THE MONEY DEMAND EQUATION AND MACROECONOMIC FORECASTING IN UKRAINE

by

Yevgen Zinovyev

A thesis submitted in partial fulfillment of
the requirements for the degree of

Master of Arts in Economics

National University of "Kyiv-Mohyla Academy"
Economics Education and Research Consortium
Master's Program in Economics

2003

Approved by ____
Ms.Svitlana Budagovska (Head of the State Examination Committee)

____

____

____

Program Authorized
to Offer Degree Master's Program in Economics, NaUKMA

Date ____

National University of "Kiev Mohyla Academy"

Abstract

THE MONEY DEMAND EQUATION AND MACROECONOMIC FORECASTING IN UKRAINE

by Yevgen Zinovyev

Head of the State Examination Committee: Ms.Svitlana Budagovska,
Economist, World Bank of Ukraine

The goal of the thesis is to study the stability of the money demand equation for Ukraine and create a parsimonious forecasting model for macroeconomic forecasting. These two aspects lie on the basis of predictable monetary policy. The stability of the money demand equation is investigated using two independent approaches (the standard cointegration analysis based on unit root tests and long-memory cointegration analysis) that allow me to increase significantly the reliability of inferences. The hypothesis of stability the money demand equation confirmed by both methods.

The second part of the thesis is creating a parsimonious forecasting model for forecasting the macroeconomic indicators forming the money demand equation. I have specified a series of models and, applying different criteria, have chosen the best ones. The result of the analysis is that Vector Error Correction model does not have better forecast performance in the short run. Unconstrained models (Vector Autoregression and ARIMA) are more suitable and parsimonious for short-run forecasts. The forecasting performance of VEC model in the long run is the goal of future research.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGMENTS

The author wishes to thank thesis supervisor Peter Kennedy for his valuable comments and assistance in writing the thesis, and also Tom Coupe for comments, and Christopher Baum (Boston College) for help and software.

LIST OF ABBREVIATIONS

ADF. Augmented Dickey-Fuller

AIC. Akaike Information Criterion

ARIMA. Autoregressive Integrated Moving Average

DEF. GDP Deflator

GDP. Gross Domestic Product

GFESM. Generalized Forecast Error Sample Moment

GPH. Geweke/Porter-Hudak

INT. NBU refinancing rate

MAE. Mean Average Error

MB. Money Base

MFE. Mean Forecast Error

NBU. National Bank of Ukraine

RMSFE. Root Mean Square Forecast Error

RSS. Residual Sum of Squares

SIC. Schwarz Information Criterion

SVAR. Structural Vector Autoregression

SUR. Seemingly Unrelated Regressions

VAR. Vector Autoregression

VEC. Vector Error Correction

Chapter 1

INTRODUCTION

The stability of the money demand equation for a country allows the authorities to conduct a predictable monetary policy and use money targeting as a policy strategy. That is why, the existence of a stable money demand equation has been extensively investigated by scientists in different countries. This task is especially challenging for Ukraine due to the small number of available observations and the structural changes occurring in economy of developing countries.

This paper consists of two parts: In the first part I test the stability of the money demand equation, and in the second part I create a parsimonious forecasting model.

The stability of the money demand equation is investigated using two independent approaches that allow me to increase significantly the reliability of inferences. The first approach is standard cointegration analysis based on unit root tests. The second approach is long-memory cointegration analysis which gives a better understanding of the money demand relationship. These two methods use a different methodology and, thus, their combination allows me to make more accurate analysis.

The hypothesis of stability of the money demand equation is confirmed by both methods, which indicates that the money demand equation in Ukraine is stable. This inference depends seriously on the data used in the analysis. Using the data adjusted for all structural changes allows me to specify a reliable model with high accuracy.

The second part of the thesis is creating a parsimonious forecasting model for forecasting the macroeconomic indicators forming the money demand equation. The analysis is based on Vector Autoregression (VAR) and Vector Error Correction (VEC) models. The main hypothesis is that the Vector Error Correction model gives the best forecasts of the money demand equation, especially in the long-term period. The VEC models are based on the cointegrating equation specified in the previous part. I also specify alternative models to compare with the forecast performance of VAR and VEC models.

In this part I specify a series of models at the first stage of the analysis. Choosing the best eight models I perform a more detailed analysis. The result of this analysis is that the VEC model does not have a better forecast performance. This is not unexpected because, having a very small sample, I am not able to examine the forecast performance of VEC model in the long run. In the short run unconstrained VAR model is a very parsimonious and reliable, but in the long run I expect the VEC model to give better forecasts.

The layout of the paper is the following. In chapter 2 I provide theoretical background and review of the previous research on the topic. Chapter 3 gives the description of the econometric methodology. The data generating process is described in chapter 4. In chapter 5 I describe the empirical results of the research. The final chapter summarizes the paper and presents some concluding remarks.

Chapter 2

THEORETICAL BACKGROUND

The stability of the long-run relationship between the real money balance, real income and the interest rate has been investigated theoretically and empirically in numerous papers, as the stable relationship lies in the basis of money targeting as an instrument of the monetary policy.

The first works testing stability of the money demand equation for the United States appeared in the early 1960s. The authors mainly focused on long-run income and interest elasticity estimates. Meltzer (1963) and Chow (1966) using a narrow definition of money and a long-term interest rate showed that a theoretical hypothesis of unitary long-run income elasticity could not be rejected. They also evaluated the long-run interest elasticity in the range from –0.6 to -0.7.

The main problem of these works is that the conclusions are not robust enough to the changing of the sample period, as was demonstrated by Meltzer (1963) and Laidler (1966).

These results were reestimated by Poole (1988). Using later data and experimenting with different interest rates he demonstrated that a money demand equation with a long-term interest rate is more robust than one with a short-term rate and evaluated the interest elasticity as -0.6. Goldfeld (1973) using a log-linear specification also confirmed the hypothesis of the stability of the money demand equation. The main feature of the early studies is that almost all empirical studies in 1960s and 1970s proved the hypothesis of the stability of the money demand equation.

More recent studies show that the stable money demand relationship has broken down for some countries (especially for the United States). Baba, Hendry and Starr (1992) suggest that it was caused by a series of policy measures that resulted in shifts in the demand for money. Also in 1979 the US Federal Reserve Board changed the priorities from controlling the interest rates to controlling the monetary base. Goldfeld and Sichel (1990) reviewed empirical works and concluded that many empirical models proved instability in the money demand.

Hoffman and Rasche (1991) state that many of the above-mentioned works demonstrating the money demand instability may give such a result due to specification errors. The authors prove the existence of a stable money demand equation for the United States. They use real M1 and the real monetary base as proxies for money; the Treasury bill rate and 10-year government bond rate as proxies for the interest rate in the money demand equation, creating four different combinations of these proxies. The authors confirm the results of the study made by Poole (1988), obtaining equilibrium interest elasticities in the range from –0.4 to –0.5 for the real M1 and for the real monetary base and income elasticities not significantly different from one for all four specifications. Contrary to Poole (1988), they obtained more robust specifications using short-term interest rates, but all the magnitudes of money demand elasticities and income elasticities are consistent with the ones estimated by Poole (1988).

Goodhart (1989) and Temperton (1991) made surveys of the existing empirical studies many of which reached a conclusion of the instability of the money demand equation because monetary aggregates are not cointegrated with nominal income. Hall et al (1990), Hendry and Ericsson (1991, 1993) state that cointegration can be achieved by adding additional variables having a similar trend as the velocity in the money demand equation. Hoffman, Rasche and

Tieslau (1995) and Hoffman and Rasche (1996) examining the stability of the money demand equation for five industrial countries solved this problem by adding a dummy variable in the equation. More detailed examination of the stability of the money demand equation for the United States can be found in Hoffman and Rasche (1997, 1998). The authors use the same approach to the problem of instability of the money demand equation by introducing a dummy variable describing the changes in monetary policy.

The main goal of estimating money demand equation is forecasting and controlling the macroeconomic indicators. The theory of forecasting is changing gradually and is more controversial than the theory of money demand. The main point of this controversy is the conflict between the theory of forecasting and the empirical evidence.

One of the best discussions of the theory of forecasting: the current situation and future perspective is made in a special issue on "The Future of Forecasting" of the International Journal of Forecasting (1988). "The aim of the special issue is to identify the major problems and to propose a research agenda to solve them."

The problem of the conflict between the theory of forecasting and the empirical evidence is discussed in Gardner and Makridakis (1988). Fischhoff (1988) stresses that all forecasting methods require the use of judgement and suggests four conditions which will lead to better judgement and improved forecasts. McNees (1988) argues "the distinction between 'structural' models, based on economic theory, and time-series models, based on data, will gradually disappear."

Ord (1988) argues that the future development in forecasting will come from a synthesis of current knowledge, and suggests to use models with estimates of parameters being regularly updated. Chatfield (1988) explains the interest in the multivariate models by improvements in computer software and stresses that, in spite of the fact that these models can be implemented automatically, they demand some subjectivity from a forecaster.

Armstrong (1985) discusses the long-term trends in forecasting methods. He stresses that the general tendency is from subjective to objective methods and from naïve methods to causal ones.

Improving forecasting techniques caused governments to change the policy and paid less attention to the short-term effects and more attention to the medium-term impact of the policy (Olding-Smee, 1989). It arises more interest in cointegration techniques to derive long-term equilibrium conditions.

Holden et all (1995) give a good review of forecasting theory and state "forecasting is important for policy design and use of macroeconomic models will remain one of the methods used to asses the impact of policy proposals."

C h a p t e r 3

ECONOMETRIC METHODOLOGY

Introduction.

Hoffman and Rasche (1997) state: ”Any exercise in empirical macroeconomics must recognize the conclusions drawn from time series analyses of macroeconomic data, and utilize specifications that are consistent with those results.” Nelson and Plosser (1982) demonstrated that macroeconomic time series data very often include a permanent shock component. In this case the time series have a unit root or integrated of order I(d). Granger has introduced the definition of cointegrated variables as variables that are integrated[1] and for witch there exists one or more linear combinations (cointegration vectors) of these variables that are integrated of order zero (the weighted sums of the variables are mean reverting or stationary). Engle and Granger (1987) formulated the Granger Representation Theorem stating that integrated variables are cointegrated if and only if there exists a Vector Error Correction representation of the time series. The Vector Error Correction representation of Z_t (a vector of economic time series dimension of px1):

$$\Delta Z_t = \mu + \Pi Z_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Z_{t-i} + \varepsilon_t = \mu + \alpha\beta Z_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Z_{t-i} + \varepsilon_t \tag{3.1}$$

[1] Nonstationary variables can be integrated of different degrees, but macroeconomics and applied econometrics usually work with variables that are integrated of order one (I(1)) and cointegration vectors that are integrated of order zero (I(0)).

where:

Γ_i - coefficient matrices (pxp),

μ - vector of constants (px1),

α, β - (pxr) matrices, where 0<r<p,

r- the number of linear combinations of the elements of Z_t.

The Vector Error Correction (VEC) model is a Vector Autoregression (VAR) model in the first differences proposed by Sims (1980), with addition of the error correction term.

The conception of cointegration has some empirical implications. First, specifying the Vector Error Correction model I automatically test the stability of the money demand equation. Second, the VEC has improved forecast performance especially in the long-run period.

Engle and Yoo (1987) say that forecasts produced by the VEC are "tied together because the cointegrating relations hold exactly in the long run." Conducting a series of Monte Carlo experiments they demonstrate that incorporating cointegration into the model can significantly reduce the mean squared forecast error at medium and the long forecast horizons. Stock (1995), Clements and Hendry (1995) and Hoffman and Rasche (1996) verified this inference in their empirical research. For example, Clements and Hendry (1995) confirmed the inferences of Engle and Yoo (1987), but only for small samples. All the authors agree that superior performance of VEC depends on the particular representation of data. However, Christofferson and Diebold (1996) came to the opposite result, arguing that the VECM gives advantages in forecasting only at the short-run horizons. Their rationale is that Engle and Yoo (1987) make wrong comparison and misinterpret the outcome of their Monte Carlo experiments.

Christofferson and Diebold (1996) isolate the effect of imposing cointegration comparing forecasts from univariate models to forecasts from vector error correction models. Engle and Yoo (1987) compare forecasts from vector autoregression models in levels to forecasts from vector error correction models. Christofferson and Diebold (1996) state that differences in forecasting results may be caused due to imposition of integration, but not cointegration. It also leads to misinterpretation of Monte Carlo experiments. They compare forecasts from VAR in differences to VEC models and make an inference that at long horizons the forecasts from the VAR are as good as the forecasts from VEC models. The main conclusion made by Christofferson and Diebold (1996) is:

"Ironically enough, although cointegration implies restriction on low-frequency dynamics, imposing cointegration is helpful for short- but not long-horizon forecasting, in contrast to the impression created in the literature. Imposing of cointegration on an estimated system, when the system is in fact cointegrated, helps the accuracy of long-horizon forecasts relative to those from systems estimated in levels with no restrictions, but that is because of the imposition of integration, not cointegration. Univariate forecasts in differences do just as well! "

The major goals of my thesis are to demonstrate the stability of the money demand equation for Ukraine and to specify a model that produces the most accurate forecasts of the macroeconomic indicators included in the money demand equation.

The stability of the money demand equation is tested with unit root tests, cointegration tests and with a series of stability tests. Testing the robustness to the length of the sample and the number of lags in the model is also the part of the stability analysis.

Testing for the order of integration.

Identifying the order of integration of each variable is the first step of any time series analysis. There are some methods of testing the order of integration. Further I introduce a brief theoretical concept of the tests.

Suppose, a nonseasonal variable y_t is generated by:

$$y_t = \rho y_{t-1} + \varepsilon_t \quad , \tag{3.2}$$

where ε_t represents a series of identically distributed stationary variables with zero means.

If y_t is generated by a random walk process (with ρ=1), the y_t is nonstationary; otherwise, if $|\rho|<1$, then y_t is a stationary time series.

Dickey and Fuller (1979) have proposed the DF test for testing the order of integration of y_t. The DF test is a unit root test that tests the null hypothesis ρ-1=0. The first peculiarity of the DF test is that the presence of a drift influences significantly the testing procedure. The second peculiarity is that the critical values of the test can be approximated only through a simulation. The description of the simulation procedure and the critical values of the test are given by Fuller (1976), Guilkey and Schmidt (1979), MacKinnon (1991) and Blangiewicz and Charemza (1990). Charemza (1997) highlights that the main drawback of the DF test is that it does not take account of possible autocorrelation in the error process. Dickey and Fuller (1981) proposed the Augmented Dickey-Fuller (ADF) test to correct this drawback.

The use of the Augmented Dickey-Fuller test is determined by the fact that the original Dickey-Fuller test does not take into account autocorrelations in the error term. The test is very sensitive to the number of lags; that is why I use two methods of choosing the number of lags (augmentation terms): using the Schwartz criterion and deletion of the insignificant augmentations using the general to specific model (proposed by Charemza (1997)).

For testing for the order of integration I use the Augmented Dickey-Fuller (1979) and Phillips-Perron (1998) tests as the basic ones. To increase reliability of inferences and taking into account low power of ADF test, I also use the newest generation of unit root tests: GLS-detrended Dickey-Fuller (Elliot, Rothenberg, and Stock, 1996), Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992), and Ng and Perron (NP, 2001) unit root tests.

