AN EMPIRICAL STUDY OF SIMPLE SUM AND DIVISIA MONETARY AGGREGATION:
A COMPARISON OF THEIR PREDICTIVE POWER REGARDING PRICES AND OUTPUT IN TURKEY

BY

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and the Graduate Faculty of the University of Kansas
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Date defended: _May 4, 2009

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Dedication

To my children M. Said, M. Fethullah, A. Fâzıl

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The fear of the Lord is the beginning of knowledge. (Bible: Proverbs/1-7)

إِنَّمَا يَخْشَى اللَّهَ مِنْ عِبَادِهِ الْعُلَمَاءُ

Allah'tan ancak âlimler hakkıyla haşyet ederler. (Qur’an: Fâtir/28)
Only those of his servants who are endowed with knowledge fear Allah. (Qur’an: Fâtir/28)

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I'd like to thank my advisor Prof. William A. Barnett for his helpful approach I've never seen from any of my professors -except A. Fâzıl Tekin- in my entire education life (which had been quite a long one!), and for his understanding of my style that never had been like a regular student.

My wife also deserves special thanks for her taking care of our kids in my absence during the writing period of this dissertation. I owe an apology more than thanks to my kids for my being away from them for long time.

Celiş has been a special person during my hard times. I want to thank her too from the bottom of my heart and wish her the best.

Erkan substituted my never-born younger brother. Thanks for everything Kuzen.

Dogan Karaman
An Empirical Study of Simple Sum and Divisia Monetary Aggregation:
A Comparison of Their Predictive Power Regarding Prices and Output in Turkey

ABSTRACT

If there is one thing economists agree on, probably it is that inflation is a monetary phenomenon. Money also is thought to be related to the output level of the economy. The consensus among economists, however, does not go any further, and views differ on the characteristics of the relationships between money and the other sectors of the economy. It is not only these relationships, but also the definition of money at macroeconomic level is controversial. There are different proposals on how to define and measure money. Among them are the traditionally used simple sum money and Divisia money proposed by W. Barnett. This dissertation makes an attempt to test which definition of money works better when facing the real world situations. Without going far into theoretical details, yet trying to be as rigorous as possible in applying the employed techniques, we use several models and methods to compare the performances of simple sum and Divisia aggregates in predicting Turkish inflation and output growth in last two decades both in-and out-of-sample. We used all time series approaches that allow us to incorporate money as explanatory variables. We also add an additional approach, neural networks, to these as an alternative forecasting tool.

Based on our results, we confidently conclude that money provides a good amount of information in predicting inflation and output in Turkey. Divisia aggregates have superior information content in predicting output, real or nominal. In forecasting inflation, we make a distinction between high- and low-inflation environments. In high-inflation state, money appears to be more and directly related to the determination prices, while in low-inflation environment the link between money and prices get looser and more indirect. In high-inflation periods, Divisia aggregates clearly provide better information than simple sum aggregates. In low-inflation periods, on the other hand, simple sum aggregates are better predictor of inflation.

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CHAPTER 1

INTRODUCTION

1.1. General Introduction and Description of the Goals

1.1.1. General Introduction

If there is one thing economists agree on, probably it is that inflation is a monetary phenomenon. This idea is put in its extreme by Milton Friedman as "Inflation is always and everywhere a monetary phenomenon." (Friedman and Schwartz, 1963). Although this proposition is challenged by many researchers[1], high and permanent inflation is never thought to be completely independent of monetary developments in an economy (Svensson, 2007).

Money also is thought to be related to the output level of the economy. Especially stabilization programs using monetary policy as a tool shed light to the relationship between money and production (Mishkin, 2000)[2]. From "quantity theory" to "Saint Louis equations", countless number of theoretical and empirical models are all based on some relationship between output and money, though the implications for the characteristics of the relationship differ across different approaches and models (Mishkin, 2002).

Well, but, what is money? Easy question, yet no simple answer, especially when we look at money from a macroeconomic perspective. Money is generally defined referring to its functions. Money essentially performs three different economic functions (Wesche, 1996): it is a medium of exchange, a unit of account, and a store of value.

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[1] See for example among many other studies: De Grauwe and Polan (2005); Bertocco (2002)
[2] The book of collected seminar articles includes more than 20 papers in this collection that touch the topic.

Consumers hold money or more clearly monetary assets because money provides some services like other commodities do, hence increase utility. The utility from money arises, in part, because some of the assets are media of exchange. A medium of exchange is not only a numeraire commodity based on which the prices of all other commodities are determined but it is also something that is revolving in transactions but is not used up by use (Samuelson, 1947, pp. 117-118). So, as being a medium of exchange, money reduces shopping time, permits taking advantage of offers of bargain sales, provides a cushion against unanticipated expenses, and reduces the amount of time spent on budget management. Also assets that are not media of exchange may provide this kind of utility as much as they are convertible to an asset that is a medium of exchange (Anderson et. al, 1997a). Some assets traditionally labeled as money but are not an immediate medium of exchange provide other benefits such as transferring resources in time, earning interest and being thus better protected against inflation (Wesche, 1996).

Economists who are trying to incorporate money into economic models consider the uses or the types of utility provided by money. Generally the economic models involving money is in one of the following three forms: (1) Some assume that money yields direct utility and incorporate money balances directly into the utility functions of the agents (money-in-the-utility-function: MIU-type models); (2) Some impose transactions costs by making asset exchanges costly, by requiring that money be used for certain types of transactions, by assuming that time and money can be combined to produce transaction services necessary for obtaining consumption goods, or by assuming that direct barter of commodities is costly (Cash-in-advance: CIA-type models); (3) Some give money the role to transfer resources intertemporally (generally modeled in overlapping generations framework) (Walsh, 2003).

When it comes to the effects of money on different economic variables, one may feel himself in a jungle. We can find at least one fancy model to give theoretical support to any kind of hypotheses about the influences of money on the economy. This fact arises from the specification-sensitive role of money (Walsh, 2003) in different theoretical models. This is the reason why we generally ignore the theoretical arguments in this dissertation. Instead we take the approach of empirical testing of the role of money using as many statistical and econometric tools as possible without worrying to find theoretical models to support any hypothesis. Indeed we even do not go after a certain hypothesis and do not try to prove that it is valid. What we try to get is a comprehensive picture displaying the effects of money on other macroeconomic variables, basically on inflation and output, in the framework of Turkish experience of the high and permanent inflation episode spanning a period longer than 3 decades.

However, defining and modeling money and its effects are not all about the controversies around money. As for the measurement of money, we meet a generally less noisy, yet even a bigger controversy: there is far less agreement on how to measure the amount of money in the economy (Anderson et. al, 1997a) than on what money is or does. Since the Federal Reserve Board started publishing monetary data in 1949 (Anderson and. Kavajecz, 1994)[3], the practice has been summing up the nominal values of all stocks of monetary assets included in each monetary aggregate defined in an ad hoc way. Indeed this is the practice of all central banks throughout the world. Simply summing over the assets assumes that the economic agents regard all monetary assets as perfect substitutes. However, according to microeconomic demand theory, if these assets were really perfect substitutes, rational consumers would choose to hold only a single asset with the lowest user cost. Thus, measuring money by defining a monetary aggregate by summing the nominal values of the included assets is not generally consistent with the economic theory of consumer decision making (Belongia, 2000a).

Using simple sum monetary aggregates has been always criticized for not being an appropriate indicator of the amount of money in the economy, or more

[3] The data series can be accessed at the following address: http://www.federalreserve.gov/releases/H6/about.htm

clearly flow of the monetary services. However, it took quite a while to solve this problem, well until late 1970s and early 1980s. William A. Barnett first derived the user costs or prices for the monetary services flow from monetary asset stocks in a 1978 paper (Barnett, 1978). Then he constructed weighted monetary aggregates (Barnett, 1980). Later on, the new approach of monetary measurement has been widely studied and extended by many authors including Barnett himself.

Having money measured in accord with theory has been a great leap forward, yet the empirical results have not proved satisfactory enough. However, it will not be wrong, I hope, to say that Divisia aggregates have an edge over simple sum counterparts as having read almost all empirical studies on the field. Nevertheless, even Divisia indexes have not helped enough to put money back in its position in empirical work like before mid-1980s. So, still there are missing parts and still there is a lot of work to be done in this field. This work is maybe not in theoretical field but in collection and classification of monetary data and in establishing separable and economically reasonable groupings of monetary assets (Chrystal and MacDonald, 1994).

1.1.2. The General Approach and Description of the Goals

First of all, I want to point out that the aim of this dissertation is not to build a perfect model or some outstanding models of inflation, output, and money for Turkish data. The primary purpose is to test the information content of different monetary aggregates at different aggregation levels constructed using different aggregation methods in predicting inflation and output. To achieve this goal, I used many different models and applied various estimation methods without trying to be very picky in functional form and theoretical foundation, yet I tried to be as much rigorous as possible in applying the statistical and econometric methods, basically time series methods. Although being somewhat loose on models, the ones we used are not arbitrary; we employed the models already used by other researchers in the literature of empirical comparison of the two aggregation methods.

I want to state an observation which does not make a good case for the profession of economics. In a vast majority of empirical research we read about the data, models, methods and results reached by the authors. However, researchers are generally ignorant in explaining everything related to their research. I use the word ignorant just to avoid that they may be hiding part of the truth. To exemplify this situation, say we do read a lot papers involving money. The authors keep saying "money is like this", "money does or does not that" etc., yet they do not say anything about what this money thing refers to exactly! We do not even understand sometimes if this is the real money or nominal money. If real, which price index is used is not mentioned. Sometimes money is referred to even not mentioning the level of aggregation. In this dissertation whatever I did I put it clearly, whether the results are good or bad for my case, luckily I avoid to have a case of my own!

Secondly, having 5 different levels of aggregation, two (simple summation and Divisia) aggregation methods, and nominal and real series for each aggregate made the study computationally very cumbersome. This forced us to follow a summation strategy, and we used summary tables abundantly / in big numbers. To avoid providing some possibly not priory / not compulsory information to get the gist of the results or better said repetitive information within the body of text, we shifted the tables and graphs in the application chapters to the appendixes, and referred to them in the text by their numbers. We also tried to cut short the theoretical information on models, methods, and literature reviews. The essential information is given briefly, and some major works on the topics are cited where necessary.

Since the so called breakdown of the previously widely accepted relationship between the quantity of money and some important macroeconomic variables in early 1980s (Friedman and Kuttner, 1992), central banks abandoned targeting monetary aggregates with some exceptions such as Bundesbank of

Germany[4] (Kole and Meade 1995; Bundesbank, 1997; von Hagen, 1999). Instead the focus of monetary policy shifted to interest rate management as formulated later on by Taylor (Taylor, 1993; Orphanides, 2007; Asso et. al., 2007). However, this situation does not reflect a consensus among economists, as some argue that this seemingly breakdown is limited to low-inflation countries (Moroney, 2002; some other references please). Moroney documents the validity of quantity theory of money almost perfectly in the long run especially for the high-inflation countries using a panel of 81 countries with post-1980 data. Being a high-inflation country over almost four decades, Turkey provides a good case to check on the results obtained by Moroney using time series data.

And lastly a prediction of mine: when the time comes that financial activities are more tied to real activities, we will be needing money again in our models and analyses. So, before that time comes, I believe not too late, we must come to a conclusion of the definition and measurement of monetary aggregates.

1.2. The Criticism of Simple Sum Monetary Aggregates

The criticism of the simple sum aggregates is not something new that emerged recently. Irving Fisher, one of the pioneers of index number theory, wrote, back in 1922, the following about the simple arithmetic index, of which simple sum monetary aggregates is an application:

> "the simple arithmetic average produces one of the very worst of index numbers, and if this book has no other effect than to lead to the total abandonment of the simple arithmetic type of index number, it will have served a useful purpose." (cited from Barnett, 1981)

Here is another citation about simple sum aggregation from Friedman and Schwartz's 1970 book, Monetary Statistics of the United States, which has been one of the most influential works in monetary economics:

[4] Central Bank of Republic of Turkey was one of those as it applied some stabilization programs based on monetary targeting, e.g. in 1998.

> "This procedure (summation of monetary assets) is a very special case of the more general approach. In brief, the general approach consists of regarding each asset as a joint product having different degrees of "moneyness," and defining the quantity of money as the weighted sum of the aggregate value of all assets, the weights for individual assets varying from zero to unity with a weight of unity assigned to that asset or assets regarded as having the largest quantity of "moneyness" per dollar of aggregate value. The procedure we have followed implies that all weights are either zero or unity. The more general approach has been suggested frequently but experimented with only occasionally. We conjecture that this approach deserves and will get much more attention than it has so far received. The chief problem with it is how to assign the weights and whether the weights assigned by a particular method will be relatively stable for different periods or places or highly erratic." (cited from Barnett et. al, 1992)

Another quote from Barnett et. al (1984) will seal the deal about the issue:

> "by equally weighting components, aggregation by summation can badly distort an aggregate. For example, if one wished to obtain an aggregate of transportation vehicles, one would never aggregate by summation over the physical units of, say, subway trains and roller skates. Instead one could construct a quantity index (such as the Department of Commerce's indexes) using weights based on the values of the different modes of transportation."

Barnett has argued that a reasonable approach to monetary aggregation must consider the utility (and production) function(s) underlying the demand for monetary assets. If not, the predictable consequence will be induced instability of money demand and supply functions, and a series of "puzzles" in the resulting applied literature. (Barnett, 2007). Bad measurement, that is the incoherence between data aggregation formulas and the models within which aggregates are embedded, may cause the stable structure to appear unstable. This phenomenon has been called the "Barnett critique" (Chrystal and MacDonald 1994).

Basically there are two lines of criticisms on the construction of official simple sum monetary aggregates. The most important criticism of simple sum monetary aggregates arises from the fact that they do not differentiate between the assets included in them and treat all those assets as if they are the same in their characteristics of being money. Said differently, simple sum aggregation assumes a constant elasticity of substitution among monetary assets[5]. This problem is related to the weighting scheme of individual monetary assets that are brought together to construct the aggregates.

The second criticism arises from the fact that the official simple sum monetary aggregates are constructed using ad hoc judgments of central bankers all around the world regarding what kind of monetary assets would make an admissible grouping to add up for defining money. This criticism may be called as the problem of weak separability.

A line of defense for simple sum aggregates is that they show the stock of nominal monetary wealth. So, even they do not measure the flow of monetary services, they will still be useful in empirical research by helping us capture any possible wealth effects. There is no question that simple sum indexes of money represent an index of the stock of nominal monetary wealth (Serletis, 2007, p. 200). However, Barnett shows that simple sum monetary aggregates are only poor indicators of monetary wealth (Barnett, 1991). From an accounting perspective, what Serletis says is true. Yet, from an economic perspective, simple sum aggregates represent monetary wealth only if the investment yield of monetary components (i.e. the interest they yield) is treated as a monetary service, which is not acceptable at all.

1.3. Theoretical Foundations of Divisia Monetary Aggregates

The approach proposed by Friedman and Schwartz in the above-mentioned citation got the attention of some economists, and even more a solution to the problem is proposed by William A. Barnett. He first derived the user costs or rental equivalent

[5] Elasticity of substitution is the elasticity of the ratio of two goods (inputs) in a utility (production) function with respect to the ratio of their marginal utilities (products). Mathematically, for the utility function involving monetary assets m_1 and m_2 among its arguments, the elasticity of substitution is defined as (Varian, 1992, pp. 13-14):

$$\sigma = \frac{d(m_2/m_1)}{m_2/m_1} \div \frac{d(U_{m_1}/U_{m_2})}{U_{m_1}/U_{m_2}}$$

prices for the monetary assets (Barnett, 1978). In a following paper, Barnett applied Divisia indexes to construct weighted monetary aggregates (Barnett, 1980).

The Divisia index for monetary services makes an attempt to separate the transactions function of money from the other functions that money performs. Instead of measuring the stock of money held in the economy, the Divisia index assesses the utility the consumer derives from holding a portfolio of different monetary assets. Money is regarded as a consumer durable, yielding a flow of monetary services. These services are performed by different monetary assets in different degrees and are proportional to the stock of monetary assets held (Wesche, 1996).

The Divisia index for monetary services is based on microeconomic models of individual decision making that do not impose strong assumptions on elasticities of substitution among monetary assets (Anderson et. al., 1997b[6]). Demand for monetary assets are modeled to be derived from a representative agent's maximizing behavior. The utility function includes real monetary assets and non-monetary goods and services and maximized subject to a budget constraint. In this model, monetary assets are treated as durable goods that provide a flow of monetary services to the consumer.

The user cost of a monetary asset is the discounted value of the interest foregone by holding the monetary asset: $p_{it} = p_t^* \dfrac{R_t - r_{it}}{1 + R_t}$ (see Barnett, 1978 for the formal derivation). Here, r_{it} is the yield on the i^{th} asset, R_t is the expected one-period holding yield on benchmark asset, and p_t^* is the true cost of living index.

The benchmark asset is assumed to provide no liquidity or other monetary services and is held solely to transfer wealth in time. In theory, R is the maximum expected holding period yield in the economy. It is usually defined in practice in such a way that the user costs for the monetary assets are positive. Note that if p* is deleted

[6] Three papers of Anderson, Jones, and Nesmith published in the January/February 1997 issue of The Federal Reserve Bank of St. Louis Review provide a very good summary of the monetary aggregation theory.

from the user cost formula, the formula produces real rather than nominal user cost. The interest rates are nominal so that inflationary expectations appear here (Serletis, 2007, p. 202).

The representative consumer optimizing his or her consumption maximizes the utility function over consumption goods, leisure, and the services of monetary assets, $U(c, \ell, m)$, subject to the budget constraint, $q'c + p'm+w\ell =Y$, where c is consumption goods, ℓ is leisure time, and m is the services of monetary assets. Y here represents the full income (somewhat broader than the usual income concept), and prices are given as w: wage rate, q: prices of the consumption goods and p: user costs of monetary assets (Serletis, 2007, pp. 203-204).

The consumer is assumed to take a sequential expenditure allocation: first stage involves the allocation of total income among totals of consumption goods, leisure, and monetary services (budgeting). The second stage is when total expenditures on each broad category are distributed to individual goods in each category (decentralization).

The two stage solution to the consumer's choice problem is possible only if the utility function is weakly separable in the services of monetary assets. That is, it must be possible to write the utility function using the monetary services aggregator function or category subutility function u(m) as a separate argument in the utility function: $u = U(c , \ell, u(m))$.

The category subutility function, $u(m_1,..., m_n)$, is an aggregator function that measures the total amount of monetary services received from holding monetary assets. If $m^*_1,...,m^*_n$ denote the optimal quantities of monetary assets chosen by the consumer, then the aggregator function defines a monetary aggregate, $M = u(m^*_1,...,m^*_n)$. The specific form of the aggregator function is usually unknown. Diewert and Barnett established that, the aggregator function at the optimal quantities, $M = u(m^*_1,...,m^*_n)$, can be approximated by a statistical index number, which Barnett calls Divisia index after the French statistician F. Divisia who established the index (Anderson et. al., 1997b).

Barnett and other economists working on the topic have extended the monetary aggregation theory using Divisia indexes to production firms, financial firms, risk, and international aggregation[7].

1.4. Outline of the Dissertation

Chapter 2 starts with a very short review of the Turkish Economy, which provides brief information on the historical record of output and inflation, and on the conduct of monetary policy. Then, the data set used in construction of the aggregates is described and a weak separability test is carried out to check if the ad hoc inclusion of monetary assets in the official definitions of money makes an admissible classification for monetary aggregation. This chapter ends with an explanation of how the Divisia monetary aggregates for Turkey are constructed.

Chapter 3 includes a preliminary analysis of Divisia and simple-sum monetary aggregates for Turkey. Here we give the basic statistical properties of monetary aggregates along with some graphical inspection of growth rates, shares of the asset components in the aggregates, and income velocities. The last part of Chapter 3 involves an analysis of the integration properties of the entire data set used in this dissertation.

Chapter 4 is dedicated to VAR analysis of nonstationary and stationary data. Levels and nominal annual growth rates are mostly I(1) variables. This chapter contains cointegration analysis and error correction models of money-income and money-price level relationships both in bivariate and multivariate frameworks. The models are used for out-of-sample forecast evaluation. Chapter continues with the analyses of stationary data. Period growth rates are mostly I(0) variables. So, nominal and real monthly and quarterly

[7] See Barnett and Serletis (2000) and Belongia and Binner (2000) for an extensive coverage of the theoretical and practical development in the area of monetary aggregation.

growth rates are put in vector autoregregression (VAR) systems, and similar analyses to nonstationary data are carried out here.

Chapter 5 involves a group of different single equation models of inflation and output. These models include ARMA and ARCH models, Saint Louis equations, structural price change equations (Phillips curve-based models), cost-push (mark-up) model of inflation. ARMA and ARCH models, structural price change equations and cost-push models are first estimated without having monetary aggregates and in-sample and out-of-sample success of them are evaluated. Then money is added to the model and once more in-sample and out-of-sample performances are evaluated to compare if money makes any improvement in model success. On the other hand, Saint Louis equations include money by construction. So they are estimated and used for out-of-sample forecasting to check which definition of monetary aggregate has better performance. In case of Saint Louis equations we also carried out a dispersion-dependency test using Divisia second moments for aggregation error in Divisia indexes as done by Barnett and Serletis (1990).

Chapter 6 adds a nonlinear test to our array of tests. Monetary aggregates are evaluated in artificial neural network (ANN) models to check for their in-sample and out-of-sample performances in explaining and predicting inflation and output.

Chapter 7 is the conclusion to the dissertation where we give an overall evaluation of our comparisons of Divisia and simple some monetary aggregates in several test environments employed throughout the thesis.

CHAPTER 2

TURKISH ECONOMY AND DIVISIA AGGREGATES FOR TURKEY

Before starting with the construction of Divisia monetary aggregates in Turkey, it will be useful to give a brief account of the historical performance of the Turkish economy. Hence, Section 2.1 is dedicated to a brief summary of the Turkish economy. Section 2.2 describes the data and data sources. Section 2.3 includes a weak separability test to assess if monetary assets covered by M2 make an admissible set of assets for aggregation purposes. Section 2.4 describes the details of the construction of Divisia aggregates for Turkey. Then we continue with a preliminary analysis of the constructed Divisia series along with simple sum aggregates in Section 2.5 from different perspectives. This chapter closes with Section 2.6 that involves the tests for integration properties of all variables used in the applications.

2.1. Historical Performance of the Turkish Economy

2.1.1. The Historical Growth Record

Table 2.1 displays inflation and real GDP growth in Turkey since it has been founded. Figure 2.1 reproduces the same information for last three and a half decades.

In the first some 30 years of 20th century, Turkey had been a country that basically relies on agriculture. Therefore, growth rates in this period mainly reflect the conditions in agricultural production. Very high rates of growth and large fluctuations in growth rates in 1920s had been due to the fact that people had had the chance to return to their farming activities after a very long period of wars, so long as 20 years, and due to weather conditions. The 15-year period from 1923 to 1938 had witnessed the high rate of average growth of 7.4%. We should also mention the effect of state-led industrialization of mid-1930s that followed the then

Table 2.1: Inflation and Growth in Turkish Economy, 1924-2007*

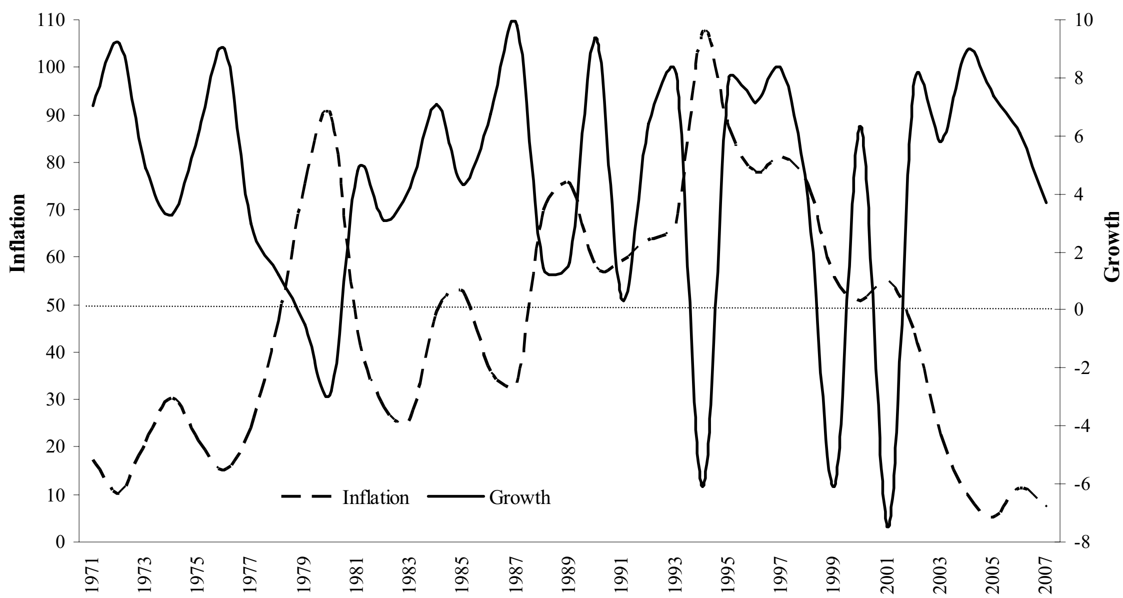
year	growth	inflation	year	growth	inflation	year	growth	inflation	year	growth	inflation
1924	14.90	10.00	1945	**-15.30**	-3.40	1966	11.99	6.39	1987	9.81	33.47
1925	12.80	12.40	1946	**31.90**	-5.00	1967	4.21	6.53	1988	1.45	69.73
1926	18.20	-8.50	1947	4.20	5.60	1968	6.67	3.92	1989	1.63	75.48
1927	-12.80	2.20	1948	4.20	20.80	1969	4.32	7.24	1990	9.37	57.64
1928	11.00	-0.10	1949	-5.00	0.40	1970	4.44	8.52	1991	0.35	59.17
1929	21.60	4.40	1950	9.40	-2.10	1971	7.05	17.36	1992	6.40	63.49
1930	2.20	**-25.40**	1951	12.83	6.46	1972	9.17	10.22	1993	8.14	67.36
1931	8.70	-19.00	1952	11.91	2.75	1973	4.91	21.10	1994	-6.08	**107.27**
1932	-10.70	-5.70	1953	11.25	4.78	1974	3.26	30.47	1995	7.95	87.15
1933	15.80	-15.90	1954	-2.98	5.10	1975	6.06	21.16	1996	7.12	78.00
1934	6.00	0.50	1955	7.93	11.30	1976	9.00	15.27	1997	8.29	81.22
1935	-3.00	11.10	1956	3.15	11.80	1977	2.99	23.97	1998	3.86	75.32
1936	23.20	5.00	1957	7.82	23.30	1978	1.23	46.72	1999	-6.08	55.75
1937	1.50	5.00	1958	4.52	14.25	1979	-0.49	75.62	2000	6.34	50.88
1938	9.50	-4.10	1959	4.07	19.90	1980	-2.78	89.63	2001	-7.50	54.81
1939	6.90	1.80	1960	3.43	3.32	1981	4.81	44.34	2002	7.94	44.13
1940	-4.90	22.50	1961	2.00	4.07	1982	3.09	28.31	2003	5.79	22.51
1941	-10.30	38.90	1962	6.18	9.50	1983	4.21	25.99	2004	8.93	9.85
1942	5.60	96.00	1963	9.69	5.75	1984	7.11	48.55	2005	7.38	5.39
1943	-9.80	65.20	1964	4.08	2.57	1985	4.30	52.89	2006	6.10	11.49
1944	-5.10	-23.70	1965	3.14	4.32	1986	6.76	35.62	2007	3.71	7.17

	growth	inflation
max	31.90	107.27
min	-15.30	-25.40
aritm. ave.	4.92	24.47
geom. ave.	4.65	21.19
st. dev.	7.56	30.03

SOURCE: Turkish Institute of Statistics (TIS)

* Growth rate is measured as the annual percentage change in real GDP and inflation rate is measured as the annual percentage change in GDP deflator.

Figure 2.1: Inflation and Growth Rate: 1971-2007



SOURCE: Turkish Institute of Statistics (TIS)

successful Soviet experience.[8] The industrial production growth had been around 10% in this period. The influence of Great Depression is mainly felt as falling prices. The price level fell down by 52% from 1929 to 1933. We can also observe the effect of precautionary measures taken during World War II, although Turkey had not taken part in it, as a shrinking economy at an average rate of -6.9% between 1940 and 1945.

1950 is the year when Turkey changed its regime from an authoritarian single-party regime to a democratic and multi-party one. Indeed, 1950 is the year when Turkey began to switch from a virtually command economy to a market-oriented economic system. The average growth rate from 1923 to 1949 had been 4.0%. From 1950 to 2007 this rate realized at 5.03% while the industrial growth in this period had been as high as 6.84%.

[8] In 1923, when the new state was founded, the shares of agriculture, industry, and services in GNP were 40%, 13%, 47% respectively. In 2007 these shares were 9%, 28%, 63% respectively. The drastic changes in the industrial structure of the economy started especially mid-1960's, and gained momentum after 1980.

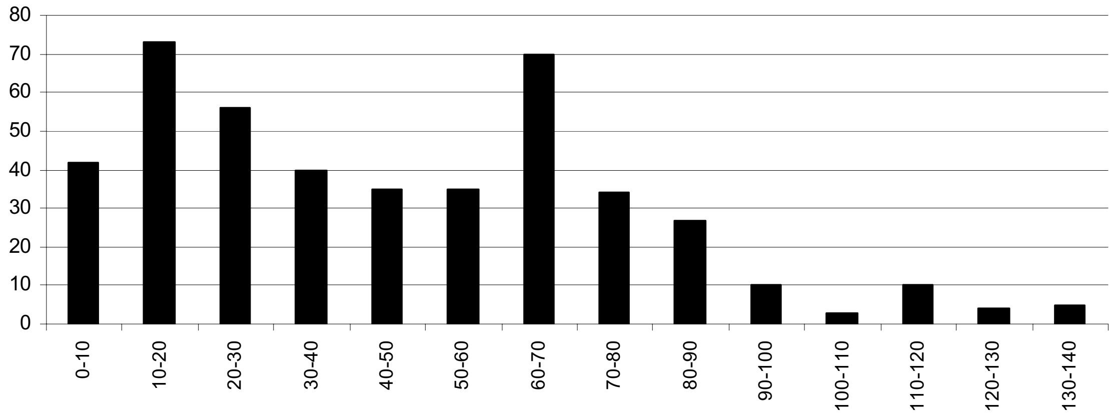
1963 represents another important cornerstone for Turkish economy. The development plans and import substitution were the strategies launched that year. The 5-year development plans and import substitution strategy had been applied strictly in the period 1963-1979, and a growth rate of 5.35% in GNP and 8.32% in industrial production had been achieved.

1980 is the year when Turkey shifted from import substitution to export-led growth strategy and when she started to eliminate the elements of non-market economy, i.e. the so-called mixed economy. Although the 5-year plans have continued, they have lost their central role in the economy. Concerning economic growth, post-1980 period also needs to be divided in some sub-periods. From 1981 to 1990 the average growth rate had been 5.22%. 1991-2001 had been a period that can be characterized with recurring crises. Turkey experienced three negative growth rates in this period as big as 6.1 (twice) and 7.5. After the collapse of last major stabilization program in 2001, the growth rates returned to higher levels at annual average of 6.6%.

2.1.2. The Historical Inflation Record

Turkey has experienced a high and volatile inflationary process over more than 3 decades from 1971 to 2007. Turkey had experienced high inflation in some periods before 1971, too. For example, the inflation rate was 96% in 1942, the annual rate had been 53.2% in the period 1940-1943, and it had been 16.0% from 1955 to 1959. However, none of the previous episodes of inflation had been prolonged, and these episodes were easy to attach to certain clear causes. From the date it was founded in 1923 up to 1970 the annual average rate of inflation had been only 6.0%. Starting in 1971, the high inflation rates averaging at 43.7% between 1971 and 2007 brought this figure up to 21.2% by the end of 2007 for the period 1923-2007. After 1970, the annual inflation rate fell down to single-digit figures first time in 2004. During this long-lasting high inflation period, three major disinflation programs launched in 1980, 1994, and 2000, collapsed.

Figure 2.2: Frequency Distribution of Monthly Year-on-Year Inflation Rates in Turkey (CPI): 1971-2007



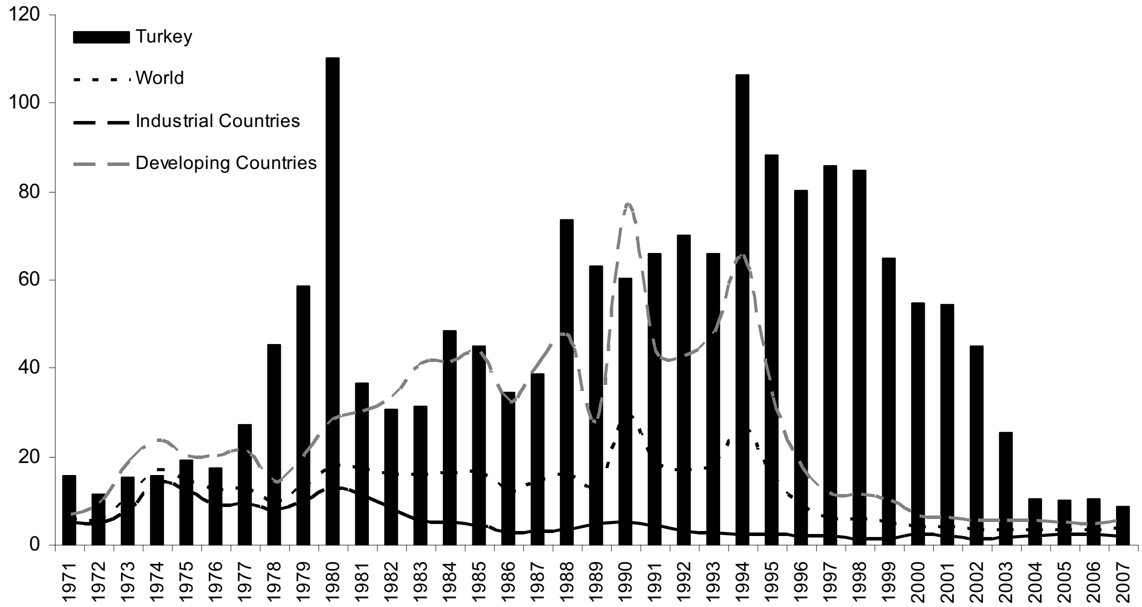
Sources: The IFS (IMF), Central Bank of the Republic of Turkey.

Although annual inflation realized at rates over 100% in certain years (observed in 22 months in terms of consumer prices inflation as measured year-on-year basis), it never reached hyperinflationary levels but increased in a stepwise fashion over time. The average annual inflation rate was 25.8% in the 1970s, 49.7% in the 1980s, 72.6% in 1990s. After continuous efforts kept after the unsuccessful disinflation program of 2000, average inflation fell down to 16.0% in the period 2002-2007.

Another aspect of the Turkish inflation is demonstrated in Figure 2.2 that gives the frequency distribution of annual inflation rates in each month of the period 1971 to 2007. Average inflation rate in this 444-month period had been 43.8%. A rate below 10% was observed in 42 months (40 times at end of the period, since 2004) and a rate above 100% was observed in 22 months, which may be easily recognized as severe crisis periods where very high inflation had coupled with other problems in the economy. In the remaining 402 months Turkey had experienced double-digit rates.

To display the severeness of the inflationary process after 1971, I want to make some comparisons with the inflation episodes in the rest of the world. Relatively higher inflation had been a phenomenon of the period of global inflation

Figure 2.3: Inflation in Turkey and the Rest of the World (CPI): 1971-2007



Source: The IFS (IMF).

from 1973 to 1993. However, the average inflation (measured as the percentage change in CPI from December to December) in Turkey was 2.7 times higher than the world average, and 30.3% higher than the average of developing countries. These figures rose to 7.0 and 259% respectively for the period 1994-2003. Figure 2.3 shows the inflation rates in Turkey and in the rest of the world.

2.1.3. A Very Short History of Monetary Policy in Turkey[9]

The establishment of the Central Bank of the Republic of Turkey (CBRT) in 1931 can be considered the beginning of a monetary policy in the modern nation-state Turkey that inherited the economic structure from its successor the Ottoman Empire with almost no favorable features. CBRT took over the right to issue money from the Ottoman Bank, which was in fact a foreign bank with a misleading name - a French, British and Austrian corporation.

[9] A very comprehensive and illustrating resource on the history of monetary policy in Turkey can be found in: Onder, Timur, Para Politikasi: Araclari, Amaclari ve Turkiye Uygulamasi (Monetary Policy: Tools, Targets and Application in Turkey), Uzmanlık Yeterlilik Tezi, Turkiye Cumhuriyet Merkez Bankasi, Ankara, Mayis 2005.

For long time, CBRT had followed policies not only for price stability, but also it had to help for financing economic development and for covering the government budget deficits. The density of using central bank resources for government needs and development finance has not been at the same degree all the time. 1950's had been not the first period for assigning the central bank those tasks beyond price stability but this approach gained strength in 1950's. CBRT started pursuing these goals heavily thereafter, and this idea had its supporters even until 1990s.

The inflationary effects of extra duties of CBRT had been observed all the time until late 1990s except for successful planning period of 1960s. 1970's had witnessed both internal crises and external shocks, which forced the governments and the CBRT to follow an expansionary monetary policy to finance budget deficits and financial needs of state enterprises. The result had been an accelerating inflationary process.

1980 is a cornerstone in the making of economic policy in Turkey that started to convert its economic system from a planning-driven, relatively closed import-substitution country to an open and liberal market economy. Within a decade almost all government controls on prices such as interest rates and exchange rates had been eliminated and both trade and capital movements had been liberalized. Istanbul Stock Exchange Market started its operation in 1986. The institutions for the conduct of modern monetary policy has been established including interbank money market, a market for foreign exchange transactions, a market for facilitating government borrowing within the CBRT. The government launched a new strategy of internal borrowing as a means of financing its deficits. Within time the government stopped relying on central bank resources as a financial support.

Starting from 1991 on, fiscal concerns had dominated monetary policy for an entire decade. Despite being equipped with all modern instruments of monetary policy after the reforms in 1980s, CBRT had no chance of conducting an independent monetary policy that focuses on price stability due to growing government borrowing of 1990s. A few monetary programs based on targeting some monetary aggregates failed. It had been a period of big corruptions coupled with unimaginably high interest rates in government borrowing[10] and all the possible political and popular opposition had been silenced using military pressure on vast majority of people.

Entering the third millennium, Turkey launched an exchange rate-based stabilization program in cooperation with the IMF that left no room for monetary policy. The program crashed as expected due to its crawling peg exchange rate regime and the weak banking system, and Turkey experienced its worst economic collapse in its 80-year economic history full of ups and downs (excluding World War II).

After the collapse of the stabilization program, Turkey prepared another program in 2001 and made a series of reforms in economic and financial structure. The governments after 2002 followed the program strictly and brought the budgetary discipline back to the country. Meanwhile CBRT started operating an inflation targeting regime which uses the interest rates as main policy tool. After controlling inflation, the national currency has been reformed and new Turkish Lira started to circulate in 2005 which is only short of six zeros compared to old Lira.

2.2. Data Description and Sources

We will be using monthly and quarterly data starting in January 1986 running up to December 2006. The sample period is mainly determined by the availability of monetary data. Prior to 1986, the money data had not been published as separate monthly series and should be collected from several Central Bank's printed publications. Data after 2006 contain monetary data series yet the publication systematic and money definitions had been altered substantially and again one has to go to the relevant departments of the Central Bank to get the disaggregated data to construct the monetary assets compatible with ones before 2007. So we limited our

[10] In late 1990's even the industrial companies had been relying on income from interest-bearing instruments instead of making their profits from their main activities. In 1997, the biggest 500 industrial companies had 53% of their profits from their financial investments. In 1998 this ratio was 88%. In 1999, the situation got even worse and all profits had been from interest revenues while those companies incurred losses in their productive activities. (reference: 500 Biggest Industrial Companies in Turkey, Istanbul Chamber of Industry, several issues. www.iso.org.tr/tr/Web/BesYuzBuyuk/BesYuzBuyukFirma.aspx)

analyses to the period where money data are publicly available and have uniformity in definitions.

We will make use of a couple of different series for price level, output and their growth rates. For inflation, we have three possibilities: one is to use GDP deflator that we have from 1924 to 2007 in annual frequency, and in quarterly frequency from 1987 to 2007. Second option is to use wholesale or producer prices index (WPI) that we have from 1941 to 2007 in annual, quarterly and monthly frequencies. The consumer prices index (CPI) is also available with the same features as the WPI but starting 1964. As for the WPI and CPI we also have the annual data from 1924 to 2007. Other prices used include import prices index, energy prices index that is a part of WPI, and at-pump gasoline prices index.

For output and economic growth we have two options: one is to use GDP and its growth rates that have the same features as the GDP deflator, which is in annual frequency from 1924 to 2007, and in quarterly frequency from 1987 to 2007. We also obtained a projection of the series back to 1968. The projection is based on the seasonal structure of the GDP components, for which we had annual figures before 1987 and quarterly figures thereafter. However, this constructed series does not enable us to use the GDP deflator data obtained from the constructed series in real and current values. The projected GDP and industrial production series have high enough correlation coefficients with the official series so that we can use those projections for the periods where data is not available in desired frequency. As for the levels, projected and actual series of GDP have a correlation of 0.96, and between the growth rates of these series the correlation coefficient is 0.82. Thus we use the GDP data for 1986 without much concern. So, for nominal and real GDP we have data from 1986 on, and for GDP deflator from 1987 on.

We also make use of output gap data in an application. The series is available for the periods starting 1988:2 and is obtained from Central Bank staff. Nominal wage rates in manufacturing sector used in cost-push model of inflation are available in quarterly frequency only and start in 1988:1. The exchange rate data consist of an index of trade-weighted exchange rates for currencies used in international transactions Turkish residents take part in.

Data on monetary assets and interest rates are obtained in monthly frequencies for the period 1986-2006. Since the components included in different monetary aggregates have changed from 2005 on, we could only construct the comparable series for only 2005 and 2006. So we restricted our sample period to 2006 for all our data. The quarterly data on money and interest rates are the 3-month average data for a quarter. To use in selection of the benchmark rate of return we used annualized average interest rates on government bonds in each month along with the annualized interest rates on TL deposits.

The raw data used in this study can be obtained from CBRT website: www.tcmb.gov.tr with one exception, at-pump gas prices. We collected gas prices from several online resources most of them being websites of gas distribution companies. Monetary data and interest rates are collected and published by the CBRT itself. Other data such as GDP, price indexes etc. are collected by the Turkish Statistical Institute (TSI, website: www.tuik.gov.tr; English version: www.turkstat.gov.tr). Yet, CBRT has a data delivery system which brings all the important economic and financial data together on the internet. The system can be accessed both in Turkish and English languages (http://evds.tcmb.gov.tr).

2.3 Weak Separability and a Test for Assets Covered in Turkish M2 Aggregate

In his 1987 paper Barnett states the importance of separability as follows: “If the concept of money has meaning, then it follows that an aggregate of monetary assets must exist which is treated by the economy as if it were a single good, which we thereby can call 'money'. Such an aggregate is a function (of its component monetary quantities) which is separable from the economy's structure. That concept of money is the subject of aggregation theory and is the concept relevant to policy, since both aggregation theory and policy postulate the appearance of a monetary aggregate as a meaningful stably defined variable in the economy's structure. Without the appropriate separability conditions, any aggregate is inherently arbitrary and spurious and does not define an economic variable." (Barnett, 1987).

Technically, weak separability in the services of monetary assets requires that the marginal rate of substitution between any two monetary assets should not depend upon the values of c and ℓ.

$$\frac{\partial}{\partial c}\left(\frac{\partial u / \partial x_i}{\partial u / \partial x_j}\right) = \frac{\partial}{\partial \ell}\left(\frac{\partial u / \partial x_i}{\partial u / \partial x_j}\right) = 0 \text{ for } i \neq j.$$

This means that the demand for monetary services is independent of relative prices outside the monetary group (Serletis, 2007, pp. 203-204).

Whether or not the utility function is weakly separable in monetary services is in fact an empirical question, and one could test whether the utility function is weakly separable in monetary services. Nevertheless, this issue has received little attention, even though it is logically prior to the choice of an appropriate aggregation formula, and weak separability is held as an untested assumption in most studies. Testing for the existence of weak separability has been done rarely on monetary data, and the standard practice for central banks and many economists still appears to be one of using an ad hoc judgment about an asset's 'moneyness' as the criterion for inclusion in an aggregate (Belongia, 2000b).

Tests for weak separability have two types: parametric and non-parametric tests. The parametric approach requires to choice a functional form. On the other hand, the non-parametric test can be carried out based only on observed prices and quantities. The defect of non-parametric test is that it has no critical values. We will use the non-parametric approach developed by Varian (1982, 1983).

The test is based on generalized axiom of revealed preference (GARP). GARP is equivalent to the existence of a well-behaved utility function which, when maximized subject to a budget constraint by a rational consumer, could have generated the observed data. If a subset of the goods satisfies GARP while an aggregate of these goods along with the other goods still satisfies the consistency property, the conditions for an admissible group of assets have been met: a utility function exists which both rationalizes the observed data and is consistent with weak separability in these goods.

The null hypothesis in these tests is that observed data conform to the restrictions implied by a stable set of well-behaved preferences., under the necessary additional restrictions that the group of commodities of interest constitutes a weakly separable group and that it is appropriate to analyze the data as having been generated by maximization of a utility function by a representative consumer. All that is necessary for the null hypothesis to be correct is that we plot the data and superimpose on our plots a set of indifference surfaces and isocost planes consistent with the rational purchase of those quantities by a consumer facing observed relative prices. A time series of prices and quantities can therefore be checked for consistency with this hypothesis using revealed preference axioms.

According to the weak axiom of revealed preference, a bundle **a** is revealed preferred to any other bundle **b** (denoted aRb) that could have been purchased instead (i.e., **a** is preferred to all points within the budget line that applies when **a** is purchased). The weak axiom is violated if any such bundle **b** is also revealed preferred to bundle **a** (i.e., **a** lies inside the budget line that applies when **b** is purchased). Such a result implies that both aRb and bRa, and the observations at hand do not support rational consumer behavior and hence weak separability. (The conduct of the test draws on Chalfant and Alston, 1988).

For each data point a, let $\mathbf{P}_a$ be the price vector and $\mathbf{Q}_a$ the quantity vector, each with length equal to N, the number of goods. The cost of purchasing bundle **a** is then $\mathbf{P}_a'\mathbf{Q}_a$. A time series including prices and quantities of N goods can be examined for consistency with the weak axiom by forming a matrix $\mathbf{\Phi}$ with typical element $\mathbf{\Phi}_{ab} = \mathbf{P}_a'\mathbf{Q}_b$ so that each element $\mathbf{\Phi}_{ab}$ gives the cost at time a prices of purchasing the bundle of goods consumed at time b, as would enter the calculation of a cost-of-living index. For instance, the elements in each column give the cost at various price vectors of obtaining the consumption bundle **b**, while the elements in any particular row allow comparisons of the cost of the various bundles at a fixed set of prices.

If actual expenditures at time a exceed the cost of bundle **b** at time a prices, so that $\mathbf{\Phi}_{aa} > \mathbf{\Phi}_{ab}$, then aRb. Violation of the weak axiom occurs if it is also true that bundle **a** was affordable at time b, so that $\mathbf{\Phi}_{bb} > \mathbf{\Phi}_{ba}$ and bRa. When well-behaved, weakly **separable** demands are kept as a maintained hypothesis, any such violation of the axioms of revealed preference must be interpreted as evidence of nonexistence of weak separability.

We tested if the Turkish M2 data might have been produced by a rationally acting consumer. M2 comprises of cash, private sight deposits, and private time deposits with maturities of 1, 3, 6, and 12 months. For the quantities we have the data on stocks of monetary assets in each quarter. The prices associated with these quantities are user costs of each asset. We have 84 observations of quarterly quantity-price vector pairs. The $\mathbf{\Phi}$ matrix has the dimension of 84x84, and 7056 elements of which 6972 are off-diagonal elements.

Our test on M2 assets for violation of GARP yields the following results: out of 6972 are off-diagonal elements, we had 834 points violating the GARP. That makes 11.9% of all possible cases. If we stick to the requirement of staying within the boundary of rational consumer behavior we will not be able to bring those assets together to define the M2 aggregate.

We may have measurement errors in our price and quantity vectors. To account for it we allowed a one percentage point violation and counted again. In this case the ratio of violations falls to only 10.6%. So, most of the violations cannot be attributed to measurement error.

Since there are no critical values for this test, we cannot report any probability of rejection for nonexistence of weak separability. However, the violations occur with so much percentage that we cannot ignore them and keep the weak separability assumption. In an application of the same test to US M1A covering 1983:1-1992:3 reveals that there are 115 violations which makes 7.6% out of 1521 possible cases (Belongia, 2000b).

2.4. Constructing Divisia Monetary Aggregates for Turkey[11]

2.4.1. Introduction and a Short Review

In this section, we explain how we compute the Divisia monetary aggregates for Turkey. To facilitate comparison with monetary aggregates published by the Central Bank of the Republic of Turkey (CBRT), the Divisia monetary aggregates and related data are constructed for the same definitions of monetary aggregates or the same groupings of monetary assets, M1, M2, M2Y, M3A, and M3AY. The indexes are built in monthly and quarterly frequencies. The data computed besides Divisia indexes include expenditures on monetary aggregates and real dual user cost indexes of Divisia aggregates.

This means that we are not seeking an admissible asset grouping having the separability property. Indeed, this is the case for almost all exercises involving the comparisons of Divisia and simple sum aggregation. Although there are attempts in constructing such groups of assets to bring together under aggregation (Hahm and Kim, 2000; Belongia, 2000b), I, personally, do not find this kind of effort fruitful and

[11] In computing the Divisia monetary indexes we closely followed the formulations provided in the following paper: Anderson Richard G. Anderson, Barry Jones, and Travis Nesmith, 1997b, "Building New Monetary Services Indexes: Concepts Data and Methods", The Federal Reserve Bank of St. Louis Review January/February 1997 Vol. 79, No.1, pp. 53-82. Indeed, the authors of this paper follow the methodology developed by W. A. Barnett in his several papers. However, they collected all the necessary components for computation together, and we find it enough to apply the same methodology without giving any further references to their paper or any other sources.

reasonable. To bring together only the assets satisfying separability may cause to exclude some assets with exactly same or very similar features in being money. So, it is still a challenge to overcome in the area of monetary aggregation.

Divisia monetary aggregates have been constructed for several countries including USA, UK, Canada, Germany, Switzerland, Netherlands, Japan, South Korea, Taiwan, Malaysia, Australia etc. Among these countries, UK is the only one where the central bank (Bank of England) publishes the Divisia aggregates along with simple sum aggregates[12]. None of these countries experienced high degrees of currency substitution, which Turkey has had to a large extent after liberalization of the economy in 1980s. So, the Divisia monetary aggregates given here accounts for currency substitution. The history of inflation in Turkey has also been pretty different than these countries. None of them have experienced a long sustained process of galloping inflation like in Turkey.

The literature on Divisia aggregation in context of Turkish monetary data is a shallow one. I could find only three studies on the topic, two of them being PhD dissertations and a discussion paper at the CBRT. The earliest of them is Kunter (1993). Kunter[13] computes monthly Divisia aggregates for Turkey spanning the period of 1986-1992. Birkan (2008) uses Divisia aggregates in an attempt to measure currency and asset substitution in Turkey. Celik (1999) computes the Divisia aggregates for Turkey for the period 1986:1-1999:2 in monthly frequency, and uses them to estimate the money demand function from an error-correction model of real money (deflated using WPI), industrial production, and interest rates (3-month deposit rates and 3-month treasury bill rates). He evaluates Divisia M1 as the most promising aggregate among

[12] Relevant information and data can be accessed in the following links: http://www.bankofengland.co.uk/mfsd/iadb/notesiadb/divisia.htm; http://www.bankofengland.co.uk/statistics/ms/2009/jan/taba6.1.xls (pages accessed on 2.16.2009)

[13] I want to thank CBRT economist Kursat Kunter for providing some of the Turkish data on monetary assets and interest rates, which are not available online.

Table 2.2: Monetary Asset Stock Data Used in Definitions of Monetary Aggregates

Monetary Assets \ Aggregates	M1	M2	M3A	M2Y	M3AY
Currency	+	+	+	+	+
Private demand deposits denominated in Turkish Lira at commercial banks	+	+	+	+	+
Certificates of demand deposits[c]	+	+	+	+	+
7-day notice TL deposits[a]		+	+	+	+
Private time deposits denominated in Turkish Lira at commercial banks[b]		+	+	+	+
Certificates of time deposits[c]		+	+	+	+
Government demand deposits at commercial banks			+		+
Government time deposits at commercial banks[d]			+		+
Demand deposits in foreign currencies at commercial banks				+	+
7-day notice foreign-currency deposits[a]				+	+
Time deposits in foreign currencies at commercial banks[e]				+	+

a) One can withdraw money from or write checks on these accounts if they give a 7-day notice to the bank. Their volume is pretty small and are combined with 1-month deposits not in computations of user costs and shares but when placing them in an aggregate. So, they are included with along 1-month time deposits in M2 and this may result in small discrepancies with official simple sum aggregates.
b) Time deposits have the following maturities: 1, 3, 6, 12 months. Any maturity different from those are possible but not common.
c) Certificates of deposits have the same maturities as deposits[14].
d) Time deposits of government entities have the same maturities as private TL deposits.
e) Time deposits denominated in foreign currencies have the same maturities as TL deposits.

simple sum, Divisia and currency equivalent[15] M1, M2 and M2Y aggregates to use in money demand studies based on the income and interest elasticities, on stability tests, and Granger causality tests between money-output and money-inflation.

[14] CDs are eliminated from the financial system around 1997. In its most popular times around mid-1980s, CDs accounted for almost 8% of total deposits when they reached their pick in popularity. On the average, CDs account for 1.3% of deposits in our sample period, In published statistics they are sometimes combined with deposits by corresponding maturity. Here, we combined all of them with deposits of the same maturity as we do not have any interest rate data on CDs.
[15] Currency equivalent index as a measure of money is proposed by Julio Rotemberg (Rotemberg and Poterba, 1987: money in the utility function: an empirical implementation, in: New Approaches to Monetary Policy, W. A. Barnett and K. J. Singleton (eds.), Cambridge: Cambridge University Press, 219-240) and it is computed with the formula: $CE_t = \sum_{i=1}^{n} \left(R_t - r_{it}\right) / \left(1+R_t\right) m_{it}^{nom}$. Barnett (1991: Reply to Rotenberg) shows exactly where the CE index falls in measuring money.

Table 2.3: Interest Rate Data Used in Computation of Monetary Asset User Costs

Interest Rate on
Private sight deposits at commercial banks[16]
Private 7-day notice deposits at commercial banks
Private 1-month time deposits at commercial banks
Private 3-month time deposits at commercial banks
Private 6-month time deposits at commercial banks
Private 12-month time deposits at commercial banks
Sight deposits in foreign currencies at commercial banks
1-month time deposits in foreign currencies at commercial banks
3-month time deposits in foreign currencies at commercial banks
6-month time deposits in foreign currencies at commercial banks
12-month time deposits in foreign currencies at commercial banks
Government sight deposits at commercial banks
Government 1-month time deposits at commercial banks
Government 3-month time deposits at commercial banks
Government 6-month time deposits at commercial banks
Government 12-month time deposits at commercial banks
Average compound interest rate on government borrowing auctions

The official definitions of Turkish monetary aggregates at different levels include the monetary assets given in Table 2.2. We also have the rate of return data on those monetary assets. However, the rates of return on FX deposits have been treated in a special manner which will be explained later on in this chapter. Table 2.3 gives a list of interest rates used in computations. The list includes interest rates on deposits interest rates on government bonds[17] in each month along with the annualized interest rates on TL deposits.

[16] Unlike most countries, sight deposits bear interest in Turkey. Hence, we do not have the problem of attaching implied rates of return for them. Another point related our computation of Divisia indexes is that we did not apply any own rate conversion or yield curve adjustment.

[17] Each month the government issues borrowing instruments that are sold by auction. The maturities differ depending on the needs of government and on the market conditions. Nonetheless, the maturities are generally short (I mean really short) and borrowing longer than a few years is an exception rather than the rule. Indeed this was one of the biggest problems of public finance, and only in recent years the government has been able to obtain some extension in the average maturity of the outstanding debt stock.

A remark to make at this point is that Turkey has a really simple and clear financial system. As for the asset types that enter the definition of money, we have only cash, sight deposits and time deposits with different maturities[18] and in different currencies as seen in Table 2.2. The simplicity of the structure can be seen when compared to 26 different types of monetary assets in the monetary services indexes (MSI) of the Federal Reserve Bank of St. Louis[19] (Anderson et. al, 1997c, p. 61). Similarly Korea's 40 types of assets listed in Hahm and Kim (2000) indicates a much more complex financial structure in Korea compared to Turkey.

2.4.2. Problems with Data Collection Practices

Measurement of money continues to be a problematic area in the conduct of monetary policy. The problems related to the measurement are not only in the subject of aggregation methods. The collection of monetary data itself continues to be a problem. To exemplify some cases, I want to mention some practices in the Turkish economy very briefly.

Regarding the measurement of money in Turkey, there is a commercial practice that is very complicated to measure and never included in official money data. However, this practice, practically creates money. It works this way: People in business generally do not use checks to make their payments[20]. Instead they give a signed document called "promissory note", which shows the amount of debt and the due date of it. Although the advances in Turkish banking system expanded the use of checking accounts for payments, the traditional way of making commercial payments is still in common use. Moreover, those promissory notes are circulating like money among business people. So, the system creates its own money whenever necessary. One more strange practice is "deferred checks". Normally a check is a payment

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[18] Introducing new types of assets to the system proved not useful and they are abolished in short time.

[19] The updated Divisia data can be accessed at: http://research.stlouisfed.org/msi (last accessed on 16.2.2009)

[20] In Turkey, banks do not issue checking books to every depositor. Check books are given only to reliable ones, where reliability implies either big amounts of money deposited with the bank, or long-time relations with the same bank.

instrument that is payable whenever submitted to the bank. Yet, the usual practice in Turkey is that checks are signed with a future date on them, so that checks are used exactly the same way as promissory notes. And they are circulated as means of commercial payments without being taken to the banks before the due date on them.

Another problem regarding the collection of monetary data is the Islamic (non-interest) banks. The deposits (profit and loss sharing accounts) in these institutions are not included in our data. These data are integrated to the banking data in last few years. However, they have been around for almost two decades. The share of non-interest funds are nowadays around 10 per cent of total deposits, which cannot be overlooked.

The period of big corruption in banking sector after the military intervention in late 1990s should have deteriorated the quality of monetary data to some extent. From 1997 to 2000, it is officially declared that the money stolen from banks using the off shore banking and other cheating methods has been amounted to 50 billion US Dollars, which was more than a quarter of the average annual GDP by that period. Later on a portion of that money has been recovered by public authorities, yet that portion is no more than 30 percent of the robbery. Actually the same corrupt people forced the parliament of that time to enact an amnesty that prevents the authorities to go after people who had stolen the money of entire population. The generals of the time had been employed by the businessmen (bank owners) after their retirement as members of administrative boards. Whatever it is and how it happened, we have no easy way to compensate for the contamination of the monetary data due such events.

The problems are still there and the same: we are far away from satisfactorily measuring economic variables, both flows and stocks.

2.4.3. Notation and Concepts Used in Computations of Divisia Indexes

In this section, we give a brief summary of the definitions of concepts used in formulations. Actually what we put here is an abbreviation of Anderson et. al (1997c).

m_{it}^{nom} denotes the nominal stock of monetary asset i in period t for assets i = 1, …, n:

$$m_t^{nom} = (m_{1t}^{nom}, \dots, m_{nt}^{nom}).$$

π_{it}^{nom} is the nominal and π_{it}^{real} is the real user cost (rental price) of asset i in period t as derived by Barnett (1978, 1987, 1990)[21]:

$$\pi_{it}^{real} = \frac{\pi_{it}^{nom}}{p_{it}^{*}} = \frac{R_t - r_{it}}{1+R_t}.$$

The total expenditure on monetary assets in period t is given by:

$$y_t = \sum_{i=1}^{n} \pi_{it}^{nom} m_{it}^{real} = \sum_{i=1}^{n} \pi_{it}^{real} m_{it}^{nom}.$$

Expenditure shares of individual monetary assets are the same for nominal and real shares. The share of asset i in period t in total expenditures on monetary assets is given by:

$$w_{it} = (\pi_{it}^{real} m_{it}^{nom} / y_t) = (R_s - r_{is}) m_{is}^{nom} / \sum_{j=1}^{n} (R_s - r_{js}) m_{js}^{nom}.$$

These relationships enable us to measure the Divisia indexes directly from observable nominal monetary asset stocks and interest rates. The nominal Divisia index of monetary services (technically chained Törnqvist-Theil quantity index), DM_t^{nom}, is measured by:

$$DM_t^{nom} = DM_{t-1}^{nom} \prod_{i=1}^{n} \left(\frac{m_{it}^{nom}}{m_{i,t-1}^{nom}} \right)^{\overline{w}_{it}},$$

where $\overline{w}_{it} = (w_{it} + w_{i,t-1})/2$. The real Divisia index can be obtained simply by deflating the nominal index using an appropriate price index.

Taking the logarithms of the formula will give

$$\log DM_t^{nom} - \log DM_{t-1}^{nom} = \sum_{i=1}^{n} \overline{w}_{it} (\log m_{it}^{nom} - \log m_{i,t-1}^{nom}).$$

[21] Here we ignore the fact that user costs will differ for consumers and firms as they face different market interest rates and prices.

Using this formula we observe that the growth rate of Divisia index is a weighted average of the growth rates of component assets.

The real dual user cost index, Π_t^{real}, is defined by:

$$\prod_t^{real} = \prod_{t-1}^{real} \left(\frac{y_t / y_{t-1}}{DM_t^{nom} / DM_{t-1}^{nom}} \right).$$

$$\log\Pi_t^{real} - \log\Pi_{t-1}^{real} = (\log y_t - \log y_{t-1}) - (\log DM_t^{nom} - \log DM_{t-1}^{nom})$$

growth rate of dual real user cost index = growth rate of expenditures on monetary assets
- growth rate of Divisia monetary index

A price index number is said to be dual to a quantity index number if their product is equal to the total expenditure on the component assets included in the indexes, a property called factor reversal. The dual of the nominal Divisia index is the real user cost index. Conversely the dual to real Divisia index is the nominal user cost index.

The Divisia index and its dual user cost index are chained superlative indexes. They therefore have the same statistical properties as GDP and its implicit GDP deflator.

Barnett and Serletis (1990) propose a dispersion dependency test, based on the Divisia second moments, i.e. variances, for the failure of the principal assumptions of aggregation theory. The Divisia variances may contain significant information during periods of changes in the financial environment. The Divisia quantity growth-rate variance is calculated using the formula:

$$K_t = \sum_{i=1}^{n} \overline{w}_{it} [\Delta\log(m_{it}^{nom}) - \Delta\log(DM_t^{nom})]^2$$

The simple sum index is formulated as the sum of the nominal monetary asset components:

$$SS_t = \sum_{i=1}^{n} m_{it}^{nom}$$

The formulas used in computation of indexes are brought together in Table 2.4.

Table 2.4: Definitions of Monetary Services Indexes, User Costs, and Related Indexes Used in Analyses in This Dissertation

Index	Formula
Simple sum index	$SSM_t = \sum_{i=1}^{n} m_{it}^{nom}$
Total expenditure on monetary assets	$y_t = \sum_{i=1}^{n} \pi_{it}^{real} m_{it}^{nom}$, where $\pi_{it}^{real} = \left(R_t - r_{it}\right) / \left(1+R_t\right)$
Nominal Divisia index	$DM_t^{nom} = DM_{t-1}^{nom} \prod_{i=1}^{n} \left(\frac{m_{it}^{nom}}{m_{i,t-1}^{nom}} \right)^{\overline{w}_{it}}$, where $\overline{w}_{it} = (w_{it} + w_{i,t-1})/2$ and $w_{it} = (\pi_{it}^{real} m_{it}^{nom} / y_t)$
Real dual user cost index	$\prod_t^{real} = \prod_{t-1}^{real} \left(\frac{y_t / y_{t-1}}{DM_t^{nom} / DM_{t-1}^{nom}} \right)$
Divisia quantity–growth rate variance	$K_t = \sum_{i=1}^{n} \overline{w}_{it} [\Delta \log(m_{it}^{nom}) - \Delta \log(DM_t^{nom})]^2$

2.4.4. How Foreign Exchange Deposits Are Treated in Computations?

Among the efforts to liberalize the Turkish economy after 1980 is the introduction of foreign exchange deposits (FXDs) at commercial banks for residents. With regulations enacted in December 1983 and July 1984 the exchange rate regime had been completely liberalized (Onder, 2005). One of the goals of this policy was to control the level of foreign reserves and to keep enough reserves so that balance of payments difficulties would be prevented (Celik, 1999). FXDs have the same maturity scheme as TL deposits. FXDs have been normally denominated in US dollars and Euro. Prior to introduction of Euro, German Mark had been the dominant foreign currency in use.

The amount of FXDs in terms of US Dollars has risen continuously with some exceptional downturns that usually couple with times of financial and economic turmoils. Figure 2.4 gives a picture of the developments in FXDs in terms of US Dollars, while Figure 2.5 shows the path of the ratio of FXDs to total private deposits.

After two big devaluations / appreciations, the TL value of FXDs rose sharply in 1994 and 2001, although the US$ amount of FXDs decreased in those occurrences. The ratio of FXDs to TL deposits started with 12% in the beginning of our sample period, reached its maximum at 65% during April 1994 devaluation, and the average of the ratio has been 43% in the 21-year sample period. In 1990s, the continuous rise in the share of FXDs had been an important factor alongside the fiscal dominance to limit the efficiency of monetary policy.

FXDs make an interesting case when it comes to their inclusion in the money supply. Are they a part of instruments that can be used as medium of exchange? Or are they pure assets, and people hold FXDs just to avoid fluctuations in the value of national currency? Are FXDs related to the volume of trade the country is engaged in? So there are many questions to be answered about FXDs. As is the case with Turkey, all these questions can be answered with a cautious or partial “yes”, keeping in mind that we may face many puzzles. Although having high, volatile and very long-standing inflation, foreign currencies never played the role of medium of exchange in Turkey, though nobody would reject being paid in Dollar or Euro. However, there had been times when some prices like house prices, rents, and even some credits are determined in or indexed to foreign currencies as in other countries that experienced currency substitution (Calvo and Vegh, 1992).

Sometimes FX deposits brought higher returns than TL ones, especially during crises periods. Sometimes it has been just the reverse, and FX deposits even yielded negative returns as in the aftermath of devaluations. Indeed, the two big devaluations of 1994 and 2001 can be easily pointed out as overshooting episodes, and as in theory, they are followed by corrective downturns in exchange rates. Especially the case after 2001 devaluation is more pronounced in this respect. The real value of foreign currencies has fallen by 40% from its peak value in October 2001 until December 2006. The average interest rate on FXDs in that period had been 5.2% only. So there is a negative combined real rate of return, yet we do not observe a resolution in FXDs and

Figure 2.4: Developments in FXDs in Terms of US Dollars: 1986-2006

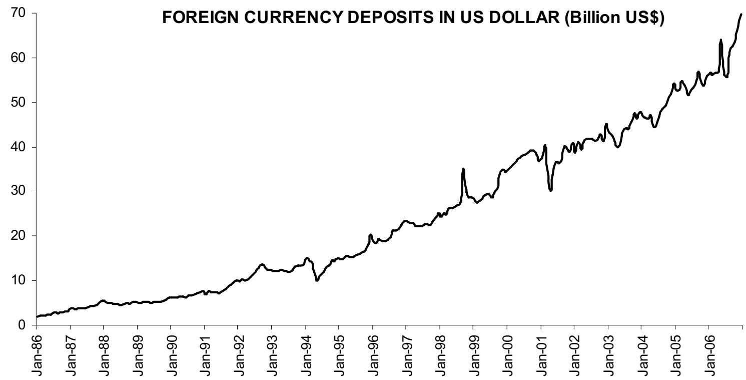
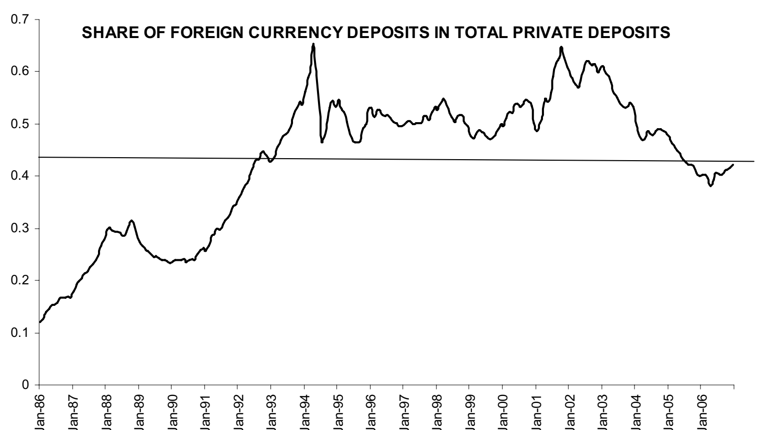


Figure 2.5: The Path of the Ratio of FXDs to Total Private Deposits: 1986-2006

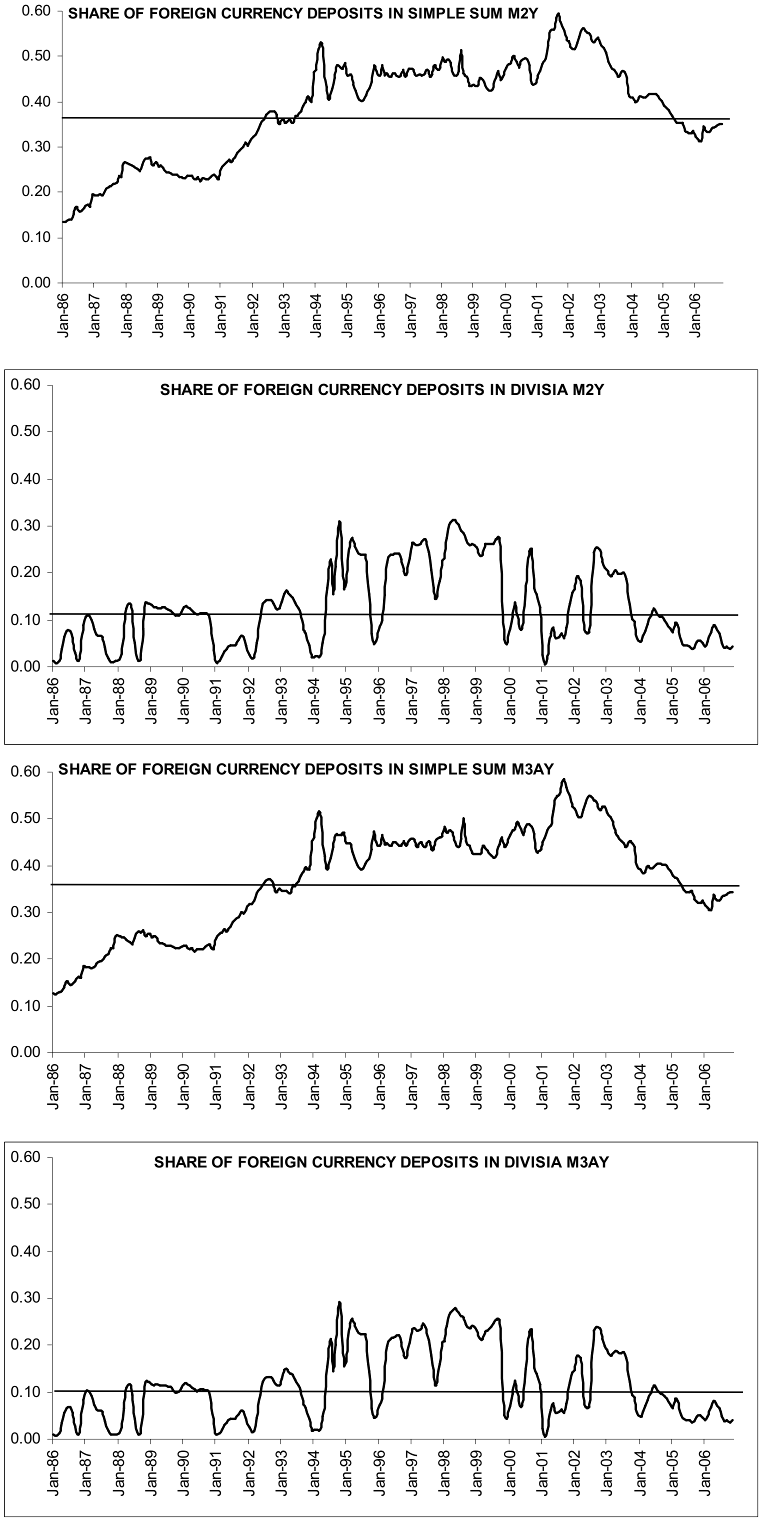


Source: CBRT website: http://evds.tcmb.gov.tr

on the contrary to expectation they increased from US$ 39 billion to US$70 billion, whereas the share of FXDs in total deposits fell to 42 from 65%.

Considering all those issues related to the FXDs, what might be the correct or appropriate way to assign a weighting scheme to them? Here are the principles that applied to creating such a scheme:

Figure 2.6: The Shares of the Foreign-Currency Deposits in the Aggregates



1. The interest rate on FXDs does not express the true rate of return of foreign-currency assets, so the expected rate of appreciation / depreciation should be taken into account.

2. FXDs are not more liquid than national currency assets, so they cannot be given a higher weight than the corresponding / similar national currency assets. Even FX sight deposits cannot be as liquid as, say, 1-month national-currency deposits.

3. In cases where the combined rate of return (interest rate plus expected rate of appreciation) on FXDs is negative, the rate of return should be assumed at least as high as the national currency asset with corresponding maturity.

4. In cases where the combined rate of return on FXDs is unreasonably high as is during financial crises times, it is reasonable to assume that they are completely illiquid, since people will have no initiative to spend their foreign money. The fall in the dollar amount of FXDs during crises times should be attached to capital outflows instead of the willingness of spending the FXDs.

Under these principles, the strategy we followed is described below.

First of all, although their amount is very small compared to FXDs, "gold deposit accounts" have been distributed to FXDs: sight gold deposits are added to sight FXDs, and time gold deposits are distributed to time FXDs according to the share of different maturities in total FXDs. 7-day-notice accounts, again a very small amount, have been added to 1-month FXDs.

The FXDs belong partly to the non-residents, and luckily we have the amount of total FXDs by residents, but not its breakdown to different maturities. So we solved this problem by making a scale dividing residents' FXDs to total FXDs and applying this scale to all maturities. In this way we equate the amount of FXDs to ones in money supply data of CBRT, and keep the proportions of different-maturity deposits.

We do not have data on the interest rates on FXDs before March 1990. To attach interest rates to the FXDs for that period, I used the average interest rates of following 12 months for all maturities. Actually, the interest rates make up the smaller portion of rate of returns on FXDs since the expected appreciation of foreign currencies had been pretty high in those periods.

Below is how we reflected the expected depreciation of TL in rates of returns on FXDs.

For all maturities, i.e. 1, 3, 6, and 12 months, the expected appreciation of ER is added to the relevant interest rate. Since sight deposits are by nature more liquid than 1-month FX deposits but not as that of national currency assets, I chose to apply 80% of monthly depreciation to sight FXDs. This choice is completely arbitrary. In adding up the rates of returns in terms of interest rate and expected appreciation, we used the compound return formula: [(1 + interest rate)*(1 + rate of appreciation) - 1].

In determining the expected rate of depreciation, I employed a hybrid formula of adaptive expectations and perfect foresight. For 1-month FXDs, I computed the depreciation of TL previous month and the following month. The same method is applied for other maturities, for instance for 3-month FX deposits, the rate of depreciation in previous three months and following three months are obtained and so on. In the second stage, the geometric average of those two rates are computed, and the resulting figures are assumed as expected rate of depreciation in Turkish Lira.

Since we do not find it reasonable that FXDs can be more liquid than TL deposits, the real user costs of assets denominated in foreign currencies are determined in a way that they are not smaller than the real user costs of the same-maturity asset denominated in Turkish Lira. There are some periods in our sample when the implied / assumed rates of return computed as described above are too small (and even negative in some 54 observations). For those instances we assigned the FXDs a rate of return that is 1 percentage point higher than the TL counterpart.

Additionally for the sight FXDs, to prevent their rates of returns to fall shorter than sight deposits in TL in periods when Lira appreciates, unlike the time deposits, we assumed that sight FXDs have a rate of return equal to 1-month TL-deposits instead of sight TL-deposits. Hence we make it sure that FXDs are less liquid than TL assets and sight FXDs have a rate of return 1-percentage point below the 1-month FXDs.

Another issue arises in times when the depreciation in Turkish Lira is very high as it was in 1994 and 2001 crises and around the big speculative fluctuation in mid 2006. Those are the instances the implied / assumed rates of return on FXDs exceed the benchmark interest rate, so we face negative real user costs. To go around this problem, for such cases we assumed a rate of return that is 1-percentage below the benchmark rate, which was naturally determined using the assets denominated in TL. Taking this path, we avoid the economically unreasonable case where an increase in deposits causes a reduction in money supply.

Similarly, for the periods when the short term depreciation of TL is higher than the long-term depreciation, we face a situation as if the longer-maturity assets are more liquid than the shorter-maturity ones. To prevent such an illogical situation to occur, we make the necessary adjustment so that longer-maturity FX assets always have a higher rate of return than the shorter-term assets. For example, if the rate of return on 3-month FXDs happens to be lower than that on 1-month FXDs, then we adjusted the returns in a way that 3-month FX assets have a higher rate of return by 1-percentage point. And this adjustment is done for all maturities in these weird instances.

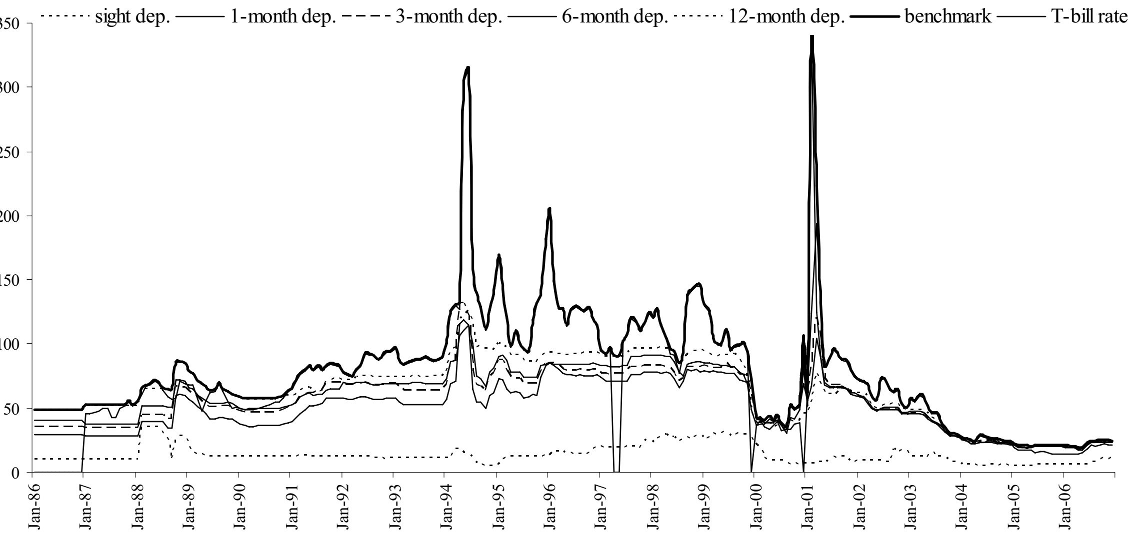
2.4.5. The Benchmark Rate of Return

Barnett and Spindt (1984) apply an “envelop” approach to get the benchmark rate of return. Here we pick the highest rate among treasury bill rates and all component assets denominated in Turkish currency at each period as the benchmark rate. That is

$$R_t = \max\{r_{1t}, r_{2t}, \ldots, r_{nt}, r_{t\text{-bill}}\}$$

The interest rates used in the computations are pictured in Figure 2.7. Out of 252 months in our sample, the treasury bill rate is the highest for 147 times. For some

Figure 2.7: Benchmark Rate of Return



Source: CBRT website: http://evds.tcmb.gov.tr

months the auctions for government securities were canceled. So, the 12-month deposit rate and t-bill rate assume the role of benchmark rate in our sample. However, there had been a time when the shorter rates have gone wild and exceeded longer rates. In February 2001, 1-month deposit interest rate was the highest among all assets, and the following month, 7-day notice deposits had the highest rate of the month. 3-month deposit interest rates assumed the benchmark rate twice, one during the 1994 crisis in April, and one during the liquidity crisis preceding the collapse of the 2000 program in December. Actually the period towards the collapse of 2000 stabilization program and the few months following the collapse had been the worst financial crisis of the Turkish economic history.

This is quite different than the case in other countries. Since people have seen the government prone to fiscal insolvency most of time, the government had to pay unreasonably high interest rates on domestic debt. For example, in 2001 the outstanding domestic debt was 51.2% of GDP, and the government made an interest payment amounting to 16.9% of GDP. The very same the outstanding public debt stock of in Italy was 108.8% of GDP and the interest payments out of government budget realized at only 6.3% of Italian GDP (Figure from Bank of Italy[22]). Another comparison can be made between Turkey and USA regarding interest rates. As for Turkey, interest rates on government securities tend to be highest rate in the country. In the same period, interest rates on t-bills in the USA had not been higher than say the rates on certificates of deposits even in a single month (information from Federal Reserve Bank[23]).

[22] http://bip.bancaditalia.it/4972unix/
[23] http://www.federalreserve.gov/Releases/H15/current/h15.txt

CHAPTER 3

PRELIMINARY ANALYSIS OF DIVISIA AND SIMPLE-SUM MONETARY AGGREGATES FOR TURKEY

3.1. Basic Statistical Properties of Monetary Aggregates

It does not look like reasonable to say anything a priory about the basic statistics of Divisia and simple sum aggregates. Checking the comparative basic statistics for other countries given in previous studies, we do not observe any tendency. However, we find it still useful to give here the mean, median, maximum and minimum values and standard deviation statistics related to period growth rates and annual growth rates of monetary aggregates.

Panel A of Table 3.1 shows the statistics for monthly growth rates. Apart from M1 aggregates, higher level Divisia aggregates have all smaller averages, yet greater dispersion as observed in ranges (max-min), and standard deviations. Based on this observation we can think that Divisia aggregates respond to the developments in the economy in a faster and more fluctuating fashion. Though this is an early and immature result to jump on, it is well in accord with the theoretical concerns related to monetary aggregation methods. It is mentioned frequently in favor of Divisia aggregation that they respond to the financial innovations and capture the effects of shifting demand for different monetary assets.

Panels B and C of Table 3.1 display the same information for real aggregates. Here again, besides M1 aggregates, Divisia aggregates exhibit smaller growth rates, yet higher volatility, even more pronouncedly compared to the case of nominal aggregates. And the price index used for deflation does not make any major difference in the picture.

We give the corresponding figures for annual growth rates in Table 3.2. For nominal aggregates in annual growths of monthly data, we still have smaller averages (save the case of M1), nevertheless the proportion has changed much. Moreover, in annual measurement, simple sum aggregates show a larger volatility than the Divisia counterparts. However, we do not stop there and see that with real aggregates, the picture is just the reverse of nominal aggregates; even more pronounced this time compared to monthly growth data.

