universität wien

Diplomarbeit

Titel der Diplomarbeit

“The Dynamics of Interest Rates in the Czech Republic, Hungary and Poland:
A Vector Autoregressive Latent Yield and Macro Factor Approach”

Verfasser

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angestrebter akademischer Grad

Magister der Sozial- und Wirtschaftswissenschaften

(Mag. rer. soc. oec.)

Wien, im September 2008

Studienkennzahl:	A-157
Studienrichtung:	Diplomstudium Internationale Betriebswirtschaft
Betreuer:	a.o. Univ.-Prof. Dipl.-Ing. Dr. Erhard Reschenhofer

“The art of simplicity is a puzzle of complexity.”

- Doug Horten

Abstract

Economic dynamics in small open economies are ruled by complex structures and interdependencies. Interest rate developments are closely related to those macroeconomic dynamics. It is therefore important for policy setters, portfolio and risk managers to better understand these dynamics. This thesis analyses interdependencies between macroeconomic variables and interest rates in an integrated setting. The aim is to model the interaction of macro variables with the term structure and to forecast the yield curve.

Interest rate dynamics are decomposed into three latent factors according to the Diebold and Li exponential component framework. Additionally, macro economic variables carrying important information of the state of the economy are defined. To utilize broader macroeconomic information the principal components methodology is used to summarize the dynamics of a collection of macroeconomic variables reducing the complexity and filtering noise. Yield and macro factors are combined in a vector autoregressive (VAR) model setting.

Models are formulated and estimated for the small open economies of the CEE-3 countries (Czech Republic, Hungary and Poland). Recursive out-of-sample yield forecasts of the yield curve with forecasting horizons up to twelve months ahead are calculated. The models´ term structure forecasting performance is evaluated and benchmarked. Moreover, interdependencies of the yield curve with the macroeconomy are analysed and interpreted.

Evaluation of the forecasting performance of the models shows good results. On average over the maturity structure the models outperform random walk forecasts for all forecasting horizons, improving forecasting performance up to 38.3%. Additionally, Hungarian and Polish models outperform implied forward rates on average for all horizons.

Granger causality tests, impulse response and variance decomposition analysis reveals strong bidirectional dependencies of the macroeconomy and the yield curve. Not unexpectedly the exchange rate channel takes centre stage.

Zusammenfassung

Makroökonomische Dynamiken in kleinen offenen Volkswirtschaften sind bestimmt von komplexen Strukturen und Interdependenzen. Veränderungen der Zinslandschaft sind wiederum maßgeblich beeinflussend für die makroökonomische Entwicklung. Es ist daher von maßgeblichem Interesse für Zentralbanker, Portfolio- und Risikomanager diese Dynamiken besser zu verstehen. Diese Diplomarbeit analysiert diese Interdependenzen der makroökonomischen Variablen mit der Zinskurve in einem integrierten Ansatz. Das Ziel ist es, die Interaktionen der Makrovariablen mit der Zinskurve zu modellieren und Zinsprognosen zu erstellen.

Veränderungen der Zinskurve werden durch drei latente Faktoren, die mit Hilfe eines von Diebold und Li entwickelten exponentiellen Komponentenverfahrens modelliert werden, dargestellt. Im Weitern werden makroökonomische Variablen definiert, die wichtige Informationen über den Status der Wirtschaftsentwicklung enthalten. Um ein größeres Spektrum an makroökonomischen Informationen zu nutzen, kommt die Principal Component Methode zum Einsatz, die die dynamische Entwicklung einer Sammlung mehrer makroökonomischer Variablen in reduzierter Form und mit herabgesetztem Rauschen darstellt. Zinsfaktoren und Makrofaktoren werden in einem Vektorautoregressiven (VAR) Modellansatz kombiniert. Verschiedene Modelle werden formuliert und für die CEE-3 Länder Tschechien, Ungarn und Polen geschätzt. Rekursive out-of-sample Prognosen der Zinsstrukturkurve mit bis zu einem maximalen Prognosehorizont von 12 Monaten werden berechnet. Die Prognosequalität der Modelle wird evaluiert und mit Benchmark-Modellen verglichen. Zusätzlich werden die Interdependenzen der Zinsstrukturkurve mit der Makoökonomie untersucht und interpretiert.

Die Evaluierung der Prognosequalität zeigt gute Resultate. Die auf unserem Modell basierenden Prognosen sind durchschnittlich über die Zinskurve gesehen für alle Prognosehorizonte den Random-walk basierenden Vorhersagen überlegen, mit bis zu 38,3% verbesserter Prognosequalität. Weiters sind die Modelle in Ungarn und Polen den impliziten Forward-Zinssätzen durchschnittlich in allen Prognosehorizonten überlegen.

Analysen der Granger-Kausalität, Impulse Response und Variance Decomposition belegen die starke bidirektionale Abhängigkeit der Makroökonomie mit der Zinsstukturkurve. Nicht unerwartet steht dabei der „Exchange Rate Channel“ im Mittelpunkt.

Acknowledgements

This work is the result of many interesting student years. Fortunately, studying is so much more than textbooks and articles. It is the interaction with others, some more some less inspiring, what makes studying the real experience. In the following I would like to point out those who have been most influential and stimulating.

I would like to thank Prof. Erhard Reschenhofer, my thesis supervisor, for his outstanding support. His openness and tutorship made the use of statistical methods and their application to macroeconomics and finance so much easier. To add scientific color, I have conducted the following research. Calculation of his longest response time to my numerous questions and requests by email revealed: I have never waited longer than four hours to receive his reply!

Additionally, I owe gratitude to Prof. Michael Hauser and Prof. Josef Zechner for helpful inputs developing the topic.

The latter was also my mentor in the Portfolio Management Program at the Institute for Strategic Market Research. The program run jointly with DI Peter Pühringer, Prof. Engelbert Dockner and Dr. Otto Randl provided a great practical learning experience in asset and risk management.

Thanks to Christian Grein, Gerhard Lecher, Horst Kuch and Thomas Wihan from UNIQA Financial Services, for lengthy discussions and helpful comments. Especially Thomas for his extensive willingness to work together with me, his mentorship means a lot to me.

Further, I am very thankful to Amir Eid for his methodological advice and Lukas Götz for cross checking the R programming code.

I appreciated Heni’s patience and thank her for providing the right mix of support and motivation which helped to drive things to the finish.

Not directly involved in the working process, but still very influential in their special way have been Prof. Glenn Buhr and his wife Florence for integrating me to their family and making together with David Peterson my stay at Simpson College possible. It was at Simpson College where I met Prof. Gary Newell who introduced me to pattern recognition techniques and Bayesian statistics. His great and personal teaching approach let me as the young tween realize that there are more “sexy” things in life, than sports and the opposite gender.

Last but not least, my parents Heidegard and Rainer. Not only for the financial assistance making so many things possible, but rather for providing me the emotional support so important in life.

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1 Introduction

As interest rate movements drive to a large extent the performance of a bond portfolio, interest rate forecasts are essential for fixed income portfolio management and asset allocation processes. Trends in the regulatory environment focusing on market based valuation and solvency, force institutional investors to face new challenges in their planning and risk management procedures. Additionally, the valuation of liabilities of life insurance companies and pension funds depends on interest rate developments. Understanding term structure developments and predicting the term structure in the future is therefore an important task for managers in this field. They face important decisions where to position on the yield curve, making the complete term-structure important for prudent management and risk analysis.

Yield curve dynamics are closely related to the macro fundamental development of the economy. From a practitioner's perspective it must be therefore the goal to better understand this integrated dynamics to improve decision making and hence portfolio performance and risk management. The purpose of this thesis is to gain understanding of the combined interaction of the yield curve and macro economic developments for the CEE-3 region and predict term structure developments into the future. The goal is to build a model accurate enough to accomplish the above mentioned tasks and to be as parsimonious as possible.

There is a wide range of financial economic research of modeling the term structure. Term structure models decomposing the yield curve into latent factors are a parsimonious and effective method to model large cross sections of the yield curve. Prominent proponents of factor term structure models are Nelsen and Siegel (1987), modeling the US yield curve parametrically by a constant and a Laguerre function. They find the best fitting values for the three coefficients building the term structure dynamics by ordinary linear least squares methodology. Their parsimonious model is able to generate most shapes of the yield curve observed in reality and has good in-sample fitting properties.

