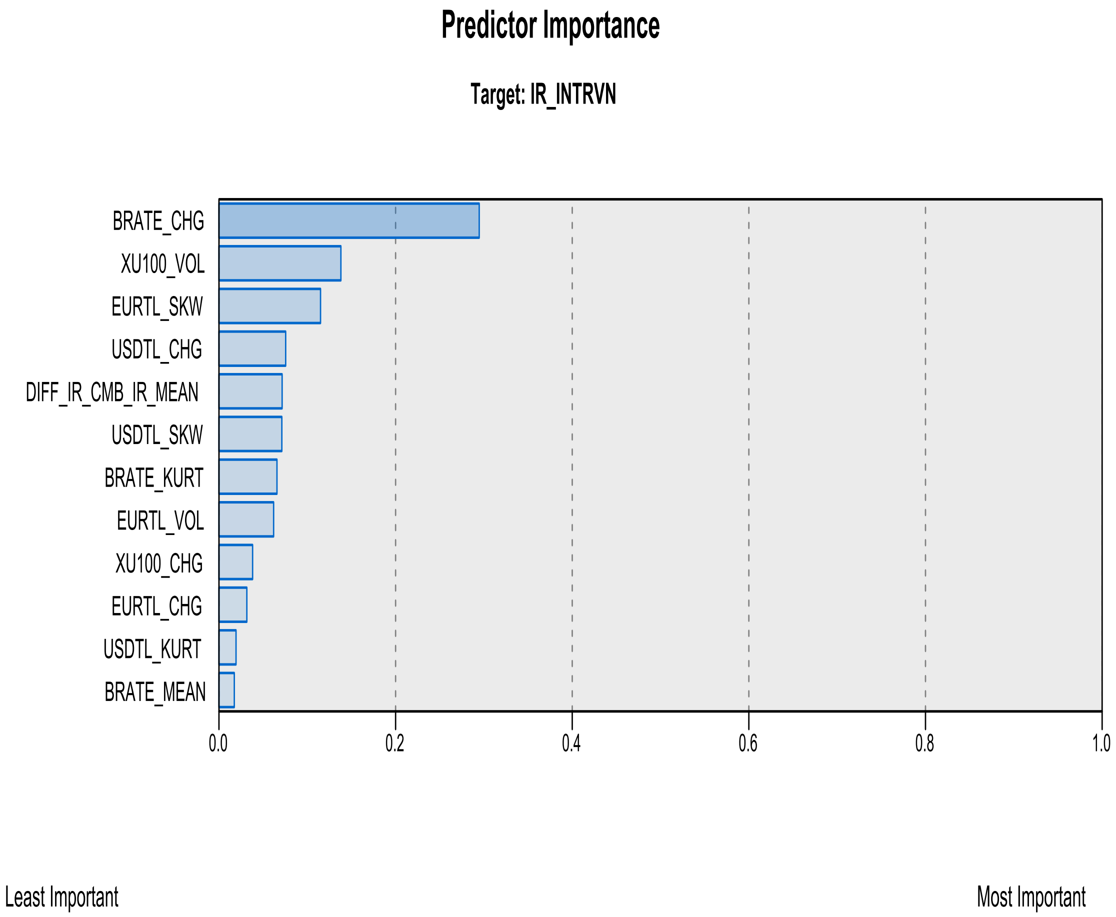
Since here logit regression results and reaction functions theory support to set up a model regarding the unbalanced data which depends on to analyze the intervention decision of Central Bank of Republic Of Turkey by the help of decision trees. The model in order to estimate the intervention and non intervention days has significant results to analyze. According to model results, as given in Table 23 below, 94,44 % percentages of the interventions are detected by the model. This rate comparatively significant than the results which is found in logit regression. Secondly model has less significant results to model non-intervention days. However model detects 71,492 % percentages of non-intervention days. These results imply that model suggests in the 766 days intervention should be realized by Central Bank of Republic Of Turkey but she did not perform these interventions. Over all when 2741 days are considered model detects 70,193% percentage of the days in a precise way. This is a crucial finding for the result the models because there is a certain success of the model to detect the interventions. However 766 days are also suggested by the model to have the possibility of intervention. But Central Bank of Republic Of Turkey did not choose to intervene in those days although she followed the same decision with the same data set and the same model in 51 days of 54. Thus it is one the main finding of this paper that Central Bank of Republic Of Turkey is too conservative to intervene the market. Thirdly even there is an unbalanced data by the help of the logit regression, reaction function and choice of successful independent variables model which are interpreted by the literature and central banks surveys

TABLE 23 Model Results for Interest Rate Intervention

IR_INTRVN		Intervention	None	Total
Intervention	**Count**	51	3	54
	Row %	94.444	5.556	100
None	**Count**	766	1921	2687
	Row %	28.508	71.492	100
Total	**Count**	817	1924	2741
	Row %	29.807	70.193	100

As it is seen in the Figure 8, number of the significant predictors regarding interest rate intervention is more than exchange rate intervention. According to Figure below and according to results of the decision tree (C5) analysis daily change of benchmark interest rate has the highest predictor importance in order to model interest rate intervention. volatility of Borsa İstanbul 100 index, skewness of EURO/TL exchange rate, daily change of USD/TL exchange rate, mean of difference of benchmark interest rate and interest rate of central bank, skewness of USD/TL exchange rate, kurtosis of benchmark interest rate, volatility of EURO/TL exchange rate, daily change of Borsa İstanbul 100 index, daily change of EURO/TL exchange rate, kurtosis of USD/TL exchange rate and mean of benchmark interest rate follows daily change of benchmark interest rate regarding predictor importance in the model.

FIGURE 8 PREDICTOR IMPORTANCE FOR INTEREST RATE INTERVENTION



Decision trees algorithms are realized with two different variables as dependent variables and independent variables. In the model dependent variables are classified as intervention (1) and non-intervention (0). Besides twenty six independent variables are formed regarding the results of the logit regression, related literature, reaction function theory and central bank surveys. Difference of benchmark interest rate and target inflation and difference of benchmark interest rate and interest rate of central bank are derived from reaction function to represent (π_t- π_t^*) by using daily market data. Besides that mean and volatility of these differences are also included in independent variables. Other independent variables are chosen to represent daily market indicators of Turkey such as EURO/TL exchange rate, USD/TL exchange rate, Borsa İstanbul 100 index and benchmark interest rate. Daily changes of these variables are included in independent variables. More over four moments of these four variables (mean, volatility, skewness and kurtosis) are also calculated and included in independent variables. This structure includes the moments of the variables strength the power of the model in order to analyze the behaviour of the Central Bank of Turkey. All variables for interest rate intervention are displayed in Table 24.

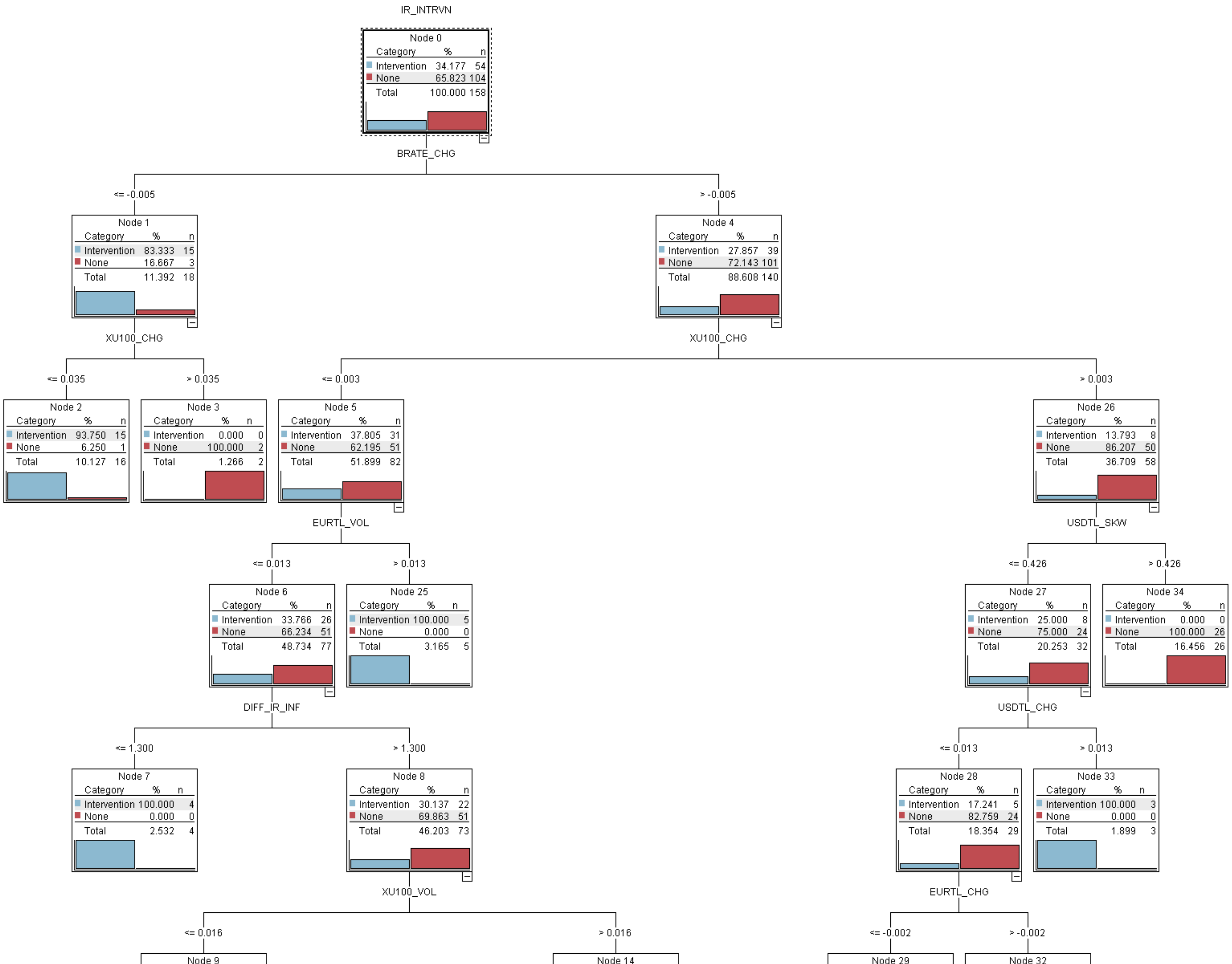
TABLE 24 Model Variables For Interest Rate Intervention

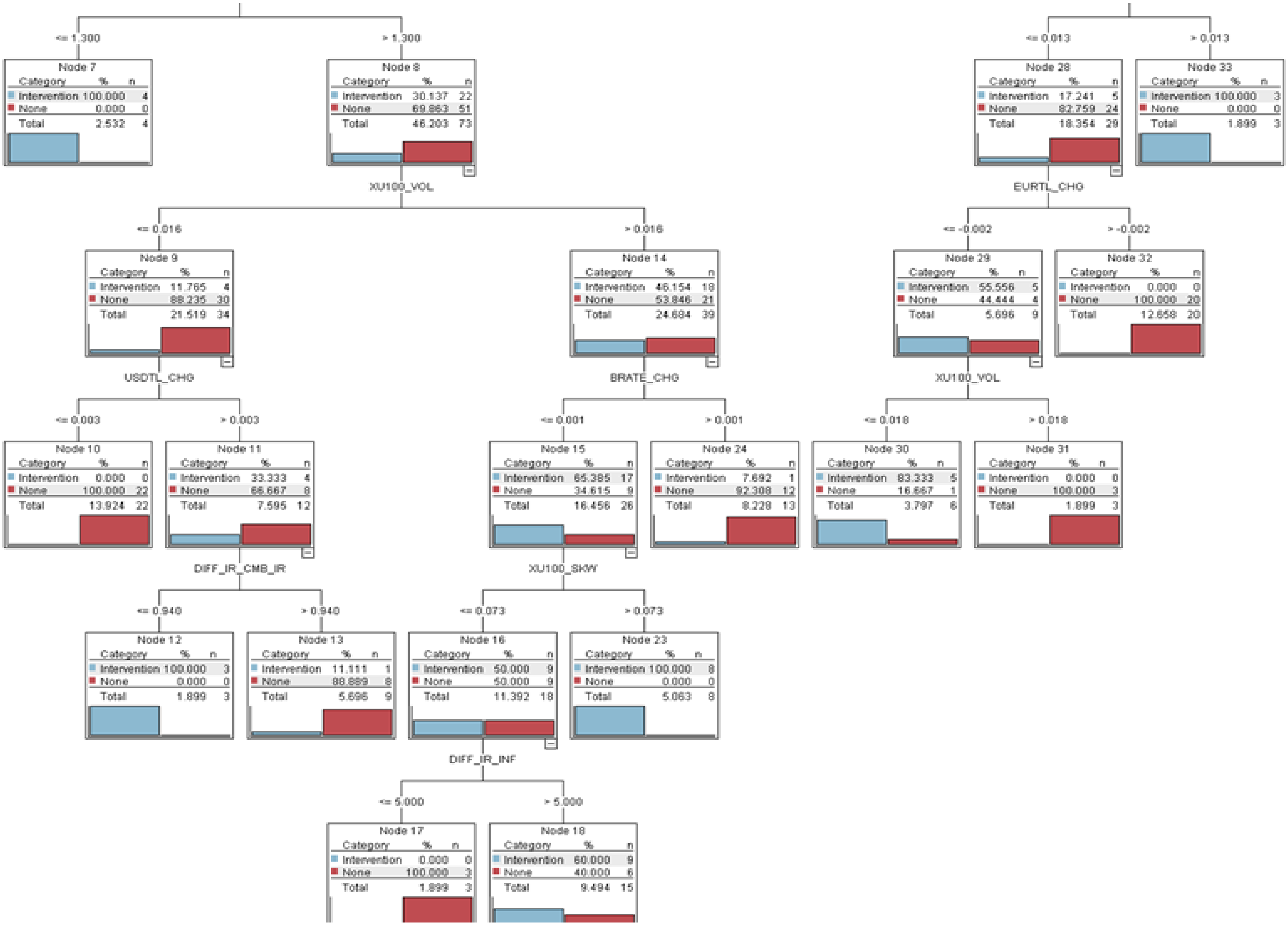
DEPENDENT VARIABLES	SYMBOLS	DEFINITION OF THE INDEPENDENT VARIABLES
Intervention (1)	DIFF_IR_INF	Difference of benchmark interest rate and target inflation
Non-Intervention (0)	DIFF_IR_CMB_IR	Difference of benchmark interest rate and interest rate of central bank
	DIFF_IR_INF_MEAN	Mean of difference of benchmark interest rate and target inflation
	DIFF_IR_CMB_IR_MEAN	Mean of benchmark interest rate and interest rate of central bank
	DIFF_IR_INF_VOL	Volatility of Difference of benchmark interest rate and target inflation
	DIFF_IR_CMB_IR_VOL	Volatility of Difference of benchmark interest rate and interest rate of central bank

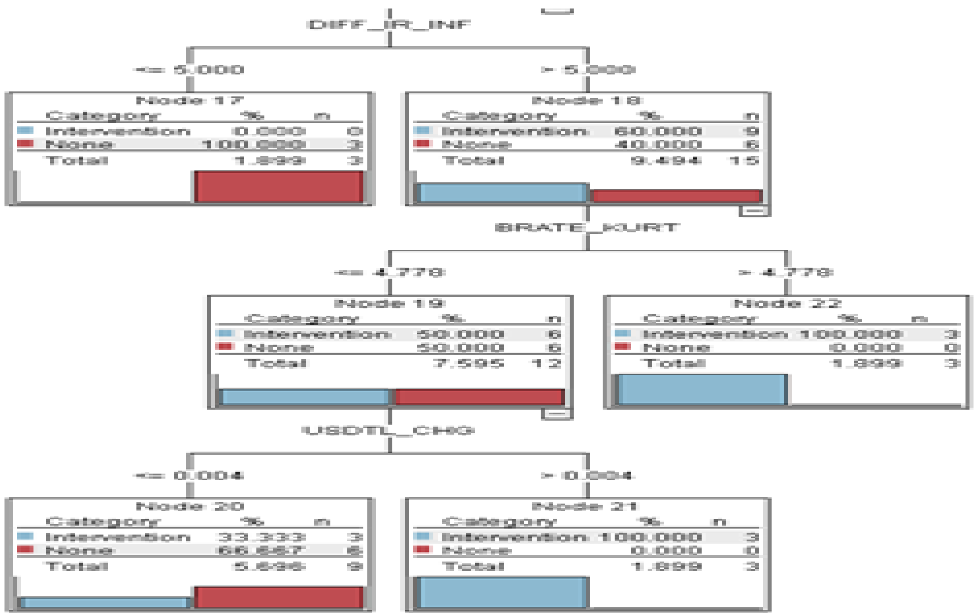
	EURTL_CHG	Daily change of EURO/Turkish Lira
	EURTL_MEAN	Mean of EURO/Turkish Lira
	EURTL_VOL	Volatility of EURO/Turkish Lira
	EURTL_SKW	Skewness of EURO/Turkish Lira
	EURTL_KURT	Kurtosis of EURO/Turkish Lira
	USDTL_CHG	Daily change of USD/Turkish Lira
	USDTL_MEAN	Mean of USD/Turkish Lira
	USDTL_VOL	Volatility of USD/Turkish Lira
	USDTL_SKW	Skewness of USD/Turkish Lira
	USDTL_KURT	Kurtosis of USD/Turkish Lira
	XU100_MEAN	Mean of Borsa İstanbul 100 index
	XU100_CHG	Daily change of Borsa İstanbul 100 index
	XU100_MEAN	Mean of Borsa İstanbul 100 index
	XU100_VOL	Volatility of Borsa İstanbul 100 index
	XU100_SKW	Skewness of Borsa İstanbul 100 index
	XU100_KURT	Kurtosis of Borsa İstanbul 100 index
	BRATE_CHG	Daily change of benchmark interest rate
	BRATE_MEAN	Mean of benchmark interest rate
	BRATE_VOL	Volatility of benchmark interest rate