3.2. Correlation Coefficients between the Growth Rates of Higher Level Monetary Aggregates and M1 Aggregates

Correlation coefficients between M1 aggregates and higher level of monetary aggregates will give some information about the characteristics of the aggregation methods. Since Divisia aggregates are meant to capture the transactions function of the money, it is expected that Divisia aggregates have a higher correlation with M1 aggregates than those of SS aggregates.

Panel A of Table 3.3 shows the correlation coefficients between the growth rates of nominal aggregates. First of all we want to point out that the correlation between Divisia M1 and simple sum M1 is almost perfect: 0.9911. This is indeed in line with expectations, because M1 includes only cash and demand/sight deposits which constitute the primary forms of payments in the economy, so that the aggregation method should not have a big effect for M1 aggregates.

However, the correlations to M1, whether to SSM1 or to DM1, reveal that Divisia aggregates have larger coefficients at all levels of aggregation compared to simple sum aggregates. This fact informs us on the capability of measuring the moneyness of different aggregation methods: at any level of aggregation Divisia indexes deserve more to be named money rather than simple sum indexes.

Panel B of Table 3.3 shows the correlation coefficients between the growth rates of real aggregates deflated using consumer prices index. The correlation between Divisia M1 and simple sum M1 is 0.9922, very high as expected. And again real Divisia aggregates have higher correlations at all levels of aggregation compared to real simple sum aggregates.

Panel C of Table 3.3 reveals the same information as in Panel B, indicating that the deflation factor does not affect the situation.

We repeat the same exercise using annual growth rates of nominal and real aggregates. The three panels of Table 3.4 give figures corresponding to those in Table 3.3. The correlations between annual growth rates provide similar information as in the case of monthly growth rates. Here we also note that whenever foreign exchange deposits are included in the monetary aggregates, simple sum aggregates have much lower correlations to M1, and this is even more pronounced in case of annual growth rates of real aggregates in comparison to the case of nominal aggregates.

Here we find it useful to look at correlations between counterpart aggregates as given in Table 3.5. As we move towards higher aggregation levels we see that the correlation coefficients between counterpart aggregates get smaller. Adding the private time deposits to M1 makes correlations diminish. Since M3A adds relatively small components to M2, the decline in the correlation is less from M2 to M3A. Foreign exchange deposits also cause a substantial decline in the correlation coefficients. Having lower degrees of correlations imply that statistical analyses using monetary aggregates based on different aggregation methods will yield pretty different results.

3.3. Shares of Component Assets in Monetary Aggregates

Figure 3.1 shows the shares of the two component assets in monthly M1 aggregates. For the shares sum up to one, the graphs of individual shares mirror each other. During the entire sample period, sight deposits have the higher share in SSM1 with a few months of exceptions. On the other hand shares of components are almost equal in DM1. Whenever the margin between the benchmark rate of return and the interest rate on sight deposits depart from each other, so does the share of deposits. For example in early 2001, the overall interest rates in Turkey jumped to very high levels during the liquidity crisis and the collapse of exchange rate-based stabilization program. However the sight deposit rates have not followed this jump closely. So, the share of deposits went up to its peak values during this period. In the following relatively stable financial environment, the share of deposits turned to much lower levels.

Figure 3.2 displays the component shares in M2 aggregates. The summary statistics of shares are given in Table 3.6. The second panel of table reveals that share of currency in DM2 is almost a triple of the share in SSM2, and we also observe that the share of sight deposits more than doubles in DM2 compared to SSM2. One of the most remarkable changes in relative shares is in 12-month deposits. It is almost 13 times higher with SSM2. As the 12-month deposit rates are closest among the monetary assets yields to the benchmark rate, we observe most substantial fall of share in these assets.

Table 3.6 summarizes all asset shares at all levels of aggregation. Examining the figures reveals some important insights on Turkish financial system. First of all we observe that there exists a tendency toward shorter-term both in TL and FX deposits. As being the longest deposit term 12 months, still people prefer 3-month maturity. Around 50% of all deposits are placed for 3 months, and only 10% of deposits have the maturity of 12 months although they yield highest return. This must be the result of long-lasting inflation and recurring financial crises. People prefer to stay as liquid as possible, yet they cannot give up the interest income completely.

3.4. Graphs of Monetary Aggregates

Figure 3.3 shows the levels, period (quarterly) growth rates, and year-on-year growth rates of nominal monetary aggregates. The same information is provided for real aggregates deflated using WPI in Figure 3.4. Since M1 data are not very different, we preferred to give the pictures of M2 aggregates. M2Y should also be informative as it includes FX deposits that are weighted very differently in different aggregation methods. Although there are differences between WPI- and CPI-deflated real money, the differences do not represent big departures easily recognizable by just inspecting by eyes. Thus, we only put the graphs for WPI-deflated money down to save space. So, the figures include only M2 and M2Y, both nominal and real. Another point is that we display the graphs for quarterly data for they are less fluctuating (so they are handsomer!), yet still having the same tendencies as the monthly-data graphs.

The levels of nominal aggregates show similar patterns for simple sum and Divisia money. We see the first recognizable departure in M2 in 1994. After the crises the two aggregates start to move separately. This can be attached to two factors: rising benchmark rates, and increasing awareness of people to interest rate changes.

Another remarkable behavior in the M2 aggregates is their parallel movement after 2001 crisis. I tend to attribute this to the hardly achieved relatively stable economic environment, where interest rates fell down along with inflation rates and the governments conducted better fiscal policies.

As for the M2Y aggregates that include the FX deposits, level graphs look pretty much similar to M2 aggregates. However, we observe that the departure between simple sum and Divisia aggregates started earlier, that must be due to increasing FX deposits. Another remarkable point is the slower growth of simple sum aggregates after 2001, which represents a period of stable nominal exchange rates. This increased the share of FX deposits in Divisia but not in simple sum aggregates.

Real aggregates do not tell too much a different story than the nominal aggregates. We have similar dates of separation for two types of aggregates, and the convergence in the late periods of our sample.

3.5. Money Growth and Inflation: Graphical View

Figure 3.5 pictures the year-on-year inflation rates as measured by consumer prices index and the annual growth rates of nominal simple sum and Divisia monetary aggregates at all five levels of aggregation.

We observe the comovement of money growth and inflation during a long time in our sample period. However this comovement has been seemingly broken in last few years. The correlation coefficients between CPI-inflation and the growth rates of monetary aggregates are given in Table 3.7 for two periods: one from beginning of sample to 2002 and the second from 2003 to the end of the sample. Not surprisingly, the reasonably high positive correlation coefficients in first subperiod turn to negative movements in the second subperiod. Based on this simple observation, we might expect overprediction for inflation if we use money to forecast it in the second period.

3.6. Income Velocities of Monetary Aggregates

The evolution of income velocities for different money definitions during the sample period are given in Figure 3.6. All the velocity graphs pretty much resemble a parabola with a small positive coefficient on second-order term. Save M1, other aggregates have clear trends. Divisia velocities exhibit negative trends, while simple sum velocities appear to have positive trends. Second order trends are also not rejected.

The information on stationarity and trends are given in Table 3.8 along with basic statistical information summary on velocities. None of the velocity series looks stationary on any measure. Considering these properties of velocities, it does not look reasonable to spend too much time on money demand estimations as done in empirical literature. So, we will not enter that territory at all in our applications.

3.7. Outliers and Integration Properties of the Variables in the Data Set Used in Applications

3.7.1. Outliers and Dummies

First we want to mention the results of tests for possible outliers in inflation data. As information is given in Chapter 2, Turkey had two episodes of severe crises in our sample period, namely 1994 and 2001 crises. These experiences yielded some observations in especially inflation series that cannot be captured easily within empirical models. So we had to use some dummy variables when modeling inflation. Although these periods of wild inflation figures coupled with substantial output decreases, they cause relatively less problems. Hence we do not mess with GDP outliers.

The outlier type we are concerned are the ones of additive type. We used Tramo-Seat procedure provided with EViews in determining the outliers. Annual inflation figures have no such problems. On the other hand quarterly and monthly inflation figures, both CPI and WPI-measured inflation have outliers in early 1988, Spring 1994 and Spring 2001. The case for 1988 was completely due to electoral reasons. These periods also witnessed high fragility in fiscal side of the economy. Hence we had outlier observations in interest rates too, both deposit rates and treasury bill rates.

3.7.2. Integration Properties of the Variables

This dissertation is all about empirics. So we will be facing many variables in the applied parts starting next Chapter. Instead of dealing with the integration properties of the series under interest everywhere we have to use them, I did all the inquiry in this section.

We employed four different unit root tests: Augmented Dickey Fuller (ADF) Test, Phillips-Perron (PP) Test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test, and Elliott-Rothenberg-Stock (ERS) Test. The null hypotheses of each test are given in Table 3.8.

The properties of the tests we used are described below.

Augmented Dickey Fuller (ADF) Test: Lag length is chosen according to SIC from a maximum length of 15. Critical values change to some degree across lag lengths. As the lag length of difference terms increase so are the critical values. However the increase is only up to 3rd digit after decimal point. The change of lag length does not only alter the critical values but also changes the computed test statistics. The critical values change also across data frequencies.

Phillips-Perron (PP) Test: Spectral estimation method uses Bartlett kernel. Bandwidth is selected using Newey-West window. Critical values do not change across bandwidths; instead a change in the bandwidth affects the computed test statistics. The critical values change across data frequencies.

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test: Spectral estimation method uses Bartlett kernel. Bandwidth is selected using Newey-West window. Critical values do not change across bandwidths; instead a change in the bandwidth affects the computed test statistics. The critical values do not change across data frequencies.

Elliott-Rothenberg-Stock (ERS) Test: Spectral estimation method uses AR spectral OLS. Lag length chosen according to SIC from a maximum length of 14. Critical values do not change across lag lengths; instead a change in the bandwidth affects the computed test statistics. The critical values change across data frequencies.

The critical values of all tests are given in Table 3.9. Table 3.10 gives the test results for all variables in monthly and quarterly frequency. Figure 3.7 displays the graphs of all variables as used in the applications.

CHAPTER 4

VAR ANALYSIS OF NONSTATIONARY AND STATIONARY DATA

4.1. Introduction

4.1.1. Some Remarks on Forecasting Schemes

Forecasting is the prediction of future values of a variable based on known past values of that variable and/or other related variables (Makridakis et. al, 1998).

Forecast variable is the variable that is predicted by some other variable or variables. The forecast variable is also called the dependent variable, regressand or response variable. In this study the forecast variables are price indexes and (nominal and real) output, either in their level values or growth rates with different time references, i.e. annual, quarterly or monthly.

An **explanatory variable** is one whose values are determined outside of the system being modeled. An explanatory variable is used to predict values of a forecast variable. Explanatory variables are also called independent variables, impulse variables, predictors or regressors. In all our applications we have monetary aggregates (in levels or growth rates) and lagged dependent variables as explanatory variables. We called the models involving only money and the forecast variable bivariate models. Some applications include additional variables such as nominal exchange rate index. These models are referred to as multivariate models.

All our forecasts presented in this study are of the nature of **ex-post forecast**, i.e. we use information beyond the time for which the forecasts are made. We prepared our forecasts for last 3 years (36 months, 12 quarters) of our sample period.

Basically there are five **approaches to economic forecasting** based on time series data: (1) exponential smoothing methods, (2) single-equation regression models, (3) simultaneous-equation regression models, (4) autoregressive moving average models (ARMA), if extended with additional explanatory variables (ARMAX), and (5) vector autoregressions (VAR) (Gujarati, 2004, p. 836). We will be using the second, fourth and fifth approaches since they allow us to incorporate monetary aggregates as explanatory variables. We also add an additional approach to these, namely neural networks will be used as an alternative forecasting tool.

The **one-step forecast error** is the difference between the actual value and the forecasted value of the forecast variable for the corresponding period:

$$e_{T+1|T} = \hat{g}_{T+1|T} - g_{T+1}$$

where $e_{T+1|T}$ is the forecast error of the forecast of g_t made for period T+1 based on information available at time T, g_{T+1} is the actual value of the forecast variable at period T+1, and $\hat{g}_{T+1|T}$ is the forecast for period T+1 predicted based on period T information. There are two sources of the forecast error for an ex-post forecast (Greene, 2003, p. 576; Davidson and MacKinnon, 1999, p. 105; Johnston and Dinardo, 1997, p. 231). To see these sources clearly, lets check the equation used in forecasting:

$$g_t = \beta x_t + \varepsilon_t\ ,\ t=1, \ldots, T$$

where x_t is a vector of explanatory variables that may include lagged values of g_t along with some other variables, and ε_t is an error term with an expectation of zero in every period t.

First source of the forecast error is a sampling variation component in it, as $\hat{g}_{T+1|T}$ is an estimate here. $\hat{\beta}_{T+1|T}$ will be different from the true value of β_{T+1} due to sampling variation.

Second source of the forecast error arises from the fact that $\hat{g}_{T+1|T}$ is obtained from an equation including an error term, ε_t, which is expected to be zero in period

T+1. However, the actual realization might be different from zero, so that it also contributes to the forecast error $e_{T+1|T}$.

For ex-ante forecasts we will have to forecast the future values of explanatory variables in x_t contained in the equation at hand. This will also make a part of the forecast error. Luckily we have no concern about this because all our forecasts will be of ex-post nature.

The **forecast horizon** is the length of time into the future for which forecasts are to be prepared. The forecast, $\hat{g}_{T+1|T}$, made for period T+1 based on information available at time T is called **one-step-ahead** forecast. It is possible and common to obtain forecasts for farther periods. $\hat{g}_{T+2|T}$ computed at time T is, for example, **two-step-ahead forecast** of g_t, and $\hat{g}_{T+h|T}$ computed at time T is for example **h-step-ahead forecast** of g_t.

At this point we need to elaborate on some technical issues regarding ex-post forecasts made for longer than one-period horizon. These issues are simple and obvious yet they may cause confusion sometimes.

To get the two-step-ahead forecast $\hat{g}_{T+2|T}$, for example, we have two options: we can use the one-step-ahead forecast of g_t, $\hat{g}_{T+1|T}$, along with estimated parameters of the equation we are using for forecasting, or we can use the actual realization g_T.

Assuming we have only one lag of the dependent variable along with other explanatory variables in the forecast equation:

$$\hat{g}_t = \hat{\beta}x_t = \hat{\beta}_z z_t + \hat{\beta}_g g_{t-1}$$

the one-step-ahead forecast will be easily defined as:

$$\hat{g}_{T+1|T} = \hat{\beta}x_{T+1} = \hat{\beta}_z z_{T+1} + \hat{\beta}_g g_T.$$

Since g_T is already observed and there is no need to forecast it at time T.

The two-step-ahead forecast of g_t may be obtained in two ways. The first is to use the formula:

$$\hat{g}_{T+2|T} = \hat{\beta}x_{T+2} = \hat{\beta}_z z_{T+2} + \hat{\beta}_g g_{T+1}$$

where we use the actual value of the forecast variable realized at time T+1. We have another option where we use the forecasted value of the forecast variable computed at time T for time T+1, $\hat{g}_{T+1|T}$, instead of the actual realization of the forecast variable:

$$\hat{g}_{T+2|T} = \hat{\beta}x_{T+2} = \hat{\beta}_z z_{T+2} + \hat{\beta}_g \hat{g}_{T+1|T}.$$

The same two strategies are available to use for any forecast horizon beyond one-step. The first type of forecast is called **static forecast**, and the second is called **dynamic forecast** (Gujarati, 2004, p. 486).

For most cases it is natural that static forecasts will yield smaller forecast errors for they do not bring any additional source of forecast error to the table. On the other hand, dynamic forecasts have an additional source of forecast error compared to one-step-ahead forecast that is carried over from the previous periods' forecasts (Johnston and Dinardo, 1997, p. 232). Including the predicted value of the lagged dependent variable simply means that each forecast error is compounded over the forecast period. Nevertheless, the dynamic forecasts often serve as a benchmark for the "worst case scenario" forecast in a dynamic model, i.e. a model including lagged dependent variables (Lin, 2000, pp. 341-2).

Static forecasts are referred to as one-step-ahead forecasts in applied work as explained in user manuals of many econometrics software packages. On the other hand, since they use the recursively computed forecasts of the lagged value of the dependent variable, the dynamic forecasts are true multi-step forecasts (RATS 5.0 User Guide, p.244; EViews 4.0 User Guide, pp. 355-356), as explained in most introductory econometrics books touching the topic (Gujarati, 2004, Wooldridge, 2002, Greene, 2003).

Another point regarding the forecast schemes is updating the estimations on which forecasts are based. When the forecaster updates his/her estimates to obtain forecasts for any horizon, we face a forecasting scheme called **rolling / sequential forecast**. A sequential forecast exercise is a projection into the future based on past performances, routinely updated on a regular schedule to incorporate data*. J.* Wooldridge gives an explanation of this sort of forecasting strategy in his Introductory Econometrics book (Wooldridge 2002, p. 597):

> A professional forecaster must usually produce a forecast for every time period. For example, at time T, she or he produces a forecast of g_{T+1}. Then, when g_{T+1} and z_{T+1} become available, he or she must forecast g_{T+2}. Even if the forecaster has settled on model $\hat{g}_t = \hat{\beta} x_t = \hat{\beta}_z z_t + \hat{\beta}_g g_{t-1}$, there are two choices for forecasting g_{T+2}. The first is to use $\hat{g}_{T+2|T} = \hat{\beta} x_{T+2} = \hat{\beta}_z z_{T+2} + \hat{\beta}_g g_{T+1}$, where the parameters are estimated using the first T observations. The second possibility is to reestimate the parameters using all T+1 observations and then to use the same formula to forecast g_{T+2}. To forecast in subsequent time periods, we can generally use the parameter estimates obtained from the initial T observations, or we can update the regression parameters each time we obtain a new data point. While the latter approach requires more computation and it can, although it need not, work better because the regression coefficients adjust at least somewhat to the new data points.

As for sequential forecasts there are two possibilities: using a recursive window of sample period and using a moving window (RATS 5.0 User Guide, pp. 251-2). In the **recursive scheme**, the forecasts are based on estimations of equations obtained from consecutive samples that are extended holding the starting period fixed. In the **moving windows** scheme, on the other hand, the forecasts are made using estimations of equations obtained from consecutive samples that are extended in a way that the starting period is also shifted forward whenever a new observation is added to the sample.

Another distinction is possible with sequential forecasts when we consider forecast horizons longer than one period. With recursive or moving windows forecasting scheme we may chose to use a static or a dynamic strategy. So there exist four possibilities: recursive static forecasting, moving window static forecasting, recursive dynamic forecasting, and moving window dynamic forecasting.

As for the one-step-ahead forecasting we do not face any different options regarding static and dynamic forecasting: both will yield the same results. On the other hand, we may choose to apply either the recursive or moving windows forecasting scheme. Moreover, as explained, static forecasts beyond first step is a legitimate replacement for sequential forecasting schemes[24]. All these different options stay in front of the empirical researcher with their pros and cons.

The problem at hand may have an influence in choosing among different options. For instance, if one is specifically interested in the stability of the coefficients in the forecasting relation, using the sequential forecasting schemes will be imperative (as in Stock and Watson, 2003). Otherwise, there is no guideline that forces the researcher to favor a certain forecasting strategy. Especially when the objective is to compare the predictive contents of different explanatory variables with respect to a certain forecast variable, the forecasting strategy is just totally irrelevant. It does off course not mean that all different strategies will yield the same results concerning the comparison of explanatory variables.

4.1.2. The Strategy Adopted in the Dissertation to Compare Out-Of-Sample Forecasts

In this study I used four different forecasting strategies. I employed static, dynamic, 1-step-ahead recursive and 4- or 12-step-ahead recursive (depending on the frequency of data) forecasting schemes throughout all applications in the dissertation. To exemplify, in case of mostly employed sample range 1986-2006, the 1-step-ahead forecasts are obtained as follows: We start with estimating the model under interest using the subsample 1986:1-2003:4/12 and get the 1-step-ahead forecast for 2004:1. Then we do the estimation for 1986:1-2004:1 and get the 1-step-ahead forecast for

[24] Among many studies check some recent ones that use static and dynamic forecasting schemes in following journal articles: Moshiri et.al. (2000); Fader et. al. (2003).

2004:2 and so on… up to the last estimation using 1986:1-2006:3/11 and the 1-step-ahead forecast for 2006:4/12.

The 4/12-step-ahead forecasts start with estimating 1986:1-2003:1 and we compute the 4/12-step-ahead dynamic forecast for 2004:1. Then we do the estimation for 1986:1-2003:2 and get the 4/12-step-ahead forecast for 2004:2 and so on… until we consume all the observations up to 1986:1-2005:4/12.

Static forecasts are all based on a single estimation carried out using the subsample 1986:1-2003:4/12. The forecasts are computed for remaining 12/36 observations. For lagged dependent variables we use the realized values of the dependent variable. Similarly dynamic forecasts are also based on estimations using the subsample 1986:1-2003:4/12, yet in this case we use forecasted values of the lagged dependent variables instead of realized values.

This way, we obtain 12 (quarterly data) or 36 (monthly data) counts of forecasted values of the forecast variable (output or inflation).

4.1.3. Forecast Evaluation Criteria

There are different methods to assess the quality of forecasts. These methods involve computation of some measures of forecast evaluation criteria based on forecast errors. Wooldridge (2002, pp. 593-603), Greene (2003, pp. 111-113), Clements and Hendry (1998, pp. 52-58) are some the resources to find information about forecast evaluation criteria.

Here we simply give the definitions of the criteria we employed in our study. $\hat{g}_t$ being the forecasted value of g_t, the forecast evaluation criteria are formulated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(\hat{g}_t - g_t)^2}{n}}\ ;\ \mathrm{MAE} = \frac{\sum_{t=1}^{n}\left|\hat{g}_t - g_t\right|}{n}\ ;\ \mathrm{MAPE} = \frac{100\sum_{t=1}^{n}\left|\frac{\hat{g}_t - g_t}{g_t}\right|}{n}.$$

where ($\hat{g}_t$ - g_t) is the forecast errors and n is the number of forecasts under evaluation. RMSE stands for the root mean square forecast error, MAE for mean absolute forecast error, and MAPE for mean absolute percentage forecast error. The measures are pretty much safe explanatory. The overall performance of forecasting is evaluated using an aggregator function over individual forecast errors.

The smaller values of these measures indicate better forecasts. RMSE and MAE are unit-dependent measures. The both can be used to compare the success of forecasts of the same variable obtained from different models, yet they cannot be used to compare the forecast performance for different variables, or not for the same variable forecasted for different periods. On the other hand, MAPE is a unit-free measure that can be used to compare the success of forecasts on different variables and for different periods.

4.1.4. No-Change Benchmark for Forecast Evaluation

Another method used to compare forecast performances is to evaluate the forecast errors obtained for a variable to the forecast errors obtained from a benchmark forecasting method for the same variable (Danielsson, 2008). Although it is possible to use other methods as benchmark, it is a common exercise to treat the forecasts from naive (zero change) forecasting method. This is proposed by H. Theil. In this method, the last observed value of the forecast variable at time T, will serve as the forecast for time T+1.

In our applications that contain static forecasting and one-step-ahead recursive forecasting, the observation right before the observation for which we compute the forecast will be the no-change forecast. This is valid only for inflation and output growth forecasts. For GDP forecasts in levels we need to consider four-quarter-back values of the forecast variable. For dynamic forecasts, on the other hand, the last observation in the estimation sample will be the no change forecast. Here too we got to use the four-quarter-back values for GDP levels.

The forecast evaluation criteria and the graphs of no-change forecasts are given in the Appendix C at the end of the dissertation. The criteria values are also given in the last columns of all tables displaying the computed criteria for all variables in all applications.

4.1.5. Forecast Averaging

Forecast averaging is an additional exercise we carried out here. We checked if averaging over forecasts based on Divisia and simple sum aggregate models helps improve the forecast performance.

We also checked if averaging over different forecasting schemes brings any improvement in forecast performance. However, we have only a single occurrence of this kind of evidence, which happened to be in neural network model of real GDP growth where CPI-deflated real money growth is used as explanatory variable.

This section examines the possibility that combining the forecasts based on the individual indicators can improve their performance. The standard logic of combination forecasts is that, by pooling forecasts based on different data, the combined forecast uses more information and thus should be more efficient than any individual forecast. Empirical research on combination forecasts has established that simple combinations, such as the average or median of a panel of forecasts, frequently outperform the constituent individual forecasts. The theory of optimal linear combination forecasts suggests that combination forecasts should be weighted averages of the individual forecasts, where the optimal weights correspond to the population regression coefficients in a regression of the true future value on the various forecasts. One of the intriguing empirical findings in the literature on combination forecasts, however, is that theoretically "optimal" combination forecasts often do not perform as well as simple means or medians. (Stock and Watson 2003, p. 820).

4.2. Introduction to the VAR Analysis of Nonstationary and Stationary Data

The integration properties of all variables are examined in Chapter 3, Section 6. The level variables in logarithms are nonstationary, as are the annual growth rates, that is logarithmic year-on-year differences of price levels and nominal money, nominal GDP, and many other nominal variables. Similarly the levels of real GDP and real monetary aggregates are also nonstationary variables. On the other hand, the period growth rates, i.e. monthly and quarterly growth rates, of variables defined as logarithmic differences are stationary variables.

We can work on stationary variables in simple VAR context, and on nonstationary variables in error-correction type VAR models. This chapter covers the bivariate and multivariate VAR analyses of monetary aggregates, prices, GDP, and some relevant variables.

4.2.1. Analysis of Stationary Data in VAR Context

The bivariate models, whether in regular regression models or VAR systems, are of the type called "indicator models" (Longworth and Joseph Atta-Mensah, 2000).

$$g_t = \alpha + \sum_{i=1}^{k} \beta_i x_{t-i} + \sum_{j=1}^{k} \gamma_i g_{t-j}$$

Here, g is the goal variable, and x is the variable(s) we use to explain the goal variable. The lag length k shall be chosen according to some information criteria that are used to determine the optimal lag lengths.

We will obtain the estimation results in a simple VAR context so that we can evaluate the predictive power of money growth in forecasting the monthly inflation (CPI- and WPI-inflation) and real output growth. The money growth variables will be monthly growth rates of nominal Divisia and simple sum aggregates for predicting inflation. The quarterly growth rates of nominal and CPI-deflated real monetary aggregates and annual growth rates of WPI-deflated real monetary aggregates will be employed in predicting real output growth.

4.2.2. Analysis of Nonstationary Data in Error-Correction VAR Context

The VAR models including nonstationary variables require a pretty much different analysis from the analysis of stationary variables. First we check the existence of a long-run relationship between the nonstationary variables of interest using a system like

$$g_t = c + \sum_{i=1}^{k} \beta_i x_{t-i} + \sum_{j=1}^{k} \gamma_j g_{t-j}$$

where, g is the goal variable, and x is the money variable plus other variables in case we employ additional ones to explain the goal variable. The lag length k can be chosen according to some information criteria that are used to determine the optimal lag lengths, or we can try different lags up to a reasonable lag length. Although it necessitates too much computation, we took the second approach since the cointegration between variables may be sensitive to the number of lags (Hall, 1991) used in the equation. So we searched for all cointegrating relationships up to 12 lags for all pairs of variables, and even up to 24 lags in some instances.

As for the type of cointegrating relationship we have different options. The software we conduct part of our research (EViews) enables us to check for the existence of all five different types of cointegrating relationships using the Johansen cointegration test. However, considering the structure of our data, we discard the model with no intercept term in data series and the model with quadratic trends in data series. So, depending on the data series at hand we will consider three types of cointegration models to test for the existence of cointegration relationships between the variables we are working on. Below are these models[25]:

Model 2: The level data have no deterministic trends and the cointegrating equations have intercepts.

Model 3: The level data have linear trends but the cointegrating equations have only intercepts.

[25] Lutkepohl (2005, pp. 327-337) explains the features and differences in testing of these different models.

Model 4: The level data and the cointegrating equations have linear trends.

In this chapter, whenever we deal with the levels of the series, we check the existence of (unique) cointegrating relationships with a trend in data and intercept in cointegrating vector with or without trends, i.e. models 3 and 4. On the other hand, when we work with year-on-year growth rates of the series, as the trends in growth rates are not so obvious, we check the cointegrating relationships using models 2, 3 and 4.

As some studies indicate that different statistics have no better power than the other (Lutkepohl et. al., 2001), we have no preference on the trace statistics or the maximum eigenvalue statistics. Wherever there is conflicting evidence from the tests we happily go with one that accepts unique cointegration. If there is more than one cointegrating relationship according to both statistics, we choose to go with the cointegrating vector associated with highest eigenvalue as it is most associated with the stationary part of the model (Stephens, 2004). Numbers of cointegrating relations are given at 5% error margin throughout this chapter.

After finding out all possible cointegrating relationships between the goal variable and the explanatory variable(s), the second step is to estimate the error correction models using all the cointegrating vectors at all lags:

$$g_t = \alpha(g_{t-1} - \beta x_{t-1}) + \sum_{i=1}^{k} \lambda_i \Delta x_{t-i} + \sum_{j=1}^{k} \delta_j \Delta g_{t-j}$$

Scrutinizing all the estimations, we determine the viable options to consider as a possible model to do further analyses on. What we check is the coefficients α and β to be in line with our priors. First of all we want $\hat{\alpha}$ to be negative and statistically significant while we want $\hat{\beta}$ coefficient(s) to have the expected signs and sizes and also be statistically significant.

The second-stage analysis includes a comparison of out-of-sample forecasts of the goal variable at hand using different monetary measures. The estimated equations described in each application are used to produce out-of-sample forecasts of the goal variables and the results are evaluated using forecast evaluation criteria. The criteria include root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). We also compare the forecasts obtained from the estimated models to a benchmark forecast. The benchmark forecasts we employ consist of no-change forecasts. If there is a base model, i.e. money is used to extend an available model of inflation or output, we compare the forecasts with and without money to check if money brings any additional contribution to the forecast performance.

A Note: We also checked for the possible relationships between levels of nominal money and price indexes, levels of nominal money and nominal GDP, levels of real money and price indexes, levels of real money and nominal GDP. However, although cointegration relationships exist between those variables, we could not find any reasonable error-correction mechanisms. So, we dropped this line of variable matches off our research. That is nominal variable - real variable mixes are not considered as viable options to bring together in error-correction models.

4.3. Bivariate Error-Correction Analysis of Annual Inflation and Money Growth

The analysis of annual logarithmic differences of money and prices[26] starts with listing all possible models (inflation-money growth pairs). For monthly data we have two measures of price level: CPI and WPI, and five definitions (aggregation levels) of money for each of nominal simple sum and Divisia (aggregation methods) measures: M1, M2, M3A, M2Y, M3AY. All combinations make 20 bivariate models to investigate. The sample involves observations running from 1987:1 to 2006:12 as we lost the 12 observations in 1986 to compute the year-on-year growth rates on the variables.

The first step is to check for possible cointegrating relationships. For this purpose we check on all lags ranging from 1 to 12. Annual difference series have a

[26] The growth rates are expressed in percentages using the formula: $x_t = 100 [\ln(X_t) - \ln(X_{t-j})]$

trend; hence we use the model with trend in data but no trend in cointegration vector. On the other hand, since the trend is not so obvious and statistically only slightly significant we try the cointegrating relationship with no trend in data too. The analysis of model 4 has shown that the estimations generally do not yield reasonable results, and whenever we find acceptable results (just in a few cases), they are not too different from the results obtained from model 3. So we do not report model 4 results.

The second step is to estimate the cointegration vectors, that is the long-run relationship between money growth and inflation. Our expectation is to observe a close to one-to-one relationship between the two variables. However, as we neglect other factors affecting the relationship between money growth and inflation, such as real GDP growth and change in income velocity, we may tolerate a larger or smaller coefficient than unity but not substantially different.

The third step will be to estimate error-correction models to see if price level converges to its long-run level dictated by the quantity of money. So, we expect a negative and significant coefficient on error-correction term.

4.3.1. Cointegration between Variables and Estimation of Bivariate Error Correction Models of Annual Inflation and Money Growth

The norm is the existence of unique cointegrating relationships at most of the lags from 1 to 12 between the annual growth rates of both money measures and both annual inflation rates. The results are summarized in Tables 4.1 and 4.2.

We estimated bivariate error-correction models for all the existing cointegrating relationships shown in Tables 4.1 and 4.2. Table 4.3 displays the coefficients on money growth variables in long-run equations along with the coefficients on the error-correction terms in all equations for CPI-measured inflation, where we found them negative and significant. Table 4.4 provides the same information for WPI-measured inflation. The tables give information on two more things: the standard deviations of estimated coefficients on money growth variables are shown so that one can build confidence intervals. The t-statistics for the error-correction terms are also reported. Other estimations carried out according to Tables 4.1 and 4.2 but not reported in Tables 4.3 and 4.4 either do not yield a negative and significant coefficient on error-correction term or the long-run coefficient on money growth term is beyond reasoning (some negative, some too small, some too big).

The observations on CPI-inflation estimates are as follows: We could not find any significant error-correction specifications for SSM2 and SSM3A growth rates. Although the coefficients are negative, the t-values range from -0.3 to -0.5 only. Yet, we still keep them in our battery of forecasting models for the sake of maintaining the parallel between Divisia and simple sum counterpart monetary aggregates.

The viable long-run relationships are concentrating at lags 8, 9 and 10. At these lags, both second and third cointegration schemes work well for long-run estimates. The coefficients on money growth range from 0.952 to 1.68, and the error-correction coefficients lie in the interval of (-0.005, -0.062). Actually the very small error-correction coefficients belong to the SSM2 and SSM3A aggregates which have very low t-values. Other aggregates have error-correction coefficients larger than 0.02 in absolute value.

The observations on WPI-inflation estimates are as follows: We again have a concentration at lags 8, 9 and 10. However, this time we also have reasonable long-run relationships for M2Y and M3AY at lags 1 and 2 for both Divisia and simple sum aggregates. We could not find any significant error-correction specifications for SSM2 and SSM3A growth rates just as in case of CPI-inflation. Additionally, there is no cointegration relationship at lag 8 for SSM2Y and SSM3AY.

The viable long-run relationships are once again concentrating at lags 8, 9 and 10 with addition of M2Y and M3AY models at lags 1 and 2. At these lags, both second and third cointegration schemes work well for long-run estimates. The coefficients on money growth range from 0.839 to 1.52, and the error-correction coefficients lie in the interval of (-0.020, -.095). Small error-correction coefficients belong to the SSM2 and SSM3A aggregates which have very low t-values.

4.3.2. Out-Of-Sample Forecast Evaluation of the Bivariate Error Correction Models of Annual Inflation and Money Growth

All models that yield viable long-run estimates are reestimated using a shorter sample leaving last 36 observations for forecasting purposes. The forecasts are evaluated using forecast criteria and the results are displayed in Tables 4.5 and 4.6. We report the results from the model with best forecasts, that is the model with cointegration vector type 3 at 8 lags. Table 4.5 displays the forecast evaluations of CPI-inflation and Table 4.6 gives the evaluations for WPI-inflation forecasts. Since there is no cointegration relationship at lag 8 for SSM2Y and SSM3AY with WPI-inflation, we used CIV type 3 at lag 2 for both Divisia and simple sum aggregates.

The uppermost panel of the tables gives the 1-month-ahead recursive forecasts, while the second panel displays the forecast criteria for static forecasts. The third panel displays the 12-month-ahead recursive forecast results, and the lowermost panel shows criteria computed for dynamic forecasts. This format is used in all tables that give information on the forecast performances of models with different monetary aggregates throughout the application chapters. The two columns of each panel next to the last column give the forecast criteria for forecasts of Divisia and simple sum aggregates averaged over five levels of aggregation. The last column reports the criteria values for no-change forecasts.

Overall forecast performances are promising for all forecasting schemes. The results from static and 1-month-ahead sequential forecasting are very close as expected. The dynamic forecasts provide a worst case scenario. We observe a slight improvement in averaged forecasts in case of static forecasts of CPI-inflation, but no improvement in other cases. The forecasts obtained from models with money as explanatory variable are better than the no-change forecasts with the exception of 1-

month-ahead sequential forecasts of CPI-inflation. Overall CPI-inflation forecasts appear more successful than WPI-inflation forecasts.

The mean absolute percentage errors (MAPE) are in the range of 5.8-8.5% for CPI-inflation in static forecasts and 7.1-8.6% in 1-step-ahead forecasts. The 12-step-ahead forecasts have a larger and wider range of 8.0-12.1%. The MAPE for the dynamic forecasts lies in the range of 18.2-78.0%.

These figures for WPI inflation are in the range of 13.8-15.2% in static forecasts and 16.0-18.5% in 1-step-ahead forecasts. The 12-step-ahead forecasts of WPI-inflation have again a larger and wider range of 17.5-20.6%. The MAPE for the dynamic forecasts of WPI-inflation lies in the range of 39.8-137.0%.

These ranges of results refer to all forecasts made using different monetary aggregates given in Tables 4.5 and 4.6.

As predictor of CPI-inflation SSM2Y and SSM3AY aggregates step forward. They have best performance in static and dynamic forecasts, respectively. On the other side, SSM1 is the best predictor of CPI-inflation according to both sequential forecasts.

Figure 4.1 shows the graphs of best out-of-sample forecasts of annual inflation as measured by consumer prices index. The forecast evaluation criteria of the best aggregate are also reported above each graph. The first panel displays the one-month-ahead sequential forecasts along with the actual data, while the second panel depicts the static forecasts. The third panel shows the graph of 12-month-ahead forecasts, and the last one gives the graph of dynamic forecasts.

Static and sequential forecasts are very successful in tracking the actual CPI-inflation. They catch almost all ups and downs of inflation. The dynamic forecasts also follow the tendencies in inflation generally, though not so closely as static ones do as indicated by the forecast criteria values. Among all forecasting schemes static forecasts look like the most successful ones in tracking the changes in actual CPI-inflation as indicated by the criteria values.

As best predictors of WPI-inflation DM2Y and SSM2Y aggregates step forward in static and dynamic forecasts, respectively. The sequential forecasts, both 1-month-ahead and 12-month-ahead, favor DM2 as the best aggregate in forecasting WPI-inflation.

Figure 4.2 graphs the best out-of-sample forecasts of annual WPI-inflation similar to Figure 4.1. Static and sequential forecasts are quite successful in tracking the actual WPI-inflation. They are well in line with the fluctuations of actual inflation rates. The dynamic forecasts on the other hand resemble a trend line instead of tracking the movements of inflation rates.

4.4. Bivariate Error-Correction Analysis of Nominal GDP Growth and Money Growth

As the nominal GDP growth and annual nominal money growth rates of monetary aggregates are all I(1) we have the chance to examine the long-run relationship between nominal GDP growth and money growth. In this section we employ data in quarterly frequency. The sample period is 1987:1-2006:4.

What we expect is to find is a long-run relationship between money growth and nominal GDP growth. We look for unique cointegrating vectors between nominal GDP growth and money growth. We also seek an error correction mechanism to exist between the two growth rates.

The coefficient on money growth in cointegrating vector is expected to be significant and around 1 to cover inflation and real GDP growth. Depending on the change in the velocity of money, not too big deviations from unity can be evaluated acceptable. We also expect the error correction term in short-run relationship to be negative and significant.

To investigate the relative performances of Divisia and simple sum aggregates we checked for all possible cointegrating relationships up to 12 lags. Wherever we found a unique cointegrating vector according to either trace or maximum eigenvalue tests, we estimated an error correction model using that vector. We used models 2, 3, and 4 as viable cointegrating relationships.

4.4.1. Cointegration between the Variables and Estimation of Bivariate Error Correction Models of Nominal GDP Growth and Money Growth

We found that unique cointegrating relationships exist at many lags from 1 to 12 between the nominal GDP growth rate and annual growth rates both money measures. The results are summarized in Table 4.7.

We estimated bivariate error-correction models for all the existing cointegrating relationships shown in Table 4.7. Table 4.8 shows the coefficients on money growth variables in long-run equations and the coefficients on the error-correction terms in all equations, where we found them negative and significant. The table shows the standard deviations of estimated coefficients on money growth rates and the t-statistics for the error-correction terms. Other estimations not reported in Table 4.8 either do not yield a negative and significant coefficient on error-correction term or the long-run coefficient on money growth term is beyond reasoning.

The general observations on the long-run relationship between nominal GDP growth and money growth are as follows: We could not find any significant error-correction specifications beyond lag 3.

The viable long-run relationships are concentrating at lags 1 to 3. At these lags, all three cointegration schemes work well for long-run estimates. The coefficients on money growth range from 0.678 to 1.448, and the error-correction coefficients lie in the interval of (-0.140, -0.594).

4.4.2. Out-Of-Sample Forecast Evaluation of the Bivariate Error Correction Models of Nominal GDP Growth and Money Growth

All models that yield viable long-run estimates are reestimated using the subsample 1986:1-2003:4, and the remaining 12 observations are saved for forecasting purposes. The forecasts are evaluated using forecast criteria and the results are displayed in Table 4.9.

Among cointegration models, model 4 appears to be the appropriate model considering out-of-sample forecasts. Yet, models 2 and 4 also work well for some aggregates. As for the 1-quarter-ahead forecasts, simple sum aggregates yield better results with a few exceptions. Among levels of aggregation, M1 and M3A aggregates provide most information in predicting nominal GDP growth.

The static and dynamic forecast results for simple sum and Divisia aggregates are very close in M1 forecasts with a slight margin in favor of simple sum aggregation. Lower level aggregates (or aggregates without FX deposits) are better predictors of nominal GDP growth.

Sequential forecasts favor Divisia aggregates over simple sum counterparts. The best results are obtained with DM3A for both forecasting schemes. Sequential forecasts yield better results than static and dynamic schemes.

Static and 1-quarter-ahead sequential forecasts are not better than the no-change forecasts. On the other hand, dynamic and 4-quarter-ahead sequential forecasts give better results compared to no-change forecasts. Forecast averaging brings improvement in static and dynamic forecasting while there is no gain from averaging in sequential forecasts.

Figure 4.3 shows the graphs of best out-of-sample forecasts of growth rates of nominal GDP. Sequential forecasts are apparently better than static and dynamic forecasts in tracking the changes in nominal GDP growth, although they can not capture some fluctuations. Dynamic forecasts show a very bad performance in 2005, otherwise they look reasonable. In 2004 and 2005 all forecasts seem to overpredict the nominal GDP growth, while in 2006 the picture is just the reverse for first three quarters.

4.5. Bivariate Error-Correction Analysis of the Levels of Real GDP and Real Monetary Aggregates

In this section, we investigate the relationship between real GDP and real money. The levels of real GDP and real monetary aggregate series are all I(1) variables. Thus we have the chance to examine the long-run relationship between the levels of real GDP and real money.

We want to see if we can establish a long-run relationship between real money stock and real GDP. For this purpose, we check the existence of cointegrating vectors between real GDP and money. We also seek an error correction mechanism to exist between the two.

The coefficient on real money in cointegrating vector is expected to be significantly positive, yet we do not have a priory judgment about the size of it. We think that the existence of enough amounts of transactions media should facilitate higher volume of transactions and hence real GDP. Depending on the velocity of money, we hope to find a positive association and do not expect to find out that the changes in the velocity to reverse this relationship. We also look for a negative and significant error correction term in the short-run relationship between GDP and money.

This section will cover real money obtained by deflating the nominal money by both CPI and WPI. To investigate the relative performances of Divisia and simple sum aggregates we checked for all possible cointegrating relationships up to 12 lags. Wherever we found a unique cointegrating vector according to either trace or maximum eigenvalue tests, we estimated an error correction model using that vector. As both series have clear trends, we used models 3 and 4 as viable cointegrating relationships.

4.5.1. Cointegration between the Variables and Estimation of Bivariate Error Correction Models of the Levels of Real GDP and Real Monetary Aggregates

Based on Johansen testing procedure, we found out several cointegrating relationships to exist at different lags from 1 to 12 between the levels of real GDP and levels of different measures of real quantity of money. The results are summarized in Tables 4.10 and 4.11.

We estimated bivariate error-correction models for all existing cointegrating relationships shown in Tables 4.10 and 4.11. Tables 4.12 and 4.13 show the coefficients on real money variables in long-run equations and the coefficients on the error-correction terms in all equations, where we found them negative and significant. The tables show the standard deviations of estimated coefficients on money growth rates and the t-statistics for the error-correction terms. Other estimations not reported in Table 4.12 and 4.13 either do not yield a negative and significant coefficient on error-correction term or the long-run coefficient on real money term is negative.

The general observations on the long-run relationship between real GDP and real money are as follows: the viable error-correction specifications exist at shorter lag lengths. Both type 3 and 4 cointegration models give results worth to examine further. The coefficients on money range from 0.017 to 0.759, and the error-correction coefficients lie in the interval of (-0.056, -0.770).

4.5.2. Out-Of-Sample Forecast Evaluation of the Bivariate Error Correction Models of the Levels of Real GDP and Real Monetary Aggregates

All models listed in Table 4.12 and 4.13 are reestimated using the subsample 1986:1-2003:4, and the remaining 12 observations are used for forecasting the level of real GDP. The forecasts are evaluated using forecast criteria and the results are displayed in Table 4.14 for CPI-deflated real money and in Table 4.15 for WPI-deflated real money.

The uppermost panel of the tables gives the 1-quarter-ahead recursive forecasts, while the second panel displays the forecast criteria for static forecasts. The third panel displays the 4-quarter-ahead recursive forecast results, and the lowermost panel shows criteria computed for dynamic forecasts.

Among cointegration models, model 4 appears to be the appropriate model considering out-of-sample forecasts for both types of real aggregates. Model 3 also works well for some aggregates. The models whose forecasts are included in Tables 4.14 and 4.15 are printed in bold in Tables 4.12 and 4.13.

As for the models with CPI-deflated real money, both 1-quarter and multi-quarter-ahead forecasts given in Tables 4.14 and 4.15 reveal that cointegration type-3 model is does not have a shot compared to the results from type-4 cointegration except the DM3A model at lag 7. In forecasting real GDP, higher level Divisia aggregates, M3A, M2Y and M3AY are superior to their simple sum counterparts, and they provide the best forecasts among all alternatives. Similar results prevail in dynamic forecasts too. Sequential forecasts are well in line with static and dynamic forecasts in this respect. Considering all static and dynamic forecasts, DM3A model at lag 7 in cointegration type 3 is the overall most promising variable in predicting real GDP. On the other hand, SSM3A produces better forecasts in sequential forecasting scheme, both 1-step-ahead and 4-step-ahead. Overall, static forecasts of real GDP level with real DM3A deflated with CPI are apparently the best among all.

The forecast evaluation results from models with WPI-deflated real money are in Table 15. Cointegration type-4 models yield better results compared to type-3 models, whenever both are possible for an aggregate. In all forecasting schemes Divisia aggregates including FX deposits, i.e. DM2Y and DM3AY are superior to their simple sum counterparts, and they provide the best forecasts among all alternatives. Considering all forecasts, DM2Y model at lag 4 in cointegration type 4 is the overall most promising variable in predicting real GDP. SSM2 and SSM3A with the same structure make also a good predictor of real GDP.

Models of real GDP level including CPI-deflated real money as explanatory variable yield better results compared to models with WPI-deflated real money.

We see not improvement in averaged forecasts for any forecasting scheme. The forecasts obtained from models with money as explanatory variable are better than the no-change forecasts without exception, i.e. for all forecasting schemes the aggregate with best forecast criteria provide forecasts superior to the naïve forecasts.

Figures 4.4 and 4.5 show the graphs of best out-of-sample forecasts of real GDP level. The forecast evaluation criteria computed for the best aggregate are also reported above each graph. The first panel displays the one- quarter-ahead sequential forecasts along with the actual data, while the second panel depicts the static forecasts. The third panel shows the graph of 4-quarter-ahead forecasts, and the fourth panel gives the graph of dynamic forecasts.

All forecasts, independent of the deflation factor of money and independent of the forecasting scheme, look very successful in tracking the actual real GDP. They move well in line with the actual data without missing any fluctuation.

4.6. Multivariate Error-Correction Analysis of Annual CPI-Inflation and Money Growth

In this section we repeat the exercise in Section 4.3, but this time with additional variables to inflation and money. The additional variables are interest rates on treasury bills, year-on-year growth rates of at-pump gas prices and nominal exchange rate index. Considering that interests paid by debtor firms are part of their costs, the model can be thought as a markup model of inflation for gas prices can proxy the energy costs and exchange rate imported input prices. Why we do not prefer to use nominal wage growth has two reasons: wage data are in quarterly frequency (we can handle this problem), but more importantly wages do not work well in inflation models. Indeed wages constitutes of a really small portion of production costs in Turkey compared to industrialized countries. Here we use only CPI-measured inflation primarily to cut the analysis short, since the process is computationally too cumbersome.

The data consist of annual logarithmic differences of consumer prices index and other variables multiplied by 100. The variables are in monthly frequency. Money has 5 aggregation levels for each of nominal simple sum and Divisia measures: M1, M2, M3A, M2Y, M3AY.

We start the analysis by examining the relationship between cost variables and inflation. After determining the possible cointegrating relationships between them, we jump to searching the cointegrating vectors between inflation and other variables but including money growth this time. We pick only the cointegration relationships that exist both without and with money. We repeat this for all 10 money definitions. Then comes the estimation of error-correction models for all possible cases.

Here we started with checking for cointegrating relationships on all lags ranging from 1 to 24. We had to extend the lag length from 12 of bivariate analysis to 24 since we could not get any reasonable results before lag 12. We tried the cointegration models 2, 3, and 4 and decided to go with model 4 since others did not yield viable error-correction estimations.

The second step is to estimate the cointegration vectors, that is the long-run relationship between inflation, cost variables and money growth. Our expectation is to observe a positive relationship between inflation and all other variables. However, we do not have any prior expectation for the size of the coefficients. We also look for the significance and any sign changes of cost variables while we add money growth to the model.

The third step will be to estimate error-correction models to see if price level converges to its long-run level. So, we expect a negative and significant coefficient on error-correction term.

The last part of this exercise will cover as usual the out-of-sample forecasts of CPI-inflation without and with money. We check if money contributes to the forecasting power of the models in general. Again the primary purpose is to compare the forecast performances of simple sum and Divisia monetary aggregates.

4.6.1. Cointegration between the Variables and Estimation of Multivariate Error-Correction Models of CPI-Annual Inflation and Money Growth

The results of Johansen cointegration tests are summarized in Table 4.16. First we check for the cointegrating vectors using t-bill rates, inflation in CPI, gas prices and nominal exchange rate index. We seek for unique CIVs for models 2, 3, and 4 at lags 1 to 24. The first row of Table 4.21 lists all unique the CIVs among these variables. After estimating error-correction models for all those CIVs, we saw that only cointegration model 4, i.e. the model with trends in data and CIV, yields negative and significant coefficients on error correction term. Thus, we search for CIVs for model 4 in the remaining part of our multivariate analysis.

Adding money growth revealed that only lags 12 to 16 work in error-correction models. Luckily we have the same for all money measures, though in a few cases we had two cointegrating vectors, for which we go on with the CIV associated with largest eigenvalue.

The estimated multivariate error-correction models for all the existing cointegrating relationships are shown altogether in a big table, Table 4.17. The table displays only long-run coefficients and the error-correction term along with t-statistics on the coefficients.

The uppermost part gives the estimates for no-money model using lag lengths from 12 to 16. All coefficients on interest rate, gas prices inflation and exchange rate change are positive and significant. We have a positive intercept term that ranges from 20.9 to 27.4. The trend term is negative and in the range of (-0.085, -0.096). The error-correction terms lie in the small interval of (-0.188, -0.222), which supposes a half life to converge to the long-run equilibrium annual inflation of around two and a half months[27].

[27] Half life is computed using $\ln(\alpha)/\ln(0.5)$.

The lower parts of Table 4.17 display the error-correction estimates of the models involving money growth from simple sum M1 to Divisia M3AY. In all inflation equations we got positive coefficients on money growth. For M1 models with 12 and 13 lags the money growth coefficients are insignificant, and all the remaining models yielded significant estimates. Including money among variables turned the coefficients on gas prices inflation to negative in some instances and to insignificant in most of the cases. While the coefficients on treasury bill rate stay positive throughout with few exceptions, they turned insignificant in most equations with the addition of money growth. The coefficients on nominal exchange rate growth are intact in all models: they are positive and significant with somewhat higher coefficients. The trend and intercept terms preserve their signs and sizes in no-money models. The error-correction terms in money-inclusive models are in the range of -0.229 to -0.404. This indicates relatively shorter convergence time of inflation rates when money is taken into account.

4.6.2. Out-Of-Sample Forecast Evaluation of the Multivariate Error-Correction Models of CPI-Annual Inflation and Money Growth

All models that yield viable long-run estimates (cointegration model 4 with lags 12 to 16) are estimated one more time but using a shorter sample leaving last 36 observations for forecasting purposes as we did with the bivariate analysis. The forecasts are evaluated using forecast criteria and the results from models with 15 lags, which yield the best forecasts, are displayed in Table 4.18. The table gives evaluations of forecasts of annual CPI-inflation up to 36 months from all four forecasting schemes as in previous cases.

The base model, i.e. the model without money, yields a MAPE of 9.5% for annual CPI-inflation forecasts in static forecast scheme. Other forecasting schemes have higher criteria values for the base model. The static and dynamic forecasts yield forecasts better than the base model, while the sequential forecasts are outperformed by the base model. Static and 1-step-ahead sequential forecasting schemes do not outperform the no-change forecasts. On the other hand, 12-step-ahead sequential forecasts and dynamic forecasts are better than the naïve ones. Averaging improves dynamic forecasts but not the forecasts from other forecasting schemes. SSM3AY is the best predictor of annual CPI-inflation in this multivariable error-correction application for all forecasting schemes but dynamic forecasting, which favors DM3AY.

Figure 4.6 shows the graphs of best out-of-sample forecasts of annual CPI inflation obtained from the multivariate error-correction model of this section. Static and sequential forecasts look pretty much similar obtained from SSM3AY growth rates are very successful in tracking the actual CPI-inflation. They catch almost all ups and downs of inflation. Among the three, static forecasts are the ones closest to the actual CPI-inflation. The dynamic forecasts from DM3AY also follow the tendencies in inflation except for 2005.

A comparison of bivariate forecasts of annual CPI-inflation in Section 4.1 (summarized in Table 4.5) and multivariate forecasts of this section (summarized in Table 4.18) reveals that the bivariate model yields much better results than the multivariate model. The best aggregates in all forecasting schemes do not coincide in two models.

Bivariate forecasts are better for all forecasting schemes but dynamic ones in bivariate case at all levels of aggregation than multivariate ones. For dynamic forecasts we have mixed results. At some levels of aggregation multivariate forecasts are better, yet considering best forecasts only, bivariate model (with SSM3AY) dominates the multivariate model (DM3AY).

4.7. Computing Forecasts of Stationary Variables from Forecasts of Nonstationary Variables

As we get pretty nice forecast results with nonstationary data, we may think of the possibility that we can compute the growth rate forecasts from level forecasts, and monthly (or quarterly) rates from annual growth rate forecasts.

4.7.1. Forecasts of Real GDP Growth Computed from Levels Forecasts of Real GDP

Here we conduct an exercise, in which we compute the growth rates of real GDP from the level forecasts. We forecasted real GDP levels up to 12 quarters in Section 4.5. We can obtain growth rates from these values simply by taking the 4 quarter differences. This way we get growth rates for 8 quarters and compute the forecast criteria. The results are given in Table 4.19.

For the real GDP growth forecasts obtained from CPI-deflated real money, growth forecasts computed from forecasted level figures comparable to the forecasts from bivariate VAR forecasts of Section 4.8 both in all forecasting schemes. Also computed forecasts are better than forecasts obtained from ARMA models of Section 5.1.6 for some forecasting schemes.

The computed GDP growth forecasts are not better than the best alternatives from other methods, yet they are still in a reasonable range. So we can try this exercise in cases where we do not obtain satisfactory results from usual forecasting models as VAR, ARMA, regression methods etc.

4.7.2. Forecasts of Monthly Inflation Computed From Forecasts of Annual Inflation

We did a similar exercise with annual inflation forecasts as we did with real GDP level forecasts. We computed monthly inflation forecasts from annual ones and evaluated the results using forecast criteria. Since we forecast annual inflation up to 36 months, we can obtain monthly inflation from these figures for last 24 months of our sample. The results are given in Table 4.20.

For CPI-measured inflation, monthly forecasts computed from annual forecast figures are far better than the forecasts from stationary monthly bivariate VAR forecasts of previous section, both in static and dynamic forecasts. Also computed dynamic forecasts are substantially better than forecasts obtained from monthly

ARMA models of section 5.1.2. Static forecasts are on the other hand not better than ARMA forecasts.

As for the WPI-measured inflation, computed monthly static forecasts are not too different from the forecasts from stationary monthly bivariate VAR forecasts and ARMA forecasts, even slightly worse. On the other hand, computed dynamic forecasts are clearly superior to forecasts obtained from monthly stationary VAR and ARMA models.

4.8. Bivariate VAR Models of Stationary Data: Monthly Inflation and Money Growth

Here we build simple models of inflation with past money growth and own history of inflation as the only explanatory variables. Since all the variables are logarithmic differences, we are working with the growth rates of price indexes and monetary aggregates.

We have two measures of inflation measured either by consumer prices index (CPI) or by wholesale prices index (WPI). As for the money growth we have five alternative definitions, M1, M2, M3A, M2Y, and M3AY each measured either by simple sum or by Divisia aggregates. Money growth in inflation models refers to the growth rates nominal monetary aggregates. All bivariate models include dummies for outliers as exogenous variables. In this section we will use monthly data. Our focus will be only on the effects of money on inflation and not the other way.

4.8.1. Choosing the Appropriate Lag Lengths for the VAR Models with Monthly Inflation and Money Growth

We searched for the appropriate lag length using standard information criteria. These are likelihood ratio (LR) and final prediction error (FPE) tests, and Akaike (AIC), Schwarz (SC), and Hannan-Quinn (HQ) information criteria. We searched for optimal lag length allowing a maximum lag length of 23. Indeed this was the largest lag length allowed by our data. Including the exogenous variables prevented us from searching for a longer lag length due to multicollinearity. Table 4.21 shows the lag lengths chosen by each criterion at 5% level.

We tried to go with the same lag length for each couple of definition of money, i.e. for SSM1 and DM1 will show up with the same lag length in our VAR, and so on. As seen in the table, picking a lag length of 12 throughout all models looks appropriate. This pick is not supported by any of the criteria only in case of SSM3A used in the model with producer prices. Actually we did all the exercises with 14 lags in this case and observed that results do not change noticeably.

4.8.2. Out-Of-Sample Forecast Performance Evaluation of VAR Models with Monthly Inflation and Money Growth

Out-of-sample forecasts of inflation rates from the estimated VAR models are evaluated using forecast evaluation criteria. The systems are reestimated using the observations of the 1986:1-2003:12 period. The forecasts are produced for 2004:1-2006:12. The results are displayed in Tables 4.22 and 4.23. Table 4.22 displays the forecast evaluations for CPI-inflation and Table 4.23 shows the evaluations for WPI-inflation up to 36 months according to different forecasting schemes.

The first thing to say is that forecasts are very bad for both inflation measures regardless of the forecasting strategy employed. Yet, still we want to maintain our format in interpreting the results disregarding how bad they are.

In 1-period-ahead sequential forecasts of CPI-inflation Divisia aggregates have better performance for all levels of aggregation. DM3A is the best aggregate for 1-period-ahead forecasting of CPI-inflation.

In static forecasts of CPI-inflation simple sum aggregates have better performance for all levels of aggregation. Lowest level of aggregation, i.e. M1 generally yields better forecasts. Overall, SSM1 is the best aggregate for static forecasting of CPI-inflation followed by DM1.

In 12-month-ahead sequential forecasts of CPI-inflation Divisia aggregates have better performance for all levels of aggregation, but M1. The best results are obtained from SSM1 followed closely by DM1.

In dynamic forecasts of CPI-inflation Divisia aggregates have better performance for higher levels of aggregation and simple sum aggregates for lower levels. The best results are obtained from M1 aggregates. And SSM1 is better forecaster at this level of aggregation.

In 1-period-ahead sequential forecasts of WPI-inflation Divisia aggregates have better performance for all levels of aggregation, but M1. DM3AY is the best aggregate as 1-period-ahead forecaster of WPI-inflation.

As for the static forecasts of WPI-inflation Divisia aggregates have better performance for aggregation levels but M1 considering MAPE. Other evaluation criteria give mixed results in comparison of aggregation methods. An overall look shows that SSM1 growth rates are the best candidate for 1-period-ahead forecasting of WPI-inflation followed by DM1.

In 12-month-ahead sequential forecasts of WPI-inflation Divisia aggregates have better performance for all levels of aggregation, but M1, which yields the best 12-month-ahead forecasts of WPI-inflation.

As for the dynamic forecasts of WPI-inflation, Divisia aggregates have better performance for all aggregation levels but M1. The overall best results come from DM2Y followed by DM2.

Forecast averaging improves the forecast performance substantially in CPI-inflation forecasts in all forecasting schemes and both for simple sum and Divisia aggregates, but static forecasting. As for the WPI-inflation forecasts, averaging helps only in sequential forecasts but not in static and dynamic forecasts. In static and 1-month-ahead sequential forecasting schemes of CPI-inflation, the models with money growth perform better than no-change forecasts. Dynamic and 12-month-ahead sequential forecasts, on he other hand, are outperformed by naïve forecasts. In case of WPI-inflation, no-change forecasts are better in all cases.

Figure 4.7 shows the graphs of best out-of-sample forecasts of monthly inflation as measured by CPI obtained bivariate VAR systems of stationary data. Static and sequential forecasts track the actual CPI-inflation to some degree, yet the forecast error margin is too big with a MAPE of more than 200%. They catch most ups and downs in inflation. The dynamic forecasts generally fail to follow the tendencies in CPI-inflation, and the MAPE is an unacceptable 393% even with the best forecasts.

Figure 4.8 displays the graphs of best out-of-sample forecasts of monthly WPI-inflation similar to CPI-inflation of Figure 4.7. The Static and sequential forecasts track the actual WPI-inflation in some periods, and the forecast errors are too big with a MAPE of 245%. The dynamic forecasts generally fail to follow the fluctuations in WPI-inflation, and the MAPE is an unacceptable 451% even with the best forecasts.

4.8.3. A Remark on the Forecast Period

At this point we find it useful to make a remark regarding the forecasting period. The period we picked for producing the forecasts is indeed a very unlucky one. The inflation forecasts are overall not satisfactory having errors more than 100% in many applications, although we have a good in-sample fit for most models. This is indeed the contradiction we have for all the results in this study.

The economy has undergone big changes in terms of the conduct of economic policies during this period. Following a very long time of unsuccessful fiscal policies, we have witnessed a solid fiscal policy starting in 2003. This enabled the CBRT to follow its price-stability goal more aggressively. Another development has been massive inflows of foreign funds, of which a good portion being in terms of direct investment and revenues collected from the privatization of state enterprises. This capital inflow has put enough pressure on FX market to keep the Turkish Lira appreciate during almost entire forecasting period.

Having a long-time experience of galloping inflation, economic agents, both consumers and producers developed adaptations to the ongoing process. However, the fundamentals that had been driving the process changed drastically after 2003, and people have not been still adjusted to the current situation and have their doubts that this improvement might be broken at some point. Unfortunately we do not have enough number of observations at the moment to analyze the period after 2003, so we have to draw our results based on the sample covering a mix of different economic structures.

Table 4.24 displays the results from an exercise about the effect of changing the sample period. M3AY, the broadest definition of money yielded worst forecasts for WPI-measured inflation, a MAPE of around 300% for static forecasts and 450 to 550% for dynamic forecasts. We estimated and forecast WPI-inflation using a sample cut-off in 2002:12. The forecast criteria computed for 2000:1-2002:12 period is given in Table 4.24 along with the entire sample results that contain the forecast criteria computed from 2004:1-2006:12 forecasts. With the shortened sample, we got much improved results. For static forecasts the MAPE is around one fifth to one sixth of the full sample forecasts. The dynamic forecasts improve around a similar ratio.

4.9. Bivariate VAR Models of Real GDP Growth and Money Growth

Here we build simple models of real GDP growth with past money growth and own history of GDP growth as the only explanatory variables. Since all the variables are logarithmic differences, we are working with the growth rates of real GDP and monetary aggregates.

In this application we will use three different types of monetary aggregates. Real money measures are deflated using either CPI or WPI. We also make us of nominal money growth here, yet there is a trick that we use quarterly growth rates unlike the real money growth rates that are defined as year-on-year logarithmic differences. Although some unit root tests reveal that quarterly nominal money growth rate series are nonstationary, still we have some tests concluding just the reverse. So, we will exploit this contradiction in test results little bit here. As will be explained soon, the results with nominal money are no worse than those with real aggregates. In this application we tried another variation and used quarterly real money growth rates for CPI-deflated money and stuck with year-on-year growth rates with WPI-deflated money.

4.9.1. Choosing the Appropriate Lag Lengths

We searched for the appropriate lag length using standard information criteria allowing a maximum lag length of 17. The lag lengths chosen by each criterion at 5% level are given Table 4.25. We want to use the same lag length for each couple of money definitions. This works for all aggregates by picking the lag length 5 but DM3A and DM3AY which require 8 lags.

4.9.2. Out-Of-Sample Forecast Performance Evaluation of Real GDP Growth-Money Growth VAR Systems

Out-of-sample forecasts of real GDP growth rates from the estimated VAR models are evaluated using forecast evaluation criteria. The systems are reestimated using the observations of the 1986:1-2003:4 period. The forecasts are produced for 2004:1-2006:4. The results are displayed in Tables 4.26 to 4.28. Table 4.26 displays the forecast evaluations of nominal money growth models, Table 4.27 shows the evaluations for models with CPI-deflated real money, and Table 4.27 for models with WPI-deflated real money up to 12 quarters.

The forecast performance of money growth at forecasting real GDP growth is in general much better compared to the VAR forecasts of inflation.

In all forecasting schemes, the forecasts of real GDP growth with quarterly nominal simple sum money growth have better performance for all levels of aggregation. Higher levels of aggregates with simple sum money generally yield better forecasts. Overall, SSM2Y is the best aggregate for all forecasting schemes. Interestingly, dynamic forecasting gives the best results among four forecasting strategies. SSM2Yis followed by SSM3AY in all cases.

In all forecasting schemes, but static forecasting, simple sum money growth produces better forecasts of real GDP growth with quarterly real money growth deflated by CPI. Higher levels of aggregates generally yield better forecasts. DM3A is the best aggregate in static forecasting. In other three schemes, SSM3A outperforms other aggregates. Once more, dynamic forecasting gives the best results among four forecasting schemes.

Annual growth rates of SSM2Y deflated using WPI are apparently the best forecaster of real GDP growth for all forecasting schemes. This time static forecasting gives the best results among four forecasting schemes.

Forecast averaging does not bring any improvement in forecast quality in any of the alternatives. In static and 4-period-ahead sequential forecasting schemes, the models with money growth perform better than no-change forecasts. Dynamic and 1-period-ahead sequential forecasts, on he other hand, are outperformed by naïve forecasts.

Figures 4.9 to 4.11 display the graphs of best out-of-sample forecasts of real GDP growth rates obtained from the bivariate VAR systems with money growth.

Figure 4.9 shows the forecasts from the system with quarterly growth rates of nominal monetary aggregates. SSM2Y aggregate is the one with best forecasts in all forecasting schemes. Actually quarterly nominal growth rates yield better forecasts than real aggregates, yet it is not a sweep situation, forecasts are just slightly better in terms of MAPE, yet in terms of RMSE and MAE results are mixed. All forecasts generally track changes in GDP growth except a period around 2005. The dynamic forecasts look like a trend curve instead of following the fluctuations in GDP growth.

Figure 4.10 graphs the best out-of-sample forecasts of real GDP growth rates obtained from the bivariate VAR systems with quarterly growth rates of real monetary aggregates deflated using CPI. The characteristic of forecasts are very similar to that of nominal aggregates. However, CPI-deflated real money forecasts fail to capture more turns than the nominal money forecasts.

Figure 4.11 depicts the best out-of-sample forecasts of real GDP growth rates obtained from the bivariate VAR systems in annual growth rates of real monetary aggregates deflated using WPI. The forecasts do not look different from that of nominal aggregates. Apparently forecasts with WPI-deflated real money growth are more successful than CPI-deflated money in catching the fluctuations in real GDP growth.

CHAPTER 5

COMPARISON OF SIMPLE SUM AND DIVISIA MONETARY AGGREGATES IN SINGLE EQUATION MODELS

There are so many theories and models of inflation and output with their strengths and weaknesses, that it is almost impossible for an empirical researcher not to get lost his way searching the suitable model. Our method here is quite different: instead of seeking the best model that fits Turkish data in our sample, we employ some of these competing theories to test the performance of different monetary aggregates in explaining the Turkish inflation and output in last 20 years.

This chapter involves a comparative analysis of simple sum and Divisia monetary aggregates' performances in predicting inflation and output parallel to the analyses in Chapters 4 and 5. We will employ four different types of models. The first will be ARMA models extended with ARCH effects. The second type of model used in this chapter is the St. Louis equations. The third model type is the one based on a Phillips curve relationship extended with exchange rate effects. The fourth kind of model is a cost-push model of inflation.

In all applications we follow the same strategy: first we estimate the model without including any monetary aggregates and evaluate the model's in-sample fit and out-of-sample forecast performance. In the second stage we estimate the same model by adding monetary aggregates one each time and evaluate the in-sample fit and out-of-sample forecast performances once more. The third stage is the comparison of the results. The comparisons are based on the information and forecast evaluation criteria.

5.1. Money in ARMA-ARCH Models of Inflation and Output

To investigate the effect of money on prices, we examined the contribution of monetary growth as an extra explanatory variable additional to the best ARMA models for inflation rates and output growth. Since inflation rates are stationary when measured from period to period (that is monthly and quarterly rates of inflation) as the monetary growth rates are, we find it useful to test for the influence of money on prices in an ARMA modeling framework using those stationary series. Similarly the real GDP growth rates are stationary as well, so we can apply the same strategy here too.

To accomplish the task, we first determined the best ARMA models for all inflation rate measures and real GDP growth rate searching among all the ARMA models from ARMA(0,0) up to ARMA(4,4). While doing this, we included seasonal dummies (without a constant term) and some dummies to account for outlier observations occurred during crises periods where necessary. As inflation and output growth in Turkey had been very volatile in last some 40 years, after determining the best ARMA model using adjusted R-squared, Akaike and Schwarz information criteria, we checked for ARCH effects. If the hypothesis of the existence of ARCH effects cannot be rejected we looked for best ARCH and GARCH specifications for each goal variable, again using information criteria.

5.1.1. Monthly ARMA-ARCH Models of Inflation: In-Sample Fit Evaluation

For both monthly inflation rates, namely CPI-inflation and WPI-inflation we found ARCH effects. So, monthly series are modeled as ARMA-ARCH models. The information about the search for the best monthly ARMA-ARCH inflation models is provided in Table 5.1.

The best ARMA model for monthly WPI-inflation data is picked as ARMA(2,0) model. Though ARMA(1,2) looks better considering $\overline{R}^2$ and AIC, we went with ARMA(2,0) since the inspection of the correlogram was favoring ARMA(2,0) and the advantage of ARMA(1,2) was very marginal. Then we used ARMA(2,0) to check for ARCH effects and we determined the best model as ARCH-1 and GARCH-1. Controlling for variance effects brought an improvement over simple ARMA model in terms of AIC and SIC.

The same procedure is applied to CPI-inflation and we ended up with ARMA(2,2) and ARCH(1)-GARCH(1) model as the best model for monthly series.

After establishing the best ARMA-ARCH models, to examine the effect of money we added money growth to these models to check if money brings any significant additional information to predict inflation rates. For monthly data, we added monetary growth rates up to 12 lags including the contemporaneous growth rate across all models.

The in-sample-fit performances of all monetary growth rates for monthly data are provided in Table 5.2. For WPI-inflation SS aggregates yield better in-sample fit except for M1. For the case of CPI-inflation we have just the reverse: Divisia aggregates give better in-sample fit for all the levels of aggregation but M2Y aggregates.

We also evaluated the in-sample contribution of money growth using F-tests for exclusion of money variables from the ARMA-ARCH equations. Results are given in Table 5.3. As for the WPI-inflation, Divisia aggregates have higher F-values for three cases and SS aggregates have higher values for two cases. The situation is the same for CPI-inflation, though or different aggregation levels.

To conclude, we can say that considering the in-sample-fit performance of the models in ARMA-ARCH models of inflation neither aggregation method has a clear-cut superiority to the other.

5.1.2. Monthly ARMA-ARCH Models of Inflation: Out-of-Sample Forecast Performance Evaluation

The estimated equations described above are used to produce out-of-sample forecasts of inflation rates and the results are evaluated using forecast evaluation criteria. The criteria include root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).

For out-of-sample forecast evaluation we reestimated all equations using the sub-sample of 1986:1-2003:12. The forecasts are obtained for the remaining 36 observations in the period of 2004:1-2006:12. We produced and evaluated the forecasts using four different forecasting schemes.

Table 5.4 displays the forecast evaluations for CPI-inflation and Table 5.5 shows the evaluations for WPI-inflation. The uppermost panel of the tables gives the 1-month-ahead recursive forecasts, while the second panel displays the forecast criteria for static forecasts. The third panel shows the 12-month-ahead recursive forecast results, and the lowermost panel dynamic forecasts. The two columns of each panel next to the last column give the forecast criteria for forecasts of Divisia and simple sum aggregates averaged over five levels of aggregation. The last column reports the criteria values for no-change forecasts.

As for the forecasts of CPI-inflation SS aggregates have better performance for most aggregation levels. SS aggregates also yielded better results compared to the base model, i.e. equations without money at all. For Divisia aggregates the case is the same and they also yield generally better forecasts of CPI-inflation than the base equation. An overall look shows that SSM2Y and SSM3AY growth rates are the best candidates for forecasting CPI-inflation. However, all forecast errors are pretty big and well above 100% as measured by MAPE.

We observe no gain from forecast averaging in any CPI-inflation forecasting scheme. The forecasts with money outperform the naïve forecasts in all cases but the 12-month-ahead sequential forecasts.

The forecasts of WPI-inflation yielded somewhat worse results than the CPI-inflation forecasts except 1-month-ahead sequential forecasts[28]. SSM1 has best performance in all forecasting schemes except dynamic forecasts, for which DM3A is the best alternative. All forecasts from models including money outperform the base model forecasts. We get no improvement from forecast averaging in any WPI-inflation forecasting scheme. The forecasts with money outperform the no-change forecasts in all schemes but the 12-month-ahead sequential forecasts as is the case with CPI-inflation.

Figure 5.1 shows the graphs of best out-of-sample forecasts of monthly CPI-inflation obtained from ARMA-ARCH models with SSM2Y and SSM3AY. The forecast evaluation criteria of the best aggregate are also reported in each forecasting scheme. The first panel displays the one-month-ahead sequential forecasts along with the actual data, while the second panel depicts the static forecasts. The third panel shows the graph of 12-month-ahead forecasts, and the last one gives the graph of dynamic forecasts.

Although the forecast criteria statistics are not so good, the graphs of forecasts do not look bad at all. All forecasts from four forecasting schemes, and especially static and dynamic forecasts seem to capture almost all ups and downs in CPI-inflation. However, they do it from quite a big distance and for sequential forecasts the error margins are even bigger. This should be evaluated as an indication of a change in the behavior of the economy. As mentioned in Section 4.8.3, this problem could be handled by shortening the sample period, yet we do not follow this kind of treatment here.

[28] **A Remark:** data frequency matter, especially when it comes to forecasting price series. Since monthly or generally high frequency data have more fluctuations and the price-money relationship is one of long-run nature, it becomes more difficult to capture the relationship. Even quarterly data (Section 5.1.3 below) are not promising in our case. On the other hand, nonstationary data analysis based on year-on-year differences of monthly data brings significant improvement over analyses based on monthly and quarterly data. We computed monthly forecasts from annual forecasts and observed a good amount of improvement over stationary monthly VAR forecasts of Chapter 4 and monthly ARMA forecasts of this section (see Section 4.7.1).

Figure 5.2 shows the graphs of best out-of-sample forecasts of monthly WPI-inflation obtained from ARMA-ARCH models with SSM1 and DM3A. The larger values of forecast evaluation criteria are seen in the inability of forecasts in catching the turns in WPI-inflation. Even when forecasts move in line with actual values, the distance is farther than CPI-inflation forecasts.

5.1.3. Quarterly ARMA Models of Inflation: In-Sample Fit Evaluation

For the quarterly inflation rates we have two measures as measured by CPI and WPI. For quarterly ARMA models we found no ARCH effects. So, quarterly series are modeled as ARMA models without extending with ARCH terms. The best ARMA models picked according to information criteria are ARMA(1,2) for WPI-inflation, ARMA(2,1) for CPI-inflation. The search process is summarized in Table 5.6.

The effect of money on the information content of ARMA models in predicting quarterly inflation rates is investigated by adding monetary growth rates up to 5 lags including the contemporaneous growth rate.

The in-sample-fit performances of all monetary growth rates for monthly data are provided in Table 5.7. For quarterly WPI-inflation SS aggregates yield better in-sample fit except for M1, just like in case of monthly data. For the case of CPI-inflation we have reverse picture: Divisia aggregates give better in-sample fit for all the levels of aggregation including M2Y, which was in favor of SS aggregation in case of monthly data.

The F-tests for exclusion of money variables from the ARMA equations are given in Table 5.8. As for the WPI- and deflator-inflation, Divisia aggregates have higher F-values for two occurrences and SS aggregates have a higher value for three occurrences. The situation is the reverse for CPI-inflation.

To conclude, we can say that considering the in-sample-fit performance of the models, as in the case of monthly data, in ARMA models of quarterly inflation neither aggregation method is clearly superior to the other.

5.1.4. Quarterly ARMA Models of Inflation: Out-of-Sample Forecast Performance Evaluation

Out-of-sample forecasts of inflation rates from the estimated equations are evaluated using forecast evaluation criteria. The equations are reestimated using the observations 1986:1-2003:4. The forecasts are produced for years 2004 to 2006. The results are displayed in Table 5.9 and 5.10. Table 5.9 displays the forecast evaluations of quarterly CPI-inflation and Table 5.10 shows the evaluations of quarterly WPI-inflation.

As for the 1-quarter-ahead forecasts of CPI-inflation, Divisia aggregates have better performance than simple sum aggregates for all aggregation levels but those including FX deposits. The best aggregate in predicting CPI-inflation seem to be SSM3AY. In 4-quarter-ahead forecasting scheme, the best aggregate is SSM1 and there is a mixed view in comparison of aggregation methods. DM1 steps forward as the best forecaster of CPI-inflation in static and dynamic forecasting.

Forecast averaging does not improve the forecast quality in any of the forecasting schemes. All of the best picks outperform the base ARMA model of CPI-inflation. Yet, no forecasting scheme produces forecasts that outperform the naïve forecasts.

The WPI-inflation forecasts are very bad. Simple sum aggregates are superior in all forecasting schemes. As it is with CPI-inflation, forecasts of WPI-inflation are better than the base model, yet all are outperformed by no-change forecasts. Averaging does not help with improving the forecasts either.

Figure 5.3 displays the graphs of best out-of-sample forecasts of quarterly CPI-inflation obtained from ARMA models along with the forecast criteria. All forecasts display reasonable moves to track the actual CPI-inflation, though not too closely, and catch most of the ups and downs of inflation. The results from quarterly ARMA model do not have a notable difference from monthly ARMA models.

Figure 5.4 gives the best out-of-sample forecasts of quarterly WPI-inflation similar to Figure 5.3. WPI-inflation forecasts' tracking ability of the actual data is much worse than the CPI-inflation forecasts in all forecasting schemes, just as the forecast criteria already revealed. An interesting case is that static and 1-step-ahead forecasts look worse than the dynamic and 4-step-ahead ones with WPI-inflation in tracking the fluctuations of actual series.

5.1.5. ARMA Models of Real GDP Growth: In-Sample Fit Evaluation

Nominal GDP growth (measured annually, as 4-quarter log differences) is nonstationary. Hence we proceed with the ARMA model of the stationary real GDP growth series and use the growth rates of real money supplies as explanatory variables additional to ARMA terms. The data set is in quarterly frequency.

Real GDP growth series exhibits no seasonality nor has any outliers according to Tramo-Seats method, thus we do not use seasonal dummies or dummy variables for crises years for modeling real GDP growth as we did with the inflation models.

There is no ARCH effects in real output ARMA(2,1) model up to 5 lags. So we tend to proceed with ARMA(2,1) model of real GDP growth. However, we found serial correlation in ARMA(2,1) model. Unfortunately we cannot get rid of the serial correlation problem until we add up to AR(5) term without an MA(q) term. Or we need to use ARMA(4,3) model, which at the same time encompasses ARMA(2,1) model in terms of adjested R-squared and AIC. The other choice is using lagged real growth rates up to 5^{th} order. In this situation our choice is to employ ARMA(4,3) model to keep the similar structure we used when modeling inflation. So our final choice for the real GDP growth is ARMA(4,3) without an ARCH term. The search process is summarized in Table 5.11.

After choosing the ARMA structure we add growth rates of monetary aggregates to the model to see if it improves the model's in-sample-fit and out-of-sample forecast capability or not. For this purpose we add up to 5 lags of money including the contemporaneous term as we did in case of modeling the quarterly inflation. For the evaluation of in-sample-fit we estimate the models using the full sample observations. Table 5.12 shows the in-sample-fit comparisons of different models involving growth rates of real money.

When using real money deflated with consumer prices index (CPI), we observe that as for the in-sample fit success the Divisia aggregates outperform their simple sum counterparts for all definitions of money but M1. Best model looks like the one with real Divisia M3AY, which improves both adjusted R-squared and Akaike information criterion. However, the improvement is not so big that Schwarz information criterion still picks the ARMA model without any money variable.

When using real money deflated with wholesale prices index (WPI), we observe that as for the in-sample fit success the Divisia aggregates outperform their simple sum counterparts for M2, M3A, and M3AY definitions of money, while simple sum aggregates outperform Divisia counterparts for M and M2Y. Best model looks like again the one with real Divisia M3AY, which improves both adjusted R-squared and Akaike information criterion. However, the improvement is not so big that Schwarz information criterion still picks the ARMA model without any money variable.

The F-tests for exclusion of money variables from the ARMA equations of real GDP growth are given in Table 5.13. As for the CPI-deflated real money growth, Divisia aggregates have higher F-values for all levels but M1. For the WPI-deflated real money growth, Divisia aggregates have higher F-values for M2, M3A and M3AY, and simple sum aggregates have higher F-values for M1 and M2Y.

To summarize the results regarding in-sample-fit performance of money in ARMA models of real GDP growth, we can say that real Divisia aggregates have an edge over their simple sum counterparts in contributing to the explanation of changes in real GDP.

5.1.6. ARMA Models of Real GDP Growth: Out-of-Sample Forecast Performance Evaluation

Out-of-sample forecasts of real GDP growth rates from the estimated equations are evaluated using forecast evaluation criteria. The equations are reestimated using the observations 1986:1-2003:4. The forecasts are produced up to 2006:4. The results are in Table 5.14 and 5.15. Table 5.14 displays the forecast evaluations for CPI-deflated real money growth models and Table 5.15 shows the evaluations for WPI-deflated real money growth models.

The 1-period-ahead sequential forecasts of real GDP growth obtained from CPI-deflated real money yield better forecasts when using Divisia aggregates at higher levels of aggregation. The best aggregate to predict real GDP growth is DM3AY. The forecasts with DM3AY are superior to base model but outperformed by naïve forecasts. Forecast averaging seems to provide no help.