Litterman and Scheikman (1991) determine common unobservable factors effecting returns of U.S. government bonds. They show that their latent three factor model can explain on average 98.4 percent of yield variance. The factors are interpreted and labeled by means of their impact on the yield curve. Additionally they show that factor models can improve hedging performance, compared to standard duration hedging.

Bliss (1997) models the U.S. yield curve by the first three principal components and by rotating factor loadings to load approximately equally on the first factor for all maturities, he verifies the interpretation of the factors as level, slope and curvature. Bliss extends the research by analyzing factor dynamics by evaluating time-series behavior. Impulse-response functions based on a VAR model are generated. He proposes hedging strategies based on factor duration of the portfolio and shows the analogy to the Macaulay duration concept.

Diebold and Li (2006) use a variation of the Nelson and Siegel exponential component framework to model the entire U.S. yield curve by three latent factors evolving dynamically. Their model is consistent with a wide range of stylized facts of the empirical term structure. Furthermore, they propose and estimate autoregressive models to describe the dynamics of the factors and use these models to produce yield forecasts for both short and long horizons.

Latent factors prove very useful in explaining changes in the yield curve, but do not convey information on the cause of the change.

Another area of research focuses on utilizing a broad set of economic information for model building. Dynamic Factor Models (DFMs) have become a popular building block of macroeconomic analysis and forecasting. Today's information systems make large datasets easily available to the researcher of empirical macroeconomics. Utilizing this larger base of information should improve economic model conclusions and forecasts. But conventional large scale economic models are prone with running into scarcity degree of freedom problems. Researchers are forced to pick a small number of variables from a larger set of potential variables. Therefore, model performance will strongly depend on the selection process of variables. DFMs alleviate this problem by aggregating the information of large information sets into a small number of factors. This dimension reduction property makes DFMs especially powerful in data-rich model settings.

In a seminal paper, Stock and Watson (2002) propose an alternative to selecting a few predictor variables by pooling the information of all candidate predictors. They suggest that the informational content from a large number of time series can be effectively summarized in a small number of estimated factors, by breaking down the cross-sectional information into common components. They build an approximate dynamic factor model, which relates the variables to be forecast to the pool of predictor variables in a two-step process. In the first step the common components are derived as factors to be included in the model. These latent factors are unobservable but can be easily ranked by their informational content and a few factors are enough to explain most of the cross-sectional variation, leading to an enormous dimension reduction by averaging away idiosyncratic variation in the individual time series. Stock and Watson label these factors “diffusion indexes”. Diffusion indexes are used to forecast economic variables of interest. They show that only 6 factors account for much of the total variance within their large macro economic data set, consisting of 215 time series for the United States. Additionally they produce very competitive regression forecasts on the basis of only a few factors, outperforming univariate autoregressions, small vector autoregressions and leading indicator models.

Bernanke, Boivin and Eliasz (2005) combine the strength of latent macro factors with the methodology of vector autoregression (VAR). They estimate a VAR model, combining factors extracted from large macro panel data and observable economic variables, as a solution to the degree of freedom problem in standard VAR analysis. Consistently they name this approach the factor augmented VAR (FAVAR) model. They use this setting to model and analyze the monetary policy transition mechanisms for the US economy on a broad macro economic data set. They show that the inclusion of a broader information set does indeed solve the liquidity puzzles observed under a standard VAR model with above named selection problems as Sims (1992) suggested. He blames the existence of the price puzzle in conventional VAR model analysis to monetary policy shocks to the fact that variables selected might not coincide with the information set available to central banks. Therefore if central banks tighten monetary conditions in anticipation of inflationary pressures as indicated in signals of the larger data and this information is not captured in the VAR variables, the monetary policy shock can not be evaluated properly. In reality the central bank reacts on grounds of better inflation information and the policy shock might offset parts of the inflation dynamics but still leading to higher price levels. If this is the case and the problem of limited information holds true this has the potential to distort all the possible impulse responses from the standard VAR methodology.

Additionally, they compare two different estimation techniques. The computationally challenging Likelihood-Based Gibbs Sampling Method, where all parameters and factors are estimated jointly, is compared to the performance of calculation in a two-step procedure. First the common components are estimated using principal components methodology. In a second step the VAR equation is estimated. They find similar performance of the two methodologies, with the two-step approach tending to produce more plausible responses.

Mönch (2005) uses the FAVAR methodology to forecast the U.S. yield curve. Applying a broad economic data set he models and forecasts yields within an affine no-arbitrage setting with encouraging results.

Despite the success of latent macro factors to utilize a wide range of macro economic information they are not easy to interpret in an economic sense. Factors can be regressed on the original time-series and their explanatory power can be evaluated. Nevertheless a clear economic interpretation is challenging. This difficulty poses a major shortcoming if mutual dynamics of the macro factors and the yield curve are evaluated. This shortcoming can be addressed by pooling time-series into groups representing economic sub-categories and performing principal components analysis within the group. This way the principal components can be assigned a specific economic interpretation.

Ang and Piazzesi (2003) address the interaction of macro factors with the yield curve by augmenting a latent factor model with macro economic factors using the latter methodology. Their approach is to estimate a model based on macro dynamics and a short rate Taylor rule as an affine no-arbitrage term structure in a two-step procedure.

They conclude that for the US yield curve up to 85% of yield variation is driven by the first principal components of macro variables explaining inflation and economic real activity and that the inclusion of there macro factors is improving out-of-sample forecasting performance. They impose independence between the latent and macro factors.

There is common agreement that the yield curve carries information about the probable macro economic developments. Harvey (1988) shows that expected real interest rates predict consumption growth well. Estrella and Hardouvelis (1991) associate the slope of the yield curve with future increases in the real activity of the economy, providing extra predictive power compared to leading indicator indexes.

Mönch (2006) models U.S. yields with Diebold Li factors in connection with four latent macro factors extracted from a set of 25 macroeconomic time series. He finds explanatory power of the curvature factor on industrial production. A shock in curvature leads to a humped shaped response of the yield curve slope factor and subsequently leading to a decline of output with a lag of around one year.

Diebold, Rudebusch and Aruoba (2006) provide a model characterization relaxing the independence between latent yield factors and observable macro factors finding strong statistical evidence of mutual dynamic influence. The probability of the yield-macro causality is somewhat weaker than vice versa.

Cushman and Zha (1997) focus on the issue of correctly identifying monetary policy in small open economies with flexible exchange rate regimes. The importance of the exchange rate channel is stressed. Small open economies are not only susceptible to domestic shocks but also to external ones. Monetary authorities in small open economies are therefore considered to respond quickly to foreign shocks, mainly to interest rate differentials and the exchange rate.

Maćkowiak (2007) concludes that macroeconomic fluctuations of emerging markets are importantly influenced by external shocks. External shocks account for approximately fifty percent of the variation in the exchange rate and the price-level and strongly affecting real activity and short-term interest rates.

To accomplish the goal to analyze macro and yield interdependencies within the CEE-3 countries the above research builds a good basis for analysis. From a practitioner's perspective the model has to balance between model accuracy and complexity. The selected model has to be parsimonious enough to be put into daily operation.

I therefore decided to model yield dynamics according to a three latent factor framework. This approach is able to model a wide range of interest rates in the term structure at reduced complexity. The latent factor yield curve dynamics are evaluated using univariate and multivariate autoregressions. Additionally latent yield factors are augmented by macro factors to analyze the economic cause of the change and its structure.

First the yield curve is decomposed period-by-period into three latent factors driving the yield curve dynamics. The time varying factors modeling the yield curve can be interpreted as level, slope and curvature. This approach has been developed by Diebold and Li as a variant of the Nelson and Siegel exponential components functional form, possessing a variety of advantages. Due to the parametric loadings, interpretation of the factors as level, slope and curvature is straightforward compared to principal components methodology where loadings may have to be rotated before interpretation is possible.