	BRATE_SKW	Skewness of benchmark interest rate
	BRATE_KURT	Kurtosis of benchmark interest rate

FIGURE 9 DECISION TREE FOR INTEREST RATE INTERVENTION


IR_INTRVN
Node 0
Category % n
Intervention 34.177 54
None 65.823 104
Total 100.000 158
BRATE_CHG
<= -0.005
> -0.005
Node 1
Category % n
Intervention 83.333 15
None 16.667 3
Total 11.392 18
Node 4
Category % n
Intervention 27.857 39
None 72.143 101
Total 88.608 140
XU100_CHG
<= 0.035
> 0.035
XU100_CHG
<= 0.003
> 0.003
Node 2
Category % n
Intervention 93.750 15
None 6.250 1
Total 10.127 16
Node 3
Category % n
Intervention 0.000 0
None 100.000 2
Total 1.266 2
Node 5
Category % n
Intervention 37.805 31
None 62.195 51
Total 51.899 82
Node 26
Category % n
Intervention 13.793 8
None 86.207 50
Total 36.709 58
EURTL_VOL
<= 0.013
> 0.013
USDTL_SKW
<= 0.426
> 0.426
Node 6
Category % n
Intervention 33.766 26
None 66.234 51
Total 48.734 77
Node 25
Category % n
Intervention 100.000 5
None 0.000 0
Total 3.165 5
Node 27
Category % n
Intervention 25.000 8
None 75.000 24
Total 20.253 32
Node 34
Category % n
Intervention 0.000 0
None 100.000 26
Total 16.456 26
DIFF_IR_INF
<= 1.300
> 1.300
USDTL_CHG
<= 0.013
> 0.013
Node 7
Category % n
Intervention 100.000 4
None 0.000 0
Total 2.532 4
Node 8
Category % n
Intervention 30.137 22
None 69.863 51
Total 46.203 73
Node 28
Category % n
Intervention 17.241 5
None 82.759 24
Total 18.354 29
Node 33
Category % n
Intervention 100.000 3
None 0.000 0
Total 1.899 3
XU100_VOL
<= 0.016
> 0.016
EURTL_CHG
<= -0.002
> -0.002
Node 9
Node 14
Node 29
Node 32


Node 7
Node 8
XU100_VOL
Node 9
Node 14
USDTL_CHG
BRATE_CHG
Node 10
Node 11
Node 15
Node 24
DIFF_IR_CMB_IR
XU100_SKW
Node 12
Node 13
Node 16
Node 23
DIFF_IR_INF
Node 17
Node 18
Node 28
Node 33
EURTL_CHG
Node 29
Node 32
XU100_VOL
Node 30
Node 31


DIFF_IR_INF
<= 5.000
> 5.000
Node 17
Category % n
Intervention 0.000 0
None 100.000 3
Total 1.899 3
Node 18
Category % n
Intervention 60.000 9
None 40.000 6
Total 9.494 15
BRATE_KURT
<= 4.778
> 4.778
Node 19
Category % n
Intervention 50.000 6
None 50.000 6
Total 7.595 12
Node 22
Category % n
Intervention 100.000 3
None 0.000 0
Total 1.899 3
USDTL_CHG
<= 0.004
> 0.004
Node 20
Category % n
Intervention 33.333 3
None 66.667 6
Total 5.696 9
Node 21
Category % n
Intervention 100.000 3
None 0.000 0
Total 1.899 3

7.5 Analysis of Decision Tree for Interest Rate Intervention

As it is mentioned above the data set is unbalanced and if we use the unbalanced data set, generated model has over fitted and over learning problem. Thus, we use random sampling for non-intervention days to be balanced with intervention days. For example, we select all of intervention days for interest rate interventions (54 days) and almost 100 of non-intervention days are chosen randomly. Then the model is extended to 2741 days and model is formed by the significant independent variables. Decision tree is formed according the predictor importance. For processing the data, decision tree C5 algorithm, the IBM SPSS Modeler 16 software have been used.

As it is observed in the Figure below the first profile divides the interventions into two main nodes (node 1 and node 4) according to daily change of benchmark interest rate. Model indicates that fifteen of the interventions are performed when the change of benchmark interest rate is less than -0,005. In order to detect rest of the thirty nine interventions model indicates the data set rule where daily change of benchmark interest rate is more than -0,005.

In the second profile predictor of daily change of Borsa İstanbul 100 index divides four nodes (node 2, node 3, node 5 and node 26) for the rule path. Node 2 and Node 3 are divided by daily change of Borsa İstanbul 100 index with the cut value of 0,035. Model indicates fifteen interventions performed if the daily change of Borsa İstanbul 100 index is less than 0,035. Node 5 and Node 26 are also divided into two nodes by daily change of Borsa İstanbul 100 index with the cut value of 0,003. Thirty one interventions are detected by the model if the daily change of Borsa İstanbul 100 index is less than 0,003 and eight interventions are found by the model if the the cut value is more than 0,003.

In the third profile decision tree splits into two different paths. One of the rule paths continue from the tree which covers thirty one interventions which follows node 5. Firstly this branch of the three is analyzed. Then rest of the eight interventions are analyzed which follows the Node 26.

The third profile is divided into two nodes (node 6 and node 25) by volatility of EURO/TL exchange rate. The cut value is 0,013. Twenty six interventions is detected by the model if volatility of EURO/TL exchange rate is less than 0,0013 and five of the interventions are fund by the rule of the model if the volatility of EURO/TL exchange rate is more than 0,0013.

The fourth profile is divided into two nodes (node 7 and node 8) by difference of benchmark interest rate and target inflation. Four of the interventions are detected if the difference of benchmark interest rate and target inflation is less than 1,300 and twenty two interventions are found if the difference of benchmark interest rate and target inflation is more than 1,300.

Next fifth profile is divided into two nodes (node 9 and node 14) by volatility of Borsa İstanbul 100 index. The cut value is 0,016. Four interventions are detected if volatility of Borsa İstanbul 100 index is less than 0,016 and 18 interventions are detected if volatility of Borsa İstanbul 100 index is more than 0,016.

The sixth profile is divided into four nodes (node 10- node 11 and node15- node 24) by different two predictors by daily change of USD/TL exchange rate and daily change of benchmark interest rate. The cut value of change of USD/TL exchange rate is 0,003 and the cut value of benchmark interest rate is 0,001.

In the sixth profile four interventions are detected by the model if the daily change of USD/TL exchange rate is more than 0,003. These four interventions are divided into two nodes (node 12-node 13) in seventh profile by difference of benchmark interest rate and interest rate of central bank. The cut value is 0,940. Three interventions are detected if the difference of benchmark interest rate and interest rate of central bank is less than 0,940 and one intervention is detected if difference of benchmark interest rate and interest rate of central bank is more than 0,940.

As it is mentioned above, the sixth profile is divided by two different predictors. Node 15 and Node 24 are divided by daily change of benchmark interest rate. Seventeen interventions are detected if the daily change of benchmark interest rate is less than 0,001 and one intervention is detected if the daily change of benchmark interest rate is more than 0,001. Next in the seventh profile these seventeen interventions are divided into two nodes (node 16 and node 23) by skewness of Borsa İstanbul 100 index. The cut value is 0,073. Nine interventions are detected if the skewness of Borsa İstanbul 100 index is less than 0,073 and eight interventions are detected if the skewness of Borsa İstanbul 100 index is more than 0,073.

In the eighth profile two nodes (node 17 and node 18) are divided by difference of benchmark interest rate and target inflation. The cut value is 5. Nine interventions are detected if the difference of benchmark interest rate and target inflation is more than 5. Next in the ninth profile these nine interventions are divided into two nodes (node 19 and node 22) by kurtosis of benchmark interest rate. The cut value is 4,778. Six interventions are detected if the kurtosis of the benchmark is less than 4,778 and three interventions are detected if the kurtosis of the benchmark is more than 4,778.

In the tenth profile two nodes (node 20 and node 21) are divided by daily change of USD/TL exchange rate. The cut value is 0,004 and three interventions are detected if the change of USD/TL exchange rate is less tan 0,004 and three interventions are detected if the change of USD/TL exchange rate is more than 0,004. As it is mentioned above, in the third profile eight interventions (node 26) is divided into two sub nodes (node 27 and node 34) by skewness of USD/TL exchange rate. Eight interventions are detected if the skewness of USD/TL exchange rate is more than 0,426.

In the fourth profile two nodes (node 28 and node 33) are divided by the predictor of daily change of USD/TL exchange rate. Five interventions are detected if daily change of USD/TL exchange rate is less than 0,013 and three interventions are detected if daily change of USD/TL exchange rate is more than 0,013. Next in the fifth profile two nodes (node 29 and node 32) are divided by predictor of daily change of EURO/TL exchange rate. Five interventions are detected if daily change of EURO/TL exchange rate is less than 0,002. Lastly in the sixth profile two nodes (node 30 and node 31) are divided by volatility of Borsa İstanbul 100 index. The cut value is 0,018. Five interventions are detected if volatility of Borsa İstanbul 100 index is less than 0,018.

These sensitive results display and answer what makes central bank intervene the interest rate market and can easily answer the disorder market for interest rate market. When decision tree diagrams of exchange rate intervention and interest rate intervention compared; it is certain that diagram of interest rate intervention is more complex. The main reason of this is derived from the number of the significant predictors in the model.

7.6 A Hypothetical Market Player Calculation by Using the Thesis Model in Interest Rate Market

In the introduction part result of this thesis is said to be beneficial for policy makers, analysts, academicians and market players. This thesis involves academic results regarding the content of the results and formation process of methodology. Moreover result of the models let the market players to get profit from the model results.

If a hypothetical investor would obey and follow the rules of the model for each market day and put money which brings him/her to get 1000 Turkish Lira at the end of the day for interest rate movements regarding the intervention or non intervention movements for 2741 days he or she would gain 1.972.000 Turkish Lira and he or she would loose 769.000 Turkish Lira. However, totally he or she would gain 1.203.000 Turkish Lira profit.

Model path for interest rate intervention is given in Table 25.

TABLE 25 Model Path For Interest Rate Intervention

BRATE_CHG <= -0.005 [Mode: Intervention] (18)
XU100_CHG <= 0.035 [Mode: Intervention] => Intervention (16; 0.938)
XU100_CHG > 0.035 [Mode: None] => None (2; 1.0)
BRATE_CHG > -0.005 [Mode: None] (140)
XU100_CHG <= 0.003 [Mode: None] (82)
EURTL_VOL <= 0.013 [Mode: None] (77)
DIFF_IR_INF <= 1.300 [Mode: Intervention] => Intervention (4; 1.0)
DIFF_IR_INF > 1.300 [Mode: None] (73)
XU100_VOL <= 0.016 [Mode: None] (34)
USDTL_CHG <= 0.003 [Mode: None] => None (22; 1.0)
USDTL_CHG > 0.003 [Mode: None] (12)
DIFF_IR_CMB_IR <= 0.940 [Mode: Intervention] => Intervention (3; 1.0)
DIFF_IR_CMB_IR > 0.940 [Mode: None] => None (9; 0.889)
XU100_VOL > 0.016 [Mode: None] (39)
BRATE_CHG <= 0.001 [Mode: Intervention] (26)
XU100_SKW <= 0.073 [Mode: Intervention] (18)
DIFF_IR_INF <= 5 [Mode: None] => None (3; 1.0)
DIFF_IR_INF > 5 [Mode: Intervention] (15)
DIFF_IR_CMB_IR_MEAN <= 3.173 [Mode: Intervention] (32)
USDTL_KURT <= 2.108 [Mode: Intervention] (30)
EURTL_VOL <= 0.007 [Mode: Intervention] => Intervention (10; 1.0)
EURTL_VOL > 0.007 [Mode: Intervention] (20)

EURTL_SKW <= 0.210 [Mode: None] => None (5; 1.0)
EURTL_SKW > 0.210 [Mode: Intervention] (15)
BRATE_KURT <= 4.778 [Mode: Intervention] (12)
USDTL_CHG <= 0.004 [Mode: None] => None (9; 0.667)
USDTL_CHG > 0.004 [Mode: Intervention] => Intervention (3; 1.0)
BRATE_KURT > 4.778 [Mode: Intervention] => Intervention (3; 1.0)
XU100_SKW > 0.073 [Mode: Intervention] => Intervention (8; 1.0)
EURTL_VOL > 0.013 [Mode: Intervention] => Intervention (5; 1.0)
XU100_CHG > 0.003 [Mode: None] (58)
USDTL_SKW <= 0.426 [Mode: None] (32)
USDTL_CHG <= 0.013 [Mode: None] (29)
EURTL_CHG <= -0.002 [Mode: Intervention] (9)
XU100_VOL <= 0.018 [Mode: Intervention] => Intervention (6; 0.833)
XU100_VOL > 0.018 [Mode: None] => None (3; 1.0)
EURTL_CHG > -0.002 [Mode: None] => None (20; 1.0)
USDTL_CHG > 0.013 [Mode: Intervention] => Intervention (3; 1.0)
USDTL_SKW > 0.426 [Mode: None] => None (26; 1.0)

CHAPTER 8

CONCLUSION

“I think and think for months and years. Ninety-nine times, the conclusion is false. The hundredth time I am right.”

Since the last financial crisis in 2008, emphasize for intervention “needs” or “calls” on mixed economies have gained power. Interventions of governments and especially central banks have been normalized. These interventions are performed on behalf markets and the sake of the markets because of deteriorations of expectations, stabilizing the market, decreasing high volatility or solving disorder.

The writer of this thesis is curious about these ambiguous concepts and tries to figure out what really triggers Central Bank of Republic of Turkey to intervene the markets. This is the dominating motive of this thesis because interventions of central banks change the dynamics of the economy. This effect is easily extended to other countries regarding the power of the central banks.

It is crucial to model, understand and analyze the intervention of central banks because they change important “prices” (exchange rate or interest rate) in the economy, they change the expectations and they give a signal to markets about their market order or disorder. These behaviours of central banks form the monetary policy. Thus understanding the motives of the central bank intervention let market players to understand the aim of the monetary policy of the central banks.

According to this information market players can estimate which indicators and level of indicators disturb the central bank policies. In order to model the interventions of central bank we study the literature, compare the methodologies, adopt the variables and support with daily data of financial indicators of the market.

8.1 Results and Findings

In the first phase logit regression analysis is used to model the central Bank of Republic of Turkey. (See Appendix B: Table B-1,B-2,B-3-B-4,B-5) The best models estimate only 72 % of exchange rate interventions and 61,5 % of interest rate interventions. Moreover logit regression can not handle the problem with unbalanced data. Thus statistical problems occurred because unbalanced data in logit regression.

The best model in logit regression finds the following variables significant to model the exchange rate interventions such as, volatility of Borsa İstanbul 100 index, volatility of benchmark interest rates, skewness of benchmark interest rate, volatility of EURO/TL exchange rate and kurtosis of EURO/TL exchange rate. The best model in logit regression finds the following variables significant to model the interest rate interventions such as daily change in Borsa İstanbul 100 index, daily change in benchmark interest rate and volatility of USD/TL exchange rate.

In this point there are two problems we have encountered. First the rate of intervention detection is not satisfactory and statistical problems affect the result in a negative way. Thus in order to solve problems firstly we try to increase the explanation power of the independent variables. Thus reaction functions are analyzed and the theories behind the reaction functions are examined. In order to accomplish that many different modifications of reaction functions are analyzed. Criticisms and positives aspects of reaction functions are compared and new independent variables are recruited from reaction functions to increase the explanatory power of our model and theoretical back ground of the model. New independent variables are put into model representing (πt- πt^*) the common independent variable in reaction functions. The deviation between existing inflation and expected inflation are transferred to our model the difference between benchmark interest rate and target inflation of central bank (also difference between benchmark and interest rate of central bank is also added in the decision tree analysis) in a daily based data.

Moreover considering the reaction function theory a modified daily reaction function is suggested. This function is applied to interest rate market and exchange rate market. OLS regression, VAR and M-Garch methods are performed in order to analyze the relations among the variable of the modified daily reaction function.

In order to see the GDP effect on modified daily reaction function a dummy is added to function and its effect is also analyzed. In OLS regression USD/TL and Dummy variable (covers GDP effect) are significant to explain the changes in interest rate of CBRT. Next the only significant variable is found as the difference between benchmark interest rate and target inflation in order to explain USD/TL when OLS regression is performed. In VAR analysis first lagged of interest rate of CBRT, first, second, third, fourth, fifth and seventh lagged of difference of benchmark interest rate and target inflation and fourth lagged of volatility of benchmark interest rate significantly affect the interest rate of CBRT. Granger Causality Tests imply that there exists one-way causality from the variable of difference of benchmark interest rate and target inflation to interest rate of CBRT. This is in line with the findings of VAR. More over there is another one-way causality is also founded from volatility of benchmark interest rate to interest rate of CBRT.

Moreover reaction of interest rate of CBRT to difference of benchmark interest rate and target inflation is considerable. A change in difference of benchmark interest rate and target inflation affects the interest rate of CBRT from the first day of the change and creates a new equilibrium in following days. After eleven days a new equilibrium is set. A change or shock can be derived from two reasons. This might be caused by the change or shock in the benchmark interest rate or target inflation. This is crucial finding because in this finding implicitly if the expectations change regarding the difference of benchmark interest rate and target inflation interest rate of CBRT adopts itself to new expectations and stay in this new equilibrium for a long time. When a change or shock happens in volatility of benchmark interest rate, interest rate of CBRT gives a response in the third day of the change and starts to fluctuate around its own path. We do not observe this fluctuation in the previous shock which is derived by difference of benchmark interest rate and target inflation. Thus the content of the variable which is based on volatility cause a fluctuation in interest rate of CBRT. Even the effect of this change is not significant when it is compared to change in difference of benchmark interest rate and target inflation, it is clear that time of adjustment takes more time.