The major problem connected with ADF test is presence of deterministic regressors (intercept and trend) in the equations. Some econometricians think that it is reasonable to test for unit root using the most general form of the equation with trend and intercept. The main problem with this reasoning is that including additional parameters reduces degrees of freedom and the power of the test. In this case I may fail to reject the null of a unit root. Campbell and Perron (1991) state that irrelevant omitting regressors causes the power of the test to approach zero. Enders (1995) writes "The key problem is that the tests for unit roots are conditional on the presence of the deterministic regressors and tests for the presence of the deterministic regressors are conditional on the presence of a unit root. "

Dolado, Jenkinson, and Sosvilla-Rivero (1990) suggest the following procedure to test for a unit root when the form of the data-generating process is unknown. A good description of the procedure can be found in Enders (1995). The scheme of the procedure is shown in figure 1.

Dickey and Fuller provide additional F-statistics (ϕ_1, ϕ_2, and ϕ_3) to test joint hypothesis on the coefficients.

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_i \tag{3.3}$$

The null hypothesis $\gamma = a_0 = 0$ is tested using the ϕ_1 statistics. The joint hypothesis $\gamma = a_0 = a_2 = 0$ is tested using the ϕ_2 statistics and the joint hypothesis $\gamma = a_2 = 0$ is tested using the ϕ_1 statistics. The statistics are constructed in the following way:

$$\phi_i = \frac{[RSS(restricted) - RSS(unrestricted)]/r}{RSS(unrestricted)/(T-k)} \tag{3.4}$$

where RSS – the sum of the squared residuals

r – number of restrictions

T – number of usable observations

K – number of parameters estimated in the unrestricted model

Calculated value of ϕ_I is compared with value reported in Dickey and Fuller (1981).

The Phillips-Perron (1988) test is an alternative (nonparametric) method of controlling for serial correlation when testing for a unit root.

Dickey-Fuller test with GLS detrending (ERS, 1996) is a modification of the ADF tests with detrending data prior to running the test regression.

The Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992) test assumes time series to be stationary under the null.

Ng and Perron (2001) test constructs test statistics that are based upon the GLS detrended data.

Some of the tests require a consistent estimate of a residual spectrum at frequency zero. For this purpose I use the kernel-based estimator that is based on a weighted sum of the autocovariances, with the weights defined by the Barlett kernel function. The properties of the kernel function can be found in Andrews (1991).

The bandwidth parameter l for the kernel-based estimators of frequency zero is computed automatically. I use Newey-West (1994) and Andrews (1991) data-based automatic bandwidth parameter methods.

The number of lags is chosen automatically to minimize the following criteria: Akaike (AIC), Schwarz (SIC), Hannan-Quinn (HQ), modified Akaike (MAIC), modified Schwarz (MSIC), and modified Hannan-Quinn (MHQ).The modified criteria are examined in NP (2001) who recommend using MAIC. I use all the criteria to increase the reliability of inferences. The upper bound to the lag length is chosen according to Hayashi (2001) using the formula:

$$k_{\max} = \mathrm{int}(12(T/100)^{1/4}) \tag{3.5}$$

Testing for cointegration.

The main concept of cointegration is that individually integrated processes are linked by stationary linear relations. Johansen and Juselius (1990), Hoffman and Rasche (1991), Baba, Hendry and Star (1992), Stock and Watson (1993), and Lucas (1994) provide evidence for the stability of the money demand equation.

The first method of testing for cointegration is analogous to testing for integration: using the Dickey-Fuller or the Augmented Dickey-Fuller tests. The two-stage procedure of testing for cointegration was proposed by Engle and Granger (1987). They also showed that cointegration implies some adjustment process which prevents errors becoming larger in the long run and any cointegrated series have an error correction representation. The detailed analysis of the topic was presented by Engle and Granger (1991), Hylleberg and Mizon (1989), and Phillips and Loretan (1991).

The second approach to testing for cointegration is the Johansen procedure (Johansen 1989). A good theoretical description of the procedure is given by Charemza (1997). The procedure follows from the Granger Representation Theorem (Engle and Granger (1987) and Johansen (1989)).

In the thesis I use the Johansen cointegration test because as Charemza (1997) states the statistical properties of the Johansen procedure are generally better and the power of the cointegration test is higher. The other advantage of the Johansen procedure is that it does not demand endo-exogenous division of variables.

Testing for Fractional Integration and Cointegration.

Standard cointegration analysis has some restrictions imposed by discrete integration. Caporale and Gil-Alana (2000) state "it might be the case that the equilibrium errors respond more slowly to shocks, which result in highly persistent deviations from equilibrium." That is why I include as an addition to standard cointegration analysis the long-memory cointegration analysis that gives better understanding of money demand relationship.

Apart from standard analysis that concentrates on integration I(d) where d=0 and d=1, long-memory cointegration analysis defines I(d) for all real d. I(1) process is covariance nonstationary and non-mean-reverting, and in this case the effect of innovations will persist forever. The process possesses long memory if the quantity

$$\lim_{n\to\infty}\sum_{j=-n}^{n}|\rho_j| \tag{3.6}$$

is nonfinite (where ρ_j is an autocorrelation function).

An I(d) process, x_t, can be defined by

$$\mathbf{(1\text{-}L)^d x_t = u_t\ ,\ \ t=1,2,\ldots,} \tag{3.7}$$

$$\mathbf{x_t = 0 \qquad t \leq 0} \tag{3.8}$$

where L is the lag operator and u_t is I(0).

For 0<d<0.5, a time series is still stationary, and lag-j autocovariance decreases very slowly (a series demonstrates long memory). For 0.5≤d<1, a time series is stationary (mean-reverting), but it is covariance nonstationary. The advantage of a series exhibiting long memory is that it may be predicted at long horizons using simple models.

For testing long memory I use Geweke/Porter-Hudak (1983) estimates and a modified form of the Geweke/Porter-Hudak estimate of the long-memory parameter d proposed by Philips(1999a, 1999b). The Geweke/Porter-Hudak test is the most reliable for testing I(0) against fractional integration, but GPH estimator is inconsistent against d>1 alternatives. It makes problematic distinguishing unit-root behavior from fractional integration. In Phillips Modified Log Periodogram Regression Estimator the dependent variable is modified to reflect the distribution of d under the null hypothesis that d=1. It was the reason to use the both tests in the analysis. I test the null of no cointegration against fractional cointegration using the two-step strategy presented in Caporale and Gil-Alana (1999).

A description of long-memory processes (including theoretical aspects, methodology and practical application is provided by Baillie (1996). Caporale and Gil-Alana (2000) provided a good description of a methodology of testing the money demand equation with fractional integration and state that stability of the money demand has

"…important policy implication, as the conduct of monetary policy in a money targeting regime relies crucially on a stable demand for money along with theory-consistent interest elasticities, in the absence of which the transmission mechanism of monetary policy becomes unpredictable."

Model Dynamics and Residual Analysis.

I examine the dynamics of the money demand equation specifying the Vector Error Correction (VEC) model and the unrestricted Vector Autoregression (VAR) models based on differences (DVAR) and levels (LVAR) of the data described by Sims (1980). The question whether to specify the vector autoregression model in levels (LVAR) or in differences (DVAR) has been discussing by many econometricians. Some of econometricians state that all variables included in the VAR model should be stationary or, otherwise, the estimated coefficients may be biased. Others, such as Sims (1980) and Doan (1992) do not recommend differencing the series even if they contain a unit root. They state that differencing "throws away" important information. Hoffman and Rasche (1996) write: "DVAR is misspecified if cointegration prevails in the system. The levels specification, LVAR, contains all the long-run information but may result in inferior forecast performance since the specification fails to explicitly recognize the long-run anchors in the data. " As the main purpose of the thesis is forecasting accuracy of the model, I specify all the three types of the models and choose the model that gives the best forecasts.

In the thesis I use the reduced form of VAR models represented mathematically as

$$\mathbf{y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + B x_t + \varepsilon_t} \qquad (3.9)$$

where y_t is a k vector of endogenous variables, x_t is a d vector of exogenous variables, $A_1,\ldots A_p$ and B are matrices of coefficients to be estimated.

The first step of specifying VAR or VEC models is choosing the number of lags. There are different approaches to this problem. Hoffman and Rasche (1991,1997) take three lags for quarterly and monthly data without any explanations; Charemza (1997) takes 5 lags for quarterly data and advises to take the number of lags which result in estimated model residuals without significant autocorrelation. Some econometricians offer to take the maximum number of lags as 10% of the number of observations and use Schwartz criterion for choosing the appropriate number of lags.

In the thesis I use two major approaches for choosing the number of lags. The first one is the Lag Exclusion Test (Chi-squared (Wald) test statistics for lag exclusion). It tests the joint significance of all endogenous variables at specific lag for each equation separately and jointly. I specify a model with a maximum number of lags and test it decreasing the number of lags while I get a parsimonious model with the statistics significantly different from zero.

The second approach is relying on the lag length criteria discussed in Lutkepohl (1991): sequential modified LR test statistic, Final prediction error, Akaike information criterion, Schwarz information criterion, Hannan-quinn information criterion.

The appropriateness of the estimated VAR can be checked also by investigating the AR roots. Lutkepohl (1991) propose to check the inverse roots of the characteristic AR polynomial. The VAR is stable if all roots have modulus less than one and lie inside the unit circle. The number of roots is kp, where k is the number of endogenous variables and p is the largest lag. For a VEC with r cointegrating equations k-r roots equal to unity.

In the thesis I perform a more advanced residual analysis than was proposed by previous authors examining this topic. I use tests and methodologies developed specially for VARs.

The first and one of the most important instruments of analysis is correlograms. I use a graphical approach displaying a matrix of pairwise cross-correlograms for the estimated residuals in the VAR. The asymptotic standard errors of the lagged correlations are computed as $1/\sqrt{T}$.

The next test is Autocorrelation LM test that reports LM test statistics for serial correlation of residuals up to a specified order. The formula of LM statistic can be found in Johansen (1995).

For testing normality of residuals I use the multivariate extensions of the Jarque-Bera residual normality test. It compares the third and the fourth moments of the residuals to those from the normal distribution. The multivariate test needs a factorization of the residuals, and I choose Cholesky factorization matrix as a method of factorization.

For testing for heteroskedasticity I use the extension of White heteroskedasticity test to systems of equations (Kelejian, 1982 and Doornik, 1995). It consists of two parts. The first part shows the joint significance of the regressors excluding the constant term for each test regression. Under the null of no heteroskedasticity, the regressors are not jointly significant. The second part shows the LM chi-squared statistics for the joint significance of all regressors in the system.

Further extension of model dynamics is testing for exogeneity and making the innovation analysis. For testing whether an endogenous variable can be treated as exogenous I use pairwise Granger causality tests. They use Wald statistics to test the joint significance of each of the other lagged endogenous variables in that equation.The tests give also the joint significance of all other lagged endogenous variables in the equation.

Impulse responses allow me to trace how a shock to the i-th variable is transmitted to all of the other endogenous variables through the dynamic structure of the VAR. Estimating the reduced form of the VAR I am faced with the problem of correlation of the innovations (residuals). Thus, they have a common component, which makes it difficult to evaluate the pure effect of a shock. To interpret the impulses correctly, I should apply a transformation to the innovations so that they become uncorrelated. For this purpose I use the inverse of the Cholesky factor of the residual covariance matrix. Estimating the residual covariance matrix I make a small sample degrees of freedom correction that is necessary for my sample.

Variance decomposition shows the relative weight of each random innovation in affecting the variable. It is also based on the inverse of the Cholesky factor of the residual covariance matrix.

Vector Error Correction Model.

A vector error correction model is a restricted form of a VAR. The cointegration relation built in the model restricts the long-run behavior of the endogenous variables to converge to the cointegrating relationship.

In the thesis I specify the vector error correction model using the previously specified VAR models and cointegration equation as the basis. I use the same set of tests to examine dynamics of the model, residuals, exogeneity, and innovations.

For testing the hypotheses I evaluate the models with restriction imposed on the cointegrating vector and on the adjustment coefficients. The main restriction on the cointegrating vector to be tested is $[1 \quad -1 \quad \beta]$, specified as[MB GDP INT]. It is the main restriction being imposed for the United States and some other countries. Restrictions imposed on the adjustment coefficients are equality to zero of some adjustment coefficient. If an adjustment coefficient is equal to zero, it is a purely autoregressive process without long-term adjustment. For testing restrictions I apply the LR test for binding restrictions.

Alternative Forecasting Models.

As an alternative model for comparison forecast performance I specify ARIMA models individually for each variable. The advantage of ARIMA models is the possibility of individual specification that allows me to capture all the peculiarities of every time series. The main disadvantage of ARIMA models is the absence of dynamic interaction between variables. Thus, it can be used only for forecasting purposes.

The model specification and selection are based on the Box-Jenkins (1976) strategy. It consists of the three main stages. In the identification stage, I visually examine the time plot of the series, autocorrelation function and partial correlation function. In the estimation stage, I estimate several possible models and examine the coefficients. The main criteria for choosing the model are Akaike information criterion and Schwartz Bayesian criterion. In the diagnostic checking stage, I examine the residuals for normality, autocorrelation, and heteroskedasticity.

One more model for comparing forecasts is a reduced VAR model. I take the specified VAR models as the basis, and specify variables and the number of lags individually for each equation. It allows me to specify the model with only significant lags[2] that is quite important when you are working with a few degrees of freedom I have. The data does not allow me to include four lags for each variable. For some variables including four lags is necessary, but for other variables two lags is enough. Reduced VAR model introduces more economic sense in modelling and creates extra efficiency. The model is specified and estimated as a system using seemingly unrelated regressions (SUR) method.

I also specify two naïve models: Naïve l and Naïve ll. Naïve l is a simple 'no-change' or random walk model with the forecast being the most recent observed value (Holden and Peel, 1986).

$$\hat{X}_{t+1} = X_t \tag{3.10}$$

Naïve ll is a 'same change' model with the forecast being the most recent observed value with added the last observed change (Holden and Peal, 1986).

[2] I determine the significance from economic theory, the data generating process and econometric testing.

Assessing Forecast Performance.

There are a number of different methodologies for assessing forecast performance. A very good empirical survey of forecasting methods is given in Holden and Peal (1986). Many econometricians and economists are constantly arguing about advantages and disadvantages of each method; that is why, I use several different methods for assessing forecast performance. The main stress I make on the works of the famous economists and methods tested on practice.

First of all, I compare the forecasts obtained with the Vector Error Correction (VEC) model with the forecasts produced by the simple (unrestricted) Vector Autoregression (VAR) models based on differences (DVAR) and levels (LVAR) of the data. For better evaluation of forecast performance I specify alternative models and compare the forecasts obtained with these models with the forecasts obtained with the basic models (Vector Error Correction and Vector Autoregression in levels and in differences). The alternative methods are: ARIMA, structural VAR, simple moving average, and naïve models.

For evaluation the forecast performance I use three major methods: Generalized Forecast Error Sample Moment (GFESM) Statistics, Root Mean Square Forecast Error (RMSFE) comparison and Mean Forecast Error (MFE) comparison.