In a second step macro dynamics are added to the model. The openness and the emerging nature of the CEE-3 countries have to be taken into account for the model building. To utilize a broader economic information two groups of macro economic data sets are established, explaining economic real activity and inflation, and are grouped accordingly. Subsequently, the complexity of this macroeconomic information in each group is reduced by principal components analysis (PCA). PCA transforms the original variation of the data set into uncorrelated unobservable factors ranked by explanatory power. The first factor is explaining the biggest share of the underlying dynamics. The first principal component of real activity and inflation, respectively, are added to the model as latent macro factors. Additionally the level spread to the German benchmark yield curve, defined as the difference of the level factor of the domestic yield curve to the German one, and the nominal effective exchange rate and the central bank base interest rate are added to the model. These unobservable and observable macro factors are used in conjunction with the yield factors level, slope and curvature to form a vector autoregressive model. This two-step approach might suffer of inefficiencies, since yield and macro factors are not estimated jointly with model parameters. Nevertheless, the two-step approach shows good empirical performance at computational simplicity and it is, therefore, chosen for my endeavor. Information criteria are used to choose the optimal lag structure of the VAR. After assessing the in-sample fit of the latent yield factor model, recursive out of sample forecasts for interest rates will be computed. The forecast performance of the models will be benchmarked to the performance of market based forecasts and the random walk.

2 Implementation with R

All calculations and programming in this thesis has been implemented within the R software environment.[1] R is a software package and programming language for statistical computing and graphics. R is available for free under the GNU license and can be viewed as an alternative implementation of the statistical programming language S, as most of the code written for S will run under R unaltered. Within the R environment a wide variety of statistical techniques is implemented. R allows users to add additional functionality by writing their own code, often officially distributed as R packages, after a quality assessment. This makes R a powerful tool for my task. I have extensively used the vars and pcaMethods R packages and owe great gratitude to the developers of these tools and R in general. Please see the appendix for a copy of the R programming code of my implementation.

[1] The R Project Homepage (http://www.r-project.org) gives detailed information on R and its developments

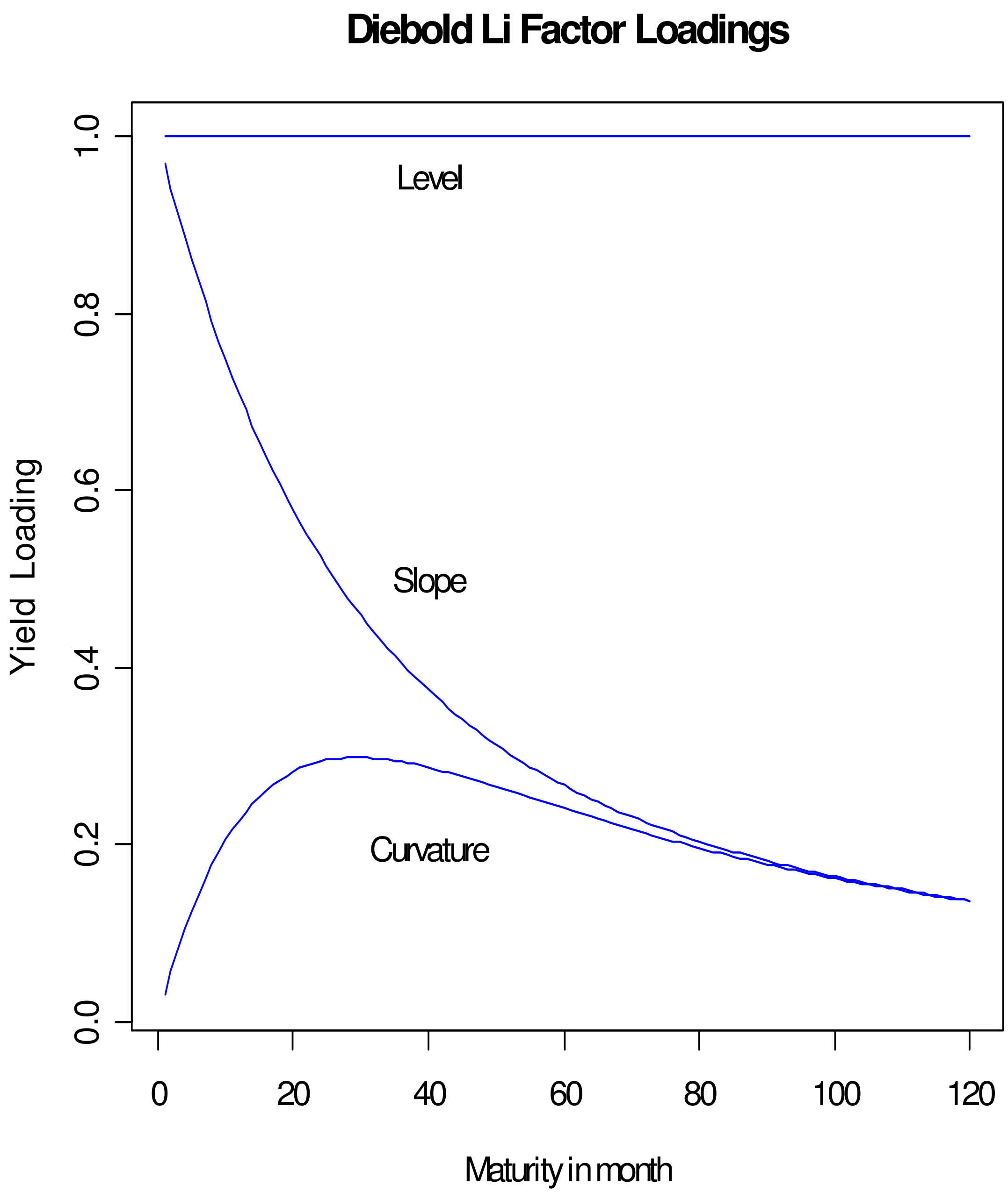
3 Modeling the Term Structure of Interest Rates

The chosen framework for fitting and forecasting the yield curve is according to the exponential component framework as proposed by Diebold and Li (2006) as a variant of the renowned Nelson-Siegel (1987) decomposition of yields. Yield curve dynamics are decomposed into three latent factors which can be interpreted by the effect on the yield curve as level, slope and curvature.
Starting point is the description of the term structure with yield data for the various maturities (denoted as τ) at certain points in time (denoted as t). Therefore $Y_t(\tau)$ is the yield of maturity τ at time t. The vector Y_t containing a collection of all maturities τ is the yield curve representation of time t.
In the Diebold-Li approach the yield curve is fitted due to the following formula

$$Y_t(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1-e^{-\lambda_t \tau}}{\lambda_t \tau}\right) + \beta_{3t}\left(\frac{1-e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau}\right), \quad (3.1)$$

where β_{1t}, β_{2t} and β_{3t} are the latent factors driving the yield curve dynamics. Within the loadings of the factors λ_t denotes a shape parameter governing the exponential decay rate and τ is the maturity of the yield curve segment to be fitted. Small values of λ_t produce slow decay fitting the long end of the yield curve better, while large values lead to faster decay giving a better fit to short maturities of the yield curve. Additionally λ_t is responsible for determining where the loading on β_{3t} achieves its maximum. The loading on β_{1t} is constant at 1 having the same impact towards all maturities. β_{2t}´s loading is starting at 1 before monotonically declining to 0 with increasing maturity. The loading on β_{3t} starts at 0 then increases for a time period before decaying back to 0, therefore inducing the strongest impact on the middle-part of the yield curve. Due to the above impact of the loading structure on different maturities of the yield curve can β_{1t} be interpreted as a long-term factor, β_{2t} as a short-term factor and β_{3t} as a medium-term factor.

Figure 1 - Diebold Li Factor Loading Graph (λ_t set to 0.0609)



To keep the modelling parsimonious λ_t is fixed at a pre-specified value facilitating the computation of the factors. When λ_t is fixed, the factors β_{1t} , β_{2t} and β_{3t} can be derived by ordinary least squares regression, simply regressing yields onto the factor loadings depending partially on τ and

λ_t. The yield $Y_t(\tau)$ can be derived back from the regression coefficients times the respective loadings and the complete yield curve can be constructed by the three factors only.

Empirically it has been shown that a value of λ_t maximizing the loading of the curvature factor β_{3t} at a maturity of 30 month has good practical properties. The value of λ_t is therefore fixed at 0.0609 achieving exactly that. The factor loading graph in Figure 1 clearly explains the interpretation of the factors as level, slope and curvature. One obvious advantage of the Diebold-Li approach is that for a set of factors any possible maturity of the yield curve can be derived by means of the parametric factor loadings. This is a clear advantage over traditional factor models where only included yield segments can be modeled without additional interpolation techniques.