The reaction of interest rate of CBRT is also limited when it is compared to change in difference of benchmark interest rate and target inflation. However interest rate of CBRT gives a response in the third day of the change and starts to fluctuate around its own path which looks like its reaction we observed in volatility of benchmark. Moreover interest rate of CBRT finds its new equilibrium in the eight day of change and do not turn back its previous path. Thus a change or shock in volatility of USD/TL exchange rate creates a combined effect of difference of benchmark interest rate and target inflation and volatility of benchmark on interest rate of CBRT. These results are also in line with VAR results of interest rate of CBRT. It is clear that CBRT is more sensitive to changes in difference of benchmark interest rate and target inflation rather than volatility of benchmark and volatility of USD/TL exchange rate.

VAR analysis is also underlined. Fifth lagged of USD/TL exchange rate, first and second lagged of difference of benchmark interest rate and target inflation, first and second lagged of volatility of benchmark interest rate, first, second, third and fifth lagged of volatility of USD/TL significantly affect the USD/TL exchange rate. There exists one-way causality from the variable of difference of benchmark interest rate and target inflation to USD/TL exchange rate. This finding is also ratifies the adoption and modification of daily reaction function of this thesis. Next there is one-way causality from USD/TL exchange rate to volatility of benchmark interest rate. Moreover it is clear that there is reciprocal causality between volatility of USD/TL exchange rate and USD/TL exchange rate.

USD/TL exchange rate gives a response in the first day of a change or shock in difference of benchmark interest rate and target inflation. The response of USD/TL is strong in this phase.Then USD/TL fluctuates on its own path and normalizes in the ninth day. This response behavior is also in line with VAR results. USD/TL exchange rate gives a response in the first day of a change or shock in volatility of benchmark interest rate. However response power of this behavior is less than the reaction that is observed to change in difference of benchmark interest rate and target inflation. Then USD/TL fluctuates on its own path and normalizes in the ninth day again. However fluctuation distance is also less than fluctuation is observed to the change in difference of benchmark interest rate and target inflation.

In the framework of M-Garch analysis, variance of interest of CBRT increases in 2002, 2003, 2006 and 2008. It is another result that conditional covariance and conditional correlation of interest rate of CBRT and difference of benchmark interest rate and target inflation also increases in 2002, 2003, 2006 and 2008. These two results also support the economic indicators because in those years in Turkey both interest rate and inflation have decreased. Moreover conditional covariance and conditional correlation of interest rate of CBRT and volatility of Benchmark fluctuates. Both indicators have positive and negative relations in different years or even in the same year. This finding also supports the same pattern when conditional covariance of interest of CBRT and volatility of CBRT is analyzed. The sign of conditional covariance and conditional correlation of interest rate of CBRT and volatility of USD/TL exchange rate fluctuates and changes quickly when it is compared to volatility of benchmark interest rate.All “A” coefficients are significant in the %99 level. Thus it implies that all variables involved in the function, is affected by their own previous volatility shocks. Their previous volatility shocks affect current volatility of the all variables. In other words all variables in the function are sensitive to their past volatility shocks. Volatility of USD/TL exchange rate and volatility of benchmark interest rate are most sensitive to their previous volatility shocks respectively. (A4=0.396288 for USD/TL and A3=0.392547). Interest rate of CBRT has the lowest coefficient and less sensitive to its previous volatility shocks. (A1=0,064160). Coefficient of difference of benchmark interest rate and target inflation A3 equals to 0.109618. All “B” coefficients are significant in % 99 level except for interest of CBRT. This is important finding. Because all variables are sensitive to and their previous volatility has a permanent effect on them. However this invalid for interest rate of CBRT. This finding is also in line with the result that is found for “A” coefficients. The highest “B” coefficient belongs to difference of benchmark interest rate and target inflation (B2=0.993478). Volatility of USD/TL exchange rate and volatility of benchmark interest rate follow it respectively.

In M-Garch analysis, variance of USD/TL exchange rate increases in 2002, 2006, 2007 and 2008. However we should underline that increase in 2008 is severe. This finding has an economic back ground considering the financial crisis in the world in 2008. Secondly conditional covariance between USD/TL exchange rate and difference of benchmark interest rate and target inflation fluctuate frequantley and the picture they form can be generalized as volatile. Moreover conditional covariance of USD/TL exchange rate and volatility of benchmark interst rate have a high observation value. Especially after 2008 this ratio sharply increases. Next conditional covariance between USD/TL exchange rate and volaitility of USD/TL exchange rate acts in the same channel. However this tendency is disturbed in 2008 the relation among them becames volatile for 2008. Thirdly when conditional correlations are analyzed, the conditional correlation between USD/TL exchange rate and difference of benchmark interest rate and target inflation is very volatile. This relation has reached its highest value in 2006, 2008 and 2011. Next conditional correlation between USD/TL exchange rate and volatility of benchmark interest graph looks like the same relation between two variables considering the conditional covariance. Conditional correlation of USD/TL exchange rate and volatility of benchmark fluctuates in a certain channel up to 2008. After 2008 this relation increases sharply. Finally conditional correlation of USD/TL exchange rate and volaitility of USD/TL exchange rate acts very volatile in a certain channel however this pattern is also disturbed in 2008 sharply.

For M-Garch results for modified results for modified daily reaction function for exchange rate All “A” coefficients are significant in the %99 level. Thus it implies that all variables involved in the function, is affected by their own previous volatility shocks. Their previous volatility shocks affect current volatility of the all variables. In other words all variables in the function are sensitive to their past volatility shocks. Volatility of benchmark interest rate and olatility of USD/TL exchange rate are most sensitive to their previous volatility shocks respectively (A3=0411433, A4=0.188812). USD/TL exchange rate has the third rank when four variables are considered among coefficients (A1=0.117423). Difference of benchmark interest rate and target inflation has the lowest coefficient and less sensitive to its previous volatility shocks (A2=0.011658) Secondly all “B” coefficients are significant in % 99 level. This is important finding. Because all variables are sensitive to and their previous volatility has a permanent effect on them. The highest B coefficient belongs to difference of benchmark interest rate and target inflation (B2=0.985871). USD/TL exchange rate and volatility of USD/TL exchange rate follow it respectively (B1=0.842214, B4=0.771681). Volatility of benchmark interest rate has the lowest coefficient and less sensitive permanence of previous volatility shocks.Finally when we compare “B” coefficients to “A” coefficients, it is observed that “B” coefficients have higher values. Thus we can conclude that volatility shocks have permanent effect on variables in the function.

OLS regression, VAR and M-Garch results, confirm the adoption of the modified function and ist variables. By this way the model of the thesis cover the central philosophy of reaction functions. Daily representation of these variables are reinforced with basic daily financial indicators of Turkey such as USD/TL exchange rate, EURO/TL, Borsa İstanbul 100 index and benchmark interest rate. Moreover four moments (mean, volatility, skewness and kurtosis) of these financial indicators are also used in independent variables to understand the intervention decision of Central bank of Republic of Turkey.

The second problem is to solve the unbalanced data and over learning problem. A technique is needed to help to solve these problems. After comparing methodologies within related literature we decided to use decision trees C5 (See also CHAID results in Table E-1, Table E-2, Figure E-1 and Figure E-2 at Appendix E) algorithm. Thus, we use random sampling for non-intervention days to be balanced with intervention days. For example, we select all of intervention days for foreign exchange rate interventions (26 days) and almost 47 of non-intervention days are chosen randomly. Then we extend the model to all data. By the help variables which are adopted from reaction functions and solutions of decision trees let us to model intervention of central Bank of Republic of Turkey better than logit regressions and without having statistical problems.

After these modifications decision tree C5 algorithm detected 96,15 % percentage of exchange rate intervention of Central Bank of Republic of Turkey and 91,44 % percentage of interest rate intervention of Central Bank of Republic of Turkey.

According to results of the decision tree (C5) analysis daily change of benchmark interest rate, kurtosis of USD/TL exchange rate, daily change of Borsa İstanbul 100 index, skewness of benchmark interest rate, kurtosis of benchmark interest rate, skewness of Borsa İstanbul 100 index, daily change of EUR/TL exchange rate and difference of benchmark interest rate and target inflation and index follow the regarding predictor importance in the model are the significant predictors to model exchange rate intervention of Central Bank of Republic of Turkey.

According to results of the decision tree (C5) analysis daily change of benchmark interest rate, volatility of Borsa İstanbul 100 index, skewness of EURO/TL exchange rate, daily change of USD/TL exchange rate, mean of difference of benchmark interest rate and interest rate of central bank, skewness of USD/TL exchange rate, kurtosis of benchmark interest rate, volatility of EURO/TL exchange rate, daily change of Borsa İstanbul 100 index, daily change of EURO/TL exchange rate, kurtosis of USD/TL exchange rate and mean of benchmark interest rate are the significant predictors to model interest rate intervention of Central Bank of Republic of Turkey.

According to cut values (or threshold values) decision tree for exchange rate intervention (Figure 7) and decision tree for interest rate intervention (Figure 9) are established. Interventions are analyzed according to these cut values and rule paths of these interventions are also analyzed by the predictors. The result of the decision trees let all market players analyze the cut values and intervention behavior of the Central Bank of Republic of Turkey by detected predictors and cut values.

Another important finding maybe the shortage of the analysis is in exchange rate model, model indicates that 545 days have similar patterns with the detected intervention days and should impose the intervention of central bank. However Central Bank of Republic of Turkey did not intervene in those days. A parallel situation exists also for interest rate interventions. Model indicates that 766 days have similar patterns with the detected intervention days and should impose the interest rate intervention of central bank. In here there are two possible explanations. Firstly Central Bank of Republic of Turkey might be too conservative to intervene the markets even there is a certain pattern in her intervention behavior which is already captured by the model with high percentages. Secondly there may be political or cyclical thresholds which can not be captured by the existing variables. This contradicted behavior of the Central Bank of Republic of Turkey will be the subject of future work.

Moreover when the decision trees of exchange rate intervention and interest rate intervention is compared, interest rate intervention decision tree is more complex and it is figured out those predictors numbers of interest rate intervention is more than exchange rate intervention. This complex tree let us make a more sensitive analysis buy the help of sub nodes in the decision tree. A market player, analyst, academician or investor can easily the follow the model, predictors of the model, cut values and analyze the direction of the decision tree and Central Bank of Republic of Turkey intervention behaviour.

8.2 FUTURE WORK

Our model aimed to model intervention behavior (decision) of Central Bank of Republic of Turkey and to analyze the factors that trigger her to intervene the market. We believe that we succeeded to model both exchange rate intervention and interest rate intervention of Central Bank of Republic of Turkey. We use a different and a relatively new methodology to model the interventions of the central bank. We take benefit of the logit regression results and support these results with the theory of reaction functions. We adopt the reaction function variables into our model and modify them with daily data. Using daily financial indicators of market data and decision trees C5 algorithm provide a consistency regarding the thesis aims and results. Using moment of the variables also empower the sensitivity of the model regarding sub nodes in decision tree.

On the other hand there are some shortages to recover and suggestions for getting better results in our model. For instance the amount of money, which will be used for intervention, creates a great concern in the market. In this model we did not seek the questions of "What amount of money should be given to the market or collected from the market?, "How much money is needed to stabilize or prevent the disorder in the market?", "Which intervention instrument should be chosen for different market conditions?" If we start to study and try to answer these questions one by one, in the future we will have better and more sensitive models and results.

As it is mentioned above, our model detected interventions with a great success. However our model suggests some other days also should be imposed intervention by central bank. But Central Bank of Republic of Turkey did not intervene in those days. In this situation we offer two possible answers. On of them is related to conservative behvaiour of central bank. This implies that even model and predictors offers to intervene Central Bank of Republic of Turkey may not intervene because they may not want to affect the dynamics of the market so often. Second explanation of this shortage is related to political or cyclical issues. Policy makers might affect or might consider the political or cyclical concerns. Thus there might be a threshold to detect these concerns. New variables or a different analysis methodology can detect this threshold. This issue can create a base for future studies.

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Appendix A

TABLE A-1 Logit Regression Variables

DEPENDENT VARIABLES	SYMBOLS	DEFINITION OF THE INDEPENDENT VARIABLES
Intervention (1)	EURTL_CHG	Daily change of EURO/Turkish Lira
Non-Intervention (0)	EURTL_MEAN	Mean of EURO/Turkish Lira
	EURTL_VOL	Volatility of EURO/Turkish Lira
	EURTL_SKW	Skewness of EURO/Turkish Lira
	EURTL_KURT	Kurtosis of EURO/Turkish Lira
	USDTL_CHG	Daily change of USD/Turkish Lira
	USDTL_MEAN	Mean of USD/Turkish Lira
	USDTL_VOL	Volatility of USD/Turkish Lira
	USDTL_SKW	Skewness of USD/Turkish Lira
	USDTL_KURT	Kurtosis of USD/Turkish Lira
	XU100_MEAN	Mean of Borsa İstanbul 100 index
	XU100_CHG	Daily change of Borsa İstanbul 100 index
	XU100_MEAN	Mean of Borsa İstanbul 100 index
	XU100_VOL	Volatility of Borsa İstanbul 100 index
	XU100_SKW	Skewness of Borsa İstanbul 100 index

	XU100_KURT	Kurtosis of Borsa İstanbul 100 index
	BRATE_CHG	Daily change of benchmark interest rate
	BRATE_MEAN	Mean of benchmark interest rate
	BRATE_VOL	Volatility of benchmark interest rate
	BRATE_SKW	Skewness of benchmark interest rate
	BRATE_KURT	Kurtosis of benchmark interest rate

APPENDIX B

TABLE B-1 Exchange Rate Intervention Results Model 1-Logit Regression Results

Logit Model 1	FORWARD	B	S.E	Wald	df	Sig	Exp (B)
	BRATE_VOL	157,086	51,160	9,428	1	,002	##########
	BRATE_KURT	,122	,041	8,771	1	,003	1,130
	Constant	-5,725	,380	226,784	1	,000	,003

Success of Logit Model 1			Percentage correct
None Intervention	**1944**	**772**	**71,6**
Exchange Rate Intervention	**7**	**18**	**72**
Over all percentage			**71,6**

TABLE B-2 Exchange Rate Intervention Results Model 2-Logit Regression

Logit Model 2	FORWARD	**B**	**S.E**	**Wald**	**df**	**Sig**	**Exp (B)**
	XU100_VOL	-146,416	40,937	12,792	1	,000	,000
	BRATE_VOL	726,859	83,731	75,357	1	,000	
	BRATE_SKW	,537	,182	8,711	1	,003	1,712
	EURTL_VOL21	-715,322	109,260	42,862	1	,000	0,000
	EURTL_KURT21	,352	,098	13,036	1	,000	1,422

Success of Logit Model 2			Percentage correct
None Intervention	1999	697	74,1
Exchange Rate Intervention	7	18	72
Over all percentage			74,1

TABLE B-3 Exchange Rate Intervention Results Model 3-Logit Regression

Logit Model 3	BACKWARD	**B**	**S.E**	**Wald**	**df**	**Sig**	**Exp (B)**
	BRATE_VOL	224,891	56,891	15,626	1	,000	##########
	BRATE_SKW	,563	,199	8,033	1	,005	1,756
	USD_VOL21	-195,900	103,138	3,608	1	,058	0,000
	Constant	-4,131	,701	34,723	1	,000	0,16

Success of Logit Model 3			Percentage correct
None Intervention	2156	580	78,5
Exchange Rate Intervention	9	16	64
Over all percentage			78,4

TABLE B-4 Exchange Rate Intervention Results Model 4-Logit Regression

Logit Model 4	BACKWARD	**B**	**S.E**	**Wald**	**df**	**Sig**	**Exp (B)**
	EURTL_VOL	-612,695	212,116	8,343	1	,004	,000
	USDTL_VOL	537,586	207,268	6,727	1	,009	##########
	XU100_VOL	-119,206	49,961	5,693	1	0,17	,000
	BRATE_VOL	687,296	104,700	43,092	1	,000	##########
	BRATE_SKW	,638	,190	11,243	1	,001	1,892
	EURTL_KURT21	,364	,106	11,828	1	,001	1,440
	USDTL_VOL21	-700,468	140,361	24,905	1	,000	,000

Success of Logit Model 4			Percentage correct
None Intervention	2001	695	74,2
Exchange Rate Intervention	9	16	64
Over all percentage			74,1

TABLE B-5 Interest Rate Intervention Results Model 1-Logit Regression

Logit Model 1	FORWARD	**B**	**S.E**	**Wald**	**df**	**Sig**	**Exp (B)**
	XU100_CHG	-24,579	6,908	12,661	1	,000	,000
	BRATE_CHG	-112,248	24,737	20,591	1	,000	,000
	USDTL_VOL21	70,896	27,237	6,775	1	0,09	##########
	Constant	-4,707	,298	249,601	1	,000	,009

Success of Logit Model 4			Percentage correct
None Intervention	1835	834	68,8
Interest Rate Intervention	20	32	61,5
Over all percentage			68,6