GFESM was proposed by Clements and Hendry (1993), and it is designed to capture the relative system-wide forecast performance of alternative models. The GFESM evaluates the relative forecast performance of a model at all horizons and for all variables as a single statistics. Clements and Hendry (1993) recommend constructing the moment matrix as

$\phi=E[EE']$, where $E'=[e'_{t+1}, e'_{t+2}, \dots e'_{t+h}]$

e'_{t+h} is the h-step ahead forecast errors for all variables in the system.

Model that minimizes $\log |\phi|$ will maximize the predictive likelihood.

For simplification I assume that the forecast errors across variables are uncorrelated and construct the moment matrix as diagonal. Hoffman and Rasche (1996) comment: "This simplification implies that the 'cross-variable' implications of system forecast ranking is lost but the 'cross-forecast horizon' nature of the comparison is retained. " It is appropriate for my case as I am mainly interested in 'cross-forecast horizon' nature of the comparison.

For making more detailed analysis I use Root Mean Squared Forecast Error (RMSFE) comparison and simple Mean Forecast Error (MFE) comparison.

$$RMSFE = \sqrt{\frac{1}{T}\sum (Y_t^f - Y_t^a)^2} \quad (3.11)$$

$$MFE = \frac{1}{T}\sum (Y_t^f - Y_t^a) \quad (3.12)$$

where Y_t^f -forecasted value of Y

Y_t^a - actual value of Y

Many econometricians use only RMSFE, but I consider MFE as a good indicator that shows a systematic bias. For better comparison of forecast performance for different variables I use RMSPFE and MPFE, which are the above-mentioned indicators in percent.

Further, I deep the analysis of forecast performance by comparing forecasts produced by the models for all variables and for five time periods. I calculate RMSFE by taking five periods (2001:1-2002:1) to produce 5 one-step ahead forecasts, 4 two-step ahead forecasts, 3 three-step ahead forecast, 2 four-step ahead forecasts, and 1 five-step ahead forecast. Then I square and average the errors and take the square root. It allows me to produce accurate forecast measures.

The next stage of the assessing forecast performance is investigation combinations of forecasts for improving forecast accuracy. Bates and Granger (1969) showed that several unbiased forecasts could be combined to produce a new forecast that is more accurate than either of its components. The main assumption they made is minimization the variance of the forecast errors.

Different methods of combining have been extensively discussed in the literature. Journal of Forecasting in 1989 devoted a special issue to this problem. Winkler and Makridakis (1983) examined five weighting procedures and concluded that moving average methods are quite appropriate for combining forecasts. Investigating US money supply Figlevski and Urich (1983) showed preference of simple average over the optimal weighting. The main reason was the instability of the estimated weights. Kang (1986) obtained the same results.

Many researches try to combine forecasts from different techniques to obtain smaller variance of the combined forecast. Lupoletti and Webb (1986) combined two econometric and a vector autoregression forecast and found that the combined forecasts generally outperform the individual forecasts. Moriarty and Adams (1984) examining judgemental and ARIMA forecasts found that combination of forecasts did not give any improvements.

The conclusion made from empirical works is that combining of forecasts does not always improve the accuracy of forecasting and there is no the best method of combining forecasts that dominates other ones in all situations.

Taking into account the very small sample I use two methods of combining forecasts: simple average of individual forecasts and the variance-covariance method proposed by Bates and Granger (1969). The regression method and the moving average methods cannot be applied properly because of insufficient number of observations. Theoretically, the forecast method gives the same results as the variance-covariance method.

Let y be a variable being forecasted and F_1 and F_2 the unbiased forecasts. For forecasts made at time t-1

$$y_t = F_{1t} + u_{1t} \tag{3.13}$$

$$y_t = F_{2t} + u_{2t} \tag{3.14}$$

where u_1 and u_2 are the forecast errors, which have zero means, variances σ_1^2 and σ_2^2 and covariance σ_{12}. I determine the weights λ_1 and λ_2, which give combined forecast c_t

$$c_t = \lambda_1 F_{1t} + \lambda_2 F_{2t} \tag{3.15}$$

$$\lambda_1 + \lambda_2 = 1 \tag{3.16}$$

Estimated values of λ_1 and λ_2 can be found as

$$\hat{\lambda}_1 = \frac{\sum u_{2t}^2 - \sum u_{1t} u_{2t}}{\sum u_{1t}^2 + \sum u_{2t}^2 - 2\sum u_{1t} u_{2t}} \tag{3.17}$$

$$\hat{\lambda}_2 = \frac{\sum u_{1t}^2 - \sum u_{1t} u_{2t}}{\sum u_{1t}^2 + \sum u_{2t}^2 - 2\sum u_{1t} u_{2t}} \tag{3.18}$$

Chapter 4

DATA DESCRIPTION

One of the most important parts of the thesis is collection and transformation the data. Kennedy (2001, p.6) states

> Even if a researcher knows the context, s/he needs to become intimately familiar with the specific data with which s/he is working. Economists are particularly prone to the complaint that researchers do not know their data very well…

Data are the basis of any research and they influence all the further steps of the specification of the model. The problems arise in two dimensions: the quality of the initial data and the right transformation of the data for specification of the model. Taking into account the great significance of the problems I decided to devote a separate part of the thesis to the data generating process.

The main problem connected with data is that all the data used in the thesis are the secondary data (collected previously by agencies). I cannot control the reliability of the data, but the task is to get as much as possible from the existing data. The problems of data in Ukraine are best described by Jean Paul Blendinieres, expert of macroeconomic task force, Ukrainian-European Policy and Legal Advice Centre[3]

> *In Ukraine, public agencies have the entire monopoly of the production of raw economic and social data, and among them, the State Committee of Statistic place a key role… Nevertheless, in the case of Ukraine, the predominance of public statistic appears as an obstacle to the introduction of methods adequate to the monitoring of a market economy. The major tools of observation of the Ukrainian society are still inspired by the devices implemented during the Soviet*

[3] "Ukrainian Economic Trends", March 2002, p. 4-5.

> *period, and international recommendations on methodology are usually hot put into practice… Even though, macroeconomic information is published according to international standard, using commonly agreed classification and terminology, we bear in mind that they are based on primary information produced according non-standard methods and whose quality is highly questionable. Is the reason why, for the major indicators we developed our own measurements, "UEPLAC calculations" are based on a sample of raw data that we submitted to quality control.*

My first step in exploring the data is studying the methods used by UEPLAC for calculating the four macroeconomic indicators.

The first indicator is Gross Domestic Product (GDP). The State Committee of Statistics (Derzhkomstat) has been calculating the quarterly GDP since 1994 and monthly cumulative GDP since 1996. Of course, not all transactions are registered, and the great part of the "shadow market" is not included in the GDP calculations. UEPLAC tries to calculate the GDP as close as possible to the official one by the method of incomes. It represented in billions of constant 1990 Rubles[4]. The GDP deflator is estimated as a weighted average of the CPI and the deflator of industrial production.

The money base is calculated as the sum of currency in circulation, commercial banks reserves and cash in vaults. It has been estimated by UEPLAC using bulletin of NBU as a source[5]. It represented in billions of constant 1990 Rubles.

---

[4] The Ruble is the currency circulated in Ukraine in 1990.

[5] The official issue of the National Bank of Ukraine.

NBU refinancing rate is estimated by UEPLAC using the official data of the National Bank of Ukraine (NBU).

The second step is transformation the data for further specification of the model. The four variables are transformed in the following way: the real money base (MB) is obtained by deflating the nominal money base by the GDP deflator expressed as a natural logarithm; the real GDP (GDP) is estimated by UEPLAC[6] and also expressed as a natural logarithm; the GDP deflator is expressed as the percent changes between two adjacent periods; the NBU refinancing rate (INT) is the nominal NBU refinancing rate estimated by UEPLAC.

The range for the quarterly data is 1994:4 – 2002:1 (31 observations).
For further investigating the data I look at the correlation matrix (table 1) that gives the information about relationship of the variables in the sample. This information will be vital for determining the right sign of the coefficients.

Table 1. Correlation matrix of the variables

	MB	DEF	GDP	INT
MB	1	-0.15	0.58	-0.12
DEF	-0.15	1	0.08	0.84
GDP	0.58	0.08	1	0.14
INT	-0.12	0.84	0.14	1

On the next step I investigate graphs to get the information about dynamic behavior of the variables. I use two-exes line graphs (figures 1, 2, and 3) to show also the relationship between variables, which will be used for estimating cointegration.

[6] The official issue of the National Bank of Ukraine.

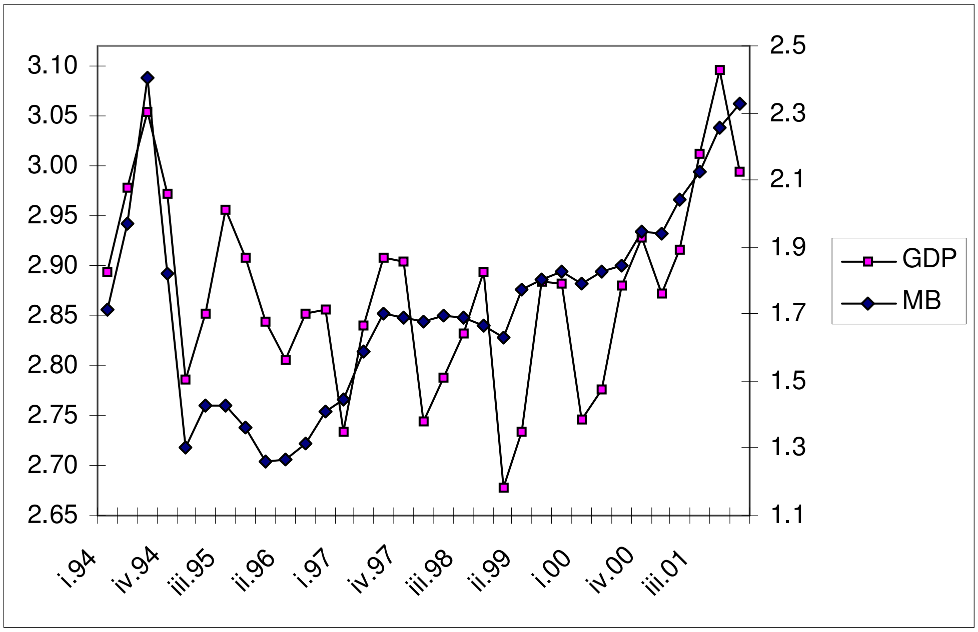


Figure 1. Gross Domestic Product (GDP) and Money Balances (MB).

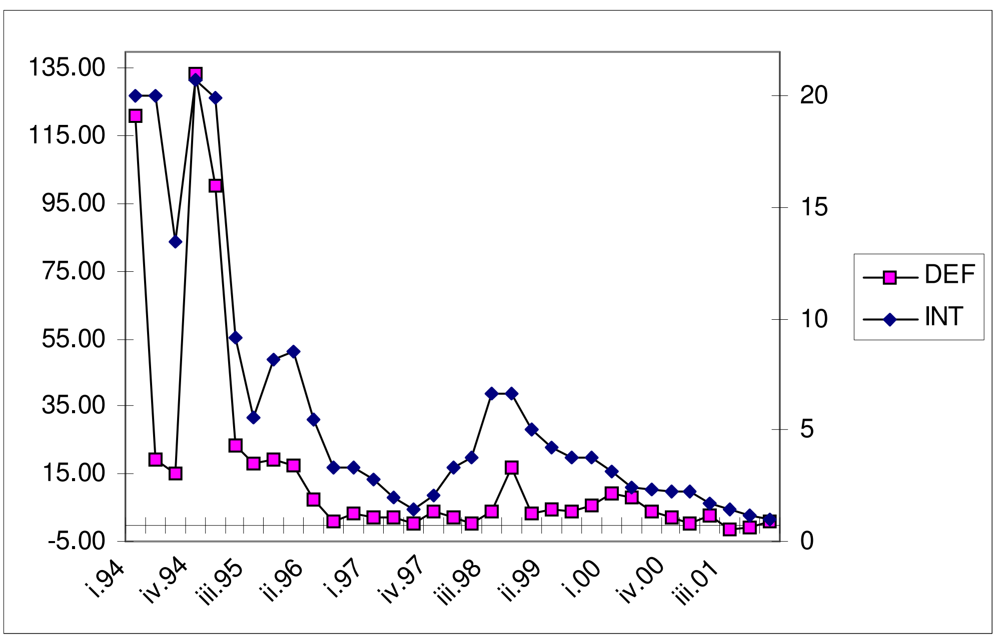


Figure 2. GDP Deflator and Refinancing rate for the sample period: 1994:1 – 2002:1

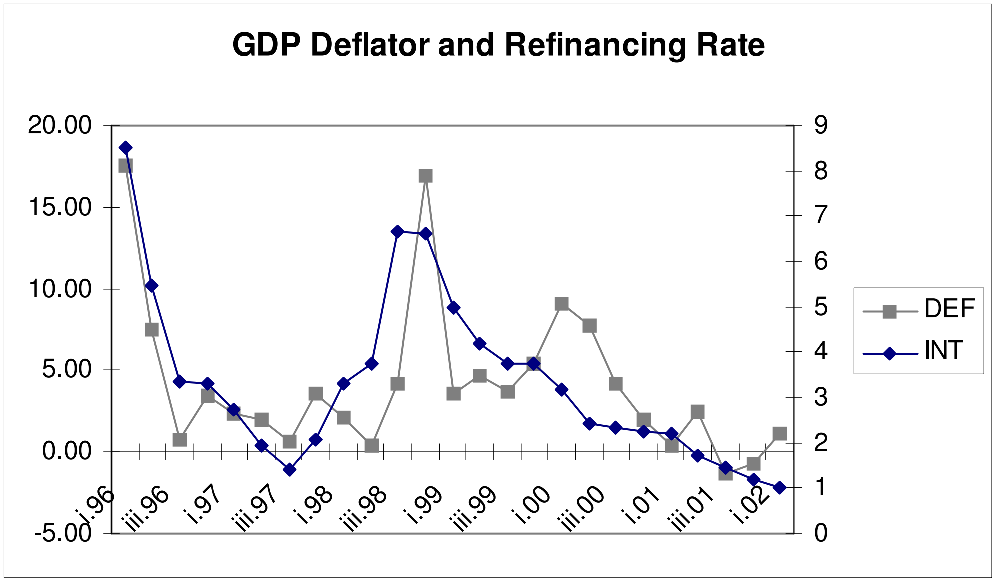


Figure 3. GDP Deflator and Refinancing rate for the period: 1996:1 – 2002:1.

The analysis of the data allows me to make some preliminary conclusions. First, the data are properly estimated and transformed. Second, the relationships between variables correspond to the theoretical model: the GDP deflator and the refinancing rate have a high positive correlation and may be cointegrated; the GDP and the money balances have a positive correlation, although the level of correlation is not high enough. It is explained by the fact that Ukraine is a country with partially fixed exchange rates that leads to weak influence of changes of the money balances on the GDP. Further, I am going to check all these preliminary inferences.

Chapter 5

EMPIRICAL RESULTS

Testing for the Order of Integration.

The methodology of unit root tests described in the methodological part of the thesis. The Augmented Dickey-Fuller test is used as the basic standard test[7]. Other tests are used as additional instruments for increasing the reliability of inferences.