Note that the chosen model does not guarantee arbitrage-free pricing of the yield curve. Nevertheless as the factors are fitted from market data it should mirror arbitrage-free pricing to the extend present in market data. As elaborated above, the focus of this thesis is from a practitioner's perspective pursuing the goal of simplicity. The main goal is to forecast the yield curve into the future and the Diebold Li framework has proven to be successful achieving this goal in a parsimonious setting, making it especially appealing to practitioners.

3.1 Yield Data

As input I use month-end yield data from June 1998 to January 2008 from Bloomberg's Zero Coupon Fair Market Yield Curve Index.[2] The chosen yield curve is the constant maturity synthetic discount bond yield representation of the bond market fitted to best price all securities of the market correctly. To achieve this task a wide range of market makers is polled and from this data base of quotes the zero-curve modeled. This allows bonds with different structures to be compared on an equivalent basis.

The chosen yields ($Y_t(\tau)$) entering the model are the 3, 6 month, 1, 2, 3, 4, 5, 6, 7, 8, 9 and 10 year maturity at the last trading day in the month (t). Please note

[2] Bloomberg Ticker information Czech Rebublic: F480XX Index; Hungary: F114XXX Index; Poland: F119XXX INDEX (XXX stands for the individual maturity segment)

that in the sequel maturity (τ) will be expressed in month. I proceed by analyzing the yield data and the different shapes of the yield curve for the sample.

3.1.1 Czech Republic

At the start of the sample in June 1998 the Czech yield curve has its highest level and is inverted. In the following the curve levels off by 8 yield percent at the short end and 4.3 percent in the long end, decreasing the inversion of the term structure. From January 1999 the curve begins to be upward sloping. The 10-year 3-month term spread is increasing to above 300 basis points at the end of the year 2003. The yield curve is continuing to decrease its level by almost 6 percent at the short end in a wave like pattern to reach a minimum in August of 2005, while the term spread is declining to below 200 basis points. Afterwards the level is increasing by 225 basis points in the 3-month yield category and around 115 basis points at the longer end of the maturity spectrum, flattening the term spread of the yield curve to below 90 basis points.

Volatility of the yield segments is decreasing with increasing maturity. Additionally, the yield volatility is considerably declining during the sample period. Comparing the first half of the data with the second half, yield volatility for the 3-month segment declines from 2.89 to 0.57, from 2.20 to 0.59 for 60-month and 1.86 to 0.54 for the 120-month segment.

Figure 2 - Yield Plot Czech Republic

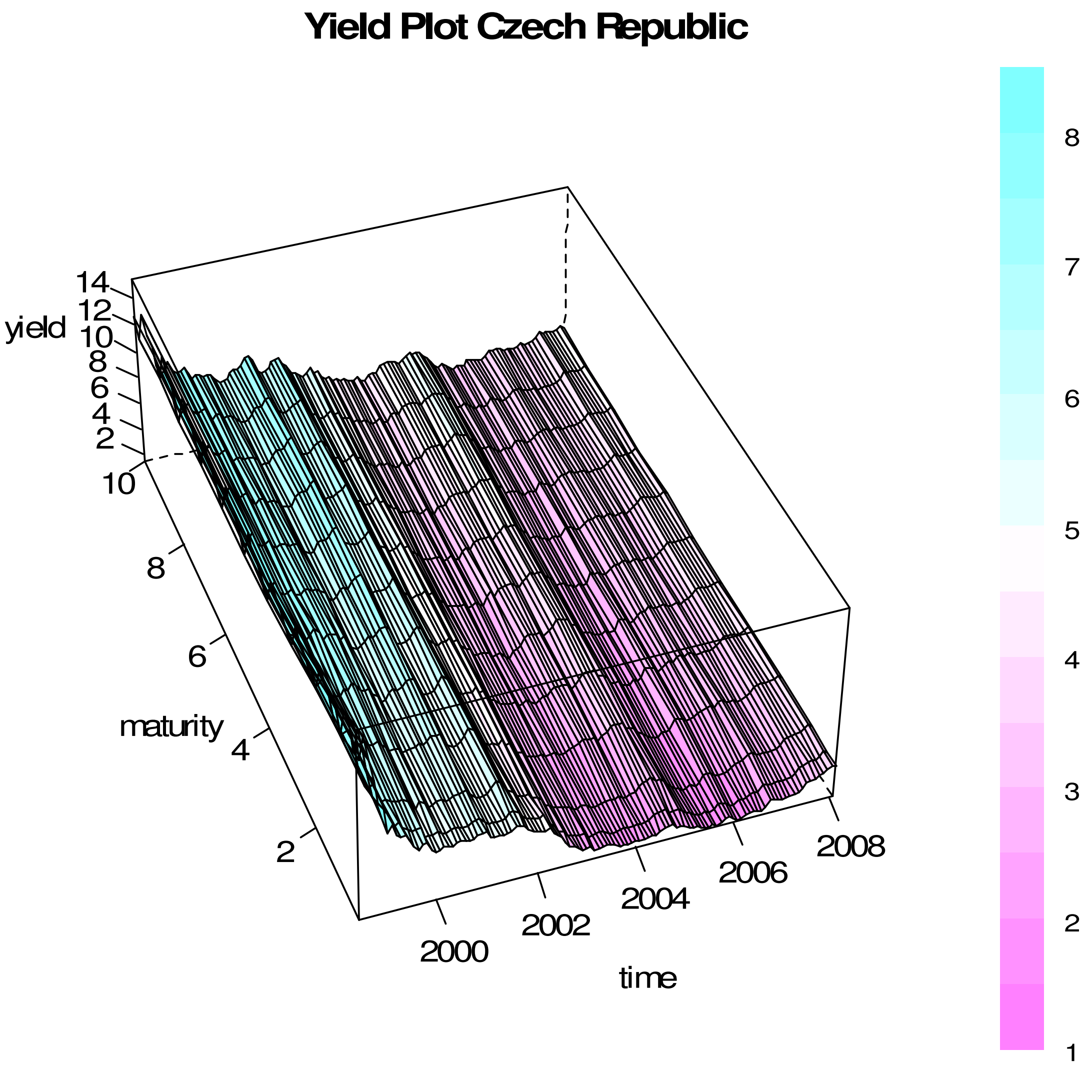


Table 1 - Yield Description Czech Republic

Yield Description Czech Republik Month end data from 1998:06 until 2008:1												
Maturity in Month	**3**	**6**	**12**	**24**	**36**	**48**	**60**	**72**	**84**	**96**	**108**	**120**
Min.	1.48	1.48	1.49	1.73	2.03	2.32	2.47	2.70	2.92	3.08	3.33	3.30
1st Qu.	2.04	2.18	2.35	2.88	3.11	3.31	3.47	3.60	3.76	3.95	4.03	4.15
Median	3.00	3.03	3.20	3.58	3.94	4.13	4.21	4.30	4.42	4.69	4.86	4.94
Mean	4.04	4.09	4.20	4.46	4.66	4.86	4.99	5.14	5.28	5.43	5.52	5.59
3rd Qu.	5.28	5.35	5.45	5.71	6.00	6.18	6.30	6.50	6.68	6.73	6.78	6.81
Max.	15.43	15.40	14.55	13.35	12.59	12.31	12.74	12.69	12.65	12.66	12.66	12.66
Standard Deviation	2.761	2.653	2.526	2.351	2.215	2.168	2.094	2.069	2.046	1.972	1.917	1.892

3.1.2 Hungary

The Hungarian yield curve has been inverted for most of the sample period. A short exception is the time between October 2005 and July 2006. The level is decreasing from the start of the sample in June 1998 until July 2000 before rising again and getting more inverted until August 2001. Thereafter the level is declining and the curve is flattening to be almost flat at January 2003. Following was a strong level increase combined with inversion until January 2004. Next the curve is levelling off to mark a new turning point in August 2005 with an almost flat term structure. The short period of an upward sloping curve is following while level is rising. The curve is inverting again in August 2006. Thereafter the level is fluctuating in a narrow range of below one percent with the term spread ranging between 15 and 137 yield basis points until the end of the sample. Yield volatility of the term structure is declining from 2.76 at the short end to 1.89 at the long end.
As in the sample for the Czech Republic the volatility declines over time. This trend is especially pronounced for longer maturities and also true for the short end of the curve but to a lesser extend. For example the 120-month yield volatility declines from 2.47 to 0.67 for the second half of the sample, while for the 3-month category it is 3.20 to 2.09 and 2.46 to 1.07 for the medium range of 60-month maturity.