When using real money deflated with CPI to produce static forecasts of real GDP growth, we observe that as for the out-of-sample forecast performance the Divisia aggregates outperform their simple sum counterparts for only broadest definitions of money, that is for M3A and M3AY. Best models look like the ones with real Divisia M3A and M3AY, both of which improve root mean squared errors, mean absolute errors and mean absolute percentage errors compared to the case with no money at all. It is also worth noting that for SSM3A and SSM3AY aggregates have a contribution in predicting real GDP. For the cases where Divisia aggregates are outperformed by simple sum counterparts, the model without money has a better out-of-sample forecast performance.

The 4-period-ahead sequential forecasts of real GDP growth obtained from CPI-deflated real money produce better forecasts when using Divisia aggregates with TL denominated assets only. The best forecaster real GDP growth is DM1. The forecasts with DM1 are better than the base model forecasts but worse than the no-change forecasts. Forecast averaging brings no improvement.

For CPI-deflated money, we observe that as for dynamic out-of-sample forecast performance the Divisia aggregates outperform their simple sum counterparts for all definitions of money including M1 this time. Best models are the ones with Divisia M3A and M3AY, both providing better forecast than simple ARMA model of GDP growth. The only case for the Divisia aggregates where money does not improve out-of-sample forecast performance is the one with M1. On the other hand, simple sum aggregates improve out-of-sample forecasts only with M3A.

The 1-period-ahead sequential forecasts of real GDP growth using real money deflated with WPI yield better forecasts when using simple sum aggregates except M1. The best aggregate to predict real GDP growth is SSM2Y. The forecasts with SSM2Y are superior to base model and almost at the same success level with naïve forecasts. Forecast averaging seems to provide no improvement.

When using real money deflated with WPI to produce static forecasts of real GDP growth, we observe that as for the out-of-sample forecast performance the Divisia aggregates outperform their simple sum counterparts for all levels of aggregation of money, with the only exception of M2Y. Best models look like the one with real Divisia M3A and M3AY, both of which improve the forecasts of real GDP over no money case. Divisia M3AY does slightly better job than M3A. As for M1 and M2, the model without money has a better out-of-sample forecast performance.

The 4-period-ahead sequential forecasts of real GDP growth obtained from WPI-deflated real money give mixed results at different levels of aggregation. The best aggregate to forecast real GDP growth SSM3A. The forecasts with SSM3A are better than the base model forecasts but worse than the naïve forecasts. Forecast averaging improves the forecast performance.

We come up with better dynamic out-of-sample forecasts for the Divisia aggregates than their simple sum counterparts virtually for all definitions of money using real money deflated with WPI, with the only exception M2Y for which we cannot judge conclusively. Best models look like the one with real Divisia M3A and M3AY, both of which improve root mean squared errors, mean absolute errors and mean absolute percentage errors. Yet, Divisia M3A does better for all three criteria. As for M1, the model without money has a better out-of-sample forecast performance.

Figure 5.5 shows the graphs of best out-of-sample forecasts of real GDP growth rates for all forecasting schemes obtained from ARMA models with annual CPI-deflated real money growth rates. Static forecasts are generally successful in tracking the actual GDP growth, except some period late 2004 and early 2005. The 1-quarter-ahead sequential forecasts follow the actual data even better, yet they do not yield a better statistics than static forecasts. The dynamic forecasts on the other hand look petty much like a trend curve. It is noteworthy that dynamic forecasts yield better values of forecast criteria, not only for DM3AY but for most aggregates. This would be interpreted as a good sign of the relationship between money and real economic activity. The 4-quarter-ahead sequential forecasts are the worst among four forecasting schemes. Especially, failing to capture the turn in the second half of 2005 raises the statistics of these forecasts to very high figures.

Figure 5.6 includes the graphs of best out-of-sample forecasts of real GDP growth rates obtained from ARMA models with annual WPI-deflated real money growth rates. Forecasts using WPI-deflated money are very similar those of CPI-deflated money, where the dynamic forecasts are not as close to the actual GDP growth as they are with CPI-deflated money. The 4-quarter-ahead sequential forecasts with WPI-deflated money produce underpredictions, yet they have better statistics than CPI-deflated money forecasts.

5.2. Saint Louis Equations-Type Models of Real GDP Growth

Having real GDP growth rates as stationary variables enables us to estimate St. Louis-type equations. For this purpose we first build the best model including only the lags of real GDP growth. Searching over lags from 1 to 8 brings forward the equation with five lags. It has no serial correlation (LM test up to 5 lags, prob: 0.587843) or heteroskedasticity (White test w/o crossterms, prob: 0.391874) problem. There are no ARCH effects (LM test up to 5 lags, prob: 0.872176), but residuals are not normal (JB, prob: 0.011667). So, ignoring nonnormality we proceed with this equation.

As for the fiscal variable we picked the year-on-year growth rate of real government expenditures (deflated using WPI) on purchases of goods and services as we think hat they are more and directly related to the economic activity compared other types of government expenditures or deficit variables. The chosen fiscal variable is evaluated stationary by all common unit root tests. So the second stage is to pick the appropriate lag structure for the fiscal variable. Again we started the search down from 8 lags and picked 1 lag of government expenditures. The addition of real government expenditure growth improved both adjusted R-squared and AIC, but deteriorated SIC. It also has all the desired properties: no serial correlation, no variance problem, and this time normal residuals (JB, prob: 0.133337).

5.2.1 In-Sample Fit Evaluation of Saint Louis Equations-Type Models of Real GDP Growth

At this stage we add growth rates of real Divisia and simple sum money one each time[29]. As the other two variables we searched for the appropriate lag length for money starting with 8 and going down to 0. Throughout all money definitions we got 5 lags as the best fitting option with only two exceptions of 8 lags for real SSM3A deflated with WPI and of 6 lags for real DM3AY deflated with CPI.

For the evaluation of in-sample-fit we estimate the models using the full sample observations. Table 5.16 shows the information criteria for in-sample-fit comparisons of different models involving growth rates of real money.

[29] As found out in previous research in this dissertation nominal money does not have a say when dealing with real growth. Yet, we still tried nominal money growth rates and achieved the same results not reported here once again. To go around the nonstationarity problem we worked with quarterly growth rates of nominal variables instead of year-on-year growth rates, but we allowed for longer lag lengths this time.

Divisia aggregates outperform their simple sum counterparts considering the in-sample fit success for all definitions of money but M1 using real money deflated either with CPI or WPI. Best model looks like the one with real Divisia M3AY, which improves both $\overline{R}^2$ and AIC, followed by Divisia M3A which brings an improvement in SIC too.

The F-tests for exclusion of money variables from the St. Louis equations of real GDP growth are given in Table 5.17. The table actually displays the same information in Table 5.16 using a different style.

In summary, the results on in-sample-fit performance of real money growth in explaining the growth of real GDP reveal that real Divisia growth rates have an advantage over their simple sum counterparts.

5.2.2. Out-of-Sample Forecast Performance Evaluation of Saint Louis Equations-Type Models of Real GDP Growth

Out-of-sample forecasts of real GDP growth rates from the estimated St. Louis equations are evaluated using RMSE, MAE and MAPE criteria. The equations are estimated for the subsample 1986:1-2003:4. The forecasts are produced for 12 quarters up to 2006:4. The results are displayed in Tables 5.18 and 5.19 for different deflation factors.

The forecasts of real GDP growth obtained from models with real money deflated with CPI reveal that Divisia aggregates outperform their simple sum counterparts and the models without money for most levels of aggregation in out-of-sample forecast performance. DM3A is the favorite aggregate in static and 1-quarter-ahead sequential forecasting schemes. In 4-period-ahead sequential and dynamic forecasts DM3AY is the best aggregate, but DM3A follows very closely. We got no improvement from forecast averaging in any case. Naïve forecasts are only better than dynamic forecasts.

In models with real money deflated using WPI Divisia aggregates yield better forecasts for higher level aggregates. However, simple sum aggregates with better forecast performance are no better than the case without money at all. DM3A steps forward as the best forecaster of real GDP growth. In 4-period-ahead sequential forecasts DM3AY is the best aggregate with slightly better statistics than DM3A. We do not observe any improvement from forecast averaging in any case. No-change forecasts are only better than dynamic forecasts as they are in CPI-deflated money too.

To summarize the results of out-of-sample forecasts of real GDP growth, we can reliably say that real Divisia money growth rates have an edge over their simple sum counterparts. It is also clear that money has a role in explaining and predicting real economic activity in case we use Divisia aggregates.

Figure 5.7 and 5.8 display the graphs of best out-of-sample forecasts of real GDP growth rates obtained from St. Louis equation with annual real DM3A and DM3AY growth rates. 1-quarter-ahead sequential and static forecasts from both CPI- and WPI-deflated money are generally successful in catching the fluctuations in actual GDP growth, except some periods. The dynamic and 4-quarter-ahead sequential forecasts from CPI-deflated money look better than WPI-deflated money. Both missed the downturn in GDP growth in 2005:2 by overpredicting. Remaining sample includes underpredictions and forecasts with WPI-deflated money lie much lower than the forecasts with CPI-deflated money.

5.2.3. Dispersion-Dependency Diagnostic Test for Aggregation Error

Barnett and Serletis (1990) advocate a dispersion dependency test, based on the Divisia second moments (variances) for the failure of the principal assumptions of aggregation theory such as not meeting the weak separability assumption. They introduce quantity variances, price (user cost) variances, and the covariances between quantities and prices as possible second moments to use along with first moments (means) in empirical applications to capture any possible aggregation errors . Here we make use of Divisia quantity growth-rate variances to apply the dispersion dependency test in context of St. Louis equations as done by the authors.

The Divisia quantity growth-rate variance is calculated using the formula:

$$\text{Divisia quantity–growth rate variance: } K_t = \sum_{i=1}^{n} \overline{w}_{it} [\Delta \log(m_{it}^{nom}) - \Delta \log(DM_t^{nom})]^2 .$$

The test involves the addition of the Divisia quantity growth-rate variance to the St. Louis equation as introduced in this section

$$LDAGDP_t = \alpha_0 + \sum_{i=1}^{5} \beta_i LDAGDP_{t-i} + \sum_{j=0}^{1} \gamma_j LDAGOV_{t-j} + \sum_{k=0}^{5} \theta_k LDADM_{t-k} + \sum_{l=0}^{5} \delta_l K_{t-l} + \varepsilon_t$$

where all GDP, government expenditures and Divisia money are in real terms and log differenced. In this application the government expenditures and Divisia money are deflated using WPI.

The results of the estimates with Divisia quantity growth-rate variance are given in the Tables 5.20 to 5.22 along with the results from models without Divisia second moments.

As shown in Table 5.20, adding the Divisia quantity variances improved the adjusted R-squared values except for M3A. The broader aggregates witnessed a bigger margin of increase in adjusted R-squared values. On the other hand, the AIC and SIC values indicate no contribution from quantity variances except for M3AY for which we had the highest increase in adjusted R-squared and AIC shows an improvement too.

Table 5.21 shows the F-test for joint insignificance of Divisia aggregates. The hypothesis that the coefficients on real Divisia growth rates are jointly zero is rejected for all levels of aggregates (row 2), though with a relatively high probability with DM2, as it was the case with the equation without any variance term (row 1). Not reported here but the government expenditure terms are significant in all equations with or without Divisia variances. We can just say that the probabilities of rejection of the insignificance hypotheses are higher in equations without variance terms.

The third row of Table 5.21 reports the F-test results for joint insignificance of Divisia quantity variances only. The hypotheses cannot be rejected at any level of aggregation. On the other hand the last row shows that we are not able to reject the joint insignificance of Divisia means and variances at lower levels of aggregation, yet we strongly reject the insignificance at higher levels.

These results of significance tests hint that we have no serious aggregation error. However, the gain in adjusted R-squared in case of highest levels of Divisia looks not negligible.

Table 5.22 displays the out-of-sample forecast criteria with and without Divisia quantity variances. Except static forecasts from DM3A, we witness substantial gains in forecasts with Divisia variances in terms of both static and dynamic forecasts.

Considering the gains in adjusted R-squared and in out-of-sample forecast performance, we evaluate that using Divisia variances at the highest levels of aggregation would contribute to the analysis of the relationship between output and money[30].

5.3. Phillips Curve Model of Inflation

In this section we will be examining the price-setting equation one of the latest practical monetary policy model developed by IMF staff (Canales-Kriljenko et. al., 2006; Berg et. al., 2006a, 2006b). The model consists of four equations in its entirety. However, we will single out the inflation equation here and work on it. In this equation inflation depends on expected and lagged inflation (actually this is one of many possible formulations of inflation expectation), the output gap, and the exchange rate change.

[30] We tried similar tests with Phillips-curve model of inflation. However, we observed no improvement in overall results. We even had worse out-of-sample forecast results with higher level Divisia aggregates. The MAPE obtained from DM3AY forecasts rose to 91% from 64% for CPI-inflation and to 440% from 391% for WPI-inflation, although we got very minor improvements with DM1.

$$\pi_t = \alpha_1 \pi 4_{t+4} + (1-\alpha_1)\pi 4_{t-1} + \alpha_2 ygap_{t-1} + \alpha_3(z_t - z_{t-1}) + \varepsilon_t$$

This equation embodies the idea that the fundamental role of monetary policy is to provide a nominal anchor for inflation and that placing weights on other objectives such as output cannot be inconsistent with this fundamental role. The important restrictions are that the coefficients on expected and lagged inflation sum to one and that the coefficients on the level of the output gap and the forward-looking inflation term be greater than zero. These restrictions ensure that monetary policy must be committed to adjusting the policy interest rate sufficiently aggressively in response to a nominal variable to provide an anchor to the system.

A standard derivation starts with the assumption that firms adjust prices only at some given frequency. When firms do adjust prices, they optimally take into account expected inflation as well as the current markup of prices over marginal cost. With the output gap as a proxy for the markup (because high aggregate demand implies a large markup), this results in something like the above equation, but with α_1 = 1. A value less than 1 can be rationalized as resulting from the idea that there is a component of backward-looking expectations or some form of indexation. The parameter α_1 decreases with the importance of backward looking expectations, which in some papers has been related to the (lack of) credibility of the central bank. α_2 would also tend to be lower when adaptive expectations are more important, because the output gap works in part through its influence on expected future price changes.

The behavior of the economy depends critically on the value of α_1. If α_1 is equal to 1, inflation is equal to the sum of all future gaps. A small but persistent increase in interest rates will have a large and immediate effect on current inflation. In this "speedboat" economy, small recalibrations of the monetary-policy wheel, if perceived to be persistent, will cause large jumps in inflation through forward-looking inflation expectations effects. If α_1 is close to 0, on the other hand, current inflation is a function of all lagged values of the gaps, and only an accumulation of many periods of interest rate adjustments can move current inflation toward some desired path. In this "aircraft carrier" economy, the wheel must be turned well in advance of the date at which inflation will begin to change substantially. Where price-setting is flexible and the monetary authorities are fully credible, high values of α_1 might be reasonable, but for most countries, values of α_1 significantly below 0.50 seem to produce results that are usually considered to be more consistent with the data.

The value of α_z determines the effects of exchange rate changes on inflation. It should be expected to be larger in economies that are very open and in cases when there is a high proportion of imported goods (either final or intermediate goods) that are eventually consumed after processing and then distributed as final consumption goods. Higher pass-through is generally observed in countries where monetary policy credibility is low and where the value-added of the distribution sector is low. There is also significant evidence of pricing-to-market behavior in many economies, suggesting that α_z would be considerably smaller than the import weight in the CPI basket.

5.3.1. Phillips Curve Model of Inflation: Estimation and In-Sample Fit Evaluation

Since we have the GDP-related variables in quarterly frequency, in this application we will be using quarterly data. For the quarterly inflation rates we have two measures as measured by CPI and WPI. The exchange rate variable is the trade-weighted nominal exchange rate basket normalized at 1986:1=100. The output gap is obtained from the formula 100*ln(real GDP/potential GDP)[31], where potential GDP is computed using smoothing methods involving Kalman filters[32]. So all variables are in log differences multiplied by 100.

The application starts with the full-sample estimate of the model. To avoid seasonality problem, we start with 4 lags of inflation and go up searching the

[31] It's positive if the actual production exceeds the potential (that is if the employment exceeds the full employment level). So the coefficient is expected to be positive in inflation equations.
[32] I want to thank CBRT researcher Cagri Sarikaya for providing the potential output series, and Ferhat Arslaner of TIS for providing the weights for exchange rate basket.

appropriate lag length for inflation. We also rely on backward-looking expectations instead of kind of mixing the backward and forward expectations. Based on information criteria we come up with 5 lags of inflation, which means at the same time the expected inflation is assumed to be completely of backward-looking nature. There is also no need to use an intercept term, as the model with 5 lags of inflation is no worse than the model with an intercept.

The search of appropriate model goes on with adding other two variables, that is output gap and exchange rate change. We evaluate both models, one for each of the two inflation measures, using information criteria to get the models with desired features. What we got from our search is given below. As for the output gap one lag is good for all models, and for the nominal exchange rate change CPI- and WPI-inflation has only the contemporaneous variable.

The base model for CPI-based inflation with t-statistics in parentheses is:

$$\text{INF-CPI} = \sum_{i=1}^{5} \text{INF-CPI}_{t-i} + \text{NER} + \text{GAP(-1)}$$

	NER	GAP(-1)
coefficient	0.3165	0.0985
t-statistics	(9.0295)	(4.1508)

The equation yields an R-squared of 0.8170. All coefficients are positive and significant with exceptions at lags 3 and 5 of lagged CPI inflation. There is no serial correlation up to 5 lags (Serial Correlation LM Test, prob: 0.2408), unfortunately we cannot reject heteroskedasticity (White Heteroskedasticity Test, prob: without cross terms 0. 04396; with cross terms 0. 01497) but we just neglect it, or ARCH effects up to order 4 (prob: 0. 1315), and residuals look normal (Jarque-Berra test, prob: 0.9953).

The base model for WPI-based inflation with t-statistics in parentheses is:

$$\text{INF-WPI} = \sum_{i=1}^{5} \text{INF-WPI}_{t-i} + \text{NER} + \text{GAP(-1)}$$

	NER	GAP(-1)
coefficient	0.5133	0.0216
t-statistics	(12.7003)	(0.8188)

The equation yields an R-squared of 0.7939. All coefficients are positive and significant with exceptions at lags 2 and 5 of lagged WPI inflation, where the coefficient at lag 5 is negative too. There is no serial correlation up to 5 lags (Breusch-Godfrey Serial Correlation LM Test, prob: 0. 2172), no heteroskedasticity (White Heteroskedasticity Test, prob: without cross terms 0. 271670; with cross terms 0. 1946) but we just neglect it, or ARCH effects up to order 4 (prob: 0. 6194), and residuals look normal (Jarque-Berra test, prob: 0.7136).

A few points on the equations deserve some comments. In the CPI equation output gap coefficient is close to 0.1 and is significant. On the other hand in the WPI equation output gap coefficient is only 0.02 and is insignificant. This should be interpreted as a sign of difference behavior of retailers and producers / importers in price-setting. As the CPI includes services, inflation measured by changes in CPI is expected to be more sensitive to demand conditions in the economy. Checking the coefficient on nominal exchange rate change reveals a similar fact. The coefficient in WPI equation is pretty bigger than in CPI equation, 0.51 to 0.31. As WPI includes commodities only, and Turkey is a quite open economy, the exchange rate pass-through is much higher in inflation measured by WPI.

The changes in the coefficients after adding money growth variables also reveal some aspects of the pricing behavior. Adding the 10 different measures of money growth to CPI equations yields coefficient estimates on output gap ranging from 0.0721 to 0.113 with an average of 0.101, and all are significant. The coefficients on the nominal exchange rate change in CPI equations lie in the interval (0.268, 0.355) with an average of 0.292, again all significant. So both variables are pretty robust to adding money to the equation.

Adding the 10 different measures of money growth to WPI equations yields coefficient estimates on output gap ranging from -0.006 to 0.016 with an average of 0.008, and all are insignificant and turning to negative in two instances. The coefficients on the nominal exchange rate change in WPI equations lie in the interval

(0.483, 0.580) with an average of 0.507, again all significant. In the WPI-inflation equation, the output gap variable appears to be redundant, yet we keep it just to maintain the symmetric structure of the analysis throughout the section. The nominal exchange rate variable on the other hand looks robust to addition of money growth, both in size and significance.

The effect of money on the information content of the policy model in predicting quarterly inflation rates is investigated by adding monetary growth rates up to 2 lags along with the contemporaneous money.

The in-sample-fit performances of all monetary growth rates are provided in Table 5.23. For CPI-inflation Divisia aggregates yield better in-sample fit except for M1, For WPI-inflation we have better fits for Divisia aggregates for definitions without FX deposits for which SS aggregates outperform Divisia counterparts.

The F-tests for exclusion of money variables from the policy model equations are given in Table 5.24. This table presents similar information to previous table in a single statistics. As for the WPI-inflation, simple sum aggregates have higher F-values for money with FX deposits and all other comparisons favor Divisia aggregates.

In conclusion, money in general improves the in-sample-fit performance of the policy models regardless of the definition of inflation or money. Divisia aggregates outperform simple sum aggregates considering all results. But simple sum aggregates add information to the inflation model, when the inflation is measured producer prices index.

5.3.2. Phillips Curve Model of Inflation: Out-of-Sample Forecast Performance Evaluation

The equations are reestimated using the observations 1986:1-2003:4. The forecasts are produced for 2004:1-2006:4. The results are displayed in Table 5.25 and 5.26. Table 5.25 displays the CPI-inflation forecast evaluations and Table 5.26 shows the WPI-inflation forecast evaluations up to 12 quarters.

As for the CPI-inflation forecasts, once again SS aggregates perform much better than Divisia aggregates. Forecasts of CPI-inflation using money also bring an improvement over no-money models. Averaging the forecasts over different aggregation levels yields better forecasts in case of 1-step-ahead sequential and static forecasts, but not in other schemes. No-change forecasts are outperformed by forecasts with money, except the 4-step-ahead sequential forecasting scheme.

The first thing to emphasize is that WPI-inflation forecasts are very bad for all forecasting schemes. Still we should say that simple sum aggregates are less bad than Divisia counterparts. There is also no improvement in 1-step-ahead sequential forecasts when money is added. For other schemes, models with money produce better forecasts than the base models. Forecast averaging helps only in case of 1-step-ahead sequential forecasts. Forecasts with money are all better than the naïve forecasts.

Considering the unsatisfactory performance of both aggregation methods in out-of-sample forecasts, we are not able to make a conclusive comment on comparative success of Divisia and simple sum aggregates. However, we should express that the choice of inflation variable is highly affecting the results.

Figure 5.9 displays the graphs of best out-of-sample forecasts of quarterly CPI-inflation obtained from Phillips curve models with SSM3A and SSM2. All schemes yield forecasts that track the actual CPI-inflation and catch ups and downs of inflation within a reasonable margin of error. Most of the time, we have overpredictions with some exceptions in 2005. The dynamic forecast results are no worse than other forecasts which is the case we face in most of the applications.

Figure 5.10 gives the best out-of-sample forecasts of quarterly WPI-inflation from Phillips curve models with SSM3A and SSM3AY similar to Figure 5.9. Save a few odd cases, WPI-inflation forecasts' tracking ability of the actual data is not worse than the CPI-inflation forecasts. However, due to these odd forecasts and due to the fact that WPI-inflation figures are around zero in many periods, the computed forecast criteria imply too bad forecasts, which is misleading considering the whole picture.

5.4. Cost-Push Model of Inflation

One of the many competing models of inflation is the mark-up model; see, for example, Bowdler and Jansen (2004), and Atesoglu (1997). The mark-up model we use here assumes that in the long run, the domestic general price level is a mark-up over total unit costs, including labor costs, import prices, and energy prices. Following the model in Brouwer and Ericsson (1998) we build the model in following equation.

$$P=\mu.WAGE^{\alpha}.IMPPRICE^{\beta}.ENERGY^{\gamma}$$

Expressing the equation in natural logarithms we get

$$\ln(P) = \ln(\mu) + \alpha\ln(WAGE) + \beta\ln(IMPPRICE) + \gamma\ln(ENERGY)$$

Without going any deeper and trying to obtain a fancy model of inflation, we simply estimate this equation in difference form, i.e. we use growth rates. Also considering the highly inertial structure of inflation in Turkey, we also added lagged inflation as an extra variable. The empirical model also includes seasonal dummies.

We used only quarterly data in this section due to availability of wage data. The data set consists of consumer prices inflation, rate increase in hourly wage index in manufacturing industry, rate of increase in import prices index measured in Turkish Lira, and rate of increase in energy prices index.

First we checked for stationarity of our variables. All are found stationary, although some unit root tests yielded conflicting results, we confidently go on relying on the majority of tests supporting the stationarity hypothesis. The tests are given in Chapter 3.

Then we fit a suitable model of consumer prices inflation using the explanatory variables. Here was no need to use lags of independent variables and only one lag of dependent variable is found to be enough using model evaluation criteria.

We called this model as the base model, and added monetary aggregates one each time to this base model to test if they bring any improvement to the model's in-sample fit and out-of-sample forecast performance.

The base model for CPI-based inflation with t-statistics in parentheses is:

INF-CPI =	CONSTANT	INF-CPI(-1)	ENERGY	IMPPRICETL	WAGEMAN
coefficient	5.049	0.397	0.354	0.081	0.106
t-statistics	(7.288)	(7.495)	(6.875)	(1.964)	(3.014)

All coefficients are positive and significant with an R-squared of 0.87. There is no serial correlation (Breusch-Godfrey Serial Correlation LM Test, prob: 0.919520), no heteroskedasticity (White Heteroskedasticity Test, prob: without cross terms 0.125179; with cross terms 0.104058), or ARCH effects up to order 4 (prob: 0.667137), and residuals look normal (Jarque-Berra test, prob: 0.486798).

The base model for WPI-based inflation with t-statistics in parentheses is:

INF-WPI =	CONSTANT	INF-WPI (-1)	ENERGY	IMPPRICETL	WAGEMAN
coefficient	2.690	0.199	0.426	0.213	0.071
t-statistics	(3.715)	(4.267)	(7.951)	(4.943)	(2.024)

All coefficients are positive and significant and the R-squared is 0.89. There is no serial correlation (Breusch-Godfrey Serial Correlation LM Test, prob: 0.233345), no heteroskedasticity (White Heteroskedasticity Test, prob: without cross terms 0.413643; with cross terms 0.613866), or ARCH effects up to order 4 (prob: 0.574472), and residuals look normal (Jarque-Berra 0.848533).

A simple inquiry of the equations reveals some basic facts about inflation in Turkey. First of all the inertial component of inflation is more emphasized with CPI-inflation, i.e. we have a bigger coefficient on lagged inflation almost twice as big. Another striking thing is that input costs in WPI-inflation are more influential. Both energy costs and imported inputs have more weights in explaining WPI-inflation than in explaining CPI-inflation.

5.4.1. Cost-Push Model of Inflation: In-Sample Fit Evaluation

The effect of money on the information content of the cost-push model in predicting quarterly inflation rates is investigated by adding monetary growth rates up to 2 lags along with the contemporaneous money.

The in-sample-fit performances of all monetary growth rates are provided in Table 5.27. For CPI-inflation Divisia aggregates yield better in-sample fit for all levels of aggregation. For WPI-inflation we have better fits for Divisia aggregates for M2 and M3A money definitions while simple sum aggregates yield better in-sample fit for M1, M2Y and M3AY.

The F-tests for exclusion of money variables from the cost-push model equations are given in Table 5.28. This table presents similar information to previous table in a single statistics, though results are little bit different. The difference arises from the fact that we seek for parsimony in cost-push models. That's why we have different lags of money growth for some equations, which naturally resulted in some discrepancy between overall fit measures and F-tests on money variables only.

In summary, money improves the in-sample-fit performance of the cost-push models regardless of the definition of inflation or money without exception. Divisia aggregates outperform simple sum aggregates considering all results. But simple sum aggregates add more information to the cost-push inflation model, when the inflation is measured producer prices index, WPI.

5.4.2. Cost-Push Model of Inflation: Out-of-Sample Forecast Performance Evaluation

All 31 equations are estimated using the observations 1986:1-2003:4, and the forecasts are obtained for the remaining 12 observations up to 2006:4. The results are displayed in Table 5.29 for CPI-inflation and in Table 5.30 for WPI-inflation. The uppermost panel of the tables gives the 1-quarter-ahead recursive forecasts, while the second panel displays the forecast criteria for static forecasts. The third panel displays the 4-quarter-ahead recursive forecast results, and the lowermost panel shows criteria computed for dynamic forecasts.

First of all we can easily say that money improves the out-of-sample forecasts for all forecasting schemes. It is also observed that WPI-inflation forecasts are much worse than CPI-inflation forecasts as they were in Phillips curve models.

The 1-period-ahead sequential forecasts of CPI-inflation yield better forecasts when using Divisia aggregates at higher levels of aggregation. The best aggregate to predict CPI-inflation is DM2Y. The forecasts with DM2Y are superior to base model but outperformed by naïve forecasts. Forecast averaging does not provide any improvement.

Static forecasts of CPI-inflation are better for Divisia aggregates than their simple sum counterparts. Best forecasts come from DM1. However, the forecasts with DM1 are better than the base model forecasts, but outperformed by no-change forecasts. Forecast averaging improves the forecast performance for both Divisia and simple sum aggregates.

The 4-period-ahead sequential and dynamic forecasts of CPI-inflation favor simple sum aggregates, SSM2Y and SSM3AY, over Divisia aggregates. 4-period-ahead sequential and forecasts are very close in evaluation statistics to both base model and naïve forecasts. On the other hand, dynamic forecasts of CPI-inflation are better than the base model, but worse than the naïve forecasts. While averaging improves dynamic forecasts, we have no gain from averaging in 4-period-ahead sequential forecasting scheme.

As for the WPI-inflation forecasts, simple sum aggregates are favored in all schemes except the static forecasting case. Since base model forecasts are the worst among all, all forecast schemes include at least one better forecaster aggregate. No change forecasts are outperformed by models with money except for dynamic scheme. Averaging yields better forecast in all cases but 4-period-ahead sequential forecasts.

Figure 5.11 displays the graphs of best out-of-sample forecasts of quarterly CPI-inflation obtained from the cost-push model for all forecasting schemes. All forecasts track the actual CPI-inflation and catch ups and downs of inflation, though with an unreasonable margin of error. We observe overpredictions all of the time with some exceptions. Among the four schemes, 4-period-ahead sequential forecasting produces closest forecasts of CPI-inflation almost without any miss of fluctuations.

Figure 5.12 gives the best out-of-sample forecasts of quarterly WPI-inflation obtained from the cost-push model for all forecasting schemes. Although WPI-inflation forecasts' tracking ability of the actual data does not look awful when compared to the CPI-inflation forecasts, the computed forecast criteria imply too bad forecasts due to the fact that we had some very small rates of inflation in some quarters.

5.4.3. The Forecast Period One More Time: Money in Cost-Push Model of Inflation Using the Sample 1986-2002

We made a remark regarding the forecasting period in Section 4.8.3. Here, we want to demonstrate the problem with the sample period once more and more strikingly. The cost-push model of inflation examined in this section provides a good opportunity for exhibiting the effect of forecast sample choice.

The mean absolute percentage errors of static forecasts of CPI-inflation using the full sample of 1988:1-2006:4 lie in the interval (104, 134). The interval for dynamic forecasts is (126, 175). These figures for WPI-inflation are just embarrassing to speak on, ranging from 500 % to 900%.

Here we estimated the CPI- and WPI-inflation models using a sample spanning 1988-2002. The in-sample fit measures are given in Table 5.31 for CPI-inflation. Comparing these values to those of full sample measures (Table 5.27 upper panel) tells us that the full-sample results are slightly better in terms of adjusted R-squared throughout and in terms of AIC and SIC in most cases. The difference in adjusted R-squared is 6 to 9 percent.

Now we check the forecast results given in Tables 5.32 and 5.33, and compare them to full sample results given in Tables 5.29 and 5.30. We observe that the shortened sample yields MAPE values that are 61 to 75 % less than the full sample MAPE values for static forecasts of CPI-inflation. The percentage gains in terms of MAPE in dynamic forecasts are even higher: 71 to 79 %. Another observation is that the best predictors of CPI-inflation turned to be the Divisia aggregates for all four forecasting schemes.

We did the same exercise for WPI-inflation too and found that SSM2Y and SSM3AY are the best aggregates in helping us predict the future WPI-inflation according to different forecasting strategies. The MAPE values of best forecasts of WPI-inflation lie now in the range of 20-22%. These figures were 410 and 630% with the full sample forecasts.

The graphs of best out-of-sample forecasts of quarterly CPI- and WPI-inflation with shorter sample are given in Figures 5.13 and 5.14. All forecasts track the actual inflation very closely and catch ups and downs of inflation. We generally got overpredictions all of the time with some exceptions in late 2005.

CHAPTER 6[33]

MONEY IN THE ARTIFICIAL NEURAL NETWORK MODELS OF INFLATION AND OUTPUT

Artificial neural networks (ANN) were developed as highly simplified models of the brain. An ANN can approximate any continuous function (of random variables) to any degree of desired accuracy, that is the ANN can provide a completely flexible mapping that can approximate highly non-linear functions to any degree of desired accuracy by appropriately structuring the ANN. This ability to approximate any unknown mapping provides researchers with a powerful tool that may enable them better to understand the interrelationships of explanatory variables.

Any evaluation of the explanatory power of a candidate variable using standard econometric methodology will be constrained by the specific functional form of the model being estimated. In the case of the relationship between money and inflation, or between money and output, any particular specified functional relationship will be arbitrary, and any conclusion made will be subject to the arbitrary model specification.

Here we use the ANN to examine the issue of how the variables are measured and explore whether the ANN can be useful in determining an appropriate measure of a variable.

We explore the explanatory power of various measures of money by identifying a specific structure of the ANN that allows for testing the effectiveness of a variety of measures of money in forecasting output and inflation. The same methodology is used for all the estimates so that we are able to compare different measures of money. Since the ANN provides a great deal of flexibility of the functional form, the primary cause of any

[33] All the results in this dissertation are replicable, but the neural network stuff. For replication, we need to save the memory vectors. Sequential forecasting would require us to save each memory vector at every stage and hence a large space, and I do not think that it is worth allocating so much space for the sake of replicability.

improvement in forecast accuracy should be directly attributable to the explanatory variable.

6.1. Methodology[34]

To evaluate the degree to which limited data on money provides information for explaining output and inflation, two simple models were estimated. Throughout the following, it should be noted that a simple and constant design was chosen so that the information content of the monetary variables could be evaluated on an equal basis. It is clear that the forecast errors of each model would be reduced by the adoption of more complex ANN specifications, and by adding more explanatory variables (input nodes). However, since our purpose is just to compare the relative performances of different money measures, we do not go after best model(s).

The first model assumes that inflation or output is a function of the current and four lagged measures of money:

$$Y_t=f(M_t, M_{t-1}, M_{t-2}, M_{t-3}, M_{t-4})$$

The second model expands the first model to include one-period lag of dependent variable:

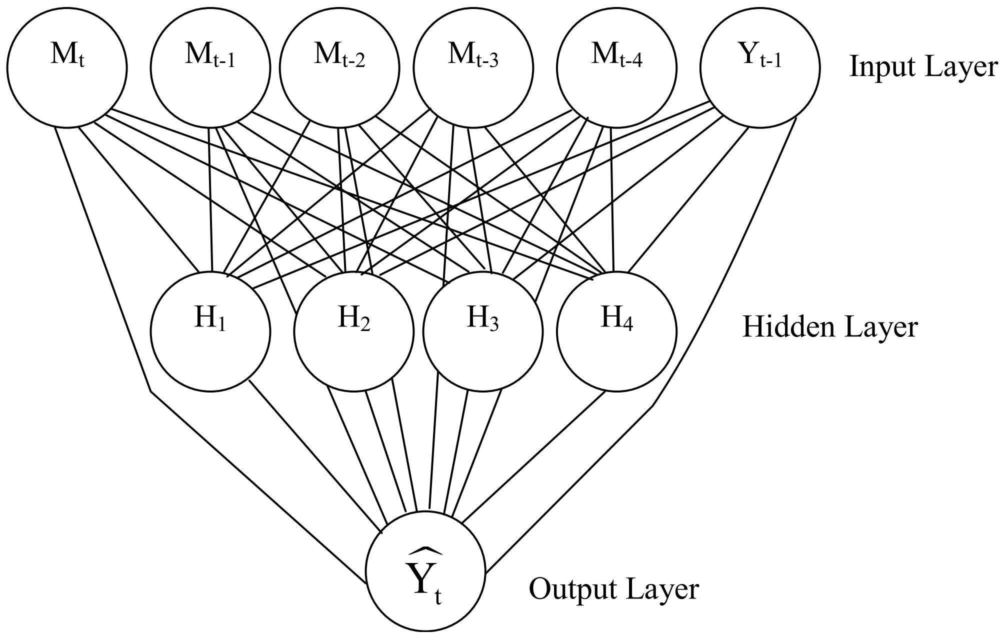
$$Y_t=f(M_t, M_{t-1}, M_{t-2}, M_{t-3}, M_{t-4}, Y_{t-1})$$

Both of these models used simple-sum and Divisia measures of M1, M2, M2Y, M3A and M3AY for Turkey. A fixed-structure ANN was used for all data sets. The ANN consists of either five (first model) or six (second model) input nodes, four hidden nodes and one output node, plus the direct connections from input nodes to the output node. Figure 6.1 shows a diagram of the structure of the neural network used with the second model which includes lagged dependent variable.

Each observation is an input to the ANN at the input layer. The values for the input variables are multiplied by weights corresponding to each of the connecting

[34] All the explanations in this section reliea on Dorsey (2000) and RATS 7 User Guide.

Figure 6.1: The Artificial Neural Network for Model with Lagged Dependent Variable



lines in the figure. Thus, the input to each of the hidden nodes is the weighted sum of the inputs including a bias weight, h_0:

$$w_i = h_{i0} + h_{i1}X_1 + h_{i2}X_2 + h_{i3}X_3 + h_{i4}X_4 + h_{i5}X_5 + h_{i6}X_6$$

The actual output of the hidden node is determined by applying a nonlinear function to the value weights, which scales the output to range between zero and one.

$$s_i = \frac{1}{(1+e^{w_i})}$$

Output nodes have a similar set of weights. For our model, we would have o_0, bias weight on output node, o_i: weight of output node for hidden node i, d_j: weight of output node on the connection with input node j. The output of this model would be:

$$O = o_0 + \sum_{i=1}^{4} o_i s_i + \sum_{j=1}^{6} d_j X_j$$

Fitting a neural network model involves "training" the model by supplying sets of known input and output values, and allowing the neural network algorithm to adjust the hidden node and output node weights until the output produced by the network matches the actual output in the training sample to the desired degree of accuracy. Once trained, the model can then be used to generate new output data from other sets of inputs (fitted values or forecasts). Assuming the fit is good, and that the relationships represented by the sample input and output data generalize to other samples, the model can produce good predictions.

However, care must be taken to avoid "overfitting" the model, This occurs when a network is trained to such close tolerances that it ends up modeling the "noise" in the training sample, not just the "signal." Such a network will generally do a poor job of predicting appropriate output values for other sets of inputs.

The parameters of the model, o_is and d_js, are selected to minimize the sum of squared errors (or another convergence criterion). The ANN works in the form of a genetic algorithm that is similar to natural selection. Each potential solution to the problem (a vector of o_is and d_js) is randomly selected from the parameter space. A population of these vectors (strings). Each vector of randomly-chosen values was used with the data to compute the sum of squared errors. A fitness value was then computed for each string.

A new generation is then selected, with replacement from the current generation. The probability of any string being selected for the new generation increases with its fitness. Once a new generation has been selected, the strings are randomly paired. A corresponding point along each pair of vectors is randomly selected and they are broken at that point and the residual fragments are swapped. This is referred to as the crossover operation. Finally, each component of each new vector has a small probability of being selected for mutation. Should a component be mutated, then that element is replaced with a new value randomly drawn from the parameter space. Each of the new strings is then used with the data to compute the sum of squared errors, and the process repeats. This process continues for a large number of generations until the solution converges to the desired criterion.

All ANN models in this chapter are fitted using the same procedure. We trained the models using 50,000 iterations and kept the convergence criteria tight enough by setting a very high R-squared value so that convergence does not occur before 50,000 iterations. We used 4 hidden nodes throughout. We also set the momentum parameter mu=0.2 so that we do not stick to a local optimum.

First we evaluated the in-sample fits of the models using the entire sample of 1986:1 to 2006:4. The in-sample fits are computed using Akaike information criterion (AIC) and adjusted R-squared. Since the models are much alike, the ranking of different in-sample measures of fit are the same for a specific model. Hence, we used only a single information criterion.

As for the out-of-sample forecast performance, we have the following strategy: First, we trained the ANN model this time with a truncated sample spanning 1986:1 to 2003:4, and left the remaining 12 quarters over 3 years for forecasting purposes. We applied the same parameters of training as in the case of full sample estimation. Then we added one observation in each successive forecast until we cover the entire sample.

In inflation applications we preferred to use the sample 1986:1-2002:4. The reason is that the full sample results turned to be unreasonable most of the time. So, the truncated sample spans 1986:1-2000:4 and the forecasts are produced for 2000:1-2002:4 in neural networks including inflation as the dependent variable.

To evaluate the out-of-sample forecasts, we employed 3 criteria, root mean squared error, mean absolute error, and mean absolute percentage error. Although the three criteria yield similar results most of the time, they do not coincide in picking the better forecasting model all the time; so we felt it right to report all three.

6.2. Neural Networks of Money-Output Growth Relationship

As for the relationship of money to economic activity, we investigate the relationship between monetary aggregates and GDP. For this purpose we estimated simple neural network models each involving a different combination of two series. All models contain a money stock variable including the current value and lags up to 4 as explanatory variables. All variables are in logarithms and growth rates are defined as four-quarter log differences multiplied by 100.

So, the models are in the form:

$$LDAGDP_t=f(LDAM_t, LDAM_{t-1}, LDAM_{t-2}, LDAM_{t-3}, LDAM_{t-4})$$
$$LDAGDP_t=f(LDAM_t, LDAM_{t-1}, LDAM_{t-2}, LDAM_{t-3}, LDAM_{t-4}, LDAGDP_{t-4})$$

In those model types the output variable is real GDP. Money is measured as real money deflated using either CPI or WPI. Both real GDP and real money stock are measured in annual logarithmic differences.

6.2.1. Neural Networks of Money-Output Growth Relationship without Lagged GDP Growth as Explanatory Variable

Tables 6.1 and 6.2 provide the comparisons of the aggregates in predicting the growth of real GDP in ANN models without lagged output growth. As for the in-sample fit simple sum aggregates have better performance for CPI-deflated M1 and M2, and WPI-deflated M1; all other aggregates favor Divisia growth rates regarding in-sample-fit success. Regarding the out-of-sample forecast performances, Divisia aggregates yield better forecasts including M1 and M2 aggregation levels without any exception. Among all aggregates, WPI-deflated DM3A and CPI-deflated DM2 make the best predictors of real GDP growth. The forecasts based on Divisia aggregates' growth rates are overall acceptable with MAPE ranging from 21% to 32% in static forecasts, and 20% to 52% in 1-quarter-ahead sequential forecasts.

Forecast averaging improves the forecast performance in static forecasts with CPI-deflated money, and the averaged forecasts have better statistics in 1-quarter-ahead sequential forecasts with WPI-deflated money. In all four cases, the best forecasters yield better values than the no-change forecasts.

Figures 6.2 and 6.3 display the best out-of-sample forecasts of real GDP growth obtained from neural networks without lagged output as explanatory variable. The first panels come from 1-quarter-ahead sequential forecasts and second panels come from static forecasts.

The models without lagged real GDP growth yield predictions of real GDP that look like trend curves. The static forecasts from WPI-deflated money appear to produce overpredictions in last two years, while 1-quarter-ahead sequential forecasts yield underpredictions systematically. Yet, still the forecast errors are comparable to other forecasts given in previous two chapters. The static forecasts from CPI-deflated money are similar to those of WPI-deflated money with less overpredictions. However, WPI-deflated money has better statistics due to better results in first and last forecast periods. The 1-quarter-ahead sequential forecasts from CPI-deflated money is apparently the best among all. Except the first few periods, they successfully follow the fluctuations in real GDP growth.

6.2.2. Neural Networks of Money-Output Growth Relationship with Lagged GDP Growth as Explanatory Variable

We evaluate the results from the neural nets including lagged GDP growth in Tables 6.3 and 6.4. The in-sample fit measures give mixed results with CPI-deflated SSM1 and SSM2, and WPI-deflated SSM1 having better fit. All other in-sample-fit measures at other aggregation levels favor Divisia aggregation over simple summation.

Static forecasts with lagged output growth once more are in favor of Divisia aggregates with a single exception in case of CPI-deflated SSM3A which yields a smaller MAPE, yet DM3A has smaller RMSE and MAE values. Regarding the dynamic forecasts we observe that Divisia aggregation again has an advantage in forecasting real GDP growth, but this time with three exceptions: CPI-deflated SSM2, WPI-deflated SSM2 and SSM2Y give better forecasts than their Divisia counterparts.

It is also worth mentioning that including lagged output does not improve the overall forecast performance. Indeed the MAPE from CPI-deflated money networks rose to 37-92% range for static forecasts, and to 29-175% for 1-quarter-ahead sequential forecasts. These values rose when using WPI-deflated money too.

Sequential forecasts with CPI-deflated money also favor Divisia aggregates over simple sum aggregates both in 1-quarter-ahead and 4-quarter-ahead. DM3AY is the best forecaster instead of DM2Y that we had in static and dynamic schemes, and sequential forecasts have smaller errors for some aggregates including DM3AY.

In case of WPI-deflated money as explanatory variable, Divisia aggregates at M3A aggregation level come forward as the best predictors of GDP growth, which were DM3AY aggregates for static and dynamic schemes.

Forecast averaging improves the forecast performance with CPI-deflated money except 1-quarter-ahead sequential forecasting. With WPI-deflated money we do not observe any improvement from forecast averaging. Naïve forecasts are better than the neural network forecasts in dynamic forecasting scheme of both CPI- and WPI-deflated money. Other forecasts from neural nets outperform no-change forecasts with the exception of 1-quarter-ahead sequential forecasting with WPI-deflated money.

Looking at the overall results reveals strikingly that Divisia aggregates are dominating simple sum aggregates in its most expressive way. Growth rates of real output is best forecasted by Divisia aggregates regardless of the price index deflator and in all forecasting schemes.

Figures 6.4 and 6.5 display the best out-of-sample forecasts of real GDP growth obtained from neural networks with lagged output as explanatory variable.

The first panels show the results from sequential forecasts and second panels show the results from static and dynamic forecasts.

The models with lagged real GDP make an attempt to track the fluctuations of real GDP growth. Unfortunately the results are not better than the models without lagged growth rates. Static and dynamic forecasts look similar in their forecast success, which is indeed not promising. Sequential forecasts look more successful than static and dynamic ones with CPI-deflated money, but not with WPI-deflated money. Although tracking ability with WPI-deflated money is better in last two year, the larger errors in 2004 make them have worse forecast statistics.

6.3. Neural Networks of Money-Inflation Relationship

To examine the information content of monetary aggregates in predicting price level we estimated simple neural network models each involving a different combination of money-price level pairs. The procedure is parallel to the case of GDP in previous section where GDP is replaced here by price level as measured by either CPI or WPI. We applied our methods to both monthly and quarterly data. However, the results with monthly data are far from reasoning, hence we do not report them and go with quarterly data only. All models contain a nominal money stock variable including the current value and lags up to 4 as explanatory variables. All variables are in logarithms and growth rates are defined as log differences multiplied by 100.

So, the models are in the form:

$$LDQPRICEINDEX_t=f(LDQM_t, LDQM_{t-1}, LDQM_{t-2}, LDQM_{t-3}, LDQM_{t-1})$$
$$LDQPRICEINDEX_t=f(LDQM_t, LDQM_{t-1}, LDQM_{t-2}, LDQM_{t-3}, LDQM_{t-4}, LDQPRICEINDEX_{t-1})$$

All ANN models are fit using the same procedure. We trained the models using 50000 iterations and kept the convergence criteria tight enough that they do not converge in 50000 iterations by setting a very high R-squared value. We used 4 hidden nodes throughout for quarterly data. We also set the momentum parameter mu=0.2 so that we do not stick to a local optimum.

We first tried estimating and forecasting the models using the entire sample of 1986:1 to 2006:4, where we did the estimations using the sample up to 2003:4 and forecasted for the remaining period of 2004:-2006:4. However, the results are not promising at all. As in previous exercises, this period we saved for forecasting is not a good pick, and with the NN method we got the worst of all results.

So, I decided to go with a shortened sample that is cut off in 2002:4. We did the estimations using data 1986:1-1999:4 and saved the last 12 observations for forecasting. Below are the results reported from this exercise.

6.3.1. Neural Networks of Money-Inflation Relationship without Lagged Inflation as Explanatory Variable

Tables 6.5 and 6.6 give a comparison of the performance of ANN estimates of quarterly CPI- and WPI-inflation based on both in-sample fit (adjusted R-squared) and out-of-sample forecast success criteria. When no lagged inflation is included as an explanatory variable, Divisia simple sum aggregates have a superior performance over simple sum aggregates in predicting both inflation series at most levels of aggregation both in-sample and out-of-sample. Simple sum aggregates have better out-of-sample forecasts for M2 in case of CPI-inflation, and for M1 in case of WPI-inflation. In general simple sum aggregates yield much higher forecast errors than their Divisia counterparts. Overall the best predictor of CPI-inflation is SSM3A in 1-step-ahead forecasts, and DM3A followed by DM2Y in static forecasts. The best predictor of WPI-inflation appears to be DM2Y in 1-step-ahead forecasts and DM3AY in static forecasts.

Forecast averaging improves the forecast performance only in forecasting WPI-inflation using static forecasting scheme, but not in other cases. Naïve forecasts are outperformed by the ANN forecasts in all cases except 1-quarter-ahead sequential forecasting of CPI-inflation.

Figures 6.6 and 6.7 picture the best out-of-sample forecasts of quarterly CPI- and WPI-inflation obtained from neural networks with no lagged inflation as explanatory variable. The first panels show the 1-quarter-ahead sequential forecasts and second panels the static forecasts.

1-quarter-ahead sequential forecasts of CPI-inflation follow the general trends in actual inflation, although missing the downturn in 2002:2. On the other side, they fail to capture the fluctuations in CPI-inflation most of the time. Static forecasts of CPI-inflation seem more successful in following the movements of actual series, except in 2001:2.

1-quarter-ahead sequential forecasts of WPI-inflation look better than CPI-inflation forecasts in following the general trends in actual inflation, although missing the upturn in 2001:2. The static forecasts of WPI-inflation are apparently very successful in following the movements of actual series, even in 2001:2, yet we get an excessive overprediction that makes the forecast statistics look worse than CPI-inflation forecasts.

6.3.2. Neural Networks of Money-Inflation Relationship with Lagged Inflation as Explanatory Variable

Tables 6.7 and 6.8 display the comparison of the performances of ANN models of quarterly CPI- and WPI-inflation based on both in-sample fit (adjusted R-squared) and out-of-sample forecast success criteria, where the models include lagged inflation as an explanatory variable. The inclusion of the lagged inflation does not change the results with respect to Divisia aggregates, but just the reverse for simple sum aggregates.

The out-of-sample forecasts of CPI-inflation give following results: DM3AY is the best aggregate to predict inflation in 1-quarter-ahead sequential and static forecasts. The 4-quarter-ahead sequential forecasts favor SSM3A, while the dynamic forecasts give best results with DM3A. Considering all forecasts, Divisia aggregates have better results compared to simple sum aggregates at high levels of aggregation. We see no improvement due to forecast averaging in any forecasting scheme. The naïve forecasts are outperformed by forecasts with money in all cases.

We can summarize the results on out-of-sample forecasts of WPI-inflation as follows: Divisia aggregates have at least one better forecaster in each forecasting scheme. DM3AY is the best aggregate to predict inflation in 1-quarter-ahead sequential and static forecasts. The 4-quarter-ahead sequential forecasts favor DM1 and the dynamic forecasts give best results with DM2. Considering all forecasts, Divisia aggregates have better results than simple sum aggregates in most comparisons of counterpart aggregates.

We get better results from averaging compared to individual forecasts in 1-quarter-ahead sequential and static forecasting schemes. There is no gain from averaging in 4-quarter-ahead sequential and dynamic forecasting. The no-change forecasts are not better than the forecasts with money in all forecasting schemes but 1-quarter-ahead sequential forecasts.

Figures 6.8 and 6.9 display the best out-of-sample forecasts of quarterly inflation obtained from neural networks with lagged inflation as explanatory variable. The first panels show the results from sequential forecasts and second panels show the results from static and dynamic forecasts.

Among all forecasting schemes, static forecasts are apparently the best in to tracking the actual CPI-inflation with overpredictions in most periods. The resulting error margin is still reasonable with a MAPE of 32%. In other three schemes, we observe that the forecasts fail to catch the upturn in 2001:2, and the general appearance is exhibiting overpredictions of CPI-inflation.

On the other hand, the WPI-inflation forecasts from 4-quarter-ahead sequential forecasting appear to be most successful one among all alternatives. Other forecasts are also able to follow the movements in actual data yet they miss the upward move in 2001:2 as in the case of CPI-inflation forecasts.

CHAPTER 7

CONCLUSION

In this last part of my dissertation, I will try to summarize the massive empirical stuff included in the applied part. Table 7.1 is the best I could attain in my effort to make an overall summary. The conclusions will be drawn based on this table and other observations we could not include in this table.

Totally we have 33 applications under consideration. Each using 4 different forecasting schemes (2 schemes only in half of the 8 neural network applications), we get 128 different cases to compare the Divisia and simple summation monetary aggregation methods. We made use of different deflation factors, i.e CPI or WPI, when using real money in models of real GDP. Combining the forecasts of real GDP (level or growth) with different deflation factors by picking the best options available in each forecasting scheme, we reduce the count of overall cases to 26. This number is obtained by discarding the inferior money variables used in forecasting real GDP. So, the following statements are based on a total of 98 cases. Table 7.1 displays the information on all comparisons.

Out of 98 cases, simple sum aggregation outperforms Divisia aggregation in 55 instances, while Divisia aggregation has better performance in 43 instances.

Out of 43 cases when the Divisia aggregates are the superior option, we have 4 times M1, 6 times M2, 12 times M3A, 9 times M2Y and 12 times M3AY. These figures are 15 times M1, 1 time M2, 11 times M3A, 17 times M2Y and 11 times M3AY for simple sum aggregates. Regardless of the aggregation method, 19 times M1, 7 times M2, 23 times M3A, 26 times M2Y and 23 times M3AY are the best alternatives. Considering all these figures, we can conclude that higher level aggregates are more useful in predicting output and prices. We can also say that money definitions including assets denominated in foreign currencies are also more useful: among 98 best picks, exactly half are M2Y and M3AY.

The best overall forecasts among all forecasting schemes are typed in bold face in Table 7.1. Considering only the best forecasters across the four forecasting schemes, out of 26 counts, simple sum aggregates are superior to Divisia aggregates 14 times, and Divisia aggregates perform better 12 times.

Considering only these best forecasters only, we have 1 time DM1, 4 times SSM1, 5 times DM3A, 2 times SSM3A, 2 times DM2Y, 5 times SSM2Y, 4 times DM3AY, and 3 times SSM3AY. Disregarding the aggregation method, we have 5 times M1, 7 times M3A, 7 times M2Y, and 7 times M3AY in total. Once more we are able to conclude that money definitions including assets denominated in foreign currencies are more useful as indicated in 14 counts out of 26.

In 69 cases out of 98, the forecasts obtained from models with money outperform the benchmark (naïve / no-change) forecasts.

In 49 cases out of 52, the forecasts obtained from models with money outperform the forecasts from base model (model without money).

When we consider only best forecasts for each application disregarding the forecasting scheme, we have 21 cases out of 26 where forecasts obtained from models with money outperform the benchmark (naïve / no-change) forecasts.

When we consider only best forecasts for each application disregarding the forecasting scheme, we have 13 cases out of 13 where forecasts obtained from models with money outperform the forecasts from base model (model without money).

The in-sample fit comparisons from Chapter 5 indicate that almost at each instance, money contributes to the success of the model positively.

These comparisons of forecasts using money to no-change forecasts and base model forecasts, we confidently conclude that money provides a good amount of information in predicting inflation and output, both in-sample and out-of-sample.

Considering inflation forecasts and output forecasts separately, we see that out of 19 cases where inflation is the forecast variable, simple sum aggregates perform better than Divisia aggregates 13 times. When output is the forecast variable, Divisia aggregates have the edge with a score of 6 to 1.

Interesting observations could be made if we look at the inflation forecasts from different perspectives. For example, 6 out of 19 cases are related to the forecasts using the sample period 1986-2002. In these applications, the best predictor of inflation happened to be Divisia aggregates in all cases but the Cost-Push model of Quarterly WPI-inflation, which is best forested using SSM2Y. Checking the figures closely for that application given in Table 5.33, we see that DM2Y in 4-quarter-ahead sequential forecasts did as good as the best SSM2Y figure that comes from static forecasting. So, this is a very close call, while in other cases Divisia aggregates are better, the margins between aggregates are quite clear.

From these observations, we conclude that Divisia aggregates have superior information content in predicting output. In forecasting inflation, we feel that we have to make a distinction between high- and low-inflation environments. In high-inflation state, money appears to be more and directly related to the determination prices, while in low-inflation environment the link between money and prices get looser and more indirect. In high-inflation periods, Divisia aggregates clearly provide better information than simple sum aggregates. In low-inflation periods, on the other hand, simple sum aggregates are better predictor of inflation.

Our results on different episodes of inflation justify Moroney's (2002) results that the validity of quantity theory of money holds for the high-inflation countries but not low-inflation countries.

To make better judgments on low-inflation-period relationship between money and prices, I think we have better wait for accumulation of enough number of observations for Turkey to repeat a similar battery of tests as done in this dissertation. Another alternative might be to conduct a similar broad research on a low-inflation country for which Divisia aggregates are produced such as USA or UK. Naturally the two alternatives will not be substitutes as the economies have quite different structures.

A Comparison across Models

Table 7.2 is produced to facilitate a comparison of forecast results across models.

For both monthly CPI- and WPI-inflation we have 2 models: VAR and ARMA. Annual inflation measures are computed from monthly price level indexes and forecasted using error-correction models. Bivariate ECM is used for both CPI- and WPI-inflation, and CPI-inflation is also forecasted using multivariate ECM. For quarterly inflation series we used ARMA, Phillips curve and cost-push inflation models in the sample period 1986:1-2006:4. To forecast inflation rates using the sample period 1986:1-2002:4, we employed cost-push inflation model and neural networks without and with lagged inflation as explanatory variables. The total count of models used in inflation forecasting amounts to 19, of which 13 are with 1986:1-2006:4 period and 6 are with 1986:1-2002:4 period.

Nominal GDP growth and real GDP level series are forecasted using bivariate ECMs. We made use of five different models to forecast real GDP growth: VAR, ARMA, St. Louis equation, and neural networks without and with lagged output growth as explanatory variables. All GDP models use the sample period 1986:1-2006:4.

Results from GDP Models

GDP forecasts produce generally acceptable forecast errors compared to inflation forecasts from full sample data. Forecasting GDP level, and then computing growth rate forecasts from the levels seem a viable option instead of directly forecasting GDP growth.

Unlike inflation models, VAR models yield better forecasts than ARMA models for GDP growth. Results from ARMA, VAR and St. Louis equations are comparable to each other in their performances. Neural networks, on the other hand, produced best forecasts for GDP growth, with quite better forecasts from models without lagged GDP than the models with lagged GDP.

GDP forecasts overall are better than inflation forecasts when we consider the entire sample period. However, the forecasts of inflation from the high-inflation era are as good as GDP forecasts.

Results from Inflation Models

Monthly Inflation

Data that cover longer time spans (i.e. annual) are better in explaining inflation compared to data covering shorter time spans (i.e. monthly and quarterly). This could be attributed to the long-run nature of the relationship between money and prices. While the forecast errors with monthly data amount to hundreds of percent, the annual inflation forecasts bear an error as measured by MAPE less than 10% in CPI-inflation, and less than 15% in WPI-inflation. Similarly, quarterly inflation forecasts are also better than monthly inflation forecasts for CPI-inflation. For the WPI-inflation we see not improvement in quarterly forecasts compared to monthly forecasts.

ARMA models yield better forecasts than VAR models for both monthly inflation measures. We got no improvement in forecasts by adding more variables to the ECM of CPI-inflation.

Quarterly Inflation

The models of inflation with different sample periods yielded substantially different results. The forecast errors in high-inflation sample are 60 to 75% lower than the errors in low-inflation sample for CPI-inflation. That figure is 95 to 97% for WPI-inflation. In the high-inflation period, even the worst single equation forecasting model yields better forecasts than the neural networks which give pretty nice results.

Especially for periods of relatively stable prices, money looses some of its informative content with regard inflation. Other factors should become relatively more influential in these times. However, we could not get better results from multivariate ECM of CPI-inflation, in which we used some cost variables. We might also try other variables but we did not go after it. It may be a further topic to investigate which factors gain more importance in inflationary process when the economy switches from a high inflation state to a low one.

Among models of quarterly inflation, the Phillips curve model yielded best forecasts compared to ARMA and cost-push models for the low-inflation era. Cost-push model gives better results than neural networks in high-inflation period. The fact that neural networks without lagged inflation yield better forecasts than the ones with lagged inflation may be implemented as a sign of the importance of money growth in determining the inflation rates.

General Observations

The method we applied in integrating the assets denominated in foreign currencies and the assets denominated in national currency in a single aggregate would make an acceptable and good attempt on how to handle the Divisia monetary aggregation problem in a dollarized economy.

When we try to explain economic activity as measured by real or nominal output, Divisia monetary aggregates have an edge over simple sum aggregates. As for the inflation, the results are mixed.

The results change drastically across different environments. Hence, whenever I read anything about the empirics of money, or empirical works in general, I take the results with a cautionary view. The data type, frequency, methods, models etc. everything has its effects on the results. As observed in our applications, even the deflator used to obtain real money from nominal matters in empirical studies. The best way around the problem seems to be taking any chance available and trying to exhaust all the possibilities. What I have tried in my dissertation was exactly this: to consume all the instruments time series analysis offers to us.

Measurement of money continues to be a problematic area in the conduct of monetary policy. The problems related to the measurement are not only in the subject of aggregation methods. The collection of monetary data itself continues to be a problem. To exemplify some cases, I mentioned some practices in the Turkish economy briefly in Chapter 2. The problems are still there and the same: we are far away from satisfactorily measuring many economic variables, both flows and stocks.

Suggestions for Further Research

The difference in the money-inflation relationship in periods of relatively stable prices and in periods of high inflation deserves some more research. The factors gaining more importance in price-setting behavior in low-inflation environment might be investigated more in depth. We could not get better results from multivariate ECM of CPI-inflation with cost variables. It is worth to try other variables

Final Words

Whatever my results are, whatever others' conclusions about money are does not change the plain truth: We cannot ignore the crucial relationships between money and other sectors of the economy. There is no way that money is something discreet, completely isolated from everything in the economy. Even in a barter economy, the available means of media of exchange, that is the amount of tradable goods and services are important in determining the functioning of and the relative prices in the economy.

Our recommendation is not setting monetary targets to achieve economic goals, but watching the quantity of money closely as it is by nature related to price level and economic activity. How hard it is to capture the exact nature of this relationship, the quantity of money deserves to be under scrutiny for any kind of economic policy. It is almost clear that money supply is endogenous to the freely and effectively functioning market economy unless forcefully dictated exogenously (Svensson, 2007). It does not mean that central banks or monetary authorities do not have any means of affecting the amount money in the economy in an economically reasonable manner. However, still we have the problem of how we define and measure money. At this point, the most favorable suggestion looks like watching a set of different monetary aggregates. The information variable concept introduced by John H. Kareken et. al. (1973) looks like a good argument for how to make use of our knowledge on the quantity of money as an additional source of information in conducting the economic policies.

The last word to conclude my dissertation is that aggregation using Divisia indexes is a great leap forward in measuring the amount of money in the economy more accurately. However, it does not solve the entire problem by itself alone. Attaining the weak separability condition looks like a hard nut to crack in empirical studies. The data collection practices also need to be improved.

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APPENDIXES

APPENDIX A

TABLE APPENDIXES TO CHAPTER 3

Table 3.1: Basic Statistics of Monthly Growth Rates of Monetary Aggregates

	DM1	SSM1	DM2	SSM2	DM2Y	SSM2Y	DM3A	SSM3A	DM3AY	SSM3AY
A. NOMINAL AGGREGATES										
Mean	3.89	3.88	3.76	4.00	3.78	4.12	3.77	3.99	3.78	4.11
Maximum	30.16	32.17	21.58	20.04	21.61	20.48	21.75	18.04	21.78	20.55
Minimum	-20.13	-22.55	-15.96	-9.16	-15.68	-7.49	-15.53	-7.35	-13.18	-6.56
Std. Dev.	7.81	8.14	6.26	4.16	5.64	3.53	5.44	3.79	5.02	3.36
B. REAL AGGREGATES DEFLATED USING CPI										
Mean	0.36	0.35	0.23	0.48	0.25	0.59	0.25	0.46	0.25	0.58
Maximum	24.38	26.39	16.00	14.16	15.60	10.72	13.53	16.00	12.37	10.86
Minimum	-35.14	-37.56	-30.97	-24.16	-30.69	-20.00	-28.07	-22.36	-27.84	-18.82
Std. Dev.	8.30	8.64	6.75	4.57	6.10	3.72	5.85	4.16	5.41	3.52
C. REAL AGGREGATES DEFLATED USING WPI										
Mean	0.47	0.46	0.33	0.58	0.35	0.70	0.35	0.57	0.36	0.69
Maximum	23.91	25.47	16.65	14.83	16.25	10.80	13.44	16.17	12.46	10.49
Minimum	-28.21	-30.63	-24.04	-17.23	-23.76	-13.06	-21.14	-15.43	-20.91	-11.89
Std. Dev.	8.19	8.52	6.65	4.53	5.97	3.61	5.80	4.16	5.34	3.43

Table 3.2: Basic Statistics of Annual Growth Rates of Monetary Aggregates

	DM1	SSM1	DM2	SSM2	DM2Y	SSM2Y	DM3A	SSM3A	DM3AY	SSM3AY
A. NOMINAL AGGREGATES										
Mean	47.12	47.09	45.67	48.93	45.87	50.16	45.79	48.71	45.84	49.94
Maximum	85.47	88.14	83.18	102.60	83.71	93.86	89.49	101.62	87.74	93.48
Minimum	10.21	11.70	11.01	15.97	11.60	6.80	12.73	16.87	13.34	8.26
Std. Dev.	14.42	14.83	15.01	18.15	15.56	20.63	15.09	18.00	15.57	20.51
B. REAL AGGREGATES DEFLATED USING CPI										
Mean	3.54	3.50	2.08	5.35	2.29	6.58	2.20	5.13	2.26	6.35
Maximum	40.72	40.92	35.92	34.02	29.19	25.80	35.05	33.53	31.43	25.50
Minimum	-32.90	-32.68	-33.18	-29.63	-31.72	-17.35	-32.25	-29.22	-30.70	-16.82
Std. Dev.	15.38	15.89	14.32	13.33	12.99	9.43	14.12	12.97	12.92	9.27
C. REAL AGGREGATES DEFLATED USING WPI										
Mean	4.78	4.75	3.33	6.59	3.53	7.82	3.44	6.37	3.50	7.60
Maximum	40.06	39.63	35.04	38.81	32.22	31.42	35.78	37.23	33.58	29.73
Minimum	-43.58	-43.36	-39.39	-37.86	-36.02	-21.06	-41.77	-37.45	-38.53	-20.65
Std. Dev.	15.85	16.35	15.36	14.21	14.02	10.03	14.96	13.81	13.76	9.84

Table 3.3: Correlations of Monthly Growth Rates of Monetary Aggregates to M1 Growth Rates

A. NOMINAL AGGREGATES										
	DM1	**SSM1**	**DM2**	**SSM2**	**DM2Y**	**SSM2Y**	**DM3A**	**SSM3A**	**DM3AY**	**SSM3AY**
SSM1	0.991	1.000	0.952	0.778	0.942	0.661	0.841	0.715	0.834	0.604
DM1	1.000	0.991	0.959	0.765	0.944	0.635	0.848	0.702	0.835	0.578
B. REAL AGGREGATES DEFLATED USING CPI										
	DM1	**SSM1**	**DM2**	**SSM2**	**DM2Y**	**SSM2Y**	**DM3A**	**SSM3A**	**DM3AY**	**SSM3AY**
SSM1	1.000	0.992	0.964	0.806	0.952	0.716	0.870	0.758	0.862	0.673
DM1	0.992	1.000	0.958	0.819	0.951	0.743	0.865	0.771	0.862	0.699
C. REAL AGGREGATES DEFLATED USING WPI										
	DM1	**SSM1**	**DM2**	**SSM2**	**DM2Y**	**SSM2Y**	**DM3A**	**SSM3A**	**DM3AY**	**SSM3AY**
SSM1	1.000	0.992	0.963	0.794	0.952	0.703	0.864	0.742	0.856	0.656
DM1	0.992	1.000	0.956	0.805	0.950	0.729	0.858	0.753	0.855	0.681

Table 3.4: Correlations of Annual Growth Rates of Monetary Aggregates to M1 Growth Rates

A. NOMINAL AGGREGATES										
	DM1	**SSM1**	**DM2**	**SSM2**	**DM2Y**	**SSM2Y**	**DM3A**	**SSM3A**	**DM3AY**	**SSM3AY**
SSM1	1.000	0.996	0.879	0.770	0.900	0.720	0.873	0.778	0.888	0.725
DM1	0.996	1.000	0.862	0.760	0.889	0.711	0.858	0.768	0.877	0.717
B. REAL AGGREGATES DEFLATED USING CPI										
	DM1	**SSM1**	**DM2**	**SSM2**	**DM2Y**	**SSM2Y**	**DM3A**	**SSM3A**	**DM3AY**	**SSM3AY**
SSM1	0.997	1.000	0.883	0.682	0.898	0.415	0.876	0.694	0.886	0.432
DM1	1.000	0.997	0.871	0.685	0.895	0.437	0.865	0.696	0.882	0.455
C. REAL AGGREGATES DEFLATED USING WPI										
	DM1	**SSM1**	**DM2**	**SSM2**	**DM2Y**	**SSM2Y**	**DM3A**	**SSM3A**	**DM3AY**	**SSM3AY**
SSM1	1.000	0.997	0.892	0.707	0.903	0.461	0.885	0.717	0.892	0.476
DM1	0.997	1.000	0.880	0.708	0.899	0.480	0.874	0.718	0.888	0.496

Table 3.5: Correlations between Growth Rates of Counterpart Monetary Aggregates

	Monthly Nominal	Monthly Real CPI	Monthly Real WPI	Annual Nominal	Annual Real CPI	Annual Real WPI
SSM1 - DM1	0.991	0.992	0.992	0.996	0.997	0.997
SSM2 - DM2	0.845	0.874	0.866	0.898	0.831	0.853
SSM3A - DM3A	0.810	0.842	0.837	0.896	0.827	0.846
SSM2Y - DM2Y	0.749	0.806	0.794	0.874	0.617	0.678
SSM3AY - DM3AY	0.734	0.787	0.780	0.873	0.616	0.668

Table 3.6: Weights of Asset Components in Monetary Aggregates

M1	weights in SSM1		weights in DM1	
	currency	sight dep. private, TL)	currency	sight dep. (private, TL)
MIN	24.78	41.99	35.57	36.55
MAX	58.01	75.22	63.45	64.43
STDEV	5.21	5.21	5.35	5.35
MEAN	44.35	55.65	50.36	49.44

M2	weights in SSM2						weights in DM2					
		deposits (private, TL)						deposits (private, TL)				
	currency	sight	1-month	3-month	6-month	12-month	currency	sight	1-month	3-month	6-month	12-month
MIN	7.41	9.01	2.98	12.60	4.29	0.58	13.95	23.61	2.25	0.63	0.40	0.00
MAX	22.39	36.36	33.52	51.14	33.63	32.17	53.56	51.59	17.80	43.54	20.56	5.57
STDEV	3.40	5.08	6.47	9.56	6.94	8.14	6.03	5.77	2.67	5.41	3.39	0.82
MEAN	13.80	17.52	12.88	32.05	14.20	9.50	38.96	38.26	6.46	10.80	4.62	0.74

M3A	weights in SSM3A						weights in DM3A					
		deposits (private + gov., TL)						deposits (private + gov., TL)				
	currency	sight	1-month	3-month	6-month	12-month	currency	sight	1-month	3-month	6-month	12-month
MIN	7.18	10.82	2.94	11.76	4.16	0.56	13.21	26.09	2.34	0.81	0.47	0.00
MAX	21.45	38.09	32.68	50.11	32.61	31.01	50.23	55.11	17.44	42.28	19.12	5.14
STDEV	3.21	5.43	6.33	9.75	6.61	7.77	5.75	5.20	2.54	4.99	3.12	0.83
MEAN	13.10	20.62	12.49	31.23	13.61	9.07	35.09	43.39	6.04	10.25	4.27	0.79

M2Y	weights in SSM2Y						weights in DM2Y					
		deposits (private, TL+FX)						deposits (private, TL+FX)				
	currency	sight	1-month	3-month	6-month	12-month	currency	sight	1-month	3-month	6-month	12-month
MIN	3.79	12.84	2.84	13.74	4.65	4.36	13.88	23.57	2.20	1.19	0.54	0.05
MAX	17.27	36.28	35.48	43.58	27.79	32.22	51.24	51.41	22.32	43.49	20.21	5.90
STDEV	3.15	4.32	8.58	7.52	4.51	7.35	6.93	5.57	4.18	6.30	3.15	0.94
MEAN	8.71	20.18	15.24	30.65	12.22	12.90	34.10	39.16	8.47	12.50	4.69	0.94

M3AY	weights in SSM3AY						weights in DM3AY					
		deposits (private + gov., TL+FX)						deposits (private + gov., TL+FX)				
	currency	sight	1-month	3-month	6-month	12-month	currency	sight	1-month	3-month	6-month	12-month
MIN	3.73	13.78	2.80	13.03	4.60	4.27	13.15	26.04	2.29	1.30	0.59	0.05
MAX	16.70	37.62	35.09	43.18	26.96	31.36	48.19	54.89	21.98	42.24	18.86	5.45
STDEV	2.99	4.81	8.47	7.69	4.36	7.07	6.46	5.42	3.98	5.85	2.93	0.93
MEAN	8.40	22.06	14.95	30.18	11.90	12.50	31.12	43.55	7.94	11.88	4.39	0.97

Table 3.7: The Correlation Coefficients between CPI-Inflation and the Growth Rates of Monetary Aggregates in Two Periods

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
1987-2002	0.349	0.319	0.524	0.679	0.549	0.690	0.571	0.788	0.593	0.791
2003-2006	-0.003	-0.056	-0.183	-0.345	-0.047	-0.190	-0.366	-0.291	-0.249	-0.219

Table 3.8: Properties of Income Velocities

A. Basic Statistics

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
Mean	0.619	0.611	0.512	0.702	0.516	0.691	0.544	1.016	0.541	0.989
Median	0.602	0.584	0.471	0.651	0.487	0.630	0.524	0.891	0.516	0.868
Maximum	1.077	1.085	1.000	1.384	1.000	1.345	1.012	2.148	1.000	2.063
Minimum	0.341	0.328	0.302	0.342	0.308	0.339	0.321	0.480	0.326	0.469
Std. Dev.	0.166	0.169	0.142	0.227	0.142	0.220	0.138	0.373	0.138	0.356

B. Testing for Linear and Quadratic Trends

	Linear			Quadratic		
	Coefficient	t-Statistic	prob.	Coefficient	t-Statistic	prob.
DM1	-0.001302	-1.765736	0.0812	0.000233	10.36597	0.0000
SSM1	-0.001211	-1.607589	0.1118	0.000242	10.78395	0.0000
DM2	-0.002552	-4.401501	0.0000	0.000167	8.572947	0.0000
SSM2	0.004788	5.440814	0.0000	0.000234	7.457383	0.0000
DM3A	-0.002126	-3.546230	0.0006	0.000181	9.370753	0.0000
SSM3A	0.004501	5.206825	0.0000	0.000236	7.753675	0.0000
DM2Y	-0.001982	-3.373873	0.0011	0.000159	7.649502	0.0000
SSM2Y	0.011568	10.49616	0.0000	0.000137	2.800349	0.0064
DM3AY	-0.001847	-3.120789	0.0025	0.000166	8.182042	0.0000
SSM3AY	0.010934	10.22702	0.0000	0.000143	3.049369	0.0031

C. Unit Root Tests

	ADF	**prob**	**PP**	**prob**	**KPSS**	**Critical V.(1%)**	**ERS**	**Critical V. (10%)**
DM1	0.2912	0.9983	-4.9692	0.0006	0.3094	0.2160	498.1767	6.7836
SSM1	-0.9807	0.9403	-4.8265	0.0009	0.3102	0.2160	86.8544	6.7836
DM2	-0.2297	0.9913	-5.7657	0.0000	0.3186	0.2160	258.3367	6.7836
SSM2	-1.6589	0.7601	-5.5646	0.0001	0.2928	0.2160	77.7873	6.7836
DM3A	-0.4413	0.9842	-5.5249	0.0001	0.2957	0.2160	312.1346	6.7836
SSM3A	-1.7129	0.7364	-5.6443	0.0001	0.3016	0.2160	92.9883	6.7836
DM2Y	-0.9472	0.9445	-6.0199	0.0000	0.3099	0.2160	156.2861	6.7836
SSM2Y	-2.4850	0.3346	-6.3176	0.0000	0.1909	0.1460(5%)	8.9002	6.7836
DM3AY	-1.0690	0.9270	-5.8700	0.0000	0.3149	0.2160	217.8781	6.7836
SSM3AY	-2.4316	0.3607	-6.3199	0.0000	0.2013	0.1460(5%)	12.6409	6.7836

Table 3.9: The Null Hypotheses Critical Values of All Unit Root Tests

Null Hypotheses

Test Type	H_0	Interpretation
Augmented Dickey Fuller (ADF)	X has a unit root	smaller stat. rejects nonstationarity
Phillips-Perron (PP)	X has a unit root	smaller stat. rejects nonstationarity
Kwiatkowski-Phillips-Schmidt-Shin (KPSS)	X is stationary	smaller stat. rejects nonstationarity
Elliott-Rothenberg-Stock (ERS)	X has a unit root	smaller stat. rejects nonstationarity

Critical values for monthly data

	Critical values with intercept and trend					Critical values with intercept only				
	ADF (0 to 15 lags)		PP	KPSS	ERS	ADF (0 to 15 lags)		PP	KPSS	ERS
1%	-3.995	-3.998	-3.997	0.216	4.032	-3.456	-3.458	-3.456	0.739	1.926
5%	-3.428	-3.429	-3.429	0.146	5.652	-2.873	-2.874	-2.873	0.463	3.188
10%	-3.137	-3.138	-3.138	0.119	6.866	-2.573	-2.573	-2.573	0.347	4.360

Critical values for quarterly data

	Critical values with intercept and trend					Critical values with intercept only				
	ADF (0 to 15 lags)		PP	KPSS	ERS	ADF (0 to 15 lags)		PP	KPSS	ERS
1%	-4.072	-4.091	-4.072	0.216	4.247	-3.511	-3.524	-3.511	0.739	1.924
5%	-3.465	-3.473	-3.465	0.146	5.666	-2.897	-2.902	-2.897	0.463	3.065
10%	-3.159	-3.164	-3.159	0.119	6.784	-2.586	-2.589	-2.586	0.347	4.087

Table 3.10: All Unit Root Test Results of Variables in Use[1]

QUARTERLY	ADF	PP	KPSS	ERS	MONTHLY	ADF	PP	KPSS	ERS
LEVELS OF NOMINAL MONEY									
LNDM1(t)	0.731	0.642	0.207	46.664	LNDM1(t)	0.356	-0.687	0.311	32.798
LNDM2(t)	-0.291	0.834	0.217	13.905	LNDM2(t)	-0.122	0.191	0.329	19.628
LNDM2Y(t)	-0.395	0.706	0.214	11.705	LNDM2Y(t)	-0.286	-0.142	0.326	15.316
LNDM3A(t)	1.020	0.491	0.210	74.793	LNDM3A(t)	0.739	0.286	0.320	65.558
LNDM3AY(t)	1.379	0.684	0.213	95.728	LNDM3AY(t)	-0.305	0.659	0.324	14.294
LNSSM1(t)	0.721	0.558	0.199	45.642	LNSSM1(t)	0.223	-0.778	0.299	27.225
LNSSM2(t)	0.123	-0.046	0.192	41.944	LNSSM2(t)	-0.633	0.551	0.292	10.921
LNSSM2Y(t)	0.390	0.749	0.216	44.094	LNSSM2Y(t)	0.871	1.218	0.328	71.866
LNSSM3A(t)	0.161	-0.009	0.191	43.566	LNSSM3A(t)	0.976	0.623	0.291	98.167
LNSSM3AY(t)	0.375	0.739	0.214	43.375	LNSSM3AY(t)	0.826	1.235	0.326	69.274
LEVELS OF CPI-DEFLATED REAL MONEY									
LRCPIDM1(t)	0.295	-0.609	0.280	50.455	LRCPIDM1(t)	-0.823	-1.562	0.413	23.272
LRCPIDM2(t)	0.196	-0.599	0.250	47.826	LRCPIDM2(t)	-1.255	-1.469	0.384	15.756
LRCPIDM2Y(t)	0.053	-0.804	0.259	45.683	LRCPIDM2Y(t)	-1.534	-1.570	0.396	13.177
LRCPIDM3A(t)	0.102	-0.546	0.254	54.438	LRCPIDM3A(t)	-1.252	-1.564	0.368	18.695
LRCPIDM3AY(t)	-0.024	-0.756	0.255	49.340	LRCPIDM3AY(t)	-1.476	-1.322	0.393	15.758
LRCPISSM1(t)	0.137	-0.627	0.286	48.131	LRCPISSM1(t)	-1.102	-1.606	0.422	19.667
LRCPISSM2(t)	-0.999	-0.920	0.265	34.863	LRCPISSM2(t)	-1.334	-1.181	0.389	35.724
LRCPISSM2Y(t)	-1.972	-1.850	0.192	14.376	LRCPISSM2Y(t)	-2.189	-2.306	0.302	16.123
LRCPISSM3A(t)	-1.005	-0.861	0.269	36.270	LRCPISSM3A(t)	-1.254	-1.150	0.397	43.316
LRCPISSM3AY(t)	-1.907	-1.784	0.202	15.714	LRCPISSM3AY(t)	-2.228	-2.146	0.299	10.473
LEVELS OF WPI-DEFLATED REAL MONEY									
LRWPIDM1(t)	-0.529	-1.632	0.257	25.414	LRWPIDM1(t)	-1.634	-2.336	0.391	10.078
LRWPIDM2(t)	-0.906	-1.610	0.186	20.760	LRWPIDM2(t)	-2.437	-2.654	0.272	**4.063**
LRWPIDM2Y(t)	-1.068	-1.815	0.175	19.909	LRWPIDM2Y(t)	-2.809	-2.305	0.254	**2.960**
LRWPIDM3A(t)	-1.614	-1.622	0.203	13.860	LRWPIDM3A(t)	-1.644	-1.946	0.300	11.529
LRWPIDM3AY(t)	-1.149	-1.893	0.185	20.549	LRWPIDM3AY(t)	-2.671	-2.067	0.270	**4.164**
LRWPISSM1(t)	-0.653	-1.619	0.264	24.446	LRWPISSM1(t)	-1.890	-2.413	0.402	8.439
LRWPISSM2(t)	-1.606	-1.616	0.199	21.577	LRWPISSM2(t)	-1.994	-1.702	0.287	16.311
LRWPISSM2Y(t)	-2.001	-2.001	0.127	12.836	LRWPISSM2Y(t)	-2.219	-2.122	0.189	9.826
LRWPISSM3A(t)	-1.595	-1.556	0.208	22.518	LRWPISSM3A(t)	-1.638	-1.659	0.302	20.602
LRWPISSM3AY(t)	-1.976	-1.881	0.134	13.480	LRWPISSM3AY(t)	-2.100	-2.115	0.198	11.034
ANNUAL GROWTH RATE OF NOMINAL MONEY									
LDANDM1(t)	-3.061	-2.644	0.265	**5.707**	LDANDM1(t)	-2.982	**-3.736**	0.369	6.257
LDANDM2(t)	-1.980	-2.126	0.258	16.093	LDANDM2(t)	-2.399	-2.782	0.385	11.058
LDANDM2Y(t)	-1.779	-1.908	0.269	18.273	LDANDM2Y(t)	-2.107	-2.363	0.415	13.164
LDANDM3A(t)	-1.876	-1.969	0.265	17.404	LDANDM3A(t)	-2.388	-2.517	0.405	10.952
LDANDM3AY(t)	-1.736	-1.841	0.275	19.117	LDANDM3AY(t)	-2.092	-2.273	0.428	13.257
LDANSSM1(t)	-3.186	-2.585	0.263	**5.029**	LDANSSM1(t)	-2.824	**-3.482**	0.364	6.626
LDANSSM2(t)	-2.548	-1.864	0.262	11.861	LDANSSM2(t)	-2.193	-2.108	0.399	13.930
LDANSSM2Y(t)	-1.372	-2.074	0.281	49.516	LDANSSM2Y(t)	-1.352	-2.087	0.435	58.345
LDANSSM3A(t)	-1.538	-1.808	0.269	40.164	LDANSSM3A(t)	-2.195	-2.109	0.415	13.787
LDANSSM3AY(t)	-1.343	-2.023	0.285	54.044	LDANSSM3AY(t)	-1.300	-2.032	0.443	58.506

[1] Variables in bold print are stationary ones; statistics in bold print show the odd results that are contrary to the majority of results; (t) means that test is carried out with an intercept and a trend; (i) means that the test is carried out with an intercept.