APPENDIX C

TABLE C-1 Unit Root Tests for Daily Modified Reaction Variables

	Level				First Differences	
	Constant		Constant and Linear Trend		Constant	
Augmented Dickey-Fuller	T-Stat	Prob.	T-Stat	Prob.	T-Stat	Prob.
CMB_IR	-5.221	0.000***	-3.385	0.0535*		
BNCH_TARGET_INFLATION	-1.985	0.2934	-2.846	0.1808	-26.716	0.0000***
BRATE_VOL	-2.363	0.1524	-2.968	0.1414	-13.627	0.0000***
USDTL_VOL	-4.044	0.0012***	-4.120	0.0059***		
USDTL	-1.658	0.4524	-2.066	0.5636	-50.978	0.0001***
Phillips-Perron						
CMB_IR	-5.584	0.000***	-3.516	0.0377**		
BNCH_TARGET_INFLATION	-2.037	0.2706	-2.865	0.1741	-51.306	0.0001***
BRATE_VOL	-2.074	0.2551	-2.685	0.2425	-51.810	0.0001***
USDTL_VOL	-3.549	0.0069***	-3.619	0.0283**		
USDTL	-1.739	0.4110	-2.153	0.5147	-50.98764	0.0001***
Kwiatkowski-Phillips-Schmidt-Shin test statistic	Constant		Constant and Linear Trend		Constant	
LM STATISTICS						
CMB_IR	4.893351		0.872755			
BNCH_TARGET_INFLATION	3.758062		0.346939		0.032093	
BRATE_VOL	3.490411		0.821330		0.039967	
USDTL_VOL	0.464212		0.398915			
USDTL	2.241279		0.982473		0.065206	

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

TABLE C-2 VAR Lag Order Selection Criteria

VAR Lag Order Selection Criteria
Endogenous variables: CMB_IR DBNCH_TARGET_INFLATION DBRATE_VOL USDTL_VOL
Exogenous variables: C
Date: 09/14/14 Time: 22:19
Sample: 4/04/2002 2/28/2013
Included observations: 2732

Lag	LogL	LR	FPE	AIC	SC	HQ
0	42470.96	NA	3.70e-19	-31.08855	-31.07989	-31.08542
1	60981.87	36954.06	4.88e-25	-44.62802	-44.58473	-44.61237
2	61060.97	157.6750	4.66e-25	-44.67421	**-44.59629***	-44.64605
3	61085.68	49.18457	4.63e-25	-44.68058	-44.56804	-44.63991
4	61116.29	60.83886	4.58e-25	-44.69128	-44.54411	-44.63809
5	61156.94	80.67827	4.50e-25	-44.70933	-44.52753	-44.64362
6	61207.43	100.0520	4.39e-25	-44.73457	-44.51815	-44.65635
7	61249.08	82.41532*	4.30e-25*	**-44.75335***	-44.50229	**-44.66261***
8	61261.81	25.15318	4.32e-25	-44.75096	-44.46527	-44.64771

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

FIGURE C-1 Impulse Response Function For Variables of Daily Modified Reaction Function

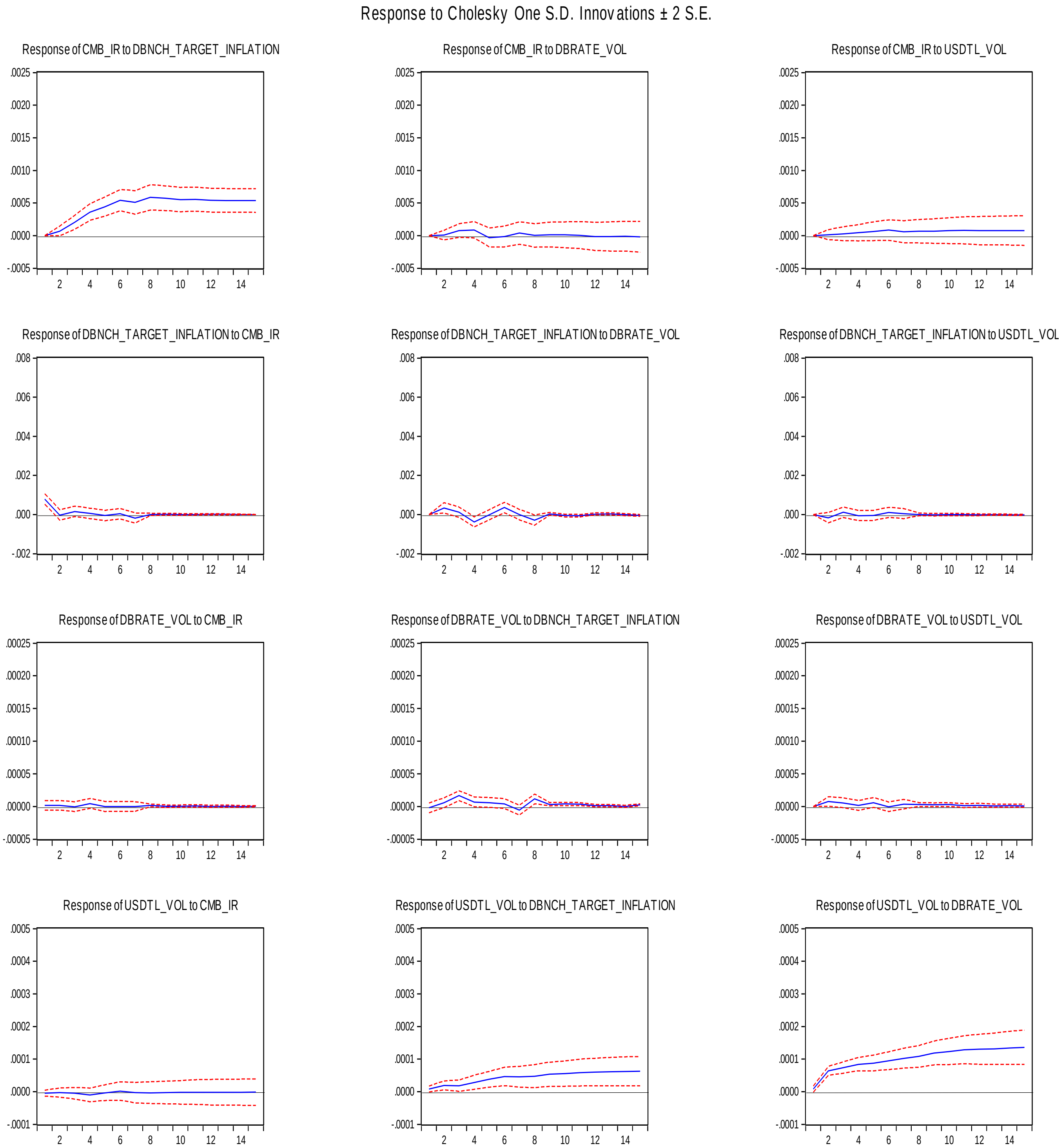


TABLE C-3 Graphs of Residuals for Modified Daily Reaction Function For Interest Rate of CBRT

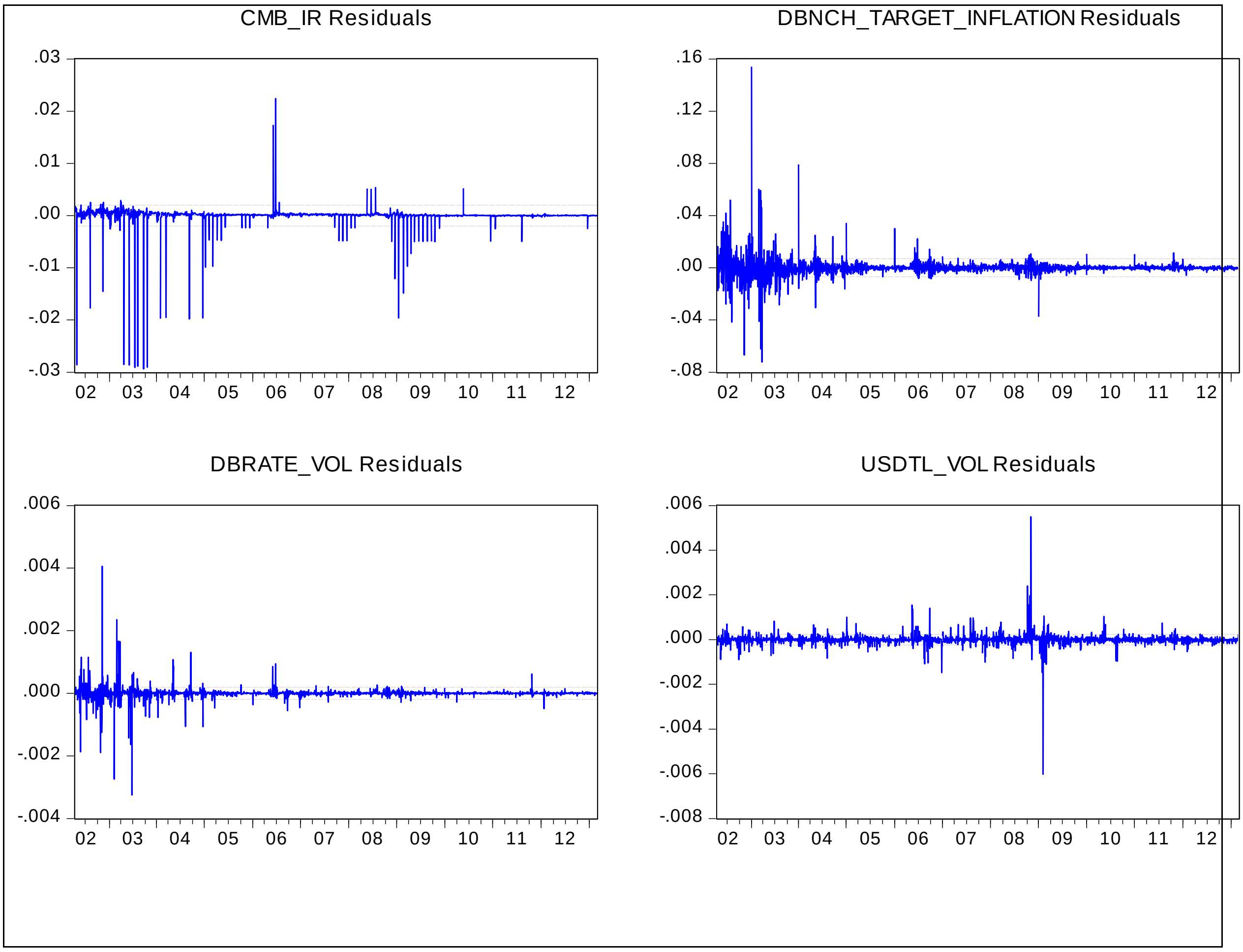


TABLE C-4 VAR Residual Serial Correlation LM Tests For Modified Daily Reaction Function For Interest Rate of CBRT

Null Hypothesis: no serial correlation at lag order h
Sample: 4/04/2002 2/28/2013
Included observations: 2738

Lags	LM-Stat	Prob
1	42.70268	0.0003
2	30.43449	0.0159
3	61.37149	0.0000
4	51.68008	0.0000
5	128.0797	0.0000
6	21.50421	0.1599
7	105.8100	0.0000
8	52.23294	0.0000
9	84.78458	0.0000
10	62.19911	0.0000
11	20.23455	0.2098
12	49.41844	0.0000

Probs from chi-square with 16 df.

TABLE C-5 VAR Residual Normality Tests For Modified Daily Reaction for Interest Rate of CBRT

Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Sample: 4/04/2002 2/28/2013
Included observations: 2738

Component	Skewness	Chi-sq	Df	Prob.
1	-10.05965	46179.40	1	**0.0000*** **
2	4.569070	9526.600	1	**0.0000*** **
3	0.171499	13.42166	1	**0.0002*** **
4	-0.675925	208.4869	1	**0.0000*** **
Joint		55927.91	4	**0.0000*** **

Component	Kurtosis	Chi-sq	Df	Prob.
1	151.4877	2515378.	1	**0.0000*** **
2	123.6351	1660235.	1	**0.0000*** **
3	152.7304	2557656.	1	**0.0000*** **
4	279.9662	8751367.	1	**0.0000*** **
Joint		15484636	4	**0.0000*** **

Component	Jarque-Bera	df	Prob.
1	2561557.	2	**0.0000*** **
2	1669762.	2	**0.0000*** **
3	2557670.	2	**0.0000*** **
4	8751575.	2	**0.0000*** **
Joint	15540564	8	**0.0000*** **

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

TABLE C-6 Variance Decomposition for Modified Daily Reaction Function for Interest Rate of CBRT

Variance Decomposition of CMB_IR:

Period	S.E.	CMB_IR	DBNCH_TARGET_INFLATION	DBRATE_VOL	USDTL_VOL
1	0.001993	100.0000	0.000000	0.000000	0.000000
2	0.002781	99.93446	0.062372	0.000585	0.002582
3	0.003371	99.53207	0.405867	0.053842	0.008219
4	0.003862	98.71305	1.175815	0.092566	0.018566
5	0.004289	97.85786	2.023756	0.080707	0.037676
6	0.004676	96.82815	3.038585	0.068719	0.064547
7	0.005017	96.19769	3.667096	0.065800	0.069410
8	0.005348	95.44058	4.425429	0.057911	0.076083
9	0.005659	94.88649	4.979179	0.052295	0.082033
10	0.005951	94.50577	5.356154	0.047713	0.090367
11	0.006230	94.17230	5.685157	0.043597	0.098950
12	0.006494	93.92689	5.928135	0.040630	0.104347
13	0.006747	93.72619	6.126001	0.038137	0.109669
14	0.006990	93.54762	6.302383	0.035764	0.114235
15	0.007224	93.39295	6.454620	0.034182	0.118248

Variance Decomposition of DBNCH_TARGET_INFLATION:

Period	S.E.	CMB_IR	DBNCH_TARGET_INFLATION	DBRATE_VOL	USDTL_VOL
1	0.006905	1.314209	98.68579	0.000000	0.000000
2	0.006919	1.311028	98.39557	0.235818	0.057583
3	0.006934	1.355119	98.29857	0.261661	0.084655
4	0.006961	1.351267	97.99336	0.564512	0.090865
5	0.006972	1.351941	97.98949	0.563460	0.095108
6	0.006989	1.349068	97.71046	0.824694	0.115782
7	0.006992	1.415433	97.63996	0.824229	0.120379
8	0.006999	1.412340	97.47669	0.990839	0.120129
9	0.007000	1.412627	97.47297	0.993497	0.120906
10	0.007000	1.412566	97.46828	0.998160	0.120992
11	0.007000	1.412505	97.46026	1.006158	0.121078
12	0.007000	1.412537	97.45899	1.006886	0.121584
13	0.007000	1.412640	97.45681	1.008959	0.121589
14	0.007000	1.412720	97.45628	1.008982	0.122020
15	0.007000	1.412654	97.45206	1.012911	0.122377

Variance Decomposition of DBRATE_VOL:

Period	S.E.	CMB_IR	DBNCH_TARGET_INFLATION	DBRATE_VOL	USDTL_VOL
1	0.000194	0.007858	0.012334	99.97981	0.000000
2	0.000195	0.015035	0.093320	99.74158	0.150062
3	0.000197	0.015205	0.795423	98.96550	0.223867
4	0.000197	0.067735	0.909607	98.79369	0.228967
5	0.000198	0.067669	0.994012	98.61801	0.320308
6	0.000198	0.067276	1.030458	98.58335	0.318915
7	0.000199	0.067058	1.109702	98.47145	0.351788
8	0.000202	0.070192	1.405874	98.16217	0.361761
9	0.000202	0.070068	1.427192	98.12751	0.375231
10	0.000202	0.070261	1.457509	98.07658	0.395650
11	0.000202	0.071487	1.485909	98.04393	0.398676
12	0.000202	0.071464	1.489217	98.03303	0.406289
13	0.000203	0.071801	1.491209	98.02876	0.408233
14	0.000203	0.071831	1.490208	98.02629	0.411672

15	0.000203	0.071927	1.503046	98.01148	0.413545

Variance Decomposition of USDTL_VOL:

Period	S.E.	CMB_IR	DBNCH_TARGET_INFLATION	DBRATE_VOL	USDTL_VOL
1	0.000243	0.036621	0.111926	0.101860	99.74959
2	0.000364	0.024403	0.320737	3.085535	96.56932
3	0.000459	0.026912	0.354615	4.491073	95.12740
4	0.000551	0.051372	0.514060	5.447998	93.98657
5	0.000640	0.040974	0.729315	5.916938	93.31277
6	0.000740	0.031116	0.939545	6.059402	92.96994
7	0.000835	0.025847	1.028728	6.260242	92.68518
8	0.000924	0.022573	1.100830	6.486991	92.38961
9	0.001009	0.019893	1.201194	6.807800	91.97111
10	0.001091	0.017474	1.283738	7.091066	91.60772
11	0.001172	0.015354	1.360441	7.347109	91.27710
12	0.001248	0.013822	1.426936	7.554128	91.00511
13	0.001321	0.012542	1.488649	7.734632	90.76418
14	0.001391	0.011455	1.542199	7.908854	90.53749
15	0.001458	0.010530	1.587899	8.069495	90.33208

Cholesky Ordering: CMB_IR DBNCH_TARGET_INFLATION DBRATE_VOL USDTL_VOL

TABLE C-7 Graphic of Residuals for Modified Daily Reaction Function for Exchange Rate