Figure 3 - Yield Plot Hungary

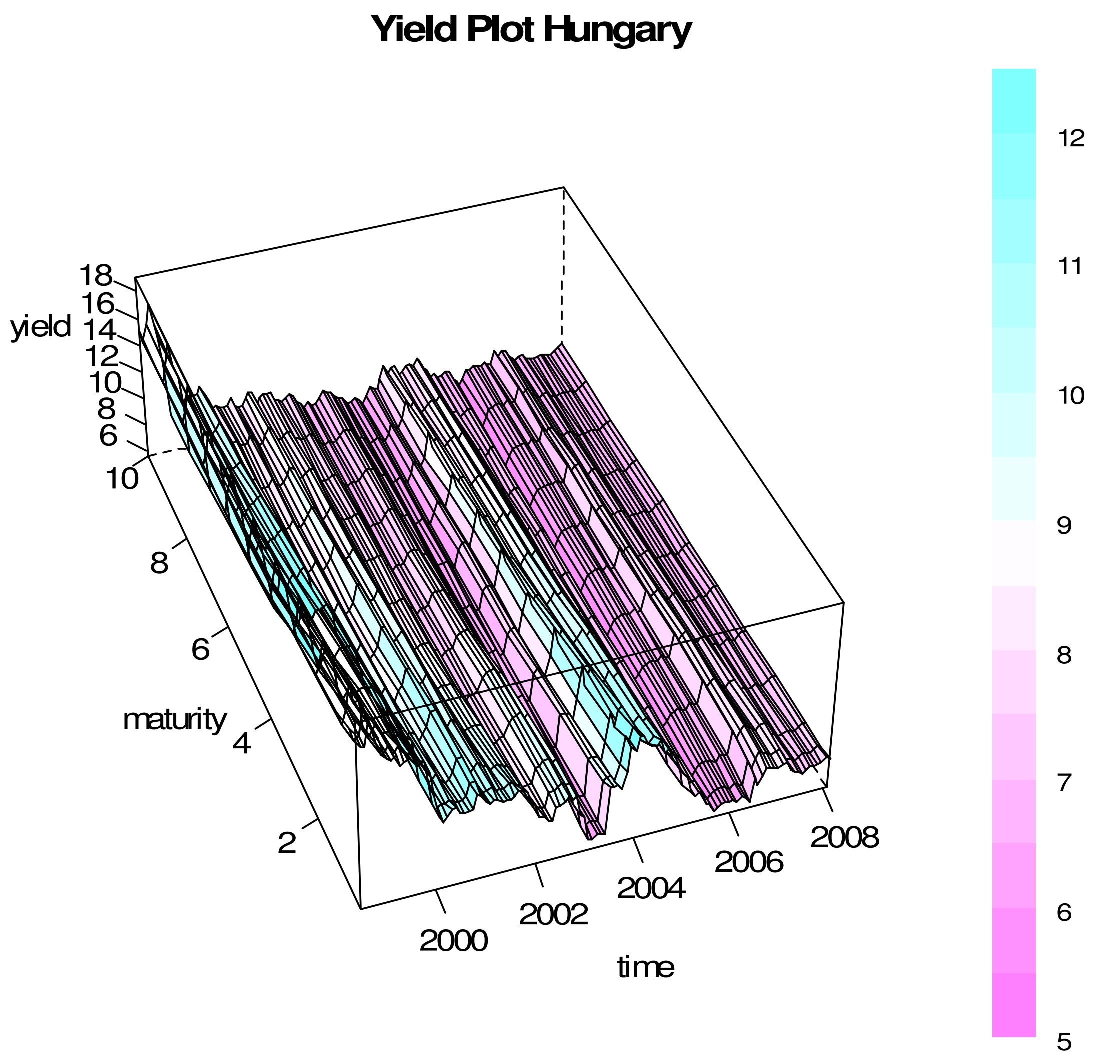


Table 2 - Yield Description Hungary

Yield Description Hungary Month end data from 1998:06 until 2008:1												
Maturity in Month	**3**	**6**	**12**	**24**	**36**	**48**	**60**	**72**	**84**	**96**	**108**	**120**
Min.	5.88	5.84	5.66	5.58	5.56	5.54	5.53	5.50	5.47	5.50	5.47	5.47
1st Qu.	7.63	7.58	7.54	7.46	7.35	7.22	7.13	7.04	6.93	6.91	6.81	6.76
Median	9.82	9.69	9.44	9.22	8.76	8.30	8.10	7.96	7.83	7.63	7.53	7.45
Mean	10.22	10.11	9.91	9.57	9.22	8.85	8.57	8.40	8.24	8.11	7.99	7.87
3rd Qu.	11.56	11.26	10.92	10.43	10.02	9.52	9.21	8.92	8.76	8.63	8.42	8.21
Max.	18.99	18.96	18.95	18.35	17.89	17.27	16.75	16.80	16.84	16.87	16.90	16.92
Standard Deviation	3.20	3.09	2.95	2.77	2.54	2.33	2.13	2.08	2.04	2.01	2.00	1.99

3.1.3 Poland

The Polish yield curve is inverted from the start of the sample until May 2003 with the level strongly decreasing in a wave form pattern. The front end of the curve is coming off by around 17 yield percent and the long end by around 11. The term spread is ranging from 600 basis points at the beginning increasing to above 900 basis points in January 2001. Thereafter the inversion is declining to become upward sloping in May 2003. Staying upward-sloping the level increases in the sequel by around 2.5 percent for shorter maturities and 1 percent for longer maturities, leading to an inverted term structure in September 2004. Thereafter the level is coming off in an almost linear fashion until the curve is flat in May 2005 also approximately marking the low of the long end of the yield curve. In the sequel the curve is getting steeper with the front end coming off 140 yield basis points, marking the all time low of the sample in November 2006, while the long end is increasing slightly. For the rest of the sample period until January 2008 the level is increasing by 150 basis points lowering the 10-year 3-month term spread from 138 basis points to 28 basis points.

Yield volatility at the long end is less than half the volatility at the short end. As clearly visible in the yield plot, the yield volatility declines during the sample period. To put this in numbers the comparison of the two sample halves shows a decline from 4.46 to 0.91 for 3-month, from 2.66 to 0.91 for 60-month and from 2.35 to 0.75 for 120-month.