QUARTERLY	ADF	PP	KPSS	ERS	MONTHLY	ADF	PP	KPSS	ERS
ANNUAL GROWTH RATE OF CPI-DEFLATED REAL MONEY									
LDARCPIDM1(t)	-4.852	-3.636	0.127	3.851	**LDARCPIDM1(t)**	-4.303	-4.418	0.130	5.335
LDARCPIDM2(t)	**-2.688**	-3.729	0.096	**10.051**	**LDARCPIDM2(t)**	-3.813	-4.085	0.100	5.649
LDARCPIDM2Y(t)	-3.252	-3.803	0.076	3.342	**LDARCPIDM2Y(t)**	-3.812	-4.032	0.078	6.667
LDARCPIDM3A(t)	**-2.825**	-3.777	0.085	**7.990**	**LDARCPIDM3A(t)**	-3.818	-3.986	0.087	5.815
LDARCPIDM3AY(t)	**-2.890**	-3.858	0.072	**8.629**	**LDARCPIDM3AY(t)**	-3.838	-4.029	0.073	6.660
LDARCPISSM1(t)	-5.025	-3.587	0.110	3.548	**LDARCPISSM1(t)**	-4.079	-4.290	0.113	5.914
LDARCPISSM2(t)	**-2.427**	-3.727	0.058	**10.481**	**LDARCPISSM2(t)**	-4.080	-3.697	0.061	3.921
LDARCPISSM2Y(t)	**-3.043**	-3.982	0.089	4.437	**LDARCPISSM2Y(t)**	**-2.626**	-3.832	0.092	**11.488**
LDARCPISSM3A(t)	**-2.512**	-3.751	0.057	**9.539**	**LDARCPISSM3A(t)**	**-2.670**	-3.599	0.061	**8.151**
LDARCPISSM3AY(t)	**-3.004**	-3.984	0.096	5.085	**LDARCPISSM3AY(t)**	**-2.719**	-4.051	0.099	**10.492**
ANNUAL GROWTH RATE OF WPI-DEFLATED REAL MONEY									
LDARWPIDM1(t)	-3.292	-4.124	0.085	5.228	**LDARWPIDM1(t)**	-4.189	-4.354	0.087	5.460
LDARWPIDM2(t)	**-2.583**	-3.798	0.066	**9.059**	**LDARWPIDM2(t)**	-3.564	-3.878	0.070	6.096
LDARWPIDM2Y(t)	**-2.514**	-3.811	0.056	**10.217**	**LDARWPIDM2Y(t)**	-3.499	-3.596	0.061	**7.308**
LDARWPIDM3A(t)	**-2.442**	-3.789	0.059	2.791	**LDARWPIDM3A(t)**	-3.582	-3.833	0.062	6.250
LDARWPIDM3AY(t)	**-2.479**	-3.842	0.054	2.365	**LDARWPIDM3AY(t)**	-3.554	-3.688	0.057	**7.234**
LDARWPISSM1(t)	-3.310	-4.001	0.075	5.234	**LDARWPISSM1(t)**	-3.990	-4.268	0.076	6.005
LDARWPISSM2(t)	**-2.234**	-3.550	0.059	**10.265**	**LDARWPISSM2(t)**	-4.113	-3.682	0.069	3.634
LDARWPISSM2Y(t)	**-1.987**	-3.470	0.096	**13.428**	**LDARWPISSM2Y(t)**	**-2.120**	-3.670	0.128	**14.517**
LDARWPISSM3A(t)	**-2.283**	-3.573	0.061	**9.743**	**LDARWPISSM3A(t)**	**-2.330**	-3.745	0.070	**10.476**
LDARWPISSM3AY(t)	-2.022	-3.460	0.102	**12.786**	**LDARWPISSM3AY(t)**	**-2.160**	-3.645	0.137	**14.273**
PERIOD GROWTH RATE OF NOMINAL MONEY									
LDQNDM1(i)	**-2.267**	-8.202	**0.595**	**5.705**	**LDMNDM1(i)**	-2.948	-26.639	0.437	**17.428**
LDQNDM2(i)	**-1.783**	-7.314	**0.508**	**7.253**	**LDMNDM2(i)**	**-2.252**	-24.375	**0.516**	**26.787**
LDQNDM2Y(i)	**-1.547**	-6.709	**0.494**	**8.040**	**LDMNDM2Y(i)**	**-1.894**	-23.013	**0.682**	**32.632**
LDQNDM3A(i)	**-1.687**	-7.224	**0.449**	**8.277**	**LDMNDM3A(i)**	**-2.092**	-21.996	**0.526**	**28.306**
LDQNDM3AY(i)	**-1.518**	-6.711	**0.493**	**8.839**	**LDMNDM3AY(i)**	**-1.843**	-21.277	**0.738**	**31.474**
LDQNSSM1(i)	**-2.300**	-8.081	**0.554**	**5.474**	**LDMNSSM1(i)**	-2.866	-26.246	0.393	**17.940**
LDQNSSM2(i)	-5.529	-5.408	0.396	0.861	**LDMNSSM2(i)**	**-1.953**	-17.056	**0.663**	**11.714**
LDQNSSM2Y(i)	-3.983	-3.783	**0.480**	1.188	**LDMNSSM2Y(i)**	-5.523	-16.819	**0.755**	0.732
LDQNSSM3A(i)	-5.493	-5.431	0.405	0.895	**LDMNSSM3A(i)**	-8.842	-15.679	**0.672**	0.324
LDQNSSM3AY(i)	-3.941	-3.789	**0.478**	1.275	**LDMNSSM3AY(i)**	-5.338	-16.354	**0.760**	0.759
PERIOD GROWTH RATE OF CPI-DEFLATED REAL MONEY									
LDQRCPIDM1(i)	-9.583	-8.287	0.332	0.380	**LDMRCPIDM1(i)**	-3.752	-24.160	0.251	**6.899**
LDQRCPIDM2(i)	-9.233	-7.762	0.337	0.365	**LDMRCPIDM2(i)**	-3.512	-22.651	0.246	**7.669**
LDQRCPIDM2Y(i)	-4.973	-7.778	0.303	1.344	**LDMRCPIDM2Y(i)**	-3.484	-22.179	0.208	8.585
LDQRCPIDM3A(i)	-4.899	-7.756	0.342	1.563	**LDMRCPIDM3A(i)**	-3.432	-20.334	0.260	**7.903**
LDQRCPIDM3AY(i)	-4.955	-7.808	0.317	1.702	**LDMRCPIDM3AY(i)**	-3.470	-20.225	0.225	**7.981**
LDQRCPISSM1(i)	-9.352	-8.096	0.313	0.400	**LDMRCPISSM1(i)**	-3.674	-24.586	0.221	**7.839**
LDQRCPISSM2(i)	-7.526	-7.439	0.428	0.938	**LDMRCPISSM2(i)**	-3.947	-17.565	0.345	0.704
LDQRCPISSM2Y(i)	-8.513	-8.171	0.162	0.624	**LDMRCPISSM2Y(i)**	-4.615	-18.049	0.091	0.021
LDQRCPISSM3A(i)	-7.606	-7.531	0.423	1.164	**LDMRCPISSM3A(i)**	-4.030	-15.936	0.329	0.449
LDQRCPISSM3AY(i)	-8.680	-8.228	0.175	0.759	**LDMRCPISSM3AY(i)**	-17.216	-17.197	0.094	0.227
PERIOD GROWTH RATE OF WPI-DEFLATED REAL MONEY									
LDQRWPIDM1(i)	-9.507	-9.185	0.254	0.327	**LDMRWPIDM1(i)**	-3.951	-23.361	0.185	**4.465**
LDQRWPIDM2(i)	-8.788	-8.233	0.211	0.335	**LDMRWPIDM2(i)**	-3.608	-20.964	0.167	**5.818**
LDQRWPIDM2Y(i)	-9.220	-8.287	0.172	0.320	**LDMRWPIDM2Y(i)**	-3.507	-20.277	0.145	**7.495**
LDQRWPIDM3A(i)	-8.540	-8.218	0.209	0.441	**LDMRWPIDM3A(i)**	-4.104	-18.695	0.178	0.707
LDQRWPIDM3AY(i)	-8.949	-8.327	0.184	0.427	**LDMRWPIDM3AY(i)**	-4.021	-18.373	0.138	1.097
LDQRWPISSM1(i)	-9.259	-9.097	0.262	0.345	**LDMRWPISSM1(i)**	-3.837	-23.334	0.172	**5.588**
LDQRWPISSM2(i)	-8.062	-8.019	0.243	0.711	**LDMRWPISSM2(i)**	-4.058	-15.815	0.222	0.399
LDQRWPISSM2Y(i)	-8.939	-8.971	0.086	0.890	**LDMRWPISSM2Y(i)**	-16.076	-16.332	0.082	0.204
LDQRWPISSM3A(i)	-8.097	-8.063	0.260	0.839	**LDMRWPISSM3A(i)**	-14.217	-14.136	0.215	0.203
LDQRWPISSM3AY(i)	-8.946	-8.955	0.084	1.082	**LDMRWPISSM3AY(i)**	-15.341	-15.464	0.083	0.205

QUARTERLY	ADF	PP	KPSS	ERS	MONTHLY	ADF	PP	KPSS	ERS
USER COSTS OF DIVISIA MONEY									
UCOSTM1(i)	-1.650	-1.560	0.465	4.406	UCOSTM1(i)	-2.032	-2.329	0.729	**3.212**
UCOSTM2(i)	-5.002	-4.904	0.312	1.016	**UCOSTM2(i)**	-6.637	-6.497	0.421	**0.473**
UCOSTM2Y(i)	-3.796	-3.685	0.317	1.525	**UCOSTM2Y(i)**	-5.698	-5.337	**0.474**	**0.649**
UCOSTM3A(i)	-4.593	-4.450	0.311	1.150	**UCOSTM3A(i)**	-6.254	-6.070	**0.479**	**0.534**
UCOSTM3AY(i)	-3.653	-3.537	0.327	1.647	**UCOSTM3AY(i)**	-5.550	-5.245	**0.491**	**0.697**
INCOME VELOCITIES									
VELNDM1(i)	-1.282	**-5.463**	0.354	9.636					
VELNDM2(t)	-1.205	**-6.044**	0.244	36.750					
VELNDM2Y(t)	-1.877	**-6.410**	0.256	16.695					
VELNDM3A(t)	-1.132	**-6.024**	0.267	59.555					
VELNDM3AY(t)	-1.775	**-6.371**	0.278	31.650					
VELNSSM1(i)	-1.401	**-5.310**	**0.339**	8.835					
VELNSSM2(t)	-2.450	**-5.662**	0.222	19.163					
VELNSSM2Y(t)	**-2.810**	-5.866	0.141	0.519					
VELNSSM3A(t)	-2.471	**-5.700**	0.235	22.941					
VELNSSM3AY(t)	**-2.731**	-5.923	0.147	1.129					
OTHER VARIABLES									
AVEDEPINT(i)	-2.562	-2.532	**0.324**	**3.028**	**AVEDEPINTM (i)**	-2.692	-3.361	0.502	2.672
TBILLRATE(i)	-2.773	-2.558	0.352	2.309	TBILLRATE(i)	-2.385	**-3.154**	0.544	**2.628**
LCPIINDEX(t)	3.623	1.938	0.249	230.418	LCPIINDEX(t)	2.509	2.865	0.427	191.844
LDACPIINDEX(t)	-1.373	-2.274	0.295	96.458	LDACPIINDEX(t)	-1.799	-2.410	0.439	84.207
LDQCPIINDEX(i)	-1.321	**-4.440**	0.593	10.036	**LDMCPIINDEX(i)**	-7.976	-7.842	**1.170**	0.415
LWPIINDEX(t)	2.657	1.647	0.240	136.974	LWPIINDEX(t)	1.814	2.478	0.413	110.069
LDAWPIINDEX(t)	-1.467	-2.697	0.266	49.412	LDAWPIINDEX(t)	-1.928	-2.652	0.413	42.027
LDQWPIINDEX(i)	-5.461	-5.605	0.527	1.100	**LDMWPIINDEX(i)**	-8.067	-7.988	**1.066**	0.337
LGDPDEFLA(t)	1.889	1.560	0.257	125.457					
LDAGDPDEFLA(t)	-1.618	-2.696	0.277	43.989					
LENERGWPI(t)	1.105	0.526	0.215	68.802	LENERGWPI(t)	1.809	1.120	0.383	110.236
LDAENERGWPI(t)	-2.003	-3.258	0.281	46.351	LDAENERGWPI(t)	-1.983	-3.260	0.347	58.582
LDQENERGWPI(i)	-6.080	-6.080	0.453	1.275	LDMENERGWPI(i)	-12.643	-12.864	**0.551**	0.229
LGASPRICE(t)	0.298	-0.048	0.206	38.929	LGASPRICE(t)	0.298	-0.128	0.301	41.974
LDAGASPRICE(t)	-2.771	-3.379	0.220	24.819	LDAGASPRICE(t)	-2.800	**-3.633**	0.248	30.030
LDQGASPRICE(i)	-6.839	-6.855	0.341	1.071	**LDMGASPRICE(i)**	-13.724	-13.842	0.352	0.253
LIMPRICETL(t)	0.733	0.418	0.230	58.896	LIMPRICETL(t)	0.331	0.350	0.344	45.574
LDAIMPPRICETL(t)	-2.354	-3.401	0.221	7.879	LDAIMPPRICETL(t)	-1.952	-3.368	0.266	27.604
LDQIMPPRICETL(i)	-6.531	-6.531	**0.456**	1.758	**LDMIMPPRICETL(i)**	-13.074	-13.140	0.499	0.310
LNER(t)	0.625	0.920	0.226	49.024	LNER(t)	0.708	1.161	0.340	53.917
LDANER(t)	-2.117	-2.556	0.243	10.727	LDANER(t)	-1.829	-2.795	0.335	19.434
LDQNER(i)	-5.868	-5.849	**0.516**	0.886	**LDMNER(i)**	-9.524	-9.507	0.731	0.275
LGOVEXPREALWPI(t)	-2.155	**-6.900**	0.207	24.612	LGOVEXPRWPI(t)	-1.943	**-10.545**	0.347	96.088
LDAGOVEXPRWPI(i)	-4.143	-4.195	0.192	1.085	**LDAGOVEXPRWPI(i)**	-4.995	-7.106	0.258	2.893
LWAGENMALLNO(t)	0.272	3.049	0.274	112.494					
LDAWAGEMALLNO(t)	-1.715	**-4.398**	0.166	29.534					
LDQWAGEMALLNO(t)	-12.661	-11.965	**0.182**	**7.025**					
LGDPNO(t)	-0.683	-2.450	0.267	**1.138**					
LDAGDPNO(t)	-1.359	-2.834	0.282	61.112					
LGDPREAL(t)	-2.093	**-10.232**	**0.094**	28.483					
LDAGDPREAL(i)	-3.359	-4.373	0.075	0.873					
GAPTOPOTGDP(i)	**-2.387**	-11.834	0.113	**16.839**					

TABLE APPENDIXES TO CHAPTER 4

Table 4.1: The Cointegrating Relationships between Annual CPI-Inflation and Annual Growth Rates of Nominal Monetary Aggregates

SSM1	Unique CIV at all lags 1-12 for both models 2 and 3. At lags 1, 2, 3 model 2 has 1 CIV according to MET only. Model 3 has one CIV throughout and model 2 has one CIV at lags 4-12 based on both TT and MET.
DM1	Unique cointegrating relationship at all lags 1-12 and for both models 2 and 3. At lags 2, 3, 4 model 2 has 1 CIV according to MET only. Model 3 has one CIV throughout and model 2 has one CIV at lags 1, 5-12 based on both TT and MET.
SSM2	Unique cointegrating relationship at lags 3, 8-10 for model 2, and at lags 1, 3, 4, 6-10 for model 3. Model 2 lags 3 and 10, and model 3 lag 1 CIVs are based on MET only, and all others are based on both TT and MET.
DM2	Unique cointegrating relationship at all lags 1-11 but lag 2 for model 2, and at lags 1-12 for model 3. Model 2 lags 1, 3 and 4, and model 3 lag 12 CIVs are based on MET only, and all others are based on both TT and MET.
SSM3A	Unique cointegrating relationship at all lags 3, 8-10 and for model 2, and at lags 1, 3, 4, 6-10 model 3. Model 2 lags 3 and 10 CIVs are based on MET only, and model 3 lag 6 CIV is based on TT only. All others are based on both TT and MET.
DM3A	Unique cointegrating relationship at lags 1, 3, 5, 6, 8-11 for model 2, and at all lags 1-12 but 4 for model 3. Model 2 lags 1, 3, 5 CIVs are based on MET only, and model 3 lag 2 CIV is based on MET only. All others are based on both TT and MET.
SSM2Y	Unique cointegrating relationship at lags 1-3, 7-11 for model 2, and at lags 1-11 for model 3. Model 2 lags 1-3, 7 and model 3 lag 11 CIVs are based on MET only, and model 3 lag 4 CIV is based on TT only. All others are based on both TT and MET.
DM2Y	Unique cointegrating relationship at lags 5-11 for model 2, and at lags 1-11 for model 3. Model 2 lags 5-7, and model 3 lag 4 CIVs are based on MET only. All others are based on both TT and MET.
SSM3AY	Unique cointegrating relationship at lags 1-3, 8-10 for model 2, and at lags 1, 3-11 for model 3. Model 2 lags 1, 2, and model 3 lag 11 CIVs are based on MET only, and model 3 lags 5, 6 CIVs are based on TT only. All others are based on both TT and MET.
DM3AY	Unique cointegrating relationship at lags 3, 5, 6, 7-11 for model 2, and at lags 1-11 but lag 2 for model 3. Model 2 lags 3, 5, 6 and model 3 lags 2, 7 CIVs are based on MET only. All others are based on both TT and MET.

Table 4.2: The Cointegrating Relationships between Annual WPI-Inflation and Annual Growth Rates of Nominal Monetary Aggregates

SSM1	Unique cointegrating relationship at all lags 1-12 and for both models 2 and 3. At lags 3, 4, 12 model 2 has 1 CIV according to MET only. Model 3 has one CIV throughout and model 2 has one CIV at lags except the ones above based on both TT and MET.
DM1	Unique cointegrating relationship at all lags 1-12 and for both models 2 and 3. At lags 4 and 12 model 2 has 1 CIV according to MET only. Model 3 has one CIV throughout and model 2 has one CIV at lags except the ones above based on both TT and MET.
SSM2	Unique cointegrating relationship at lags 8-10 for model 2, and at lags 1-10 but 5 for model 3. Model 2 lag 10 the CIV is based on MET only, and other two are based on both TT and MET. Model 3 lags 2, 3, 4, and 6 the CIVs are based on TT only, and other two are based on both TT and MET. Model 3 lag 8 CIV is not unique based on both tests.
DM2	Unique cointegrating relationship at all lags 1, 2 and 5-11 for model 2, and at lags 1-11 for model 3. Model 2 lags 1, 3, 5 and 6, and model 3 lag 4 CIVs are based on MET only, and all others are based on both TT and MET.
SSM3A	Unique cointegrating relationship at all lags 1, 8-10 and for model 2, and at lags 1, 2, 6-10 model 3. Model 2 lags 1 and 10 CIVs are based on MET only, and model 3 lag 6 CIV is based on TT only. All others are based on both TT and MET. Model 3 lag 8 CIV is not unique based on both tests.
DM3A	Unique cointegrating relationship at lags 1, 6-11 for model 2, and at all lags 1-12 but 4 for model 3. Model 2 lags 6, 7, and model 3 lag 12 CIVs are based on MET only, and model 3 lag 2 CIV is based on MET only. All others are based on both TT and MET.
SSM2Y	Unique cointegrating relationship at lags 1, 9, 10 for model 2, and at lags 1, 2, 9, 10 for model 3. Model 3 lags 2 CIV is based on TT only. All others are based on both TT and MET.
DM2Y	Unique cointegrating relationship at lags 1, 8-11 for model 2, and at lags 1, 2, 6-11 for model 3. Model 2 lags 1, 11 CIVs are based on MET only. All others are based on both TT and MET.
SSM3AY	Unique cointegrating relationship at lags 1, 9, 10 for model 2, and at lags 1, 2, 9, 10 for model 3. Model 2 lags 9 CIV is based on MET only, and model 3 lags 2 CIV is based on TT only. All others are based on both TT and MET.
DM3AY	Unique cointegrating relationship at lags 1, 8-11 for model 2, and at lags 1-3, 6-11 for model 3. Model 2 lag 1 and model 3 lags 3 CIVs are based on MET only. All others are based on both TT and MET.

Table 4.3: The Estimated Error-Correction Models between Annual CPI-Inflation and Annual Growth Rates of Nominal Monetary Aggregates*

Lag	8	**8**	9	9	10	10
CI Model	2	**3**	2	3	2	3
Coefficient on SSM1	1.527	**1.526**	1.548	1.548	1.656	1.656
Std. Deviation	0.217	**0.218**	0.180	0.181	0.176	0.176
Coefficient on EC term	-0.025	**-0.025**	-0.030	-0.031	-0.031	-0.031
t-value	-2.241	**-2.256**	-2.596	-2.611	-2.638	-2.636
Coefficient on DM1	1.566	**1.565**	1.573	1.573	1.680	1.680
Std. Deviation	0.209	**0.209**	0.175	0.175	0.165	0.166
Coefficient on EC term	-0.027	**-0.027**	-0.033	-0.033	-0.034	-0.034
t-value	-2.334	**-2.345**	-2.700	-2.712	-2.766	-2.761
Coefficient on SSM2	1.135	**1.134**	1.136	1.135	1.173	1.173
Std. Deviation	0.147	**0.147**	0.148	0.149	0.168	0.168
Coefficient on EC term	-0.005	**-0.005**	-0.006	-0.006	-0.004	-0.004
t-value	-0.340	**-0.349**	-0.398	-0.403	-0.294	-0.295
Coefficient on DM2	1.359	**1.361**	1.359	1.359	1.438	1.438
Std. Deviation	0.166	**0.180**	0.166	0.167	0.178	0.178
Coefficient on EC term	-0.023	**-0.020**	-0.023	-0.024	-0.020	-0.020
t-value	-1.763	**-1.605**	-1.763	-1.771	-1.521	-1.518
Coefficient on SSM3A	1.128	**1.128**	1.132	1.132	1.159	1.159
Std. Deviation	0.145	**0.146**	0.152	0.153	0.159	0.159
Coefficient on EC term	-0.007	**-0.007**	-0.004	-0.005	-0.006	-0.006
t-value	-0.481	**-0.487**	-0.303	-0.308	-0.389	-0.391
Coefficient on DM3A	1.298	**1.297**	1.314	1.313	1.410	1.410
Std. Deviation	0.196	**0.197**	0.188	0.188	0.180	0.181
Coefficient on EC term	-0.023	**-0.023**	-0.021	-0.021	-0.020	-0.020
t-value	-1.795	**-1.801**	-1.608	-1.616	-1.550	-1.547
Coefficient on SSM2Y	0.967	**0.967**	0.951	0.951	0.958	0.959
Std. Deviation	0.079	**0.079**	0.071	0.072	0.076	0.076
Coefficient on EC term	-0.039	**-0.039**	-0.056	-0.056	-0.062	-0.062
t-value	-1.830	**-1.835**	-2.496	-2.496	-2.666	-2.653
Coefficient on DM2Y	1.252	**1.252**	1.264	1.263	1.325	1.325
Std. Deviation	0.159	**0.159**	0.139	0.140	0.153	0.153
Coefficient on EC term	-0.026	**-0.026**	-0.031	-0.031	-0.026	-0.026
t-value	-1.848	**-1.855**	-2.076	-2.083	-1.766	-1.758
Coefficient on SSM3AY	0.968	**0.968**	0.953	0.952	0.958	0.958
Std. Deviation	0.081	**0.081**	0.077	0.077	0.076	0.076
Coefficient on EC term	-0.041	**-0.041**	-0.052	-0.052	-0.060	-0.060
t-value	-1.891	**-1.893**	-2.267	-2.268	-2.620	-2.609
Coefficient on DM3AY	1.237	**1.236**	1.246	1.245	1.312	1.312
Std. Deviation	0.168	**0.169**	0.158	0.158	0.154	0.154
Coefficient on EC term	-0.028	**-0.028**	-0.027	-0.027	-0.027	-0.027
t-value	-1.985	**-1.990**	-1.856	-1.863	-1.833	-1.827

* The models with bold print are the ones that yield best out-of-sample forecasts. Relevant tables report results obtained from these estimations

Table 4.4: The Estimated Error-Correction Models between Annual WPI-Inflation and Annual Growth Rates of Nominal Monetary Aggregates*

Lag	1	1	2	8	**8**	9	9	10	10
CI Model	2	3	3	2	**3**	2	3	2	3
Coefficient on SSM1				1.391	**1.390**	1.420	1.419	1.496	1.496
Std. Deviation				0.215	**0.215**	0.179	0.179	0.176	0.176
Coefficient on EC term				-0.040	**-0.040**	-0.050	-0.050	-0.051	-0.051
t-value				-2.570	**-2.571**	-3.071	-3.079	-2.998	-2.997
Coefficient on DM1				1.428	**1.428**	1.443	1.442	1.520	1.520
Std. Deviation				0.205	**0.206**	0.172	0.172	0.164	0.165
Coefficient on EC term				-0.043	**-0.044**	-0.054	-0.055	-0.056	-0.056
t-value				-2.670	**-2.676**	-3.193	-3.199	-3.122	-3.119
Coefficient on SSM2				0.994	**0.994**	0.979	0.978	0.996	0.996
Std. Deviation				0.159	**0.159**	0.152	0.152	0.170	0.171
Coefficient on EC term				-0.020	**-0.021**	-0.023	-0.023	-0.022	-0.022
t-value				-1.140	**-1.144**	-1.236	-1.239	-1.105	-1.105
Coefficient on DM2				1.226	**1.225**	1.220	1.220	1.278	1.278
Std. Deviation				0.186	**0.186**	0.172	0.173	0.182	0.183
Coefficient on EC term				-0.034	**-0.034**	-0.041	-0.041	-0.038	-0.038
t-value				-2.053	**-2.058**	-2.330	-2.334	-2.071	-2.069
Coefficient on SSM3A				0.988	**0.988**	0.956	0.955	0.990	0.989
Std. Deviation				0.151	**0.152**	0.150	0.151	0.164	0.164
Coefficient on EC term				-0.023	**-0.023**	-0.025	-0.026	-0.023	-0.023
t-value				-1.241	**-1.243**	-1.293	-1.295	-1.143	-1.143
Coefficient on DM3A				1.155	**1.155**	1.166	1.166	1.249	1.249
Std. Deviation				0.186	**0.186**	0.177	0.178	0.176	0.177
Coefficient on EC term				-0.038	**-0.038**	-0.041	-0.041	-0.040	-0.040
t-value				-2.218	**-2.221**	-2.264	-2.267	-2.148	-2.146
Coefficient on SSM2Y	0.863	0.863	**0.884**			0.841	0.840	0.839	0.839
Std. Deviation	0.102	0.103	**0.119**			0.097	0.097	0.090	0.090
Coefficient on EC term	-0.078	-0.078	**-0.064**			-0.082	-0.082	-0.095	-0.095
t-value	-3.526	-3.521	**-2.807**			-3.063	-3.060	-3.426	-3.418
Coefficient on DM2Y	1.121	1.119	**1.152**	1.111	1.110	1.129	1.129	1.167	1.167
Std. Deviation	0.225	0.226	**0.231**	0.177	0.177	0.158	0.158	0.166	0.167
Coefficient on EC term	-0.027	-0.027	**-0.025**	-0.040	-0.040	-0.047	-0.047	-0.045	-0.045
t-value	-1.833	-1.846	**-1.637**	-2.222	-2.225	-2.505	-2.507	-2.273	-2.268
Coefficient on SSM3AY	0.863	0.863	**0.882**			0.829	0.828	0.839	0.839
Std. Deviation	0.102	0.102	**0.119**			0.100	0.100	0.090	0.090
Coefficient on EC term	-0.079	-0.079	**-0.067**			-0.083	-0.083	-0.094	-0.094
t-value	-3.510	-3.505	**-2.864**			-3.024	-3.021	-3.403	-3.395
Coefficient on DM3AY	1.126	1.124	**1.173**	1.092	1.092	1.101	1.101	1.158	1.158
Std. Deviation	0.213	0.214	**0.236**	0.172	0.173	0.162	0.162	0.159	0.159
Coefficient on EC term	-0.027	-0.028	**-0.026**	-0.043	-0.043	-0.047	-0.047	-0.048	-0.048
t-value	-1.848	-1.860	**-1.688**	-2.320	-2.322	-2.418	-2.420	-2.401	-2.397

* The models with bold print are the ones that yield best out-of-sample forecasts. Relevant tables report results obtained from these estimations

Table 4.5: Out-of-Sample Forecast Evaluation of the Bivariate Error Correction Models of Annual CPI-Inflation and Annual Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.777	**0.762**	0.884	0.868	0.849	0.899	0.873	0.915	0.859	0.902	0.822	0.815	0.681
MAE	0.673	**0.658**	0.840	0.811	0.768	0.818	0.797	1.126	0.823	1.094	0.669	0.635	0.508
MAPE	7.246	**7.071**	8.611	7.698	7.889	8.059	8.457	8.146	8.136	8.090	7.818	7.484	5.867

Static Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.697	0.677	0.777	0.713	0.846	0.735	1.034	**0.649**	0.865	0.660	0.760	0.627	0.681
MAE	0.552	0.531	0.645	0.527	0.679	0.572	0.713	**0.491**	0.704	0.495	0.627	0.485	0.508
MAPE	6.444	6.183	7.571	6.128	7.942	6.705	8.299	**5.778**	8.271	5.836	7.319	5.671	5.867

12-Period-Ahead Sequential Forecasts

	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.874	**0.859**	0.984	1.058	0.941	1.074	1.000	1.373	0.971	1.334	0.930	1.088	7.258
MAE	0.878	**0.859**	1.030	1.234	0.985	1.172	1.052	1.957	1.071	1.894	0.758	0.848	11.497
MAPE	8.146	**7.975**	9.566	9.955	8.981	9.991	9.685	12.090	9.363	11.803	8.872	10.171	57.619

Dynamic Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	**SSM3AY**	DAVG	SSAVG	NCF
RMSE	4.478	4.557	4.853	2.137	6.621	2.379	3.049	1.785	4.014	**1.693**	4.576	2.346	3.677
MAE	4.128	4.198	4.559	1.954	6.359	2.100	2.704	1.648	3.772	**1.506**	4.304	2.117	3.541
MAPE	51.483	52.299	56.629	24.341	78.048	26.576	34.075	20.104	46.909	**18.246**	53.427	26.606	43.933

Table 4.6: Out-of-Sample Forecast Evaluation of the Bivariate Error Correction Models of Annual WPI-Inflation and Annual Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	**DM2**	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.643	1.651	**1.650**	1.711	1.653	1.613	1.745	1.527	1.760	1.537	1.657	1.555	1.638
MAE	1.146	1.118	**1.130**	1.300	1.056	1.229	1.374	1.173	1.307	1.189	1.308	1.236	1.254
MAPE	16.138	16.214	**15.958**	17.095	17.808	16.932	16.830	16.110	18.513	16.135	16.729	16.134	15.981

Static Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	**DM2Y**	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.497	1.507	1.496	1.463	1.506	1.347	**1.507**	1.423	1.542	1.395	1.465	1.350	1.638
MAE	1.160	1.175	1.198	1.192	1.172	1.114	**1.134**	1.135	1.137	1.101	1.132	1.087	1.254
MAPE	13.971	14.329	14.632	15.191	15.547	14.881	**13.840**	15.125	15.111	14.759	14.300	14.231	15.981

12-Period-Ahead Sequential Forecasts

	DM1	SSM1	**DM2**	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.787	1.784	**1.790**	1.939	1.787	1.832	1.881	1.733	1.899	1.743	1.798	1.758	9.622
MAE	1.273	1.236	**1.387**	1.701	1.262	1.708	1.529	1.581	1.545	1.567	1.456	1.430	11.790
MAPE	18.096	18.068	**17.485**	19.543	19.602	19.529	18.723	18.394	20.576	18.356	18.609	18.453	106.02

Dynamic Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	6.347	6.469	7.267	4.882	9.391	5.730	5.035	**3.435**	5.585	3.373	6.660	4.355	4.668
MAE	4.863	4.977	5.695	3.792	7.808	4.515	3.999	**2.822**	4.584	2.832	5.255	3.483	3.810
MAPE	90.850	92.696	105.30	71.036	137.01	84.132	74.521	**39.755**	83.410	42.899	97.177	63.294	69.590

Table 4.7: The Cointegrating Relationships between Nominal GDP Growth and Annual Growth Rates of Nominal Monetary Aggregates

SSM1	Unique CIV at lags 1-3, 6, 7 for model 2; at lags 1-3, 6, 7, 11, 12 model 3 and at lags 1-3, 6, 7, 11 model 4. CIVs for lag 6, 7 model 2 and lag 11 model 4 exist based on MET only. All other CIVs are based on both TT and MET.
DM1	Unique CIV at lags 1-3, 7 for model 2; at lags 1-3, 6, 7, 11, 12 model 3 and at lags 1-3, 6, 7, 11 model 4. CIVs for lag 7 model 2, CIVs for lag 11, 12 model 3 and lag 11 model 4 exist based on MET only. All other CIVs are based on both TT and MET.
SSM2	Unique CIV for lag 3 for model 2; at lags 2, 3 for model 3 and at lags 1-3 model 4. CIVs for lag 2 model 3 and lag 1, 2 model 4 exist based on trace test only. All other CIVs are based on both TT and MET.
DM2	Unique CIV at lags 1-3, 6, 7 for model 2; at lags 1-7 for model 3 and at lags 1-3 for model 4. CIVs for lag 6, 7 model 2, lag 4,5 model 3 exist based on MET only. All other CIVs are based on both TT and MET.
SSM3A	Unique CIV at lags 3 for models 2 and 3, and at lags 1-3 for model 4. The CIV for lag 1 model 4 exists based on trace test only. All other CIVs are based on both TT and MET.
DM3A	Unique CIV at lags 1-3, 6 for model 2; at lags 1-3, 6, 7 model 3 and at lags 1-3 model 4. CIVs for lag 1, 6 model 2 and lag 7 model 3 exist based on MET only. All other CIVs are based on both TT and MET.
SSM2Y	Unique CIV for lag 3, 6, 7 for models 2, 3 and 4. CIV for lag 3 model exist based on MET only. All other CIVs are based on both TT and MET.
DM2Y	Unique CIV for lag 3 for model 2; at lags 2, 3 models 3 and 4. The existence of all CIVs are based on both TT and MET.
SSM3AY	Unique CIV for lag 3 for models 2, 3 and 4. The CIV for model 2 at lag 3 is based on MET only. The other CIVs are based on both TT and MET.
DM3AY	Unique CIV for lag 3 for model 2; at lags 2, 3, 6 for model 3 and at lags 1-3 for model 4. CIV for lag 6 model 3 exists based on MET only. All other CIVs are based on both TT and MET.

Table 4.8: The Estimated Error-Correction Models of Nominal GDP Growth and Annual Nominal Money Growth

Lag	1	2	3	3	**3**
CI Model	4	4	2	3	**4**
Coefficient on SSM1		1.103		1.448	**1.077**
Std. Deviation		0.170		0.192	**0.123**
Coefficient on EC term		-0.212		-0.140	**-0.371**
t-value		-2.083		-1.558	**-3.265**
Coefficient on DM1		1.159		1.471	**1.128**
Std. Deviation		0.168		0.172	**0.117**
Coefficient on EC term		-0.208		-0.161	**-0.387**
t-value		-1.974		-1.692	**-3.310**
Coefficient on SSM2	0.777			1.012	**0.764**
Std. Deviation	0.131			0.149	**0.093**
Coefficient on EC term	-0.333			-0.147	**-0.400**
t-value	-3.602			-1.676	**-3.395**
Coefficient on DM2	1.005			1.259	**1.000**
Std. Deviation	0.163			0.146	**0.104**
Coefficient on EC term	-0.287			-0.177	**-0.405**
t-value	-3.211			-1.806	**-3.359**
Coefficient on SSM3A	0.765			1.002	**0.756**
Std. Deviation	0.121			0.145	**0.084**
Coefficient on EC term	-0.369			-0.157	**-0.458**
t-value	-3.789			-1.724	**-3.668**
Coefficient on DM3A	0.937			1.240	**0.959**
Std. Deviation	0.140			0.145	**0.084**
Coefficient on EC term	-0.357			-0.174	**-0.508**
t-value	-3.626			-1.708	**-3.809**
Coefficient on SSM2Y			0.842	0.841	**0.678**
Std. Deviation			0.098	0.099	**0.068**
Coefficient on EC term			-0.304	-0.306	**-0.585**
t-value			-3.099	-3.095	**-4.784**
Coefficient on DM2Y		0.860		1.139	**0.898**
Std. Deviation		0.131		0.139	**0.095**
Coefficient on EC term		-0.380		-0.215	**-0.488**
t-value		-3.333		-2.070	**-3.833**
Coefficient on SSM3AY			0.843	0.843	**0.678**
Std. Deviation			0.097	0.098	**0.063**
Coefficient on EC term			-0.303	-0.305	**-0.622**
t-value			-3.048	-3.044	**-4.895**
Coefficient on DM3AY		0.852		1.144	**0.896**
Std. Deviation		0.113		0.132	**0.077**
Coefficient on EC term		-0.468		-0.224	**-0.594**
t-value		-3.826		-2.063	**-4.283**

* The models with bold print are the ones that yield best out-of-sample forecasts. Relevant tables report results obtained from these estimations

Table 4.9: Out-of-Sample Forecast Evaluation of the Bivariate Error Correction Models of Nominal GDP Growth and Annual Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.806	3.816	3.187	3.671	**2.887**	3.654	3.581	4.137	3.300	4.083	3.259	3.673	3.173
MAE	3.361	3.363	2.791	2.923	**2.569**	2.919	2.979	3.208	2.744	3.243	2.842	2.991	2.625
MAPE	22.612	22.432	18.516	19.175	**16.691**	19.114	19.857	20.946	17.925	21.256	18.870	19.669	16.471

Static Forecasts

	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.408	**4.293**	9.281	9.668	10.888	9.940	9.300	6.734	11.094	6.478	3.435	3.123	3.173
MAE	3.675	**3.543**	8.899	9.344	10.530	9.651	8.911	6.169	10.736	5.912	2.949	2.787	2.625
MAPE	25.751	**24.678**	60.213	63.912	69.925	65.579	61.447	43.119	72.744	41.400	20.318	19.269	16.471

4-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	5.001	4.933	4.034	3.937	**3.647**	4.003	4.629	4.466	4.573	5.057	4.403	4.796	8.459
MAE	4.284	4.233	3.384	3.552	**3.082**	3.606	3.914	3.373	3.600	3.715	3.613	3.728	7.175
MAPE	28.685	28.189	22.419	23.495	**20.144**	23.932	25.784	21.810	23.492	24.194	23.822	24.335	47.022

Dynamic Forecasts

	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	5.764	**5.465**	11.133	10.296	13.143	11.036	9.881	9.222	10.906	8.911	5.609	5.436	17.471
MAE	4.251	**4.160**	10.332	9.741	12.413	10.538	8.951	8.594	10.053	8.192	4.239	4.159	17.205
MAPE	33.218	**32.187**	72.417	67.827	85.047	72.751	64.117	60.479	70.574	58.093	32.776	32.043	118.30

Table 4.10: The Cointegrating Relationships between Real GDP Level and Levels of Real Monetary Aggregates Deflated Using CPI

SSM1	Unique CIV for lag 1and 11 for model 3. Model 4 yields unique CIVs at lags 1 and 2. Model 3 at lag 11 has 1 CIV according to MET only. Other CIVs are based on both TT and MET.
DM1	Unique CIV for lag 1 for model 3. Model 4 yields unique CIVs at lags 1 and 2. All CIVs are based on both TT and MET.
SSM2	Unique CIV for lag 1 for model 3 and at lags 1, 2, 4 for model 4. All CIVs are based on both TT and MET.
DM2	Unique CIV for lag 1 for model 3 and at lags 1 and 2 for model 4. All CIVs are based on both TT and MET.
SSM3A	Unique CIV for lag 1 for model 3. Model 4 yields unique CIVs at lags 1, 2, 4, and 5. Model 4 at lag 4 has 1 CIV according to trace statistics only. Other CIVs are based on both TT and MET.
DM3A	Unique CIV at lags 1, 7 for model 3 and at lags 1 and 2 for model 4. All CIVs are based on both TT and MET.
SSM2Y	Unique CIV at lags 1, 2, 4-7 for model3 and at lags lags 1, 2, 4-7, 12 for model 4. At lags 6 and 12 model 4 has 1 CIV according to trace statistics only. All other CIVs are based on both TT and MET.
DM2Y	Unique CIV for lag 1for model 3 and at lags 1, 2, 4 for model 4. All CIVs are based on both TT and MET.
SSM3AY	Unique CIV at lags 1, 2, 4-7 for model 3 and at lags 1, 2, 4-7, 12 for model 4. At lags 6 and 12 model 4 has 1 CIV according to trace statistics only. All other CIVs are based on both TT and MET.
DM3AY	Unique CIV at lags 1, 5-7 for model 3 and at lags lags 1, 2, 5-7 for model 4. For lag 6 model 3 and lag 7 model 4 has 1 CIV according to MET only. The CIV at lag 5 for model 4 exists according to TT only. All other CIVs are based on both TT and MET.

Table 4.11: The Cointegrating Relationships between Real GDP Level and Levels of Real Monetary Aggregates Deflated Using WPI

SSM1	Unique CIV for lag 1 model 3 and at lags 1, 2 for model 4. All CIVs are based on both TT and MET.
DM1	Unique CIV for lag 1 model 3 and at lags 1, 2 for model 4. All CIVs are based on both TT and MET.
SSM2	Unique CIV at lags 1 for models 3 and at lags 1, 2, 4 for model 4. All CIVs are based on both TT and MET.
DM2	Unique CIV at lags 1 for models 3 and at lags 1, 2 for model 4. All CIVs are based on both TT and MET.
SSM3A	Unique CIV at lags 1 for models 3 and at lags 1, 2, 4 for model 4. All CIVs are based on both TT and MET.
DM3A	Unique CIV at lags 1 for models 3 and at lags 1, 2 for model 4. All CIVs are based on both TT and MET.
SSM2Y	Unique CIV at lags 1, 2, 7 for model 3. For model 4 we have Unique CIVs at lags 1, 2, 4, 5, 8, and 12. At lags 6 and 7 model 4 has 2 CIVs. All CIVs are based on both TT and MET.
DM2Y	Unique CIV for lag 1 for model 3 and lags 1, 2, 4 for model 4. All CIVs are based on both TT and MET.
SSM3AY	Unique CIV at lags 1, 2, 7 for model 3. For model 4 we have Unique CIVs at lags 1, 2, 4, 5, 8, and 12. At lags 6 and 7 model 4 has 2 CIVs. The CIV for model 4 at lag 8 exists only according to TT. All other CIVs are based on both TT and MET.
DM3AY	Unique CIV for lag 1 for model 3 and lags 1, 2, 4, 7 for model 4. he CIV for model 4 at lag 7 exists only according to TT. All other CIVs are based on both TT and MET.

Table 4.12: Error Correction Models of Real GDP Level and Levels of Real Monetary Aggregates Deflated Using CPI*

Lag	1	2	4	5	7	7
CI Model	3	3	4	4	3	4
Coefficient on SSM1	**0.223**					
Std. Deviation	**0.203**					
Coefficient on EC term	**-0.518**					
t-value	**-4.689**					
Coefficient on DM1	**0.210**					
Std. Deviation	**0.211**					
Coefficient on EC term	**-0.518**					
t-value	**-4.714**					
Coefficient on SSM2			**0.022**			
Std. Deviation			**0.056**			
Coefficient on EC term			**-0.421**			
t-value			**-3.986**			
Coefficient on DM2	**0.047**					
Std. Deviation	**0.270**					
Coefficient on EC term	**-0.498**					
t-value	**-4.658**					
Coefficient on SSM3A			0.030	**0.051**		
Std. Deviation			0.057	**0.059**		
Coefficient on EC term			-0.414	**-0.385**		
t-value			-3.985	**-3.302**		
Coefficient on DM3A	0.156				**0.034**	
Std. Deviation	0.236				**0.264**	
Coefficient on EC term	-0.526				**-0.056**	
t-value	-4.866				**-1.832**	
Coefficient on SSM2Y		0.487		**0.040**		
Std. Deviation		0.049		**0.075**		
Coefficient on EC term		-0.568		**-0.422**		
t-value		-3.316		**-3.068**		
Coefficient on DM2Y	0.295		**0.028**			
Std. Deviation	0.282		**0.078**			
Coefficient on EC term	-0.507		**-0.386**			
t-value	-4.523		**-3.609**			
Coefficient on SSM3AY		0.487	0.017	**0.074**		
Std. Deviation		0.051	0.082	**0.077**		
Coefficient on EC term		-0.544	-0.409	**-0.383**		
t-value		-3.230	-3.497	**-2.938**		
Coefficient on DM3AY	0.311			**0.096**		0.026
Std. Deviation	0.254			**0.094**		0.125
Coefficient on EC term	-0.536			**-0.256**		-0.128
t-value	-4.781			**-2.611**		-1.846

* The models with bold print are the ones that yield best out-of-sample forecasts. Relevant tables report results obtained from these estimations.

Table 4.13: Error Correction Models of Real GDP Level and Levels of Real Monetary Aggregates Deflated Using WPI*

Lag	1	2	4
CI Model	3	3	4
Coefficient on SSM1	**0.565**		
Std. Deviation	**0.125**		
Coefficient on EC term	**-0.727**		
t-value	**-5.577**		
Coefficient on DM1	**0.590**		
Std. Deviation	**0.126**		
Coefficient on EC term	**-0.746**		
t-value	**-5.665**		
Coefficient on SSM2			**0.019**
Std. Deviation			**0.053**
Coefficient on EC term			**-0.485**
t-value			**-3.856**
Coefficient on DM2	**0.669**		
Std. Deviation	**0.180**		
Coefficient on EC term	**-0.653**		
t-value	**-5.074**		
Coefficient on SSM3A			**0.027**
Std. Deviation			**0.053**
Coefficient on EC term			**-0.479**
t-value			**-3.822**
Coefficient on DM3A	**0.672**		
Std. Deviation	**0.145**		
Coefficient on EC term	**-0.739**		
t-value	**-5.597**		
Coefficient on SSM2Y		**0.404**	
Std. Deviation		**0.038**	
Coefficient on EC term		**-0.526**	
t-value		**-2.947**	
Coefficient on DM2Y	0.759		**0.054**
Std. Deviation	0.138		**0.076**
Coefficient on EC term	-0.770		**-0.435**
t-value	-5.582		**-3.397**
Coefficient on SSM3AY		**0.406**	
Std. Deviation		**0.038**	
Coefficient on EC term		**-0.522**	
t-value		**-2.930**	
Coefficient on DM3AY	0.757		**0.094**
Std. Deviation	0.123		**0.077**
Coefficient on EC term	-0.836		**-0.422**
t-value	-6.003		**-3.292**

* The models with bold print are the ones that yield best out-of-sample forecasts. Relevant tables report results obtained from these estimations.

Table 4.14: Out-of-Sample Forecast Evaluation of the Bivariate Error Correction Models of Real GDP Level and Real Money Level Deflated Using CPI

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.287	0.290	0.254	0.046	0.032	**0.030**	0.037	0.042	0.032	0.041	0.113	0.074	0.078
MAE	0.238	0.242	0.199	0.035	0.029	**0.025**	0.028	0.029	0.028	0.028	0.096	0.064	0.074
MAPE	2.252	2.288	1.879	0.333	0.278	**0.240**	0.273	0.277	0.265	0.272	0.905	0.604	0.702

Static Forecasts

	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.207	0.205	0.228	0.029	**0.026**	0.028	0.030	0.036	0.030	0.036	0.090	0.054	0.078
MAE	0.161	0.160	0.177	0.024	**0.021**	0.023	0.026	0.030	0.026	0.029	0.072	0.045	0.074
MAPE	1.521	1.511	1.676	0.231	**0.201**	0.222	0.246	0.282	0.243	0.274	0.684	0.424	0.702

4-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.311	0.315	0.267	0.051	0.033	**0.030**	0.040	0.044	0.032	0.043	0.123	0.082	0.078
MAE	0.272	0.277	0.221	0.041	0.030	**0.025**	0.030	0.029	0.027	0.028	0.109	0.074	0.074
MAPE	2.574	2.624	2.088	0.389	0.286	**0.237**	0.284	0.276	0.259	0.269	1.028	0.702	0.702

Dynamic Forecasts

	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.347	0.343	0.380	0.071	**0.061**	0.074	0.072	0.078	0.079	0.071	0.179	0.121	0.169
MAE	0.311	0.307	0.342	0.063	**0.054**	0.065	0.064	0.070	0.069	0.063	0.167	0.114	0.157
MAPE	2.945	2.904	3.240	0.601	**0.512**	0.621	0.611	0.664	0.661	0.601	1.579	1.084	1.495

Table 4.15: Out-of-Sample Forecast Evaluation of the Bivariate Error Correction Models of Real GDP Level and Real Money Level Deflated Using WPI

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.307	0.307	0.302	0.045	0.300	0.043	0.037	0.229	**0.034**	0.229	0.190	0.162	0.078
MAE	0.257	0.257	0.251	0.034	0.248	0.034	0.027	0.189	**0.027**	0.192	0.161	0.134	0.074
MAPE	2.437	2.428	2.377	0.326	2.344	0.322	0.262	1.792	**0.254**	1.815	1.524	1.267	0.702

Static Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.150	0.151	0.175	0.030	0.158	0.029	0.029	0.100	**0.028**	0.099	0.097	0.068	0.078
MAE	0.128	0.128	0.146	0.025	0.134	0.025	0.025	0.078	**0.024**	0.076	0.083	0.053	0.074
MAPE	1.210	1.213	1.382	0.240	1.273	0.236	0.236	0.736	**0.231**	0.724	0.788	0.503	0.702

4-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.342	0.341	0.332	0.050	0.331	0.048	0.040	0.233	**0.037**	0.233	0.211	0.173	0.078
MAE	0.305	0.304	0.293	0.040	0.291	0.040	0.031	0.192	**0.030**	0.193	0.189	0.146	0.074
MAPE	2.893	2.881	2.774	0.385	2.753	0.380	0.297	1.812	**0.287**	1.828	1.794	1.382	0.702

Dynamic Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	**DM2Y**	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.230	0.232	0.308	0.0637	0.276	0.0639	**0.0644**	0.127	0.066	0.126	0.181	0.114	0.169
MAE	0.190	0.192	0.275	0.0570	0.239	0.0570	**0.0570**	0.111	0.058	0.111	0.162	0.103	0.157
MAPE	1.794	1.808	2.606	0.5435	2.258	0.5429	**0.5431**	1.055	0.554	1.047	1.537	0.979	1.495

Table 4.16: The Cointegrating Relationships between Annual CPI-Inflation, Annual Growth Rates of Nominal Monetary Aggregates and Annual Growth Rates of Cost Variables

NO MONEY[2]	Unique CIV at lags 2, 12-17, and 21 for model 4; at lags 6, 12, 16 for model 3; at lags 6, 10, 11 for model 2. Model 2 CIVs at lags 12 and 16, model 3 CIV at lag 16, and model 4 CIVs at lags 16, 17 and 21 exist only based on TT. Model 2 and 3 CIVs at lag 6, and model 4 CIV at lag 2 are based on MET only. Model 3 has one CIV at lag 12 and model 4 at lags 12-16 according to both TT and MET.
SSM1	Unique CIV at all lags 13-17, 21 and two CIVs at lag 12. At lags 16, 17, 21 CIVs exist according to TT only. All other CIVs are based on both TT and MET.
DM1	Unique CIV at all lags 13-17, 21 and two CIVs at lag 12. At lags 16 and 17 CIVs exist according to TT only. All other CIVs are based on both TT and MET.
SSM2	Unique CIV at all lags 12 to 16 based on both TT and MET.
DM2	Unique CIV at all lags 12 to 16 based on both TT and MET.
SSM3A	Unique CIV at all lags 12 to 16 based on both TT and MET.
DM3A	Unique CIV at all lags 12 to 16 based on both TT and MET.
SSM2Y	Unique CIV at all lags 12 to 15 based on both TT and MET. Two CIVs exist at lag 16 according to TT. MET finds unique CIV at lag 16 too.
DM2Y	Unique CIV at all lags 12 to 16 based on both TT and MET.
SSM3AY	Unique CIV at all lags 12 to 15 based on both TT and MET. Two CIVs exist at lag 16 according to TT. MET finds unique CIV at lag 16 too.
DM3AY	Unique CIV at all lags 12 to 16 based on both TT and MET.

[2] For only model 4 cointegration relationships work well in error-correction models without money, for systems involving money we only check on the model 4 cointegrating vectors.

Table 4.17: The Estimated Error-Correction Models between Annual CPI-Inflation, Annual Growth Rates of Nominal Monetary Aggregates and Annual Growth Rates of Cost Variables*

LAG	CPI-inflation		BASE	TBILL	GASPR.	NOMER	Trend	Cons.	ECTERM
12	coefficient		None	0.143	0.089	0.429	-0.096	24.402	-0.220
	t-value			4.552	1.880	6.624	-9.951		-5.372
13	coefficient		None	0.113	0.018	0.525	-0.104	27.421	-0.188
	t-value			2.809	0.305	6.266	-8.555		-4.955
14	coefficient		None	0.141	0.123	0.410	-0.094	23.393	-0.222
	t-value			4.178	2.370	5.713	-9.266		-4.275
15	**coefficient**		**None**	**0.139**	**0.169**	**0.396**	**-0.086**	**20.946**	**-0.213**
	t-value			**4.332**	**3.389**	**5.746**	**-9.052**		**-3.774**
16	coefficient		None	0.126	0.173	0.416	-0.085	20.868	-0.203
	t-value			3.677	3.206	5.598	-8.386		-3.408
			SSM1						
12	coefficient		0.030	0.140	0.073	0.427	-0.101	24.711	-0.265
	t-value		0.359	4.321	1.524	7.603	-11.887		-6.089
13	coefficient		0.124	0.101	-0.003	0.494	-0.107	25.121	-0.235
	t-value		1.263	2.683	-0.054	7.547	-11.089		-5.526
14	coefficient		0.263	0.091	0.006	0.431	-0.102	20.722	-0.257
	t-value		2.985	2.743	0.124	7.267	-11.998		-4.867
15	**coefficient**		**0.268**	**0.103**	**0.051**	**0.381**	**-0.096**	**18.575**	**-0.257**
	t-value		**3.214**	**3.309**	**1.070**	**6.814**	**-12.121**		**-3.996**
16	coefficient		0.227	0.092	0.089	0.402	-0.090	17.924	-0.229
	t-value		2.530	2.815	1.732	6.769	-10.728		-3.194
			DM1						
12	coefficient		0.033	0.139	0.074	0.427	-0.100	24.448	-0.267
	t-value		0.378	4.186	1.559	7.659	-11.922		-6.057
13	coefficient		0.139	0.096	-0.002	0.495	-0.104	24.342	-0.238
	t-value		1.343	2.508	-0.037	7.601	-11.002		-5.468
14	coefficient		0.300	0.079	-0.008	0.449	-0.099	19.594	-0.247
	t-value		3.143	2.252	-0.147	7.417	-11.595		-4.736
15	**coefficient**		**0.308**	**0.090**	**0.036**	**0.398**	**-0.094**	**17.492**	**-0.249**
	t-value		**3.399**	**2.758**	**0.724**	**6.961**	**-11.781**		**-3.912**
16	coefficient		0.255	0.079	0.066	0.430	-0.089	17.490	-0.234
	t-value		2.584	2.281	1.231	7.026	-10.503		-3.334
			SSM2						
12	coefficient		0.237	0.045	-0.023	0.497	-0.096	23.044	-0.283
	t-value		3.958	1.250	-0.489	8.819	-12.088		-6.097
13	coefficient		0.244	0.030	-0.016	0.515	-0.095	22.590	-0.297
	t-value		4.389	0.891	-0.356	9.603	-12.968		-5.787
14	coefficient		0.258	0.018	0.037	0.495	-0.087	20.052	-0.279
	t-value		5.263	0.595	0.928	10.053	-13.488		-4.567
15	**coefficient**		**0.233**	**0.038**	**0.049**	**0.470**	**-0.089**	**20.413**	**-0.294**
	t-value		**4.552**	**1.166**	**1.154**	**8.954**	**-13.309**		**-4.073**
16	coefficient		0.246	0.011	0.038	0.517	-0.087	20.224	-0.293
	t-value		4.718	0.345	0.861	9.522	-12.683		-3.951

LAG	CPI-inflation		BASE	TBILL	GASPR.	NOMER	Trend	Cons.	ECTERM
			DM2						
12	coefficient		0.253	0.059	0.010	0.483	-0.090	20.224	-0.318
	t-value		3.995	1.804	0.246	9.442	-12.582		-6.280
13	coefficient		0.288	0.033	-0.014	0.526	-0.089	19.968	-0.301
	t-value		4.317	0.961	-0.339	9.662	-12.197		-5.589
14	coefficient		0.322	0.030	0.020	0.495	-0.083	17.312	-0.313
	t-value		5.749	1.041	0.540	10.561	-13.584		-4.749
15	**coefficient**		**0.326**	**0.032**	**0.042**	**0.481**	**-0.079**	**15.965**	**-0.306**
	t-value		**6.304**	**1.179**	**1.239**	**10.962**	**-14.206**		**-4.023**
16	coefficient		0.340	0.013	0.036	0.513	-0.076	15.476	-0.318
	t-value		6.795	0.496	1.089	11.969	-14.362		-3.837
			SSM3A						
12	coefficient		0.247	0.034	-0.023	0.505	-0.097	23.151	-0.272
	t-value		3.728	0.884	-0.487	8.685	-11.842		-5.946
13	coefficient		0.262	0.023	-0.018	0.511	-0.096	22.699	-0.296
	t-value		4.389	0.644	-0.417	9.510	-13.174		-5.807
14	coefficient		0.276	0.008	0.039	0.493	-0.088	20.007	-0.269
	t-value		5.245	0.254	0.974	10.014	-13.655		-4.420
15	**coefficient**		**0.257**	**0.025**	**0.043**	**0.475**	**-0.088**	**20.274**	**-0.288**
	t-value		**4.609**	**0.717**	**1.011**	**8.912**	**-13.178**		**-3.987**
16	coefficient		0.268	-0.005	0.027	0.533	-0.087	20.367	-0.276
	t-value		4.458	-0.137	0.581	9.106	-11.909		-3.789
			DM3A						
12	coefficient		0.217	0.056	0.027	0.490	-0.094	21.396	-0.293
	t-value		2.919	1.429	0.627	8.591	-12.360		-5.991
13	coefficient		0.276	0.026	0.005	0.522	-0.093	20.763	-0.290
	t-value		3.618	0.635	0.104	8.863	-12.398		-5.518
14	coefficient		0.323	0.014	0.038	0.499	-0.087	18.070	-0.297
	t-value		4.860	0.390	0.964	9.549	-13.555		-4.749
15	**coefficient**		**0.325**	**0.011**	**0.053**	**0.501**	**-0.082**	**16.663**	**-0.292**
	t-value		**5.189**	**0.317**	**1.434**	**10.093**	**-13.790**		**-4.099**
16	coefficient		0.357	-0.023	0.030	0.561	-0.078	16.027	-0.261
	t-value		5.297	-0.627	0.756	10.405	-12.377		-3.525
			SSM2Y						
12	coefficient		0.299	0.082	0.012	0.309	-0.093	22.080	-0.305
	t-value		3.834	2.534	0.278	5.785	-12.088		-6.413
13	coefficient		0.318	0.080	0.004	0.300	-0.094	22.195	-0.341
	t-value		4.362	2.639	0.090	5.961	-13.297		-6.429
14	coefficient		0.314	0.080	0.042	0.283	-0.090	20.679	-0.366
	t-value		4.881	2.946	1.107	6.233	-14.432		-5.719
15	**coefficient**		**0.303**	**0.091**	**0.070**	**0.254**	**-0.089**	**20.064**	**-0.350**
	t-value		**5.083**	**3.580**	**1.929**	**5.955**	**-15.468**		**-4.745**
16	coefficient		0.310	0.090	0.062	0.255	-0.090	20.097	-0.404
	t-value		5.516	3.736	1.789	6.234	-16.242		-4.841

LAG	CPI-inflation		BASE	TBILL	GASPR.	NOMER	Trend	Cons.	ECTERM
			DM2Y						
12	coefficient		0.267	0.076	0.012	0.421	-0.092	20.817	-0.345
	t-value		4.670	2.751	0.326	9.616	-14.317		-6.440
13	coefficient		0.290	0.061	-0.008	0.448	-0.093	20.949	-0.344
	t-value		4.994	2.166	-0.216	10.007	-14.587		-5.934
14	coefficient		0.296	0.062	0.029	0.422	-0.088	19.156	-0.372
	t-value		6.089	2.622	0.890	10.959	-16.640		-5.240
15	**coefficient**		**0.301**	**0.066**	**0.047**	**0.402**	**-0.085**	**18.141**	**-0.381**
	t-value		**6.902**	**3.074**	**1.578**	**11.390**	**-18.019**		**-4.542**
16	coefficient		0.304	0.055	0.051	0.421	-0.083	17.674	-0.392
	t-value		7.157	2.628	1.724	12.144	-18.027		-4.156
			SSM3AY						
12	coefficient		0.311	0.073	0.008	0.316	-0.094	22.337	-0.294
	t-value		3.690	2.085	0.169	5.737	-11.830		-6.222
13	coefficient		0.333	0.072	0.005	0.297	-0.095	22.245	-0.335
	t-value		4.343	2.263	0.113	5.890	-13.336		-6.345
14	coefficient		0.329	0.072	0.049	0.276	-0.090	20.497	-0.367
	t-value		5.056	2.647	1.308	6.307	-14.929		-5.716
15	**coefficient**		**0.319**	**0.082**	**0.072**	**0.253**	**-0.089**	**19.916**	**-0.345**
	t-value		**5.108**	**3.076**	**1.988**	**5.965**	**-15.452**		**-4.622**
16	coefficient		0.314	0.089	0.067	0.246	-0.091	20.326	-0.396
	t-value		5.164	3.440	1.862	5.893	-16.041		-4.662
			DM3AY						
12	coefficient		0.262	0.057	0.021	0.449	-0.094	21.205	-0.318
	t-value		3.854	1.694	0.518	9.262	-13.734		-6.144
13	coefficient		0.300	0.039	0.006	0.464	-0.094	20.977	-0.328
	t-value		4.492	1.183	0.150	9.688	-14.498		-5.784
14	coefficient		0.318	0.036	0.040	0.439	-0.090	19.138	-0.351
	t-value		5.599	1.270	1.166	10.595	-16.494		-5.158
15	**coefficient**		**0.316**	**0.038**	**0.054**	**0.432**	**-0.086**	**18.191**	**-0.363**
	t-value		**5.883**	**1.413**	**1.661**	**10.925**	**-17.036**		**-4.541**
16	coefficient		0.318	0.022	0.050	0.466	-0.083	17.895	-0.343
	t-value		5.520	0.771	1.411	10.874	-15.433		-3.911

* The models with bold print are the ones that yield best out-of-sample forecasts. Relevant tables report results obtained from these estimations.

Table 4.18: Out-of-Sample Forecast Evaluation of the Multivariate Error Correction Models of Annual CPI-Inflation, Annual Growth Rates of Nominal Monetary Aggregates and Annual Growth Rates of Cost Variables

1-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	**SSM3AY**	DAVG	SSAVG	NCF
RMSE	**1.268**	1.452	1.448	1.686	1.660	1.623	1.673	1.680	1.289	1.650	**1.260**	1.400	1.579	0.681
MAE	**1.204**	1.271	1.284	1.523	1.713	1.373	1.589	1.504	1.138	1.344	**1.070**	1.182	1.310	0.508
MAPE	**12.869**	14.810	14.756	17.471	17.542	16.131	17.321	17.514	13.548	15.912	**13.145**	14.630	16.171	5.867

Static Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	**SSM3AY**	DAVG	SSAVG	NCF
RMSE	0.953	1.091	1.061	1.032	0.945	1.048	0.985	0.996	0.792	1.027	**0.775**	1.060	1.045	0.681
MAE	0.777	0.817	0.799	0.807	0.751	0.814	0.780	0.773	0.619	0.788	**0.616**	0.838	0.799	0.508
MAPE	9.472	10.061	9.849	9.876	9.179	9.963	9.577	9.418	7.494	9.592	**7.430**	10.357	9.913	5.867

12-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	**SSM3AY**	DAVG	SSAVG	NCF
RMSE	**1.421**	1.614	1.622	1.875	2.100	1.798	2.009	1.841	1.519	1.805	**1.455**	1.610	1.644	7.258
MAE	**1.374**	1.436	1.454	1.729	2.352	1.605	2.046	1.600	1.484	1.526	**1.387**	1.311	1.378	11.497
MAPE	**14.803**	16.505	16.558	19.095	20.910	17.688	20.012	18.483	15.977	17.321	**15.495**	16.335	17.145	57.619

Dynamic Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.541	3.417	3.307	2.886	2.109	3.676	1.943	2.095	5.123	**1.957**	4.491	2.029	2.096	3.677
MAE	2.906	2.755	2.671	2.009	1.780	2.833	1.582	1.837	4.304	**1.590**	3.752	1.525	1.779	3.541
MAPE	36.156	34.193	33.132	25.211	21.142	35.040	19.390	21.653	49.721	**19.215**	43.355	19.017	21.875	43.933

Table 4.19: Out-of-Sample Forecast Evaluation of the Real GDP Growth Rates Computed from Real GDP Level Forecasts Compared to Forecasts Obtained Directly from Growth Rates

	Real GDP Level	**Real GDP Growth**	**Real GDP Growth**	**Real GDP Growth**
	ECM	**COMPUTED**	**VAR**	**ARMA**
1-Step:	SSM3A/CPI	SSM3A/CPI	SSM2Y/WPI	SSM2Y/WPI
RMSE	0.030	4.672	3.452	3.139
MAE:	0.025	3.793	2.641	2.602
MAPE:	0.240	60.486	36.033	38.112
Static:	DM3A/CPI	DM3A/CPI	SSM2Y/NOM	DM3AY/WPI
RMSE	0.026	3.536	2.817	3.327
MAE:	0.021	2.591	2.047	2.764
MAPE:	0.201	40.2255	29.517	40.702
12-Step:	SSM3A/CPI	SSM3A/CPI	SSM2Y/WPI	SSM3A/WPI
RMSE	0.030	4.639	3.338	5.719
MAE:	0.025	3.906	2.555	4.689
MAPE:	0.237	62.805	33.291	58.450
Dynamic:	DM3A/CPI	DM3A/CPI	SSM2Y/NOM	DM3AY/CPI
RMSE	0.061	3.840	3.135	1.919
MAE:	0.054	2.566	2.408	1.626
MAPE:	0.512	36.048	28.379	25.366

Table 4.20: Out-of-Sample Forecast Evaluation of Monthly Inflation Rates Computed from Annual Inflation Forecasts Compared to Forecasts Obtained Directly from Monthly Data

CPI-INFLATION

	Annual Inf. Forecasts		**Computed Forecasts**			VAR Forecasts		ARMA Forecasts	
	Static	Dynamic	**Static**	**Dynamic**		Static	Dynamic	Static	Dynamic
	SSM2Y	SSM3AY	**SSM2Y**	**SSM3AY**		SSM1	SSM1	SSM3AY	DM3AY
RMSE	0.649	1.651	**0.737**	**0.459**		0.609	0.830	0.733	0.941
MAE	0.491	1.117	**0.688**	**0.381**		0.460	0.672	0.597	0.824
MAPE	5.778	13.632	**111.54**	**64.012**		202.34	393.37	103.89	159.18

WPI-INFLATION

	Annual Inf. Forecasts		**Computed Forecasts**			VAR Forecasts		ARMA Forecasts	
	Static	Dynamic	**Static**	**Dynamic**		Static	Dynamic	Static	Dynamic
	DM2Y	SSM2Y	**DM2Y**	**SSM2Y**		SSM1	DM2Y	DM2Y	SSM2Y
RMSE	1.507	3.435	**1.475**	**1.399**		1.226	1.530	1.529	1.617
MAE	1.134	2.822	**1.399**	**1.224**		1.038	1.349	1.200	1.373
MAPE	13.840	39.755	**248.07**	**164.96**		245.64	451.45	219.42	408.73

Table 4.21: Optimal Lag Lengths for VARs Including Consumer and Producer Prices Inflation and Money Chosen out of 23 Maximum Lags

	Consumer Prices Inflation						**Producer Prices Inflation**				
	LR	FPE	AIC	SC	HQ		LR	FPE	AIC	SC	HQ
SSM1M	23	23	23	12	12		19	12	12	1	12
DM1M	23	23	23	12	12		21	12	12	1	12
SSM2M	21	14	14	12	12		12	13	13	2	12
DM2M	23	14	14	12	12		21	12	12	1	12
SSM3AM	23	14	14	3	12		13	14	14	2	4
DM3AM	23	14	14	1	12		12	12	12	1	12
SSM2YM	16	14	14	2	12		19	12	12	2	4
DM2YM	21	12	12	12	12		12	12	12	1	12
SSM3AYM	16	12	12	2	12		16	12	12	2	4
DM3AYM	23	13	13	6	12		12	12	12	1	12

Table 4.22: Out-of-Sample Forecast Evaluation of VAR Model of Monthly CPI-Inflation and Monthly Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.528	0.531	0.582	0.622	**0.650**	0.643	0.628	0.801	0.679	0.785	0.928	0.898	0.751
MAE	0.501	0.509	0.543	0.610	**0.554**	0.637	0.598	0.806	0.607	0.754	0.734	0.707	0.601
MAPE	229.5	222.2	248.0	267.4	**205.2**	278.8	263.2	297.0	203.3	286.7	164.262	151.188	215.6

Static Forecasts

	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.624	**0.609**	0.716	0.658	0.724	0.668	0.709	0.649	0.733	0.659	1.535	1.325	0.751
MAE	0.477	**0.460**	0.561	0.508	0.610	0.523	0.551	0.507	0.627	0.522	1.234	1.043	0.601
MAPE	204.0	**202.3**	268.1	251.7	206.4	239.1	280.1	217.9	217.5	204.2	434.313	335.015	215.6

12-Period-Ahead Sequential Forecasts

	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.695	**0.695**	0.773	0.843	0.837	0.845	0.826	1.082	0.882	1.070	0.730	0.567	1.225
MAE	0.812	**0.785**	0.904	0.984	0.918	0.959	0.970	1.273	0.995	1.282	0.606	0.462	0.919
MAPE	294.2	**275.4**	313.0	352.8	262.0	360.5	333.3	398.3	265.1	388.0	126.082	137.434	163.2

Dynamic Forecasts

	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	0.855	**0.830**	0.890	0.840	0.906	0.835	0.876	1.000	0.895	1.005	0.760	0.556	0.670
MAE	0.690	**0.672**	0.723	0.685	0.730	0.676	0.722	0.851	0.724	0.852	0.634	0.453	0.513
MAPE	411.5	**393.4**	422.1	414.2	449.0	419.7	415.4	501.4	446.0	508.0	213.646	105.369	138.4

Table 4.23: Out-of-Sample Forecast Evaluation of VAR Model of Monthly WPI-Inflation and Monthly Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.725	1.700	1.771	1.850	1.770	1.881	1.788	1.819	**1.769**	1.815	1.496	1.525	1.366
MAE	1.783	1.752	1.845	1.859	1.833	1.840	1.868	1.837	**1.854**	1.829	1.288	1.304	1.086
MAPE	362.4	358.7	366.9	372.4	341.1	366.0	363.4	424.9	**347.7**	415.0	292.4	323.5	226.6

Static Forecasts

	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.229	**1.226**	1.295	1.301	1.293	1.311	1.321	1.289	1.333	1.288	1.274	1.259	1.366
MAE	1.043	**1.038**	1.106	1.105	1.097	1.126	1.118	1.074	1.124	1.060	1.093	1.060	1.086
MAPE	253.7	**245.6**	285.7	289.2	282.6	300.1	291.5	305.1	297.6	308.7	281.1	288.0	226.6

12-Period-Ahead Sequential Forecasts

	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.858	**1.837**	1.902	2.019	1.904	2.042	1.918	2.038	1.904	2.033	1.677	1.754	1.638
MAE	2.075	**2.046**	2.139	2.229	2.145	2.215	2.147	2.190	2.149	2.207	1.457	1.499	1.254
MAPE	429.6	**426.5**	430.0	444.7	409.5	439.9	426.7	510.8	416.1	501.0	362.8	407.9	219.1

Dynamic Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	**DM2Y**	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.642	1.633	1.550	1.641	1.560	1.638	**1.530**	1.780	1.529	1.791	1.559	1.691	1.254
MAE	1.444	1.438	1.368	1.423	1.371	1.421	**1.349**	1.537	1.332	1.549	1.368	1.473	0.986
MAPE	495.4	483.9	452.7	480.3	473.9	492.3	**451.5**	543.9	464.4	554.2	467.2	510.9	210.8

Table 4.24: Comparison of Out-of-Sample Forecast Performances of Bivariate VAR Models of Monthly WPI-Inflation Using Samples 1986-2006 and 1986-2002*

	STATIC FORECASTS				**DYNAMIC FORECASTS**			
	DM3AY **(86-06)**	DM3AY **(86-02)**	SSM3AY **(86-06)**	SSM3AY **(86-02)**	DM3AY **(86-06)**	DM3AY **(86-02)**	SSM3AY **(86-06)**	SSM3AY **(86-02)**
RMSE	1.333	1.657	1.288	1.556	1.529	2.086	1.791	1.969
MAE	1.124	1.296	1.060	1.102	1.332	1.689	1.549	1.624
MAPE	297.58	65.719	308.65	56.402	464.41	103.75	554.19	94.113

* Do not compare RMSE and MAE in these forecasts as the forecasted values are pretty different in these two sample periods.