The first step of the integration analysis is determining whether the trend or the intercept should be included in the integration equation of the ADF test. The preliminary analysis is based on the data-generating process and the graph of the variables. Relying on the data-generating process and the graph of the variables I make a preliminary inference that an intercept should be included in the equations for all the variables. A deterministic trend could be included only in the equation of money balances, because it is the only variable that can have a trend in this period.

More accurate inferences can be obtained applying three additional F-statistics (ϕ_1, ϕ_2, and ϕ_3) described in Dickey and Fuller (1981). Calculated and critical values of the statistics are provided in table 2. The critical values for the sample size of 25 observations are taken from Enders (1995). Further process of testing for the unit root is based on the procedure presented in figure A1 of the appendix A.

---

[7] I use the ADF as the basic test because it is the most widespread test.

Table 2. Calculated and critical values of F-statistics.

	Calculated Values			Critical Values		
	GDP	INT	MB	1%	5%	10%
ϕ_3	0.22	3.90	7.82	10.61	7.27	5.91
ϕ_2	6.25	5.81	5.71	8.21	5.68	4.67
ϕ_1	12.63	6.99	2.89	7.88	5.18	4.12

For gross domestic product (GDP) the calculated value ϕ_3=0.22 is less than critical value for any significance level. It is possible to conclude that the restriction $a_2=\gamma=0$ is not binding. Thus, I do not include a time trend in the integration equation. The examining of the data show that GDP series may contain a quadratic trend or a structural break. The software does not allow me to examine it more closely. That is why, I assume no trend in the data and that a drift is a good approximation of the series. This assumption does not significantly influence the results. The calculated values of ϕ_2 and ϕ_1 are more than the critical values; thus, it is possible to conclude that the restriction $a_2=\gamma=0$ is binding, and I include an intercept (the drift term) in the integration equation. The ADF test with an intercept and the six criteria for choosing the lag length is provided in table A1. The table shows the number of lags chosen automatically for each information criteria. According to the table I cannot reject the null hypothesis of the unit root for 1%, 5%, and 10% significance levels and for any criteria. Table A1 provides also the results of the DFGLS and NG Perron tests for the six criteria. The results of the tests confirm the inference of presence the unit root for 1%, 5%, and 10% significance levels and for any criteria. Table A2 shows the KPSS and Phillip-Perron tests with the Newey-West (1994) and Andrews (1991) data-based automatic bandwidth parameter methods. Both the tests confirm the inference of the unit root at 5% or 10% significance levels. Thus, summing up the results of the test, I conclude that the unit root is present in GDP time series.

The results for the refinancing rate (INT) are similar to the results for the GDP. Table 2 shows that the trend should not be included in the integration equation, and the intercept should be included (for 5% and 10% significance levels). Almost all the tests (tables A1 and A2) do not reject the null hypothesis of the unit root. Only ADF test for some criteria reject the hypothesis, but it does not reject it for the modified criteria that are more reliable. Thus, I conclude that the unit root is present in GDP time series.

For monetary base (MB) the calculated value ϕ_3=7.82 is more than critical value for 5% and 10% significance levels. It is possible to conclude that the restriction $a_2=\gamma=0$ is binding. Thus, I should include the time trend in the integration equation. The calculated values of ϕ_1 is less than the critical value; thus, it is possible to conclude that the restriction $a_2=\gamma=0$ is not binding, but not with a great significance. From these I can conclude that presence of a trend without an intercept is a very questionable matter. For this case I estimate the integration equation with a trend and without a trend to increase reliability of inferences. The result, provided in table A1 and A2, do not reject the hypothesis of the unit root for all tests with a trend and without a trend. Thus, I conclude that the unit root is present in GDP time series.

The main inference that can be made after the testing for the order of integration is that all the time series have the unit root (integrated of the same order I(1)) and, thus, may form a cointegrating relation.

Testing for Cointegration.

At the first stage I apply the Johansen procedure with all five sets of assumptions. Both Akaike and Schwarz information criteria represented in table B1 advise not to include the trend and the intercept in the cointegration equation. The maximum eigenvalue statistics and the trace statistics show the presence of only one cointegration relation. Both Akaike and Schwarz information criteria confirm this inference (their values are minimal for one cointegration equation without the trend and the intercept). For increasing the reliability of inferences I apply the test for of presence of an intercept in cointegrating vector described in Enders (1995). It is a type of LR-test that has a chi-squared distribution. The estimated value is 10.66 that is bigger than the critical value of chi-squared with two degrees of freedom (5.99). Thus, as Johansen (1991) suggests it is possible to reject the null hypothesis of an intercept in the cointegrating vector.

At the second stage I apply the cointegration test without a deterministic trend and an intercept to three variables (MB, GDP, INT) for a sample from 1994:3 to 2000:4. The results are represented in table B2. The final cointegration equation is: [1 -1.05228 0.287789] for variables ranged as [MB GDP INT]. All the coefficients in the cointegrating equation are significantly different from zero and have the right signs.

On the next stage I compare obtained results with theoretical economic models and empirical econometric models. Hoffman and Rasche (1997) offer the model in which some coefficients are taken as "known" (offered by economic theory), and only one coefficient (INT) is evaluated by the authors. Hoffman and Rasche (1991) evaluating money demand equation obtained the cointegrating equations represented in table 3. They state that equilibrium interest elasticity is -0.3 to –0.4 for real monetary base money demands.

Table 3. Cointegrating equations obtained by Hoffman and Rasche (1991)

Sample	MB	INCOME	Inter. rate
53:1-74:12	1	-0.967	0.314
53:1-81:12	1	-0.858	0.312
53:1-88:12	1	-0.75	0.25

Thus, I can conclude that there exist cointegration between variables in the money demand equation and the magnitudes and signs of the cointegrating coefficients are in accordance with economic theory and previous empirical research.

Further, I examine the robustness of the estimated coefficients and stability of the cointegration equation by reestimating the model recursively starting with sample that begins in 2000:3. The results are reported in table 4.

Table 4. Examining the robustness of the cointegration equation

	The Money Demand Equation		
Sample	MB	GDP	INT
1994:3-2000:3	1	-1.034 (-0.195)	0.278 (-0.115)
1994:3-2000:4	1	-1.052 (-0.194)	0.288 (-0.115)
1994:3-2001:1	1	-1.038 (-0.174)	0.281 (-0.104)
1994:3-2001:2	1	-1.041 (-0.162)	0.282 (-0.097)
1994:3-2001:3	1	-1.035 (-0.146)	0.278 (-0.089)
1994:3-2001:4	1	-1.059 (-0.149)	0.292 (-0.091)

The inference is that the equation is very stable: the estimated coefficients change insignificantly as the sample length is increased even despite small number of observations.

Testing for Fractional Integration and Cointegration.

At the first stage, I test the order of integration of each of the time series; and in the second step, I test the degree of integration of the residuals of the cointegration relation.

Table 5 demonstrates the results of modified GPH test for all the variables (GDP, INT and MB). In this case I test the presence of the unit root against fractional d that is why I do not use simple GPH test because it is inconsistent against d>1 alternatives[8]. I use the standard recommended power of the test (0.5)[9].

Table 5. Modified LPR estimate of fractional differencing parameter

	Est d	Std Err	t (H0: d=0)	P>|t|	z (H0: d=1)	P>|z|
GDP	1.059	0.022	47.16	0	0.21	0.837
INT	0.674	0.496	1.36	0.23	-1,14	0.255
MB	0.991	0.119	8.32	0	-0.03	0.976

Relying on the results of the tests represented in table 5 I cannot reject the hypothesis that GDP, INT and MB are not significantly different from 1 and exhibit a unit root. This inference confirms my previous inferences of presence

[8] The GPH test is the most reliable for testing I(0) against fractional integration.

[9] The number of ordinates in a regression of the ordinates of the log spectral density on trigonometric function m is typically chosen as $m=T^{1/2}$. The authors of the test call 0.5 as "power of the test".

the unit root in time series and admits the possibility of cointegration between GDP, INT and MB.

As the second step of the analysis, I find the degree of fractional integration in the errors obtained from the money demand equation. The results from the Geweke/Porter-Hudak test and the modified Geweke/Porter-Hudak test are presented in table 6.

Table 6. GPH and modified GPH tests of the cointegration equation.

GPH estimate of fractional differencing parameter

Est d	StdErr	t(H0: d=0)	P>|t|	StdErr	z(H0: d=0)	P>|z|
0.35	0.27	1.29	0.29	0.52	0.68	0.50

Modified LPR estimate of fractional differencing parameter

Est d	StdErr	t(H0: d=0)	P>|t|	z(H0: d=1)	P>|z|
0.37	0.28	1.32	0.25	-2.21	0.03

Both tests show the presence of long-memory component in the error-term series. GPH test estimates d=0.353 and the modified GPH test estimates d=0.367. Thus, I can conclude that error term time series obtained from the cointegration equation demonstrate long memory (mean-reverting and covariance stationary). This inference is not absolutely accurate due to the problem of micronumerocity (small number of observations). I cannot reject the hypothesis that d=0, but using the modified GPH I reject the null hypothesis that d=1.

From the long-memory analysis I can make the main inference that error term series is fractionaly integrated (d=0.353 or d=0.367) or not integrated (d=0). In any case it shows the stability of the money demand equation. It conforms the results obtained from classical cointegration analysis.

Model Dynamics and Residual Analysis.

First, I specify VAR models in differences as the basis for constructing Vector Error Correction models. I give a detailed analysis of VAR in differences (DVAR) omitting the description of VAR in levels (LVAR). This is done for several reasons: the properties and the method of specification of LVAR and DVAR are the similar, and LVAR is not a basic model (it has very poor forecast performance for my sample, and, thus, I use it only for comparing forecasts as an alternative model).

The first step of specifying VAR is choosing the number of lags. I begin the specification from a more general model with four lags and apply the Lag exclusion test and the Lag length criteria for choosing the number of lags. Table C1 shows chi-squared test statistics for lag exclusion. The individual and joint tests show that the fourth lag can be excluded from the model. Table C2 applying the lag length criteria confirms this inference (all the criteria show that the model should contain the number of lags less than four). Additionally, the tests show that two roots are outside the unit circle, and the VAR model does not satisfy the main stability condition. Thus, I should specify a model with a number of lags less than four.

The next model is the model with three lags. Some lag length criteria presented in table C2 suggest three lags to be included in he model. Table C3 shows the lag exclusion test for a model with three lags. Individually, the third lag should not be included for MB and INT. The joint tests admit inclusion of the third lag at 5% significance level. The model satisfies the stability condition: all the roots lie inside the unit circle. VAR residual serial correlation LM test cannot reject the null hypothesis of no serial correlation up to the twelfth lag. VAR residual heteroskedasticity test shows the absence of residual heteroskedasticity in the model. VAR residual normality test rejects the null (at 5% significance level) that the residuals are multivariate normal. To sum up, the model does not satisfy the criterion of residuals normality and significance of the third lag for some variables, but it satisfies all the other criteria. Thus, it can be used for analysis and forecasting if a more parsimonious and accurate model is not found.

For the model with two lags (table C5) the lag exclusion test does not recommend to exclude the second lag both individually for each variable (except MB) and jointly for all variables. The model satisfies the stability condition: all the roots lie inside the unit circle. VAR residual serial correlation LM test cannot reject the null hypothesis of no serial correlation up to the twelfth lag. VAR residual heteroskedasticity test shows the absence of residual heteroskedasticity in the model. VAR residual normality test does not reject the null (at 5% significance level) that the residuals are multivariate normal. Pairwise cross-correlograms confirm the appropriateness of the model. To sum up, the model is quite appropriate; it outperforms the model with three lags and, thus, is preferred as more reliable and more parsimonious.

The model with one lag has heteroskedastic residuals and serial correlation on the fourth and the eighth lags, although all the other criteria are quite good. However, this model does not outperform the model with two lags and can be used only for comparing forecasts.

One more model that is parsimonious and appropriate is the model with the first and the fourth lags (table C6). I think that these two lags are the most appropriate for the model that is due to the nature of the data: for quarterly data the first and the fourth lags are always very significant. The lag exclusion test, represented in table C5, does not recommend excluding the fourth lag both individually for each variable (except MB) and jointly for all variables. The model satisfies the stability condition: all the roots lie inside the unit circle. VAR residual serial correlation LM test cannot reject the null hypothesis of no serial correlation up to the twelfth lag. VAR residual heteroskedasticity test shows the absence of residual heteroskedasticity in the model. VAR residual normality test does not reject the null (at 5% and 10% significance levels) that the residuals are multivariate normal. Pairwise cross-correlograms represented on figure C1 confirm the appropriateness of the model and show that the cross-correlograms are better than for the model with two lags. To sum up, the model is quite appropriate; it outperforms the model with three lags and is not worse, or even better, than the model with two lags.

Summing up the process of the specification VAR models I can make the inference that, taking into account all the criteria, I can choose two parsimonious and accurate models: the VAR model with the first and the second lags and the VAR model with the first and the fourth lags. These two models correspond all the criteria for VAR models and can be used on practice.

Vector Error Correction Model.

On the basis of specified cointegration relation and the VAR models I specify three Vector Error Correction models.

The first model is specified with one lag and cointegration equation described above. The residual analysis shows the appropriateness of the model. VAR residual serial correlation LM test cannot reject the null hypothesis of no serial correlation up to the twelfth lag (except the first lag at 5% significance level). VAR residual heteroskedasticity test shows the absence of residual heteroskedasticity in the model. VAR residual normality test cannot rejects the null (at 5% significance level) that the residuals are multivariate normal. The model satisfies the conditions of stability: all the impulse response functions converge to steady states. The estimated coefficients of the vector error-correction model (VECM) are presented in table 7. Changes of lagged INT and GDP are significantly different from zero for all the ADL equations, though changes in lagged MB are not significantly different from zero for GDP. The estimated error-correction coefficients for MB and INT are significantly different from zero, but the estimated coefficient for GDP is not significantly different from zero, and GDP is "weakly exogenous" in the model and changes in GDP is an autoregressive process.

Table 7. Estimated vector Error correction model.

Cointegrating Eq:	CointEq1		
MB(-1)	1.000000		
GDP(-1)	-1.052280		
	(0.19410)		
	(-5.42144)		
INT(-1)	0.287789		
	(0.11467)		
	(2.50979)		
Error Correction:	**D(MB)**	**D(GDP)**	**D(INT)**
CointEq1	-0.071148	0.035946	-0.951386
	(0.03914)	(0.03834)	(0.75225)
	(-1.81773)	(0.93757)	(-1.26471)
D(MB(-1))	-0.185350	0.471279	2.911759
	(0.36444)	(0.35698)	(7.00426)
	(-0.50858)	(1.32018)	(0.41571)
D(GDP(-1))	-0.415181	-0.336308	6.328554
	(0.23465)	(0.22984)	(4.50970)
	(-1.76938)	(-1.46321)	(1.40332)
D(INT(-1))	-0.020929	-0.007446	0.430718
	(0.00799)	(0.00783)	(0.15361)
	(-2.61863)	(-0.95116)	(2.80404)

The second model is the model with the first and the second lags. The main drawback of the model is that variable INT in cointegration equation is not significantly different from zero. That is why, I do not take it as a base model, but use this model only as an alternative forecasting model.