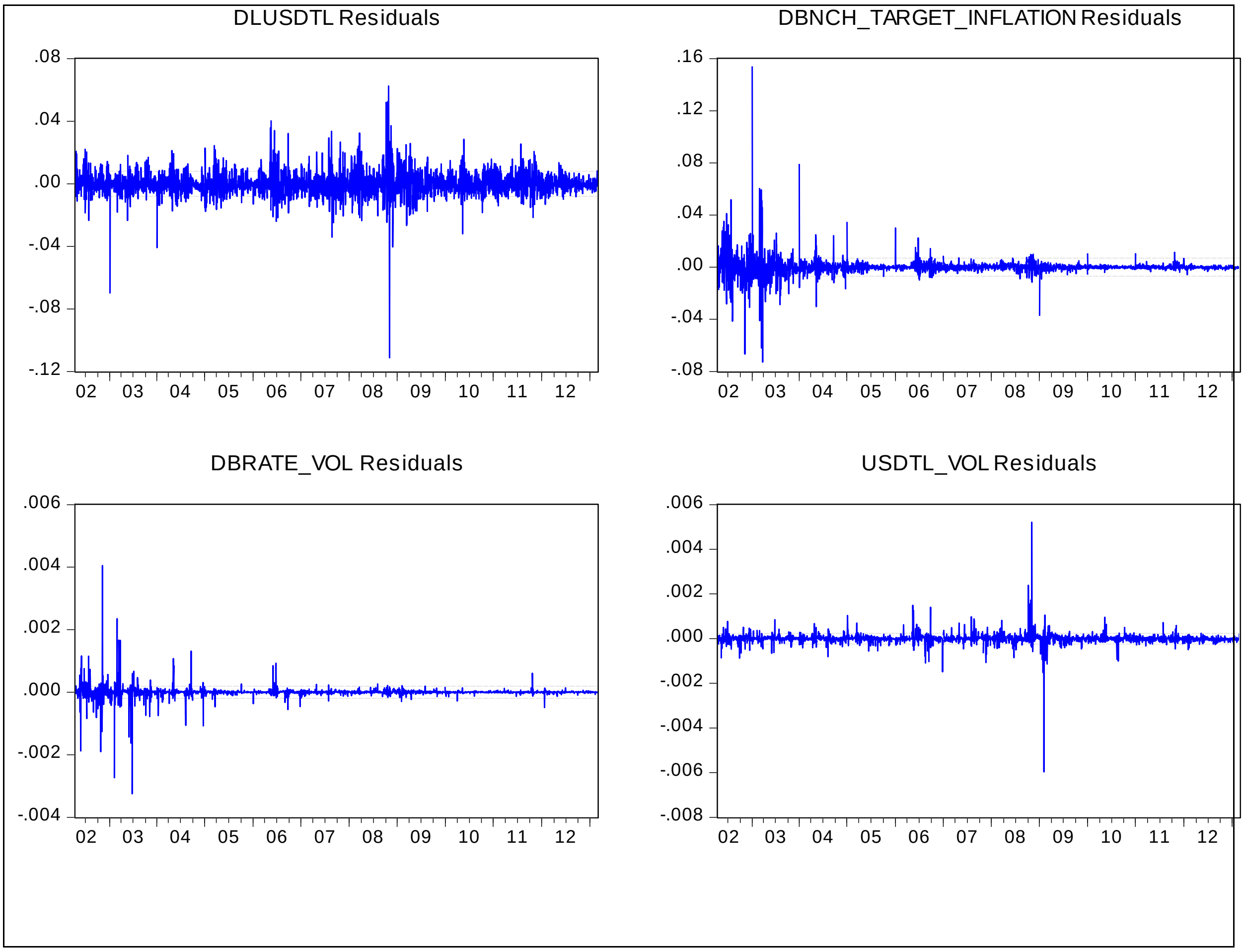


TABLE C-8 VAR Residual Serial Correlation LM Tests forModified Daily Reaction Function for Exchange Rate

Null Hypothesis: no serial correlation at lag order h
Date: 09/15/14 Time: 00:09
Sample: 4/04/2002 2/28/2013
Included observations: 2733

Lags	LM-Stat	Prob
1	13.92558	0.6043
2	33.31415	0.0067
3	52.70237	0.0000
4	74.00922	0.0000
5	60.38552	0.0000
6	38.44399	0.0013
7	23.38591	0.1038
8	25.32232	0.0643
9	64.14244	0.0000
10	56.39067	0.0000
11	19.25410	0.2557
12	26.38455	0.0489

Probs from chi-square with 16 df.

TABLE C-9 Residual Normality Tests for Modified Daily Reaction for Exchange Rate

Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Sample: 4/04/2002 2/28/2013
Included observations: 2733

Component	Skewness	Chi-sq	Df	Prob.
1	-0.544540	135.0664	1	**0.0000*** **
2	4.531930	9355.235	1	**0.0000*** **
3	0.592306	159.8015	1	**0.0000*** **
4	-1.013992	468.3362	1	**0.0000*** **
Joint		10118.44	4	**0.0000*** **

Component	Kurtosis	Chi-sq	Df	Prob.
1	22.56149	43574.46	1	**0.0000*** **
2	122.6332	1629790.	1	**0.0000*** **
3	144.8551	2291493.	1	**0.0000*** **
4	246.1952	6735014.	1	**0.0000*** **
Joint		10699871	4	**0.0000*** **

Component	Jarque-Bera	df	Prob.
1	43709.53	2	**0.0000*** **
2	1639145.	2	**0.0000*** **
3	2291653.	2	**0.0000*** **
4	6735482.	2	**0.0000*** **
Joint	10709990	8	**0.0000*** **

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

FIGURE C-2 Impulse Reaction Function For Modified Daily Reaction Function for Exchange Rate

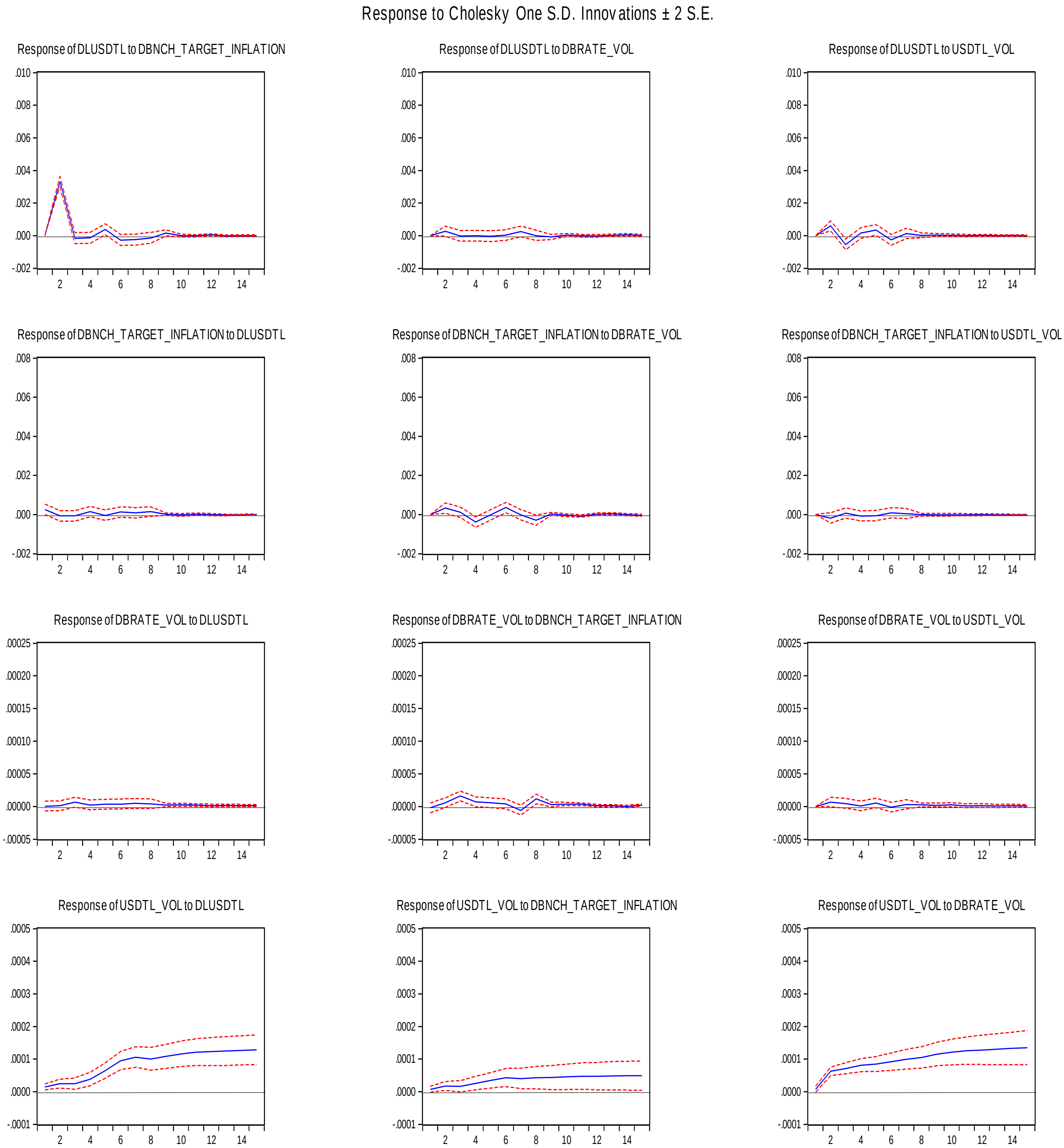


TABLE C-10 Variance Decomposition for Modified Daily Reaction Function for Exchange Rate

Variance Decomposition of DLUSDTL:

Period	S.E.	DLUSDTL	DBNCH_TARGET_INFLATION	DBRATE_VOL	USDTL_VOL
1	0.008079	100.0000	0.000000	0.000000	0.000000
2	0.008769	85.07782	14.35130	0.098605	0.472278
3	0.008788	84.71506	14.32432	0.098657	0.861957
4	0.008791	84.67163	14.33624	0.098641	0.893489
5	0.008814	84.40202	14.45675	0.099632	1.041600
6	0.008827	84.26947	14.50937	0.100611	1.120545
7	0.008836	84.12261	14.55581	0.180544	1.141034
8	0.008838	84.10396	14.57477	0.180477	1.140788
9	0.008840	84.06836	14.60065	0.188979	1.142018
10	0.008841	84.06658	14.60015	0.190593	1.142684
11	0.008841	84.06631	14.60017	0.190760	1.142766
12	0.008841	84.06293	14.60289	0.191324	1.142854
13	0.008841	84.06222	14.60304	0.191897	1.142845
14	0.008841	84.05938	14.60254	0.195218	1.142855
15	0.008841	84.05926	14.60255	0.195337	1.142853

Variance Decomposition of DBNCH_TARGET_INFLATION:

Period	S.E.	DLUSDTL	DBNCH_TARGET_INFLATION	DBRATE_VOL	USDTL_VOL
1	0.006905	0.142226	99.85777	0.000000	0.000000
2	0.006919	0.149939	99.55692	0.224036	0.069108
3	0.006931	0.159397	99.50861	0.250939	0.081054
4	0.006960	0.201814	99.14454	0.560277	0.093368
5	0.006971	0.204503	99.13680	0.559435	0.099260
6	0.006989	0.237301	98.83137	0.815932	0.115392
7	0.006989	0.252894	98.81213	0.816250	0.118724
8	0.006999	0.298760	98.59778	0.984909	0.118550
9	0.006999	0.299053	98.59505	0.986808	0.119085
10	0.006999	0.300040	98.59089	0.989757	0.119314
11	0.007000	0.300575	98.57929	1.000652	0.119485
12	0.007000	0.300699	98.57834	1.001336	0.119628
13	0.007000	0.301568	98.57413	1.004385	0.119912
14	0.007000	0.301858	98.57341	1.004431	0.120302
15	0.007000	0.301847	98.56938	1.008223	0.120555

Variance Decomposition of DBRATE_VOL:

Period	S.E.	DLUSDTL	DBNCH_TARGET_INFLATION	DBRATE_VOL	USDTL_VOL
1	0.000194	0.000560	0.011965	99.98747	0.000000
2	0.000195	0.003811	0.098824	99.78059	0.116773
3	0.000197	0.114950	0.757982	98.95830	0.168772
4	0.000197	0.127533	0.885644	98.81674	0.170078
5	0.000198	0.155551	0.965605	98.63164	0.247207
6	0.000198	0.187403	0.998637	98.56612	0.247845
7	0.000199	0.241651	1.082801	98.40223	0.273323
8	0.000202	0.274052	1.377023	98.06931	0.279616
9	0.000202	0.284210	1.397186	98.03171	0.286892
10	0.000202	0.299457	1.426901	97.97147	0.302171
11	0.000202	0.308577	1.453981	97.93356	0.303884
12	0.000202	0.312638	1.456850	97.92203	0.308480
13	0.000203	0.319765	1.457983	97.91298	0.309269
14	0.000203	0.323835	1.456964	97.90763	0.311571

15	0.000203	0.328414	1.467820	97.89123	0.312534

Variance Decomposition of USDTL_VOL:

Period	S.E.	DLUSDTL	DBNCH_TARGET_INFLATION	DBRATE_VOL	USDTL_VOL
1	0.000240	0.353847	0.078748	0.085649	99.48176
2	0.000357	0.638503	0.259981	3.095097	96.00642
3	0.000450	0.694783	0.293130	4.470982	94.54110
4	0.000539	0.994522	0.428862	5.375877	93.20074
5	0.000627	1.791830	0.620196	5.796874	91.79110
6	0.000728	3.027966	0.809114	5.884509	90.27841
7	0.000824	4.018101	0.868825	6.042512	89.07056
8	0.000912	4.490292	0.924168	6.252935	88.33260
9	0.000998	4.927740	0.962721	6.565388	87.54415
10	0.001080	5.343169	0.995451	6.850948	86.81043
11	0.001161	5.713165	1.030172	7.104948	86.15171
12	0.001238	6.018544	1.052267	7.317758	85.61143
13	0.001311	6.266339	1.073803	7.509089	85.15077
14	0.001381	6.485902	1.092859	7.690604	84.73064
15	0.001448	6.681113	1.108855	7.860577	84.34946

Cholesky Ordering: DLUSDTL DBNCH_TARGET_INFLATION DBRATE_VOL USDTL_VOL

TABLE C-11 M-GARCH Results for Modified Daily Recation for Interest Rate of CBRT (CMB_IR VAR(7)-MGARCH(1,1))

System: UNTITLED
Estimation Method: ARCH Maximum Likelihood (Marquardt)
Covariance specification: **Diagonal BEKK**
Included observations: 2733
Total system (balanced) observations 10932
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 100 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	3.99E-05	7.07E-05	0.564538	0.5724
C(2)	2.70E-05	5.18E-05	0.521897	0.6017
C(3)	-6.22E-06	3.52E-06	-1.767312	**0.0772***
C(4)	-3.39E-06	2.44E-06	-1.390442	0.1644
Variance Equation Coefficients				
C(5)	2.48E-06	2.26E-06	1.099718	0.2715
C(6)	5.41E-09	3.75E-10	14.45181	**0.0000*****
C(7)	5.84E-09	6.71E-11	87.02268	**0.0000*****
C(8)	7.76E-09	1.27E-10	61.16883	**0.0000*****
C(9)	0.064160	0.015171	4.229242	**0.0000*****
C(10)	0.109618	0.000897	122.1911	**0.0000*****
C(11)	0.392547	0.004738	82.85682	**0.0000*****
C(12)	0.396288	0.006821	58.09806	**0.0000*****
C(13)	0.622541	0.449076	1.386272	**0.1657**
C(14)	0.993478	5.04E-05	19723.20	**0.0000*****
C(15)	0.785679	0.001998	393.1793	**0.0000*****
C(16)	0.788737	0.003754	210.1072	**0.0000*****

Log likelihood	64905.70	Schwarz criterion	-47.45144
Avg. log likelihood	5.937221	Hannan-Quinn criter.	-47.47355
Akaike info criterion	-47.48606		

Equation: RESID_CMB_IR_1 = C(1)			
R-squared	-0.000405	Mean dependent var	-5.11E-16
Adjusted R-squared	-0.000405	S.D. dependent var	0.001983
S.E. of regression	0.001983	Sum squared resid	0.010746
Durbin-Watson stat	2.006982		
Equation: RESID_BTAR_INF_1 = C(2)			
R-squared	-0.000015	Mean dependent var	-3.14E-18
Adjusted R-squared	-0.000015	S.D. dependent var	0.006870
S.E. of regression	0.006870	Sum squared resid	0.128939
Durbin-Watson stat	2.003835		
Equation: RESID_BRATE_VOL_1 = C(3)			
R-squared	-0.001045	Mean dependent var	4.14E-19
Adjusted R-squared	-0.001045	S.D. dependent var	0.000193
S.E. of regression	0.000193	Sum squared resid	0.000101
Durbin-Watson stat	2.000431		
Equation: RESID_USDTL_VOL_1 = C(4)			
R-squared	-0.000197	Mean dependent var	-1.05E-18
Adjusted R-squared	-0.000197	S.D. dependent var	0.000242
S.E. of regression	0.000242	Sum squared resid	0.000160
Durbin-Watson stat	2.000723		

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

TABLE C-12 Covariance specification: Diagonal BEKK for Modified Daily Recation for Interest Rate of CBRT

GARCH = M + A1*RESID(-1)*RESID(-1)'*A1 + B1*GARCH(-1)*B1
M is a diagonal matrix
A1 is a diagonal matrix
B1 is a diagonal matrix

Transformed Variance Coefficients

	Coefficient	Std. Error	z-Statistic	Prob.
M(1,1)	2.48E-06	2.26E-06	1.099718	0.2715
M(2,2)	5.41E-09	3.75E-10	14.45181	**0.0000*** **
M(3,3)	5.84E-09	6.71E-11	87.02268	**0.0000*** **
M(4,4)	7.76E-09	1.27E-10	61.16883	**0.0000*** **
A1(1,1)	0.064160	0.015171	4.229242	**0.0000*** **
A1(2,2)	0.109618	0.000897	122.1911	**0.0000*** **
A1(3,3)	0.392547	0.004738	82.85682	**0.0000*** **
A1(4,4)	0.396288	0.006821	58.09806	**0.0000*** **
B1(1,1)	0.622541	0.449076	1.386272	0.1657
B1(2,2)	0.993478	5.04E-05	19723.20	**0.0000*** **
B1(3,3)	0.785679	0.001998	393.1793	**0.0000*** **
B1(4,4)	0.788737	0.003754	210.1072	**0.0000*** **

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

TABLE C-13 Estimation Command for Modified Daily Recation for Interest Rate of CBRT