Table 4.25: Optimal Lag Lengths for VARs Including Real GDP Growth and Different Measures of Money Growth Chosen out of 17 Maximum Lags*

Nominal						CPI-deflated						WPI-deflated					
	LR	FPE	AIC	SC	HQ		LR	FPE	AIC	SC	HQ		LR	FPE	AIC	SC	HQ
SSM1	5	5	5	1	5	SSM1	14	5	5	1	5	SSM1	14	5	5	1	5
DM1	5	5	5	1	5	DM1	14	5	5	1	5	DM1	14	5	5	1	5
SSM2	5	5	5	1	5	SSM2	5	5	5	1	1	SSM2	5	5	5	1	5
DM2	7	5	5	1	5	DM2	5	7	7	1	5	DM2	16	5	5	1	5
SSM3A	5	5	5	1	5	SSM3A	5	5	5	1	1	SSM3A	5	5	5	1	5
DM3A	7	7	7	1	5	DM3A	8	8	8	1	**8**	DM3A	5	5	5	1	5
SSM2Y	5	5	5	1	5	SSM2Y	12	5	5	1	1	SSM2Y	5	5	15	1	5
DM2Y	5	5	5	1	5	DM2Y	8	8	8	2	5	DM2Y	5	5	5	1	5
SSM3AY	5	5	5	1	5	SSM3AY	12	5	5	1	1	SSM3AY	5	5	15	1	5
DM3AY	16	5	8	1	5	DM3AY	8	8	8	1	**8**	DM3AY	5	5	5	5	5

* Quarterly growth rates of nominal and real money deflated using CPI,
year-on-year growth rates of real money deflated using WPI

Table 4.26: Out-of-Sample Forecast Evaluation of VAR Models of Real GDP Growth and Quarterly Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.631	3.614	3.893	3.687	4.099	3.690	3.895	**3.672**	4.088	3.722	3.901	3.586	3.290
MAE	3.087	3.079	3.352	3.083	3.586	3.127	3.263	**2.651**	3.501	2.780	3.358	2.944	2.459
MAPE	48.568	48.459	51.598	46.058	56.345	47.062	51.384	**37.755**	56.073	39.943	52.793	43.855	37.286

Static Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.138	3.131	3.270	3.176	3.440	3.166	3.312	**2.817**	3.457	2.884	3.310	2.966	3.290
MAE	2.678	2.676	2.829	2.673	3.018	2.695	2.776	**2.047**	2.954	2.159	2.851	2.450	2.459
MAPE	42.230	42.203	43.779	40.073	47.636	40.788	43.741	**29.517**	47.290	31.451	44.935	36.806	37.286

4-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.659	3.634	4.049	3.810	4.258	3.830	4.001	**3.926**	4.201	3.981	3.586	4.013	4.426
MAE	3.175	3.157	3.508	3.170	3.766	3.221	3.457	**2.844**	3.702	2.961	2.944	3.508	3.400
MAPE	48.313	48.156	51.772	45.264	56.796	46.382	51.506	**36.650**	56.276	38.697	43.855	52.758	47.323

Dynamic Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.090	3.166	3.215	3.459	3.153	3.432	2.977	**3.135**	2.970	3.141	3.066	3.204	2.924
MAE	2.604	2.673	2.687	2.780	2.654	2.776	2.523	**2.408**	2.510	2.415	2.562	2.572	1.990
MAPE	35.038	36.274	34.397	33.377	34.061	33.483	33.132	**28.379**	32.766	28.497	33.279	31.344	22.483

Table 4.27: Out-of-Sample Forecast Evaluation of VAR Models of Real GDP Growth and Quarterly Growth Rates of Real Monetary Aggregates Deflated Using CPI

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.387	3.407	3.321	3.316	3.323	**3.258**	3.399	3.500	3.415	3.490	3.350	3.350	3.290
MAE	2.942	2.970	2.873	2.756	2.892	**2.700**	2.973	2.890	2.939	2.902	2.907	2.844	2.459
MAPE	45.924	46.364	45.336	42.240	46.631	**41.893**	46.592	41.870	47.616	42.285	46.294	42.930	37.286

Static Forecasts

	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	2.973	2.986	2.974	2.999	**2.689**	2.966	3.042	3.050	2.786	3.067	2.828	2.974	3.290
MAE	2.568	2.588	2.568	2.480	**2.359**	2.452	2.640	2.545	2.446	2.572	2.482	2.527	2.459
MAPE	40.481	40.793	40.273	37.768	**36.700**	37.755	41.184	36.843	37.629	37.449	38.620	38.122	37.286

4-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.326	3.349	3.198	3.213	3.155	**3.140**	3.300	3.505	3.262	3.475	3.223	3.298	4.426
MAE	2.948	2.972	2.830	2.712	2.744	**2.659**	2.924	2.871	2.853	2.859	2.860	2.811	3.400
MAPE	44.211	44.688	43.149	39.818	43.615	**39.558**	44.628	40.228	45.164	40.362	44.153	40.879	47.323

Dynamic Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.414	3.489	3.166	3.255	3.331	**3.214**	3.202	3.526	3.474	3.495	3.245	3.323	2.924
MAE	2.925	2.978	2.623	2.595	2.805	**2.578**	2.688	2.887	2.964	2.862	2.752	2.765	1.990
MAPE	39.622	40.616	33.735	31.470	37.644	**31.583**	34.464	35.045	40.150	34.735	36.089	34.389	22.483

Table 4.28: Out-of-Sample Forecast Evaluation of VAR Models of Real GDP Growth and Annual Growth Rates of Real Monetary Aggregates Deflated Using WPI

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.896	3.891	3.662	3.538	3.634	3.523	3.712	**3.452**	3.700	3.443	3.699	3.485	3.290
MAE	3.306	3.284	3.060	2.856	3.034	2.829	3.035	**2.641**	3.063	2.654	3.100	2.805	2.459
MAPE	47.061	46.890	43.341	41.160	43.771	41.143	42.728	**36.033**	43.752	36.494	44.131	39.616	37.286

Static Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.254	3.282	3.199	3.156	3.199	3.149	3.274	**3.062**	3.286	3.067	3.229	3.080	3.290
MAE	2.786	2.791	2.673	2.551	2.673	2.534	2.686	**2.353**	2.727	2.376	2.709	2.478	2.459
MAPE	40.430	40.542	38.042	36.693	38.580	36.745	38.033	**32.173**	38.986	32.732	38.814	35.071	37.286

4-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.002	3.982	3.658	3.488	3.598	3.474	3.721	**3.338**	3.686	3.341	3.707	3.433	4.426
MAE	3.371	3.375	2.993	2.787	2.978	2.771	3.029	**2.555**	2.993	2.582	3.038	2.750	3.400
MAPE	46.737	47.011	40.954	38.693	41.552	38.845	41.814	**33.291**	41.361	33.968	41.814	37.252	47.323

Dynamic Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.747	3.791	3.652	3.781	3.605	3.793	3.779	**3.303**	3.742	3.327	3.677	3.481	2.924
MAE	3.138	3.182	2.963	2.972	2.874	2.958	3.126	**2.605**	3.053	2.626	3.028	2.681	1.990
MAPE	39.294	40.114	35.858	35.445	34.616	35.184	38.774	**32.328**	37.487	32.391	37.148	31.773	22.483

TABLE APPENDIXES TO CHAPTER 5

Table 5.1: Choosing the Best ARMA-ARCH Model of Monthly Inflation

CPI	ARMA (0,0)	ARMA (1,0)	ARMA (0,1)	ARMA (1,1)	ARMA (2,0)	ARMA (0,2)	ARMA (2,1)	ARMA (1,2)	**ARMA (2,2)**	**+ARCH**
$\overline{R}^2$	0.389	0.662	0.559	0.714	0.686	0.630	0.665	0.719	0.706	0.704
AIC	4.289	3.702	3.967	3.541	3.634	3.796	3.707	3.526	3.410	3.392
SIC	4.500	3.927	4.191	3.781	3.874	4.035	3.976	3.779	3.707	3.703

WPI	ARMA (0,0)	ARMA (1,0)	ARMA (0,1)	ARMA (1,1)	ARMA (2,0)	ARMA (0,2)	ARMA (2,1)	**ARMA (1,2)**	ARMA (2,2)	**+ARCH**
$\overline{R}^2$	0.422	0.642	0.554	0.661	0.663	0.642	0.663	0.667	0.662	0.604
AIC	4.449	3.976	4.195	3.927	3.922	3.977	3.926	3.913	3.933	3.582
SIC	4.667	4.208	4.426	4.172	4.168	4.222	4.186	4.172	4.207	3.869

Table 5.2: Comparison of In-Sample Fits of ARMA-ARCH Models of Monthly Inflation with Monthly Growth Rates of Nominal Monetary Aggregates Using Information Criteria

CPI	DM1	SSM1	DM2	SSM2	DM2Y	SSM2Y	DM3A	SSM3A	DM3AY	SSM3AY
$\overline{R}^2$	0.610	0.588	0.588	0.609	0.637	0.636	0.619	0.597	0.623	0.632
AIC	3.420	3.419	3.281	3.362	3.313	3.284	3.279	3.288	3.265	3.281
SIC	3.947	3.946	3.808	3.889	3.840	3.811	3.805	3.815	3.791	3.808

WPI	DM1	SSM1	DM2	SSM2	DM2Y	SSM2Y	DM3A	SSM3A	DM3AY	SSM3AY
$\overline{R}^2$	0.573	0.573	0.599	0.599	0.552	0.647	0.583	0.624	0.634	0.651
AIC	3.625	3.634	3.619	3.575	3.511	3.403	3.588	3.558	3.580	3.408
SIC	4.123	4.131	4.117	4.072	4.027	3.919	4.086	4.056	4.078	3.905

Table 5.3: Comparison of F-Tests for Joint Significance on Coefficients of Monthly Growth Rates of Nominal Monetary Aggregates in ARMA-ARCH Models of Monthly Inflation

	DM1	SSM1	DM2	SSM2	DM2Y	SSM2Y	DM3A	SSM3A	DM3AY	SSM3AY
CPI	**7.086**	3.611	**11.059**	3.154	6.347	**15.861**	**5.953**	5.391	7.037	**13.740**
WPI	**7.624**	6.629	5.755	**7.531**	**15.174**	10.443	**10.701**	6.877	5.651	**8.314**

Table 5.4: Out-of-Sample Forecast Evaluation of ARMA-ARCH Models of Monthly CPI-Inflation with Monthly Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.003	1.037	1.100	1.057	1.103	1.060	1.030	0.956	**0.744**	1.075	0.788	0.928	0.898	0.751
MAE	0.798	0.793	0.886	0.850	0.853	0.830	0.798	0.744	**0.573**	0.833	0.636	0.734	0.707	0.601
MAPE	193.8	154.6	189.5	244.9	199.4	218.0	202.3	156.1	**167.7**	204.6	122.0	164.3	151.2	215.6

Static Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	**SSM3AY**	DAVG	SSAVG	NCF
RMSE	0.833	0.813	0.828	0.740	0.647	0.767	0.631	0.690	0.521	0.751	**0.415**	0.730	0.567	0.751
MAE	0.662	0.674	0.667	0.641	0.524	0.615	0.504	0.584	0.430	0.608	**0.350**	0.606	0.462	0.601
MAPE	177.4	169.8	159.4	167.6	151.8	136.5	144.0	184.9	160.7	206.6	**109.0**	126.1	137.4	215.6

12-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.405	1.593	1.590	1.566	1.884	1.657	1.708	1.348	**0.982**	1.402	1.040	1.535	1.325	1.225
MAE	1.051	1.319	1.254	1.324	1.571	1.317	1.355	1.082	**0.748**	1.147	0.801	1.234	1.043	0.919
MAPE	337.1	414.7	418.7	381.1	518.7	516.3	292.6	365.2	**211.7**	394.7	283.3	434.3	335.0	163.2

Dynamic Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	**SSM3AY**	DAVG	SSAVG	NCF
RMSE	0.922	0.991	0.867	0.759	0.698	0.822	0.680	0.698	0.548	0.921	**0.409**	0.760	0.556	0.670
MAE	0.820	0.737	0.685	0.621	0.596	0.686	0.581	0.574	0.469	0.815	**0.331**	0.634	0.453	0.513
MAPE	317.5	217.8	233.6	175.1	134.8	249.1	125.4	130.6	128.3	351.6	**121.5**	213.6	105.4	138.4

Table 5.5: Out-of-Sample Forecast Evaluation of ARMA-ARCH Models of Monthly WPI-Inflation with Monthly Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	BASE	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.512	1.307	**1.231**	1.365	1.408	1.369	1.445	1.283	1.232	1.388	1.229	1.219	1.251	1.366
MAE	1.187	0.897	**0.842**	1.110	1.132	1.074	1.174	1.005	1.027	1.097	1.014	0.943	0.972	1.086
MAPE	199.2	168.8	**150.5**	281.0	227.2	313.0	245.3	288.9	175.1	317.2	192.3	254.1	189.3	226.6

Static Forecasts

	BASE	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.306	1.091	**1.059**	1.180	1.036	1.025	1.122	1.037	1.012	1.064	1.010	0.972	0.998	1.366
MAE	1.038	0.729	**0.690**	0.955	0.782	0.732	0.887	0.729	0.818	0.885	0.824	0.715	0.757	1.086
MAPE	188.6	129.3	**124.6**	197.6	140.3	142.0	181.8	138.4	158.3	173.0	155.5	115.2	124.9	226.6

12-Period-Ahead Sequential Forecasts

	BASE	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.079	1.790	**1.721**	1.852	2.345	2.019	2.078	1.708	1.945	1.735	1.872	1.839	1.838	1.638
MAE	2.884	1.438	**1.395**	1.626	2.101	1.723	1.828	1.454	1.769	1.456	1.657	1.565	1.592	1.254
MAPE	902.1	359.7	**351.8**	463.9	635.3	469.9	575.1	455.4	525.1	478.2	531.1	471.0	475.7	219.1

Dynamic Forecasts

	BASE	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	2.446	1.409	1.341	1.578	1.232	**1.240**	1.601	1.334	1.333	1.363	1.302	1.276	1.262	1.254
MAE	2.086	0.985	0.907	1.340	0.900	**0.890**	1.344	1.006	1.102	1.105	1.066	0.967	0.987	0.986
MAPE	737.8	223.4	195.8	410.3	270.6	**210.2**	464.6	265.3	330.9	375.4	327.0	286.7	307.2	210.8

Table 5.6: Choosing the Best ARMA-ARCH Model of Quarterly Inflation

CPI	ARMA (0,0)	ARMA (1,0)	ARMA (0,1)	ARMA (1,1)	ARMA (2,0)	ARMA (0,2)	**ARMA (2,1)**	ARMA (1,2)	ARMA (2,2)	+ARCH
$\bar{R}^2$	0.337	0.846	0.645	0.855	0.854	0.796	0.866	0.854	0.864	NO
AIC	6.158	4.704	5.544	4.661	4.670	4.999	4.595	4.676	4.619	ARCH
SIC	6.391	4.968	5.807	4.954	4.966	5.290	4.920	4.998	4.974	EFFECT

WPI	ARMA (0,0)	ARMA (1,0)	ARMA (0,1)	ARMA (1,1)	ARMA (2,0)	ARMA (0,2)	ARMA (2,1)	**ARMA (1,2)**	ARMA (2,2)	+ARCH
$\bar{R}^2$	0.469	0.763	0.685	0.774	0.760	0.709	0.781	0.787	0.784	NO
AIC	6.095	5.306	5.583	5.269	5.330	5.517	5.250	5.219	5.248	ARCH
SIC	6.299	5.541	5.817	5.533	5.596	5.779	5.546	5.512	5.573	EFFECT

Table 5.7: Comparison of In-Sample Fits of ARMA Models of Quarterly Inflation with Quarterly Growth Rates of Nominal Monetary Aggregates Using Information Criteria

CPI	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
$\bar{R}^2$	0.885	0.884	0.892	0.886	0.895	0.888	0.886	0.886	0.890	0.888
AIC	4.533	4.543	4.472	4.525	4.444	4.507	4.520	4.524	4.490	4.509
SIC	5.054	5.064	4.993	5.046	4.966	5.028	5.042	5.045	5.011	5.030

WPI	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
$\bar{R}^2$	0.795	0.791	0.806	0.807	0.813	0.814	0.803	0.821	0.813	0.828
AIC	5.290	5.307	5.234	5.230	5.197	5.191	5.248	5.151	5.196	5.111
SIC	5.777	5.794	5.721	5.717	5.684	5.678	5.735	5.638	5.683	5.598

Table 5.8: Comparison of F-Tests for Joint Significance of Coefficients on Quarterly Growth Rates of Nominal Monetary Aggregates in ARMA Models of Quarterly Inflation

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
CPI	**1.350**	1.264	**1.808**	1.270	**2.138**	1.453	1.202	**4.013**	1.788	**4.216**
WPI	**1.539**	1.404	1.804	**2.250**	**2.545**	2.521	3.294	**11.833**	2.338	**13.057**

Table 5.9: Out-of-Sample Forecast Evaluation of ARMA Models of Quarterly CPI-Inflation and Quarterly Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	**SSM3AY**	DAVG	SSAVG	NCF
RMSE	2.374	2.254	2.330	2.270	2.223	2.235	2.193	2.608	2.487	2.413	**2.324**	2.201	2.117	1.701
MAE	2.027	1.922	1.984	1.971	2.043	1.923	2.013	2.290	1.852	2.146	**1.747**	1.931	1.846	1.390
MAPE	97.370	100.88	102.74	107.65	113.92	103.89	112.61	106.91	78.347	98.143	**77.346**	93.995	91.900	70.364

Static Forecasts

	BASE	**DM1**	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	2.773	**2.294**	2.371	3.006	2.710	2.803	2.679	9.813	3.014	2.899	12.699	2.682	4.102	1.701
MAE	2.072	**1.957**	2.015	2.405	2.164	2.289	2.116	7.873	2.366	2.368	9.666	2.422	3.027	1.390
MAPE	90.633	**104.47**	106.46	110.71	100.12	105.52	96.955	451.76	105.49	115.22	471.23	133.20	133.91	70.364

4-Period-Ahead Sequential Forecasts

	BASE	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.572	2.541	**2.446**	4.068	3.747	4.081	3.730	3.950	4.001	4.229	3.608	3.389	3.183	1.546
MAE	3.812	1.814	**1.714**	3.282	2.885	3.287	2.863	3.280	3.656	3.718	3.156	2.513	2.447	1.124
MAPE	231.38	100.55	**91.736**	193.25	169.03	196.03	168.87	188.32	191.39	200.23	167.06	139.83	129.12	60.763

Dynamic Forecasts

	BASE	**DM1**	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	5.570	**2.068**	2.189	5.081	4.699	4.641	4.514	4.924	4.250	4.661	2.705	3.755	3.119	1.231
MAE	4.853	**1.584**	1.644	4.712	4.224	4.285	4.069	4.634	3.904	4.405	2.354	3.401	2.582	1.094
MAPE	259.47	**104.62**	109.39	245.13	219.22	220.38	209.56	265.22	200.97	235.17	117.72	177.42	124.26	77.411

Table 5.10: Out-of-Sample Forecast Evaluation of ARMA Models of Quarterly WPI-Inflation and Quarterly Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.012	3.936	3.822	5.150	4.679	5.244	4.789	4.312	**3.377**	4.334	3.478	4.413	3.779	3.288
MAE	3.280	3.208	3.228	4.389	3.513	4.415	3.610	3.807	**2.870**	3.794	3.030	3.892	3.155	2.953
MAPE	1287.7	1191.2	1075.5	1278.2	1020.4	1170.7	1024.4	1283.3	**1157.4**	1144.2	1200.4	1212.7	1093.2	936.3

Static Forecasts

	BASE	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.983	4.935	**3.819**	17.554	10.935	26.286	13.911	16.634	3.730	26.066	8.158	17.091	4.303	3.288
MAE	4.170	4.222	**2.981**	13.703	8.768	18.608	11.030	12.584	2.953	18.441	5.835	12.401	3.136	2.953
MAPE	1989.1	1647.6	**1188.7**	1946.4	4079.8	4944.7	5024.0	2407.5	1485.2	5255.0	2135.8	2848.7	1757.3	936.3

4-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	6.669	5.676	5.505	7.512	6.059	7.012	6.089	5.959	**3.408**	6.378	3.592	5.955	4.768	3.202
MAE	5.929	4.695	4.366	6.523	5.296	6.176	5.285	5.298	**2.630**	5.376	3.074	5.187	4.079	2.763
MAPE	2080.7	1120.6	1172.1	2055.7	1795.4	1663.2	1759.5	1727.1	**960.7**	1691.3	951.0	1593.4	1296.2	566.0

Dynamic Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	**SSM3AY**	DAVG	SSAVG	NCF
RMSE	8.423	7.528	3.008	8.205	6.007	8.657	6.189	8.028	4.317	8.290	**3.297**	8.116	4.309	2.477
MAE	7.479	6.709	2.565	7.272	5.002	7.895	5.202	7.162	3.530	7.549	**2.548**	7.317	3.414	2.036
MAPE	3028.5	2636.6	644.9	2592.7	1787.2	2846.7	1835.6	2728.4	1471.1	2823.9	**977.3**	2725.7	1334.5	462.8

Table 5. 11: Choosing the Best ARMA Model of Real GDP Growth

ARMA	(1,0)	(0,1)	(1,1)	(2,0)	(0,2)	**(2,1)**	(1,2)	(2,2)	**(4,3)**
$\bar{R}^2$	0.401	0.396	0.405	0.412	0.388	0.570	0.463	0.452	0.604
AIC	5.898	5.892	5.903	5.904	5.917	5.602	5.812	5.858	5.528
SIC	5.958	5.952	5.993	5.995	6.007	5.723	5.932	6.009	5.774

Table 5.12: Comparison of In-Sample Fits of ARMA Models of Real GDP Growth with Growth Rates of Real Monetary Aggregates Using Information Criteria

Real Money deflated using CPI

	BASE	DM1	SSM1	DM2	SSM2	DM2Y	SSM2Y	DM3A	SSM3A	DM3AY	SSM3AY
$\bar{R}^2$	0.604	0.632	0.636	0.627	0.598	0.634	0.582	0.658	0.650	0.604	0.632
AIC	5.528	5.537	5.528	5.552	5.625	5.533	5.665	5.463	5.489	5.528	5.537
SIC	5.774	5.983	5.974	5.998	6.072	5.979	6.111	5.910	5.935	5.774	5.983

Real Money deflated using WPI

	BASE	DM1	SSM1	DM2	SSM2	DM2Y	SSM2Y	DM3A	SSM3A	DM3AY	SSM3AY
$\bar{R}^2$	0.604	0.639	0.640	0.625	0.588	0.643	0.656	0.665	0.598	0.604	0.639
AIC	5.528	5.517	5.516	5.558	5.649	5.508	5.472	5.444	5.627	5.528	5.517
SIC	5.774	5.963	5.962	6.004	6.096	5.955	5.918	5.890	6.073	5.774	5.963

Table 5.13: Comparison of F-Tests for Joint Significance of Coefficients on Growth Rates of Real Monetary Aggregates in ARMA Models of Real GDP Growth

Deflated w/	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
CPI	2.417	**2.736**	**2.336**	1.402	**3.715**	2.229	**2.512**	0.791	**3.811**	0.798
WPI	2.612	**2.670**	**2.161**	1.070	**3.985**	1.367	2.843	**24.642**	**4.350**	1.634

Table 5.14: Out-of-Sample Forecast Evaluation of ARMA Models of Real GDP Growth Rates with Growth Rates of Real Monetary Aggregates Deflated Using CPI

1-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.332	5.061	4.658	4.878	4.369	3.541	3.980	4.402	4.978	**3.773**	4.462	4.012	3.927	3.290
MAE	3.631	4.325	4.082	3.910	3.558	2.680	3.060	3.125	3.662	**2.656**	3.262	3.162	2.970	2.459
MAPE	54.182	65.309	61.763	65.105	57.115	46.446	50.033	51.211	53.466	**45.055**	49.566	52.033	46.992	37.286

Static Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM2Y	SSM2Y	DM3A	SSM3A	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.834	4.971	4.887	4.528	4.445	4.793	3.940	3.283	3.545	**3.289**	3.813	10.267	8.643	3.290
MAE	3.439	4.368	4.254	3.980	3.743	4.127	3.190	2.757	3.036	**2.749**	3.105	6.618	6.060	2.459
MAPE	50.483	67.823	65.696	63.336	55.656	64.472	44.850	44.948	46.133	**44.104**	43.916	116.96	101.19	37.286

4-Period-Ahead Sequential Forecasts

	BASE	**DM1**	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	9.524	**6.340**	6.482	10.410	11.169	9.169	10.313	10.781	9.765	9.337	9.255	7.465	6.131	4.426
MAE	8.827	**5.007**	4.980	9.198	9.845	8.055	9.434	8.149	8.563	8.681	7.891	6.751	5.312	3.400
MAPE	119.85	**68.128**	68.192	133.26	144.78	110.60	139.03	124.00	122.51	125.56	112.08	97.717	77.442	47.323

Dynamic Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.296	4.952	5.174	2.755	4.499	3.425	5.791	2.052	3.197	**1.919**	5.597	5.166	5.151	2.924
MAE	3.801	4.370	4.605	2.477	3.341	2.928	4.520	1.519	2.412	**1.626**	4.364	4.737	4.717	1.990
MAPE	48.900	61.346	64.140	33.983	39.931	40.358	56.177	24.305	29.674	**25.366**	54.167	78.886	74.000	22.483

Table 5.15: Out-of-Sample Forecast Evaluation of ARMA Models of Real GDP Growth Rates with Growth Rates of Real Monetary Aggregates Deflated Using WPI

1-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.332	3.665	3.826	4.297	3.685	3.970	3.448	4.397	**3.139**	4.358	3.836	3.829	3.398	3.290
MAE	3.631	3.164	3.232	3.729	2.979	3.049	2.630	3.633	**2.602**	3.549	3.064	3.242	2.704	2.459
MAPE	54.182	44.590	48.215	53.958	43.957	47.001	38.019	53.156	**38.112**	55.568	42.001	48.299	39.135	37.286

Static Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM2Y	SSM2Y	DM3A	SSM3A	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.834	4.476	4.492	3.941	4.650	4.132	3.469	3.327	4.965	**3.327**	3.386	3.520	28.836	3.290
MAE	3.439	3.460	3.532	3.482	3.813	3.048	2.871	2.779	4.294	**2.764**	2.780	2.841	18.506	2.459
MAPE	50.483	51.314	52.157	52.392	55.846	45.941	43.002	41.034	63.790	**40.702**	41.178	42.626	292.86	37.286

4-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	9.524	6.317	6.527	5.978	6.033	8.622	**5.719**	9.010	9.082	8.956	6.560	4.391	3.363	4.426
MAE	8.827	5.590	5.953	5.134	4.833	6.789	**4.689**	7.086	7.215	7.266	5.813	3.929	2.966	3.400
MAPE	119.85	75.330	82.660	68.135	59.184	103.90	**58.450**	97.344	105.75	115.75	86.471	59.690	41.550	47.323

Dynamic Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	**DM2Y**	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.296	4.696	4.754	3.610	4.394	3.817	3.990	**2.747**	4.088	2.970	3.861	5.063	3.631	2.924
MAE	3.801	4.067	4.176	2.977	3.691	3.269	3.089	**2.158**	3.397	2.480	2.977	4.744	2.960	1.990
MAPE	48.900	59.056	60.152	38.808	47.658	45.887	38.206	**28.016**	43.742	34.468	36.743	67.103	36.136	22.483

Table 5.16: Comparison of In-Sample Fits of St. Louis Equations of Real GDP Growth with Growth Rates of Real Monetary Aggregates Using Information Criteria

Real Money deflated using CPI											
	GDP	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
$\overline{R}^2$	0.599	0.624	0.671	0.676	0.670	0.654	0.715	0.657	0.685	0.659	0.726	0.641
AIC	5.522	5.482	5.413	5.399	5.418	5.464	5.271	5.454	5.371	5.450	5.256	5.502
SIC	5.707	5.729	5.845	5.831	5.851	5.896	5.704	5.887	5.804	5.882	5.723	5.935

Real Money deflated using WPI												
	GDP	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
$\overline{R}^2$	0.599	0.624	0.673	0.675	0.671	0.646	0.717	0.657	0.696	0.659	0.732	0.691
AIC	5.522	5.482	5.407	5.400	5.415	5.487	5.265	5.454	5.336	5.450	5.210	5.395
SIC	5.707	5.729	5.839	5.833	5.847	5.919	5.698	5.887	5.769	5.882	5.642	5.932

Table 5.17: Comparison of F-Tests for Joint Significance of Coefficients on Growth Rates of Real Monetary Aggregates in ARMA Models of Real GDP Growth

Deflated w/	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
CPI	2.417	**2.736**	**2.336**	1.402	**3.715**	2.229	**2.512**	0.791	**3.811**	0.798
WPI	2.697	**2.779**	**2.593**	1.707	**4.654**	2.101	**3.635**	2.156	**5.498**	2.831

Table 5.18: Out-of-Sample Forecast Evaluation of St. Louis Equations of Real GDP Growth with Growth Rates of Real Monetary Aggregates Deflated Using CPI

1-Period-Ahead Sequential Forecasts

	GDP	BASE	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.310	3.346	3.106	3.180	3.184	3.440	**2.861**	3.293	3.132	3.600	2.881	3.521	2.968	3.311	3.290
MAE	2.820	2.867	2.696	2.747	2.480	2.642	**2.252**	2.500	2.571	2.569	2.394	2.499	2.456	2.560	2.459
MAPE	40.77	38.72	37.79	38.46	34.57	35.77	**32.84**	34.41	36.10	32.49	34.68	31.81	34.71	33.94	37.29

Static Forecasts

	GDP	BASE	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.399	3.518	3.310	3.395	2.956	3.473	**2.599**	3.283	2.995	3.583	2.643	3.486	2.799	3.362	3.290
MAE	2.849	3.049	2.879	2.961	2.297	2.731	**2.089**	2.550	2.446	2.660	2.223	2.540	2.327	2.648	2.459
MAPE	40.46	41.24	39.93	41.04	29.86	35.45	**29.06**	33.46	33.23	33.18	31.59	31.65	31.56	34.32	37.29

4-Period-Ahead Sequential Forecasts

	GDP	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	6.231	6.529	4.342	4.462	4.033	5.754	2.975	5.228	3.581	6.072	**2.656**	5.882	4.196	3.855	4.426
MAE	5.366	5.778	3.531	3.736	2.963	4.428	2.385	4.093	2.842	5.070	**2.330**	4.845	3.265	2.994	3.400
MAPE	69.16	76.67	45.78	48.78	37.09	54.62	32.78	50.50	37.28	66.48	**34.90**	63.08	41.35	36.86	47.32

Dynamic Forecasts

	GDP	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.166	4.699	4.482	4.686	3.420	4.947	2.942	4.560	3.553	4.980	**2.871**	4.778	3.162	4.705	2.924
MAE	3.666	4.252	4.215	4.418	2.842	4.169	2.479	3.772	3.059	4.290	**2.435**	4.094	2.677	4.061	1.990
MAPE	47.00	57.73	59.54	62.31	37.58	55.11	34.07	49.25	42.63	58.63	**36.12**	55.80	36.50	54.61	22.48

Table 5.19: Out-of-Sample Forecast Evaluation of St. Louis Equations of Real GDP Growth with Growth Rates of Real Monetary Aggregates Deflated Using WPI

1-Period-Ahead Sequential Forecasts

	GDP	BASE	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.310	3.346	3.485	3.502	3.636	3.797	**3.350**	3.444	3.508	3.704	3.326	3.656	3.417	3.496	3.290
MAE	2.820	2.867	2.996	3.008	2.829	2.933	**2.570**	2.815	2.906	2.696	2.753	2.657	2.809	2.750	2.459
MAPE	40.77	38.72	40.88	41.24	37.65	38.52	**35.24**	40.20	39.77	34.44	38.20	34.08	38.32	36.59	37.29

Static Forecasts

	GDP	BASE	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.399	3.518	3.985	3.934	4.461	3.936	**3.274**	3.792	3.576	3.677	3.259	3.556	3.519	3.596	3.290
MAE	2.849	3.049	3.456	3.454	4.021	3.171	**2.479**	3.024	2.837	2.608	2.642	2.948	2.813	2.860	2.459
MAPE	40.46	41.24	47.05	47.11	56.78	40.92	**31.76**	39.12	37.40	31.72	34.93	41.37	36.72	37.18	37.29

4-Period-Ahead Sequential Forecasts

	GDP	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	6.231	6.529	5.659	5.512	5.377	6.365	3.769	5.992	4.708	5.686	**3.711**	5.607	5.031	4.274	4.426
MAE	5.366	5.778	4.977	4.943	4.254	5.283	3.029	4.906	4.072	4.757	**2.975**	4.637	4.232	3.649	3.400
MAPE	69.16	76.67	68.76	68.38	55.83	68.40	40.36	69.11	56.11	64.25	**41.07**	62.26	56.38	48.35	47.32

Dynamic Forecasts

	GDP	BASE	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.166	4.699	6.131	5.953	6.676	5.748	**4.483**	5.482	5.084	5.106	4.529	4.784	4.996	5.197	2.924
MAE	3.666	4.252	5.815	5.650	5.982	4.940	**3.889**	4.680	4.434	4.382	3.914	3.856	4.313	4.547	1.990
MAPE	47.00	57.73	84.39	81.45	87.73	67.25	**54.04**	63.33	63.65	60.78	55.82	57.72	61.00	63.47	22.48

Table 5.20: Comparison of In-Sample Fits of St. Louis Equations of Real GDP Growth with Growth Rates of WPI-Deflated Real Monetary Aggregates Using Information Criteria

	DM1		DM2		DM3A		DM2Y		DM3AY	
	No K_t	w/K_t	No K_t	w/K_t	No K_t	w/K_t	No K_t	w/K_t	No K_t	w/K_t
$\overline{R}^2$	0.673	**0.675**	0.671	**0.672**	**0.717**	0.713	0.696	**0.712**	0.732	**0.748**
AIC	**5.407**	5.457	**5.415**	5.467	**5.265**	5.335	**5.336**	5.336	5.210	**5.202**
SIC	**5.839**	6.075	**5.847**	6.085	**5.698**	5.953	**5.769**	5.954	**5.642**	5.820

Table 5.21: Comparison of F-Tests for Joint Significance of Coefficients on Growth Rates of Real Monetary Aggregates in St. Louis Equations of Real GDP Growth

	DM1		DM2		DM3A		DM2Y		DM3AY	
	F-Value	Prob	F-Value	Prob	F-Value	Prob	F-Value	Prob	F-Value	Prob
DM from Eq'n w/o K	2.697	0.022	2.593	0.027	4.654	0.001	3.635	0.004	5.498	0.000
DM Only	2.510	0.036	2.227	0.059	4.087	0.003	3.381	0.008	5.007	0.001
K Only	0.902	0.503	0.864	0.529	0.893	0.509	0.892	0.510	1.001	0.437
DM+K	1.697	0.101	1.649	0.114	2.522	0.013	2.159	0.033	3.060	0.003

Table 5.22: Out-of-Sample Forecast Evaluation of St. Louis Equations of Real GDP Growth with Growth Rates of WPI-Deflated Real Monetary Aggregates

Static Forecasts											
	DM1		DM2		DM3A		DM2Y		DM3AY		NCF
	No K_t	**w/K_t**	No K_t	**w/K_t**	No K_t	w/K_t	No K_t	**w/K_t**	No K_t	**w/K_t**	
RMSE	3.985	3.526	4.461	3.096	3.274	3.139	3.576	2.989	3.259	2.912	3.290
MAE	3.456	2.811	4.021	2.355	2.479	2.315	2.837	2.295	2.642	2.320	2.459
MAPE	47.047	38.389	56.781	31.085	31.761	31.921	37.397	30.418	34.933	31.159	37.286
Dynamic Forecasts											
	DM1		DM2		DM3A		DM2Y		DM3AY		NCF
	No K_t	**w/K_t**	No K_t	**w/K_t**	No K_t	**w/K_t**	No K_t	**w/K_t**	No K_t	**w/K_t**	
RMSE	6.131	5.396	6.676	4.135	4.483	3.421	5.084	3.315	4.529	3.105	2.924
MAE	5.815	4.885	5.982	3.429	3.889	2.690	4.434	2.587	3.914	2.494	1.990
MAPE	84.390	74.929	87.725	49.703	54.035	39.382	63.645	40.150	55.818	37.963	22.483

Table 5.23: Comparison of In-Sample Fits of Phillips Curve Model of Inflation with Growth Rates of Nominal Monetary Aggregates Using Information Criteria

CPI	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
$\overline{R}^2$	0.801	0.822	0.824	0.841	0.818	0.837	0.818	**0.840**	0.823	0.834	0.820
AIC	4.921	4.842	4.834	4.732	4.866	4.757	4.868	**4.739**	4.839	4.776	4.853
SIC	5.139	5.154	5.145	5.044	5.177	5.068	5.179	**5.050**	5.150	5.087	5.164
WPI	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
$\overline{R}^2$	0.776	0.785	0.784	0.797	0.774	0.792	0.774	0.798	**0.816**	0.794	0.813
AIC	5.269	5.262	5.267	5.202	5.310	5.228	5.309	5.200	**5.103**	5.217	5.124
SIC	5.487	5.573	5.579	5.513	5.622	5.540	5.621	5.511	**5.415**	5.529	5.435

Table 5.24: Comparison of F-Tests for Joint Significance of Coefficients on Growth Rates of Nominal Monetary Aggregates in Phillips Curve Models of Inflation

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
CPI	3.700	**3.915**	**6.610**	3.114	**5.927**	3.061	**6.429**	3.784	**5.417**	3.434
WPI	**1.977**	1.846	**3.419**	0.875	**3.037**	0.895	2.768	**5.979**	3.476	**5.432**

Table 5.25: Out-of-Sample Forecast Evaluation of Phillips Curve Models of CPI-Inflation with Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.122	1.265	1.285	1.540	1.078	1.453	**1.069**	1.633	1.332	1.569	1.314	1.457	1.075	1.701
MAE	0.909	1.149	1.156	1.219	0.866	1.168	**0.856**	1.285	1.126	1.188	1.119	1.157	0.931	1.390
MAPE	58.577	71.210	71.544	70.111	48.830	61.985	**49.032**	72.009	72.068	61.820	71.175	65.833	57.445	70.364

Static Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.128	1.255	1.280	1.617	1.152	1.547	**1.148**	1.736	1.313	1.694	1.300	1.561	1.088	1.701
MAE	0.912	1.146	1.160	1.253	0.922	1.185	**0.926**	1.369	1.107	1.299	1.106	1.211	0.944	1.390
MAPE	59.006	70.726	71.343	68.687	49.977	59.355	**50.940**	72.956	71.901	64.056	71.029	66.014	57.490	70.364

4-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	**SSM2**	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.432	1.376	1.367	1.791	**1.363**	1.801	1.372	1.805	1.347	1.894	1.327	1.582	1.278	1.546
MAE	1.223	1.130	1.123	1.376	**1.178**	1.441	1.194	1.373	1.126	1.532	1.125	1.258	1.022	1.124
MAPE	81.578	80.801	80.167	81.606	**68.104**	79.172	68.784	76.735	75.821	85.951	74.993	74.258	67.797	60.763

Dynamic Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.736	1.166	1.171	1.776	1.356	1.751	**1.345**	1.934	1.238	1.927	1.235	1.635	1.093	1.231
MAE	1.565	1.057	1.058	1.365	1.102	1.324	**1.124**	1.539	1.018	1.481	1.017	1.284	0.914	1.094
MAPE	96.867	71.805	71.511	70.176	54.919	61.777	**56.240**	76.071	68.461	70.091	66.807	66.272	56.557	77.411

Table 5.26: Out-of-Sample Forecast Evaluation of Phillips Curve Models of WPI-Inflation with Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	**SSM3AY**	DAVG	SSAVG	NCF
RMSE	2.759	2.837	2.779	2.859	2.624	2.735	2.595	2.925	2.569	2.763	**2.600**	2.812	2.564	3.288
MAE	1.691	2.053	1.988	2.193	1.883	2.088	1.866	2.172	1.728	2.030	**1.758**	2.105	1.718	2.953
MAPE	193.13	365.73	341.44	404.87	299.61	312.47	299.03	349.82	275.26	276.80	**268.19**	340.86	209.44	936.27

Static Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	2.770	2.840	2.789	2.833	2.563	2.662	**2.533**	2.904	2.625	2.690	2.653	2.828	2.570	3.288
MAE	1.723	2.055	1.999	2.214	1.789	2.053	**1.764**	2.227	1.803	2.024	1.805	2.184	1.734	2.953
MAPE	225.12	489.86	454.58	539.04	218.96	415.35	**214.62**	498.18	409.97	390.86	393.86	494.13	335.98	936.27

4-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.041	2.854	2.824	2.727	2.678	2.616	**2.663**	2.798	2.800	3.082	2.838	2.769	2.672	3.202
MAE	1.991	1.924	1.894	1.930	1.741	1.863	**1.749**	1.917	1.882	2.224	1.884	1.915	1.758	2.763
MAPE	381.70	502.70	483.37	517.07	213.99	403.00	**212.39**	454.87	435.69	520.50	427.30	417.03	375.10	566.00

Dynamic Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.173	3.096	3.051	2.819	2.645	2.652	**2.622**	2.840	2.812	2.658	2.839	2.866	2.723	2.477
MAE	2.328	2.361	2.313	2.078	1.765	1.927	**1.740**	2.065	1.989	1.892	1.987	2.087	1.807	2.036
MAPE	528.77	739.31	706.96	698.55	352.09	547.96	**343.97**	642.59	619.63	513.26	603.97	676.84	519.73	462.81

Table 5.27: Comparison of In-Sample Fits of Cost-Push Model of Inflation with Growth Rates of Nominal Monetary Aggregates Using Information Criteria

CPI	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
$\overline{R}^2$	0.859	0.891	0.890	0.893	0.878	0.879	0.860	0.893	0.880	0.892	0.880
AIC	4.574	4.349	4.361	4.329	4.468	4.480	4.578	4.356	4.473	4.361	4.469
SIC	4.821	4.689	4.701	4.669	4.808	4.882	4.857	4.758	4.875	4.762	4.870
WPI	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
$\overline{R}^2$	0.877	0.869	0.883	0.886	0.883	0.885	0.881	0.879	0.888	0.876	0.883
AIC	4.669	4.615	4.636	4.613	4.641	4.636	4.663	4.523	4.493	4.556	4.500
SIC	4.916	4.955	4.945	4.922	4.950	4.976	5.003	4.829	4.935	4.896	4.840

Table 5.28: Comparison of F-Tests for Joint Significance of Coefficients on Growth Rates of Nominal Monetary Aggregates in Cost-Push Models of Inflation (Full Sample Estimation)

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
CPI	**9.114**	9.017	**11.006**	6.145	**10.761**	4.896	**22.242**	3.282	**12.669**	8.139
WPI	**2.947**	2.926	**3.748**	2.739	**2.533**	1.897	**9.309**	3.344	4.476	**5.291**

Table 5.29: Out-of-Sample Forecast Evaluation of Cost-Push Models of CPI-Inflation with Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	**DM2Y**	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.796	1.858	1.850	1.861	1.812	2.007	1.891	**1.714**	1.935	1.945	1.896	1.854	1.853	1.701
MAE	1.586	1.610	1.626	1.581	1.634	1.758	1.724	**1.442**	1.759	1.643	1.704	1.607	1.689	1.390
MAPE	92.862	95.911	95.842	91.651	94.565	100.65	99.628	**83.483**	105.49	92.769	99.210	92.893	98.947	70.364

Static Forecasts

CPI	BASE	**DM1**	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.055	**2.646**	2.664	2.785	2.966	2.714	2.887	2.726	2.768	2.745	2.716	2.036	1.991	1.701
MAE	2.591	**2.158**	2.172	2.368	2.517	2.285	2.410	2.274	2.240	2.272	2.187	1.619	1.682	1.390
MAPE	134.42	**104.68**	106.71	115.38	126.74	111.35	119.70	109.56	110.05	109.14	108.29	90.594	96.115	70.364

4-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	1.375	1.408	1.420	1.766	1.655	2.026	1.842	1.594	**1.439**	1.957	1.699	1.675	1.613	1.546
MAE	1.226	1.170	1.188	1.401	1.314	1.765	1.523	1.293	**1.187**	1.515	1.369	1.347	1.292	1.124
MAPE	62.166	61.018	60.875	73.557	66.772	92.291	78.724	66.180	**61.846**	76.364	69.910	69.076	65.695	60.763

Dynamic Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	**SSM3AY**	DAVG	SSAVG	NCF
RMSE	3.625	3.190	3.229	3.342	3.566	3.209	3.443	3.218	3.085	3.200	**3.017**	2.222	2.136	1.231
MAE	3.196	2.785	2.826	2.944	3.221	2.778	3.080	2.809	2.597	2.763	**2.516**	1.642	1.602	1.094
MAPE	175.01	149.24	152.74	152.70	173.68	144.42	164.79	145.64	131.34	143.43	**126.66**	81.753	83.209	77.411

Table 5.30: Out-of-Sample Forecast Evaluation of Cost-Push Models of WPI-Inflation with Growth Rates of Nominal Monetary Aggregates

1-Period-Ahead Sequential Forecasts

	BASE	DM1	**SSM1**	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	2.718	2.668	**2.650**	2.664	2.678	2.728	2.747	2.670	2.486	2.700	2.706	2.685	2.630	3.288
MAE	2.390	2.346	**2.336**	2.362	2.338	2.420	2.414	2.362	2.224	2.398	2.421	2.377	2.328	2.953
MAPE	644.54	639.52	**635.07**	638.25	595.01	642.76	628.58	624.51	725.04	622.60	606.63	633.53	637.69	936.27

Static Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	**DM2Y**	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.393	3.114	3.128	3.133	3.327	3.099	3.283	**3.075**	3.288	3.115	3.411	2.725	2.615	3.288
MAE	2.680	2.453	2.458	2.492	2.612	2.448	2.565	**2.478**	2.625	2.499	2.695	2.270	2.215	2.953
MAPE	732.70	603.06	618.31	599.78	655.23	586.12	622.75	**570.64**	510.39	598.22	562.85	478.15	501.94	936.27

4-Period-Ahead Sequential Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	2.884	2.845	2.842	2.847	2.831	2.962	3.153	2.864	**2.466**	2.902	2.812	2.876	2.818	3.202
MAE	2.289	2.242	2.243	2.234	2.278	2.338	2.513	2.234	**2.061**	2.283	2.278	2.270	2.283	2.763
MAPE	451.79	415.27	418.79	434.17	443.67	443.26	436.02	433.30	**411.06**	444.17	453.45	435.83	428.72	566.00

Dynamic Forecasts

	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.720	3.386	3.407	3.421	3.600	3.367	3.558	3.366	**3.353**	3.366	3.504	2.711	2.526	2.477
MAE	3.039	2.712	2.734	2.794	2.912	2.693	2.869	2.722	**2.692**	2.736	2.798	2.007	1.980	2.036
MAPE	893.34	738.60	755.81	737.25	787.93	719.66	759.42	693.41	**535.45**	723.97	611.66	353.43	323.43	462.81

Table 5.31: Comparison of In-Sample Fits of Cost-Push Models of Inflation with Growth Rates of Nominal Monetary Aggregates Using Information Criteria (Sample 1986-2002)

CPI	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
$\bar{R}^2$	0.803	0.816	0.817	0.819	0.807	0.823	0.808	0.822	0.813	0.827	0.824
AIC	4.480	4.452	4.432	4.408	4.474	4.384	4.466	4.392	4.442	4.364	4.392
SIC	4.845	4.927	4.870	4.809	4.875	4.785	4.867	4.794	4.844	4.766	4.830

Table 5.32: Out-of-Sample Forecast Evaluation of Cost-Push Models of Quarterly CPI-Inflation with Quarterly Growth Rates of Nominal Monetary Aggregates (Sample 1986-2002)

1-Period-Ahead Sequential Forecasts

CPI	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	**DM2Y**	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	2.388	2.149	2.138	2.015	2.423	2.086	2.475	**2.143**	2.743	2.196	2.479	2.091	2.406	5.269
MAE	1.911	1.841	1.868	1.668	2.017	1.718	2.049	**1.696**	2.230	1.827	1.895	1.717	1.972	4.385
MAPE	28.743	25.478	25.906	24.424	28.404	25.188	28.389	**24.633**	33.027	26.757	27.652	24.728	28.034	50.366

Static Forecasts

CPI	BASE	DM1	SSM1	**DM2**	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	2.938	2.806	2.796	**2.395**	3.024	2.497	3.024	2.615	3.295	2.586	3.175	2.557	3.006	5.269
MAE	2.298	2.481	2.496	**1.955**	2.595	1.982	2.598	2.108	2.602	2.050	2.608	2.085	2.572	4.385
MAPE	35.729	36.066	36.365	**29.655**	38.214	30.379	38.244	31.731	38.855	31.553	39.206	31.389	38.120	50.366

4-Period-Ahead Sequential Forecasts

CPI	BASE	DM1	SSM1	**DM2**	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	2.535	2.366	2.354	**2.088**	2.666	2.204	2.665	2.266	2.887	2.285	2.741	2.331	2.509	6.997
MAE	2.021	2.060	2.061	**1.724**	2.334	1.804	2.307	1.817	2.352	1.897	2.243	1.919	2.127	6.009
MAPE	30.018	28.169	28.312	**24.822**	32.159	26.076	32.055	25.803	33.800	27.263	32.064	27.001	30.104	84.505

Dynamic Forecasts

CPI	BASE	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.536	3.337	3.345	2.753	3.398	**2.750**	3.337	3.032	3.752	2.867	3.343	2.928	3.387	7.695
MAE	2.869	2.976	3.010	2.338	2.932	**2.237**	2.886	2.599	2.966	2.366	2.811	2.503	2.919	6.964
MAPE	43.445	42.669	43.117	34.511	43.102	**33.361**	42.339	37.920	44.963	35.153	41.990	36.723	43.089	105.71

Table 5.33: Out-of-Sample Forecast Evaluation of Cost-Push Models of Quarterly CPI-Inflation with Quarterly Growth Rates of Nominal Monetary Aggregates (Sample 1986-2002)

1-Period-Ahead Sequential Forecasts

WPI	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.569	3.576	2.015	3.528	2.176	3.601	2.150	3.549	**1.880**	3.552	1.951	2.047	1.957	7.445
MAE	2.876	2.905	1.592	2.863	1.810	2.964	1.831	2.876	**1.654**	2.911	1.627	1.602	1.688	5.246
MAPE	36.426	36.173	22.107	35.831	22.685	37.960	23.501	35.868	**20.389**	36.405	21.557	21.852	21.844	54.719

Static Forecasts

WPI	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.807	3.814	2.229	3.754	2.502	3.772	2.420	3.779	**2.003**	3.757	2.168	2.235	2.195	7.445
MAE	3.057	3.088	1.776	3.032	2.084	3.079	1.936	3.052	**1.721**	3.071	1.820	1.769	1.833	5.246
MAPE	40.431	40.087	24.888	39.786	27.005	40.784	25.808	40.063	**22.367**	40.156	24.702	24.562	24.541	54.719

4-Period-Ahead Sequential Forecasts

WPI	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	**SSM2Y**	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	2.113	2.182	2.152	2.126	2.234	2.144	2.165	2.092	**1.909**	2.172	2.044	2.146	2.002	10.211
MAE	1.692	1.749	1.725	1.663	1.850	1.674	1.765	1.657	**1.687**	1.691	1.685	1.689	1.662	8.378
MAPE	22.843	23.566	23.553	23.012	24.000	22.991	23.444	22.422	**21.403**	22.797	22.719	22.840	22.349	108.03

Dynamic Forecasts

WPI	BASE	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	**SSM3AY**	DAVG	SSAVG	NCF
RMSE	3.747	3.756	2.087	3.665	2.292	3.682	2.409	3.727	1.988	3.659	**1.997**	2.047	2.061	7.488
MAE	2.941	2.966	1.666	2.921	1.853	2.978	1.833	2.961	1.727	2.952	**1.627**	1.600	1.699	6.550
MAPE	38.323	37.812	23.478	37.577	24.051	38.777	24.724	38.205	22.441	37.840	**22.131**	22.423	22.855	95.779

TABLE APPENDIXES TO CHAPTER 6

Table 6.1: In- and Out-of-Sample Performance of Real Divisia and Simple Sum Money Deflated with CPI in ANN Model of Real GDP Growth without Lagged GDP Growth

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
AIC	6.210	6.157	6.286	6.271	6.220	6.260	6.290	6.392	6.236	6.396

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	**DM2**	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.903	3.774	**2.644**	5.220	2.465	3.523	3.538	6.922	3.515	6.555	2.805	4.970	3.290
MAE	3.796	3.289	**1.738**	4.292	2.076	2.554	2.686	5.192	2.940	4.871	2.084	3.973	2.459
MAPE	52.126	43.399	**20.338**	56.695	31.023	29.677	33.647	60.969	41.227	56.918	26.489	48.164	37.286

Static Forecasts

	DM1	SSM1	**DM2**	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	2.821	3.798	**2.223**	4.798	2.229	4.374	2.914	6.773	2.256	6.700	2.212	5.151	3.290
MAE	2.434	3.282	**1.655**	3.350	1.877	2.996	2.204	5.241	1.681	5.092	1.671	3.945	2.459
MAPE	31.920	42.645	**21.743**	37.241	28.795	33.031	26.532	63.620	22.993	61.300	21.427	46.623	37.286

Table 6.2: In- and Out-of-Sample Performance of Real Divisia and Simple Sum Money Deflated with WPI in ANN Model of Real GDP Growth without Lagged GDP Growth

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
AIC	6.089	6.054	6.211	6.606	**6.105**	6.571	6.219	6.655	6.135	6.590

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	2.623	3.304	4.397	3.685	4.021	**3.366**	3.573	5.499	3.370	5.235	3.142	4.109	3.290
MAE	2.344	2.833	3.458	2.770	3.255	**2.531**	2.898	4.625	2.507	4.422	2.349	3.422	2.459
MAPE	34.005	39.288	44.289	32.017	43.160	**29.423**	37.478	57.925	33.840	55.526	29.978	42.525	37.286

Static Forecasts

	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	2.728	3.573	2.373	4.093	**2.143**	3.896	2.692	5.681	2.235	4.631	2.284	4.125	3.290
MAE	2.312	3.085	1.718	3.123	**1.578**	2.808	2.067	4.860	1.727	4.129	1.761	3.578	2.459
MAPE	31.940	42.511	21.068	36.664	**21.221**	32.409	25.868	61.885	22.434	57.562	22.648	45.779	37.286

Table 6.3: In- and Out-of-Sample Performance of Real Divisia and Simple Sum Money Deflated with CPI in ANN Model of Real GDP Growth Including Lagged GDP Growth

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
AIC	5.948	5.925	5.905	5.893	5.803	5.922	5.838	6.111	5.744	6.126

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	9.151	14.233	5.656	6.023	2.504	13.401	4.896	9.894	**2.434**	9.604	4.038	7.731	3.290
MAE	8.429	11.580	4.577	5.574	2.189	11.733	3.922	9.012	**2.004**	8.210	3.418	6.753	2.459
MAPE	128.95	174.64	60.276	85.925	32.338	174.13	52.632	123.65	**29.403**	113.03	46.105	92.435	37.286

Static Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	**DM2Y**	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.215	5.845	4.803	7.640	4.151	6.271	**3.072**	6.036	3.902	6.879	2.636	6.150	3.290
MAE	3.734	5.220	4.508	6.710	3.959	4.618	**2.525**	5.543	3.614	6.182	2.350	5.609	2.459
MAPE	56.611	74.249	73.977	91.844	62.653	55.397	**37.222**	80.649	56.238	83.440	35.597	76.500	37.286

4-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	5.561	16.973	4.611	8.130	2.591	16.190	3.641	9.235	**2.453**	9.496	2.851	9.317	4.426
MAE	4.879	15.732	3.469	6.837	2.402	15.491	2.640	7.497	**2.073**	7.480	2.204	8.433	3.400
MAPE	72.824	234.04	41.217	102.21	35.755	241.24	30.890	97.772	**30.308**	99.271	27.487	117.73	47.323

Dynamic Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	**DM2Y**	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.563	4.538	4.841	6.575	4.004	6.235	**2.886**	5.028	3.826	6.440	2.639	5.208	2.924
MAE	3.094	3.813	4.553	5.334	3.611	4.504	**2.349**	4.232	3.406	5.120	2.333	4.186	1.990
MAPE	46.098	51.227	74.650	69.891	57.376	52.708	**34.117**	61.104	53.145	67.123	35.546	53.378	22.483

Table 6.4: In- and Out-of-Sample Performance of Real Divisia and Simple Sum Money Deflated with WPI in ANN Model of Real GDP Growth Including Lagged GDP Growth

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
AIC	7.230	5.861	5.927	6.162	5.801	6.091	6.014	6.135	5.880	6.112

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	6.693	12.495	7.768	4.846	**4.992**	12.246	8.554	7.082	8.628	8.609	6.916	8.259	3.290
MAE	6.254	11.447	5.330	3.498	**3.230**	10.962	6.168	6.021	5.635	7.633	5.166	7.831	2.459
MAPE	95.776	172.48	62.729	45.864	**39.074**	179.26	76.288	78.749	65.439	104.79	65.712	114.87	37.286

Static Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.349	4.921	4.714	5.147	3.360	7.914	5.117	5.681	**3.711**	5.780	3.965	5.485	3.290
MAE	2.806	4.364	3.787	4.390	2.757	5.504	4.021	5.504	**2.681**	5.458	2.923	5.020	2.459
MAPE	37.668	63.589	48.845	57.022	38.232	69.198	50.795	80.379	**33.105**	76.478	36.927	69.010	37.286

4-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	5.948	14.381	7.634	5.294	**5.042**	9.761	8.153	6.581	8.591	6.943	6.594	6.541	4.426
MAE	5.664	13.202	5.082	3.753	**3.355**	8.379	5.165	4.987	5.649	5.580	4.372	5.881	3.400
MAPE	84.104	191.78	60.051	49.799	**41.716**	140.93	61.512	62.447	67.387	74.610	53.232	82.863	47.323

Dynamic Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	3.435	4.662	5.184	4.452	3.741	7.203	5.227	4.269	**3.895**	4.344	4.227	4.766	2.924
MAE	2.791	3.764	4.551	3.133	3.140	5.096	4.267	3.810	**2.965**	3.598	3.376	3.951	1.990
MAPE	38.843	54.143	63.434	35.665	44.241	64.898	57.046	54.002	**37.885**	46.638	45.418	52.052	22.483

Table 6.5: In- and Out-of-Sample Performance of Nominal Divisia and Simple Sum Money in ANN Model of Quarterly CPI Inflation without Lagged CPI

CPI	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
$\overline{R}^2$	0.695	0.210	0.767	0.570	0.798	0.557	0.771	0.421	0.750	0.387

1-Period-Ahead Sequential Forecasts

CPI	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	7.390	7.166	6.359	5.457	5.113	**4.631**	5.282	5.906	5.010	4.825	5.248	5.889	5.269
MAE	6.855	6.231	5.340	4.874	3.899	**3.845**	4.063	4.882	3.837	4.105	4.261	4.960	4.385
MAPE	88.864	91.526	76.520	72.112	62.133	**54.894**	58.880	74.707	55.039	54.941	63.378	71.945	50.366

Static Forecasts

CPI	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.973	5.168	5.565	4.714	**3.018**	13.870	2.557	12.051	3.682	11.618	3.298	8.334	5.269
MAE	3.918	4.429	4.459	3.772	**2.061**	9.057	2.108	8.878	3.029	8.161	2.846	6.618	4.385
MAPE	45.712	66.737	56.015	53.216	**25.169**	155.56	30.660	135.46	45.242	123.27	36.538	104.39	50.366

Table 6.6: In- and Out-of-Sample Performance of Nominal Divisia and Simple Sum Money in ANN Model of Quarterly WPI Inflation without Lagged WPI

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
$\overline{R}^2$	0.745	0.734	0.831	0.623	0.738	0.656	0.748	0.402	0.873	0.493

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	**DM2Y**	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	9.985	7.434	6.163	17.086	5.442	5.605	**4.629**	6.452	5.420	4.628	5.764	6.746	7.445
MAE	7.605	4.966	4.390	12.180	3.869	4.271	**3.420**	5.325	4.735	3.418	4.465	4.759	5.246
MAPE	98.881	39.746	58.200	173.17	50.874	53.019	**40.896**	70.860	58.179	41.784	57.706	62.260	54.719

Static Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	5.838	6.018	6.065	5.944	5.562	18.155	6.267	15.626	**5.196**	15.939	4.035	10.267	7.445
MAE	4.139	4.171	4.322	4.363	3.582	11.477	4.206	10.051	**3.359**	10.714	3.239	8.097	5.246
MAPE	51.490	50.372	46.953	51.202	35.178	154.94	44.712	128.56	**30.663**	132.22	37.958	103.02	54.719

Table 6.7: In- and Out-of-Sample Performance of Nominal Divisia and Simple Sum Money in ANN Model of Quarterly CPI Inflation with Lagged CPI

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
$\bar{R}^2$	0.565	0.567	0.639	0.620	0.613	0.630	0.709	0.525	0.729	0.650

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	5.432	6.274	5.688	5.734	5.684	4.549	5.255	6.351	**4.364**	5.556	5.037	5.060	5.269
MAE	4.852	5.341	4.749	4.915	4.977	3.988	4.392	5.427	**3.678**	4.659	4.339	4.643	4.385
MAPE	67.946	72.381	64.233	68.043	66.816	53.182	62.030	82.899	**52.004**	59.267	60.413	65.006	50.366

Static Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.484	4.314	3.628	5.304	3.650	7.510	3.200	7.759	**2.577**	5.163	3.357	4.929	5.269
MAE	3.901	3.378	2.953	4.761	2.944	6.211	2.665	6.237	**2.082**	4.790	2.848	4.649	4.385
MAPE	54.864	48.783	46.088	56.152	46.003	89.003	40.208	75.504	**31.999**	62.353	43.335	63.755	50.366

4-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	**SSM3A**	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	6.807	5.691	6.304	6.637	6.733	**5.824**	6.229	6.114	5.233	6.701	5.975	5.324	6.997
MAE	6.063	4.912	5.146	5.144	6.051	**4.806**	5.563	4.659	4.397	5.613	5.266	4.773	6.009
MAPE	86.265	62.650	70.404	78.282	83.997	**60.090**	78.682	75.563	67.018	74.850	76.025	68.259	84.505

Dynamic Forecasts

	DM1	SSM1	DM2	SSM2	**DM3A**	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	4.914	4.578	4.124	5.035	**3.412**	8.327	4.118	8.062	4.054	5.160	3.945	5.100	7.695
MAE	4.265	3.692	2.944	4.583	**2.458**	6.743	2.972	6.329	3.208	4.741	2.973	4.785	6.964
MAPE	60.446	54.777	43.135	57.674	**37.420**	96.349	39.808	73.739	41.937	60.597	42.628	65.949	105.71

Table 6.8: In- and Out-of-Sample Performance of Nominal Divisia and Simple Sum Money in ANN Model of Quarterly WPI Inflation with Lagged WPI

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY
$\bar{R}^2$	0.787	0.864	0.796	0.881	0.795	0.647	0.793	0.769	0.779	0.870

1-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	7.331	7.647	7.758	11.535	6.950	6.277	6.470	12.317	**7.248**	5.519	6.756	6.974	7.445
MAE	4.858	5.176	5.495	7.683	5.178	4.998	5.375	8.745	**5.779**	4.513	5.014	5.591	5.246
MAPE	52.626	52.028	69.825	101.21	63.693	67.416	65.893	108.92	**66.988**	62.382	61.112	74.146	54.719

Static Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	**DM3AY**	SSM3AY	DAVG	SSAVG	NCF
RMSE	6.139	4.979	6.141	12.788	5.292	7.474	5.615	7.838	**5.274**	8.009	5.426	6.565	7.445
MAE	4.584	4.100	4.282	8.854	4.068	5.612	4.221	4.379	**3.931**	5.363	3.806	5.273	5.246
MAPE	56.962	52.400	43.678	133.49	47.684	75.858	49.863	49.734	**48.854**	73.146	46.365	73.895	54.719

4-Period-Ahead Sequential Forecasts

	DM1	SSM1	DM2	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	**3.416**	7.190	8.471	12.124	7.874	5.956	7.044	11.929	7.660	4.974	6.619	6.648	10.211
MAE	**2.664**	5.208	7.193	8.532	6.584	4.742	5.622	8.287	6.030	3.859	5.473	5.376	8.378
MAPE	**34.676**	57.848	96.239	115.55	82.602	61.570	69.553	111.66	73.381	54.093	70.294	74.819	108.03

Dynamic Forecasts

	DM1	SSM1	**DM2**	SSM2	DM3A	SSM3A	DM2Y	SSM2Y	DM3AY	SSM3AY	DAVG	SSAVG	NCF
RMSE	5.815	5.799	**5.214**	8.165	5.748	6.006	5.282	6.553	5.313	7.557	5.225	5.595	7.488
MAE	4.191	4.495	**3.483**	5.664	4.386	4.753	3.733	4.173	3.970	5.550	3.498	4.559	6.550
MAPE	46.875	58.600	**36.023**	80.212	54.504	64.236	45.840	50.446	49.398	80.319	42.827	63.924	95.779

TABLE APPENDIXES TO CHAPTER 7

Table 7.1: A Summary of All Results - Aggregates with Best Forecasts

Model and Forecast Variable	1-Step	Static	12/4-Step	Dynamic
ECM (B)- Annual CPI-Inf.	SSM1	**SSM2Y***	SSM1*	SSM3AY*
ECM (M)- Annual CPI-Inf.	SSM3AY	**SSM3AY***‡	SSM3AY*	DM3AY*‡
ECM (B)- Annual WPI-Inf.	DM2*	**DM2Y***	DM2*	SSM2Y*
VAR - Monthly CPI-Inf.	DM3A*	**SSM1***	SSM1	SSM1
ARMA - Monthly CPI-Inf.	SSM2Y*‡	SSM3AY*‡	SSM2Y*‡	**SSM3AY***‡
VAR - Monthly WPI-Inf.	DM3AY	**SSM1**	SSM1	DM2Y
ARMA - Monthly WPI-Inf.	**SSM1***‡	SSM1*‡	SSM1*‡	DM3A*‡
ARMA - Quarterly CPI-Inf.	SSM3AY‡	DM1‡	**SSM1**‡	DM1‡
Phillips Curve - Quarterly CPI-Inf.	**SSM3A***‡	SSM3A*‡	SSM2*‡	SSM3A*‡
Cost-Push - Quarterly CPI-Inf.	DM2Y‡	DM1‡	**SSM2Y**‡	SSM3AY‡
ARMA - Quarterly WPI-Inf.	SSM2Y‡	SSM1‡	SSM2Y‡	**SSM3AY**‡
Phillips Curve - Quarterly WPI-Inf.	SSM3AY*‡	SSM3A*‡	**SSM3A***‡	SSM3A*‡
Cost-Push - Quarterly WPI-Inf.	SSM1*‡	DM2Y*‡	**SSM2Y***‡	SSM2Y
Cost-Push (00-02) - Quarterly CPI-Inf.	**DM2Y***‡	DM2*‡	DM2*‡	DM3A*‡
NN No Lag (00-02) - Quarterly CPI-Inf.	SSM3A*	**DM3A***		
NN W/Lag (00-02) - Quarterly CPI-Inf.	DM3AY*	**DM3AY***	SSM3A*	DM3A*
Cost-Push (00-02) - Quarterly WPI-Inf.	**SSM2Y***‡	SSM2Y*‡	SSM2Y*‡	SSM3AY*‡
NN No Lag (00-02) - Quarterly WPI-Inf.	DM2Y*	**DM3AY***		
NN W/Lag (00-02) - Quarterly WPI-Inf.	DM3AY*	DM3AY*	**DM1***	DM2*
ECM (B)- Nom. GDP Growth	**DM3A***	SSM1	DM3A*	SSM1*
ECM (B)- R. GDP Levels	SSM3A/C*	**DM3A/C***	SSM3A/C*	DM3A/C*
VAR - R. GDP Growth	SSM2Y/W	**SSM2Y***	SSM2Y/W*	SSM2Y
ARMA - R. GDP Growth	SSM2Y/W‡	**DM3AY/C**‡	SSM3A/W‡	DM2Y/W‡
St Louis Eq. - R. GDP Growth	DM3A/C*‡	**DM3A/C***‡	DM3AY/C*‡	DM3AY/C*‡
NN No Lag - R. GDP Growth	DM2/C*	**DM3A/W***		
NN W/Lag - R. GDP Growth	**DM3AY/C***	DM2Y/C*	DM3AY/C*	DM2Y/C

Unless indicated (by :00-02), all forecasts are made for 2004-2006 period.
Bold type indicates the best overall forecast among all forecasting schemes
ECM (B): Bivariate Error-Correction Model
ECM (M): Multivariate Error-Correction Model
NN: Neural Network
/C: Real Money Deflated Using CPI
/W: Real Money Deflated Using WPI
*: An asterisk sign following the variable indicates that we obtain better forecasts than the benchmark (naïve / no-change) forecasts.
‡: A double dagger sign following the variable indicates that we obtain better forecasts from models with money than the forecasts from base model (model without money).

Table 7.2: A Comparison across Models

Table 7.2.A: GDP Models (2004:1-2006:12)

	Nom. GDP Growth	**Real GDP Level**	**Real GDP Growth**	**Real GDP Growth**	**Real GDP Growth**	**Real GDP Growth**	**Real GDP Growth**	**Real GDP Growth**
	ECM	**ECM**	**COMP.**	**VAR**	**ARMA**	**ST.LOUIS**	**NN:NO LAG**	**NN:W/LAG**
1-Step:	DM3A	SSM3A/C	SSM3A/C	SSM2Y/W	SSM2Y/W	DM3A/C	**DM2/C**	DM3AY/C
RMSE	2.887	0.030	4.672	3.452	3.139	2.861	**2.644**	2.434
MAE:	2.569	0.025	3.793	2.641	2.602	2.252	**1.738**	2.004
MAPE:	16.691	0.240	60.486	36.033	38.112	32.839	**20.338**	29.403
Static:	SSM1	DM3A/C	DM3A/C	SSM2Y/NOM	DM3AY/W	DM3A/C	**DM3A/W**	DM2Y/C
RMSE	4.293	0.026	3.536	2.817	3.327	2.599	**2.143**	3.072
MAE:	3.543	0.021	2.591	2.047	2.764	2.089	**1.578**	2.525
MAPE:	24.678	0.201	40.2255	29.517	40.702	29.056	**21.221**	37.222
12-Step:	DM3A	SSM3A/C	SSM3A/C	SSM2Y/W	SSM3A/W	DM3AY/C		**DM3AY/C**
RMSE	3.647	0.030	4.639	3.338	5.719	2.656		**2.453**
MAE:	3.082	0.025	3.906	2.555	4.689	2.330		**2.073**
MAPE:	20.144	0.237	62.805	33.291	58.450	34.903		**30.308**
Dynamic:	SSM1	DM3A/C	DM3A/C	SSM2Y/NOM	**DM3AY/C**	DM3AY/C		DM2Y/C
RMSE	5.465	0.061	3.840	3.135	**1.919**	2.871		2.886
MAE:	4.160	0.054	2.566	2.408	**1.626**	2.435		2.349
MAPE:	32.187	0.512	36.048	28.379	**25.366**	36.118		34.117

/C: Real Money Deflated Using CPI
/W: Real Money Deflated Using WPI
COMP: Forecasts growth computed from level forecasts

Table 7.2.B: Models with Monthly Data (2004:1-2006:12)

	Monthly CPI-Inf.		**Monthly WPI-Inf.**		**Annual CPI-Inf.**		**An. WPI-Inf.**
	VAR	**ARMA**	**VAR**	**ARMA**	**ECM(B)**	**ECM(M)**	**ECM(B)**
1-Step:	**DM3A**	SSM2Y	DM3AY	**SSM1**	**SSM1**	SSM3AY	**DM2**
RMSE	**0.650**	0.744	1.769	**1.231**	**0.762**	1.260	1.650
MAE:	**0.554**	0.573	1.854	**0.842**	**0.658**	1.070	1.130
MAPE:	205.242	**167.664**	347.699	**150.455**	**7.071**	13.145	15.958
Static:	SSM1	**SSM3AY**	SSM1	**SSM1**	**SSM2Y**	SSM3AY	**DM2Y**
RMSE	0.609	**0.415**	1.226	**1.059**	**0.649**	0.775	1.507
MAE:	0.460	**0.350**	1.038	**0.690**	**0.491**	0.616	1.134
MAPE:	202.300	**109.013**	245.600	**124.550**	**5.778**	7.430	13.840
12-Step:	SSM1	**SSM2Y**	SSM1	**SSM1**	**SSM1**	SSM3AY	**DM2**
RMSE	0.695	0.982	1.837	**1.721**	**0.859**	1.455	1.790
MAE:	0.785	**0.748**	2.046	**1.395**	**0.859**	1.387	1.387
MAPE:	275.438	**211.659**	426.458	**351.791**	**7.975**	15.495	17.485
Dynamic:	SSM1	**SSM3AY**	DM2Y	**DM3A**	**SSM3AY**	DM3AY	**SSM2Y**
RMSE	0.830	**0.409**	1.530	**1.240**	**1.693**	1.957	3.435
MAE:	0.672	**0.331**	1.349	**0.890**	**1.506**	1.590	2.822
MAPE:	393.400	**121.469**	451.500	**210.241**	**18.246**	19.215	39.755

Table 7.2.C: Models with Quarterly Data (2004:1-2006:12)

	Quarterly CPI-Inf.				**Quarterly WPI-Inf.**		
	ARMA	**P. CURVE**	**COST-PUSH**		**ARMA**	**P. CURVE**	**COST-PUSH**
1-Step:	SSM3AY	**SSM3A**	DM2Y		SSM2Y	**SSM3AY**	SSM1
RMSE	2.324	**1.069**	1.714		3.377	**2.600**	2.650
MAE:	1.747	**0.856**	1.442		2.870	**1.758**	2.336
MAPE:	77.346	**49.032**	83.483		1157.372	**268.192**	635.070
Static:	DM1	**SSM3A**	DM1		SSM1	**SSM3A**	DM2Y
RMSE	2.294	**1.148**	2.646		4.935	**2.533**	3.075
MAE:	1.957	**0.926**	2.158		4.222	**1.764**	2.478
MAPE:	104.466	**50.940**	104.680		1647.552	**214.620**	570.640
12-Step:	SSM1	**SSM2**	SSM2Y		SSM2Y	**SSM3A**	SSM2Y
RMSE	2.446	**1.363**	1.439		3.408	**2.663**	2.466
MAE:	1.714	**1.178**	1.187		2.630	**1.749**	2.061
MAPE:	91.736	68.104	**61.846**		960.695	**212.394**	411.060
Dynamic:	DM1	**SSM3A**	SSM3AY		SSM3AY	**SSM3A**	SSM2Y
RMSE	2.068	**1.356**	3.017		3.297	**2.622**	3.353
MAE:	1.584	**1.102**	2.516		2.548	**1.740**	2.692
MAPE:	104.623	**54.919**	126.660		977.277	**343.970**	535.450

Table 7.2.D: Models with Quarterly Data (2000:1-2002:4)

	Quarterly CPI-Inf.				**Quarterly WPI-Inf.**		
	COST-PUSH	**NN:NO LAG**	**NN:W/LAG**		**COST-PUSH**	**NN:NO LAG**	**NN:W/LAG**
1-Step:	**DM2Y**	SSM3A	DM3AY		**SSM2Y**	DM2Y	DM3AY
RMSE	**2.143**	4.631	4.364		**1.880**	4.629	7.248
MAE:	**1.696**	3.845	3.678		**1.654**	3.420	5.779
MAPE:	**24.633**	54.894	52.004		**20.389**	40.896	66.988
Static:	**DM2**	DM3A	DM3AY		**SS2Y**	DM3AY	DM3AY
RMSE	**2.395**	3.018	2.577		**2.003**	5.196	5.274
MAE:	**1.955**	2.061	2.082		**1.721**	3.359	3.931
MAPE:	**29.655**	25.169	31.999		**22.367**	30.663	48.854
12-Step:	**DM2**		SSM3A		**SSM2Y**		DM1
RMSE	**2.088**		5.824		**1.909**		3.416
MAE:	**1.724**		4.806		**1.687**		2.664
MAPE:	**24.822**		60.090		**21.403**		34.676
Dynamic:	**DM3A**		DM3A		**SSM3AY**		DM2
RMSE	**2.750**		3.412		**1.997**		5.214
MAE:	**2.237**		2.458		**1.627**		3.483
MAPE:	**33.361**		37.420		**22.131**		36.023

APPENDIX B: FIGURES OF APPLICATION CHAPTERS

FIGURE APPENDIXES TO CHAPTER 3

Figure 3.1: The Shares of the Asset Components in M1 Aggregates

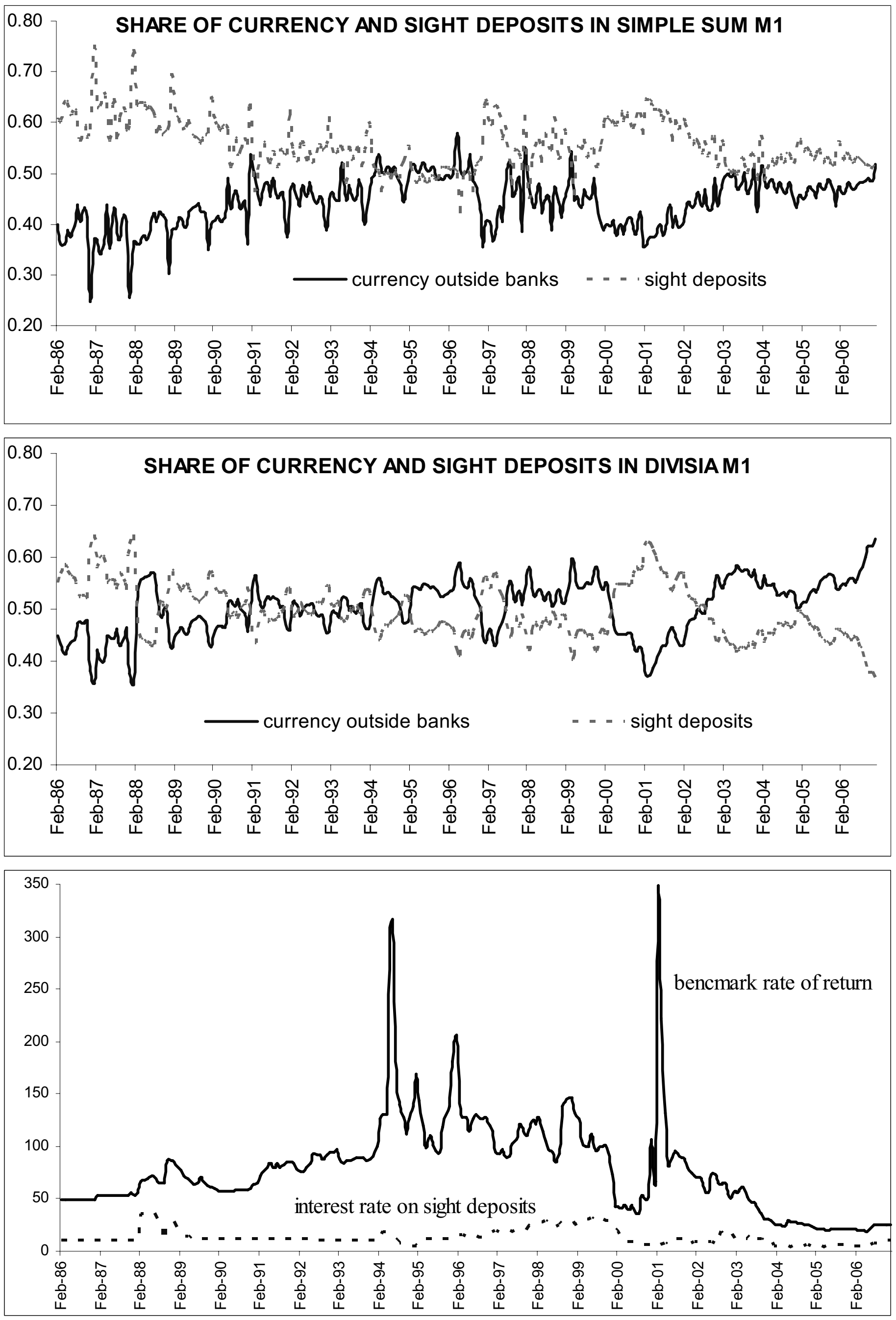


Figure 3.2: The Shares of the Asset Components in M2 Aggregates

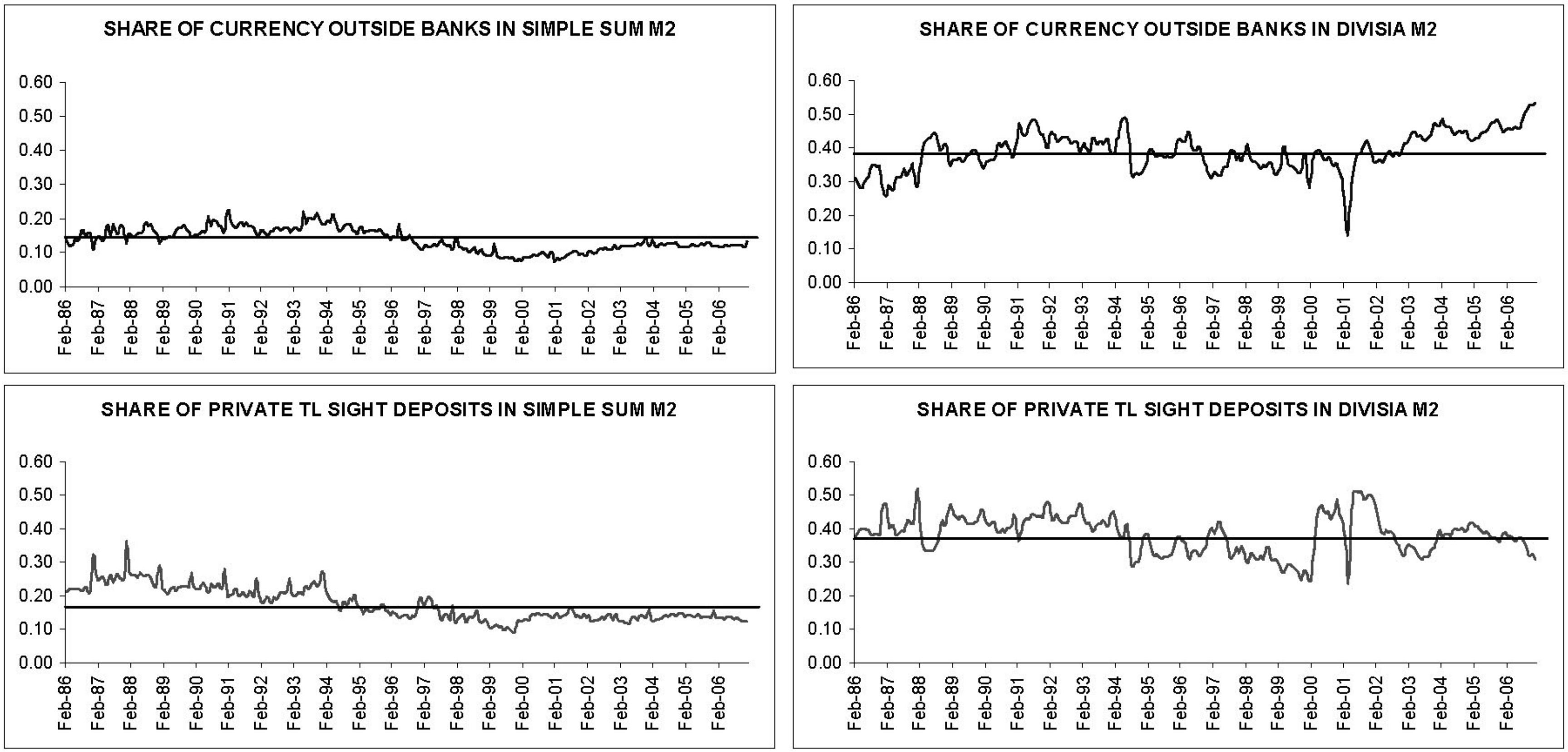


Figure 3.2: The Shares of the Asset Components in M2 Aggregates (Cont'd)

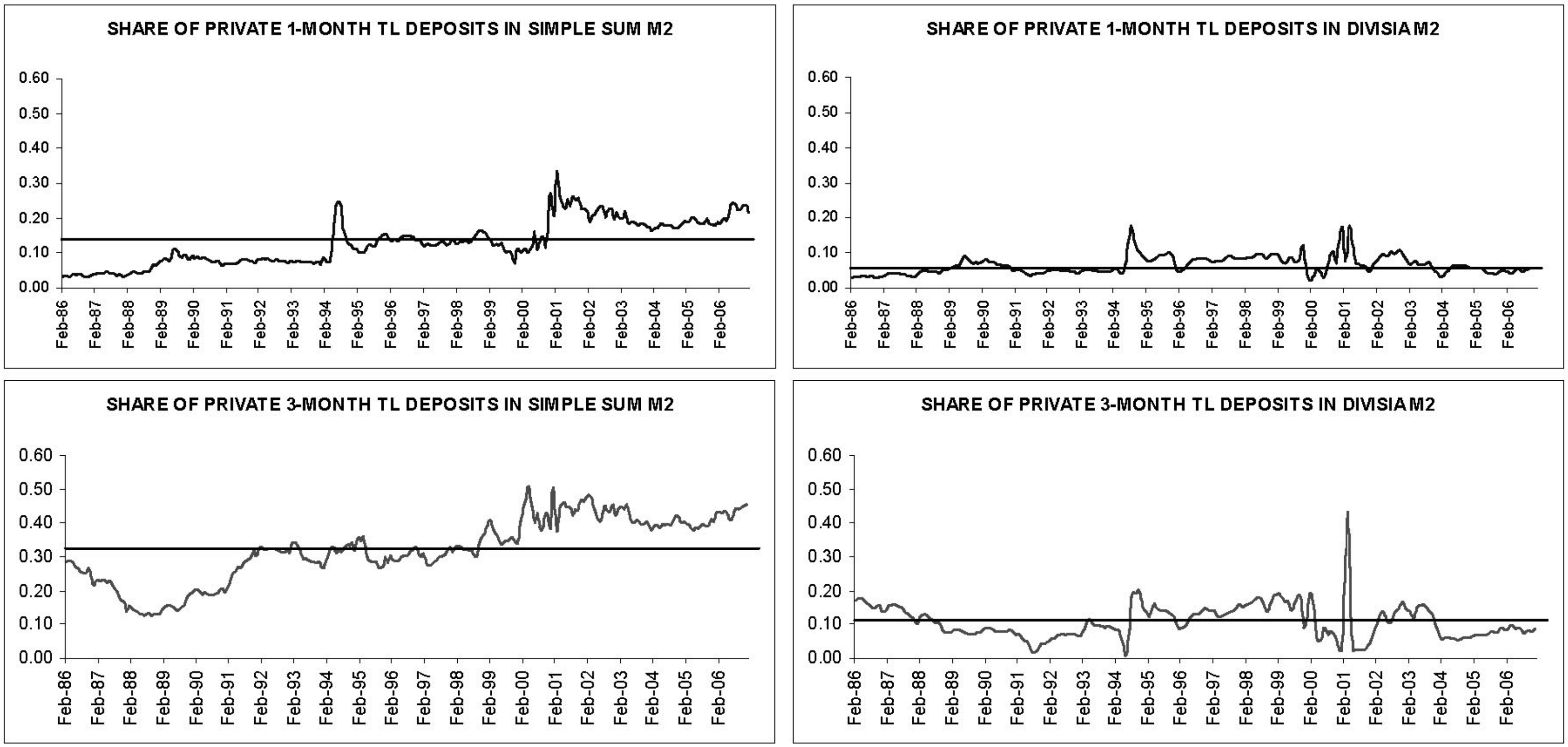


Figure 3.2: The Shares of the Asset Components in M2 Aggregates (Cont'd)

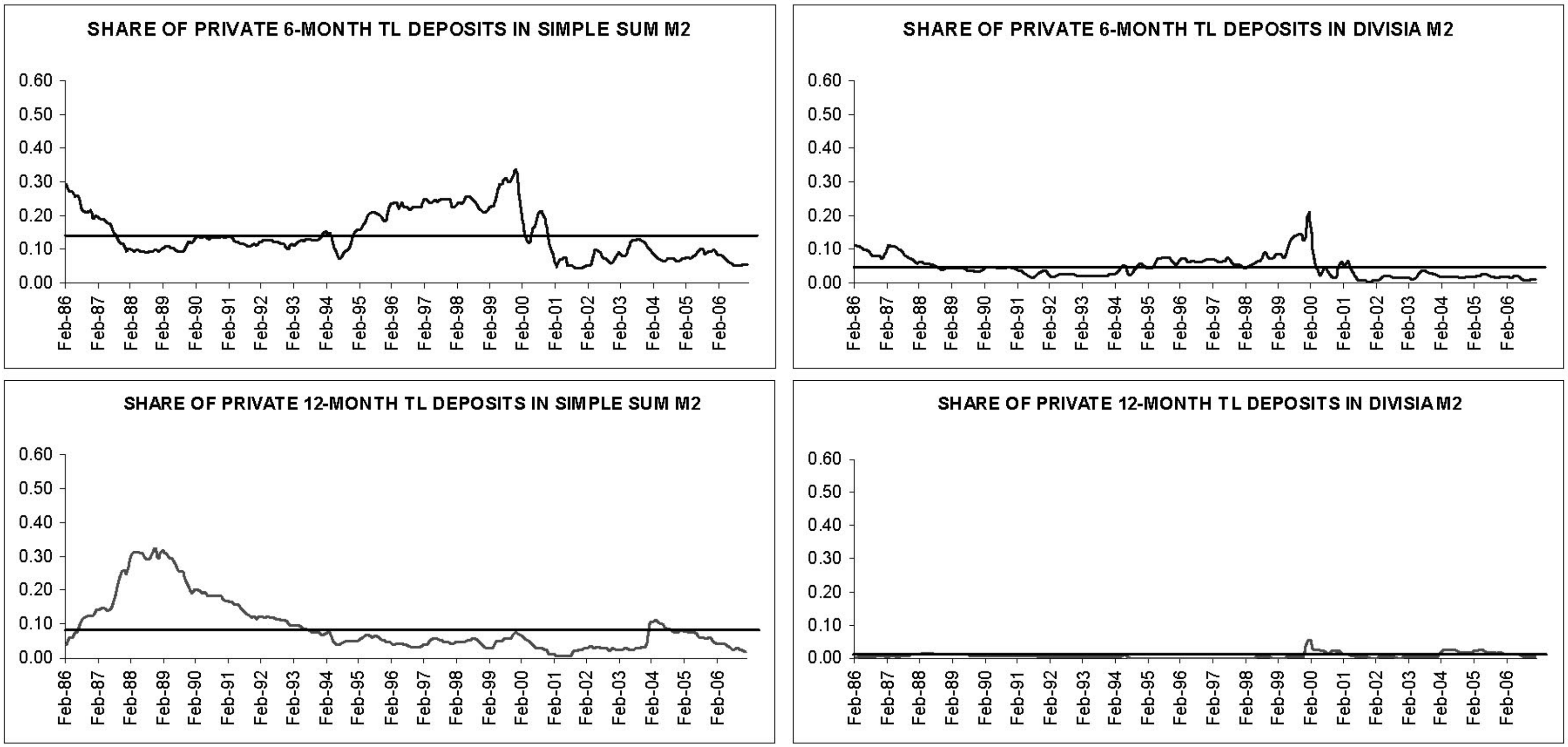
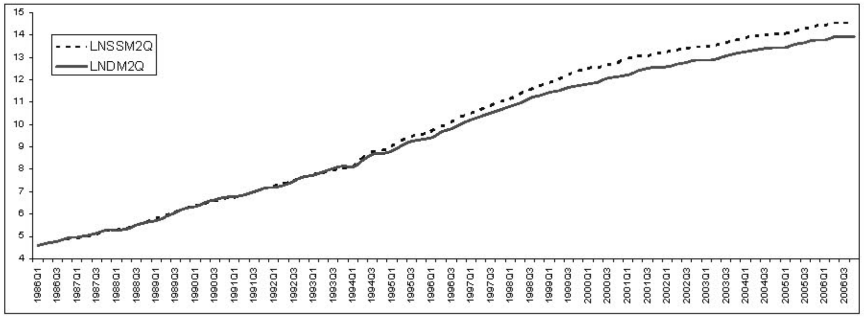
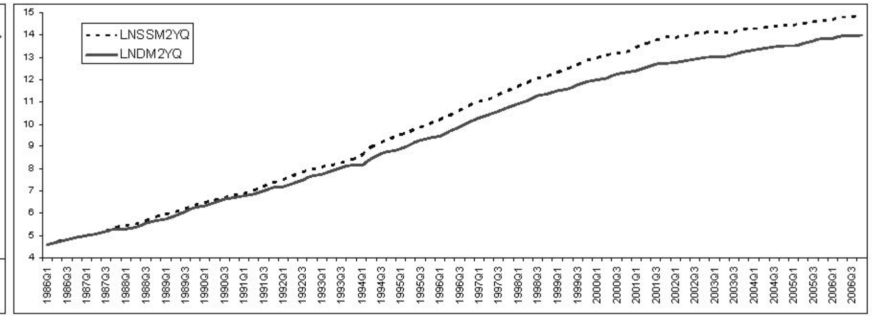