The third model is the model with the first and the fourth lags. The residual analysis shows the appropriateness of the model. VAR residual serial correlation LM test cannot reject the null hypothesis of no serial correlation up to the twelfth lag (except the fifth lag at 5% significance level). VAR residual heteroskedasticity test shows the absence of residual heteroskedasticity in the model. VAR residual normality test cannot rejects the null (at 5% significance level) that the residuals are multivariate normal. The model satisfies the conditions of stability: all the impulse response functions converge to steady states. The estimated coefficients of the vector error-correction model (VECM) are presented in table C7. The estimated error-correction coefficients for MB and INT are significantly different from zero, but the estimated coefficient for GDP is not significantly different from zero, and GDP is "weakly exogenous" in the model and changes in GDP is an autoregressive process. All the coefficients in the cointegration equation are significantly different from zero and have appropriate signs.

Further analysis of VEC models consists of implying restriction on the coefficients in the cointegration equation and on the adjustment coefficient. My first restriction on the cointegrating equation is MB=INT (it is the basic restriction implied by American econometricians and, especially, by Hoffman and Rasche (1997). LR test for binding restrictions shows that this restriction is binding (LR test does not reject the imposed restriction at conventional levels). The new cointegration equation is [1 -1 0.26] that totally corresponds the result obtained by Hoffman and Rasche (1997). The second restriction is that the adjustment coefficient before GDP is equal zero (GDP is weakly exogenous). LR test does not reject the imposed restriction at conventional levels conforming the inference of exogeneity of GDP.

To sum up the analysis of Vector Error Correction models, I choose two models as the basic ones: VEC model with one lag and VEC model with the first and the fourth lag. These models are accurately specified and can be justified on the basis of economic theory and previous empirical research.

Alternative Forecasting Models.

As alternative forecasting models I specify Naïve l, Naïve ll, ARIMA model, and structural VAR model. Naïve l and Naïve ll models are too simple to describe here; the methodology is described above in the methodology part, and forecasting accuracy will be evaluated in the next part.

I apply the Box-Jenkins methodology for specifying ARIMA models. The models, specified individually for each variable, are:

$$D(GDP) = C(1) + [SAR(4)=C(2)] \tag{5.1}$$

$$D(INT) = C(1) + [SAR(4)=C(2),MA(1)=C(3),SMA(4)=C(4)] \tag{5.2}$$

$$D(MB) = C(1) + [AR(1)=C(2),AR(2)=C(3),SAR(4)=C(4),SMA(4)=C(5)] \tag{5.3}$$

where: SAR(4)=C(4) means that coefficient C(4) in an equation is the coefficient of the seasonal autoregressive process of the fourth order.

SMA(4)=C(4) means that coefficient C(4) in an equation is the coefficient of the seasonal moving average process of the fourth order.

As a result I obtained very parsimonious model for GDP including only the seasonal autoregressive component. It is possible because GDP demonstrates very good quarter seasonality pattern that is confirmed by using the dummy variable approach or other methods. Quarter seasonality in the other time series is not so obvious. That is why the specifications of INT and MB are more complex. All the residual tests show the appropriateness of the specified models.

One more forecasting model is a structural VAR model, evaluated as a system. I include the deflator (DEF) in the model to improve forecasting performance of the model. Inclusion of the DEF in the models is reasonable since it is an explanatory variable which correlates with INT and MB and cointegrates with INT. The specified equations are:

d(MB)=C(1)*d(MB(-1))+c(2)*d(GDP(-1))+c(5)*d(int(-1))+c(4) (5.4)

d(gdp)=C(11)*d(MB(-1))+c(15)*d(gdp(-4))+c(12) (5.5)

d(int)=c(22)*d(int(-4))+c(23)*d(INT(-1))+c(25)*d(def(-1)) (5.6)

d(DEF)=c(31)*d(def(-4))+c(32)*d(def(-1))+c(33)*d(int(-1))+c(34)*d(gdp(-1)) (5.7)

The equations are evaluated as a system using SUR method.

Assessing Forecast Performance.

For forecasting purpose I estimate the models for the period 1994:3-2000:4 and leave five time periods (2001:1-2002:1) for a post-estimation experiment. To improve forecast performance I include in all the specifications the deflator (DEF) as an exogenous and endogenous variable. This variable has a cointegration relation with interest rate through the Fisher equation and should improve forecast performance of the models. At the first stage I compare forecast performance of thirty models: nine LVAR models, eleven DVAR models, six VEC models, ARIMA for each variable, Naïve 1, Naïve 2, and structural VAR. The models differ by the number of lags, the number of exogenous and endogenous variables.

Tables 8, 9, and 10 summarize the estimates of forecasting criteria (RMSPE, RMSE, MAE, MFE, and GFESM) for all thirty models and compares dynamic forecasts produced by the models for five periods ahead. Highlighted are the models having the best forecast performance for each variable. Table 10 gives also the value of the total GFESM criterion showing the overall forecast performance of the models (ability to forecast accurately all the variables).

Table 8. Assessing forecast performance for GDP.

	GDP				
	RMSPE	RMSE	MAE	MFE	GFESM
LVAR(1 1)	0.519	0.158	0.132	-0.132	-26.6
LVAR(1 2)	0.569	0.171	0.164	-0.164	-18.6
LVAR(1,4)	0.437	0.131	0.125	-0.125	-21.3
LVAR(1 1)D	0.589	0.179	0.158	-0.158	-20.4
LVAR(1 2)D	0.665	0.200	0.195	-0.195	-16.7
LVAR(1,4)D	0.474	0.143	0.137	-0.137	-20.3
LVAR4(1 1)	0.547	0.167	0.144	-0.144	-22.6
LVAR4(1 2)	0.579	0.175	0.164	-0.164	-19.1
LVAR4(1,4)	0.509	0.153	0.145	-0.145	-19.9
DVAR(1 1)	0.356	0.109	0.089	-0.067	-28.9
DVAR(1 2)	0.435	0.132	0.115	-0.115	-24.5
DVAR(1 3)	0.511	0.331	0.148	-0.148	-19.6
DVAR(1,4)	0.117	0.036	0.024	-0.024	-44.1
DVAR(1 1)D	0.211	0.064	0.052	-0.007	-33.9
DVAR(1 2)D	0.475	0.145	0.129	-0.129	-22.1
DVAR(1 3)D	0.510	0.333	0.149	-0.149	-19.4
DVAR(1,4)D	0.148	0.046	0.032	-0.032	-39.2
DVAR4(1 1)	0.323	0.099	0.081	-0.054	-30.3
DVAR4(1 2)	0.420	0.127	0.118	-0.118	-22.7
DVAR4(1,4)	0.140	0.043	0.030	-0.025	-40
VECM(1 1)	0.336	0.102	0.085	-0.055	-30.8
VECM(1 2)	0.424	0.129	0.111	-0.111	-25
VECM(1,4)	0.129	0.040	0.029	-0.027	-39.9
VECM(1 1)D	0.210	0.062	0.057	0.015	-29.8
VECM(1 2)D	0.406	0.124	0.108	-0.108	-24.5
VECM(1,4)D	0.189	0.058	0.043	-0.043	-38.8
ARIMA	0.145	0.045	0.034	-0.034	-37.3
SVAR	0.111	0.034	0.024	-0.020	-45.6
Naive1	0.273	0.082	0.079	-0.013	-25.7
Naive2	0.384	0.114	0.091	0.031	-18.5

Table 9. Assessing forecast performance for INT.

	INT				
	RMSPE	RMSE	MAE	MFE	GFESM
LVAR(1 1)	35.808	4.853	4.820	4.820	15.7
LVAR(1 2)	23.501	3.049	3.014	3.014	10.9
LVAR(1,4)	22.417	2.624	2.352	2.352	6.9
LVAR(1 1)D	8.807	1.102	1.068	1.068	0.3
LVAR(1 2)D	6.240	0.703	0.612	0.612	-6.5
LVAR(1,4)D	11.239	1.309	1.106	1.106	-6.8
LVAR4(1 1)	29.936	4.018	4.006	4.006	13.8
LVAR4(1 2)	17.943	2.239	2.178	2.178	7.5
LVAR4(1,4)	28.448	3.478	3.348	3.348	11.6
DVAR(1 1)	15.621	2.010	1.956	1.956	6.3
DVAR(1 2)	3.431	0.398	0.336	0.302	-13.5
DVAR(1 3)	2.382	0.607	0.272	-0.272	-17.9
DVAR(1,4)	4.639	0.544	0.490	0.222	-8.4
DVAR(1 1)D	3.207	0.426	0.374	-0.373	-18.6
DVAR(1 2)D	3.825	0.677	0.598	-0.598	-6.6
DVAR(1 3)D	2.137	0.667	0.298	-0.298	-18.6
DVAR(1,4)D	3.015	0.390	0.348	0.020	-12.5
DVAR4(1 1)	14.597	1.857	1.793	1.793	5.3
DVAR4(1 2)	2.394	0.359	0.337	-0.148	-11.7
DVAR4(1,4)	10.270	1.192	1.105	1.105	0.3
VECM(1 1)	20.146	2.510	2.406	2.406	8.2
VECM(1 2)	14.612	1.758	1.633	1.633	3.7
VECM(1,4)	12.682	1.422	1.179	0.827	-1.6
VECM(1 1)D	4.888	0.637	0.591	-0.591	-7
VECM(1 2)D	15.312	1.730	1.501	1.298	2.1
VECM(1,4)D	9.900	1.120	0.926	0.571	-4.4
ARIMA	2.613	0.391	0.326	0.326	-13
SVAR	3.870	0.441	0.339	0.339	-20.8
Naive1	1.938	0.283	0.246	0.246	-16.6
Naive2	1.286	0.212	0.152	0.020	-23.3

Table 10. Assessing forecast performance for GDP.

	MB					Total
	RMSPE	RMSE	MAE	MFE	GFESM	GFESM
LVAR(1 1)	2.257	0.504	0.456	-0.456	-9.4	-20.4
LVAR(1 2)	1.650	0.367	0.341	-0.341	-11.6	-19.3
LVAR(1,4)	1.223	0.278	0.224	-0.224	-19.1	-33.4
LVAR(1 1)D	0.740	0.167	0.141	-0.141	-24.2	-44.2
LVAR(1 2)D	0.694	0.156	0.137	-0.137	-21.4	-44.6
LVAR(1,4)D	0.839	0.192	0.150	-0.150	-24.4	-51.5
LVAR4(1 1)	2.021	0.451	0.410	-0.410	-10.4	-19.1
LVAR4(1 2)	1.274	0.285	0.259	-0.259	-14.7	-26.3
LVAR4(1,4)	1.424	0.323	0.265	-0.265	-17.6	-25.8
DVAR(1 1)	0.891	0.202	0.168	-0.156	-21.1	-43.6
DVAR(1 2)	0.702	0.159	0.130	-0.130	-24.1	-62
DVAR(1 3)	0.620	0.261	0.117	-0.117	-23.9	-61.3
DVAR(1,4)	0.561	0.128	0.097	-0.082	-29.1	-81.6
DVAR(1 1)D	0.276	0.056	0.050	0.026	-31.4	-83.8
DVAR(1 2)D	0.513	0.117	0.088	-0.085	-30.4	-59.1
DVAR(1 3)D	0.615	0.261	0.117	-0.117	-23.9	-61.9
DVAR(1,4)D	0.547	0.125	0.095	-0.081	-31.2	-83
DVAR4(1 1)	0.742	0.168	0.140	-0.123	-22.4	-47.4
DVAR4(1 2)	0.563	0.128	0.104	-0.104	-26.3	-60.7
DVAR4(1,4)	0.635	0.144	0.122	-0.100	-23.3	-63
VECM(1 1)	1.135	0.257	0.211	-0.210	-22.8	-45.4
VECM(1 2)	1.135	0.257	0.218	-0.218	-17.9	-39.2
VECM(1,4)	0.644	0.148	0.110	-0.098	-27.4	-68.9
VECM(1 1)D	0.246	0.050	0.045	0.045	-32.3	-69.1
VECM(1 2)D	0.686	0.157	0.120	-0.116	-26.8	-49.2
VECM(1,4)D	0.614	0.140	0.106	-0.094	-28.3	-71.5
ARIMA	0.635	0.235	0.202	-0.187	-18.6	-68.8
SVAR	0.769	0.177	0.127	-0.109	-28.2	-94.6
Naive1	0.409	0.089	0.079	-0.077	-28.9	-71.3
Naive2	0.367	0.075	0.065	0.005	-29.6	-71.4

Further, I deep the analysis of forecast performance by comparing forecasts produced by the models for all variables for every time period. It is done for the best models chosen from tables 8, 9, and 10. I calculate RMSFE by taking five periods (2001:1-2002:1) to produce 5 one-step ahead forecasts, 4 two-step ahead forecasts, 3 three-step ahead forecast, 2 four-step ahead forecasts, and 1 five-step ahead forecast. It allows me to produce accurate forecast measures and evaluate forecast performance of the models for different time periods. In table 11 I provide Root Mean Square Percent Error (RMSPE) comparison and Mean Forecast Error (MFE) comparison for five time periods.

Table 11. RMSPE and MFE for five time periods.

		GDP		INT		MB	
		RMSPE	MFE	RMSPE	MFE	RMSPE	MFE
DVAR(1 1)D							
	1	0.29	0.19	3.45	0.09	0.37	-0.02
	2	0.35	-0.06	5.58	0.16	0.57	-0.08
	3	0.45	-0.10	4.82	-0.12	0.80	-0.11
	4	0.42	-0.13	9.25	0.33	1.20	-0.20
	5	0.01	0.00	3.33	-0.34	0.20	-0.05
DVAR(1,4)D							
	1	0.18	0.21	2.20	0.10	0.25	-0.03
	2	0.13	-0.02	4.41	0.39	0.51	-0.10
	3	0.21	-0.04	6.93	0.60	0.78	-0.16
	4	0.23	-0.07	10.44	0.93	1.02	-0.23
	5	0.11	-0.03	5.29	0.54	0.93	-0.22
VECM(1,4)							
	1	0.18	0.21	3.52	0.22	0.25	-0.04
	2	0.10	-0.02	10.21	1.04	0.54	-0.11
	3	0.20	-0.03	17.75	1.85	0.87	-0.18
	4	0.22	-0.07	24.36	2.52	1.20	-0.27
	5	0.09	-0.03	22.51	2.30	1.14	-0.27
VECM(1,4)D							
	1	0.19	0.21	3.55	0.17	0.25	-0.04
	2	0.16	-0.03	8.80	0.88	0.54	-0.11
	3	0.26	-0.06	14.39	1.45	0.84	-0.17
	4	0.30	-0.09	20.96	2.11	1.16	-0.26
	5	0.16	-0.05	17.88	1.82	1.07	-0.25

Table 11 (continued).