ARCH(DERIV=AA) @DIAGBEKK C(DIAG) ARCH(1,DIAG) GARCH(1,DIAG)
Estimated Equations:
RESID_CMB_IR_1 = C(1)
RESID_BTAR_INF_1 = C(2)
RESID_BRATE_VOL_1 = C(3)
RESID_USDTL_VOL_1 = C(4)
Substituted Coefficients:
RESID_CMB_IR_1 = 3.98971170513e-05
RESID_BTAR_INF_1 = 2.70154180643e-05
RESID_BRATE_VOL_1 = -6.2244196904e-06
RESID_USDTL_VOL_1 = -3.38967477387e-06
Variance-Covariance Representation:
GARCH = M + A1*RESID(-1)*RESID(-1)'*A1 + B1*GARCH(-1)*B1
Variance and Covariance Equations:
GARCH1 = M(1,1) + A1(1,1)^2*RESID1(-1)^2 + B1(1,1)^2*GARCH1(-1)
GARCH2 = M(2,2) + A1(2,2)^2*RESID2(-1)^2 + B1(2,2)^2*GARCH2(-1)
GARCH3 = M(3,3) + A1(3,3)^2*RESID3(-1)^2 + B1(3,3)^2*GARCH3(-1)
GARCH4 = M(4,4) + A1(4,4)^2*RESID4(-1)^2 + B1(4,4)^2*GARCH4(-1)
COV1_2 = A1(1,1)*A1(2,2)*RESID1(-1)*RESID2(-1) + B1(1,1)*B1(2,2)*COV1_2(-1)
COV1_3 = A1(1,1)*A1(3,3)*RESID1(-1)*RESID3(-1) + B1(1,1)*B1(3,3)*COV1_3(-1)
COV1_4 = A1(1,1)*A1(4,4)*RESID1(-1)*RESID4(-1) + B1(1,1)*B1(4,4)*COV1_4(-1)
COV2_3 = A1(2,2)*A1(3,3)*RESID2(-1)*RESID3(-1) + B1(2,2)*B1(3,3)*COV2_3(-1)
COV2_4 = A1(2,2)*A1(4,4)*RESID2(-1)*RESID4(-1) + B1(2,2)*B1(4,4)*COV2_4(-1)
COV3_4 = A1(3,3)*A1(4,4)*RESID3(-1)*RESID4(-1) + B1(3,3)*B1(4,4)*COV3_4(-1)
Substituted Coefficients:
GARCH1 = 2.48271964169e-06+0.0041165601635*RESID1(-1)^2+0.38755734103*GARCH1(-1)
GARCH2 = 5.41498515531e-09+0.0120160069148*RESID2(-1)^2+0.986998005804*GARCH2(-1)
GARCH3 = 5.83679186122e-09+0.154092870807*RESID3(-1)^2+0.617292079382*GARCH3(-1)
GARCH4 = 7.76098304147e-09+0.15704397536*RESID4(-1)^2+0.622106503196*GARCH4(-1)
COV1_2 = 0.00703310851543*RESID1(-1)*RESID2(-1) + 0.618480656716*COV1_2(-1)
COV1_3 = 0.0251859598476*RESID1(-1)*RESID3(-1) + 0.489117651413*COV1_3(-1)
COV1_4 = 0.0254259901063*RESID1(-1)*RESID4(-1) + 0.491021325623*COV1_4(-1)
COV2_3 = 0.0430300011753*RESID2(-1)*RESID3(-1) + 0.780554963695*COV2_3(-1)
COV2_4 = 0.0434400908592*RESID2(-1)*RESID4(-1) + 0.783592928792*COV2_4(-1)
COV3_4 = 0.155561425187*RESID3(-1)*RESID4(-1) + 0.619694615883*COV3_4(-1)

TABLE C-14 Normality Tests for Modified Daily Reaction Function of Interest Rate of CBRT

System Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Sample: 4/16/2002 2/28/2013
Included observations: 2733

Component	Skewness	Chi-sq	df	Prob.
1	-9.355537	39868.13	1	**0.0000*** **
2	3.027743	4175.673	1	**0.0000*** **
3	-3.461400	5457.477	1	**0.0000*** **
4	-0.063420	1.832058	1	0.1759
Joint		49503.11	4	**0.0000*** **

Component	Kurtosis	Chi-sq	df	Prob.
1	138.6126	2094249.	1	**0.0000*** **
2	46.13581	211887.0	1	**0.0000*** **
3	131.2294	1872422.	1	**0.0000*** **
4	103.5028	1150231.	1	**0.0000*** **
Joint		5328788.	4	**0.0000*** **

Component	Jarque-Bera	df	Prob.
1	2134117.	2	**0.0000*** **
2	216062.6	2	**0.0000*** **
3	1877879.	2	**0.0000*** **
4	1150233.	2	**0.0000*** **
Joint	5378292.	8	**0.0000*** **

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

TABLE C-15 Conditional Covariance for the Variables of Modified Daily Reaction Function of Interest Rate of CBRT

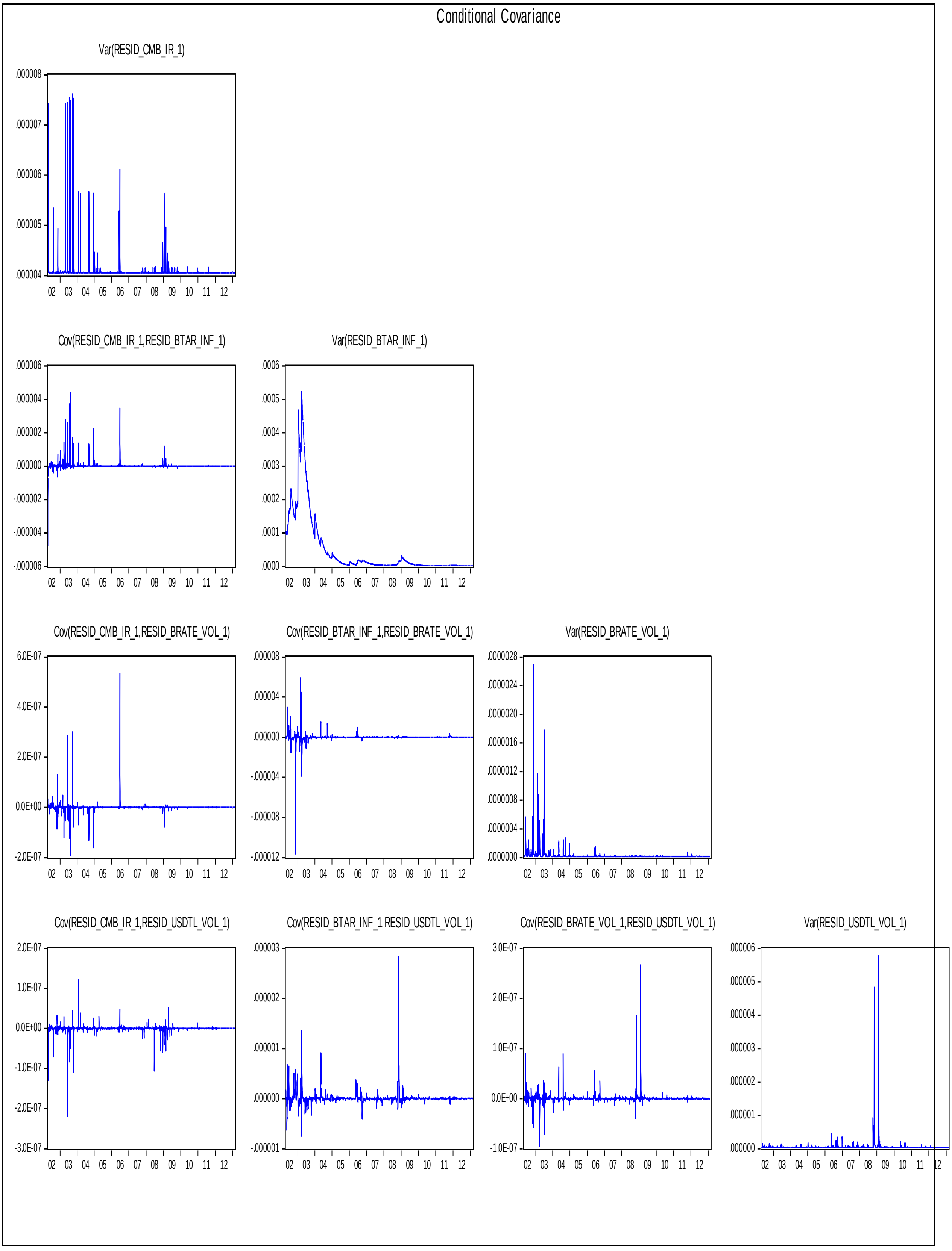


TABLE C-16 Conditional Correlation for the Variables of Modified Daily Reaction Function of Interest Rate of CBRT

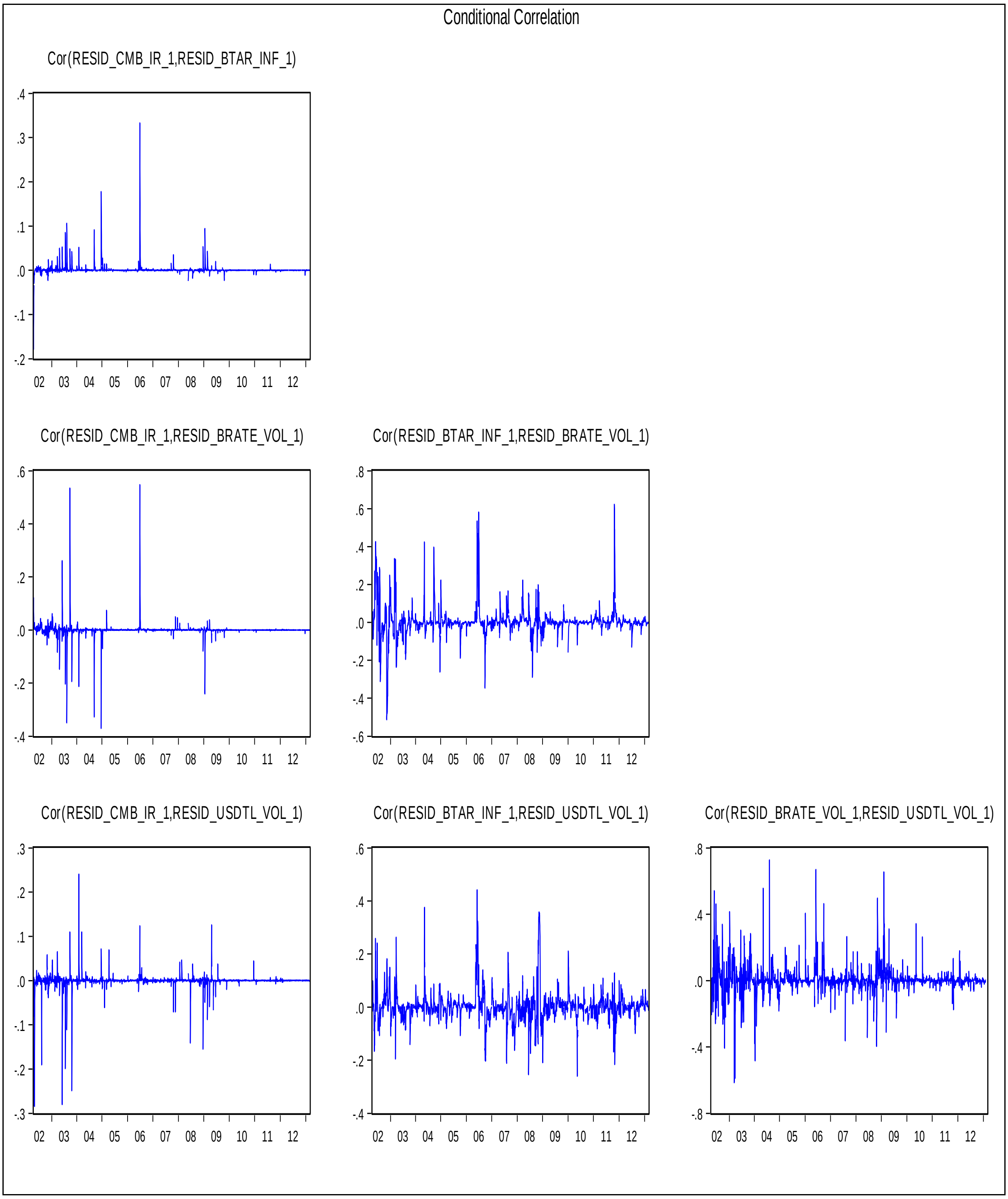


TABLE C-17 Conditional Variance for the Variables of Modified Daily Reaction Function of Interest Rate of CBRT

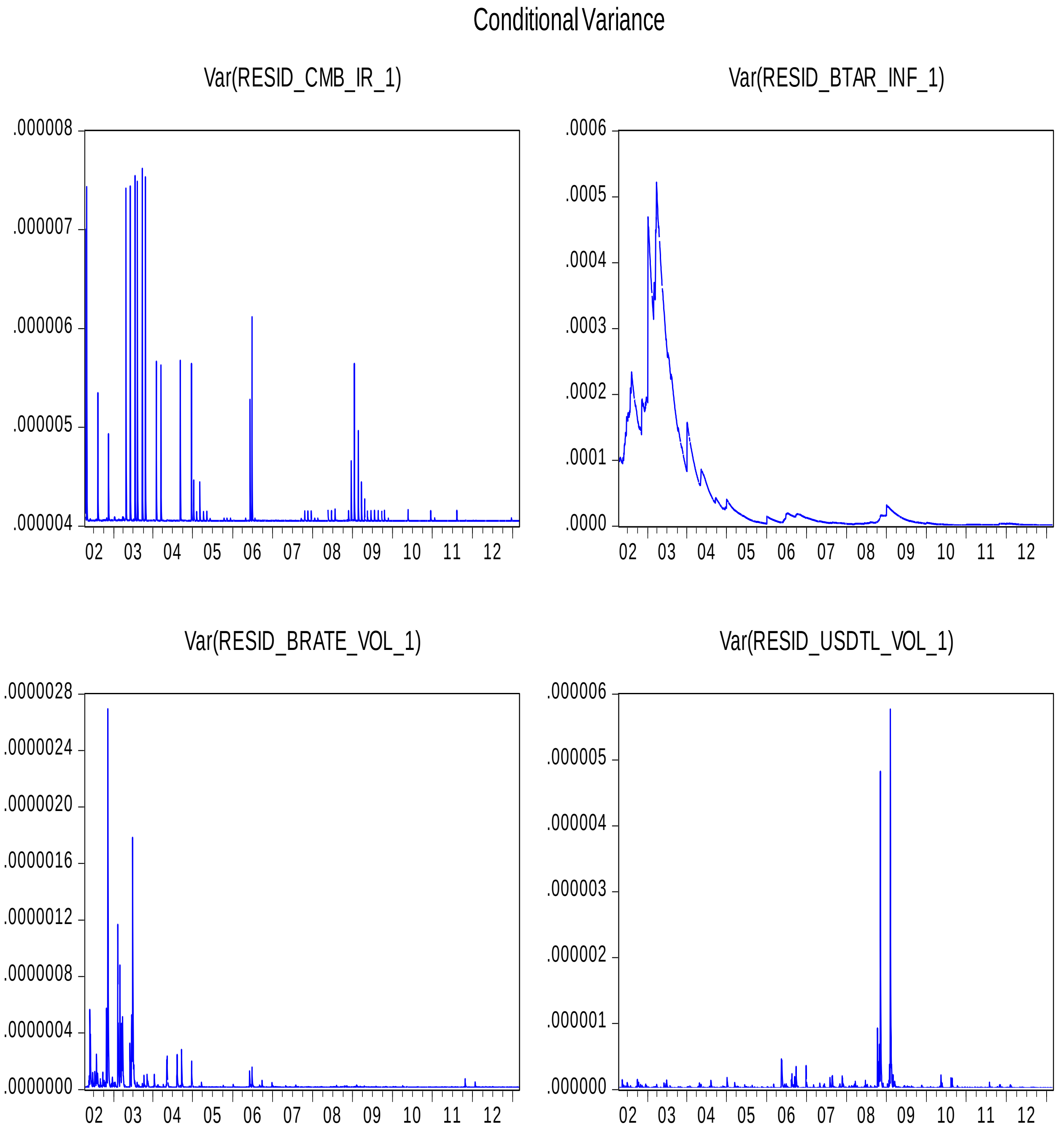


TABLE C-18 M-GARCH Results for Modififed Daily Recation Function for Exchange Rate (DLUSDTL VAR(7)-MGARCH(1,1))

Estimation Method: ARCH Maximum Likelihood (BHHH)
Covariance specification: Diagonal VECH
Sample: 4/16/2002 2/28/2013
Included observations: 2733
Total system (balanced) observations 10932
Presample covariance: backcast (parameter =0.6)
Convergence achieved after 56 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.000330	0.000119	-2.766164	**0.0057*** **
C(2)	-7.47E-05	4.93E-05	-1.516131	0.1295
C(3)	-1.06E-05	1.42E-06	-7.461574	**0.0000*** **
C(4)	-4.75E-06	2.90E-06	-1.636060	0.1018
	Variance Equation Coefficients			
C(5)	2.56E-06	3.39E-07	7.551308	**0.0000*** **
C(6)	2.90E-07	5.49E-07	0.528063	0.5975
C(7)	1.11E-11	2.44E-11	0.453041	0.6505
C(8)	1.21E-08	1.07E-09	11.25699	**0.0000*** **
C(9)	1.13E-08	6.12E-10	18.52140	**0.0000*** **
C(10)	1.75E-08	6.93E-09	2.523103	**0.0116** **
C(11)	8.33E-11	2.66E-10	0.313777	0.7537
C(12)	3.68E-09	4.93E-11	74.64906	**0.0000*** **
C(13)	1.43E-11	1.68E-11	0.853141	0.3936
C(14)	2.58E-09	1.10E-10	23.56899	**0.0000*** **
C(15)	0.117423	0.011447	10.25807	**0.0000*** **
C(16)	0.018150	0.012380	1.466020	0.1426
C(17)	-0.001243	0.000387	-3.206978	0.0013
C(18)	0.055900	0.003465	16.13282	**0.0000*** **
C(19)	0.011658	0.000208	56.14036	**0.0000*** **
C(20)	0.017898	0.007377	2.426142	0.0153
C(21)	-0.000809	0.002404	-0.336752	0.7363
C(22)	0.411433	0.011096	37.08028	**0.0000*** **
C(23)	0.006366	0.004024	1.582093	0.1136
C(24)	0.188812	0.007401	25.51131	**0.0000*** **
C(25)	0.842214	0.012785	65.87766	**0.0000*** **
C(26)	-0.627824	0.471475	-1.331616	0.1830
C(27)	1.001694	0.000667	1502.418	**0.0000*** **
C(28)	0.897427	0.003268	274.5726	**0.0000*** **
C(29)	0.985871	0.000117	8417.845	**0.0000*** **
C(30)	0.676491	0.125294	5.399243	**0.0000*** **
C(31)	0.971131	0.046814	20.74443	**0.0000*** **
C(32)	0.529673	0.003757	140.9992	**0.0000*** **
C(33)	0.973337	0.018951	51.36135	**0.0000*** **
C(34)	0.771681	0.007349	105.0062	**0.0000*** **