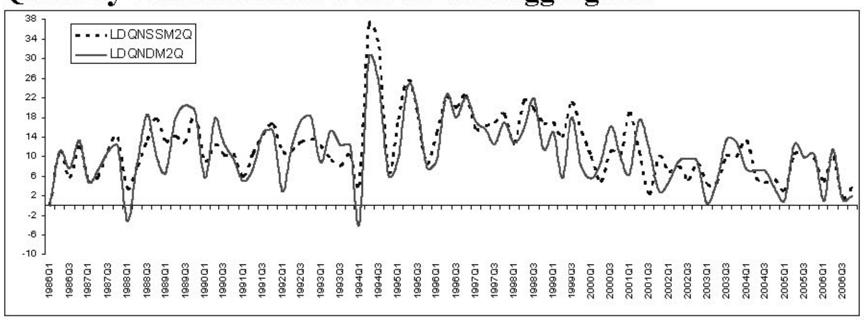
Figure 3.3: The Log Level Graphs of Simple Sum and Divisia M2 and M2Y Aggregates

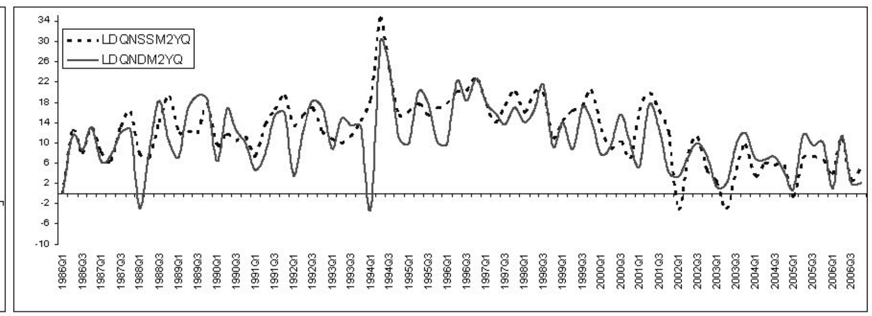
Nominal Levels



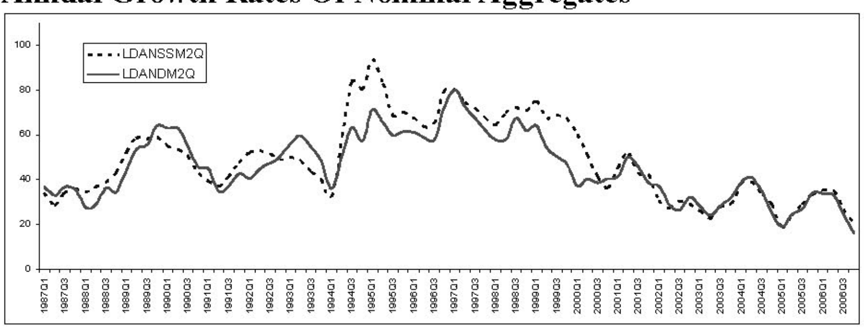


Quaterly Growth Rates Of Nominal Aggregates





Annual Growth Rates Of Nominal Aggregates



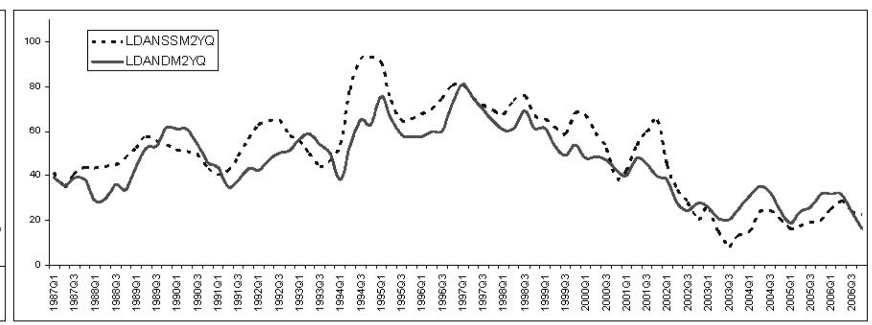
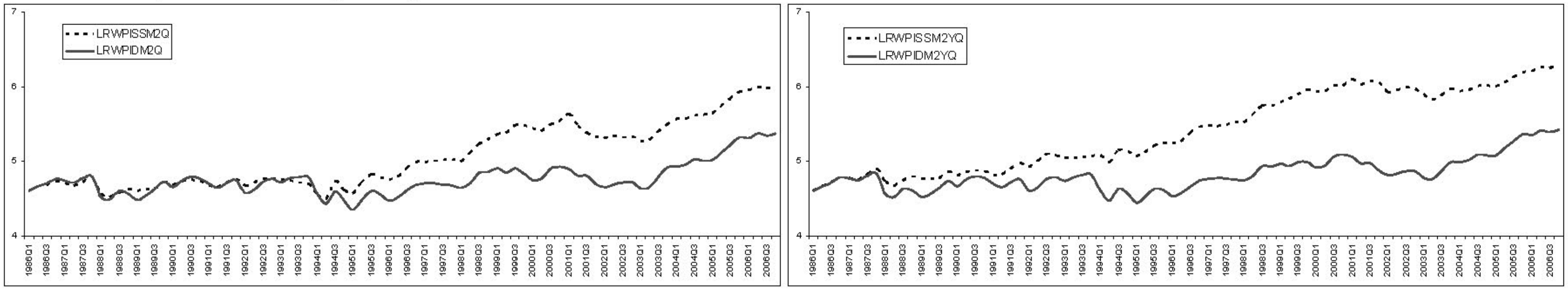
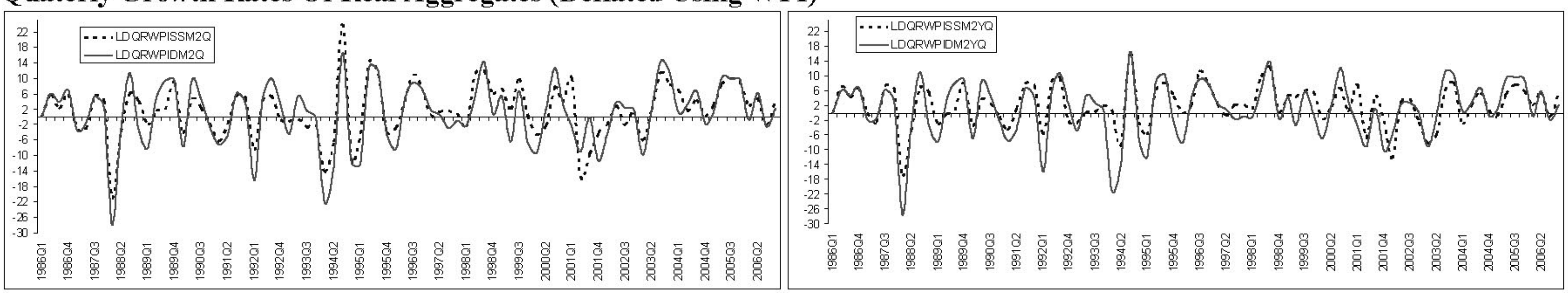


Figure 3.4: The Growth Rate Graphs of Simple Sum and Divisia M2 and M2Y Aggregates

Real Levels (Deflated Using WPI)



Quaterly Growth Rates Of Real Aggregates (Deflated Using WPI)



Annual Growth Rates Of Real Aggregates (Deflated Using WPI)

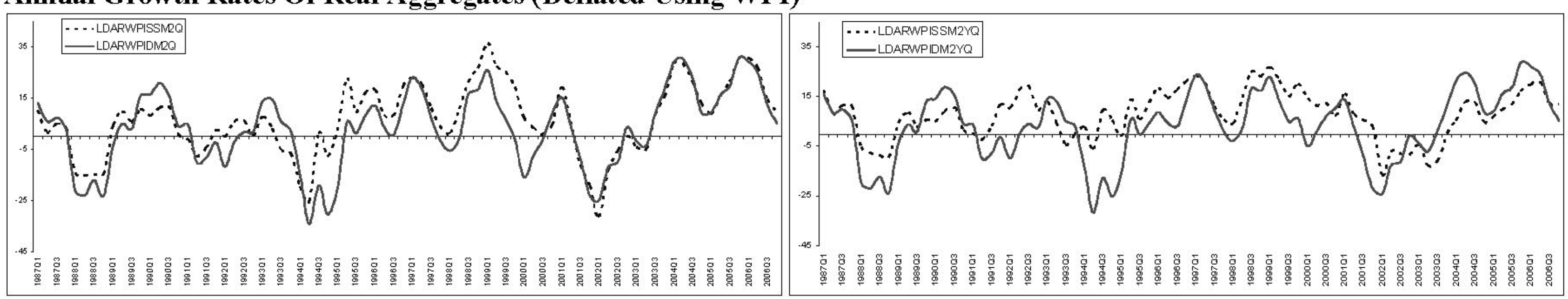


Figure 3.5. Year-on-Year CPI-Inflation and Nominal Money Growth Rates (Monthly Data)

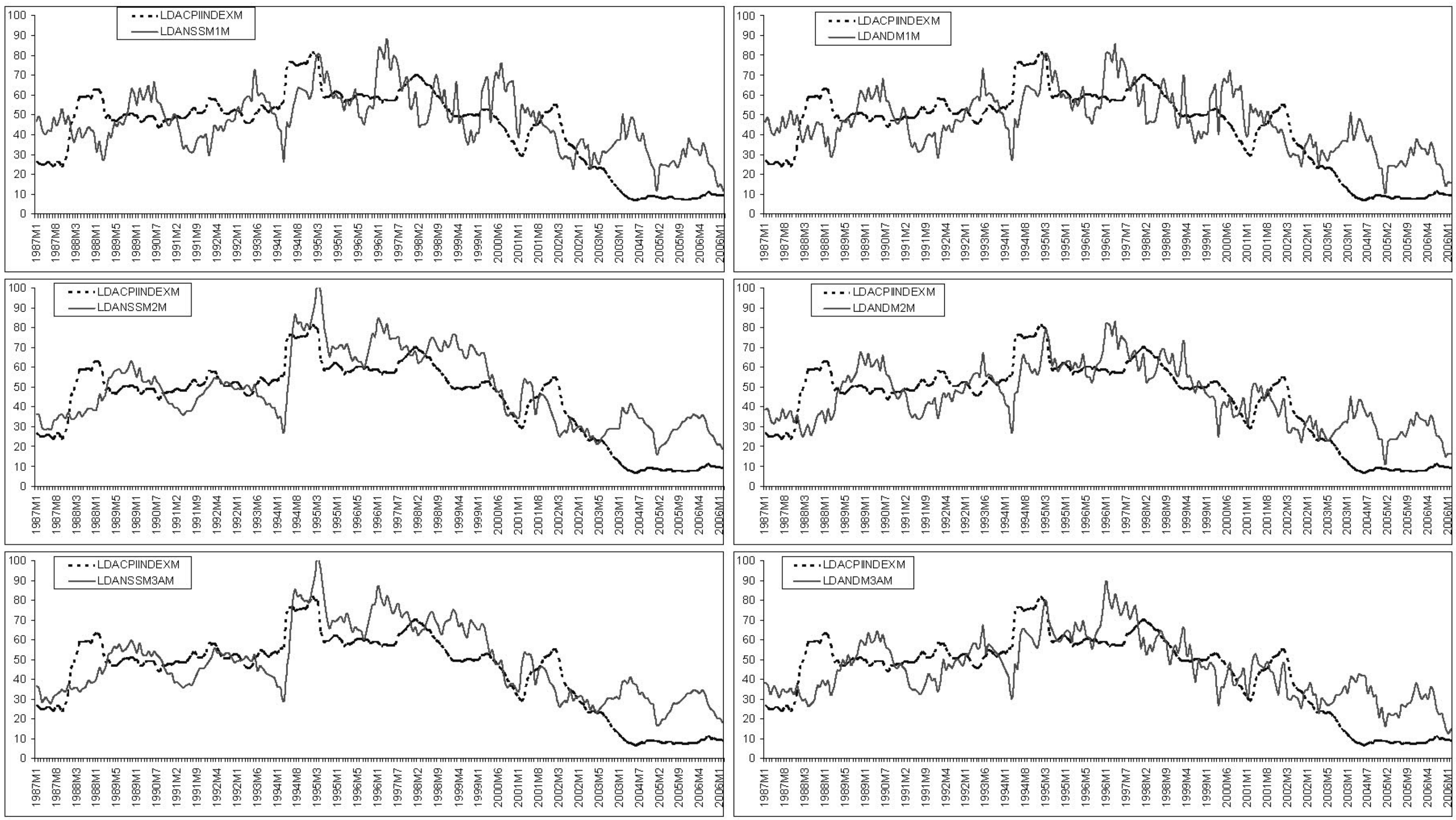


Figure 3.5. Year-on-Year CPI-Inflation and Nominal Money Growth Rates (Monthly Data) (Cont'd)

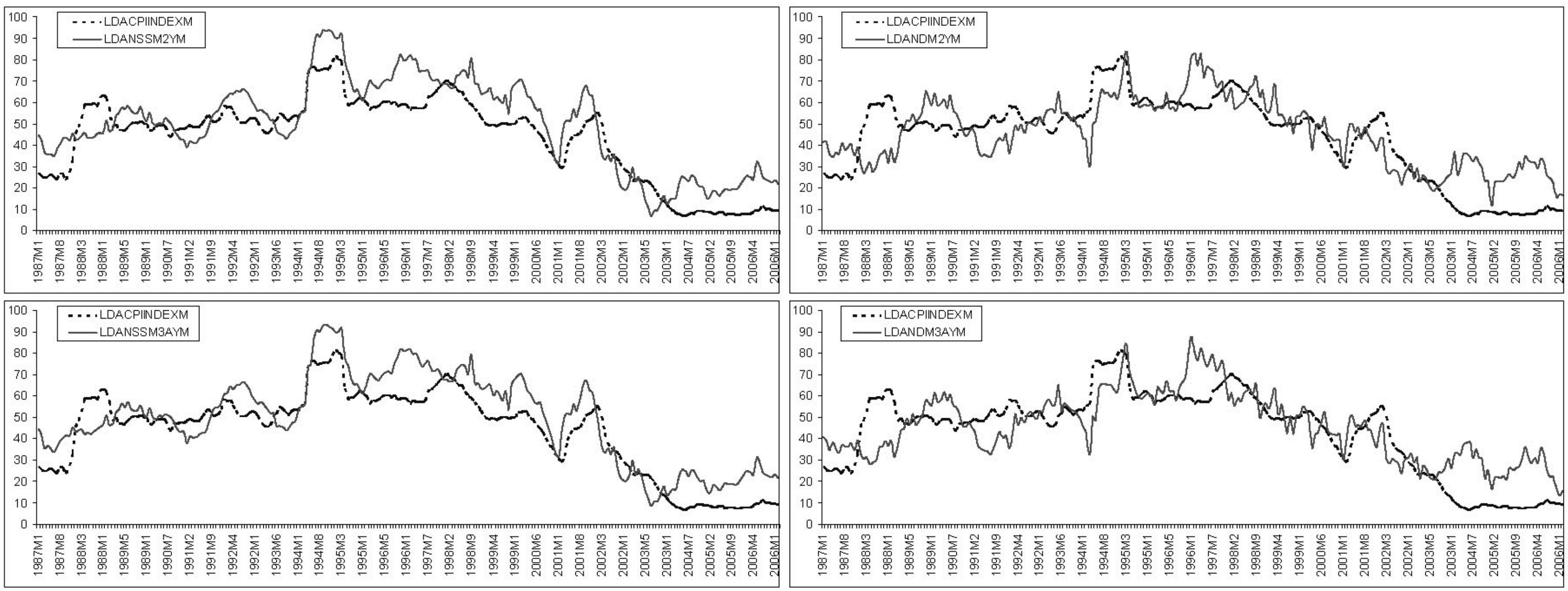


Figure 3.6: Income Velocities of Divisia and Simple Sum Monetary Aggregates

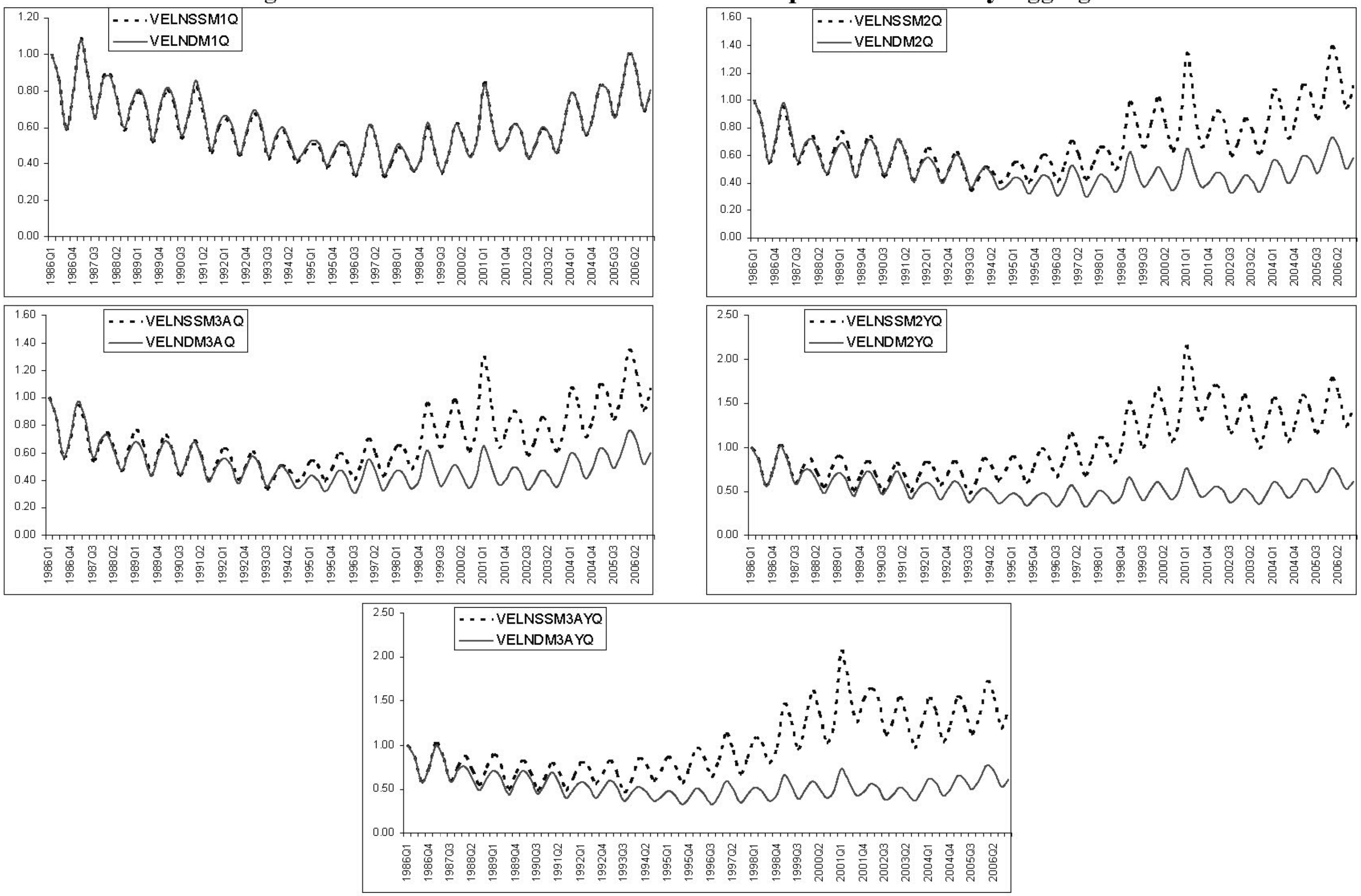


Figure 3.7: Graphs of All Variables Other than Money

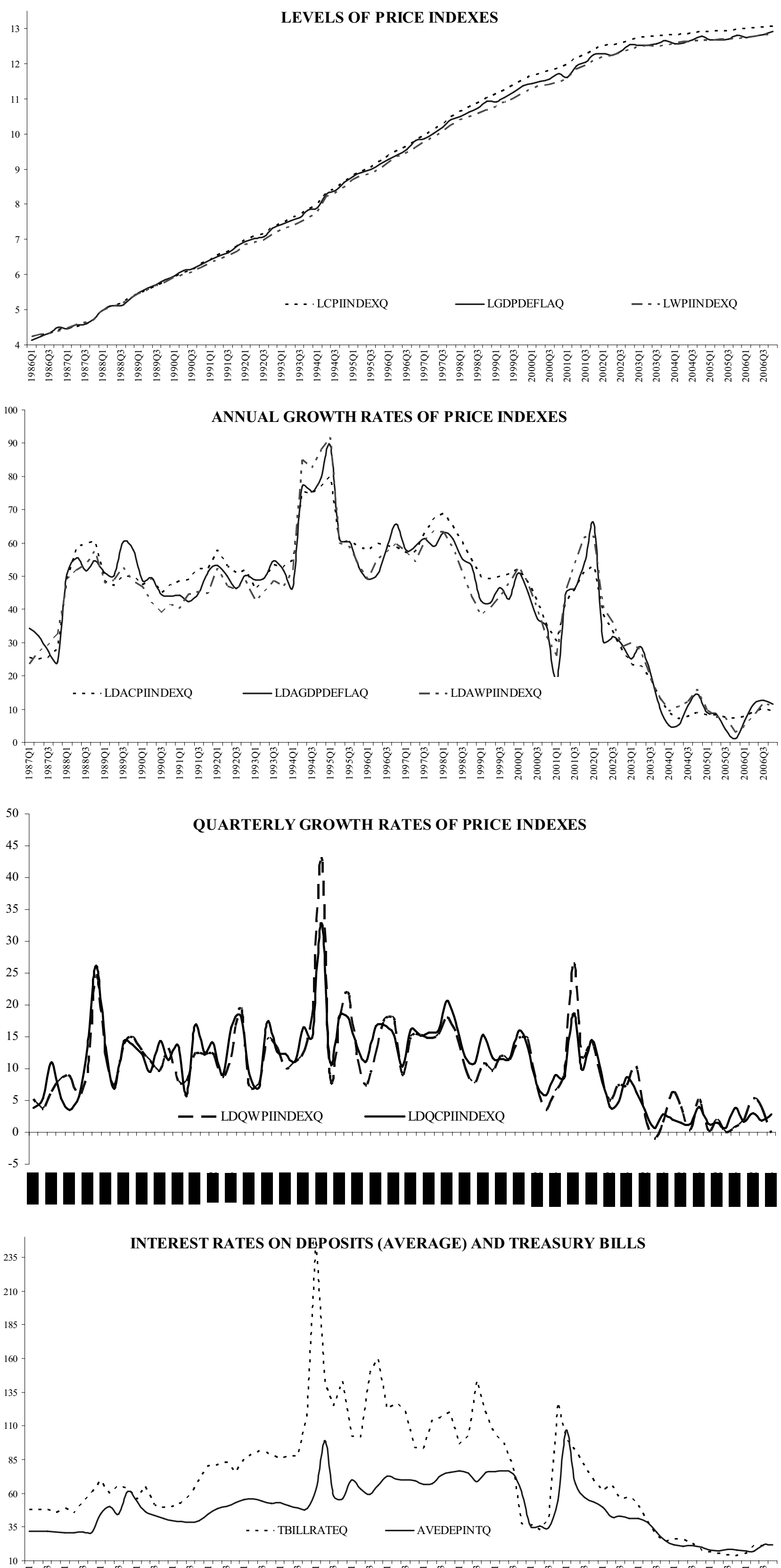
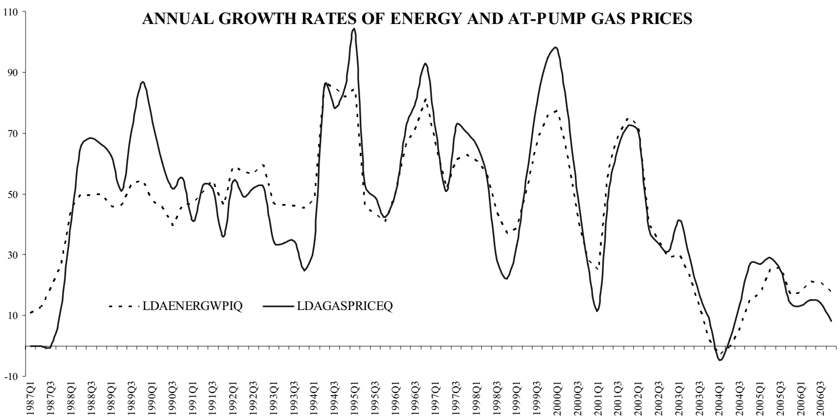
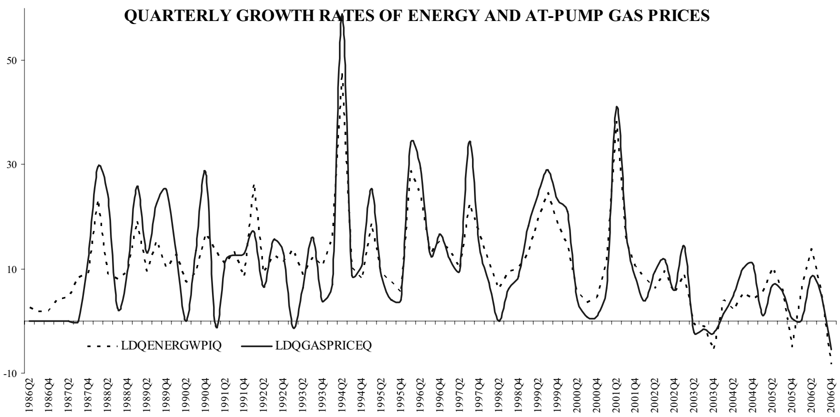
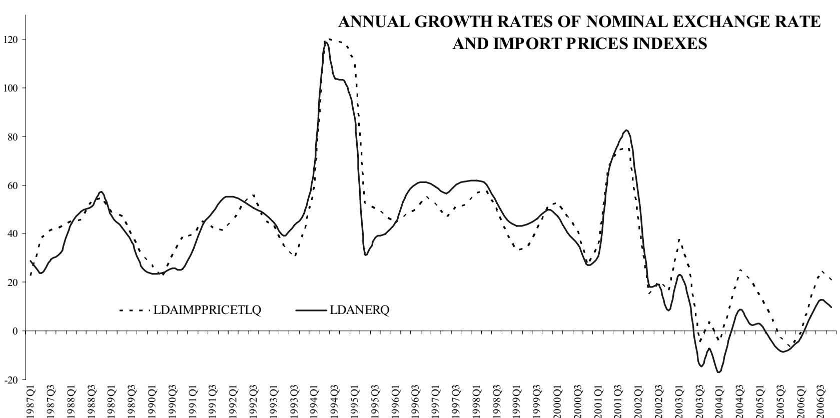


Figure 3.7: Graphs of All Variables Other than Money (Cont'd)







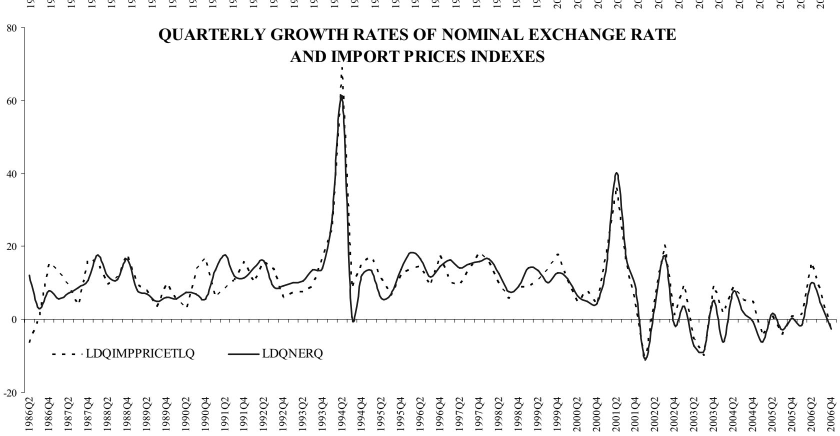


Figure 3.7: Graphs of All Variables Other than Money (Cont'd)

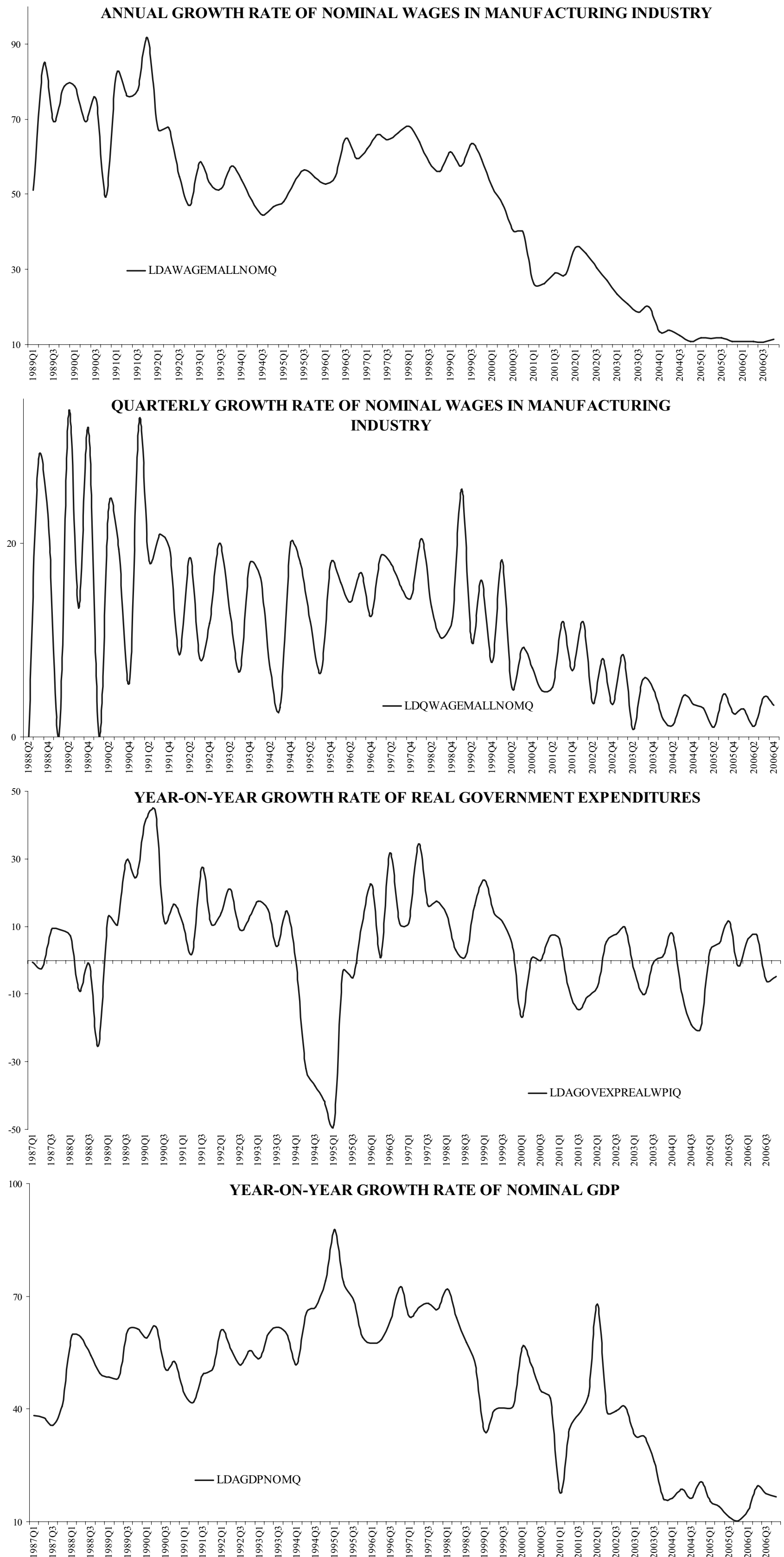


Figure 3.7: Graphs of All Variables Other than Money (Cont'd)

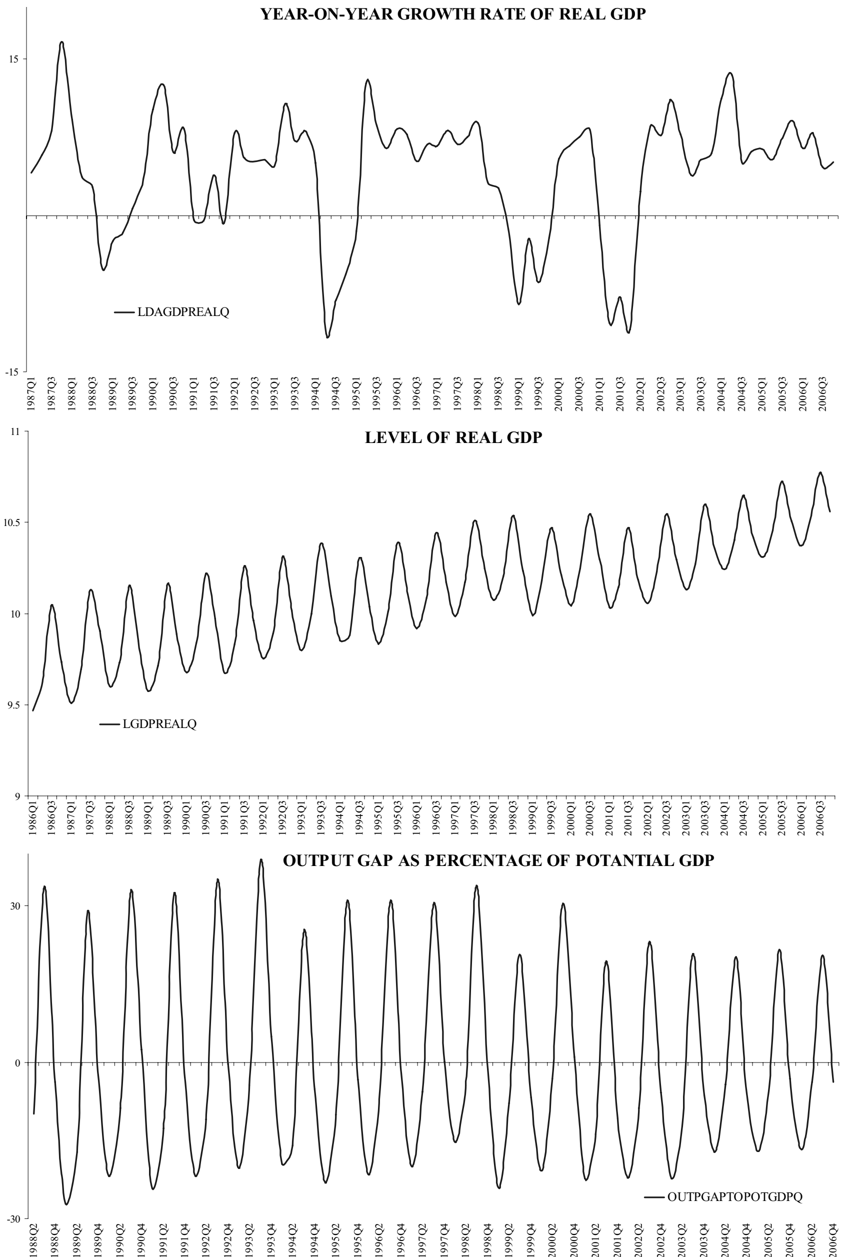
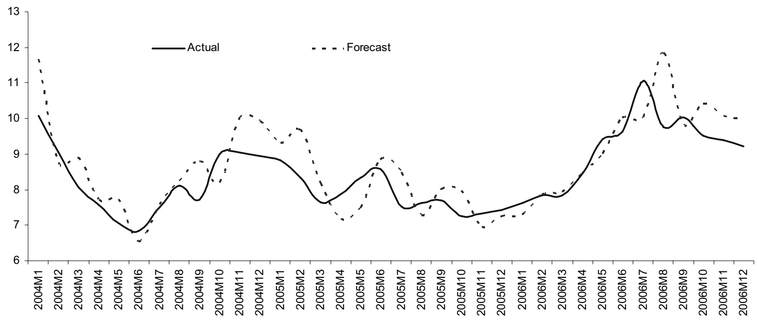


FIGURE APPENDIXES TO CHAPTER 4

Figure 4.1: Actual Data and Out-Of-Sample Forecasts of Annual CPI-Inflation from Bivariate Error-Correction Model

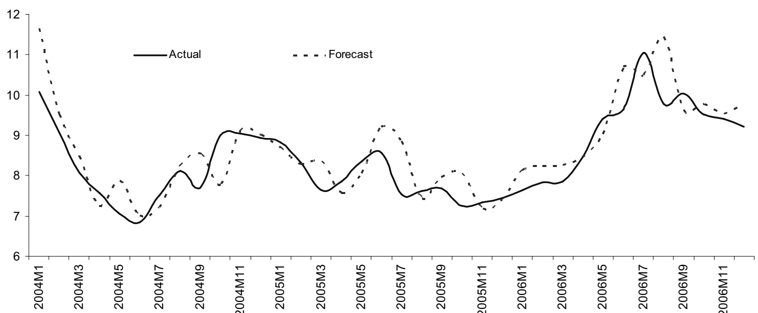
1-Step: SSM1

RMSE: 0.762; MAE: 0.658; MAPE: 7.071



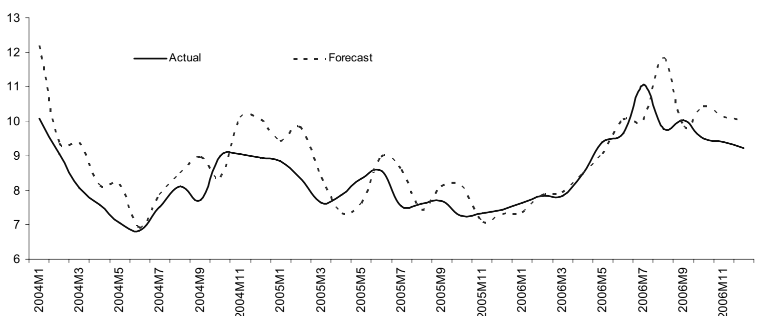
Static: SSM2Y

RMSE: 0.649; MAE: 0.491; MAPE: 5.778



12-Step: SSM1

RMSE: 0.859; MAE: 0.859; MAPE: 7.975



Dynamic: SSM3AY

RMSE: 1.693; MAE: 1.506; MAPE: 18.246

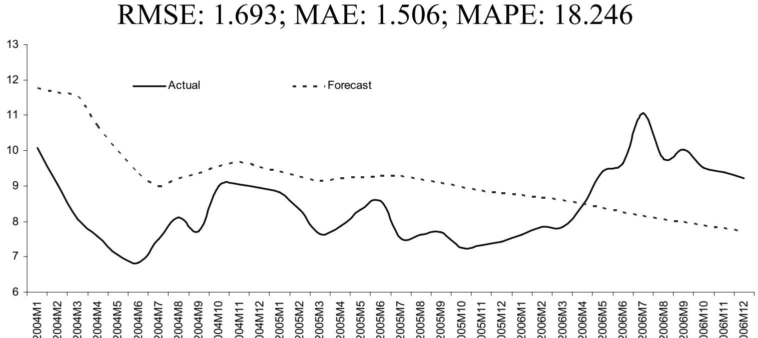
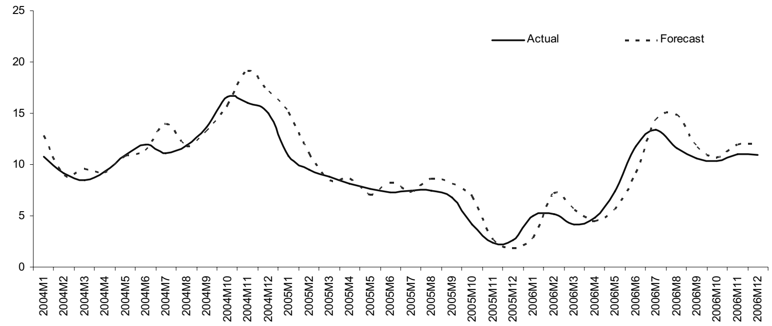


Figure 4.2: Actual Data and Out-Of-Sample Forecasts of Annual WPI-Inflation from Bivariate Error-Correction Model

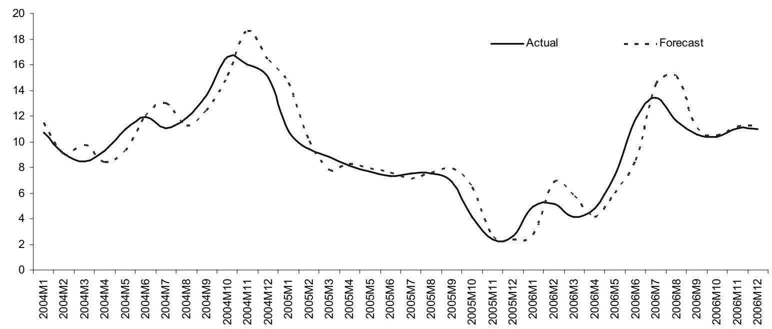
1-Step: DM2

RMSE: 1.650; MAE: 1.130; MAPE: 15.958



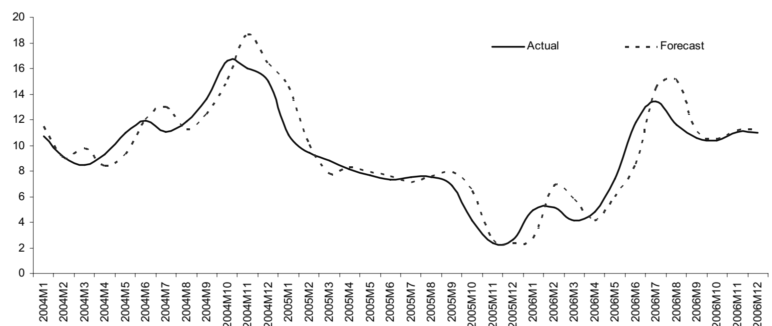
Static: DM2Y

RMSE: 1.507; MAE: 1.134; MAPE: 13.840



12-Step: DM2

RMSE: 1.790; MAE: 1.387; MAPE: 17.485



Dynamic: SSM2Y

RMSE: 3.435; MAE: 2.822; MAPE: 39.755

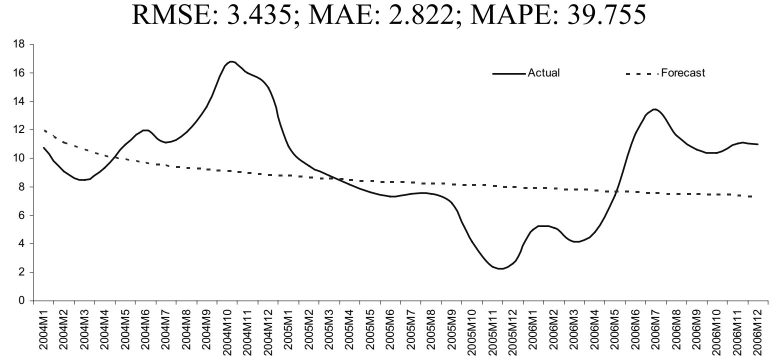
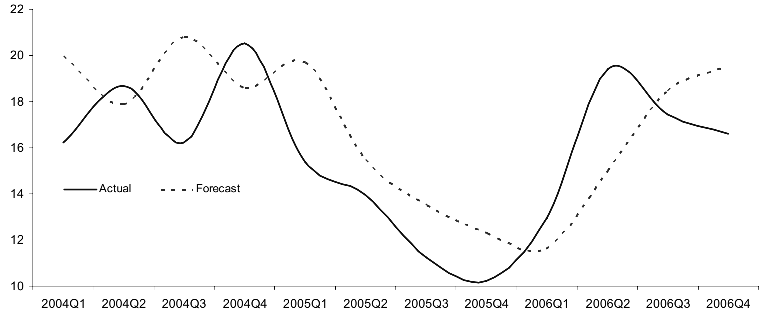


Figure 4.3: Actual Data and Out-Of-Sample Forecasts of Nominal GDP Growth from Bivariate Error-Correction Model

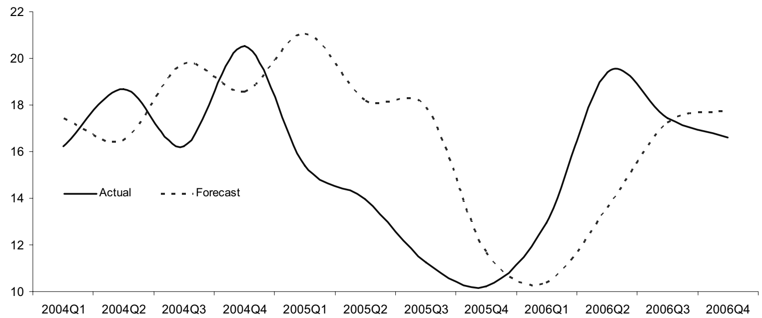
1-Step: DM3A

RMSE: 2.887; MAE: 2.569; MAPE: 16.691



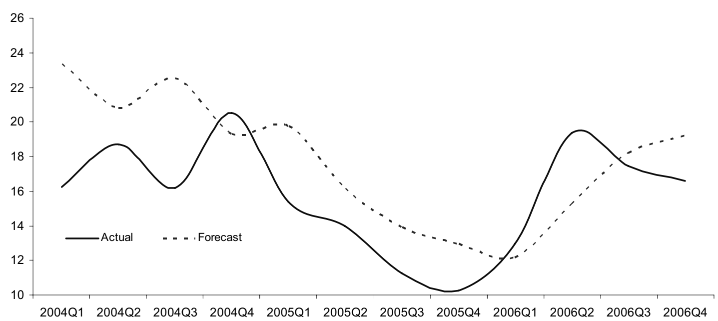
Static: SSM1

RMSE: 4.293; MAE: 3.543; MAPE: 24.678



4-Step: DM3A

RMSE: 3.647; MAE: 3.082; MAPE: 20.144



Dynamic: SSM1

RMSE: 5.465; MAE: 4.160; MAPE: 32.187

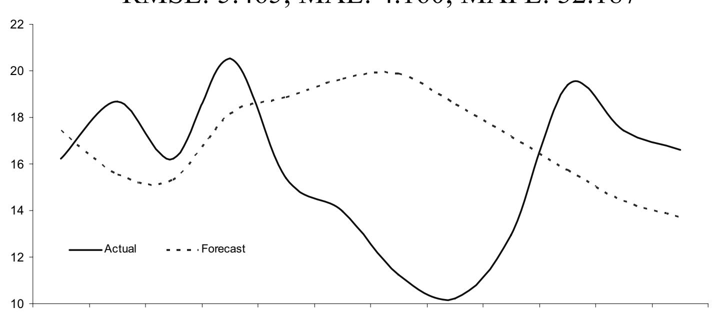
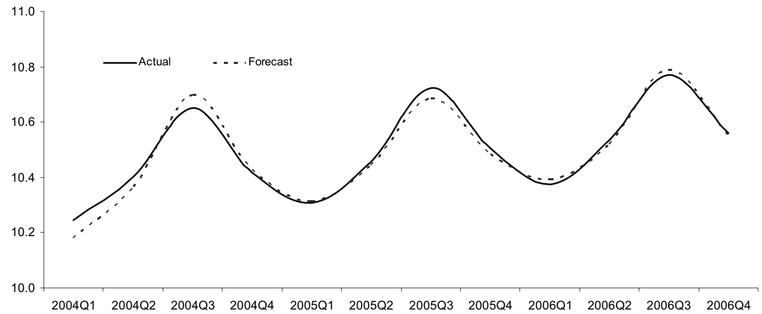


Figure 4.4: Actual Data and Out-Of-Sample Forecasts of Real GDP Level from Bivariate Error-Correction Model Using CPI-Deflated Real Money

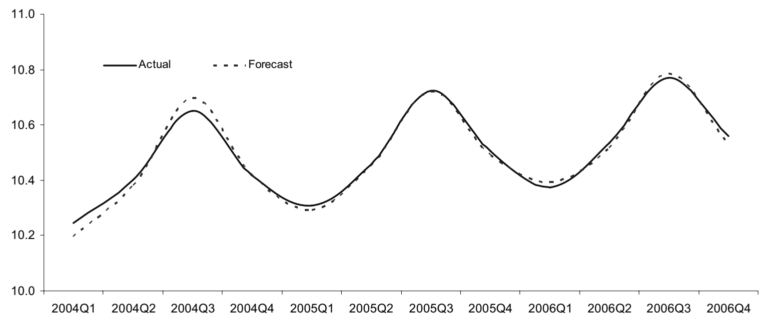
1-Step: SSM3A

RMSE: 0.030; MAE: 0.025; MAPE: 0.240



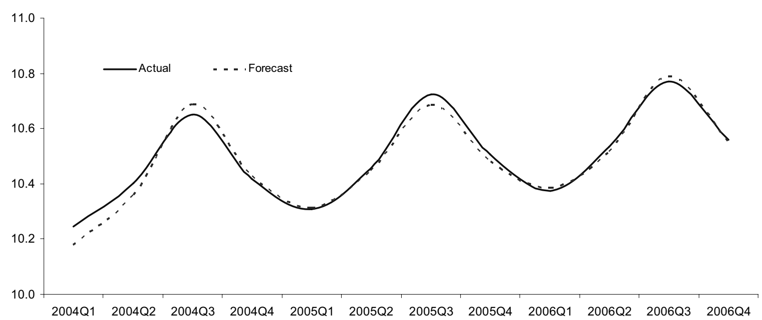
Static: DM3A

RMSE: 0.026; MAE: 0.021; MAPE: 0.201



4-Step: SSM3A

RMSE: 0.030; MAE: 0.025; MAPE: 0.237



Dynamic: DM3A

RMSE: 0.061; MAE: 0.054; MAPE: 0.512

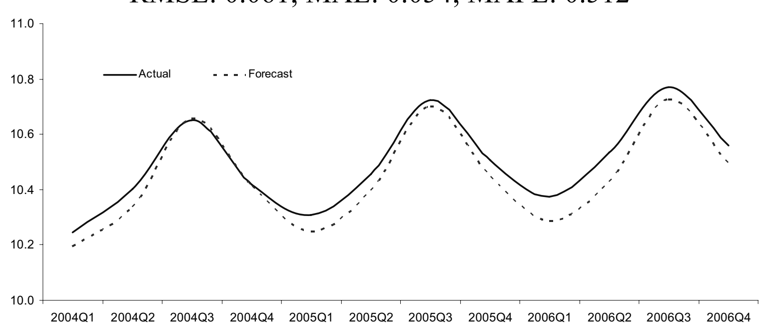
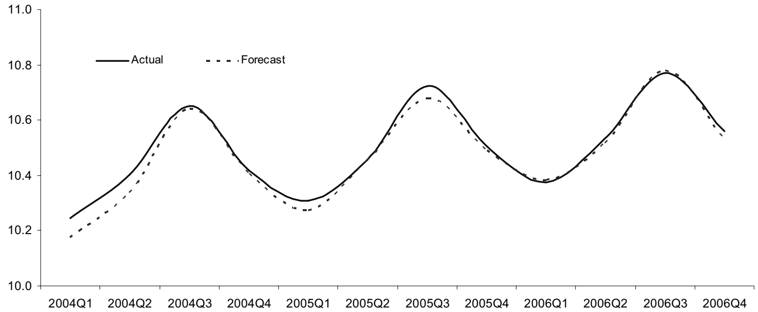


Figure 4.5: Actual Data and Out-Of-Sample Forecasts of Real GDP Level from Bivariate Error-Correction Model Using WPI-Deflated Real Money

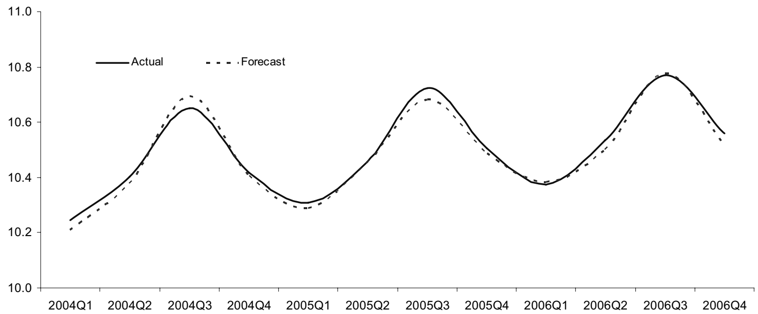
1-Step: DM3AY

RMSE: 0.034; MAE: 0.027; MAPE: 0.254



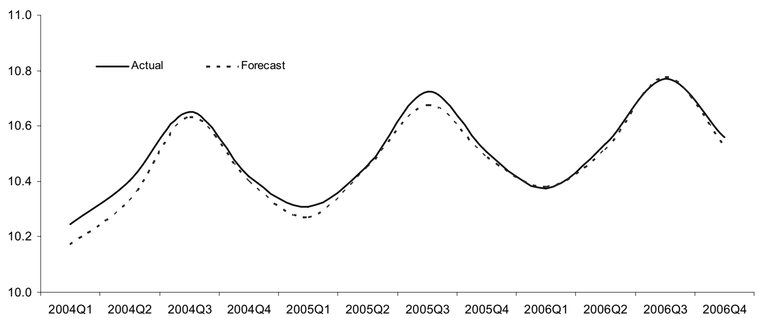
Static: DM3AY

RMSE: 0.028; MAE: 0.024; MAPE: 0.231



4-Step: DM3AY

RMSE: 0.037; MAE: 0.030; MAPE: 0.287



Dynamic: DM2Y

RMSE: 0.064; MAE: 0.057; MAPE: 0.543

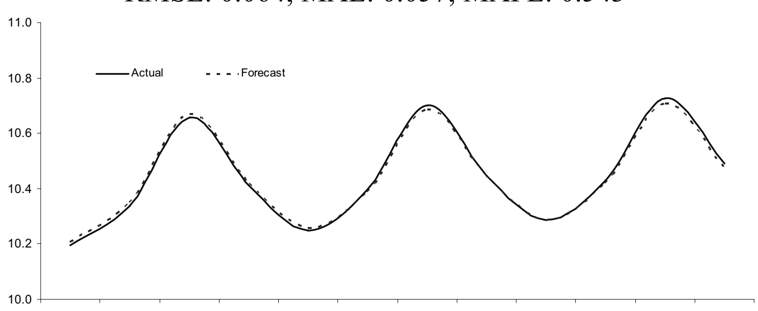
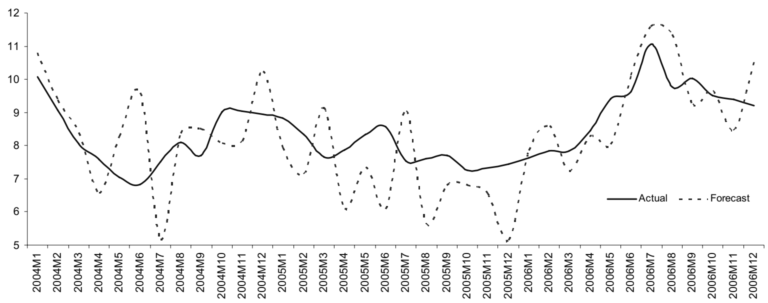


Figure 4.6: Actual Data and Out-Of-Sample Forecasts of Annual CPI-Inflation from Multivariate Error-Correction Model

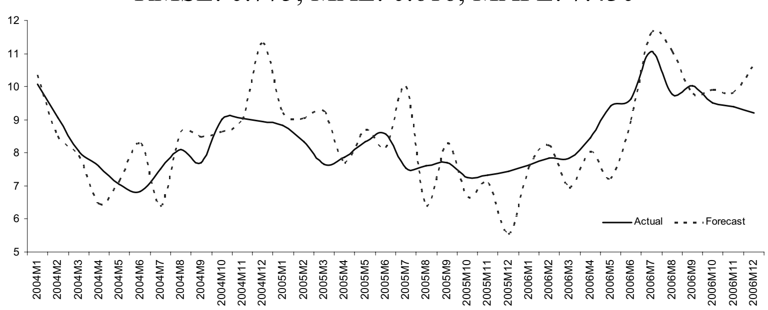
1-Step: SSM3AY

RMSE: 1.260; MAE: 1.070; MAPE: 13.145



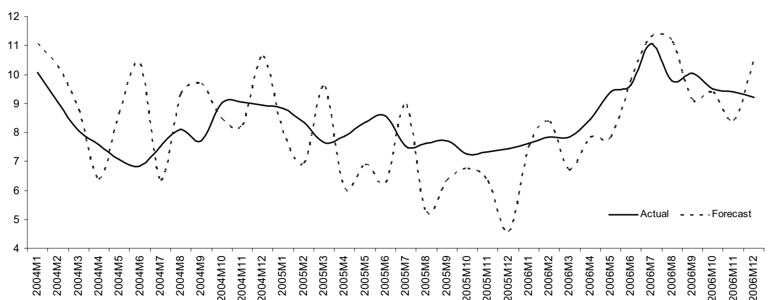
Static: SSM3AY

RMSE: 0.775; MAE: 0.616; MAPE: 7.430



12-Step: SSM3AY

RMSE: 1.455; MAE: 1.387; MAPE: 15.495



Dynamic: DM3AY

RMSE: 1.957; MAE: 1.590; MAPE: 19.215

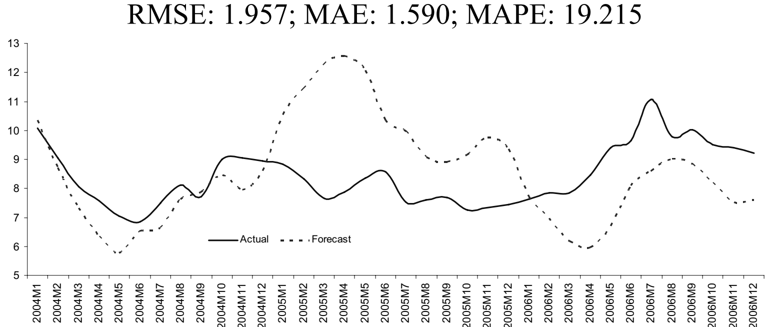
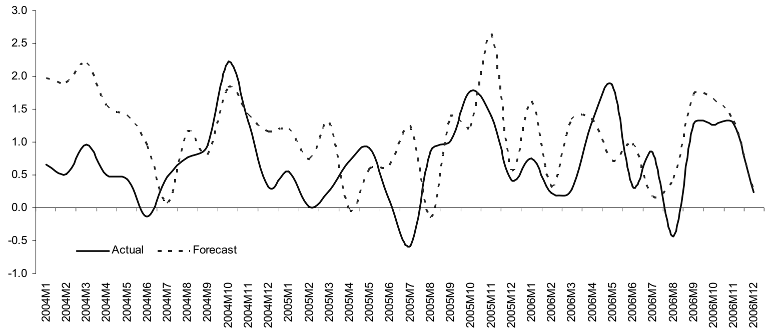


Figure 4.7: Actual Data and Out-Of-Sample Forecasts of Monthly CPI-Inflation from Bivariate VAR Model

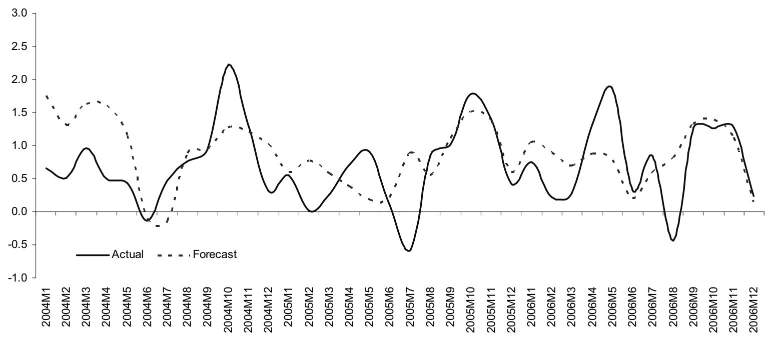
1-Step: DM3A

RMSE: 0.650; MAE: 0.554; MAPE: 205.242



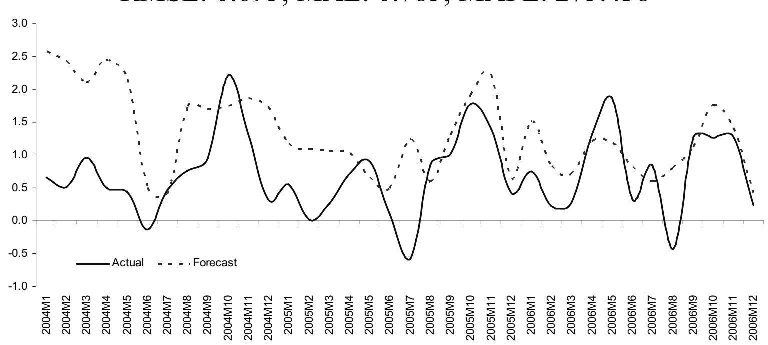
Static: SSM1

RMSE: 0.609; MAE: 0.460; MAPE: 202.300



12-Step: SSM1

RMSE: 0.695; MAE: 0.785; MAPE: 275.438



Dynamic: SSM1

RMSE: 0.830; MAE: 0.672; MAPE: 393.400

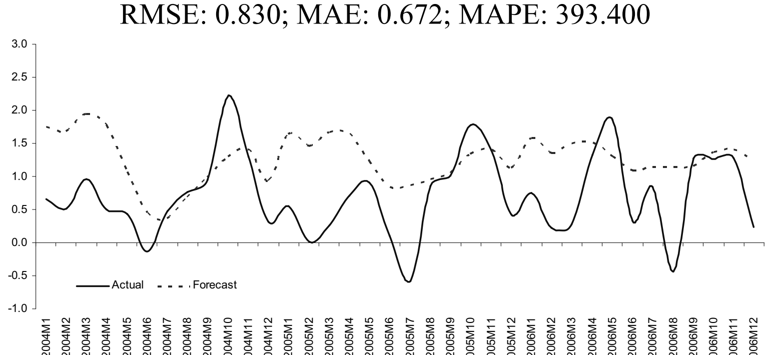
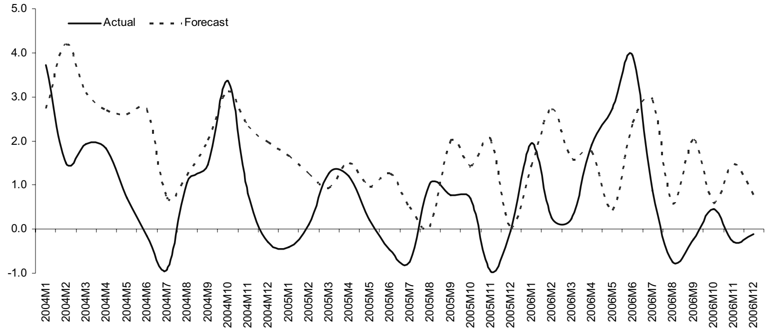


Figure 4.8: Actual Data and Out-Of-Sample Forecasts of Monthly WPI-Inflation from Bivariate VAR Model

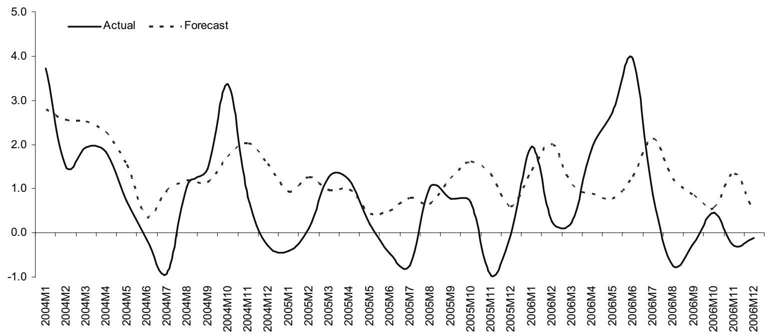
1-Step: DM3AY

RMSE: 1.769; MAE: 1.854; MAPE: 347.699



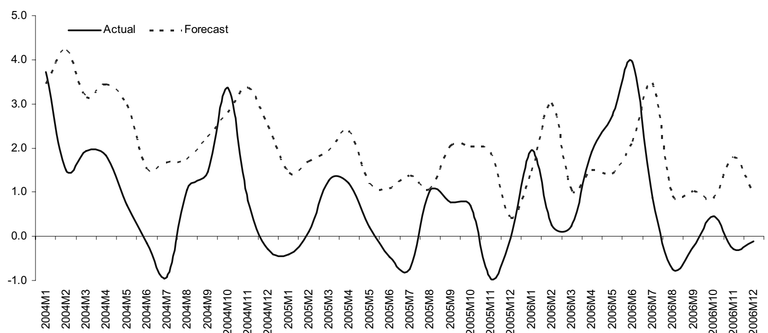
Static: SSM1

RMSE: 1.226; MAE: 1.038; MAPE: 245.600



12-Step: SSM1

RMSE: 1.837; MAE: 2.046; MAPE: 426.458



Dynamic: DM2Y

RMSE: 1.530; MAE: 1.349; MAPE: 451.500

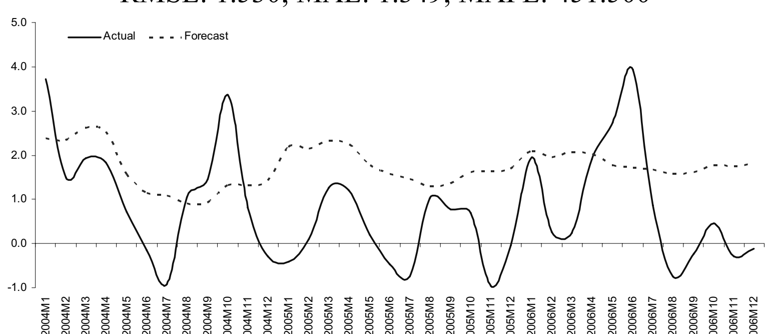
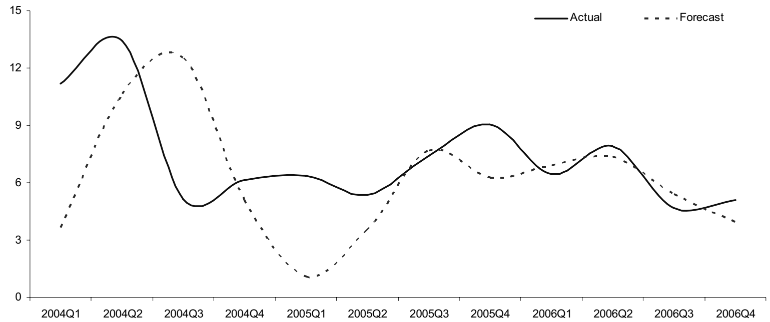


Figure 4.9: Out-Of-Sample Forecasts of Real GDP Growth from Bivariate VAR Model Using Quarterly Growth Rates of Nominal Money

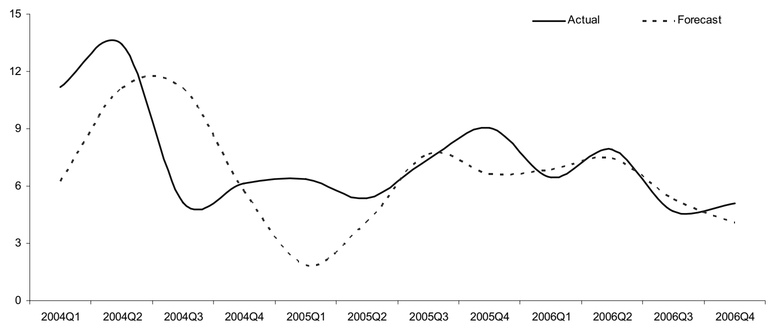
1-Step: SSM2Y

RMSE: 3.672; MAE: 2.651; MAPE: 37.755



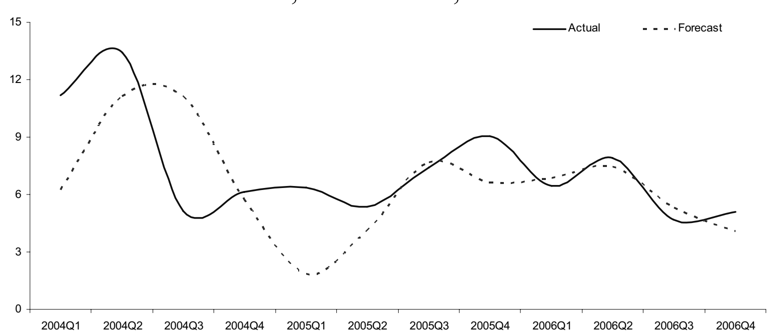
Static: SSM2Y

RMSE: 2.817; MAE: 2.047; MAPE: 29.517



4-Step: SSM2Y

RMSE: 3.926; MAE: 2.844; MAPE: 36.650



Dynamic: SSM2Y

RMSE: 3.135; MAE: 2.408; MAPE: 28.379

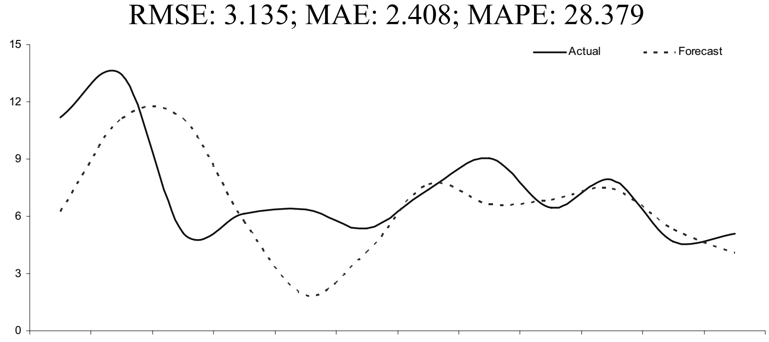
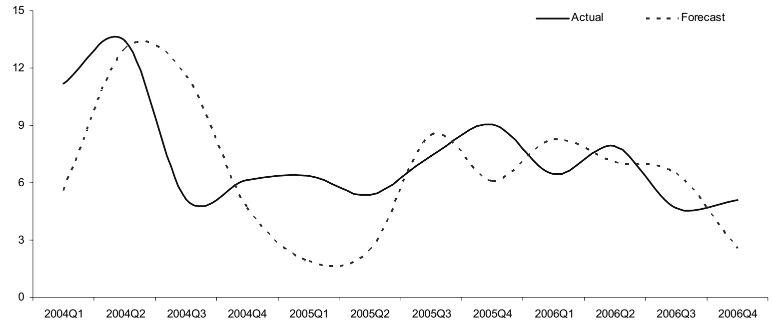


Figure 4.10: Out-Of-Sample Forecasts of Real GDP Growth from Bivariate VAR Model Using Quarterly Growth Rates of CPI-Deflated Real Money

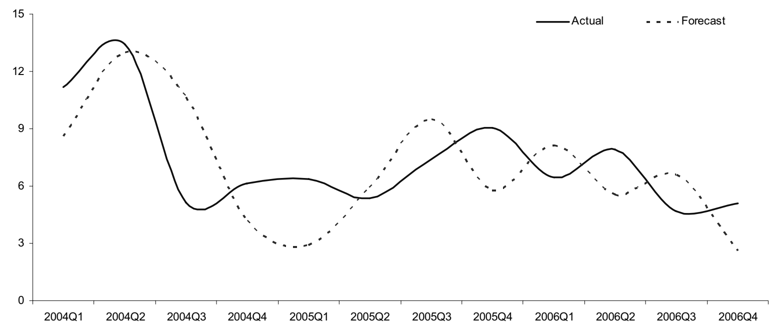
1-Step: SSM3A

RMSE: 3.258; MAE: 2.700; MAPE: 41.893



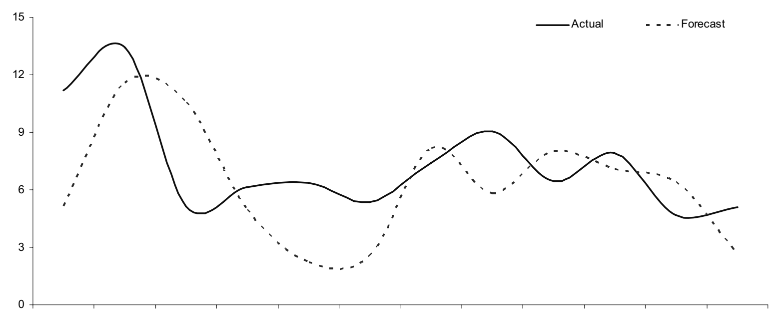
Static: DM3A

RMSE: 2.689; MAE: 2.359; MAPE: 36.700



4-Step: SSM3A

RMSE: 3.140; MAE: 2.659; MAPE: 39.558



Dynamic: SSM3A

RMSE: 3.214; MAE: 2.578; MAPE: 31.583

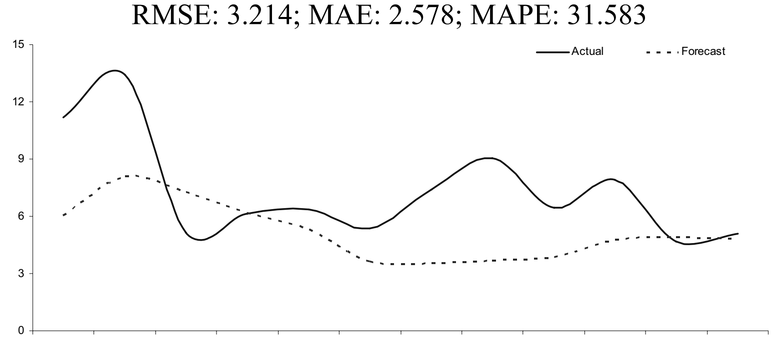
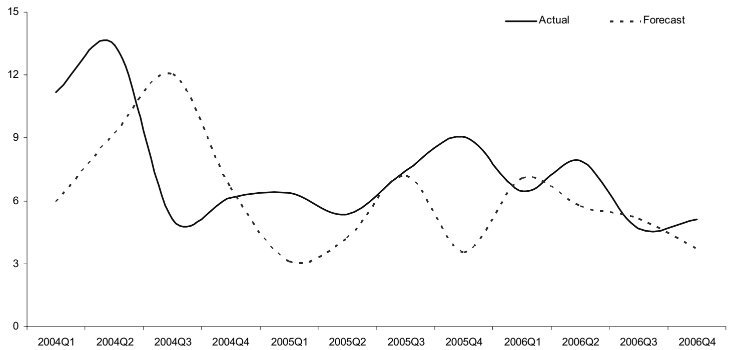


Figure 4.11: Out-Of-Sample Forecasts of Real GDP Growth from Bivariate VAR Model Using Annual Growth Rates of WPI-Deflated Real Money

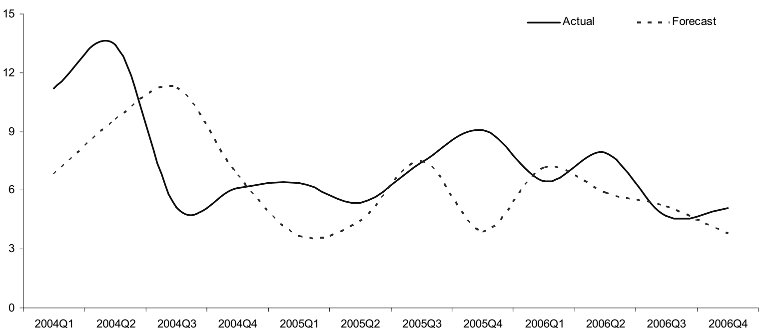
1-Step: SSM2Y

RMSE: 3.452; MAE: 2.641; MAPE: 36.033



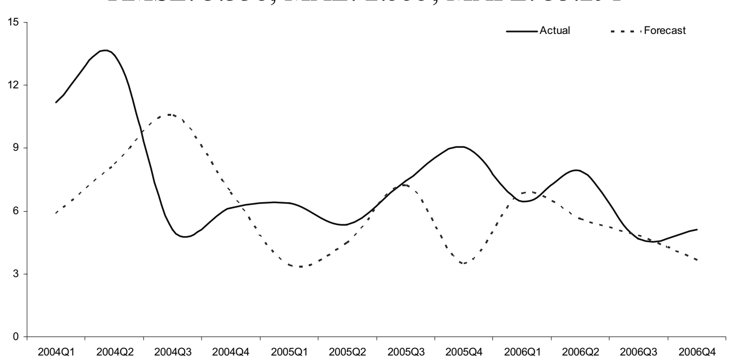
Static: SSM2Y

RMSE: 3.062; MAE: 2.353; MAPE: 32.173



4-Step: SSM2Y

RMSE: 3.338; MAE: 2.555; MAPE: 33.291



Dynamic: SSM2Y

RMSE: 3.303; MAE: 2.605; MAPE: 32.328

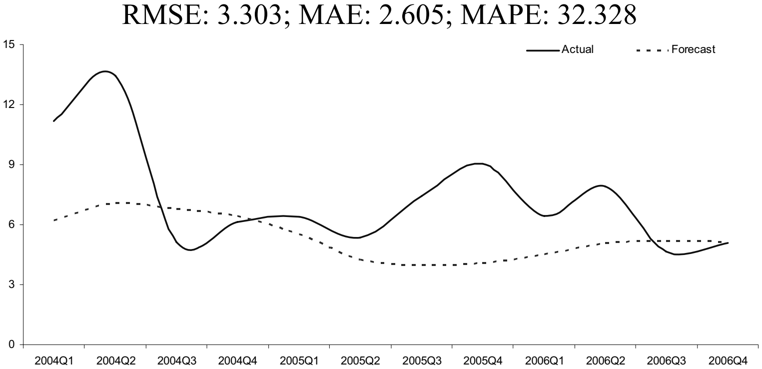
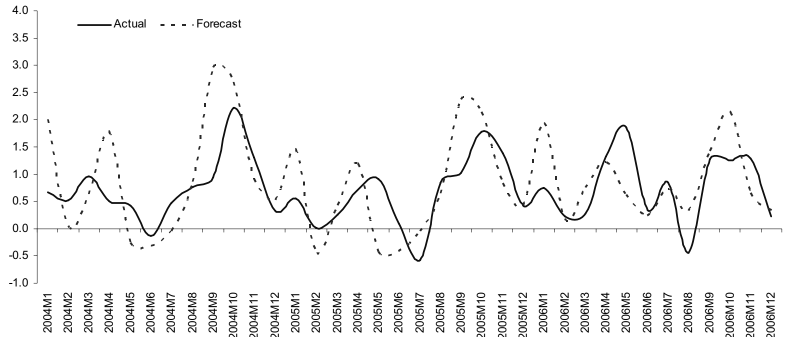


FIGURE APPENDIXES TO CHAPTER 5

Figure 5.1: Actual Data and Out-Of-Sample Forecasts of Monthly CPI-Inflation from ARMA-ARCH Model

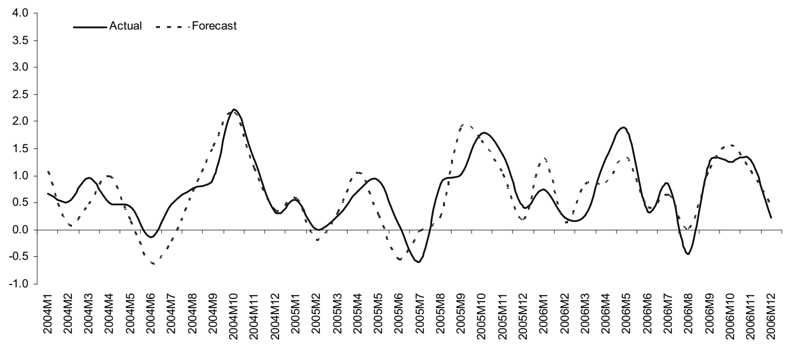
1-Step: SSM2Y

RMSE: 0.744; MAE: 0.573; MAPE: 167.664



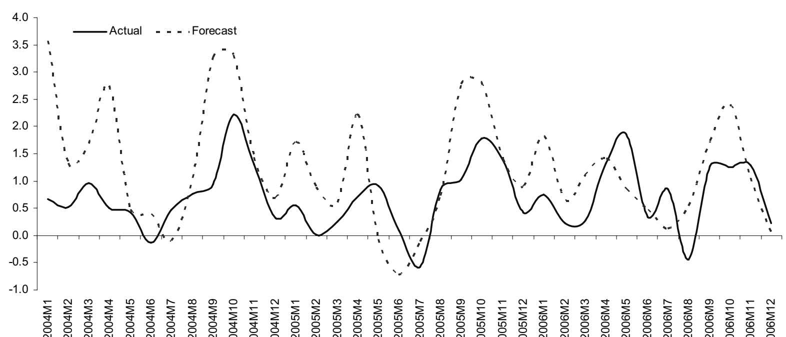
Static: SSM3AY

RMSE: 0.415; MAE: 0.350; MAPE: 109.013



12-Step: SSM2Y

RMSE: 0.982; MAE: 0.748; MAPE: 211.659



Dynamic: SSM3AY

RMSE: 0.409; MAE: 0.331; MAPE: 121.469

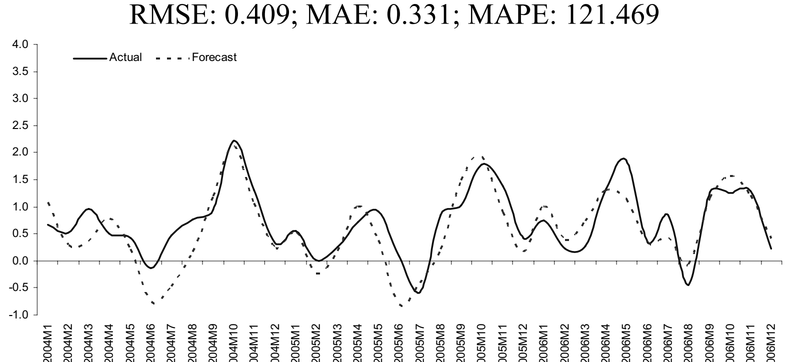
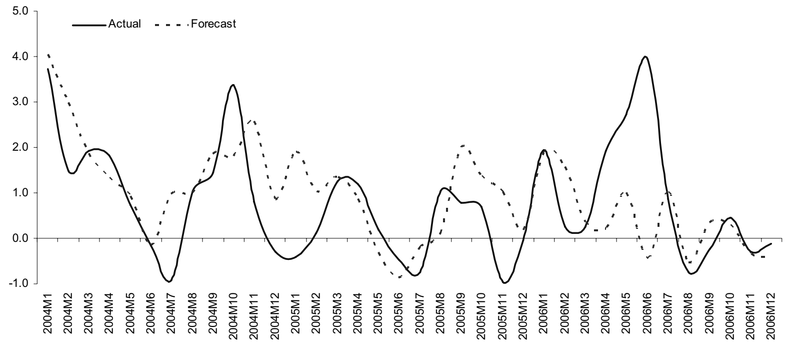