		GDP		INT		MB	
		RMSPE	MFE	RMSPE	MFE	RMSPE	MFE
VECM(1 1)D							
	1	0.30	0.20	3.93	0.01	0.28	-0.02
	2	0.32	-0.05	5.42	0.09	0.34	-0.05
	3	0.38	-0.08	4.31	-0.30	0.42	-0.05
	4	0.28	-0.08	6.19	-0.11	0.53	-0.08
	5	0.14	0.04	6.66	-0.68	0.12	0.03
ARIMA							
	1	0.15	0.20	3.04	0.10	0.40	-0.05
	2	0.13	-0.02	4.98	0.14	0.74	-0.15
	3	0.17	-0.03	2.07	-0.08	1.13	-0.24
	4	0.20	-0.04	2.52	0.25	1.64	-0.37
	5	0.03	-0.01	3.49	0.36	1.58	-0.37
SVAR							
	1	0.16	0.21	1.94	0.15	0.32	-0.05
	2	0.12	-0.01	3.63	0.34	0.73	-0.14
	3	0.16	-0.02	5.20	0.51	1.12	-0.23
	4	0.16	-0.03	7.87	0.82	1.48	-0.32
	5	0.04	0.01	6.14	0.63	1.40	-0.33
DVAR(1 3)D							
	1	0.32	0.12	3.56	0.11	0.31	-0.06
	2	0.46	-0.13	4.13	0.28	0.49	-0.10
	3	0.46	-0.13	4.39	0.37	0.67	-0.15
	4	0.52	-0.15	8.27	0.51	0.92	-0.21
	5	0.60	-0.18	0.68	-0.07	1.03	-0.24

After assessing forecast performance, I can sum up all the results and make the conclusion. First of all, VECM does not give better forecasts than ARIMA and DVAR and does not confirm the assumption that incorporating cointegration information in a model improves forecasts. This assumption is true for long-term forecasts, but my forecasting period (2001:1-2002:1) is quite short to demonstrate the advantages of VECM. Clements and Hendry (1991) state:

> *"Forecast performance of the simple VAR models can match or even slightly outperform that of the VECM forecasts. It is clear that the VECM does not uniformly result in improved forecast performance for all the variables in the simple*

cointegrated system – especially at short- or intermediate-term horizons of less than three years."

Good forecast performance of ARIMA model is explained by the fact that I have specified the equations for each variable separately taking into account the peculiarities of each time series. For example, GDP has quarter seasonality. Specifying GDP as Seasonal AR (4) gives very accurate forecasts. The individual approach to specification is the advantage of ARIMA. The main disadvantage of ARIMA is not taking into account dynamic interaction between variables.

A good alternative forecasting model is a Structural VAR model (SVAR). It has one important advantage over the other model – possibility of accurate specification of the model taking only necessary lags and variables. It is especially valuable for small samples allowing saving degrees of freedom. In my case, I cannot include many lags or variables in the model to increase its forecast performance that is due to the very small sample. The SVAR model has also some disadvantages. First of all, the process of specification requires knowledge of economic theory and takes a lot of time and professionalism of an econometrician. Second, it requires more advanced techniques for evaluating the model (SUR).

The main conclusion is that ARIMA, DVAR, SVAR, and VEC can be used for short-term forecasting. In short-term period VECM do not give better forecasts than DVAR, and, thus, DVAR is more preferable as more parsimonious model that do not demand the presence of cointegration relationship between variables. In long-term period VEC is expected to give more accurate forecasts as it takes into account the long-term relationship between variables (but it cannot be checked now due to a small number of available observations). As VEC gives short-run forecasts comparable with ones produced by DVAR, VEC is expected to have better overall forecast performance incorporating short-term and long-term forecasts (it will have lower GFESM statistics).

The next stage of assessing forecast performance is combining forecasts. For calculating weights I take the time period 1994:4-2000:4 and evaluate performance of the combined forecasts for 2001:1-2002:1. For every variable I choose three best models plus Naïve 1 and Naïve 2 models and compare forecast performance of each model with forecast performance of combined model using Root mean square error (RMSE) criterion. The first method of combination the forecasts is the variance-covariance method with weights calculated according to formulae 3.17 and 3.18. The second method is the simple mean of individual forecasts. The RMSE criteria for each variable are presented in tables 12-14.

Table 12. Comparing combined forecasts for GDP.

Forecast	RMSE
VECM(1,4)	0.040
ARIMA	0.045
SVAR	**0.034**
Combination of VECM (1,4) and ARIMA [0.07, 0.93]	0.044
Simple mean of VECM (1,4) and ARIMA	0.041
Combination of VECM (1,4) and SVAR [0.86, 0.14]	0.039
Simple mean of VECM (1,4) and SVAR	**0.036**
Combination of ARIMA and SVAR [0.94, 0.06]	0.044
Simple mean of ARIMA and SVAR	0.039
Simple mean of VECM (1,4), ARIMA and SVAR	0.039
Naïve 1	0.082
Naïve 2	0.114
Simple mean of Naïve 1 and Naïve 2	0.093
Simple mean of Naïve 1, Naïve 2 and ARIMA	0.068

Note: weights λ_1 and λ_2 are given in square brackets.

Table 12 shows that combination of forecasts for GDP does not give improvement of forecast over individual forecasts. Simple mean gives better forecast accuracy than combination of the forecasts. In this case the SVAR model can be accepted as the model giving the most accurate forecasts.

Table 13. Comparing combined forecasts for INT.

Forecast	RMSE
DVAR (1 3)D	0.442
ARIMA	0.391
SVAR	0.441
Combination of DVAR (1 3)D and ARIMA [0.6, 0.4]	0.223
Simple mean of DVAR (1 3)D and ARIMA	**0.201**
Combination of DVAR (1 3)D and SVAR [1, 0]	0.442
Simple mean of DVAR (1 3)D and SVAR	0.280
Combination of ARIMA and SVAR [0.65, 0.35]	0.354
Simple mean of ARIMA and SVAR	0.357
Simple mean of DVAR (1 3)D, ARIMA and SVAR	0.222
Naïve 1	0.283
Naïve 2	0.212
Simple mean of Naïve 1 and Naïve 2	0.210
Simple mean of Naïve 1, Naïve 2 and ARIMA	0.265

Note: weights λ_1 and λ_2 are given in square brackets.

Table 13 shows that for INT combination of forecasts improves forecast accuracy over individual forecasts in all cases, but simple mean gives better forecast than combination (except one case: combination of ARIMA and SVAR). Thus, combination of forecasts should be used for improving forecast accuracy of refinance rate, and the simple mean is the best method of combination.

Table 14 shows the mix results: in some cases combination gives better accuracy than individual forecasts, and simple mean sometimes gives better accuracy than combination. The best forecast accuracy gives the simple mean of Naïve 1, Naïve 2, and ARIMA models.

Table 14. Comparing combined forecasts for MB.

Forecast	RMSE
VECM(1,4)D	0.140
ARIMA	0.126
SVAR	0.177
Combination of VECM (1,4)D and ARIMA [0.81, 0.19]	0.121
Simple mean of VECM (1,4)D and ARIMA	0.104
Combination of VECM (1,4)D and SVAR [1, 0]	0.140
Simple mean of VECM (1,4)D and SVAR	0.158
Combination of ARIMA and SVAR [0.22, 0.78]	0.148
Simple mean of ARIMA and SVAR	0.122
Simple mean of VECM (1,4)D, ARIMA and SVAR	0.113
Naïve 1	0.089
Naïve 2	0.075
Simple mean of Naïve 1 and Naïve 2	0.067
Simple mean of Naïve 1, Naïve 2 and ARIMA	**0.060**

Note: weights λ_1 and λ_2 are given in square brackets.

The main conclusion made from testing forecast performance of combined forecasts is that simple mean often gives the best accuracy and should be used for increasing forecast accuracy. It does not allow me to reject the variance-covariance method of combination forecasts. The poor performance of the method can be explained by several reasons. The first reason is the very short sample I have. I use only five observations for constructing the weights and only five observations for testing forecast performance. It decreases my degrees of freedom by ten observations. The bigger sample can give more accurate results. This reason also does not allow me to apply regression-based method of combining forecasts. The second reason is that the variance-covariance matrix of forecast errors may not be constant over time. In this case using the fixed weighting scheme may produce poor combined forecasts. In my case I am not able to use changing weights and evaluate properly the properties of the variance-covariance matrix over time.

Chapter 6

CONCLUSIONS

At the first stage of my work I have found a cointegration equation and tested its robustness. Results show, it appears to be robust to adding or excluding new observation to the data set, but it is not robust to including additional lags to the model. This is not the problem with the equation: the Schwartz Information Criterion shows that inclusion of additional lags in the specification tends to worsen the model. All the coefficients in the cointegration equation are significantly different from zero and have the signs and values corresponding to those expected from economic theory and previous research.

The important step of the thesis is investigating the long memory in time series and confirming the stability of the cointegration equation applying the fractional integration approach. As a result I have confirmed the stability of the cointegration equation and found the presence of the long memory in the error terms of the cointegration equation. It gives the possibility to conduct predictable money demand policy and gives the opportunity to specify a more accurate forecasting models (for example, Autoregressive Fractionally Integrated Moving Average (ARFIMA) model, that has all the advantages of ARIMA and is able to produce long-term forecasts). In this work specification of ARFIMA model is impossible because of I insufficient number of observations.

At the next stage of the thesis I have specified three models: the vector error-correction (VEC) model, simple vector autoregression (VAR) model based on differences (DVAR) and levels (LVAR) of the data to find the model with the best forecast performance. Additionally, I have included several alternative models as simple models producing accurate short-term forecasts. All the models are stable and have parsimonious specification. Some information criteria show the preferability of this specification over ones with multiple lags. I think it is caused by the problem of micronumerocity: including additional lags seriously decreases the degrees of freedom and causes the worsening of the dynamic structure of the model.

For evaluation the forecast performance I use three methods: Generalized Forecast Error Sample Moment (GFESM) Statistics, Root Mean Square Forecast Error (RMSFE) comparison and Mean Forecast Error (MFE) comparison. All the methods give the similar results: LVAR model is not appropriate for producing accurate forecasts, but the other models give the similar results. VEC does not produce superior forecasts that can be explained by the small forecasting horizon (5 quarters). It does not contradict econometric theory, because VEC gives the best forecast for long-term periods (more than 12 quarters). Thus, for producing short-term forecasts the ARIMA and the DVAR are more appropriate as more parsimonious models that do not demand the presence of a cointegration relation between variables; but for producing long-term forecasts or complex forecast for all periods the VEC is expected to produce more accurate forecasts.

Testing methods of combination forecasts showed that almost in all cases the simple mean gives better forecast accuracy than sophisticated method of combination (the variance-covariance method). It does not allow me to make final conclusions about inappropriability of this method, but only shows that for short samples the simple mean is quite accurate and parsimonious method of combining forecasts.

The total conclusion is that I have achieved the planned goals: I have created the parsimonious and accurate forecasting models, and confirmed the stability of the money demand equation for Ukraine.

My major idea was writing an empirical work, which has practical implication. The result of the thesis can be used for future academic research or for development the monetary policy in Ukraine.

The possible extensions of the work for the future are checking the forecast performance in the long run, testing more advanced method of combination forecasts and specifying models based on the fractional integration approach to use the advantages of the long memory. As bigger sample is available, the future development of the models in the above-mentioned direction can significantly increase the accuracy of forecasts and serve as the basis for monetary policy in Ukraine.

BIBLIOGRAPHY

Andrews, Donald W.K. *Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation*. Econometrica, 1991, 59, 817-858.

Armstrong, J.S. *Long-Range Forecasting*. New York: Willey, 1985.

Baba, Y., D.F. Hendry and R.M. Starr. *The Demand for M1 in the USA, 1960-1988*. Review of Economic Studies, 1992, 59, 25-61.

Baillie, R.. *Long Memory Processes and Fractional Integration in Econometrics*. Journal of Econometrics, 73, 1996, 5-59.

Bates, J.M. and Granger C.W.J. *The Combination of Forecasts.* Operational Research Quarterly, 1969, 20, 451-468.

Blangiewitch, M. and W.W. Charemza. *Cointegration in Small Samples: Empirical Percentiles, Drifting Moments and Customized Testing*. Oxford Bulletin of Economics and Statistics, 1990, 52, 303-315.

Box, G. and G. Jenkins. *Time Series Analysis, Forecasting , and Control.* San Francisco, Calif.: Holden Day, 1976.

Campbell, John Y. and Pierre Perron. *Pitfalls and Opportunities: What Macroeconomists Should Know about Unit Roots*. NBER Macroeconomics Annual, 1991, 141-201.

Caporale, G.M. and L.A. Gil-Alana. *Fractional Cointegration and Aggregate Money Demand Function*. Working Paper, Department of Economics, University of East London, 2000 (September).

Caporale, G.M. and L.A. Gil-Alana. *Fractional Cointegration and Tests of Present Value Models*. Working Paper no 21-99, Department of Economics, University of East London, 1999.

Carlson, John B., Dennis Hoffman, Benjamin D. Keen. *Results of a Study of the Stability of Cointegrating Relations Comprised of Broad Monetary Aggregates*. Working Paper 9917.

Charemza, Wojciech W., Derek F. Deadman. *New Directions in Econometric Practice: General to Specific Modelling, Cointegration and Vector Autoregression.* Northampton, MA: Edward Elgar, 1998.

Chatfield, C. *The Future of Time-series Forecasting*. International Journal of Forecasting, 1988, vol. 4, 411-19.

Chow, G.C. *On the Long-Run and Short-Run Demand for Money*. Journal of Political Economy 1966, 74, 111-131.

Christofferson, P.F. and F.X. Diebold. *Cointegration and Long-Horizon Forecasting*. Mimeo, Department of Economics, University of Pensilvania, 1996 (June).

Clements, M.P. and D.F. Hendry. *On the limitations on Comparing Mean

Square Forecast Errors. Journal of Forecasting, 1993, 617-637.

Dickey, D.A. and W.A. Fuller. *Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root.* Econometrica, 1981, 49, 1057-1072.

Dickey, D.A. and W.A. Fuller. *Distribution of the Estimators for Autoregressive Time Series with a Unit Root.* Journal of the American Statistical Association, 1979, 74, 427-431.

Doan, Thomas. *RATS User Manual.* Evanston, Ill., Estima, 1992,

Doldado, Juan, Tim Jenkinson, and Simon Sosvilla-Rivero. *Cointegration and Unit Roots.* Journal of Economic Surveys 4, 1990, 249-273.

Doornik, Jurgen A. *Testing General Restrictions on the Cointegrating Space,* manuscript.

Elliot, Graham, Thomas J. Rothenberg and James H. Stock. *Efficient Tests for an Autoregressive Unit Root.* Econometrica, 1996, 64, 813-836.

Enders, Walter. *Applied Econometric Time Series.* John Wiley & Sons, Inc., 1995.

Engle, Robert F. and C.W.J. Granger. *Co-integration and Error Correction: Representation, Estimation, and Testing.* Econometrica, 1987, 55, 251-276.

Engle, Robert F. and C.W.J. Granger (eds). *Long-Run Economic Relations: Readings in Cointegration.* Oxford University Press, Oxford, 1991.

Engle, R.F. and B.S. Yoo. *Forecasting and Testing in Cointegrated Systems.* Journal of Econometrics, 1987, 35, 143-159.

Figlewski, S. and T. Urich. *Optimal Aggregation of Money Supply Forecasts: Accuracy, Profitability and Market Efficiency,* Journal of Finance, 1983, vol. 28, 695-710.

Fischhoff, B. *Judgmental Aspects of Forecasting: Needs and Possible Trends.* International Journal of Forecasting, 1988, vol.4, 331-9.