Log likelihood	62025.86	Schwarz criterion	-45.29186
Avg. log likelihood	5.673789	Hannan-Quinn criter.	-45.33884
Akaike info criterion	-45.36543		

Equation: RESID_USDTL_1 = C(1)

R-squared	-0.001682	Mean dependent var	-1.22E-17
Adjusted R-squared	-0.001682	S.D. dependent var	0.008038
S.E. of regression	0.008045	Sum squared resid	0.176807

Durbin-Watson stat	1.995781		

Equation: RESID_BTAR_INF_U1 = C(2)

R-squared	-0.000118	Mean dependent var	8.02E-19
Adjusted R-squared	-0.000118	S.D. dependent var	0.006870
S.E. of regression	0.006870	Sum squared resid	0.128953
Durbin-Watson stat	2.004198		

Equation: RESID_BRATE_VOL_U1 = C(3)

R-squared	-0.003022	Mean dependent var	-1.21E-19
Adjusted R-squared	-0.003022	S.D. dependent var	0.000193
S.E. of regression	0.000193	Sum squared resid	0.000102
Durbin-Watson stat	1.996634		

Equation: RESID_USDTL_VOL_U1 = C(4)

R-squared	-0.000395	Mean dependent var	-5.83E-19
Adjusted R-squared	-0.000395	S.D. dependent var	0.000239
S.E. of regression	0.000239	Sum squared resid	0.000156
Durbin-Watson stat	1.999870		

Covariance specification: Diagonal VECH
GARCH = M + A1.*RESID(-1)*RESID(-1)' + B1.*GARCH(-1)
M is an indefinite matrix*
A1 is an indefinite matrix
B1 is an indefinite matrix*

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

TABLE C-19 Transformed Variance Coefficients for Modified Daily Reaction Function of Exchange Rate

	Coefficient	Std. Error	z-Statistic	Prob.
M(1,1)	2.56E-06	3.39E-07	7.551308	**0.0000*** **
M(1,2)	2.90E-07	5.49E-07	0.528063	0.5975
M(1,3)	1.11E-11	2.44E-11	0.453041	0.6505
M(1,4)	1.21E-08	1.07E-09	11.25699	**0.0000*** **
M(2,2)	1.13E-08	6.12E-10	18.52140	**0.0000*** **
M(2,3)	1.75E-08	6.93E-09	2.523103	0.0116
M(2,4)	8.33E-11	2.66E-10	0.313777	0.7537
M(3,3)	3.68E-09	4.93E-11	74.64906	**0.0000*** **
M(3,4)	1.43E-11	1.68E-11	0.853141	0.3936
M(4,4)	2.58E-09	1.10E-10	23.56899	**0.0000*** **
A1(1,1)	0.117423	0.011447	10.25807	**0.0000*** **
A1(1,2)	0.018150	0.012380	1.466020	0.1426
A1(1,3)	-0.001243	0.000387	-3.206978	**0.0013*** **
A1(1,4)	0.055900	0.003465	16.13282	**0.0000*** **
A1(2,2)	0.011658	0.000208	56.14036	**0.0000*** **
A1(2,3)	0.017898	0.007377	2.426142	**0.0153** **
A1(2,4)	-0.000809	0.002404	-0.336752	0.7363
A1(3,3)	0.411433	0.011096	37.08028	**0.0000*** **
A1(3,4)	0.006366	0.004024	1.582093	0.1136
A1(4,4)	0.188812	0.007401	25.51131	**0.0000*** **
B1(1,1)	0.842214	0.012785	65.87766	**0.0000*** **
B1(1,2)	-0.627824	0.471475	-1.331616	0.1830
B1(1,3)	1.001694	0.000667	1502.418	**0.0000*** **
B1(1,4)	0.897427	0.003268	274.5726	**0.0000*** **
B1(2,2)	0.985871	0.000117	8417.845	**0.0000*** **
B1(2,3)	0.676491	0.125294	5.399243	**0.0000*** **
B1(2,4)	0.971131	0.046814	20.74443	**0.0000*** **
B1(3,3)	0.529673	0.003757	140.9992	**0.0000*** **
B1(3,4)	0.973337	0.018951	51.36135	**0.0000*** **
B1(4,4)	0.771681	0.007349	105.0062	**0.0000*** **

* Coefficient matrix is not PSD.

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

TABLE C-20 System Residual Normality Tests for Modified Daily Reaction Function of Exchange Rate

Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Sample: 4/16/2002 2/28/2013
Included observations: 2733

Component	Skewness	Chi-sq	df	Prob.
1	-0.061222	1.707275	1	0.1913
2	3.439830	5389.673	1	**0.0000*** **
3	-7.120467	23094.33	1	**0.0000*** **
4	0.786729	281.9286	1	**0.0000*** **
Joint		28767.64	4	**0.0000*** **

Component	Kurtosis	Chi-sq	df	Prob.
1	10.93069	7162.258	1	**0.0000*** **
2	53.90688	295108.3	1	**0.0000*** **
3	267.9666	7994855.	1	**0.0000*** **
4	70.70849	522053.0	1	**0.0000*** **
Joint		8819179.	4	**0.0000*** **

Component	Jarque-Bera	df	Prob.
1	7163.966	2	**0.0000*** **
2	300498.0	2	**0.0000*** **
3	8017950.	2	**0.0000*** **
4	522334.9	2	**0.0000*** **
Joint	8847947.	8	**0.0000*** **

***,**, *** indicates significance at the 90%, 95 % and 99 % level respectively**

TABLE C-21 Estimation Command: for Modified Daily Reaction Function of Exchange Rate

ARCH(DERIV=AA, B, BACKCAST=0.6) @DIAGVECH C(INDEF) ARCH(1,INDEF) GARCH(1,INDEF)
Estimated Equations:
RESID_USDTL_1 = C(1)
RESID_BTAR_INF_U1 = C(2)
RESID_BRATE_VOL_U1 = C(3)
RESID_USDTL_VOL_U1 = C(4)
Substituted Coefficients:
RESID_USDTL_1 = -0.000329573391202
RESID_BTAR_INF_U1 = -7.46936750991e-05
RESID_BRATE_VOL_U1 = -1.05836062866e-05
RESID_USDTL_VOL_U1 = -4.74740197424e-06
Variance-Covariance Representation:
GARCH = M + A1.*RESID(-1)*RESID(-1)' + B1.*GARCH(-1)
Variance and Covariance Equations:
GARCH1 = M(1,1) + A1(1,1)*RESID1(-1)^2 + B1(1,1)*GARCH1(-1)
GARCH2 = M(2,2) + A1(2,2)*RESID2(-1)^2 + B1(2,2)*GARCH2(-1)
GARCH3 = M(3,3) + A1(3,3)*RESID3(-1)^2 + B1(3,3)*GARCH3(-1)
GARCH4 = M(4,4) + A1(4,4)*RESID4(-1)^2 + B1(4,4)*GARCH4(-1)
COV1_2 = M(1,2) + A1(1,2)*RESID1(-1)*RESID2(-1) + B1(1,2)*COV1_2(-1)
COV1_3 = M(1,3) + A1(1,3)*RESID1(-1)*RESID3(-1) + B1(1,3)*COV1_3(-1)
COV1_4 = M(1,4) + A1(1,4)*RESID1(-1)*RESID4(-1) + B1(1,4)*COV1_4(-1)
COV2_3 = M(2,3) + A1(2,3)*RESID2(-1)*RESID3(-1) + B1(2,3)*COV2_3(-1)
COV2_4 = M(2,4) + A1(2,4)*RESID2(-1)*RESID4(-1) + B1(2,4)*COV2_4(-1)
COV3_4 = M(3,4) + A1(3,4)*RESID3(-1)*RESID4(-1) + B1(3,4)*COV3_4(-1)
Substituted Coefficients:
GARCH1 = 2.55848714862e-06 + 0.117423498799*RESID1(-1)^2 + 0.842214295219*GARCH1(-1)
GARCH2 = 1.13428194802e-08 + 0.0106575171482*RESID2(-1)^2 + 0.983871161698*GARCH2(-1)
GARCH3 = 3.67722746872e-09 + 0.41143309245*RESID3(-1)^2 + 0.529673479137*GARCH3(-1)
GARCH4 = 2.58135550898e-09 + 0.188812033958*RESID4(-1)^2 + 0.771681449559*GARCH4(-1)
COV1_2 = 2.89747011121e-07 + 0.0181495428686*RESID1(-1)*RESID2(-1) -0.627823618111*COV1_2(-1)
COV1_3 = 1.10653268888e-11 -0.00124264642045*RESID1(-1)*RESID3(-1) + 1.00169381945*COV1_3(-1)
COV1_4 = 1.20839559928e-08 + 0.0559004332328*RESID1(-1)*RESID4(-1) + 0.89742697614*COV1_4(-1)
COV2_3 = 1.74928204774e-08 + 0.0178982354788*RESID2(-1)*RESID3(-1) + 0.676491211523*COV2_3(-1)
COV2_4 = 8.33240345238e-11 -0.00080945907598*RESID2(-1)*RESID4(-1) + 0.971131139049*COV2_4(-1)
COV3_4 = 1.43370935396e-11 + 0.00636618623063*RESID3(-1)*RESID4(-1) + 0.973336600305*COV3_4(-1)

TABLE C-22 Conditional Covariance for Modified Daily Reaction Function of Exchange Rate

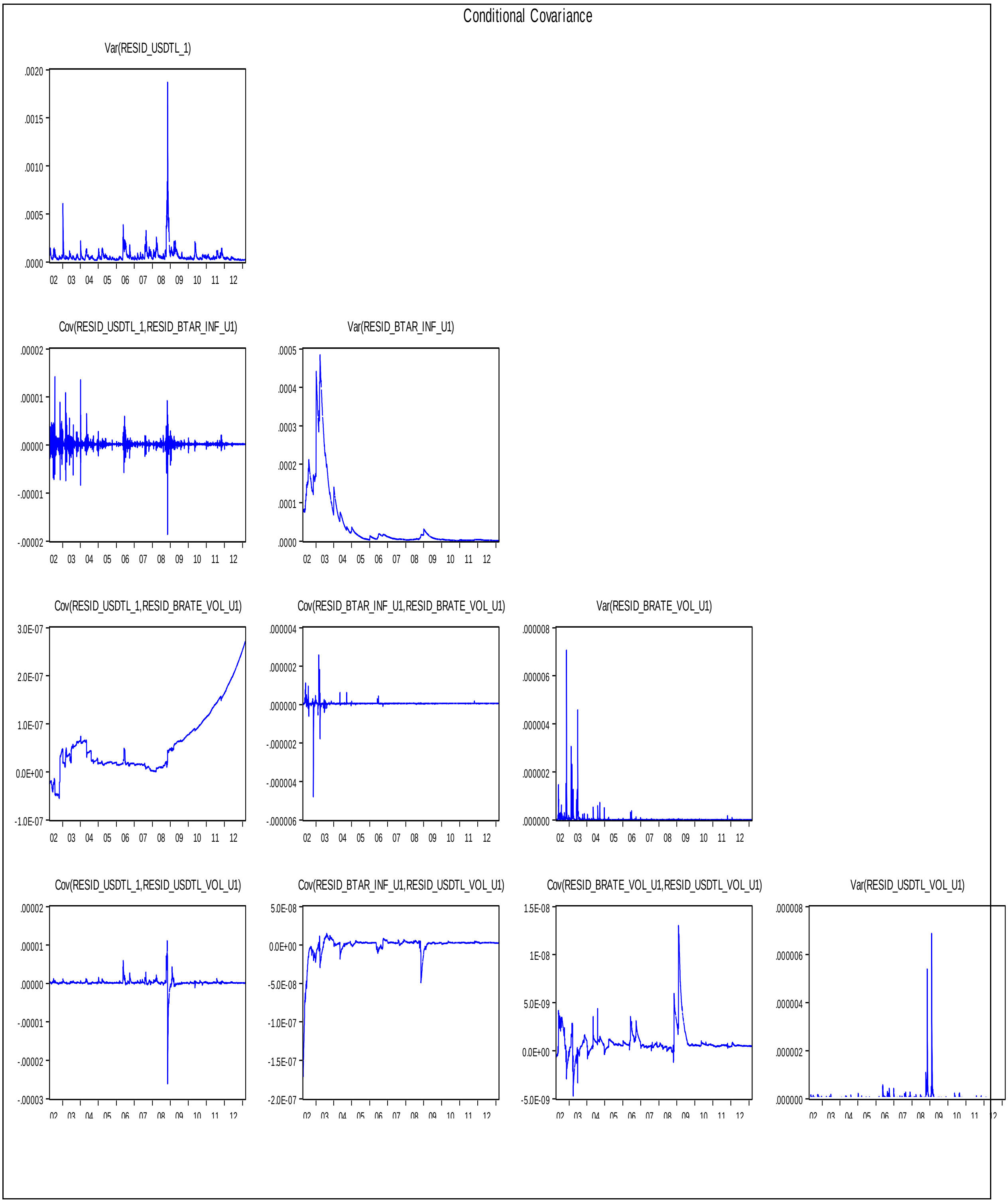


TABLE C-23 Conditional Correlation for Modified Daily Reaction Function of Exchange Rate