Figure 4 - Yield Plot Poland

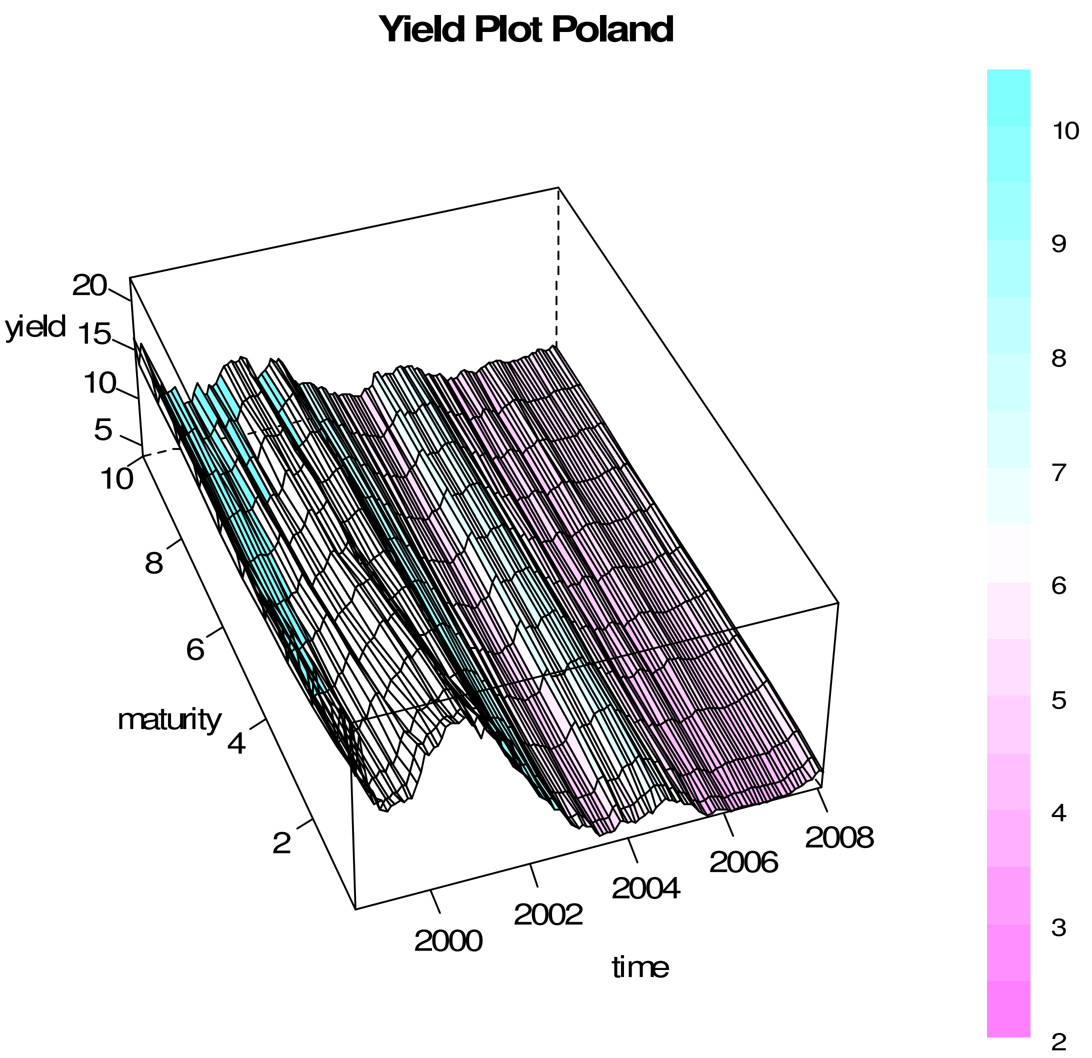


Table 3 - Yield Description Poland

Yield Description Poland Month end data from 1998:06 until 2008:1												
Maturity in Month	**3**	**6**	**12**	**24**	**36**	**48**	**60**	**72**	**84**	**96**	**108**	**120**
Min.	3.79	3.92	3.93	4.04	4.20	4.35	4.43	4.50	4.58	4.55	4.59	4.65
1st Qu.	4.90	4.90	4.92	5.08	5.26	5.37	5.44	5.49	5.50	5.51	5.54	5.56
Median	6.43	6.44	6.88	7.01	7.00	7.06	7.03	7.01	7.02	7.03	6.94	6.77
Mean	9.66	9.55	9.33	9.02	8.79	8.58	8.27	8.19	8.10	7.95	7.80	7.62
3rd Qu.	14.59	14.23	13.57	13.18	12.85	12.09	11.04	10.84	10.62	10.28	9.96	9.72
Max.	22.15	21.71	20.33	19.05	18.21	16.86	15.82	15.93	16.01	16.07	16.12	16.15
Standard Deviation	5.74	5.52	5.11	4.58	4.11	3.67	3.23	3.11	3.00	2.83	2.69	2.55

3.2 Diebold – Li Yield Decomposition

Next the yield curve time series are decomposed into the Diebold-Li yield factors as described in the opening of this chapter. When λ_t is fixed at 0.0609, β_{1t}, β_{2t} and β_{3t} can be calculated by ordinary least squares methodology. The factor loadings depending on the maturity of the yield curve segment can be calculated and serve as the regressors of the multiple linear regression analysis. β_{1t}, β_{2t} and β_{3t} are the coefficient estimates of the best least-squares regression fit. Continuing to do this for every month end (t) representation of the yield curve gives us a time series of β_{1t}, β_{2t} and β_{3t} best fitting the term structure. Please see the appendix for the R code of the calculation.

3.2.1 Czech Republic

There is obvious temporal variation in the latent yield factors. The level factor ranges from 12.90 at its maximum at the beginning of the sample in June 1998 to decline with several local peaks and minima to its global minimum at 3.92 in January 2006, before increasing slightly again. Slope peaks at the beginning of the sample at 3.63 to decline into negative territory by January 1999 and stays negative for the remainder of the sample. The absolute minimum of the slope factor is in May 2004 at -4.24. Thereafter increasing again to -0.92 at the end of the sample in January 2008. Curvature starts the sample period at -5.40 in June 1998 and fluctuates widely between its global maximum at 2.44 in September 1999 and the global minimum at -5.48 in June 2003.
The level factor is the most persistent with a standard deviation of around 30% of its mean. One sigma of the slope factor is 67% of its mean and the curvature factor is the most volatile with above 82%. Visually in the chart it appears that the volatility of the factors is declining over the sample period, with the exception of the curvature factor. Separating the sample in half and computing the standard deviation of the latent factors confirms it. All three factors have a lower standard deviation in the second part of the sample. The sigma declines from 1.70 to 0.67 for the level factor and from 1.56 to 0.85 for the slope factor. Curvature’s standard deviation also declines marginally form 1.86 to 1.66.

The pairwise correlation for the curvature factor with the other factors is close to zero, while it is 0.57 for level with slope.