Figure 5.2: Actual Data and Out-Of-Sample Forecasts of Monthly WPI-Inflation from ARMA-ARCH Model

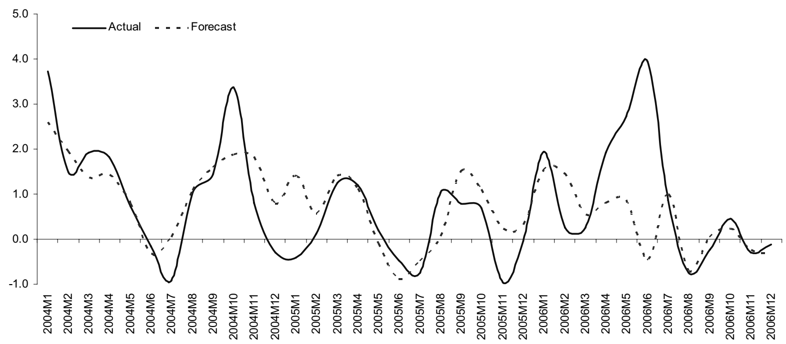
1-Step: SSM1

RMSE: 1.231; MAE: 0.842; MAPE: 150.455



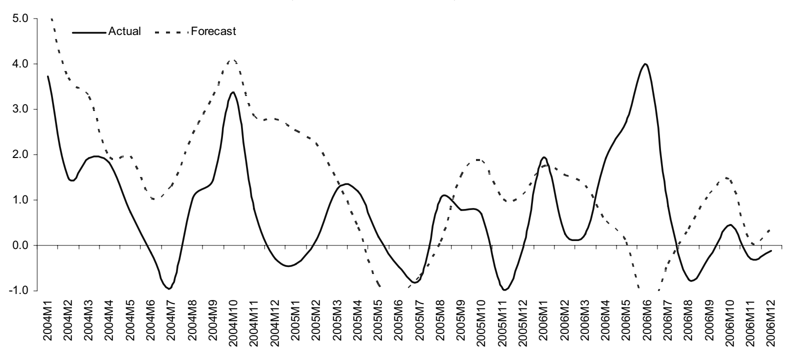
Static: SSM1

RMSE: 1.059; MAE: 0.690; MAPE: 124.550



12-Step: SSM1

RMSE: 1.721; MAE: 1.395; MAPE: 351.791



Dynamic: DM3A

RMSE: 1.240; MAE: 0.890; MAPE: 210.241

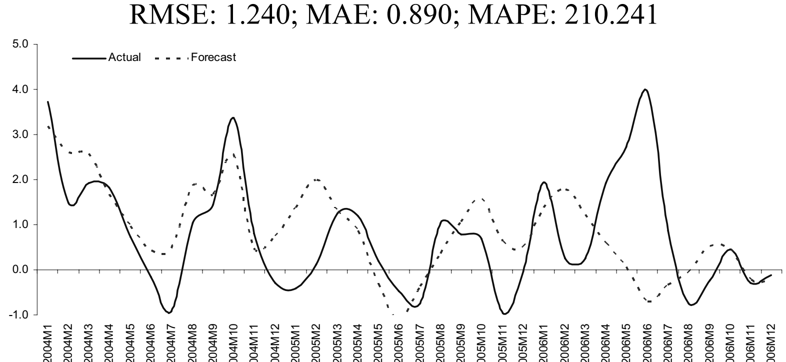
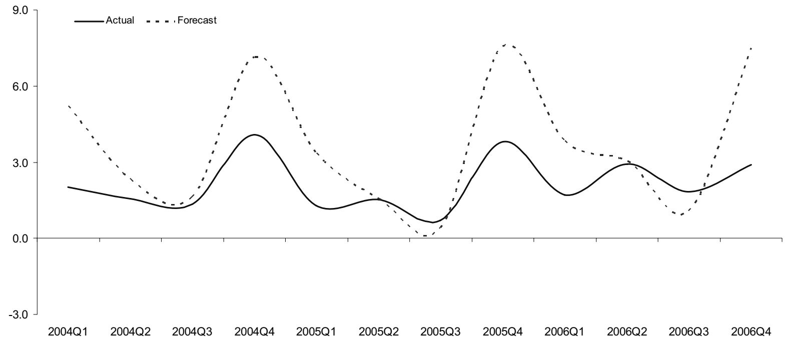


Figure 5.3: Actual Data and Out-Of-Sample Forecasts of Quarterly CPI-Inflation from ARMA Model

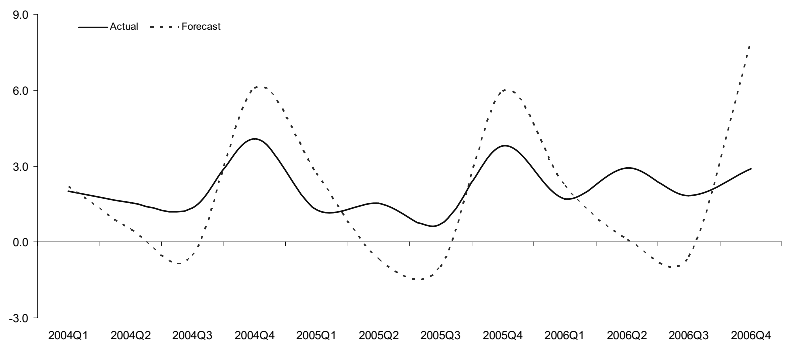
1-Step: SSM3AY

RMSE: 2.324; MAE: 1.747; MAPE: 77.346



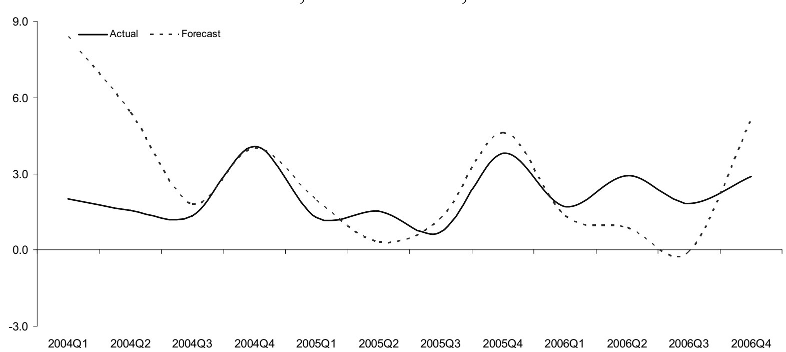
Static: DM1

RMSE: 2.294; MAE: 1.957; MAPE: 104.466



4-Step: SSM1

RMSE: 2.446; MAE: 1.714; MAPE: 91.736



Dynamic: DM1

RMSE: 2.068; MAE: 1.584; MAPE: 104.623

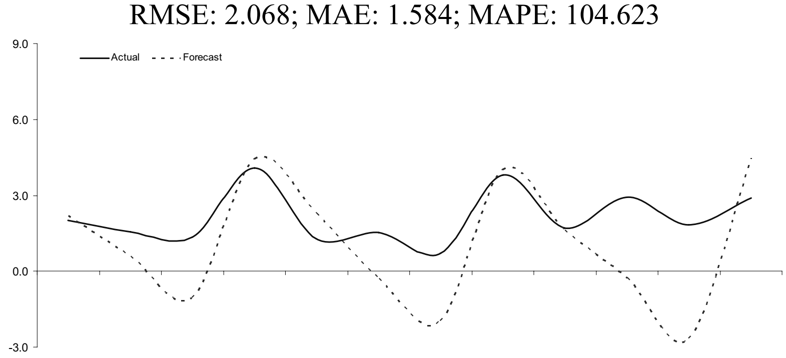
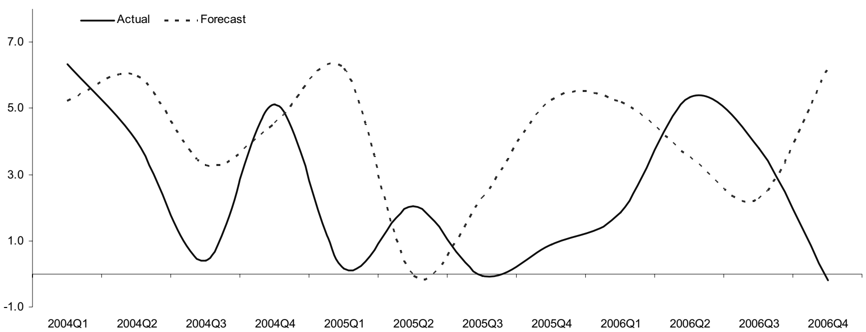


Figure 5.4: Actual Data and Out-Of-Sample Forecasts of Quarterly WPI-Inflation from ARMA Model

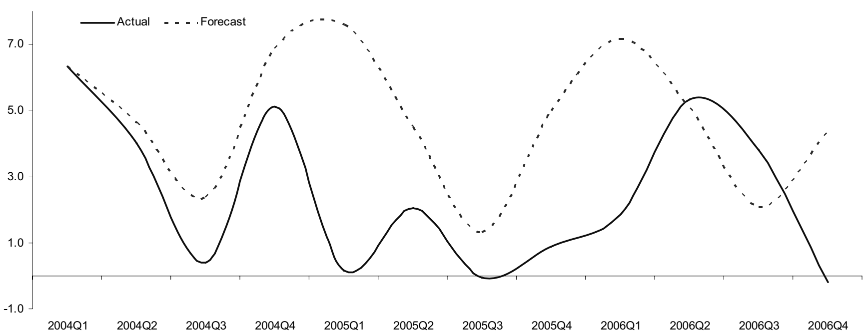
1-Step: SSM2Y

RMSE: 3.377; MAE: 2.870; MAPE: 1157.372



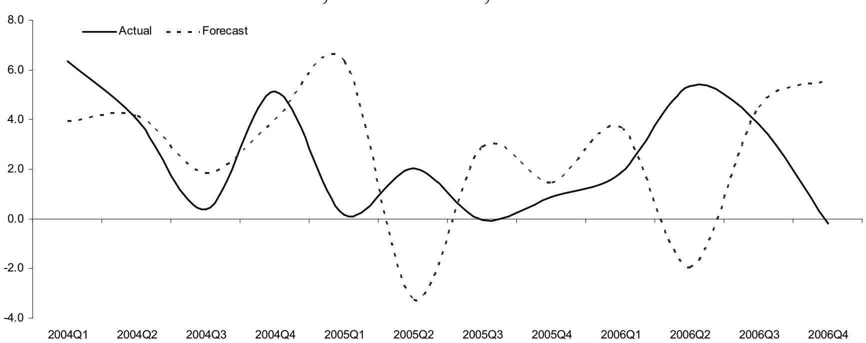
4-Step: SSM2Y

RMSE: 3.408; MAE: 2.630; MAPE: 960.695



Static: SSM1

RMSE: 4.935; MAE: 4.222; MAPE: 1647.552



Dynamic: SSM3AY

RMSE: 3.297; MAE: 2.548; MAPE: 977.277

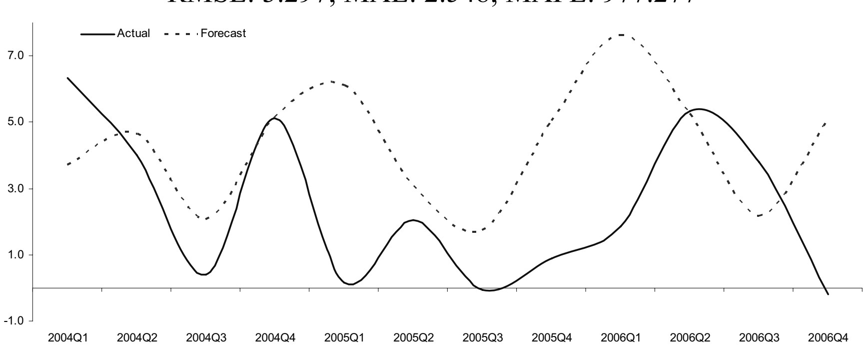
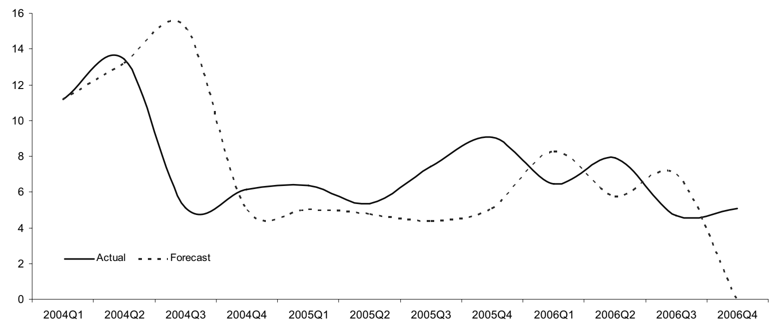


Figure 5.5: Actual Data and Out-Of-Sample Forecasts of Real GDP Growth from ARMA Model with CPI-Deflated Real Money Growth

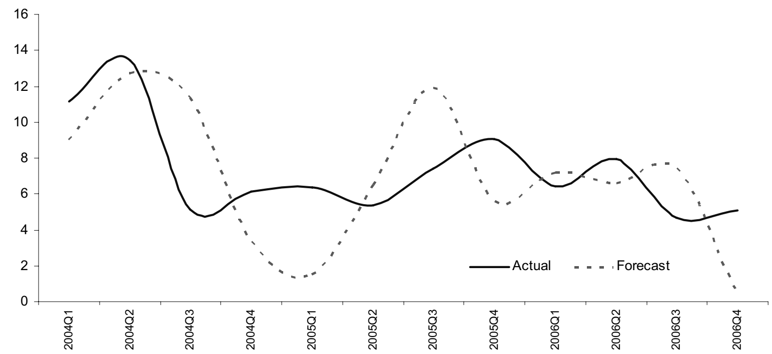
1-Step: DM3AY

RMSE: 3.773; MAE: 2.656; MAPE: 45.055



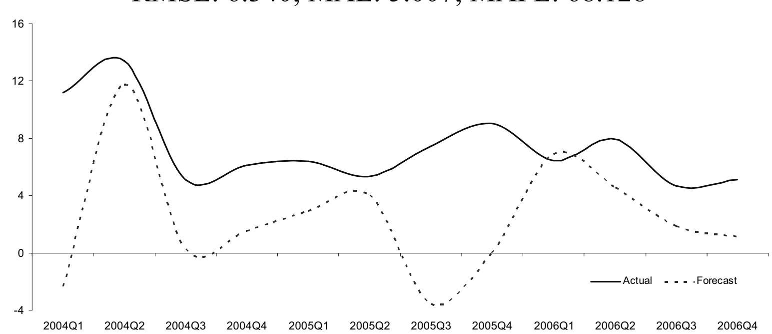
Static: DM3AY

RMSE: 3.289; MAE: 2.749; MAPE: 44.104



4-Step: DM1

RMSE: 6.340; MAE: 5.007; MAPE: 68.128



Dynamic: DM3AY

RMSE: 1.919; MAE: 1.626; MAPE: 25.366

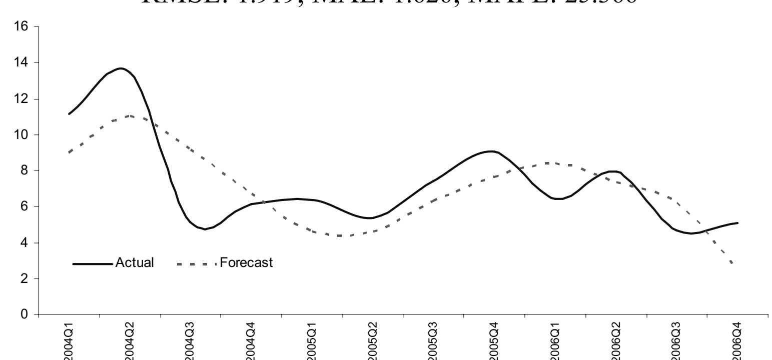
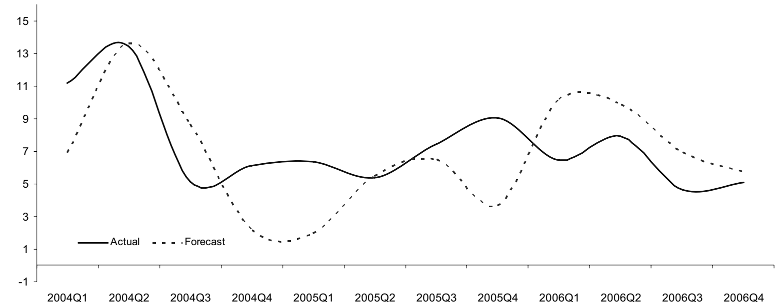


Figure 5.6: Actual Data and Out-Of-Sample Forecasts of Real GDP Growth from ARMA Model with WPI-Deflated Real Money Growth

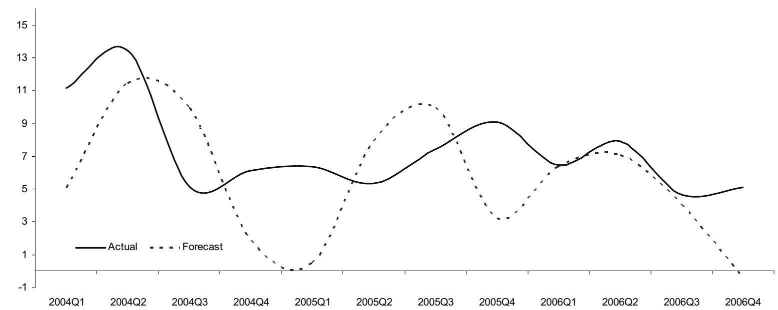
1-Step: SSM2Y

RMSE: 3.139; MAE: 2.602; MAPE: 38.112



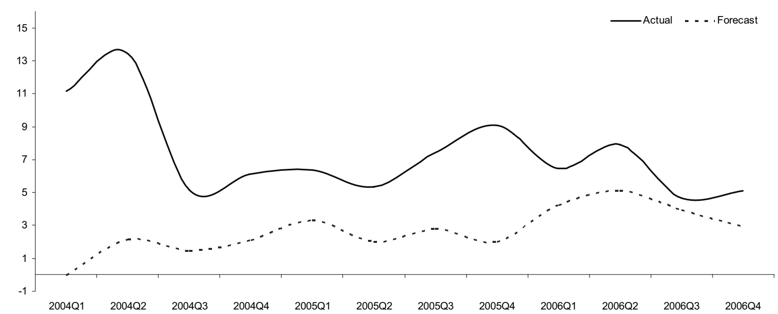
Static: DM3AY

RMSE: 3.327; MAE: 2.764; MAPE: 40.702



4-Step: SSM3A

RMSE: 5.719; MAE: 4.689; MAPE: 58.450



Dynamic: DM2Y

RMSE: 2.747; MAE: 2.158; MAPE: 28.016

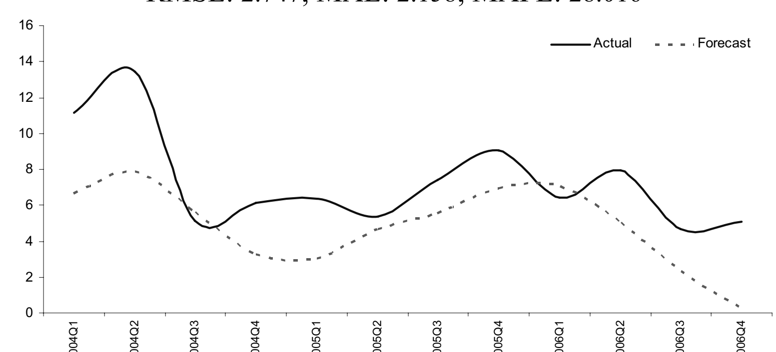
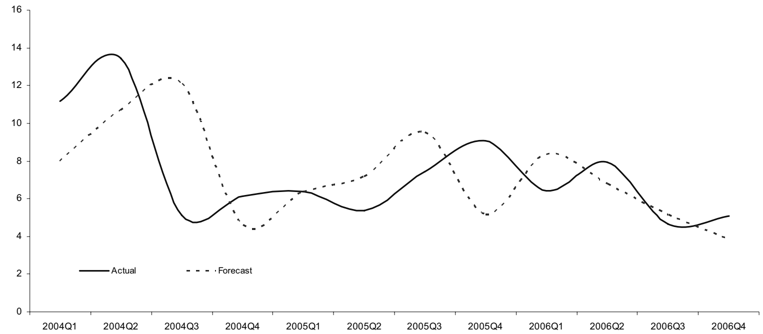


Figure 5.7: Actual Data and Out-Of-Sample Forecasts of Real GDP Growth from St. Louis Equation with CPI-Deflated Real Money Growth

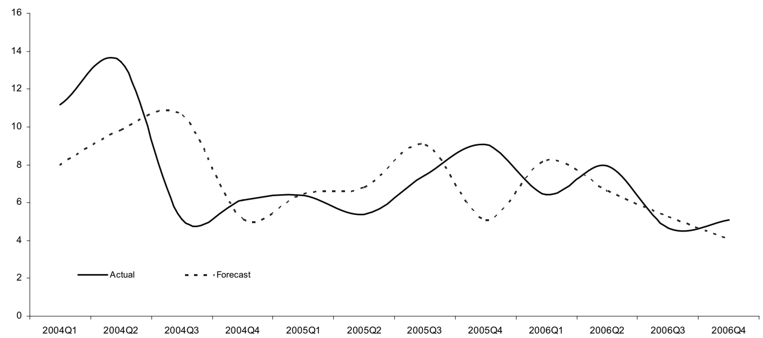
1-Step: DM3A

RMSE: 2.861; MAE: 2.252; MAPE: 32.839



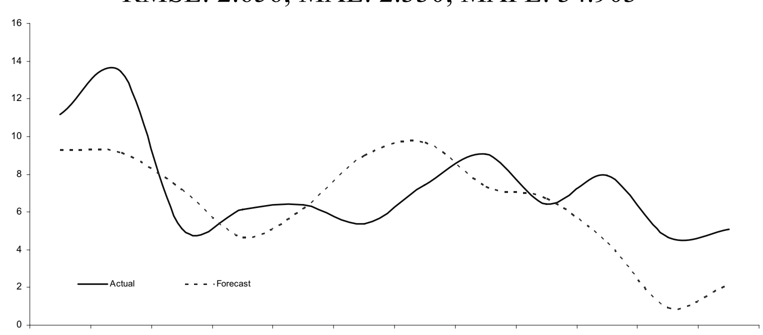
Static: DM3A

RMSE: 2.599; MAE: 2.089; MAPE: 29.056



4-Step: DM3AY

RMSE: 2.656; MAE: 2.330; MAPE: 34.903



Dynamic: DM3AY

RMSE: 2.871; MAE: 2.435; MAPE: 36.118

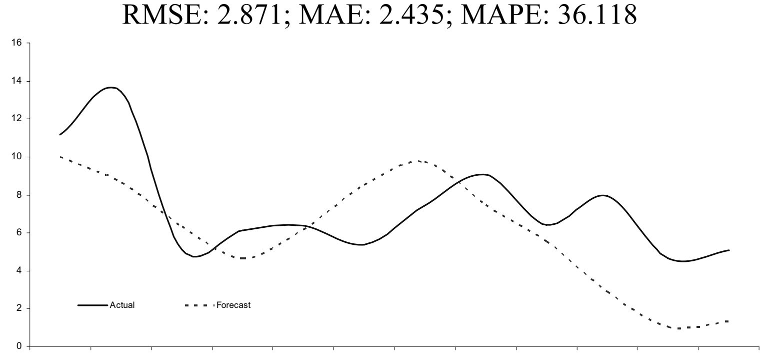
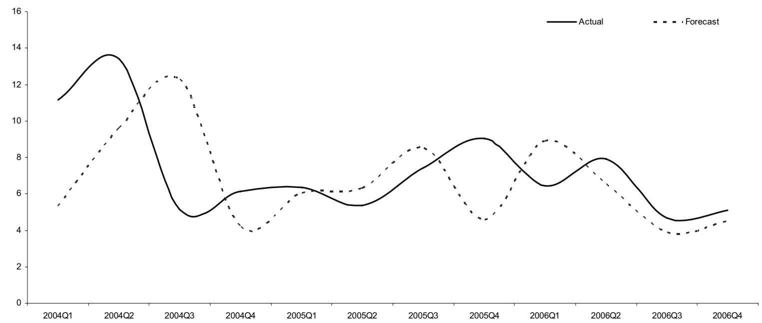


Figure 5.8: Actual Data and Out-Of-Sample Forecasts of Real GDP Growth from St. Louis Equation with WPI-Deflated Real Money Growth

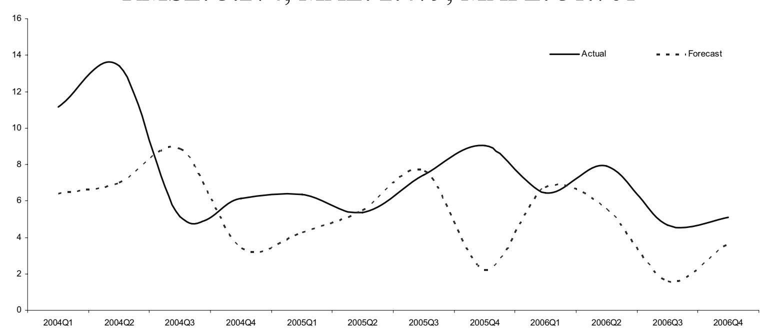
1-Step: DM3A

RMSE: 3.350; MAE: 2.570; MAPE: 35.240



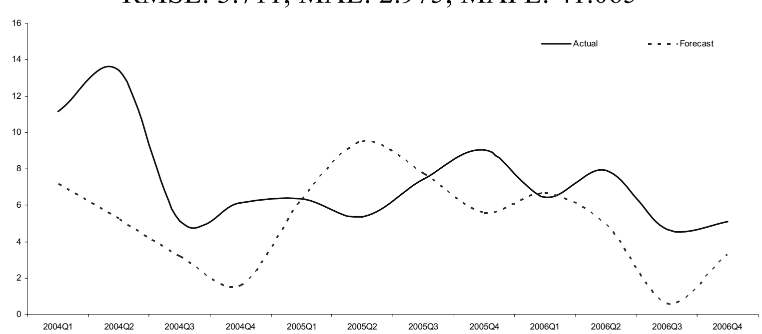
Static: DM3A

RMSE: 3.274; MAE: 2.479; MAPE: 31.761



4-Step: DM3AY

RMSE: 3.711; MAE: 2.975; MAPE: 41.065



Dynamic: DM3A

RMSE: 4.483; MAE: 3.889; MAPE: 54.035

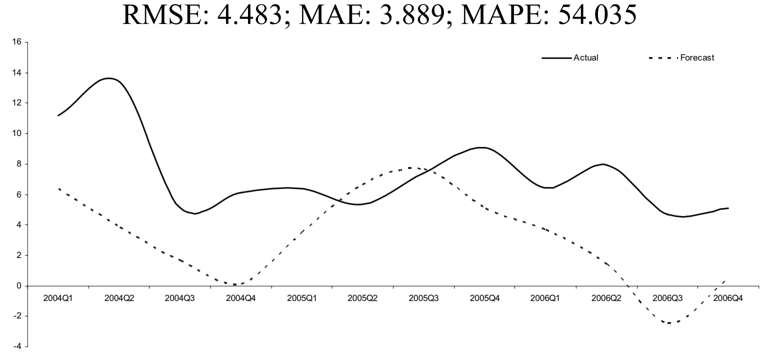
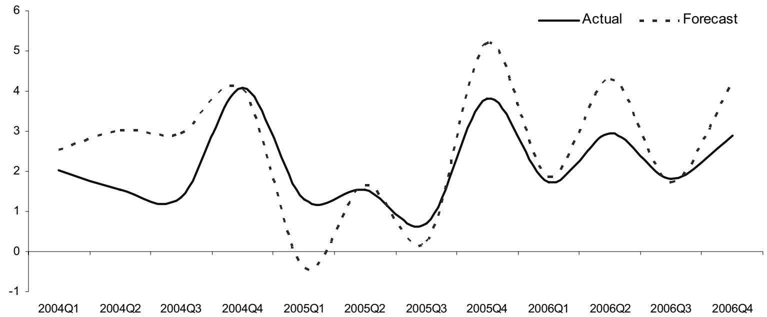


Figure 5.9: Actual Data and Out-Of-Sample Forecasts of Quarterly CPI-Inflation from Phillips Curve Model

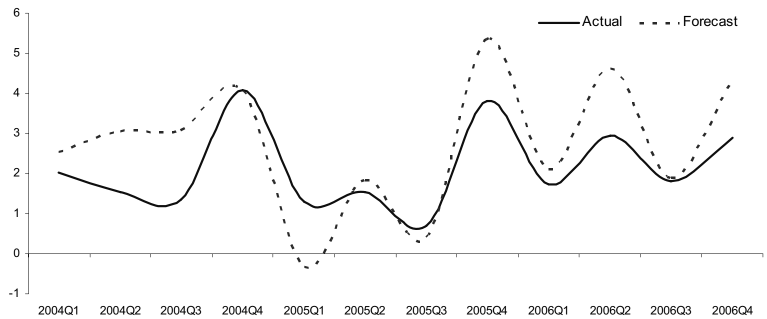
1-Step: SSM3A

RMSE: 1.069; MAE: 0.856; MAPE: 49.032



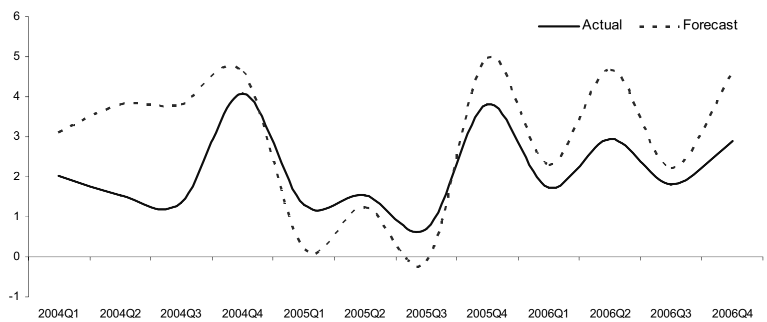
Static: SSM3A

RMSE: 1.148; MAE: 0.926; MAPE: 50.940



4-Step: SSM2

RMSE: 1.363; MAE: 1.178; MAPE: 68.104



Dynamic: SSM3A

RMSE: 1.356; MAE: 1.102; MAPE: 54.919

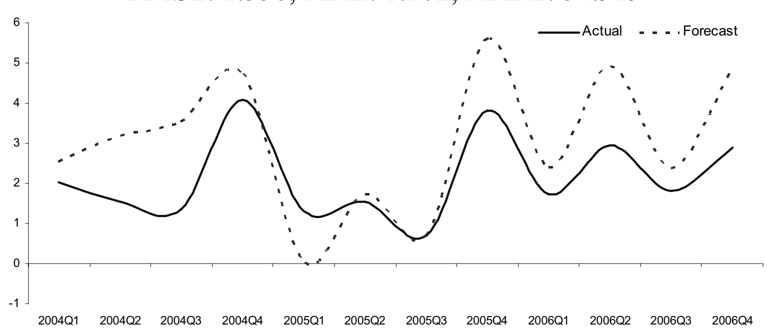
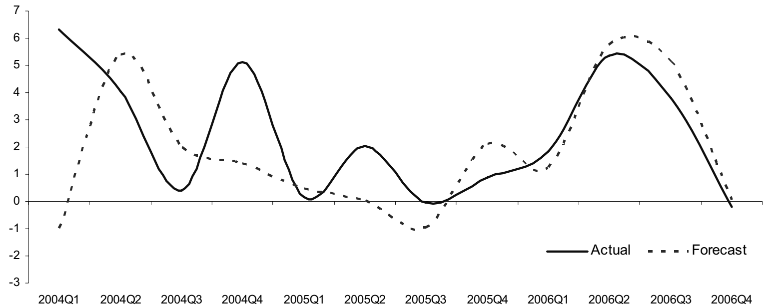
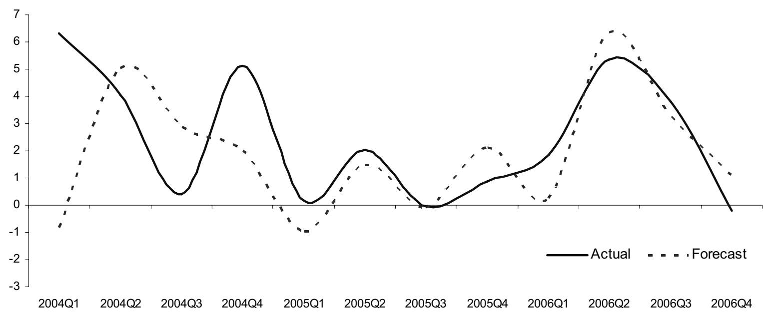


Figure 5.10: Actual Data and Out-Of-Sample Forecasts of Quarterly WPI-Inflation from Phillips Curve Model

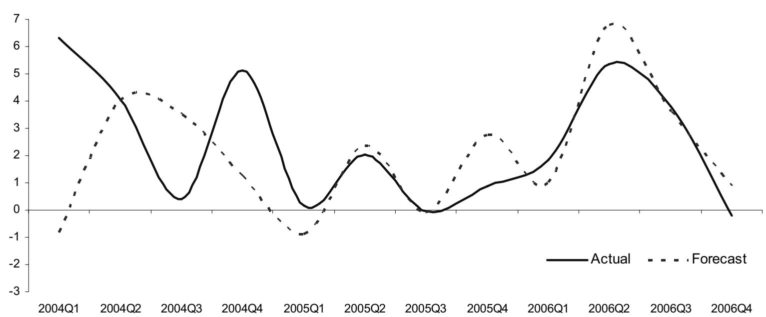
1-Step: SSM3AY
RMSE: 2.600; MAE: 1.758; MAPE: 268.192



Static: SSM3A
RMSE: 2.533; MAE: 1.764; MAPE: 214.620



4-Step: SSM3A
RMSE: 2.663; MAE: 1.749; MAPE: 212.394



Dynamic: SSM3A
RMSE: 2.622; MAE: 1.740; MAPE: 343.970

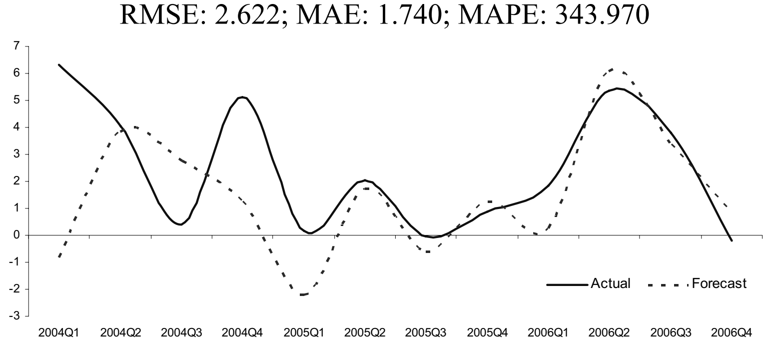
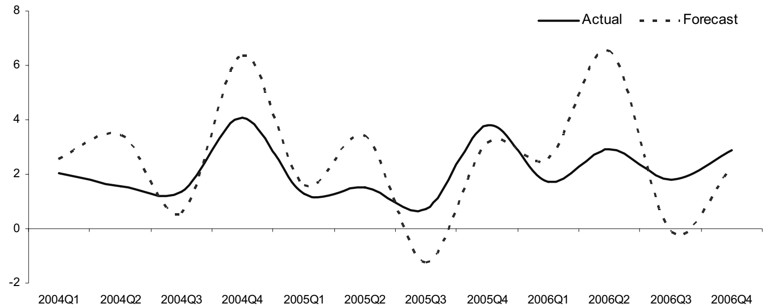


Figure 5.11: Actual Data and Out-Of-Sample Forecasts of Quarterly CPI-Inflation from Cost-Push Model

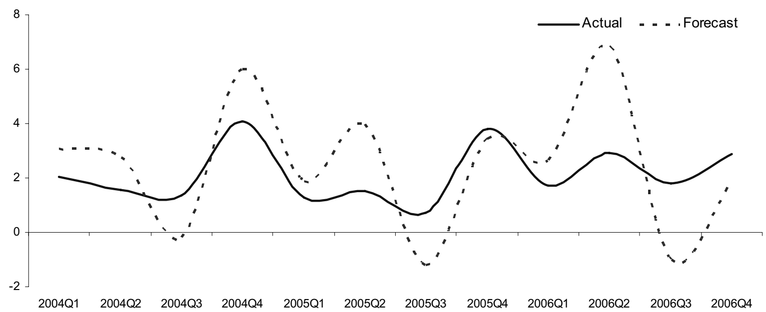
1-Step: DM2Y

RMSE: 1.714; MAE: 1.442; MAPE: 83.483



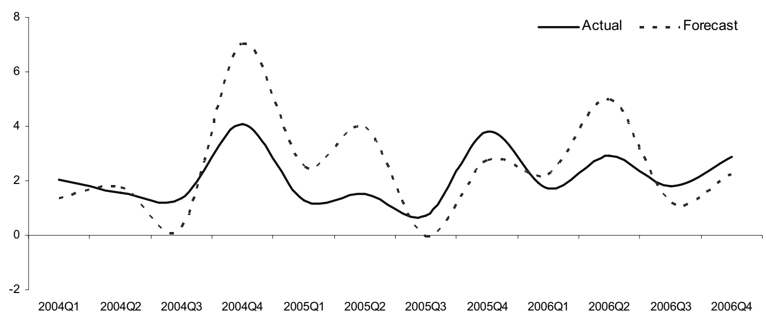
Static: DM1

RMSE: 2.646; MAE: 2.158; MAPE: 104.680



4-Step: SSM2Y

RMSE: 1.439; MAE: 1.187; MAPE: 61.846



Dynamic: SSM3AY

RMSE: 3.017; MAE: 2.516; MAPE: 126.660

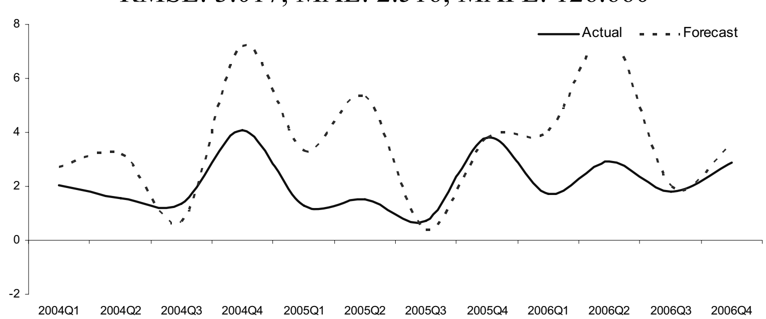
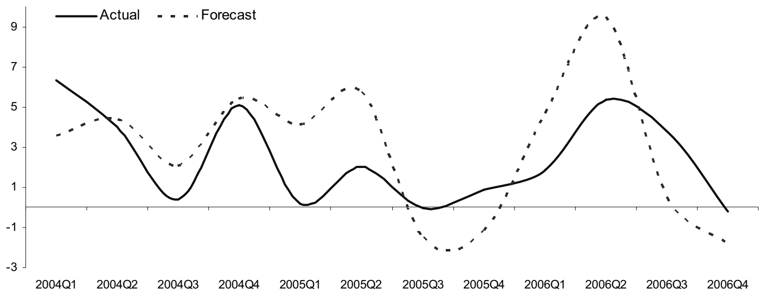


Figure 5.12: Actual Data and Out-Of-Sample Forecasts of Quarterly WPI-Inflation from Cost-Push Model

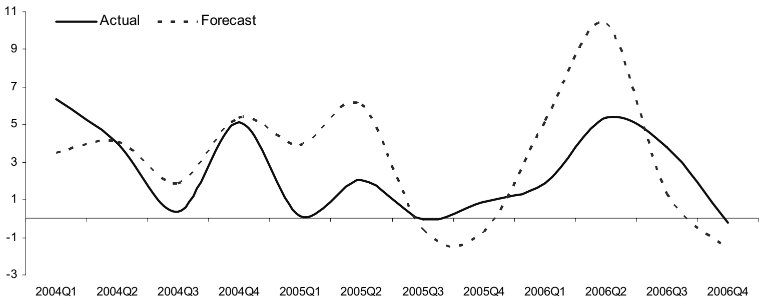
1-Step: SSM1

RMSE: 2.650; MAE: 2.336; MAPE: 635.070



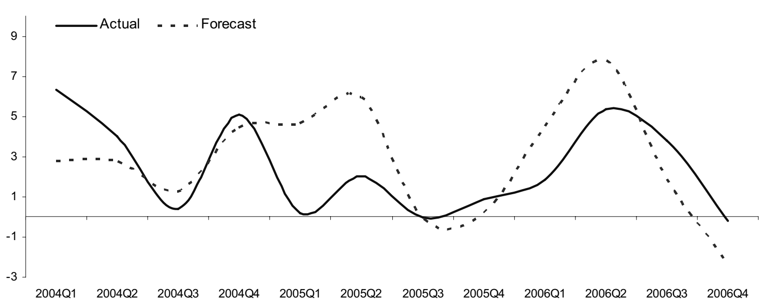
Static: DM2Y

RMSE: 3.075; MAE: 2.478; MAPE: 570.640



4-Step: SSM2Y

RMSE: 2.466; MAE: 2.061; MAPE: 411.060



Dynamic: SSM2Y

RMSE: 3.353; MAE: 2.692; MAPE: 535.450

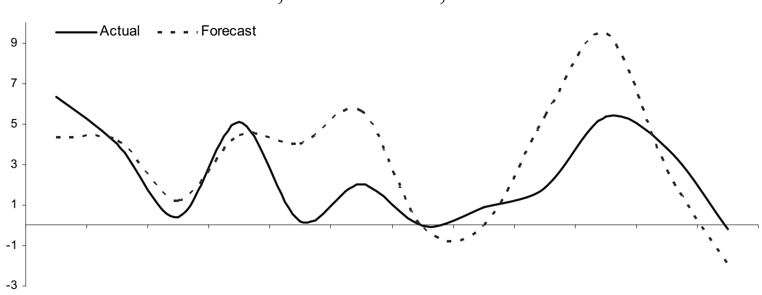
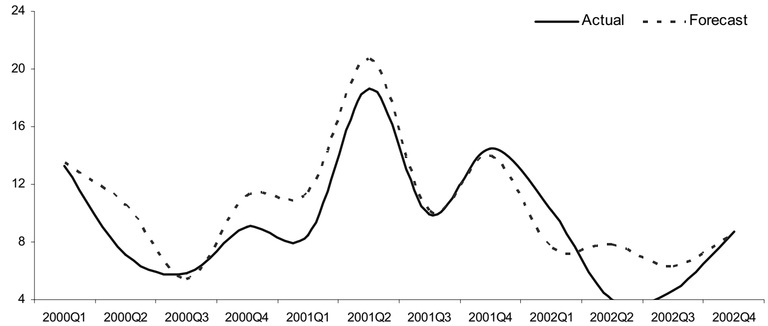


Figure 5.13: Actual Data and Out-Of-Sample Forecasts of Quarterly CPI-Inflation from Cost-Push Model (Short Sample: 1986-2002)

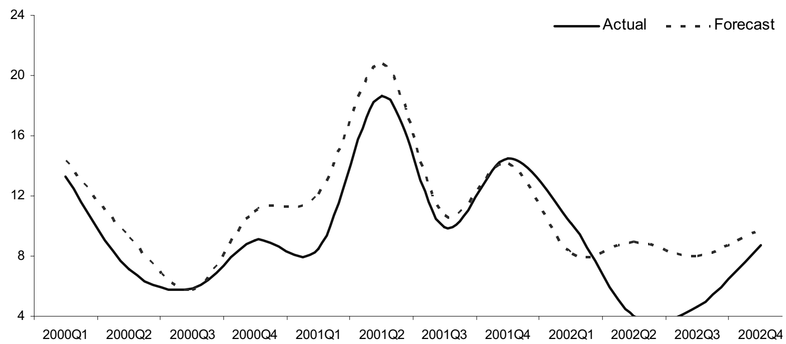
1-Step: DM2Y

RMSE: 2.143; MAE: 1.696; MAPE: 24.633



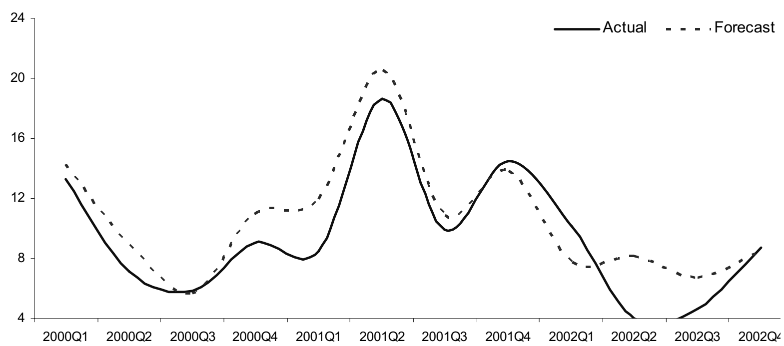
Static: DM2

RMSE: 2.395; MAE: 1.955; MAPE: 29.655



4-Step: DM2

RMSE: 2.088; MAE: 1.724; MAPE: 24.822



Dynamic: DM3A

RMSE: 2.750; MAE: 2.237; MAPE: 33.361

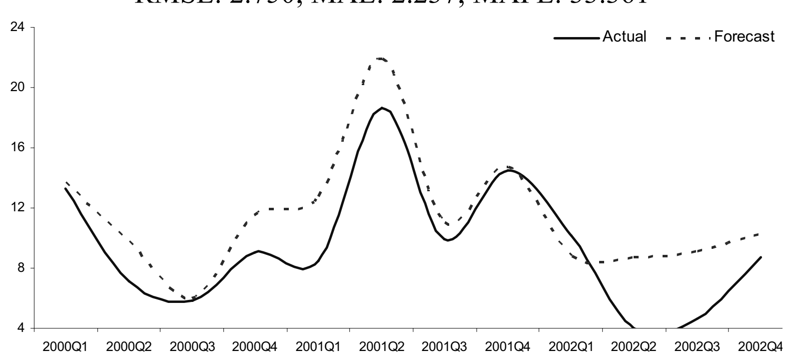
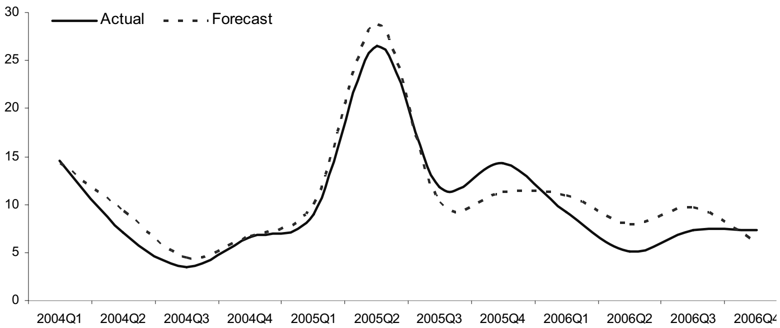


Figure 5.14: Actual Data and Out-Of-Sample Forecasts of Quarterly WPI-Inflation from Cost-Push Model (Short Sample: 1986-2002)

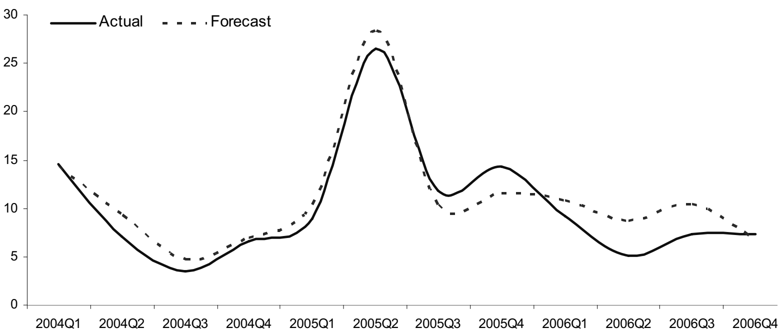
1-Step: SSM2Y

RMSE: 1.880; MAE: 1.654; MAPE: 20.389



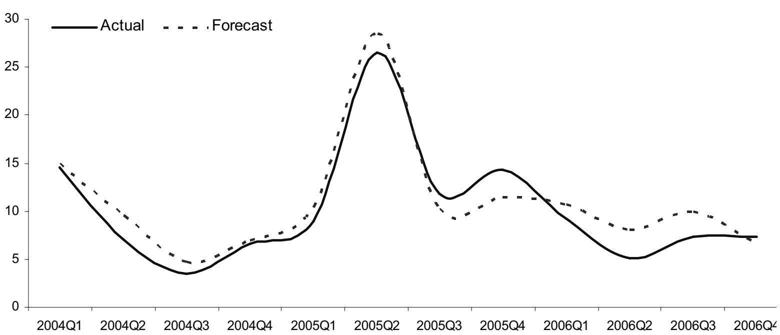
Static: SS2Y

RMSE: 2.003; MAE: 1.721; MAPE: 22.367



4-Step: SSM2Y

RMSE: 1.909; MAE: 1.687; MAPE: 21.403



Dynamic: SSM3AY

RMSE: 1.997; MAE: 1.627; MAPE: 22.131

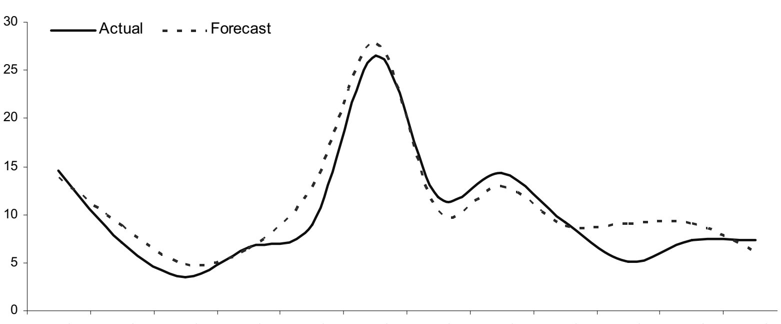
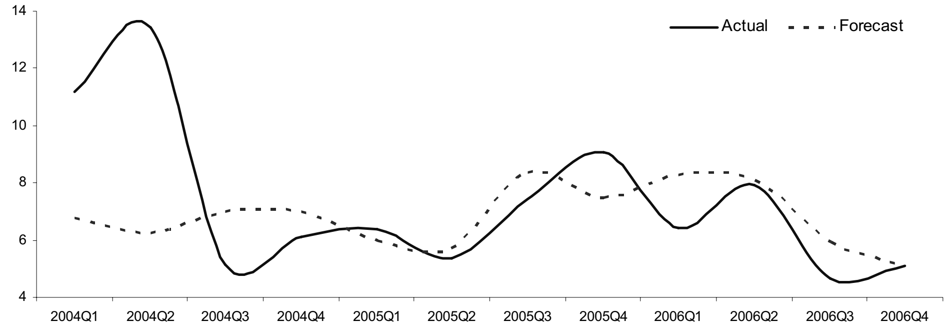


FIGURE APPENDIXES TO CHAPTER 6

Figure 6.2: Actual Data and Out-Of-Sample Forecasts of Real GDP Growth from Bivariate NN with CPI-Deflated Real Money without Lagged GDP

1-Step: DM2

RMSE: 2.644; MAE: 1.738; MAPE: 20.338



Static: DM2

RMSE: 2.223; MAE: 1.655; MAPE: 21.743

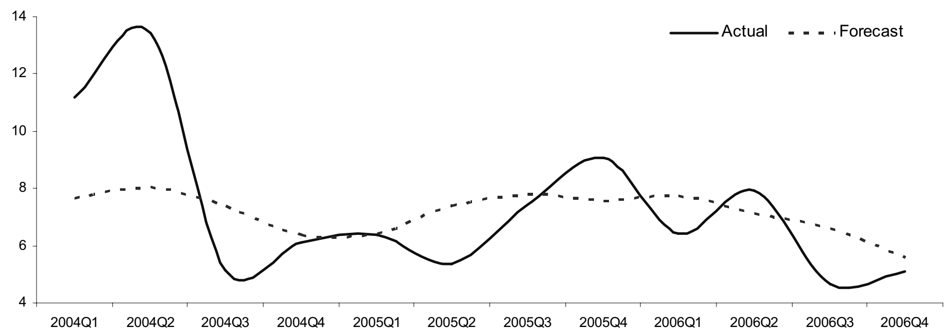
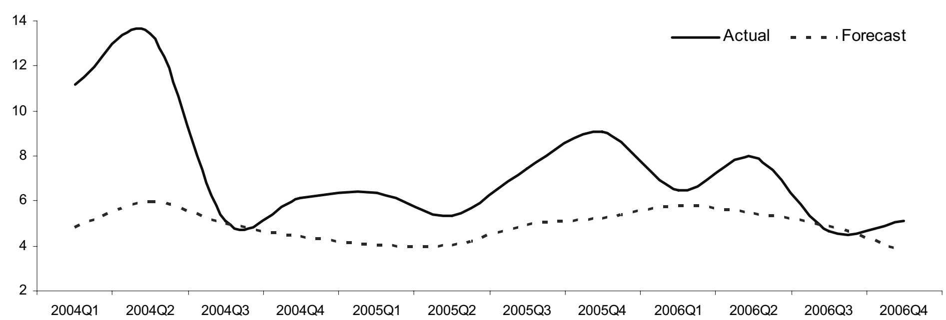


Figure 6.3: Actual Data and Out-Of-Sample Forecasts of Real GDP Growth from Bivariate NN with WPI-Deflated Real Money without Lagged GDP

1-Step: SSM3A

RMSE: 3.370; MAE: 2.507; MAPE: 33.840



Static: DM3A

RMSE: 2.143; MAE: 1.578; MAPE: 21.221

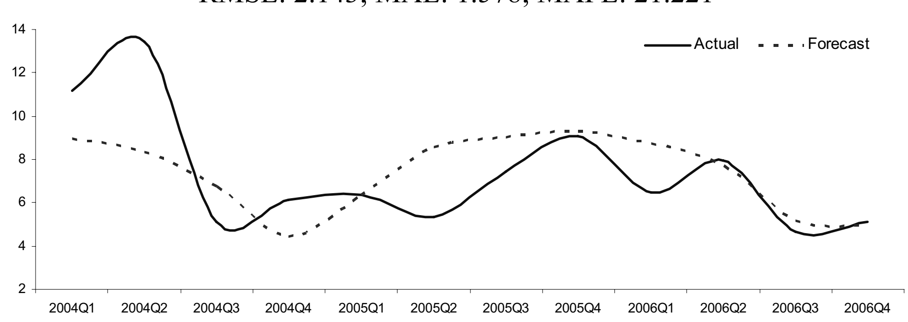
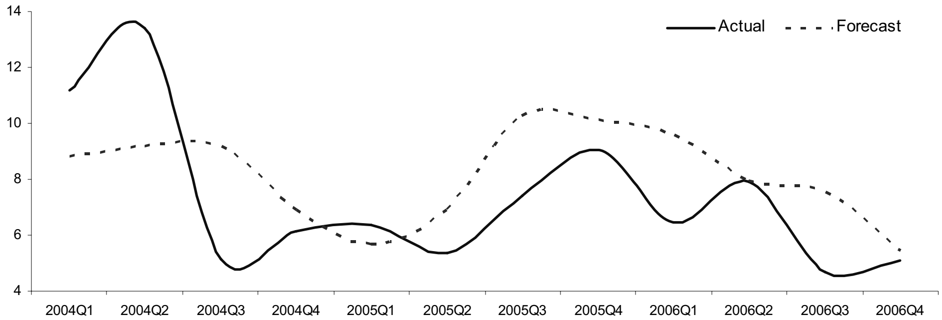


Figure 6.4: Actual Data and Out-Of-Sample Forecasts of Real GDP Growth from Bivariate NN with CPI-Deflated Real Money with Lagged GDP

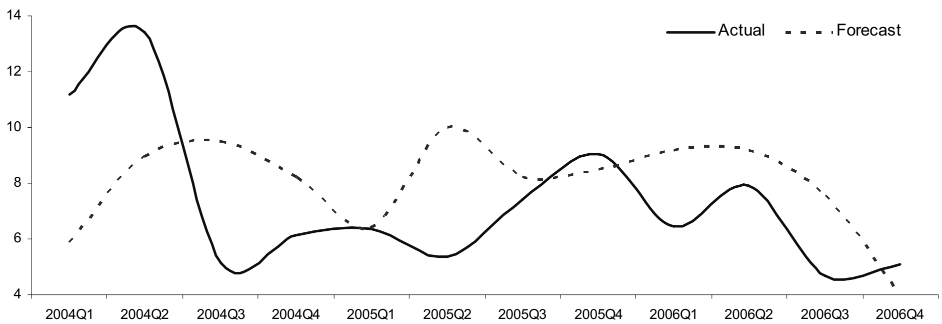
1-Step: DM3AY

RMSE: 2.434; MAE: 2.004; MAPE: 29.403



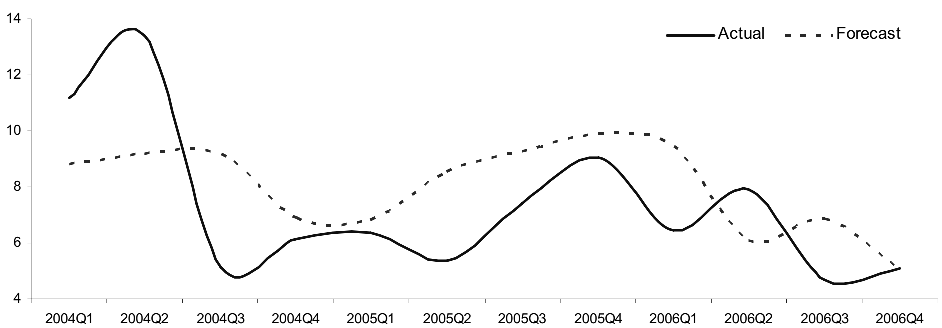
Static: DM2Y

RMSE: 3.072; MAE: 2.525; MAPE: 37.222



4-Step: DM3AY

RMSE: 2.453; MAE: 2.073; MAPE: 30.308



Dynamic: DM2Y

RMSE: 2.886; MAE: 2.349; MAPE: 34.117

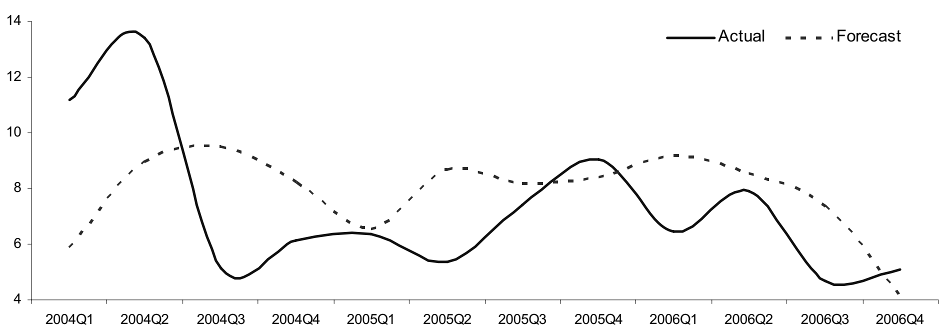
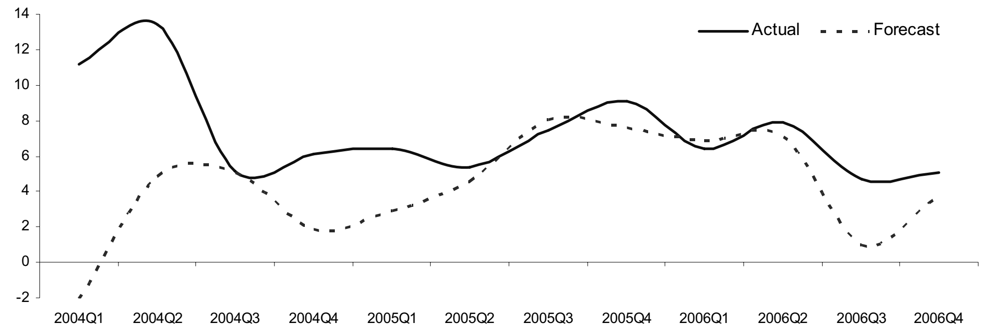
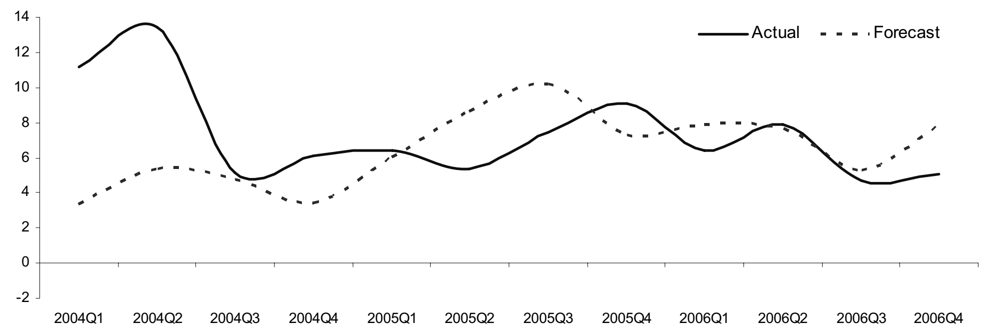


Figure 6.5: Actual Data and Out-Of-Sample Forecasts of Real GDP Growth from Bivariate NN with WPI-Deflated Real Money with Lagged GDP

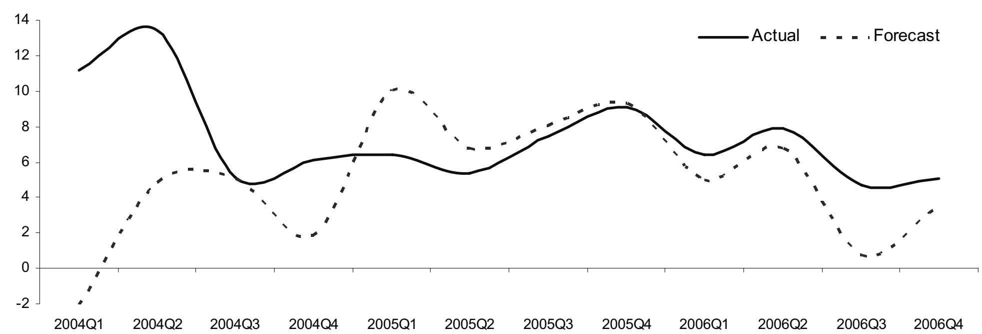
1-Step: DM3A
RMSE: 4.992; MAE: 3.230; MAPE: 39.074



Static: DM3AY
RMSE: 3.711; MAE: 2.681; MAPE: 33.105



4-Step: DM3A
RMSE: 5.042; MAE: 3.355; MAPE: 41.716



Dynamic: DM3AY
RMSE: 3.895; MAE: 2.965; MAPE: 37.885

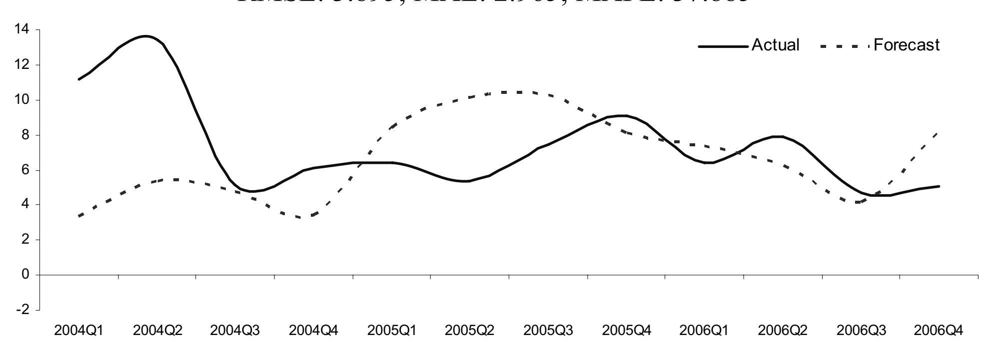
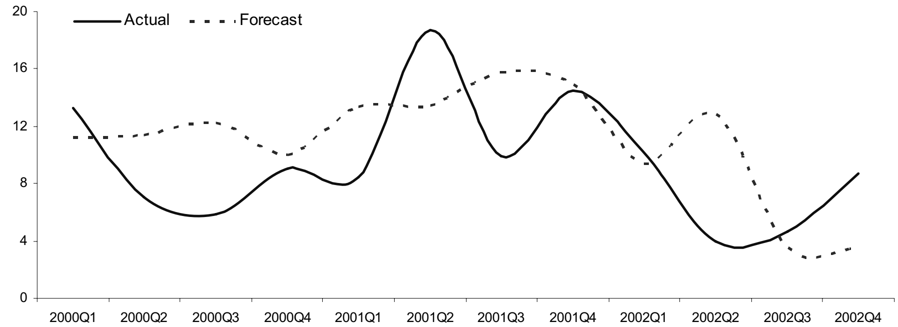


Figure 6.6: Actual Data and Out-Of-Sample Forecasts of Quarterly CPI-Inflation from Bivariate NN without Lagged Inflation

1-Step: SSM3A

RMSE: 4.631; MAE: 3.845; MAPE: 54.894



Static: DM3A

RMSE: 3.018; MAE: 2.061; MAPE: 25.169

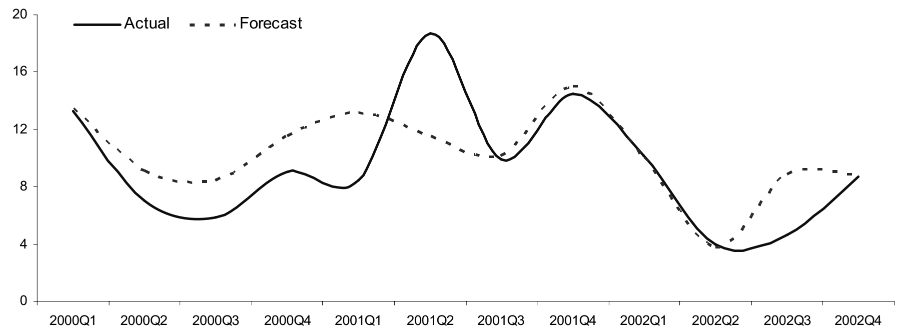
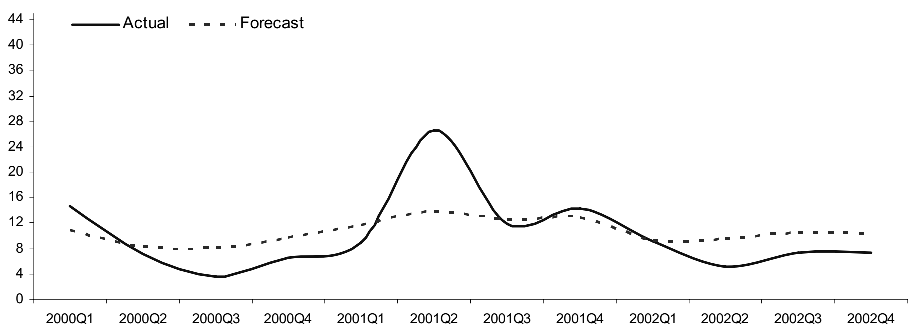


Figure 6.7: Actual Data and Out-Of-Sample Forecasts of Quarterly WPI-Inflation from Bivariate NN without Lagged Inflation

1-Step: DM2Y

RMSE: 4.629; MAE: 3.420; MAPE: 40.896



Static: DM3AY

RMSE: 5.196; MAE: 3.359; MAPE: 30.663

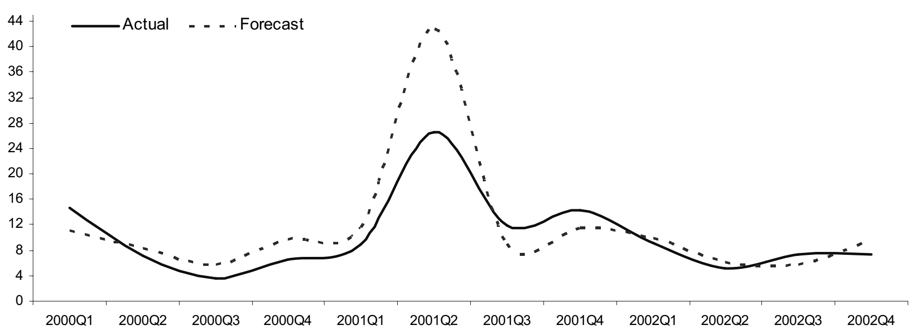
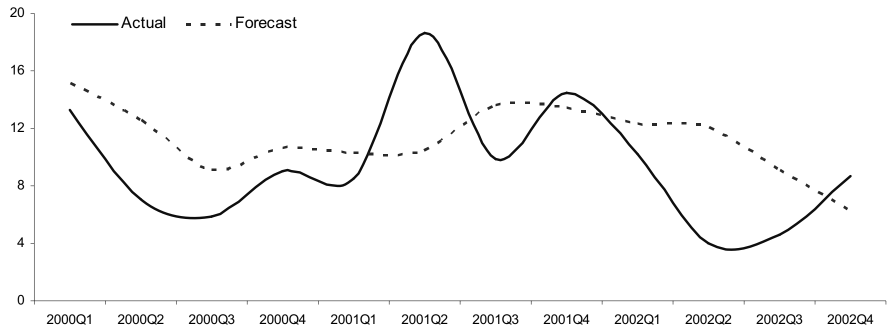


Figure 6.8: Actual Data and Out-Of-Sample Forecasts of Quarterly CPI-Inflation from Bivariate NN with Lagged Inflation

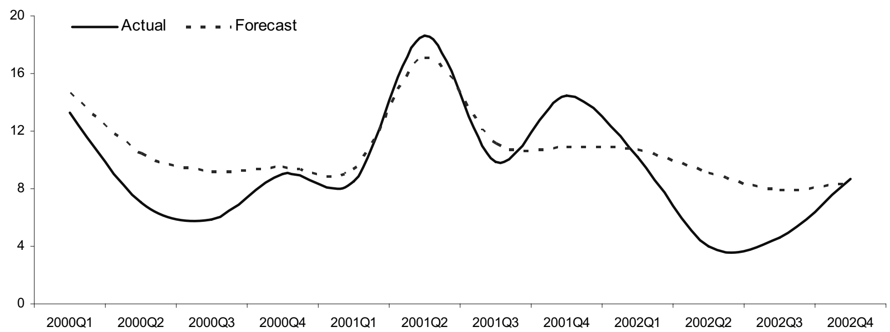
1-Step: DM3AY

RMSE: 4.364; MAE: 3.678; MAPE: 52.004



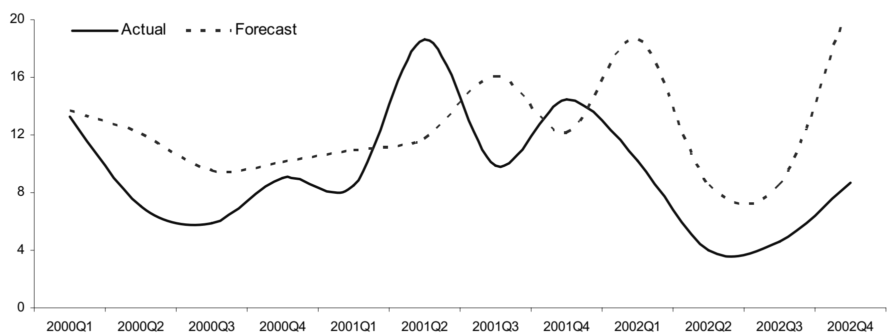
Static: DM3AY

RMSE: 2.577; MAE: 2.082; MAPE: 31.999



4-Step: SSM3A

RMSE: 5.824; MAE: 4.806; MAPE: 60.090



Dynamic: DM3A

RMSE: 3.412; MAE: 2.458; MAPE: 37.420

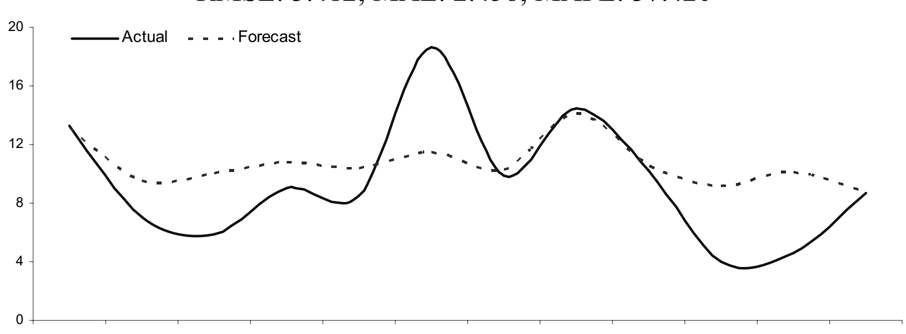
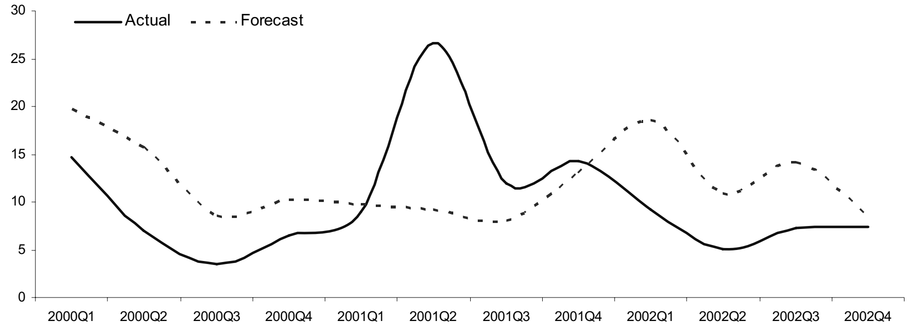


Figure 6.9: Actual Data and Out-Of-Sample Forecasts of Quarterly WPI-Inflation from Bivariate NN with Lagged Inflation

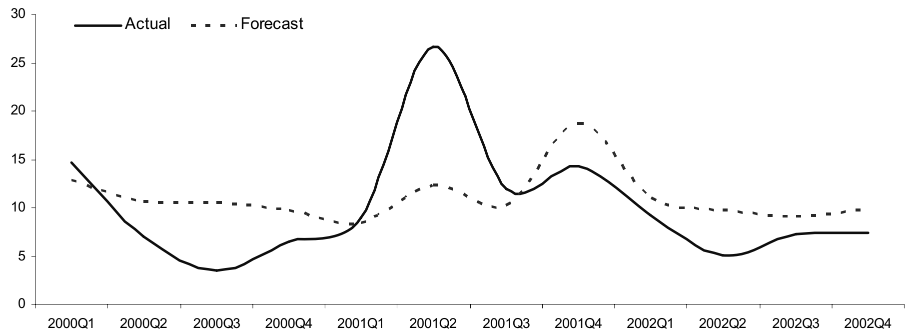
1-Step: DM3AY

RMSE: 7.248; MAE: 5.779; MAPE: 66.988



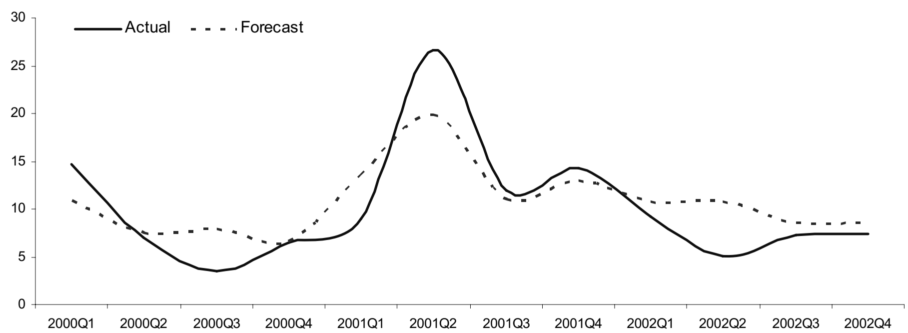
Static: DM3AY

RMSE: 5.274; MAE: 3.931; MAPE: 48.854



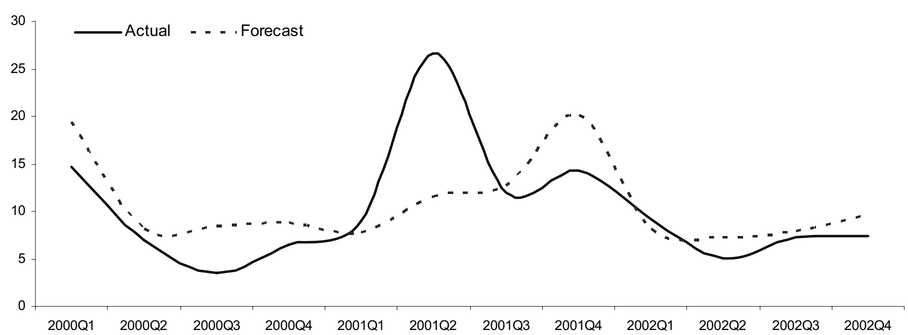
4-Step: DM1

RMSE: 3.416; MAE: 2.664; MAPE: 34.676



Dynamic: DM2

RMSE: 5.214; MAE: 3.483; MAPE: 36.023



APPENDIX C: NO-CHANGE FORECASTS

Table: Definitions of No-Change Forecasts

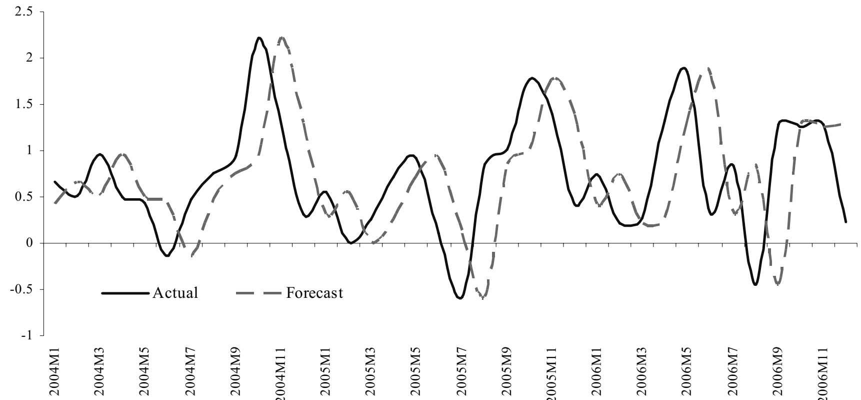
	Static/I-Step	Dynamic	4/12-Step
Inflation			
Monthly CPI-Inflation: 2004:1-2006:12	1 -period shift	2003:12 value	12-period shift forward
Monthly WPI- Inflation: 2004:1-2006:12	1-period shift	2003:12 value	12-period shift forward
Annual CPI- Inflation (monthly): 2004:1-2006:12	1-period shift	2003:12 value	12-period shift forward
Annual WPI- Inflation (monthly): 2004:1-2006:12	1 -period shift	2003:12 value	12-period shift forward
Quarterly CPI- Inflation: 2004:1-2006:4	1-period shift	2003:4 value	4-period shift forward
Quarterly WPI- Inflation: 2004:1-2006:4	1 -period shift	2003:4 value	4-period shift forward
Quarterly CPI- Inflation: 2000:1-2002:4	1-period shift	1999:4 value	4-period shift forward
Quarterly WPI- Inflation: 2000:1-2002:4	1-period shift	1999:4 value	4-period shift forward

GDP			
Real GDP Level: 2004:1-2006:4	4-period shift	2003 values	4-period shift annually
Nominal GDP Growth: 2004:1 -2006:4 1	1-period shift	2003:4 values	4-period shift forward
Real GDP Growth: 2004:1 -2006:4	1-period shift	2003:4 values	4-period shift forward

Monthly CPI-Inflation: Actual Values and No-Change Forecasts

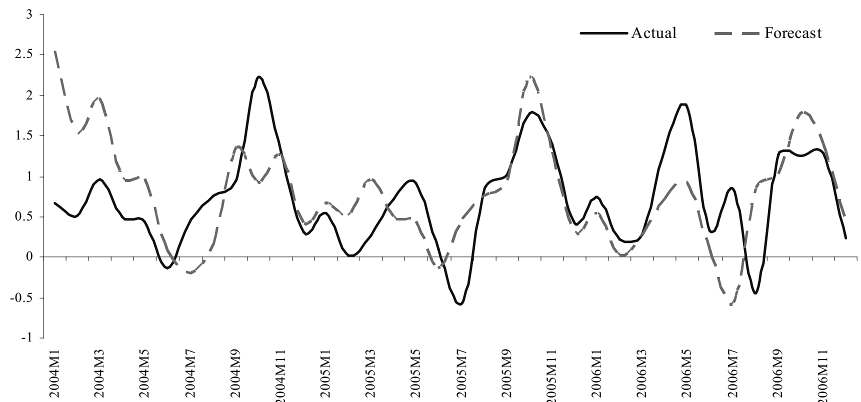
Static / 1-Step

RMSE:0.751; MAE:0.601; MAPE:215.6



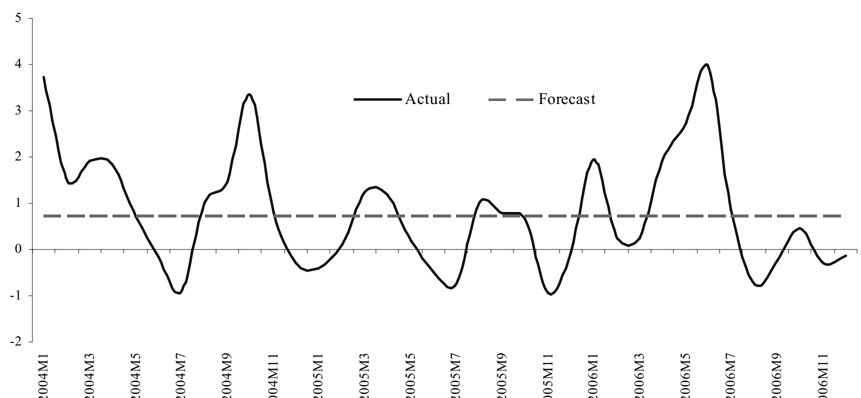
12-Step

RMSE: 1.225; MAE:0.919; MAPE: 163.2



Dynamic

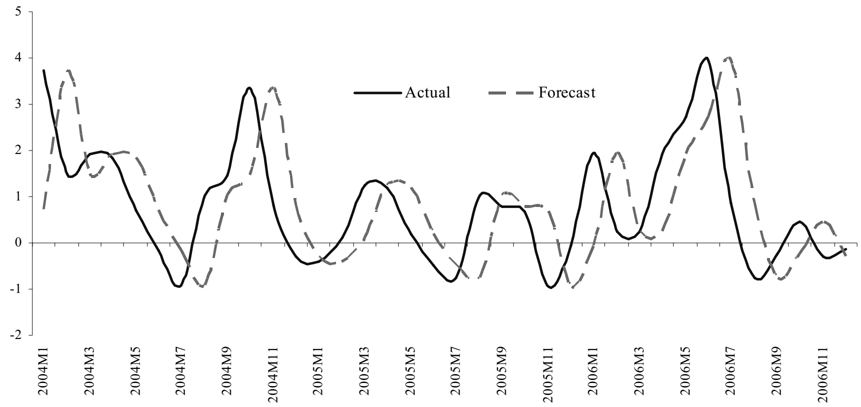
RMSE: 1.254; MAE: 0.986; MAPE: 210.8



Monthly WPI-Inflation: Actual Values and No-Change Forecasts

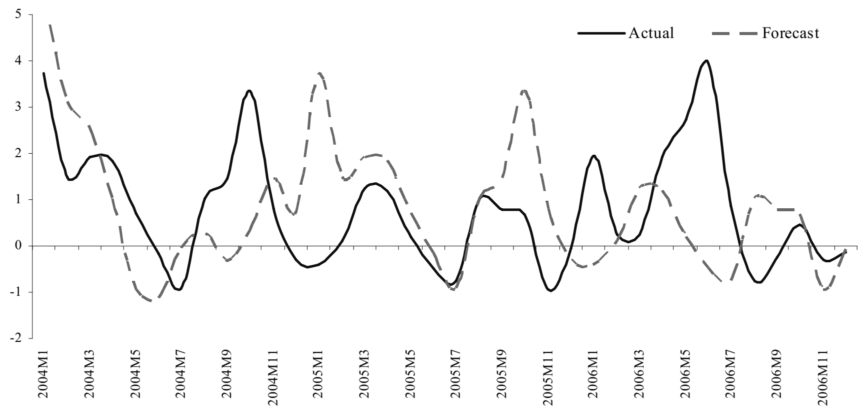
1-Step / Static

RMSE: 1.366; MAE: 1.086; MAPE:: 226.6



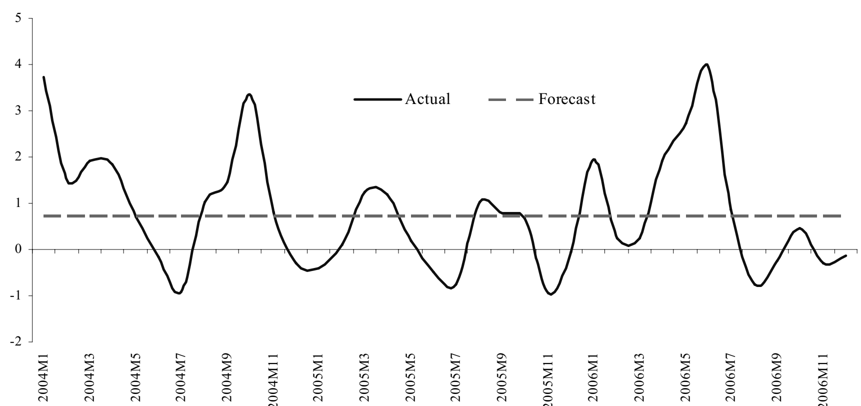
12-Step

RMSE: 1.638; MAE: 1.254; MAPE: 219.1



Dynamic

RMSE: 1.254; MAE: 0.986; MAPE: 210.8



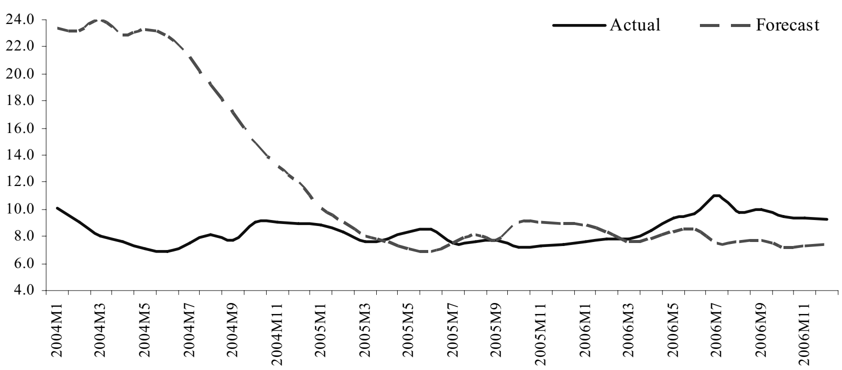
Annual CPI-Inflation From Monthly Data: Actual Values and No-Change Forecasts