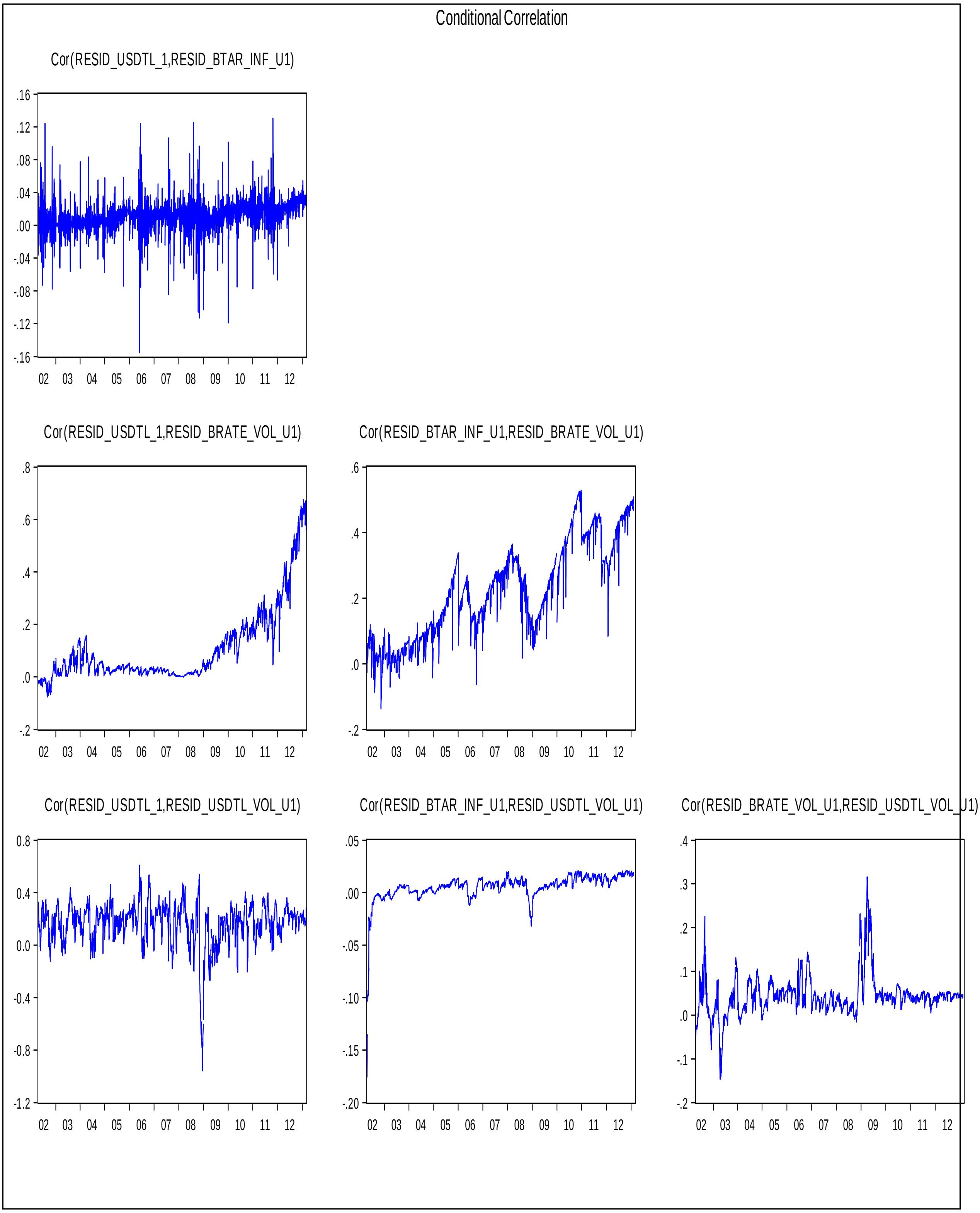
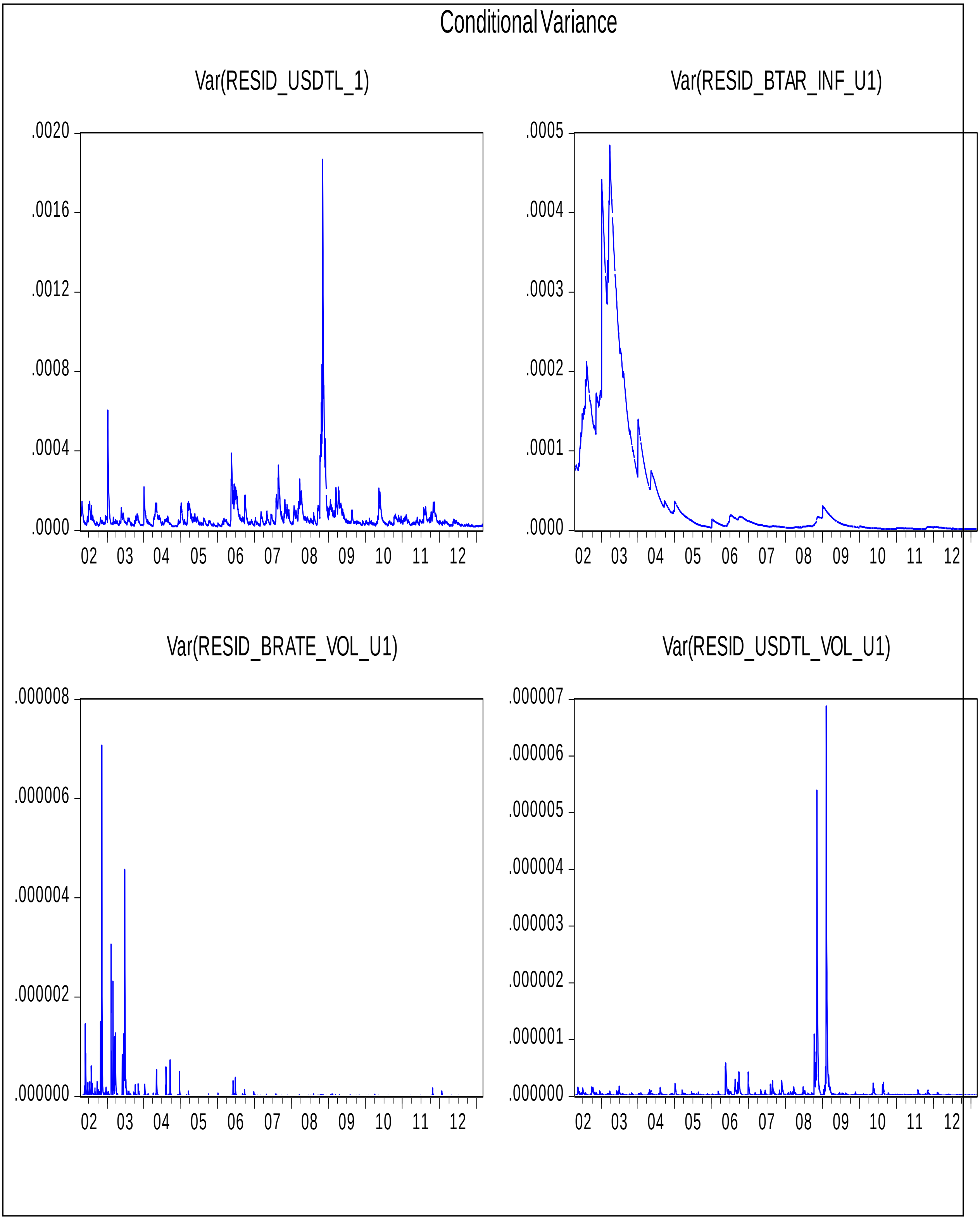
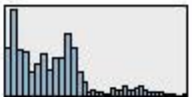
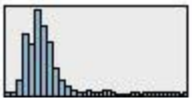
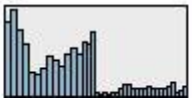
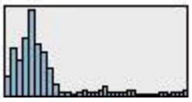
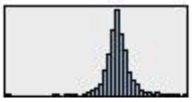
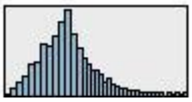
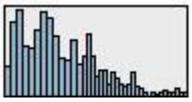
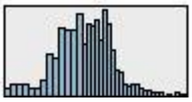
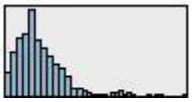


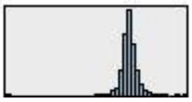
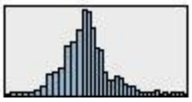
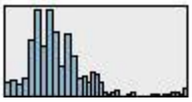
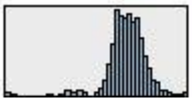
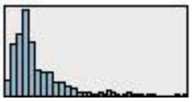
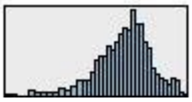
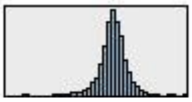
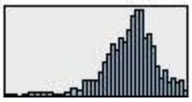
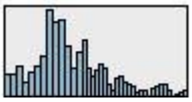
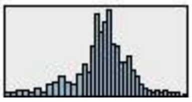
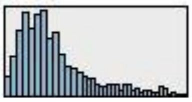
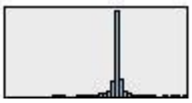
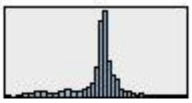
TABLE C-24 Conditional variance for Modified Daily Reaction Function of Exchange Rate

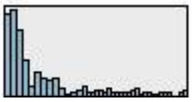
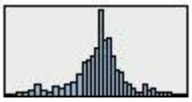
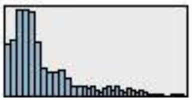


APPENDIX D

TABLE D-1 DATA PREVIEW

Field	Sample Graph	Measurement	Min	Max	Mean	Std. Dev	Skewness
DIFF_IR_INF		Continuous	0.240	53.150	11.305	9.534	1.427
DIFF_IR_CMB_IR		Continuous	-2.470	29.410	3.916	5.183	2.795
DIFF_IR_INF_MEAN		Continuous	0.903	40.059	11.665	9.381	1.177
DIFF_IR_CMB_IR_MEAN		Continuous	-0.465	24.862	4.033	4.850	2.475
DIFF_IR_INF_VOL		Continuous	0.103	10.325	1.588	2.017	2.226
DIFF_IR_CMB_IR_VOL		Continuous	0.103	9.214	1.230	1.496	2.715
EURTL_CHG		Continuous	-0.068	0.055	0.000	0.009	0.565
EURTL_MEAN		Continuous	-0.138	0.384	0.015	0.077	1.246
EURTL_VOL		Continuous	0.003	0.020	0.008	0.003	1.077
EURTL_SKW		Continuous	-1.189	2.662	0.260	0.548	0.162
EURTL_KURT		Continuous	-0.869	12.999	1.186	1.453	2.203

USDTL_CHG		Continuous	-0.119	0.070	0.000	0.009	-0.005
USDTL_MEAN		Continuous	-0.214	0.359	0.006	0.077	1.114
USDTL_VOL		Continuous	0.002	0.026	0.008	0.004	2.356
USDTL_SKW		Continuous	-2.713	2.207	0.337	0.504	-0.646
USDTL_KURT		Continuous	-1.071	15.772	1.112	1.867	2.945
XU030_MEAN		Continuous	-0.597	0.455	0.042	0.159	-0.361
XU100_CHG		Continuous	-0.133	0.121	0.001	0.020	-0.085
XU100_MEAN		Continuous	-0.629	0.418	0.043	0.156	-0.479
XU100_VOL		Continuous	0.008	0.041	0.019	0.007	1.044
XU100_SKW		Continuous	-1.755	1.799	-0.062	0.514	-0.116
XU100_KURT		Continuous	-0.836	6.251	0.856	1.353	1.518
BRATE_CHG		Continuous	-0.076	0.061	-0.000	0.006	-0.357
BRATE_MEAN		Continuous	-0.236	0.253	-0.014	0.051	-0.362

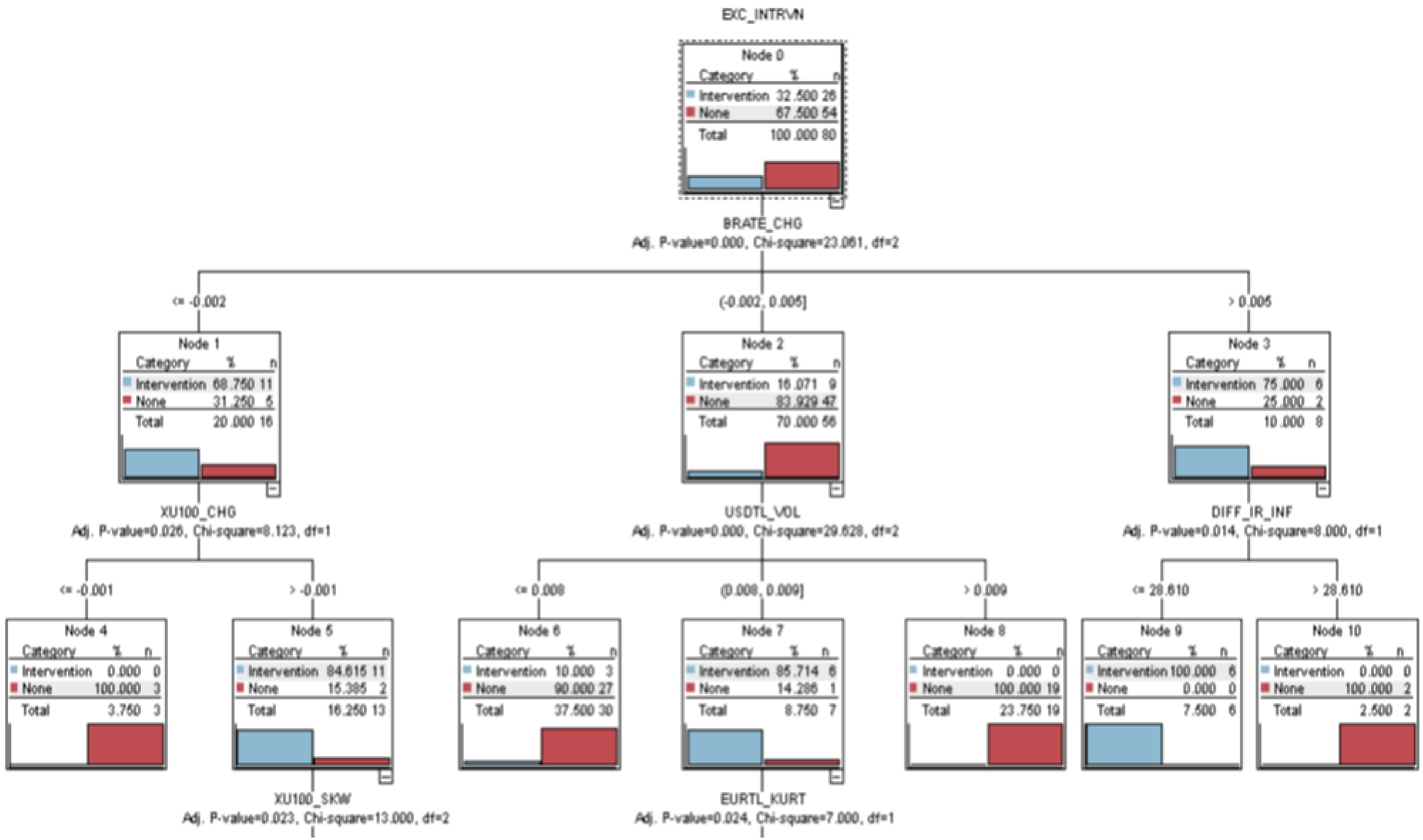
BRATE_VOL		Continuous	0.000	0.022	0.004	0.005	2.124
BRATE_SKW		Continuous	-3.138	3.848	0.016	0.939	0.302
BRATE_KURT		Continuous	-0.951	21.360	2.791	3.574	1.913

APPENDIX E

TABLE E-1 Chaid Results

CHAID	EXC_INTRVN		Intervention	None	Total
	Intervention	Count	23	3	26
		Row %	88.46	11.54	100
	None	Count	473	2242	2715
		Row %	17.42	82.58	100
	Total	Count	496	2245	2741
		Row %	18.10	81.90	100

FIGURE E-1 CHAID DECISION TREES FOR EXCHANGE RATE INTERVENTIONS


EXC_INTRVN
Node 0
Category % n
Intervention 32.500 26
None 67.500 54
Total 100.000 80
BRATE_CHG
Adj. P-value=0.000, Chi-square=23.061, df=2
<= -0.002
(-0.002, 0.005]
> 0.005
Node 1
Category % n
Intervention 68.750 11
None 31.250 5
Total 20.000 16
Node 2
Category % n
Intervention 16.071 9
None 83.929 47
Total 70.000 56
Node 3
Category % n
Intervention 75.000 6
None 25.000 2
Total 10.000 8
XU100_CHG
Adj. P-value=0.026, Chi-square=8.123, df=1
USDTL_VOL
Adj. P-value=0.000, Chi-square=29.628, df=2
DIFF_IR_INF
Adj. P-value=0.014, Chi-square=8.000, df=1
<= -0.001
> -0.001
<= 0.008
(0.008, 0.009]
> 0.009
<= 28.610
> 28.610
Node 4
Category % n
Intervention 0.000 0
None 100.000 3
Total 3.750 3
Node 5
Category % n
Intervention 84.615 11
None 15.385 2
Total 16.250 13
Node 6
Category % n
Intervention 10.000 3
None 90.000 27
Total 37.500 30
Node 7
Category % n
Intervention 85.714 6
None 14.286 1
Total 8.750 7
Node 8
Category % n
Intervention 0.000 0
None 100.000 19
Total 23.750 19
Node 9
Category % n
Intervention 100.000 6
None 0.000 0
Total 7.500 6
Node 10
Category % n
Intervention 0.000 0
None 100.000 2
Total 2.500 2
XU100_SKW
Adj. P-value=0.023, Chi-square=13.000, df=2
EURTL_KURT
Adj. P-value=0.024, Chi-square=7.000, df=1

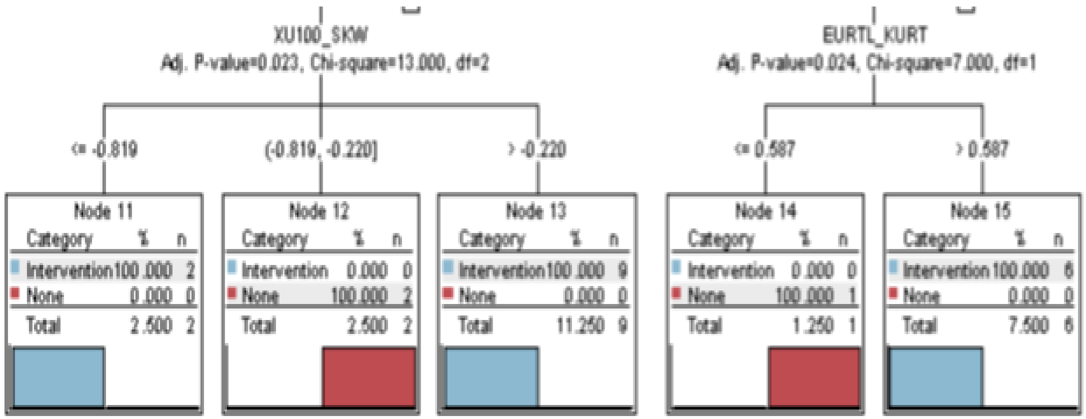

XU100_SKW
Adj. P-value=0.023, Chi-square=13.000, df=2
<= -0.819
(-0.819, -0.220]
> -0.220
Node 11
Category % n
Intervention 100.000 2
None 0.000 0
Total 2.500 2
Node 12
Category % n
Intervention 0.000 0
None 100.000 2
Total 2.500 2
Node 13
Category % n
Intervention 100.000 9
None 0.000 0
Total 11.250 9
EURTL_KURT
Adj. P-value=0.024, Chi-square=7.000, df=1
<= 0.587
> 0.587
Node 14
Category % n
Intervention 0.000 0
None 100.000 1
Total 1.250 1
Node 15
Category % n
Intervention 100.000 6
None 0.000 0
Total 7.500 6

TABLE E-2 CHAID Rule Path For Exchange Rate Interventions

BRATE_CHG <= -0.002 [Mode: Intervention]
XU100_CHG <= -0.001 [Mode: None] => None
XU100_CHG > -0.001 [Mode: Intervention]
XU100_SKW <= -0.819 [Mode: Intervention] => Intervention
XU100_SKW > -0.819 and XU100_SKW <= -0.220 [Mode: None] => None
XU100_SKW > -0.220 [Mode: Intervention] => Intervention
BRATE_CHG > -0.002 and BRATE_CHG <= 0.005 [Mode: None]
USDTL_VOL <= 0.008 [Mode: None] => None
USDTL_VOL > 0.008 and USDTL_VOL <= 0.009 [Mode: Intervention]
EURTL_KURT <= 0.587 [Mode: None] => None
EURTL_KURT > 0.587 [Mode: Intervention] => Intervention
USDTL_VOL > 0.009 [Mode: None] => None
BRATE_CHG > 0.005 [Mode: Intervention]
DIFF_IR_INF <= 28.610 [Mode: Intervention] => Intervention
DIFF_IR_INF > 28.610 [Mode: None] => None

FIGURE E-2 Predictor Importance-CHAID Results