Fuller, W.A. *Introduction to Statistical Time Series.* New York, Wiley, 1976.

Gardner, E.S. and S. Makridakis. *The Future of Forecasting.* International Journal of Forecasting, 1988, vol. 4, 325-30.

Geweke, J. and Porter-Hudak, S. *The Estimation and Application of Long Memory Time Series Models.* Journal of Time Series Analysis, 1983, 221-238.

Goldfeld, S.M. *The Demand for Money Revisited.* Brookings Papers on Economic Activity, 1973, 577-646.

Goldfeld, S.M. and D.E. Siechel. *The Demand for Money.* Handbook of Monetary Economics, 1990, 1, 299-356, Amsterdam, North-Holland.

Goodhart, C. *The Conduct of Monetary Policy.* Economic Journal, 1989, 99, 293-346.

Guilkey, D.K. and P. Schmidt. *Extended Tabulations for Dickey-Fuller Tests.* Economics Letters, 1989, 31, 355-357.

Hall, S.G., S.G.B. Henry and J. Wilcox. *The long run Determination of the UK Monetary Aggregates.*

Economic Modelling at the Bank of England, Chapman and Hall, London, 1990.
Hayashi, Fumio. *Econometrics,* Princeton University Press, 2001.
Hendry, D.F. *Dynamic Econometrics.* Oxford University Press, 1995.
Hendry, D.F. and N.R. Erricson. *Modelling the Demand for Narrow Money in the United Kingdom and the United States.* European Economic Review, 1991, 35, 833-881.
Hendry, D.F. and N.R. Erricson. *An Econometric Analysis of UK Money Demand in Monetary Trends in the United States and the United Kingdom.* European Economic Review, 1993, 81, 1, 8-38-.
Hoffman, Dennis L., Robert H. Rasche. *Assessing Forecast Performance in a Cointegrated System.* Journal of Applied Econometrics, Volume 11, Issue 5, Special Issue: Econometric Forecasting (Sep. – Oct., 1996), 495-517.
Hoffman, Dennis L., Robert H. Rasche. *STLS/US-VECM 6.1: A Vector Error-Correction Forecasting Model of the US Economy.* Working Paper 1997-008A.
Hoffman, Dennis L., Robert H. Rasche. *Long-Run Income and Interest Elasticities of Money Demand in the United States.* The review of Economics and statistics, Volume 73, Issue 4 (Nov. 1991), 665-674.
Hoffman, Dennis L., Robert H. Rasche and M.A. Tieslau. *The Stability of Long-Run Money Demand in Five Industrialized Countries.* Journal of Monetary Economics, 1995, 35, 317-339.
Holden, K. and D.A. Peal. *An Empirical Investigation of Combination of Economic Forecasts.* Journal of Forecasting, 1986, 5, 229-242.
Hylleberg, S. and G.E. Mizon. *Cointegration and Error Correction Mechanisms.* The Economic Journal (Supplement), 1989, 99, 113-125.
Johansen, Soren. *Likelihood-based Inference in Cointegrated Vector Autoregressive Models.* Oxford University Press, 1995.
Johansen, Soren. *Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregression Models.* Institute for Mathematical Statistics, University of Copenhagen, 1989.
Johansen, S. and K. Juselius. *Maximum Likelihood Estimationand Inference on Cointegration – With Application to the Demand for Money.* Oxford Bulletin of Economics and Statistics, 1990, 52, 169-210.
Kang, H. *Unstable Weights in the Combination of Forecasts.* Management Science, 1986, vol. 32, 683-755.
Kennedy, Peter E. *Sinning in the Basement: What are the Rules? The Ten Commandments of Applied Econometrics.* Current draft: May 24, 2001.
Kelejian, H.H. *An Extension of a Standard Test for Heteroskedasticity to a Systems Framework.* Journal of Econometrics. 1982, 20, 325-333.
Kwiatkowski, Dennis, Peter C.B. Phillips, Peter Schmidt & Yongcheol Shin. *Testing the Null Hypothesis of Stationary Against the*

Alternative of a Unit Root. Journal of Econometrics, 1992, 54, 159-178.
Laidler, D. *Monetarist Perspectives.* Cambridge, Harvard University Press, 1966.
Lucas, R.E. *On the Welfare Cost of Inflation.* The University of Chicago, 1994 (February).
Lupoletti, W.M. and R,H. Webb. *Defining and Improving the accuracy of Macroeconomic Forecasts: Contribution from a VAR Model.* Journal of Business, 1986, vol. 59, 263-285.
Lutlepohl, Helmut. *Introduction to Multiple Time Series Analusis.* Springer-Verlag, 1991.
MacKinnon, J.G. *Critical Values for Cointegration Tests.* In R.F. Engle and C.W.J. Granger (eds), Long-run Economic Relationships, Oxford University Press, Oxford, 1991.
McNees, S.K. *On the Future of Macroeconomic Forecasting.* International Journal of Forecasting, 1988, vol. 4, 359-62.
Meltzer, A.H. *The Demand for Money: The Evidence from the Time Series.* Journal of Political Economy, 1963, 71, 219-246.
Moriarty, M.M. and A.J. Adams. *Management Judgement Forecasts, Composite Forecasting Models and Conditional Efficiency.* Journal of Marketing Research, 1984, vol. 21, 239-250.
Nelson, C. and C.I. Plosser. *Trends and Random Walks in Macroeconomic Time Series: Some Evidence and Implications.* Journal of Monetary Economics, 1982, 10, 139-162.
Newey, Whitney and Kenneth West. *Automatic Lag Selection in Covariance Matrix Estimation.* Review of Economic Studies, 1994, 61, 631-653.
Ng, Serena and Pierre Perron. *Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power.* Econometrica, 2001, 69(6), 1519-1554.
Olding-Smee, J. *Comment on "The Exchange Rate and External Trade".* Policemaking with Macroeconomic Models, Aldershot: Gower Publishing, 1989.
Ord, J.K. *Future Developments in Forecasting.* International Journal of Forecasting, 1988, vol. 4, 389-401.
Phillips, Peter C.B. *Discrete Fourier Transforms of Fractional Processes*, 1999a. Unpublished working paper No. 1243, Cowles Foundation for Research in Economics, Yale University.
Phillips, Peter C.B. *Unit Root Log Periodogram Regression*. 1999b. Unpublished working paper No. 1244, Cowles Foundation for Research in Economics, Yale University.
Phillips, P.C.B. and M. Loretan. *Estimating Long-Run Economic Equilibria.* Review of Economic Studies, 1991, 5, 407-436.
Phillips, P.C.B. and P. Perron. *Testing for a Unit Root in Time Series Regression.* Biometrica, 1988, 75, 335-346.
Poole, W. *Monetary Policy Lessons of Recent Inflation and Deflation.*

Economic Perspectives, 1988, 73-100.
Sims, C.A. *Macroeconomics and Reality.* Econometrica, 1980, 48, 1-48.
Stock, J.H. *Point Forecasts and Prediction Intervals for Long Horizon Forecasts.* (Mimeo), J.F.K. School of Government, Harvad University, 1995.
Stock, J.H. and M.W. Watson. *A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems.* Econometrica, 1993, 61, 783-820.
Temperton, P. *UK Monetary Policy – The Challenge for the 1990s.* MacMillan, London, 1991.
Winkler, R.L. and S. Makridakis. *The combination of Forecasts,* Journal of the Royal Statistical Society, Series A, 1983, vol. 146, 150-157.

APPENDIX A. TESTING FOR THE ORDER OF INTEGRATION.

Table A1. ADF, DFGLS, and NG Perron unit root tests.

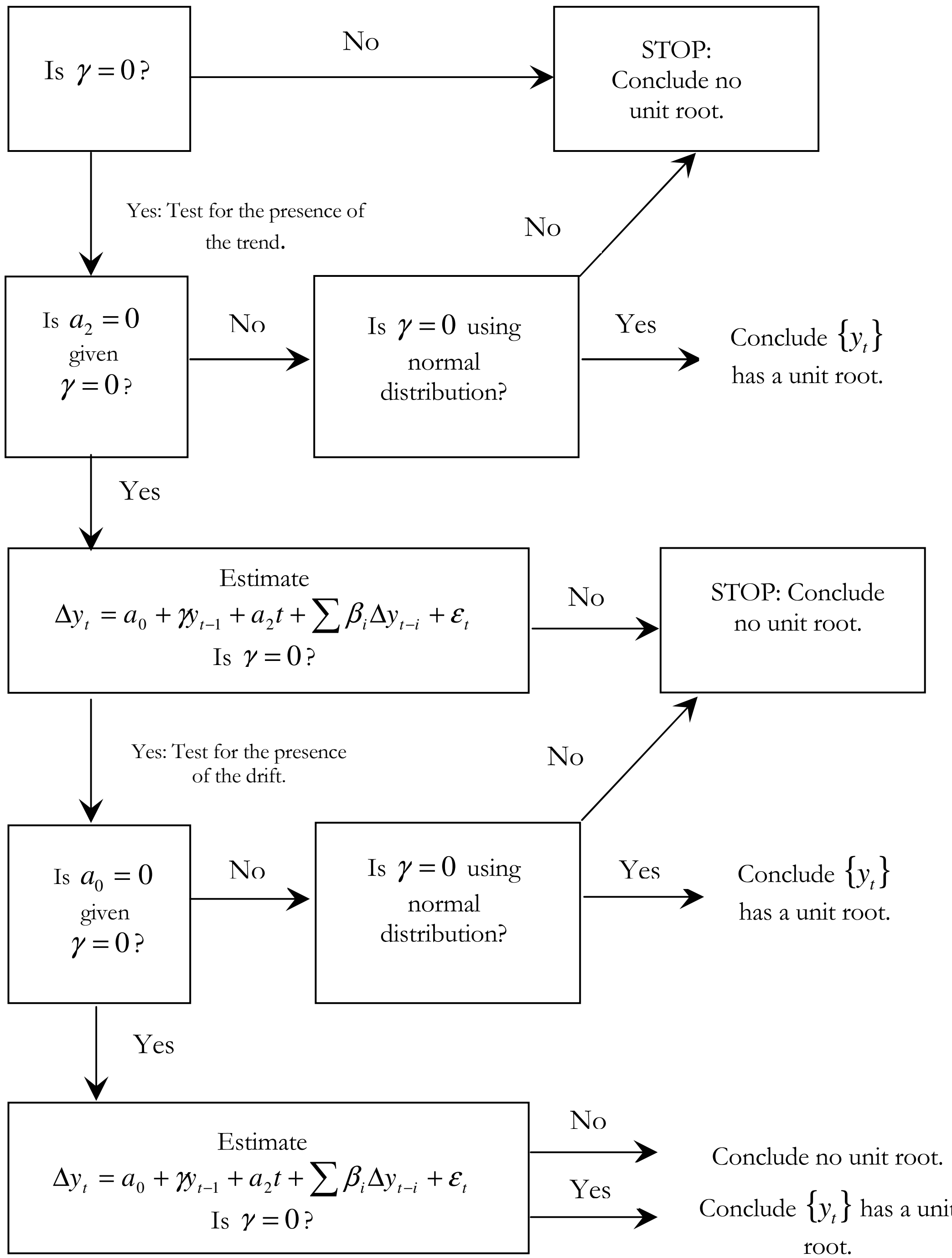
	GDP	INT	MB with intercept	MB with trend
ADF				
AIC	4+	1-	6+	2+
SIC	4+	1-	5+	2+
HQ	4+	1-	6+	2+
MAIC	5+	0+	2+	0+
MSIC	5+	0+	2+	0+
MHQ	5+	0+	2+	0+
DFGLS				
AIC	4+	0+	6+	6+
SIC	4+	0+	6+	6+
HQ	4+	0+	6+	6+
MAIC	4+	0+	5+	5+
MSIC	4+	0+	4+	4+
MHQ	4+	0+	5+	4+
NG Perron				
AIC	4+	0+	6+	6+
SIC	4+	0+	6+	6+
HQ	4+	0+	6+	6+
MAIC	4+	0+	5+	5+
MSIC	4+	0+	4+	4+
MHQ	4+	0+	5+	4+

Table A2. PP and KPSS unit root tests.

	GDP		INT		MB with intercept		MB with trend	
	Banwidth	Level of accept	Banwidth	Level of accept	Banwidth	Level of accept	Banwidth	Level of accept
PP								
NW	10	5%	29	10%	1	10%	10	10%
Andrews	1.2	4%	1.55	10%	1.29	10%	1.32	10%
KPSS								
NW	2,0	10%	4	1%	4	5%	3.4	5%
Andrews	4.1	10%	10	5%	10.7	10%	4.14	5%

Figure A1. A procedure to test for unit roots.

Estimate $\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \sum \beta_i \Delta y_{t-i} + \varepsilon_t$



APPENDIX B. TESTING FOR THE ORDER OF COINTEGRATION.

Table B1. The Johansen test with five assumptions.

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	1	1	1	2	3
Max-Eig	1	1	1	1	1
Log Likelihood by Rank (rows) and Model (columns)					
0	13.56992	13.56992	14.73826	14.73826	17.12090
1	28.50543	28.50544	29.65551	30.26028	31.97965
2	29.75982	34.70370	35.73960	38.28022	39.76920
3	30.42937	35.75376	35.75376	44.03993	44.03993
Akaike Information Criteria by Rank (rows) and Model (columns)					
0	-0.315167	-0.315167	-0.188845	-0.188845	-0.146269
1	-0.931409*	-0.862444	-0.803828	-0.776571	-0.757217
2	-0.604125	-0.807151	-0.809628	-0.846912	-0.880635
3	-0.236508	-0.396811	-0.396811	-0.761375	-0.761375
Schwarz Criteria by Rank (rows) and Model (columns)					
0	0.109166	0.109166	0.376932	0.376932	0.560953
1	-0.224187*	-0.108074	0.044838	0.119244	0.232893
2	0.385986	0.277256	0.321927	0.378940	0.392365
3	1.036491	1.017633	1.017633	0.794514	0.794514

Table B2. The Johansen test without a trend and an intercept.

Unrestricted Cointegration Rank Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 Percent Critical Value	1 Percent Critical Value
None *	0.648673	28.25281	24.31	29.75
At most 1	0.121282	3.147886	12.53	16.31
At most 2	0.001869	0.044907	3.84	6.51

*(**) denotes rejection of the hypothesis at the 5%(1%) level
Trace test indicates 1 cointegrating equation(s) at the 5% level
Trace test indicates no cointegration at the 1% level

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5 Percent Critical Value	1 Percent Critical Value
None **	0.648673	25.10493	17.89	22.99
At most 1	0.121282	3.102979	11.44	15.69
At most 2	0.001869	0.044907	3.84	6.51

*(**) denotes rejection of the hypothesis at the 5%(1%) level
Max-eigenvalue test indicates 1 cointegrating equation(s) at both 5% and 1% levels

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

MB	GDP	INT
2.086567	-2.195653	0.600491
4.684440	-2.759126	-0.050859
-2.443111	0.971367	0.058154

Unrestricted Adjustment Coefficients (alpha):

D(MB)	-0.034098	-0.005636	-0.003390
D(GDP)	0.017227	0.019372	-0.002557
D(INT)	-0.455958	0.352436	0.052292

1 Cointegrating Equation(s): Log likelihood 21.71549

Normalized cointegrating coefficients (std.err. in parentheses)

MB	GDP	INT
1.000000	-1.052280	0.287789
	(0.08381)	(0.04619)

Adjustment coefficients (std.err. in parentheses)

D(MB)	-0.071148
	(0.03914)
D(GDP)	0.035946
	(0.03834)
D(INT)	-0.951386
	(0.75225)

APPENDIX C. MODEL DYNAMICS AND RESIDUAL ANALYSIS.