Static / 1-Step

RMSE:0.681; MAE:0.508; MAPE:5.867

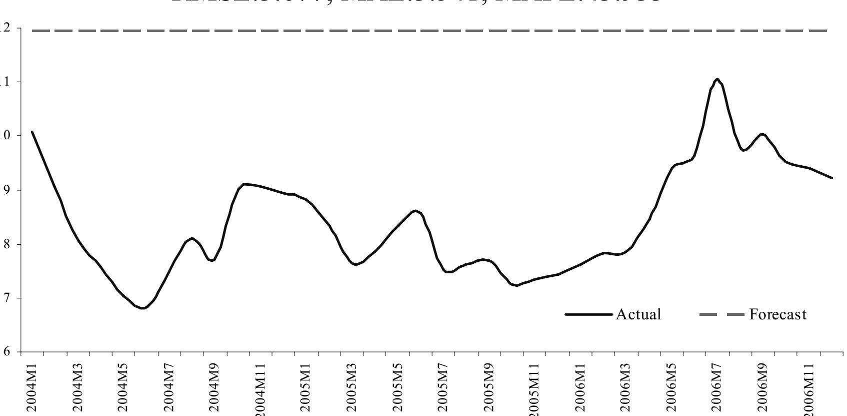
12-Step

RMSE:7.258; MAE:11.497; MAPE:57.619



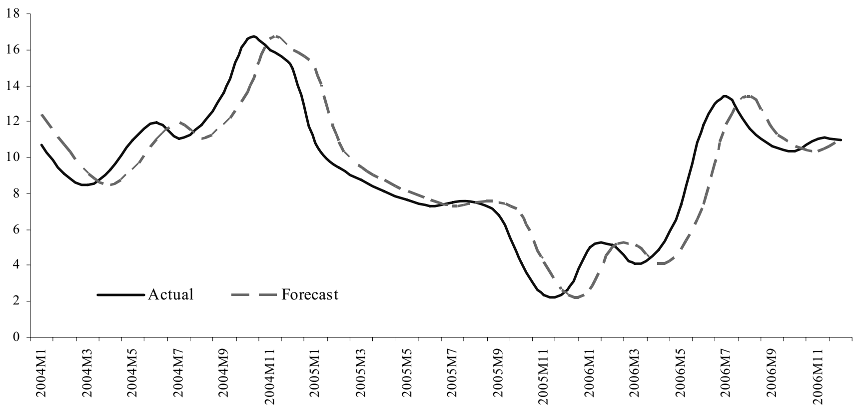
Dynamic

RMSE:3.677; MAE:3.541; MAPE:43.933

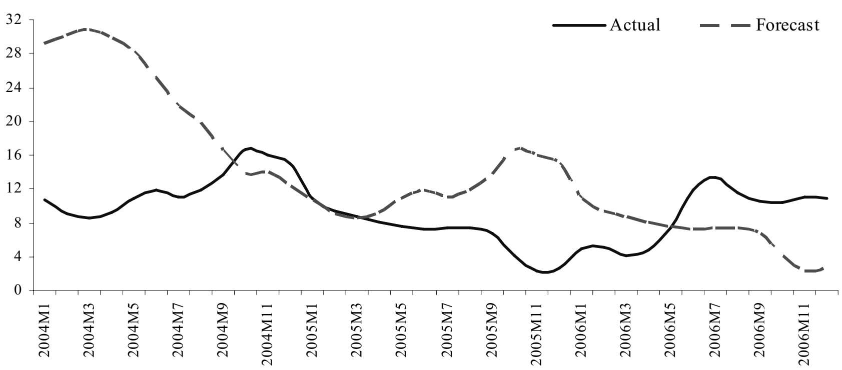


Annual WPI-Inflation From Monthly Data: Actual Values and No-Change Forecasts

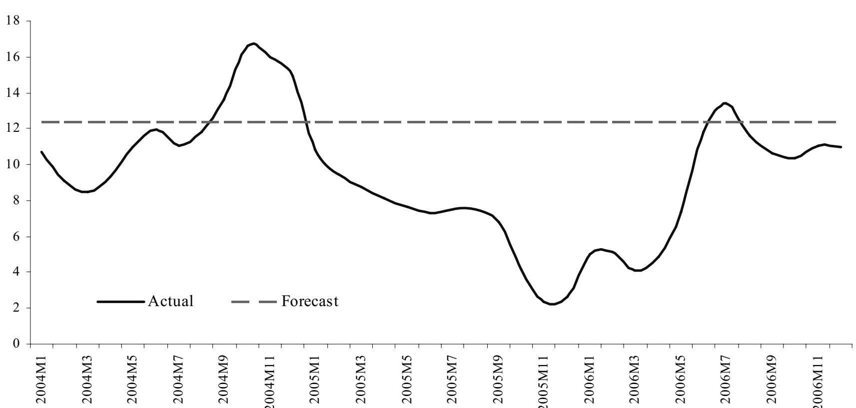
1-Step / Static
RMSE:1.638; MAE:1.254; MAPE:15.981



12-Step
RMSE:9.622; MAE:11.79; MAPE:106.015

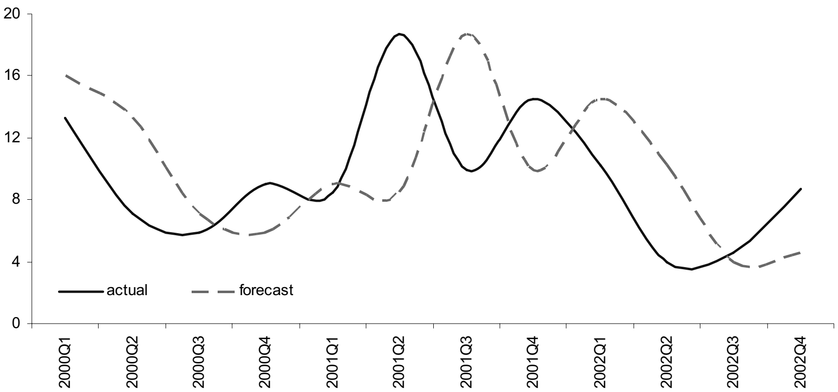


Dynamic
RMSE:4.668; MAE:3.81; MAPE:69.59

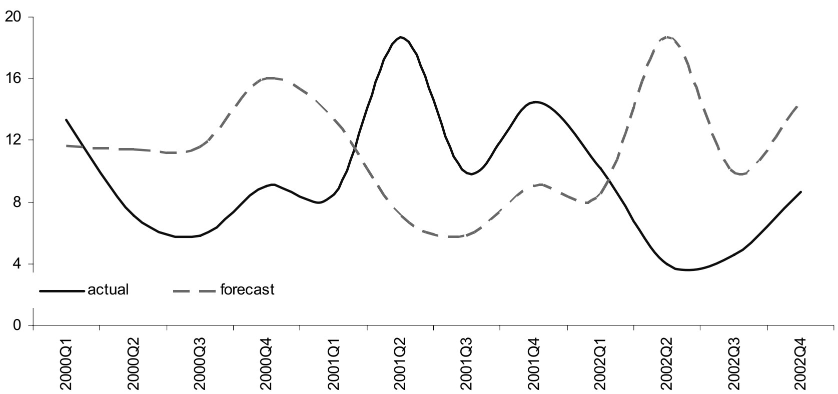


Quarterly CPI-Inflation Sample 2000-2002: Actual Values and No-Change Forecasts

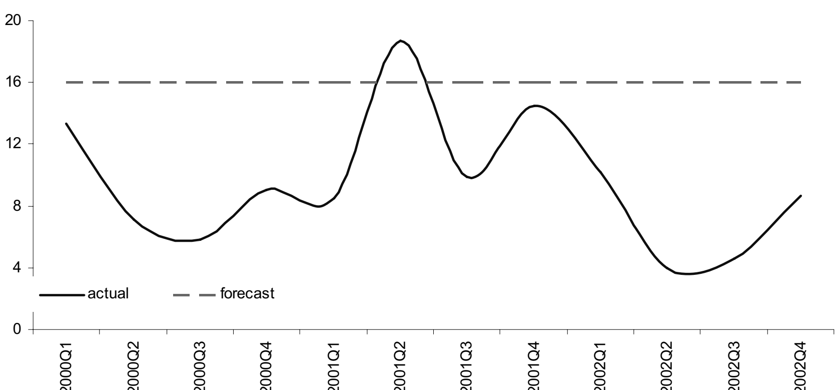
Static / 1-Step
RMSE:5.269; MAE:4.385; MAPE:50.366



4-Step
RMSE:6.997; MAE:6.009; MAPE:84.505



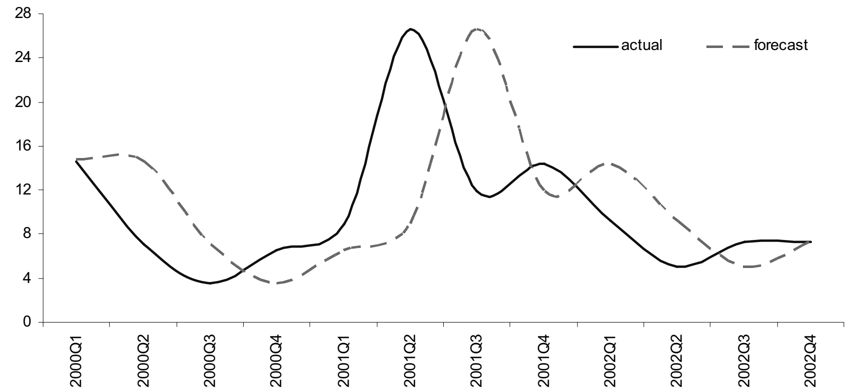
Dynamic
RMSE:7.695; MAE:6.964; MAPE:105.708



Quarterly WPI-Inflation Sample 2000-2002: Actual Values and No-Change Forecasts

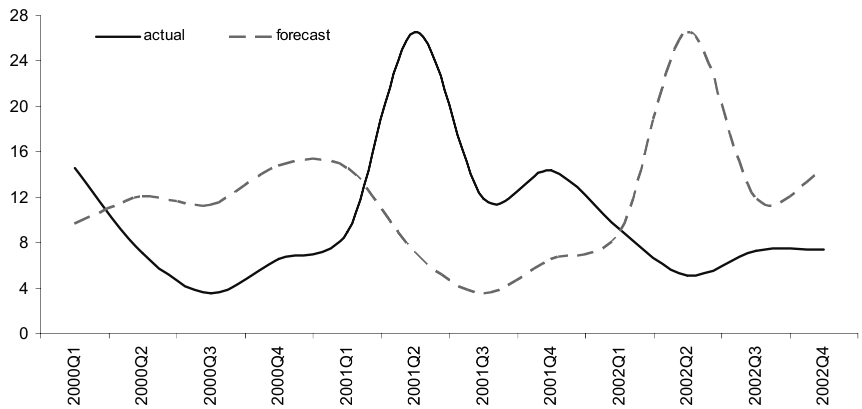
1-Step / Static

RMSE:7.445; MAE:5.246; MAPE:54.719



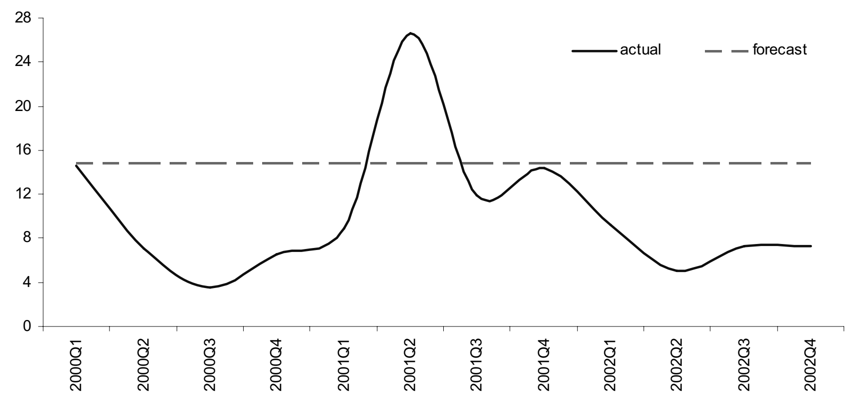
4-Step

RMSE:10.211; MAE:8.378; MAPE:108.034



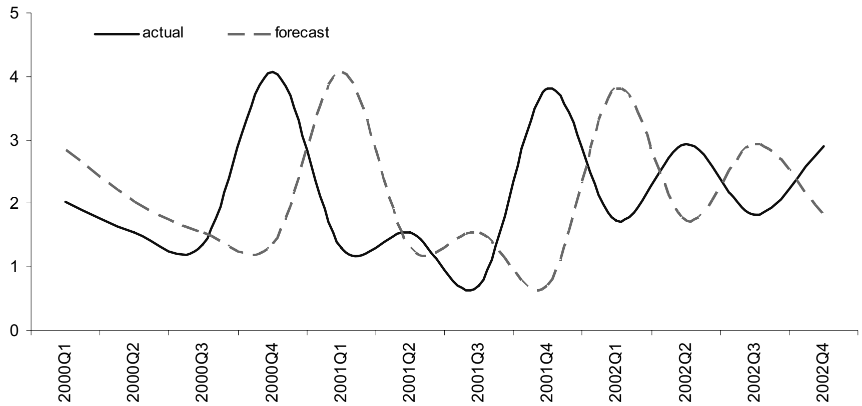
Dynamic

RMSE:7.488; MAE:6.55; MAPE:95.779

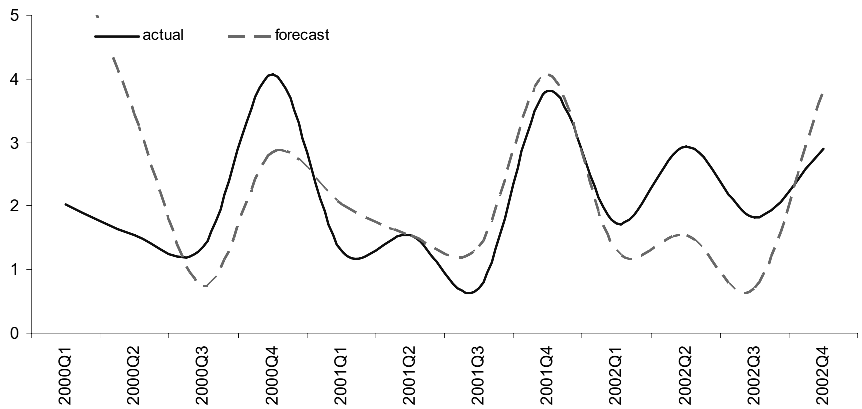


Quarterly CPI-Inflation Sample 2004-2006: Actual Values and No-Change Forecasts

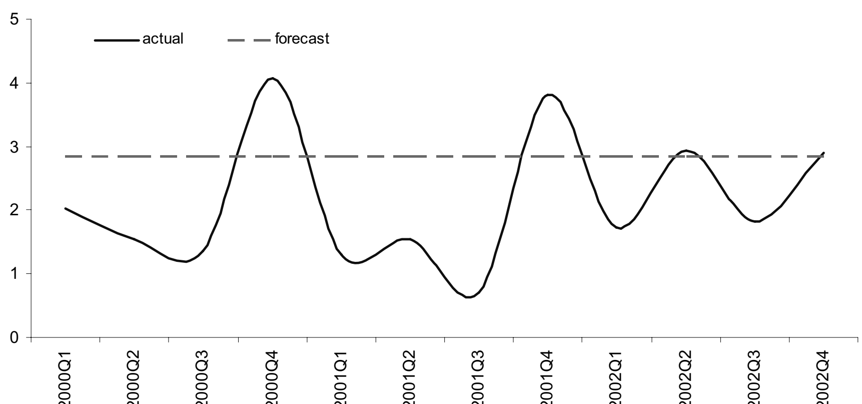
Static / 1-Step
RMSE:1.701; MAE:1.39; MAPE:70.364



4-Step
RMSE:1.546; MAE:1.124; MAPE:60.763

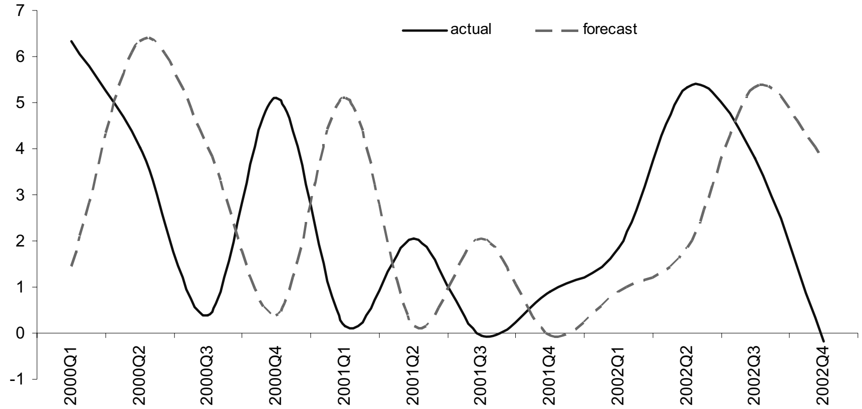


Dynamic
RMSE:1.231; MAE:1.094; MAPE:77.411

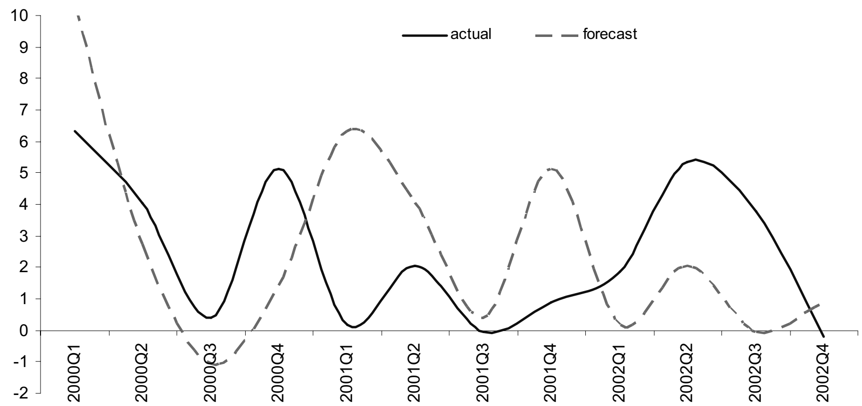


Quarterly WPI-Inflation Sample 2004-2006: Actual Values and No-Change Forecasts

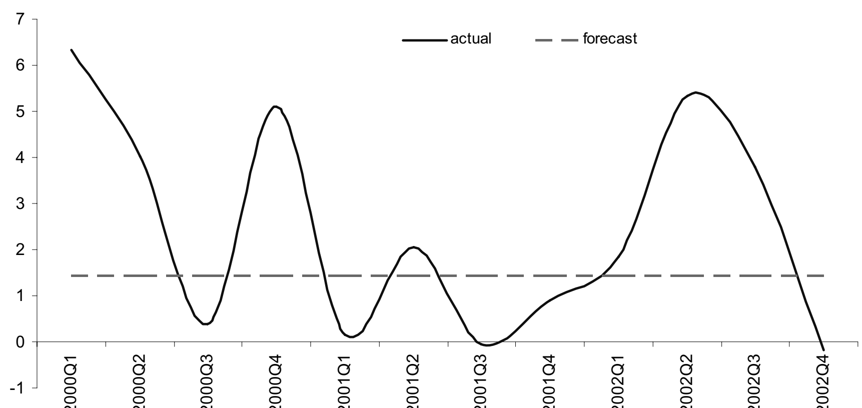
1-Step / Static
RMSE:3.288; MAE:2.953; MAPE:936.273



4-Step
RMSE:3.202; MAE:2.763; MAPE:566



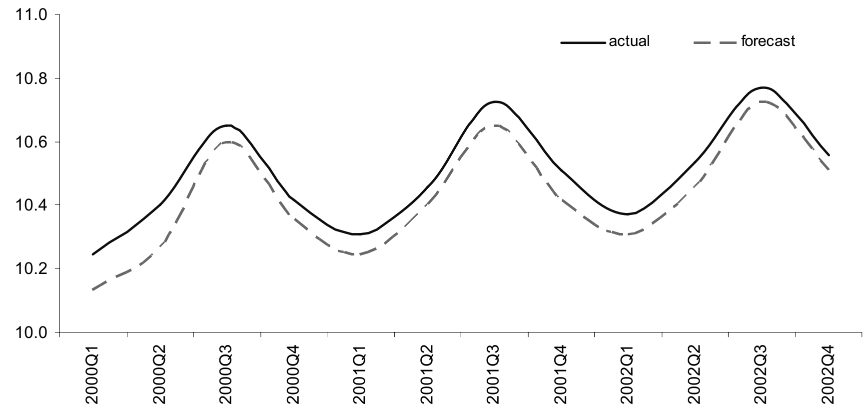
Dynamic
RMSE:2.477; MAE:2.036; MAPE:462.809



Real GDP Levels: Actual Values and No-Change Forecasts

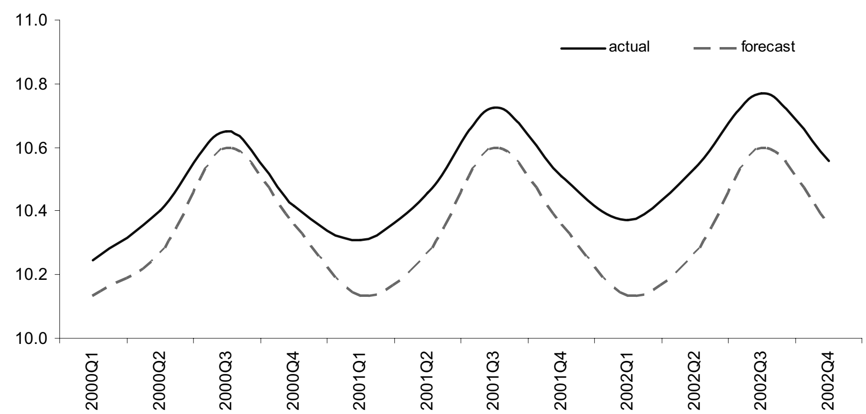
Static / 1-Step / 4-Step

RMSE:0.078; MAE:0.074; MAPE:0.702



Dynamic

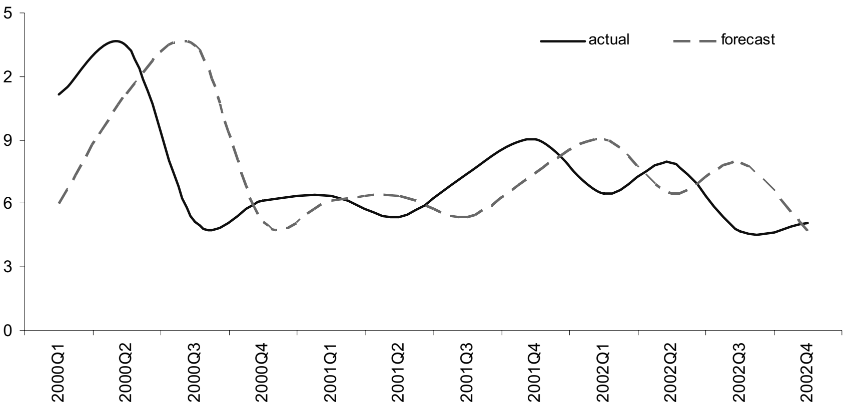
RMSE:0.169; MAE:0.157; MAPE:1.495



Real GDP Growth: Actual Values and No-Change Forecasts

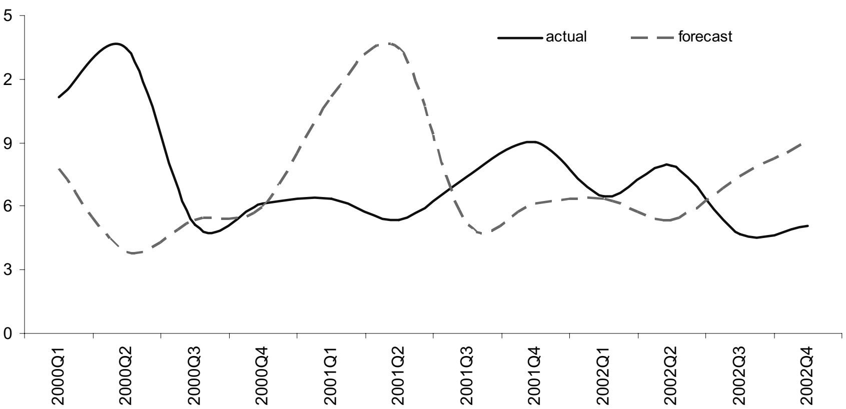
1-Step / Static

RMSE:3.29; MAE:2.459; MAPE:37.286



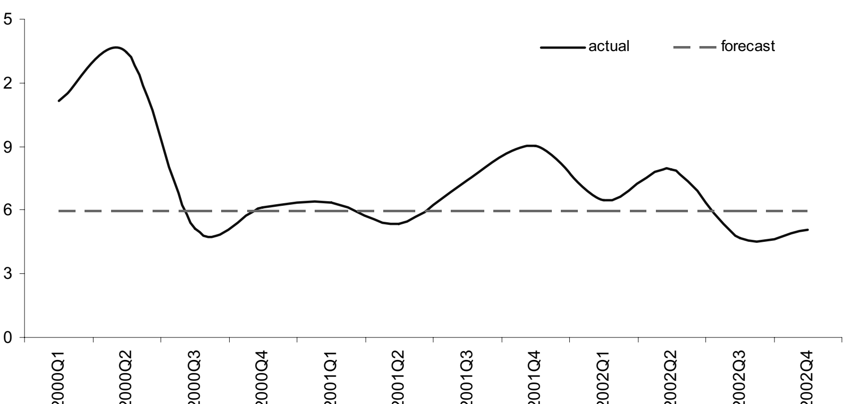
4-Step

RMSE:4.426; MAE:3.4; MAPE:47.323



Dynamic

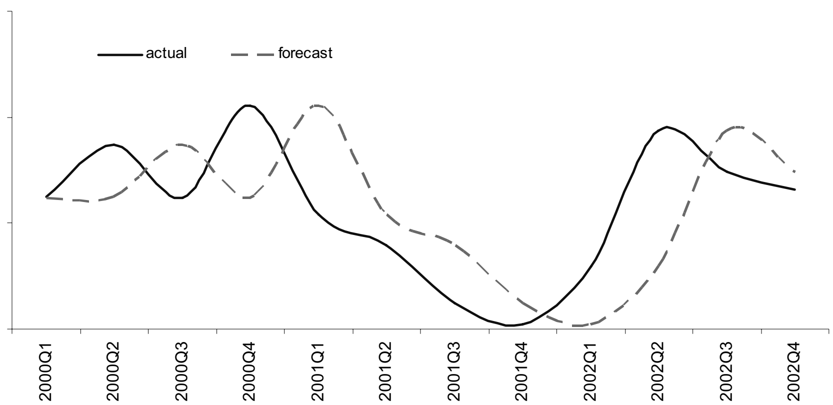
RMSE:2.924; MAE:1.99; MAPE:22.483



Nominal GDP Growth: Actual Values and No-Change Forecasts

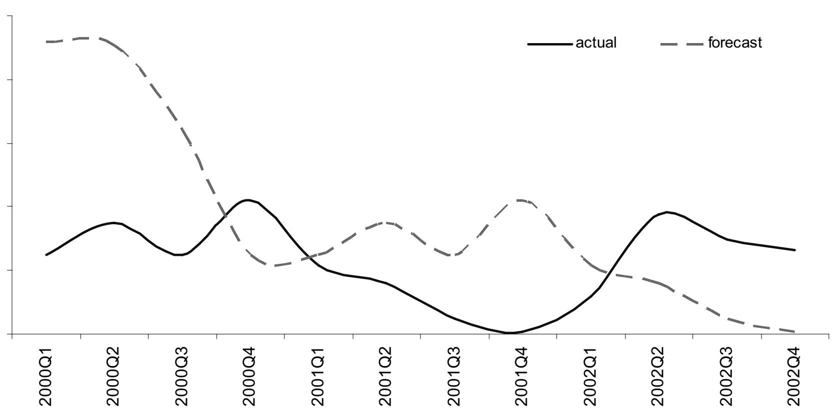
1-Step / Static

RMSE:3.173; MAE:2.625; MAPE:16.471



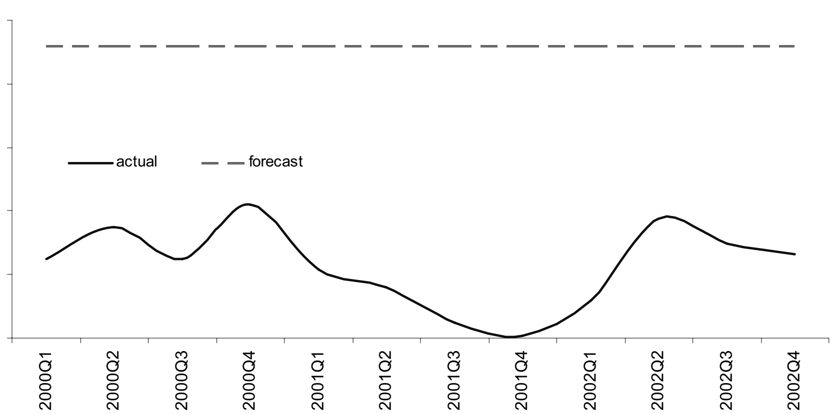
4-Step

RMSE:8.459; MAE:7.175; MAPE:47.022



Dynamic

RMSE:17.471; MAE:17.205; MAPE:118.296



APPENDIX D: DATA APPENDIXES

Nominal Divisia and Simple Sum Monetary Aggregates, Consumer Prices, Wholesale Prices, and Nominal and Real GDP Indexes: Quarterly Data (normalized at 1986:1)

	SSM1	DM1	SSM2	DM2	SSM3	DM3	SSM2Y	DM2Y	SSM3Y	DM3Y	CPI	WPI.	GDP	RGDP
1986:1	100	100	100	100	100	100	100	100	100	100	100	100	100	100.0
1986:2	114	114	111	112	113	114	113	112	115	114	105	104	133	118.5
1986:3	127	128	118	121	122	125	122	122	125	126	109	110	218	178.6
1986:4	151	150	133	138	134	139	139	139	140	140	117	122	189	130.8
1987:1	159	158	140	145	139	143	151	148	150	146	127	129	147	104.2
1987:2	172	172	149	156	152	160	161	160	163	163	138	134	193	125.5
1987:3	203	203	166	174	168	176	183	180	184	181	146	142	311	193.9
1987:4	247	244	191	196	191	196	216	204	214	203	161	162	284	154.5
1988:1	237	235	198	190	199	193	233	198	232	201	206	211	266	114.1
1988:2	260	260	214	207	215	211	250	215	249	218	232	241	350	130.3
1988:3	311	320	245	250	247	256	288	259	288	263	250	258	536	199.1
1988:4	337	341	293	277	294	281	348	287	346	290	287	298	466	146.8
1989:1	343	348	334	297	330	294	393	308	387	305	334	342	432	111.4
1989:2	409	417	385	355	379	347	444	364	436	356	379	386	568	128.1
1989:3	508	520	438	436	431	422	501	441	491	428	423	425	986	200.4
1989:4	609	619	528	527	516	504	597	531	583	511	466	491	859	152.0
1990:1	627	639	578	557	568	540	658	566	645	550	532	550	779	123.3
1990:2	764	784	656	665	646	644	739	669	725	650	576	630	1055	145.1
1990:3	877	903	727	755	715	729	820	758	805	735	624	667	1634	212.9
1990:4	971	989	807	831	794	803	918	838	900	813	706	789	1451	165.2
1991:1	994	1033	855	874	832	827	988	878	960	835	797	894	1207	122.8
1991:2	1065	1097	951	943	932	908	1130	949	1103	918	902	1029	1604	144.4
1991:3	1231	1269	1097	1094	1066	1036	1334	1106	1294	1052	983	1125	2669	221.3
1991:4	1438	1473	1294	1273	1259	1208	1616	1295	1567	1234	1106	1326	2407	164.0
1992:1	1439	1483	1444	1310	1401	1245	1850	1341	1790	1280	1344	1594	2226	132.9
1992:2	1630	1679	1615	1478	1582	1436	2159	1521	2101	1483	1443	1747	2795	152.6
1992:3	1966	2026	1838	1761	1796	1693	2557	1825	2480	1763	1556	1872	4471	233.1
1992:4	2394	2454	2108	2107	2054	2006	2890	2160	2798	2069	1797	2227	4192	172.9
1993:1	2578	2654	2382	2302	2320	2197	3215	2357	3114	2263	2055	2528	3803	139.4
1993:2	3077	3177	2617	2685	2572	2594	3553	2732	3461	2651	2271	2861	5101	169.9
1993:3	3546	3655	2840	3038	2811	2961	3978	3125	3888	3054	2533	3197	8295	250.4
1993:4	4043	4157	3148	3429	3104	3314	4591	3563	4471	3451	2868	3771	7606	187.5
1994:1	3737	3859	3283	3299	3245	3227	5534	3457	5373	3387	3447	4376	6392	146.6
1994:2	4914	5106	4748	4462	4673	4356	7822	4660	7583	4556	5312	6076	9846	151.7
1994:3	6589	6841	6569	5726	6453	5616	9994	5983	9699	5875	5782	6777	16230	230.9
1994:4	7410	7677	7031	6089	6868	5914	11669	6669	11265	6491	6921	8140	15950	177.2
1995:1	7806	8110	8395	6715	8258	6687	13707	7362	13287	7344	8617	9738	15372	144.4
1995:2	10068	10461	10854	8594	10532	8326	16345	9002	15753	8814	9667	11108	20600	172.3
1995:3	12226	12697	13019	10413	12740	10252	19069	10732	18484	10648	10398	12424	32358	251.6
1995:4	12978	13441	14184	11250	13862	11025	22551	11872	21796	11680	11785	14685	28826	188.9
1996:1	13827	14333	16449	12366	16408	12951	26912	13102	26286	13731	14064	17365	27292	157.0
1996:2	17198	17925	20487	15509	20213	15805	32866	16348	31926	16690	16814	20243	36952	186.2
1996:3	20306	21083	25006	18565	24594	18832	40255	19623	39034	19960	18408	22459	61159	264.9
1996:4	25857	26382	31334	23184	31190	24181	50502	24623	49294	25586	21380	26421	59485	202.2
1997:1	31725	32217	36662	27548	36525	28731	60257	29421	58805	30544	24923	30722	52023	167.8
1997:2	37065	37792	43174	32169	42974	33510	69331	34459	67679	35721	28931	35944	72292	202.0
1997:3	39655	41148	51077	36451	51608	39583	82468	39501	81161	42213	33726	42158	120815	283.5
1997:4	46769	47974	61548	43182	62237	46910	100830	46849	99217	50042	40362	51813	115779	217.9
1998:1	52215	54258	69910	49091	69470	50707	118387	53918	115264	54844	46999	61221	106739	183.3
1998:2	60344	61839	86519	57502	86194	60325	144508	63582	140950	65428	52039	68938	137650	208.5
1998:3	76824	78331	105291	71544	103894	72998	176330	78829	171095	79538	56180	76852	214985	291.1
1998:4	81144	83019	124637	80282	121418	79601	197013	86451	190106	85594	62567	89591	194274	215.2
1999:1	90567	94295	147815	93316	143937	92590	227364	99443	219475	98609	68958	100661	150185	168.3
1999:2	94869	96768	169929	98774	166811	101628	267702	108510	259450	110322	77802	112851	204787	204.0
1999:3	112217	115020	209869	118325	202070	114406	317764	128591	304839	124764	87108	126712	321318	272.9
1999:4	131710	133758	243884	127891	235885	126906	389448	148455	374221	144337	100987	148776	292640	210.7

	SSM1	DM1	SSM2	DM2	SSM3	DM3	SSM2Y	DM2Y	SSM3Y	DM3Y	CPI	WPI.	GDP	RGDP
2000:1	163885	162719	269569	135068	261584	136315	443039	160336	426248	155991	116882	169943	264046	177.8
2000:2	186857	185769	282848	147857	274859	149377	483527	176273	465198	171910	125454	182426	343492	218.1
2000:3	220608	219505	316224	173730	306146	172291	535571	205986	514356	198149	129948	193435	502168	294.3
2000:4	238423	237425	350405	191749	341374	194248	574078	226604	553536	219398	138755	211731	449583	228.7
2001:1	266360	264244	423511	204480	409278	205084	676210	239074	649472	231584	151704	230494	314833	176.0
2001:2	312579	310546	473117	243468	457931	243906	824527	284857	791381	276621	197860	277819	485593	196.8
2001:3	355196	353889	484237	273614	469677	273439	971349	324116	931090	313762	222832	306775	738416	272.2
2001:4	364974	363454	535293	281865	518474	281836	1095210	337640	1048862	325344	257164	354547	694171	205.1
2002:1	384094	383942	574361	295681	563488	308321	1061754	349001	1024710	346743	281918	392595	621246	180.0
2002:2	415308	416795	622020	323287	607754	331384	1150434	375422	1108101	371573	296604	408517	717396	214.4
2002:3	470320	471167	655001	355912	643622	366471	1284604	414914	1239087	411858	319025	427821	1095788	293.9
2002:4	521131	523104	713886	389730	700731	399634	1344835	446805	1297686	442464	343348	466619	1039693	229.2
2003:1	513599	520714	744924	391859	736424	409443	1373895	452359	1330936	451398	380696	496760	863657	194.6
2003:2	550427	556992	780226	411631	778499	436358	1332542	461721	1299846	466382	391208	514165	995079	222.8
2003:3	648115	653052	864035	470926	863838	499143	1397711	509636	1367407	519236	387086	517962	1421435	310.1
2003:4	751113	754118	953378	536128	949383	562066	1538131	574724	1501616	582169	392656	532945	1222630	243.2
2004:1	794750	802263	1088732	577406	1082900	611093	1592010	615787	1558486	626610	418348	543838	1015879	217.6
2004:2	862265	867081	1151651	620555	1145764	663912	1689742	658345	1654204	680322	435518	552309	1199589	254.8
2004:3	937233	940367	1206985	666893	1190761	697434	1787686	707226	1740685	717139	437222	559834	1671624	326.4
2004:4	971018	970186	1272529	690287	1262344	728794	1889930	737546	1846148	752101	460167	583133	1501199	258.6
2005:1	974616	973379	1311621	698267	1294451	747365	1877077	744838	1830108	767510	460893	590727	1184959	231.9
2005:2	1105404	1105973	1457690	791139	1431108	825487	2011423	835419	1956869	843527	470402	599868	1379510	268.8
2005:3	1214507	1219567	1611154	872815	1574683	912550	2165715	917831	2102449	929177	470183	604112	1870454	351.6
2005:4	1357103	1357176	1775594	968953	1728527	1016496	2312470	1015311	2240919	1029823	474410	627548	1662913	283.1
2006:1	1356541	1357839	1866951	978984	1813996	1026419	2403591	1024555	2326896	1038823	483275	638458	1348834	247.4
2006:2	1527336	1532350	2061723	1099043	1996217	1149396	2680620	1147417	2588284	1166872	509806	657496	1674529	291.0
2006:3	1541970	1552258	2096814	1112970	2029047	1152350	2753348	1170340	2656905	1172168	529470	669540	2226672	368.4
2006:4	1553740	1577434	2175183	1135597	2102366	1175077	2900227	1194300	2795492	1196832	528465	689230	1963225	297.9

Nominal Divisia and Simple Sum Monetary Aggregates, Consumer Prices, Wholesale Prices Indexes in Logarithms: Monthly Data (normalized at 1986:1)

	SSM1	DM1	SSM2	DM2	SSM3A	DM3A	SSM2Y	DM2Y	SSM3AY	DM3AY	WPI	CPI
Jan-86	4.6052	4.6052	4.6052	4.6052	4.6052	4.6052	4.6052	4.6052	4.6052	4.6052	4.6052	4.6052
Feb-86	4.6239	4.6253	4.6332	4.6314	4.6336	4.6316	4.6437	4.6323	4.6434	4.6325	4.6297	4.6224
Mar-86	4.6787	4.6718	4.7088	4.6867	4.7248	4.6951	4.7186	4.6877	4.7321	4.6960	4.6425	4.6353
Apr-86	4.7119	4.7045	4.7261	4.7092	4.7419	4.7129	4.7419	4.7108	4.7548	4.7143	4.6634	4.6391
May-86	4.7970	4.7960	4.7709	4.7759	4.7853	4.7947	4.7877	4.7796	4.7993	4.7975	4.6798	4.6580
Jun-86	4.7922	4.7885	4.7783	4.7727	4.8107	4.8209	4.8094	4.7762	4.8356	4.8219	4.6906	4.6816
Jul-86	4.8237	4.8248	4.7881	4.7879	4.8311	4.8528	4.8377	4.8038	4.8715	4.8636	4.7053	4.7001
Aug-86	4.9016	4.9121	4.8218	4.8496	4.8523	4.8768	4.8593	4.8579	4.8834	4.8834	4.7092	4.7088
Sep-86	4.9038	4.9065	4.8375	4.8487	4.8710	4.8753	4.8779	4.8605	4.9043	4.8851	4.7301	4.7315
Oct-86	4.9143	4.9233	4.8750	4.8750	4.8999	4.9049	4.9216	4.8875	4.9403	4.9153	4.7656	4.8023
Nov-86	4.9685	4.9733	4.9027	4.9107	4.9199	4.9323	4.9587	4.9238	4.9702	4.9432	4.7804	4.8249
Dec-86	5.2329	5.1974	5.0278	5.0870	5.0221	5.0690	5.0764	5.0960	5.0691	5.0776	4.7902	4.8411
Jan-87	5.0752	5.0680	4.9670	4.9894	4.9709	4.9869	5.0521	5.0178	5.0510	5.0126	4.8260	4.8701
Feb-87	5.1177	5.1099	4.9903	5.0202	4.9833	4.9984	5.0699	5.0459	5.0602	5.0234	4.8628	4.8746
Mar-87	5.1100	5.0968	5.0041	5.0197	5.0103	5.0172	5.0852	5.0470	5.0862	5.0417	4.8961	4.8858
Apr-87	5.1096	5.1002	5.0112	5.0257	5.0513	5.0765	5.0960	5.0545	5.1245	5.0978	4.9368	4.8880
May-87	5.2218	5.2290	5.0630	5.1202	5.0762	5.1276	5.1444	5.1450	5.1511	5.1485	4.9524	4.9186
Jun-87	5.2089	5.1979	5.0620	5.1019	5.0887	5.1308	5.1566	5.1329	5.1735	5.1560	4.9627	4.9283
Jul-87	5.3095	5.3155	5.1171	5.1781	5.1418	5.2049	5.2193	5.2130	5.2340	5.2339	4.9929	4.9399
Aug-87	5.3472	5.3443	5.1573	5.1952	5.1751	5.2120	5.2621	5.2325	5.2711	5.2438	5.0077	4.9741
Sep-87	5.3806	5.3732	5.1969	5.2089	5.2046	5.2108	5.3083	5.2486	5.3089	5.2453	5.0223	4.9913
Oct-87	5.4405	5.4432	5.2379	5.2522	5.2461	5.2583	5.3549	5.2922	5.3556	5.2930	5.0347	5.0382
Nov-87	5.4221	5.4223	5.2431	5.2339	5.2581	5.2545	5.3804	5.2751	5.3853	5.2903	5.0638	5.0993
Dec-87	5.7289	5.6959	5.3992	5.4466	5.3946	5.4365	5.5305	5.4870	5.5205	5.4717	5.2065	5.1729
Jan-88	5.5034	5.4946	5.3077	5.2870	5.3211	5.3058	5.4806	5.3302	5.4824	5.3433	5.2873	5.3230
Feb-88	5.4800	5.4681	5.3267	5.2690	5.3363	5.2901	5.4991	5.3126	5.4980	5.3280	5.3475	5.3597
Mar-88	5.5138	5.5011	5.3600	5.2954	5.3693	5.3169	5.5285	5.3386	5.5274	5.3544	5.4141	5.4136
Apr-88	5.5424	5.5443	5.3857	5.3342	5.3887	5.3401	5.5511	5.3754	5.5454	5.3768	5.4581	5.4741
May-88	5.6086	5.6038	5.4146	5.3779	5.4266	5.4015	5.5769	5.4172	5.5782	5.4346	5.4711	5.5081
Jun-88	5.6199	5.6229	5.4367	5.4011	5.4496	5.4265	5.5916	5.4356	5.5940	5.4552	5.4791	5.5170
Jul-88	5.7454	5.7787	5.5084	5.5301	5.5334	5.5708	5.6583	5.5606	5.6702	5.5947	5.5055	5.5329
Aug-88	5.7717	5.7951	5.5489	5.5596	5.5589	5.5736	5.7161	5.5956	5.7156	5.6034	5.5389	5.5565
Sep-88	5.7914	5.8220	5.5779	5.5839	5.5916	5.6049	5.7639	5.6208	5.7652	5.6355	5.5838	5.6139
Oct-88	5.7534	5.7819	5.6245	5.5707	5.6519	5.6259	5.8115	5.6081	5.8229	5.6564	5.6310	5.6683
Nov-88	5.7861	5.8109	5.7062	5.6218	5.7171	5.6474	5.8957	5.6626	5.8947	5.6829	5.6846	5.7203
Dec-88	5.9996	5.9821	5.8316	5.7784	5.8239	5.7567	5.9978	5.8068	5.9840	5.7868	5.7250	5.7446
Jan-89	5.8156	5.8281	5.7792	5.6620	5.7851	5.6770	5.9573	5.7049	5.9532	5.7157	5.7941	5.8085
Feb-89	5.8864	5.8992	5.8710	5.7455	5.8629	5.7317	6.0348	5.7807	6.0208	5.7669	5.8300	5.8552
Mar-89	5.9003	5.9182	5.9120	5.7765	5.9023	5.7602	6.0795	5.8167	6.0641	5.8002	5.8658	5.8851
Apr-89	5.9966	6.0137	5.9656	5.8598	5.9552	5.8392	6.1260	5.8920	6.1105	5.8724	5.9171	5.9455
May-89	6.0508	6.0650	6.0000	5.9051	5.9857	5.8754	6.1452	5.9297	6.1271	5.9028	5.9607	5.9755
Jun-89	6.0844	6.1043	6.0263	5.9586	6.0238	5.9491	6.1734	5.9801	6.1644	5.9714	5.9926	5.9962
Jul-89	6.1952	6.2165	6.0772	6.0551	6.0749	6.0412	6.2205	6.0693	6.2117	6.0573	6.0428	6.0262
Aug-89	6.2570	6.2792	6.1257	6.1124	6.1113	6.0757	6.2634	6.1244	6.2456	6.0924	6.0685	6.0608
Sep-89	6.3258	6.3491	6.1784	6.1699	6.1638	6.1323	6.3165	6.1820	6.2984	6.1491	6.0935	6.1156
Oct-89	6.3805	6.4003	6.2563	6.2445	6.2478	6.2185	6.3901	6.2562	6.3770	6.2337	6.1209	6.1755

	SSM1	DM1	SSM2	DM2	SSM3A	DM3A	SSM2Y	DM2Y	SSM3AY	DM3AY	WPI	CPI
Nov-89	6.3941	6.4133	6.2976	6.2708	6.2840	6.2366	6.4288	6.2822	6.4118	6.2523	6.1618	6.2181
Dec-89	6.5472	6.5505	6.3817	6.3884	6.3562	6.3294	6.5102	6.3935	6.4840	6.3418	6.2093	6.2410
Jan-90	6.4478	6.4626	6.3742	6.3319	6.3678	6.3126	6.5091	6.3479	6.4975	6.3309	6.2528	6.2788
Feb-90	6.4620	6.4785	6.4023	6.3489	6.3892	6.3183	6.5378	6.3660	6.5210	6.3387	6.2979	6.3220
Mar-90	6.5073	6.5261	6.4373	6.3964	6.4215	6.3597	6.5747	6.4144	6.5558	6.3817	6.3387	6.3726
Apr-90	6.6415	6.6576	6.5001	6.5001	6.4958	6.4810	6.6276	6.5071	6.6179	6.4909	6.3625	6.4368
May-90	6.6125	6.6307	6.5110	6.4887	6.5028	6.4647	6.6425	6.5013	6.6297	6.4804	6.3777	6.4677
Jun-90	6.7501	6.7861	6.5793	6.6170	6.5627	6.5732	6.7000	6.6164	6.6810	6.5787	6.3923	6.4820
Jul-90	6.7695	6.7913	6.6034	6.6256	6.5980	6.6027	6.7319	6.6320	6.7215	6.6125	6.4090	6.4728
Aug-90	6.8136	6.8437	6.6359	6.6706	6.6208	6.6297	6.7631	6.6735	6.7452	6.6382	6.4524	6.4979
Sep-90	6.8391	6.8670	6.6603	6.6932	6.6496	6.6599	6.7875	6.6965	6.7729	6.6680	6.5084	6.5813
Oct-90	6.8576	6.8791	6.6983	6.7148	6.6859	6.6799	6.8319	6.7227	6.8157	6.6924	6.5536	6.6475
Nov-90	6.8395	6.8646	6.7140	6.7122	6.7094	6.6930	6.8550	6.7252	6.8446	6.7086	6.5809	6.6963
Dec-90	7.0205	7.0271	6.7993	6.8437	6.7864	6.8057	6.9313	6.8499	6.9149	6.8165	6.6055	6.7136
Jan-91	6.9526	6.9961	6.7721	6.8202	6.7542	6.7733	6.8978	6.8237	6.8777	6.7819	6.6504	6.7611
Feb-91	6.9402	6.9754	6.7996	6.8160	6.7761	6.7612	6.9564	6.8213	6.9311	6.7715	6.7016	6.8139
Mar-91	6.9052	6.9351	6.8164	6.7911	6.7925	6.7383	6.9865	6.7976	6.9604	6.7497	6.7490	6.8567
Apr-91	6.9711	6.9945	6.8583	6.8461	6.8529	6.8295	7.0364	6.8529	7.0239	6.8403	6.8014	6.9202
May-91	6.9599	6.9891	6.8879	6.8491	6.8705	6.8104	7.0729	6.8570	7.0512	6.8229	6.8301	6.9529
Jun-91	7.0700	7.1021	6.9580	6.9576	6.9375	6.9095	7.1338	6.9633	7.1102	6.9202	6.8436	6.9821
Jul-91	7.0802	7.1066	6.9843	6.9665	6.9664	6.9253	7.1762	6.9764	7.1540	6.9395	6.8658	6.9951
Aug-91	7.1404	7.1740	7.0432	7.0334	7.0183	6.9764	7.2471	7.0441	7.2194	6.9921	6.9120	7.0342
Sep-91	7.2147	7.2412	7.1035	7.0989	7.0788	7.0420	7.3154	7.1115	7.2877	7.0594	6.9549	7.0932
Oct-91	7.2495	7.2775	7.1553	7.1382	7.1427	7.1075	7.3776	7.1531	7.3582	7.1257	6.9894	7.1571
Nov-91	7.2265	7.2551	7.1790	7.1246	7.1617	7.0876	7.4166	7.1453	7.3934	7.1114	7.0272	7.2082
Dec-91	7.4195	7.4318	7.2918	7.2860	7.2574	7.2091	7.5191	7.3033	7.4842	7.2322	7.0706	7.2509
Jan-92	7.2491	7.2767	7.2726	7.1606	7.2466	7.1091	7.5129	7.1839	7.4836	7.1367	7.1753	7.3405
Feb-92	7.3036	7.3349	7.3220	7.2169	7.2885	7.1475	7.5799	7.2411	7.5451	7.1764	7.2264	7.3896
Mar-92	7.3524	7.3790	7.3631	7.2630	7.3486	7.2372	7.6284	7.2875	7.6064	7.2657	7.2684	7.4372
Apr-92	7.3913	7.4150	7.3990	7.2960	7.3862	7.2741	7.6767	7.3214	7.6554	7.3033	7.2900	7.4740
May-92	7.4044	7.4352	7.4261	7.3202	7.4078	7.2864	7.7254	7.3502	7.6997	7.3203	7.2970	7.4828
Jun-92	7.4851	7.5122	7.4686	7.3870	7.4569	7.3653	7.7831	7.4182	7.7614	7.3991	7.2995	7.4876
Jul-92	7.5443	7.5756	7.5122	7.4466	7.4980	7.4178	7.8411	7.4826	7.8173	7.4569	7.3177	7.5007
Aug-92	7.6160	7.6440	7.5621	7.5112	7.5467	7.4788	7.8994	7.5469	7.8746	7.5181	7.3649	7.5382
Sep-92	7.6799	7.7050	7.6074	7.5685	7.5860	7.5227	7.9514	7.6066	7.9226	7.5659	7.4257	7.6100
Oct-92	7.7249	7.7521	7.6412	7.6119	7.6259	7.5776	7.9824	7.6475	7.9575	7.6170	7.4797	7.6829
Nov-92	7.7634	7.7895	7.6694	7.6486	7.6519	7.6091	7.9986	7.6769	7.9727	7.6425	7.5140	7.7305
Dec-92	7.9348	7.9517	7.7795	7.7979	7.7527	7.7370	8.0783	7.8125	8.0471	7.7601	7.5494	7.7575
Jan-93	7.8187	7.8451	7.7645	7.7136	7.7482	7.6793	8.0786	7.7410	8.0538	7.7113	7.5986	7.8091
Feb-93	7.8887	7.9172	7.8294	7.7841	7.8031	7.7289	8.1318	7.8071	8.1009	7.7594	7.6494	7.8481
Mar-93	7.9469	7.9729	7.8651	7.8334	7.8463	7.7919	8.1695	7.8555	8.1434	7.8195	7.6959	7.8946
Apr-93	7.9657	7.9918	7.8785	7.8503	7.8757	7.8392	8.1909	7.8743	8.1751	7.8641	7.7217	7.9376
May-93	8.1309	8.1680	7.9399	7.9936	7.9296	7.9609	8.2409	8.0008	8.2205	7.9734	7.7500	7.9837
Jun-93	8.0851	8.1110	7.9244	7.9464	7.9035	7.8974	8.2493	7.9707	8.2213	7.9280	7.7732	8.0019
Jul-93	8.1522	8.1827	7.9650	8.0101	7.9637	7.9942	8.2928	8.0338	8.2773	8.0203	7.8195	8.0495
Aug-93	8.2166	8.2443	8.0041	8.0657	7.9974	8.0389	8.3451	8.0932	8.3257	8.0697	7.8564	8.0759
Sep-93	8.2436	8.2701	8.0192	8.0892	8.0140	8.0644	8.3808	8.1238	8.3617	8.1014	7.8957	8.1303
Oct-93	8.2925	8.3248	8.0572	8.1393	8.0476	8.1056	8.4322	8.1764	8.4099	8.1456	7.9308	8.1969
Nov-93	8.2734	8.3013	8.0644	8.1247	8.0674	8.1148	8.4606	8.1659	8.4452	8.1570	7.9924	8.2589

	SSM1	DM1	SSM2	DM2	SSM3A	DM3A	SSM2Y	DM2Y	SSM3AY	DM3AY	WPI	CPI
Dec-93	8.4343	8.4530	8.1721	8.2597	8.1547	8.2120	8.5540	8.2985	8.5268	8.2538	8.0210	8.2945
Jan-94	8.2527	8.2790	8.1080	8.1249	8.1108	8.1198	8.5981	8.1701	8.5793	8.1666	8.0725	8.3376
Feb-94	8.3057	8.3374	8.1798	8.1851	8.1613	8.1409	8.6832	8.2311	8.6524	8.1892	8.1683	8.4007
Mar-94	8.2109	8.2435	8.1353	8.1020	8.1336	8.0951	8.7258	8.1528	8.7015	8.1469	8.2498	8.4573
Apr-94	8.4244	8.4641	8.3120	8.3178	8.3134	8.3126	8.9306	8.3689	8.9070	8.3646	8.5338	8.6674
May-94	8.5671	8.6020	8.5123	8.4695	8.4879	8.4130	9.0022	8.5104	8.9685	8.4579	8.6198	8.7467
Jun-94	8.5935	8.6287	8.6744	8.5215	8.6683	8.5203	9.1084	8.5624	9.0864	8.5611	8.6385	8.7671
Jul-94	8.7406	8.7768	8.8313	8.6718	8.8147	8.6491	9.2136	8.6950	9.1869	8.6762	8.6472	8.7979
Aug-94	8.8520	8.8865	8.8250	8.6898	8.8167	8.6785	9.2521	8.7358	9.2290	8.7247	8.6741	8.8259
Sep-94	8.8755	8.9115	8.8487	8.7061	8.8372	8.6904	9.3162	8.7695	9.2901	8.7534	8.7268	8.8859
Oct-94	8.9175	8.9519	8.8431	8.7106	8.8439	8.7129	9.3656	8.7996	9.3447	8.7961	8.7933	8.9559
Nov-94	8.8880	8.9219	8.8861	8.7157	8.8654	8.6861	9.3991	8.8119	9.3669	8.7855	8.8553	9.0167
Dec-94	9.0155	9.0477	8.9749	8.8216	8.9439	8.7728	9.4810	8.9117	9.4435	8.8712	8.9355	9.0843
Jan-95	8.8750	8.9094	8.9662	8.7340	8.9660	8.7548	9.4989	8.8409	9.4771	8.8590	9.0157	9.1525
Feb-95	9.0778	9.1146	9.1034	8.9107	9.0846	8.8892	9.5837	8.9858	9.5532	8.9711	9.0837	9.2001
Mar-95	9.0183	9.0554	9.1613	8.8919	9.1497	8.8923	9.6443	8.9899	9.6178	8.9901	9.1431	9.2442
Apr-95	9.2023	9.2374	9.2745	9.0383	9.2450	8.9990	9.7152	9.0988	9.6796	9.0718	9.1818	9.3009
May-95	9.2265	9.2627	9.3239	9.0773	9.3061	9.0621	9.7424	9.1275	9.7140	9.1194	9.1984	9.3334
Jun-95	9.3128	9.3503	9.4084	9.1659	9.3826	9.1344	9.8007	9.1982	9.7682	9.1787	9.2111	9.3589
Jul-95	9.4076	9.4431	9.4829	9.2491	9.4702	9.2427	9.8640	9.2738	9.8397	9.2742	9.2348	9.3891
Aug-95	9.4398	9.4754	9.5290	9.2886	9.5108	9.2722	9.9126	9.3190	9.8848	9.3113	9.2637	9.4316
Sep-95	9.4790	9.5154	9.5441	9.3228	9.5277	9.3082	9.9445	9.3597	9.9174	9.3529	9.3103	9.5056
Oct-95	9.5007	9.5335	9.5431	9.3353	9.5462	9.3566	9.9723	9.3812	9.9558	9.4050	9.3532	9.5668
Nov-95	9.4697	9.5031	9.6026	9.3466	9.5816	9.3236	10.0581	9.4014	10.0270	9.3829	9.3956	9.6129
Dec-95	9.5352	9.5683	9.6648	9.4103	9.6329	9.3616	10.1841	9.4724	10.1458	9.4288	9.4355	9.6499
Jan-96	9.4520	9.4863	9.6864	9.3584	9.7006	9.4398	10.1837	9.4202	10.1709	9.4993	9.5135	9.7297
Feb-96	9.6260	9.6592	9.7778	9.5090	9.7762	9.5429	10.2563	9.5608	10.2354	9.5973	9.5675	9.7738
Mar-96	9.6096	9.6443	9.7912	9.5030	9.7895	9.5394	10.3122	9.5653	10.2899	9.6028	9.6319	9.8283
Apr-96	9.8283	9.8769	9.9277	9.7052	9.9091	9.6954	10.4035	9.7431	10.3733	9.7426	9.7167	9.8932
May-96	9.7204	9.7558	9.9544	9.6348	9.9567	9.6844	10.4425	9.6994	10.4234	9.7438	9.7561	9.9374
Jun-96	9.7996	9.8333	10.0322	9.7151	10.0250	9.7421	10.5071	9.7731	10.4832	9.8005	9.7783	9.9624
Jul-96	9.8599	9.8946	10.0794	9.7723	10.0706	9.7943	10.5686	9.8308	10.5434	9.8542	9.7994	9.9836
Aug-96	9.9602	10.0000	10.1751	9.8768	10.1629	9.8899	10.6618	9.9311	10.6349	9.9479	9.8341	10.0300
Sep-96	10.0230	10.0554	10.2532	9.9403	10.2421	9.9576	10.7275	9.9961	10.7015	10.0161	9.8884	10.0896
Oct-96	10.0346	10.0652	10.3157	9.9717	10.3206	10.0304	10.7951	10.0373	10.7779	10.0893	9.9416	10.1524
Nov-96	10.1370	10.1600	10.3561	10.0421	10.3617	10.0979	10.8560	10.1130	10.8384	10.1620	9.9955	10.2028
Dec-96	10.3727	10.3778	10.5096	10.2310	10.5039	10.2565	10.9841	10.2799	10.9611	10.3062	10.0337	10.2364
Jan-97	10.2778	10.2942	10.4999	10.1733	10.5092	10.2397	11.0054	10.2487	10.9896	10.3045	10.0863	10.2934
Feb-97	10.4080	10.4248	10.5485	10.2659	10.5467	10.3007	11.0549	10.3312	11.0330	10.3638	10.1455	10.3485
Mar-97	10.4911	10.4990	10.6115	10.3348	10.6107	10.3711	11.1113	10.3946	11.0902	10.4289	10.1979	10.4010
Apr-97	10.5552	10.5662	10.6714	10.3955	10.6887	10.4718	11.1507	10.4572	11.1404	10.5221	10.2492	10.4651
May-97	10.5141	10.5382	10.7033	10.3905	10.6917	10.4059	11.1882	10.4654	11.1617	10.4822	10.2987	10.5110
Jun-97	10.5844	10.6019	10.7760	10.4583	10.7743	10.4974	11.2535	10.5299	11.2327	10.5649	10.3306	10.5393
Jul-97	10.5858	10.6181	10.8349	10.4959	10.8520	10.5824	11.3174	10.5777	11.3069	10.6476	10.3864	10.6000
Aug-97	10.5805	10.6250	10.8638	10.5150	10.8771	10.5942	11.3664	10.6042	11.3529	10.6674	10.4456	10.6602
Sep-97	10.6877	10.7166	10.9551	10.6062	10.9730	10.6964	11.4288	10.6791	11.4190	10.7537	10.5048	10.7307
Oct-97	10.7224	10.7528	11.0203	10.6526	11.0595	10.7971	11.5012	10.7322	11.5031	10.8526	10.5705	10.8107
Nov-97	10.6696	10.7069	11.0198	10.6265	11.0589	10.7767	11.5404	10.7211	11.5401	10.8434	10.6271	10.8749
Dec-97	10.9397	10.9469	11.1696	10.8365	11.1472	10.8124	11.6694	10.9106	11.6366	10.8857	10.6786	10.9250

	SSM1	DM1	SSM2	DM2	SSM3A	DM3A	SSM2Y	DM2Y	SSM3AY	DM3AY	WPI	CPI
Jan-98	10.8889	10.9424	11.1823	10.8411	11.1724	10.8496	11.6924	10.9171	11.6661	10.9181	10.7382	10.9947
Feb-98	10.8495	10.8810	11.1695	10.7938	11.1665	10.8249	11.7243	10.9039	11.7004	10.9190	10.7801	11.0379
Mar-98	10.9425	10.9670	11.2460	10.8771	11.2565	10.9417	11.7816	10.9747	11.7654	11.0168	10.8160	11.0800
Apr-98	11.0064	11.0252	11.3284	10.9428	11.3402	11.0137	11.8741	11.0517	11.8582	11.0969	10.8533	11.1256
May-98	10.9749	11.0091	11.3892	10.9572	11.3891	11.0046	11.9191	11.0695	11.8974	11.0972	10.8869	11.1600
Jun-98	11.1292	11.1449	11.5124	11.0822	11.5083	11.1187	12.0011	11.1667	11.9785	11.1896	10.9006	11.1841
Jul-98	11.2274	11.2507	11.5872	11.1772	11.5891	11.2264	12.0631	11.2466	12.0442	11.2804	10.9214	11.2171
Aug-98	11.2804	11.3066	11.5886	11.2103	11.5705	11.2041	12.0860	11.2833	12.0556	11.2759	10.9489	11.2558
Sep-98	11.3310	11.3348	11.6509	11.2546	11.6443	11.2810	12.2374	11.4002	12.2108	11.4102	10.9992	11.3209
Oct-98	11.2837	11.3144	11.7013	11.2701	11.6836	11.2701	12.1900	11.3554	12.1600	11.3515	11.0332	11.3796
Nov-98	11.2934	11.3154	11.7530	11.2965	11.7402	11.3137	12.2257	11.3778	12.1988	11.3874	11.0666	11.4217
Dec-98	11.4225	11.4337	11.8720	11.4166	11.8426	11.3856	12.3089	11.4762	12.2734	11.4510	11.0935	11.4540
Jan-99	11.3511	11.3738	11.8976	11.3965	11.8732	11.3847	12.3334	11.4684	12.3007	11.4568	11.1276	11.5009
Feb-99	11.3524	11.3844	11.9357	11.4197	11.9169	11.4266	12.3746	11.4964	12.3451	11.4988	11.1582	11.5321
Mar-99	11.6091	11.6642	12.0092	11.6104	11.9899	11.6016	12.4469	11.6581	12.4171	11.6509	11.1989	11.5719
Apr-99	11.4672	11.4864	12.0182	11.4968	12.0069	11.5286	12.4889	11.5903	12.4629	11.6102	11.2506	11.6194
May-99	11.4621	11.4838	12.0774	11.5160	12.0738	11.5788	12.5422	11.6143	12.5206	11.6575	11.2872	11.6484
Jun-99	11.5430	11.5562	12.1631	11.5956	12.1407	11.5971	12.6132	11.6880	12.5814	11.6847	11.3093	11.6804
Jul-99	11.5779	11.6046	12.2360	11.6468	12.2025	11.6120	12.6598	11.7351	12.6221	11.7045	11.3534	11.7179
Aug-99	11.7025	11.7241	12.3008	11.7389	12.2669	11.7005	12.7181	11.8144	12.6803	11.7818	11.3882	11.7591
Sep-99	11.6931	11.7134	12.3568	11.7636	12.3279	11.7441	12.7809	11.8517	12.7458	11.8324	11.4433	11.8172
Oct-99	11.6935	11.7302	12.3812	11.7627	12.3483	11.7327	12.8494	11.8847	12.8114	11.8552	11.4897	11.8786
Nov-99	11.7034	11.7187	12.4136	11.7547	12.3893	11.7629	12.9117	11.9119	12.8779	11.8971	11.5343	11.9197
Dec-99	12.0251	12.0203	12.5455	11.8650	12.5197	11.8711	13.0054	12.0328	12.9715	12.0020	11.6032	11.9775
Jan-00	12.0023	11.9884	12.5662	11.8479	12.5400	11.8563	13.0373	12.0186	13.0030	11.9887	11.6544	12.0249
Feb-00	12.0384	12.0320	12.5346	11.8428	12.5130	11.8622	13.0466	12.0147	13.0139	11.9973	11.6924	12.0613
Mar-00	12.0725	12.0654	12.5473	11.8593	12.5224	11.8682	13.0752	12.0332	13.0405	12.0069	11.7212	12.0901
Apr-00	12.0996	12.0951	12.5800	11.8839	12.5526	11.8856	13.1107	12.0592	13.0747	12.0273	11.7462	12.1130
May-00	12.1775	12.1653	12.5761	11.9395	12.5507	11.9414	13.1371	12.1143	13.1015	12.0854	11.7652	12.1350
Jun-00	12.2268	12.2203	12.6354	11.9949	12.6192	12.0290	13.1731	12.1741	13.1427	12.1669	11.7697	12.1417
Jul-00	12.3383	12.3267	12.7189	12.0956	12.6945	12.0979	13.2287	12.2648	13.1946	12.2319	11.7799	12.1639
Aug-00	12.3224	12.3167	12.6950	12.0899	12.6668	12.0801	13.2345	12.2628	13.1978	12.2216	11.7917	12.1854
Sep-00	12.3453	12.3418	12.7131	12.1194	12.6859	12.1112	13.2650	12.2903	13.2286	12.2569	11.8150	12.2157
Oct-00	12.3597	12.3531	12.7428	12.1257	12.7214	12.1354	13.2879	12.3074	13.2547	12.2775	11.8392	12.2462
Nov-00	12.3700	12.3618	12.7864	12.1596	12.7670	12.1815	13.3051	12.3372	13.2735	12.3113	11.8620	12.2827
Dec-00	12.5030	12.4990	12.8993	12.3066	12.8792	12.3226	13.3430	12.4538	13.3126	12.4218	11.8819	12.3070
Jan-01	12.3890	12.3787	12.9084	12.1604	12.8794	12.1673	13.3540	12.3170	13.3185	12.2899	11.9010	12.3318
Feb-01	12.5876	12.5776	13.0006	12.2522	12.9751	12.2630	13.4790	12.4074	13.4450	12.3849	11.9228	12.3496
Mar-01	12.5824	12.5728	13.0867	12.3704	13.0562	12.3713	13.5820	12.5293	13.5449	12.4932	12.0232	12.4086
Apr-01	12.6352	12.6256	13.0984	12.3984	13.0743	12.4135	13.6268	12.5572	13.5925	12.5359	12.1647	12.5069
May-01	12.6659	12.6564	13.1024	12.4147	13.0755	12.4193	13.6512	12.5737	13.6151	12.5443	12.2233	12.5562
Jun-01	12.7471	12.7405	13.1346	12.5014	13.1053	12.4972	13.7413	12.6569	13.7031	12.6287	12.2579	12.5871
Jul-01	12.7863	12.7762	13.0813	12.5265	13.0650	12.5540	13.7588	12.6936	13.7254	12.6866	12.2924	12.6107
Aug-01	12.8413	12.8335	13.1452	12.5774	13.1167	12.5688	13.8297	12.7459	13.7907	12.7050	12.3300	12.6397
Sep-01	12.8066	12.8075	13.1767	12.5633	13.1480	12.5522	13.9195	12.7377	13.8796	12.6978	12.3804	12.6969
Oct-01	12.7995	12.7921	13.1942	12.5452	13.1738	12.5660	13.9637	12.7302	13.9269	12.7147	12.4407	12.7559
Nov-01	12.8002	12.7963	13.2178	12.5518	13.1907	12.5531	13.9393	12.7405	13.9004	12.6994	12.4792	12.7973
Dec-01	12.9124	12.9054	13.2916	12.6561	13.2613	12.6442	13.9713	12.8272	13.9316	12.7822	12.5134	12.8290
Jan-02	12.8102	12.8043	13.2597	12.5568	13.2479	12.6104	13.8964	12.7468	13.8660	12.7358	12.5495	12.8808

	SSM1	DM1	SSM2	DM2	SSM3A	DM3A	SSM2Y	DM2Y	SSM3AY	DM3AY	WPI	CPI
Feb-02	12.9668	12.9642	13.3176	12.6905	13.3087	12.7427	13.9465	12.8388	13.9177	12.8549	12.5708	12.8982
Mar-02	12.8865	12.8877	13.3386	12.6487	13.3197	12.6778	13.9379	12.8122	13.9049	12.7952	12.5896	12.9100
Apr-02	12.9145	12.9136	13.3638	12.6696	13.3487	12.7086	13.9556	12.8226	13.9246	12.8201	12.6092	12.9304
May-02	12.9573	12.9578	13.3837	12.7078	13.3657	12.7343	14.0010	12.8558	13.9681	12.8503	12.6170	12.9361
Jun-02	13.0289	13.0339	13.4088	12.7873	13.3897	12.8062	14.0627	12.9370	14.0285	12.9236	12.6363	12.9420
Jul-02	13.0688	13.0688	13.4250	12.8038	13.4155	12.8489	14.1169	12.9592	14.0863	12.9692	12.6685	12.9563
Aug-02	13.0665	13.0721	13.4212	12.7983	13.4067	12.8198	14.1015	12.9605	14.0689	12.9403	12.6913	12.9779
Sep-02	13.1402	13.1345	13.4649	12.8538	13.4539	12.8838	14.1344	12.9988	14.1036	12.9954	12.7207	13.0121
Oct-02	13.1612	13.1557	13.4955	12.8776	13.4870	12.9121	14.1582	13.0228	14.1287	13.0218	12.7504	13.0444
Nov-02	13.1786	13.1956	13.5118	12.9049	13.5021	12.9356	14.1335	13.0486	14.1045	13.0295	12.7638	13.0731
Dec-02	13.2433	13.2375	13.5616	12.9454	13.5417	12.9651	14.1979	13.0692	14.1637	13.0688	12.7872	13.0894
Jan-03	13.1533	13.1615	13.5472	12.8866	13.5417	12.9344	14.1911	13.0396	14.1635	13.0439	12.8410	13.1150
Feb-03	13.1930	13.2061	13.5582	12.9225	13.5533	12.9712	14.1762	13.0677	14.1496	13.0664	12.8721	13.1303
Mar-03	13.1944	13.2084	13.5917	12.9357	13.5852	12.9801	14.1874	13.0707	14.1605	13.0702	12.8975	13.1497
Apr-03	13.1904	13.2030	13.5764	12.9233	13.5812	12.9934	14.1544	13.0569	14.1337	13.0735	12.9077	13.1595
May-03	13.2068	13.2230	13.6056	12.9354	13.6122	13.0013	14.1407	13.0583	14.1224	13.0692	12.8983	13.1691
Jun-03	13.3446	13.3466	13.6531	13.0308	13.6528	13.0802	14.1677	13.1230	14.1464	13.1346	12.8870	13.1699
Jul-03	13.3764	13.3828	13.6836	13.0654	13.6922	13.1335	14.1849	13.1519	14.1689	13.1786	12.8864	13.1680
Aug-03	13.3876	13.4010	13.7043	13.0841	13.7081	13.1406	14.1933	13.1674	14.1751	13.1828	12.8891	13.1696
Sep-03	13.4724	13.4702	13.7535	13.1455	13.7579	13.2048	14.2276	13.2155	14.2103	13.2381	12.8859	13.1830
Oct-03	13.5110	13.5160	13.7816	13.1863	13.7858	13.2427	14.2790	13.2534	14.2607	13.2809	12.8892	13.1922
Nov-03	13.5501	13.5657	13.8032	13.2301	13.8129	13.2996	14.2942	13.3030	14.2792	13.3334	12.9038	13.2048
Dec-03	13.6176	13.6041	13.8517	13.2677	13.8431	13.2935	14.3199	13.3382	14.2954	13.3288	12.9111	13.2091
Jan-04	13.6569	13.6694	13.9410	13.3394	13.9252	13.3449	14.3359	13.4066	14.3093	13.3722	12.9483	13.2157
Feb-04	13.5735	13.5812	13.9307	13.2648	13.9472	13.3754	14.3226	13.3301	14.3156	13.4002	12.9633	13.2208
Mar-04	13.6189	13.6209	13.9641	13.3028	13.9647	13.3670	14.3383	13.3653	14.3222	13.3920	12.9825	13.2303
Apr-04	13.6753	13.6818	13.9924	13.3583	13.9922	13.4197	14.3722	13.4161	14.3555	13.4441	13.0008	13.2353
May-04	13.6803	13.6843	13.9969	13.3597	13.9927	13.4199	14.3941	13.4208	14.3744	13.4483	13.0080	13.2396
Jun-04	13.7388	13.7393	14.0153	13.4059	14.0216	13.4947	14.4089	13.4663	14.3956	13.5173	13.0063	13.2383
Jul-04	13.7431	13.7478	14.0251	13.4149	14.0160	13.4611	14.4161	13.4759	14.3936	13.4867	12.9971	13.2430
Aug-04	13.7950	13.7948	14.0496	13.4568	14.0422	13.5052	14.4502	13.5120	14.4284	13.5333	13.0075	13.2506
Sep-04	13.8065	13.8063	14.0703	13.4682	14.0636	13.5168	14.4773	13.5301	14.4558	13.5485	13.0220	13.2601
Oct-04	13.8105	13.8151	14.0857	13.4774	14.0915	13.5591	14.4925	13.5434	14.4784	13.5877	13.0557	13.2823
Nov-04	13.7994	13.7950	14.0946	13.4640	14.0892	13.5082	14.4990	13.5326	14.4784	13.5425	13.0637	13.2953
Dec-04	13.8417	13.8332	14.1235	13.5023	14.1165	13.5480	14.5197	13.5684	14.4984	13.5814	13.0608	13.2985
Jan-05	13.7739	13.7715	14.1007	13.4495	14.0950	13.5066	14.4816	13.5226	14.4615	13.5380	13.0567	13.3040
Feb-05	13.8205	13.8160	14.1228	13.4894	14.1159	13.5947	14.4841	13.5540	14.4639	13.6190	13.0578	13.3042
Mar-05	13.8666	13.8638	14.1701	13.5377	14.1608	13.5877	14.5246	13.5963	14.5031	13.6140	13.0704	13.3068
Apr-05	13.9225	13.9244	14.2048	13.5939	14.1938	13.6360	14.5527	13.6493	14.5304	13.6601	13.0824	13.3139
May-05	13.9187	13.9180	14.2284	13.5942	14.2162	13.6494	14.5558	13.6515	14.5334	13.6716	13.0843	13.3230
Jun-05	13.9977	13.9925	14.2771	13.6635	14.2627	13.7031	14.5893	13.7163	14.5659	13.7236	13.0796	13.3241
Jul-05	14.0117	14.0156	14.3089	13.6882	14.2930	13.7301	14.6098	13.7405	14.5858	13.7485	13.0721	13.3183
Aug-05	14.0320	14.0325	14.3349	13.7068	14.3179	13.7662	14.6384	13.7572	14.6135	13.7846	13.0824	13.3268
Sep-05	14.0784	14.0806	14.3674	13.7518	14.3490	13.7932	14.6709	13.8021	14.6451	13.8125	13.0902	13.3370
Oct-05	14.1412	14.1485	14.4090	13.8145	14.3890	13.8423	14.6857	13.8643	14.6595	13.8571	13.0970	13.3547
Nov-05	14.0885	14.0885	14.4238	13.7707	14.4031	13.8368	14.6942	13.8201	14.6678	13.8517	13.0875	13.3687
Dec-05	14.2220	14.2099	14.4698	13.8735	14.4474	13.9321	14.7361	13.9168	14.7087	13.9435	13.0871	13.3728
Jan-06	14.1188	14.1201	14.4451	13.7985	14.4237	13.8402	14.7192	13.8472	14.6922	13.8553	13.1065	13.3803
Feb-06	14.1464	14.1437	14.4830	13.8247	14.4601	13.8917	14.7403	13.8716	14.7127	13.9034	13.1091	13.3825

	SSM1	DM1	SSM2	DM2	SSM3A	DM3A	SSM2Y	DM2Y	SSM3AY	DM3AY	WPI	CPI
Mar-06	14.1886	14.1871	14.5243	13.8679	14.4999	13.9100	14.7724	13.9110	14.7440	13.9214	13.1116	13.3852
Apr-06	14.2180	14.2224	14.5490	13.9007	14.5237	13.9332	14.7913	13.9420	14.7624	13.9442	13.1308	13.3985
May-06	14.2762	14.2759	14.5874	13.9508	14.5608	14.0100	14.8761	13.9891	14.8453	14.0294	13.1581	13.4171
Jun-06	14.3142	14.3144	14.6142	13.9860	14.5868	14.0367	14.8897	14.0372	14.8586	14.0530	13.1975	13.4205
Jul-06	14.2650	14.2688	14.5919	13.9451	14.5651	13.9829	14.8626	13.9981	14.8321	14.0000	13.2061	13.4289
Aug-06	14.2762	14.2807	14.5934	13.9543	14.5666	13.9870	14.8756	14.0038	14.8448	14.0056	13.1986	13.4245
Sep-06	14.2980	14.3037	14.6169	13.9775	14.5893	14.0201	14.9016	14.0278	14.8702	14.0375	13.1963	13.4373
Oct-06	14.2798	14.2885	14.6210	13.9667	14.5933	14.0013	14.9104	14.0176	14.8789	14.0205	13.2008	13.4499
Nov-06	14.2391	14.2456	14.6338	13.9346	14.6057	13.9642	14.9304	13.9878	14.8984	13.9851	13.1979	13.4627
Dec-06	14.3407	14.3641	14.6573	14.0336	14.6285	14.0801	14.9548	14.0830	14.9223	14.0971	13.1967	13.4650