Figure 5 - Diebold Li Factor Graph Czech Republic

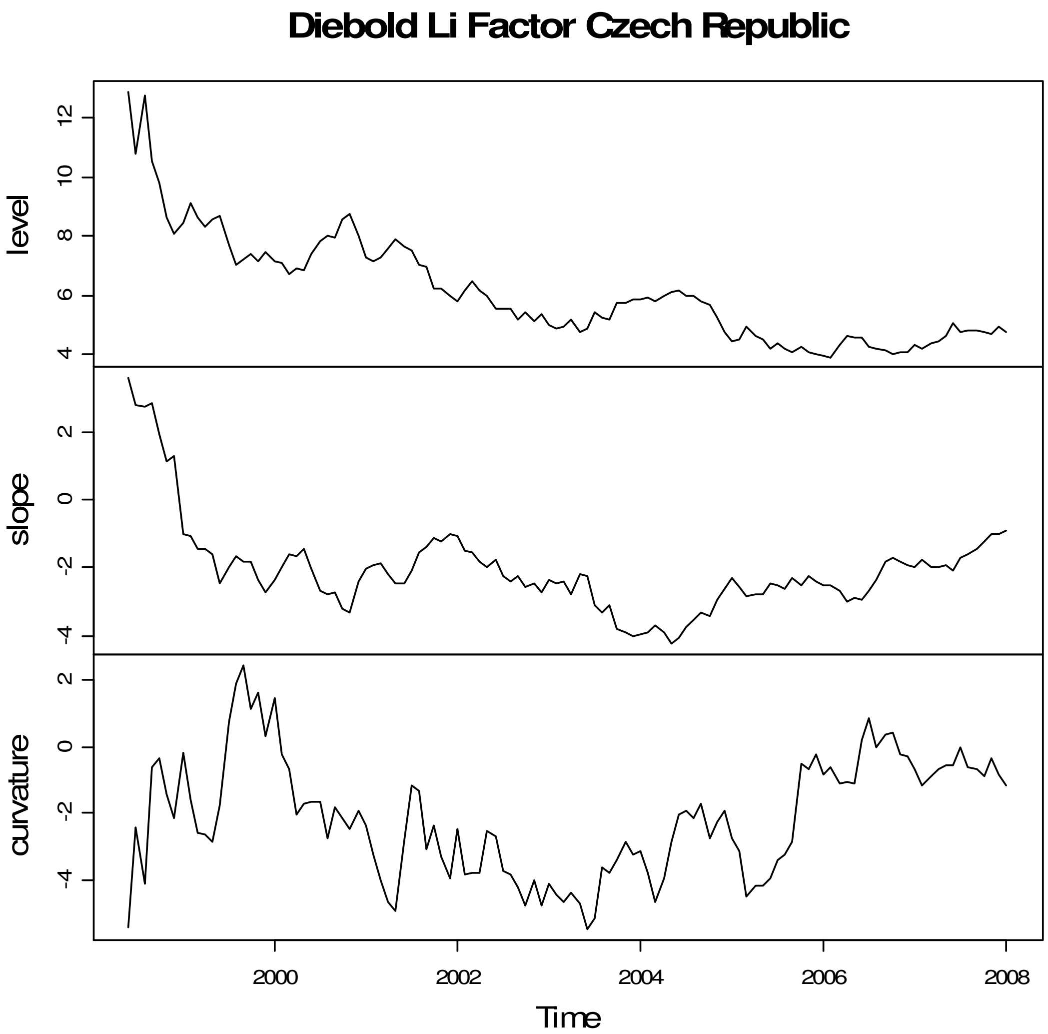


Table 4 - Yield Factor Description Czech Republic

Diebold Li Factor Description Czech Republik Month end data from 1998:06 until 2008:01			
Factor	**level**	**slope**	**curvature**
Min.	3.92	-4.24	-5.48
1st Qu.	4.72	-2.71	-3.75
Median	5.77	-2.23	-2.21
Mean	6.11	-2.05	-2.14
3rd Qu.	7.22	-1.66	-0.68
Max.	12.90	3.63	2.44
Standard Deviation	1.82	1.38	1.76
Correlation Matrix	**level**	**slope**	**curvature**
level	1.00	0.57	-0.06
slope	0.57	1.00	0.11
curvature	-0.06	0.11	1.00
Autocorrelation	**lag 1**	**lag 12**	**lag 30**
level	0.90	0.46	0.20
slope	0.88	0.11	-0.03
curvature	0.84	0.30	-0.18

3.2.2 Hungary

In Hungary the level factor quickly decreases from high readings at the beginning of the sample with the global maximum of 16.01 in September of 1998 to the global minimum at 5.27 in April 1999. Thereafter the level moves in a stationary pattern in the range of 7.98 in September 1999 and 5.33 in October 2003. Slope is declining the first couple of months of the sample from 4.15 in June 1998 to mark a local minimum at 2.72 in August 1998 and then increasing to the global maximum at 10.34 in January 1999. Just to decline to a level below 4 again in January 2000. For the next two years the level stays in a range of 3.16 and 4.70 before declining to 0.12 in February 2003. After increasing back to 6.20 in February 2004 the slope factor declines to its global minimum of the sample period at -0.81 in February 2006. For the remainder of the sample slope stays in the range of this slightly negative number and below positive 2. The Curvature factor starts from the all time low at –0.91 in June 1998 and peaks at the early part of the sample at 12.48 in April 1999. Thereafter curvature appears to move in volatility clustering with the level of volatility declining. While the local minima are constant in the region slightly above negative 1 for the sample period, the local maxima are visibly declining.

Sililar to the Czech Republic the level factor is the most persistent with a standard deviation of around 26% of its sample mean. The slope factor is more volatile with 77% of the mean and curvature is most volatile at around 107%. Comparing the factor volatility of the first half of the sample with the second half shows that it is lower for all three factors. The level factor's dispersion is coming down significantly from 2.45 to 0.41 and the curvature factor from 3.71 to 1.68. The volatility decline for the slope factor is less pronounced with a move from 2.19 to 1.97.

The level factor is slightly positive correlated with the slope factor at 0.15 and slightly negative with the curvature factor at -0.15. Slope's correlation with curvature is at 0.65 and substantially higher compared to the sample of the Czech Republic but comparable to the one of Poland.

Figure 6 - Diebold Li Factor Graph Hungary

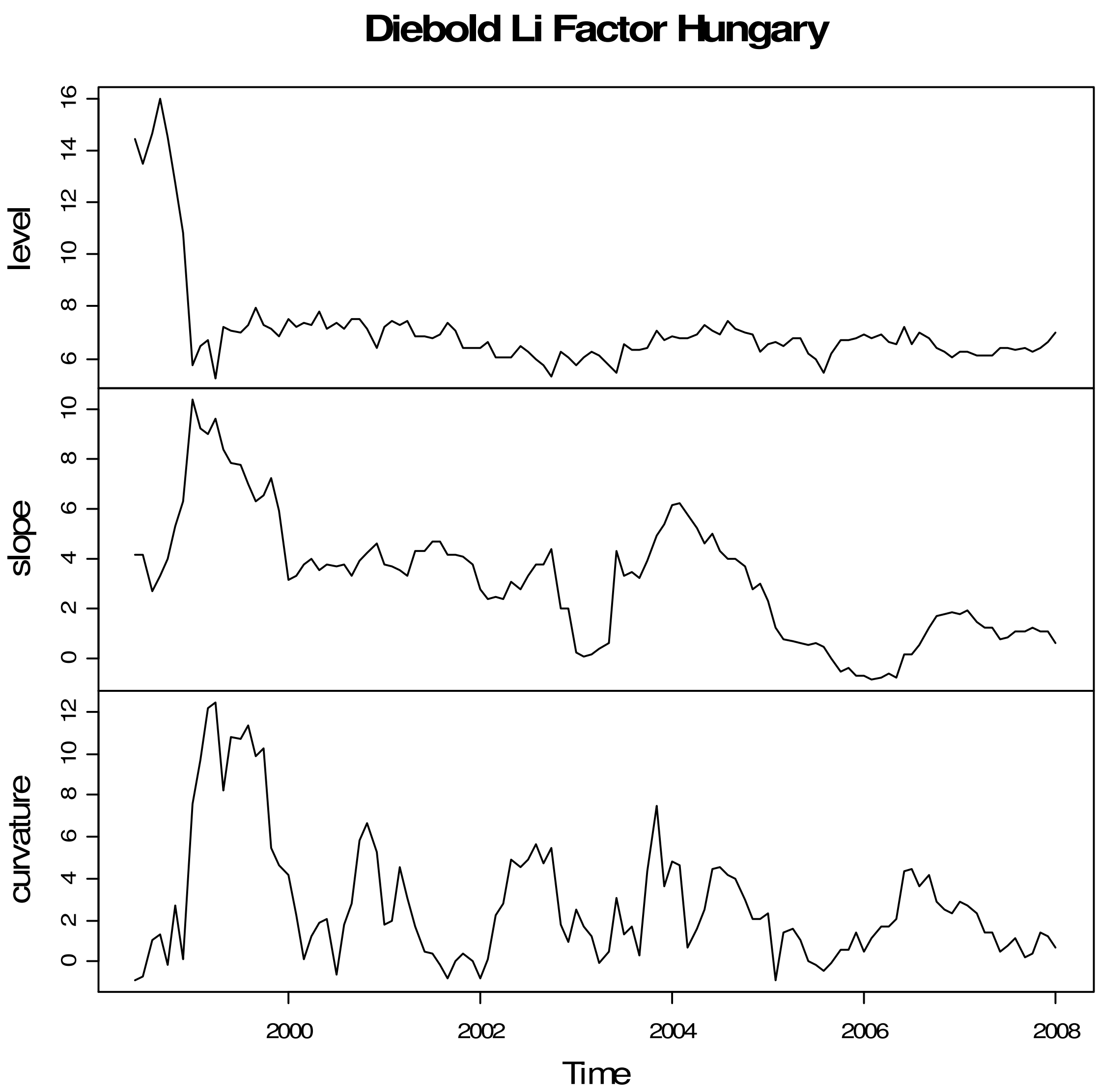


Table 5 - Yield Factor Description Hungary

Diebold Li Factor Description Hungary Month end data from 1998:06 until 2008:01			
Factor	**level**	**slope**	**curvature**
Min.	5.27	-0.81	-0.91
1st Qu.	6.29	1.13	0.65
Median	6.74	3.33	1.95
Mean	7.09	3.14	2.79
3rd Qu.	7.16	4.30	4.37
Max.	16.01	10.34	12.48
Standard Deviation	1.83	2.42	2.97
Correlation Matrix	**level**	**slope**	**curvature**
level	1.00	0.15	-0.15
slope	0.15	1.00	0.65
curvature	-0.15	0.65	1.00
Autocorrelation	**lag 1**	**lag 12**	**lag 30**
level	0.85	0.07	0.03
slope	0.94	0.22	0.11
curvature	0.82	-0.24	-0.18

3.2.3 Poland

As in the samples above the Polish level factor is decreasing strongly in the beginning of the sample form a maximum reading of 14.90 in June 1998 to a local minimum in March 2000 at 6.53. Thereafter the level is increasing in a wave like pattern back to 10.07 in August 2001 before levelling off to the global minimum of 4.72 in June 2005, marking a local minimum at 5.29 in June 2003 and a local maximum at 7.38 in November 2003. For the remaining sample period the level factor increases slightly staying in the range between 5 and 6. Slope decreases from 8.34 in June 1998 to 3.37 in February 1999 to increase to the global maximum at 12.35 around one year later in March 2000. Staying at high levels above 10 for the rest of the year and the beginning of the next it then declines in a rather linear fashion to a local minimum at 2.16 in November 2003. From there the slope increases again to positive levels for the period of fall 2003 and beginning of 2004 before declining to the global minimum at -2.27 in June 2006. For the remaining sample period the slope factor increases but stays in negative territory. Curvature is negative and slightly above zero until April 1999 marking the global minimum in January 1999 at -5.43 before strongly increasing to the absolute maximum of 14.80 in October 2000. In the sequel curvature is declining to -1.70 in January 2002. For the rest of the sample the curvature factor is in the range of above -1 and 5 fluctuating between local maxima and minima.