Table C1. Chi-squared test statistics for lag exclusion.

	D(MB)	D(GDP)	D(INT)	Joint
Lag 1	9.215456	4.684113	5.474987	22.11910
	[0.026559]	[0.196444]	[0.140142]	[0.008509]
Lag 2	2.896446	2.996049	7.081992	21.07982
	[0.407868]	[0.392235]	[0.069330]	[0.012301]
Lag 3	4.085767	2.796767	1.705745	13.34518
	[0.252351]	[0.424032]	[0.635657]	[0.147599]
Lag 4	1.853680	0.375271	1.595294	5.970101
	[0.603324]	[0.945302]	[0.660457]	[0.742907]
df	3	3	3	9

Note: Numbers in [ ] are p-values

Table C2. The lag length criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	18,25	NA	4,7E-05	-1,45	-1,30*	-1,42
1	25,25	11,32	5,8E-05	-1,26	-0,66	-1,13
2	39,69	19,25*	3,7E-05	-1,78	-0,74	-1,55
3	54,83	15,86	2,4E-05*	-2,36*	-0,87	-2,04*
4	61,12	4,80	4,6E-05	-2,11	-0,17	-1,69

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

Table C3. Chi-squared test statistics for lag exclusion.

	D(MB)	D(GDP)	D(INT)	Joint
Lag 1	11.64960	14.24383	2.868565	24.99030
	[0.008685]	[0.002591]	[0.412337]	[0.002982]
Lag 2	6.794024	21.89509	9.928710	42.66446
	[0.078761]	[6.86E-05]	[0.019182]	[2.48E-06]
Lag 3	3.745986	13.49620	2.222486	19.72659
	[0.290232]	[0.003678]	[0.527533]	[0.019677]
df	3	3	3	9

Note: Numbers in [ ] are p-values

Table C4. VAR model with two lags.

	D(MB)	D(GDP)	D(INT)
D(MB(-1))	-0.158344	0.093510	7.061394
	(0.18722)	(0.24026)	(3.79262)
	(-0.84578)	(0.38920)	(1.86188)
D(MB(-2))	0.310602	-0.020321	6.576342
	(0.18598)	(0.23867)	(3.76750)
	(1.67012)	(-0.08514)	(1.74555)
D(GDP(-1))	-0.240111	-0.288490	-0.783242
	(0.16050)	(0.20598)	(3.25139)
	(-1.49603)	(-1.40060)	(-0.24089)
D(GDP(-2))	-0.274991	-0.659257	-2.890934
	(0.18011)	(0.23115)	(3.64873)
	(-1.52677)	(-2.85211)	(-0.79231)
D(INT(-1))	-0.015098	0.001258	0.176504
	(0.00928)	(0.01191)	(0.18795)
	(-1.62727)	(0.10567)	(0.93910)
D(INT(-2))	0.010073	-0.004591	-0.285070
	(0.00621)	(0.00797)	(0.12578)
	(1.62243)	(-0.57613)	(-2.26644)
C	0.024557	-0.004581	-0.644378
	(0.01353)	(0.01737)	(0.27415)
	(1.81456)	(-0.26374)	(-2.35043)

Note: standard errors & t-statistics in parentheses

Table C5. Chi-squared test statistics for lag exclusion.

	D(MB)	D(GDP)	D(INT)	Joint
Lag 1	7.949304	5.093642	2.083391	14.08240
	[0.047071]	[0.165067]	[0.555280]	[0.119424]
Lag 4	4.066337	23.94939	10.23104	39.04823
	[0.254389]	[2.56E-05]	[0.016701]	[1.13E-05]
df	3	3	3	9

Note: Numbers in [ ] are p-values

Table C6. VAR model with the first and the fourth lags.

	D(MB)	D(GDP)	D(INT)
D(MB(-1))	0.412210	0.601712	-1.134401
	(0.24775)	(0.28867)	(5.47251)
	(1.66380)	(2.08446)	(-0.20729)
D(MB(-4))	0.094804	-0.150401	-0.805878
	(0.09119)	(0.10625)	(2.01437)
	(1.03958)	(-1.41548)	(-0.40007)
D(GDP(-1))	-0.266922	-0.266810	1.848543
	(0.15013)	(0.17492)	(3.31611)
	(-1.77797)	(-1.52533)	(0.55744)
D(GDP(-4))	0.072892	0.821517	2.599974
	(0.14776)	(0.17216)	(3.26378)
	(0.49332)	(4.77186)	(0.79661)
D(INT(-1))	-0.014491	0.009929	0.244390
	(0.00860)	(0.01002)	(0.19003)
	(-1.68444)	(0.99052)	(1.28608)
D(INT(-4))	-0.001684	0.001165	0.277824
	(0.00473)	(0.00551)	(0.10452)
	(-0.35595)	(0.21132)	(2.65805)
C	0.014551	-0.006678	0.069401
	(0.01376)	(0.01603)	(0.30397)
	(1.05739)	(-0.41647)	(0.22831)

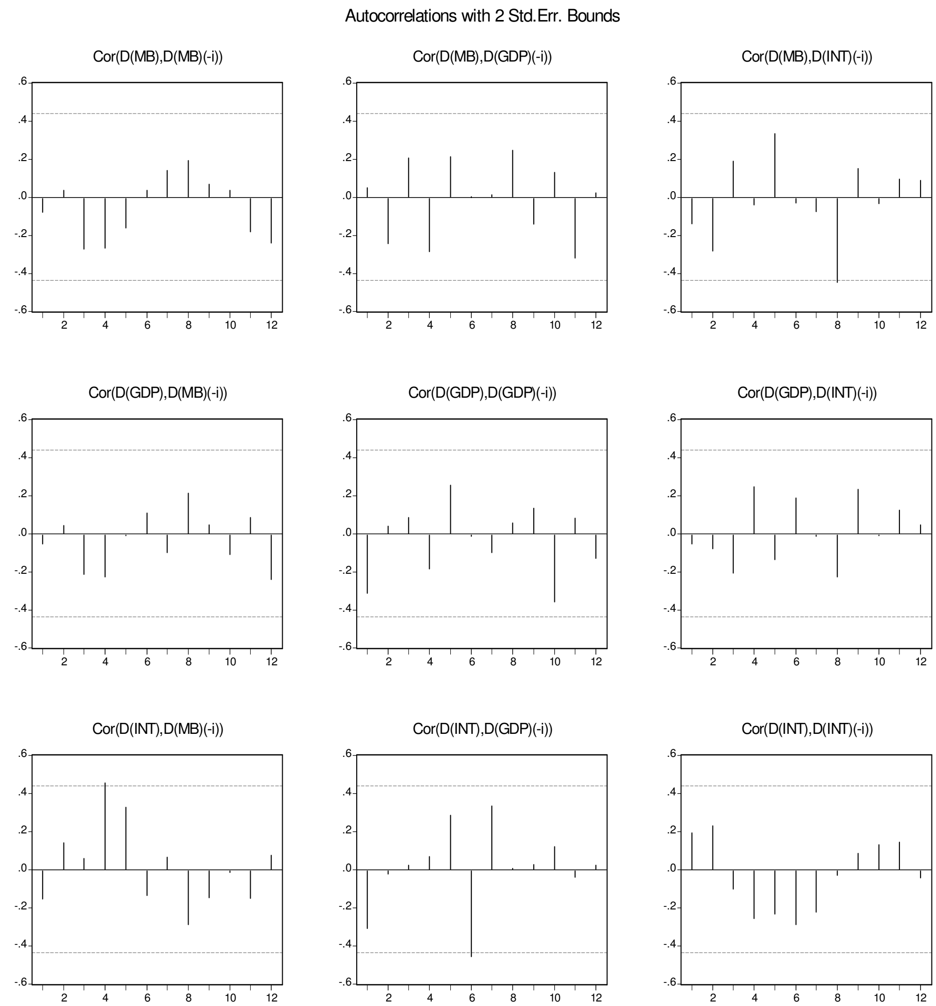


Figure C1. Pairwise autocorrelations for the VAR model with the first and the fourth lags.

Table C7. VEC model with the first and the fourth lags.

Cointegrating Eq:	CointEq1		
MB(-1)	1.000000		
GDP(-1)	-0.961360		
	(0.16188)		
	(-5.93875)		
INT(-1)	0.212341		
	(0.09243)		
	(2.29724)		
Error Correction:	**D(MB)**	**D(GDP)**	**D(INT)**
CointEq1	-0.040892	0.039600	-1.809579
	(0.04014)	(0.04572)	(0.74229)
	(-1.01872)	(0.86605)	(-2.43785)
D(MB(-1))	0.335160	0.734288	-9.035853
	(0.29181)	(0.33241)	(5.39628)
	(1.14854)	(2.20901)	(-1.67446)
D(MB(-4))	0.063447	-0.134764	-1.052103
	(0.08727)	(0.09940)	(1.61372)
	(0.72707)	(-1.35572)	(-0.65197)
D(GDP(-1))	-0.268474	-0.279395	2.871647
	(0.15042)	(0.17135)	(2.78167)
	(-1.78478)	(-1.63057)	(1.03235)
D(GDP(-4))	0.092493	0.796159	3.961607
	(0.15100)	(0.17201)	(2.79239)
	(0.61252)	(4.62860)	(1.41871)
D(INT(-1))	-0.012155	0.006962	0.402318
	(0.00927)	(0.01056)	(0.17150)
	(-1.31064)	(0.65906)	(2.34593)
D(INT(-4))	-0.002594	0.001042	0.315368
	(0.00448)	(0.00511)	(0.08291)
	(-0.57863)	(0.20406)	(3.80370)

Note: standard errors & t-statistics in parentheses

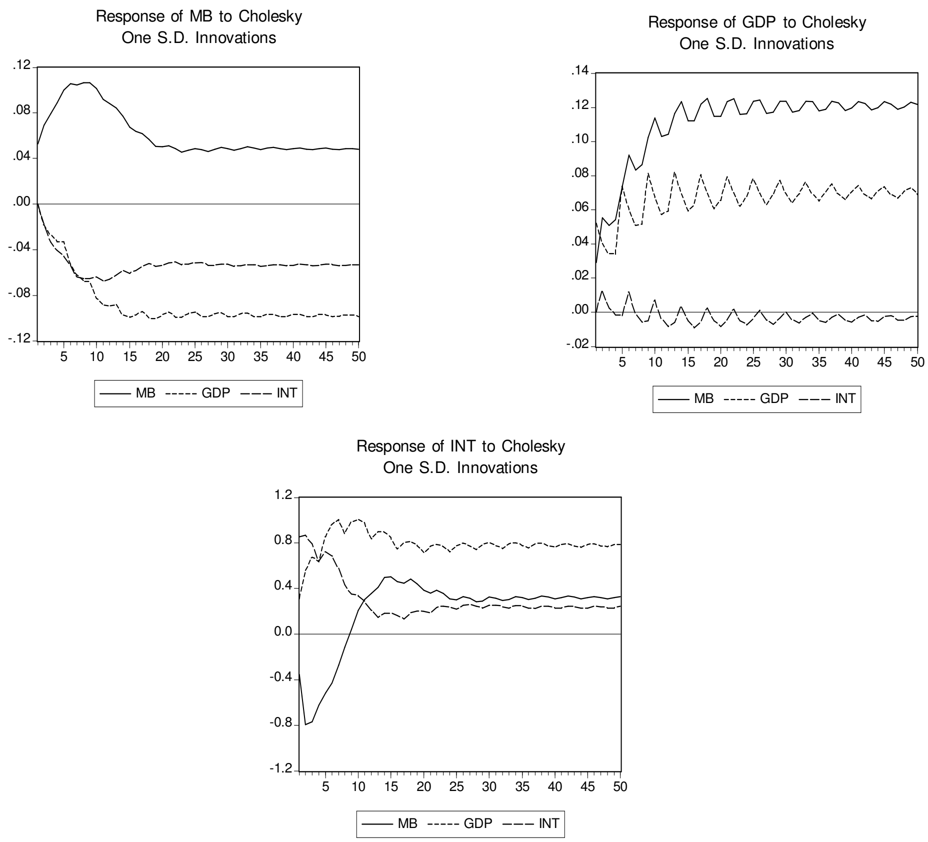


Figure C2. Impulse response functions for the VEC model with the first and the fourth lags.

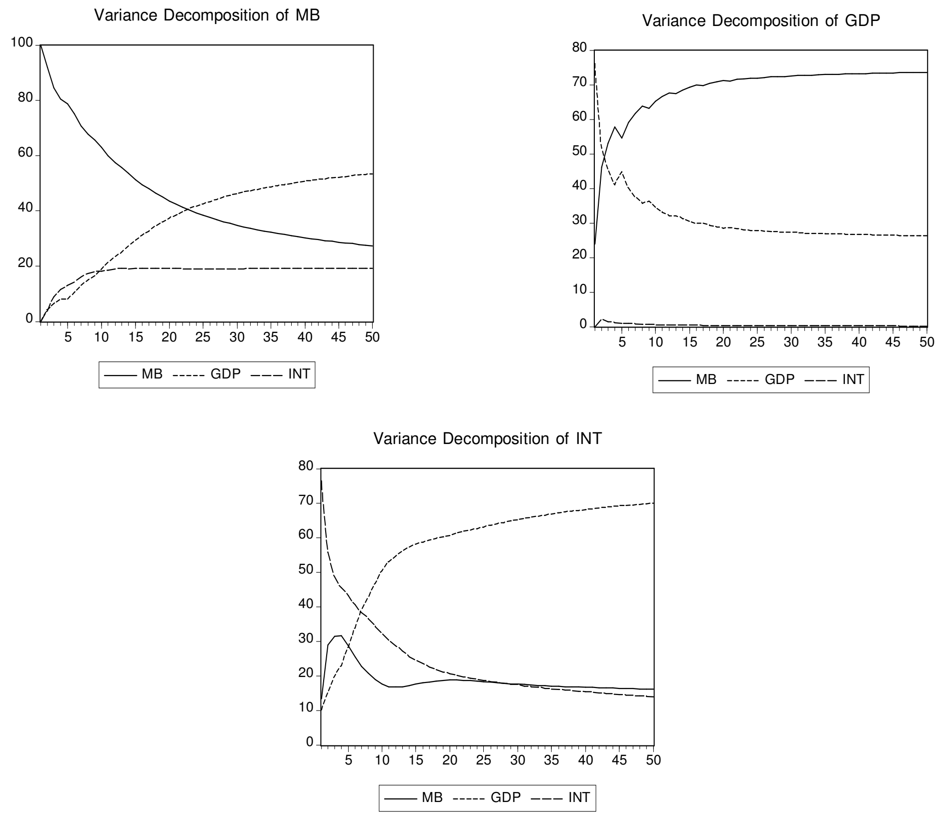


Figure C3. Variance decomposition functions for the VEC model with the first and the fourth lags.