Visually it appears that volatility of the three factors declines over the sample period. Testing shows that the standard deviation of the level factor for the first 58 month (June 1998 until March 2003) is slightly above 2 compared to 0.64 for the second 58 month of the sample. The same holds true for the slope factor where sigma decreases from 3.70 to below 0.83 and the curvature factor with a decline from 4.93 to 1.70.

As in the countries analysed before level factor is the most persistent of the three factors with the standard deviation being around 27% of its mean. This is followed by the slope factor and curvature factor with 177% and 189%, which is considerably higher compared to the other two samples.

The highest correlation is between the slope and the curvature factor with 0.68, slightly above the correlation of level and slope with 0.60. Level and Curvature are slightly positively correlated at 0.16.

Figure 7 - Diebold Li Factor Graph Poland

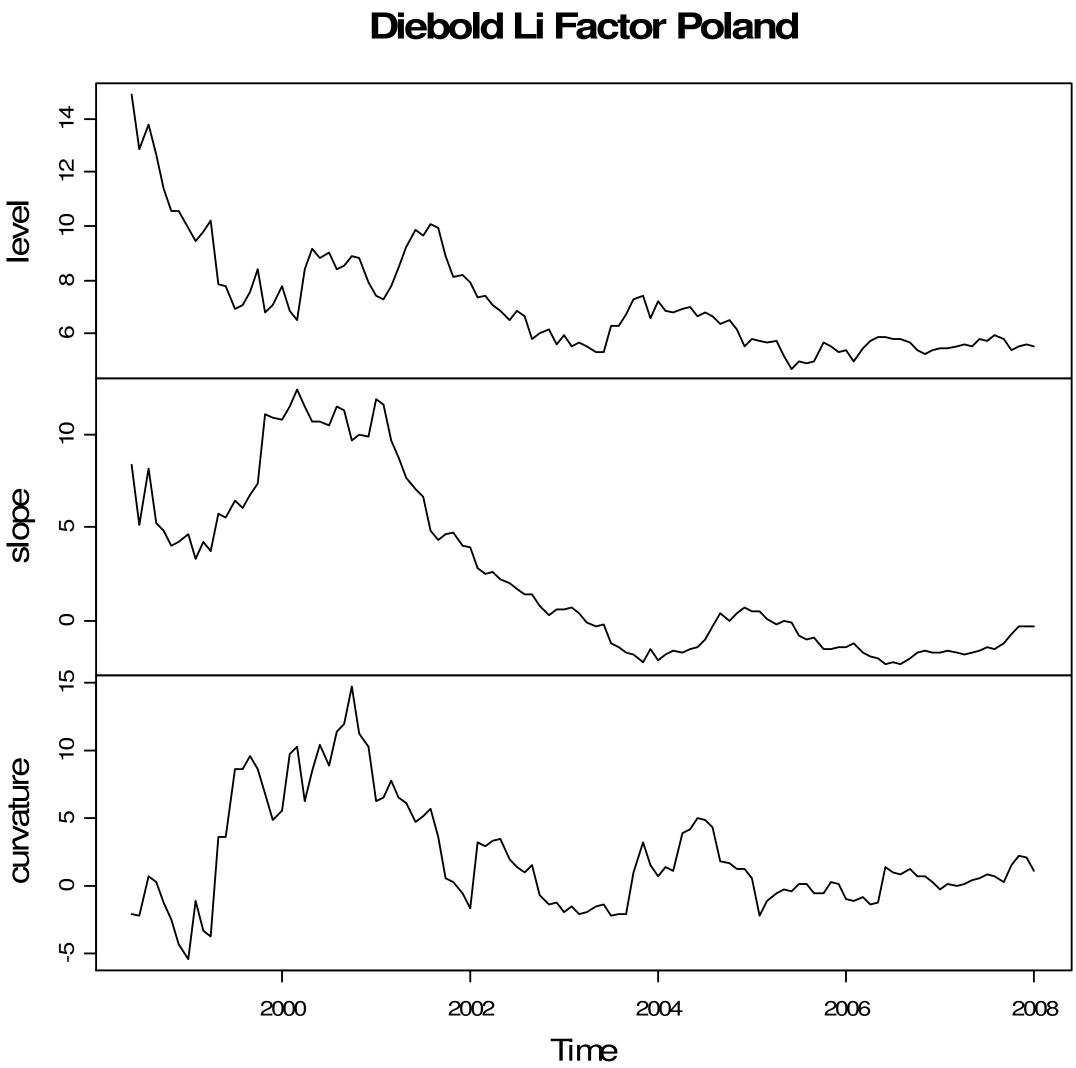


Table 6 - Yield Factor Description Poland

Diebold Li Factor Description Poland Month end data from 1998:06 until 2008:01			
Factor	**level**	**slope**	**curvature**
Min.	4.72	-2.27	-5.43
1st Qu.	5.67	-1.35	-0.59
Median	6.65	0.51	0.93
Mean	7.12	2.54	2.11
3rd Qu.	7.98	5.35	4.19
Max.	14.90	12.35	14.80
Standard Deviation	1.95	4.50	3.98
Correlation Matrix	**level**	**slope**	**curvature**
level	1.00	0.60	0.16
slope	0.60	1.00	0.68
curvature	0.16	0.68	1.00
Autocorrelation	**lag 1**	**lag 12**	**lag 30**
level	0.88	0.26	0.23
slope	0.97	0.67	0.08
curvature	0.90	0.20	-0.23

3.3 Yield Model Fit

A large cross-section of the yield curve is estimated by the three latent factors β_{1t}, β_{2t} and β_{3t} by least squares regression analysis. Please note that the fit of the regression is not perfect and contains residual pricing errors due to estimation error.

It is, therefore, essential to evaluate these pricing errors to make sure the Diebold-Li methodology fits the empirical data well. This is done in the sequel by deriving the model implied yields and residuals are calculated by comparing these to actual yields.

The results show that the Diebold Li model provides a decent fit for the three country samples. There seems to be the general trend of improving model fit for the second part of the sample.

3.3.1 Czech Republic

Looking at the residual plot reveals that the model fits the data generally well, with the average residual not exceeding a couple of basis points. There are two visible outliers for the medium maturity spectrum at the start of the sample and around 2004. There seems to be a general trend for the model to perform better as time passes in the sample. This is not entirely surprising as our earlier analysis of yields showed decreasing volatility. The mean residual of the model implied yield compared to the actual yield is the largest for the 72-month maturity spectrum with a mean deviation of -6.0 basis points, which is around -1.17% of the average yield level. The maximum deviation of the model is +70.11 basis points for the 48-month maturity segment in June 1999, corresponding to around 8.61% of the actual yield level or 14.42% of the average yield level. The volatility of the residuals is also the highest for the 48-month category at 0.15. However, the residual mean and a look at the residual histogram reveal, that the residual distribution is closely centred to zero, without major fat tails.

The Diebold-Li three factor methodology is able to fit the actual yields of the Czech Republic well over the chosen period and is able to model the different observed yield curve shapes.

Figure 8 – Model Fit Residual Plot Czech Republic

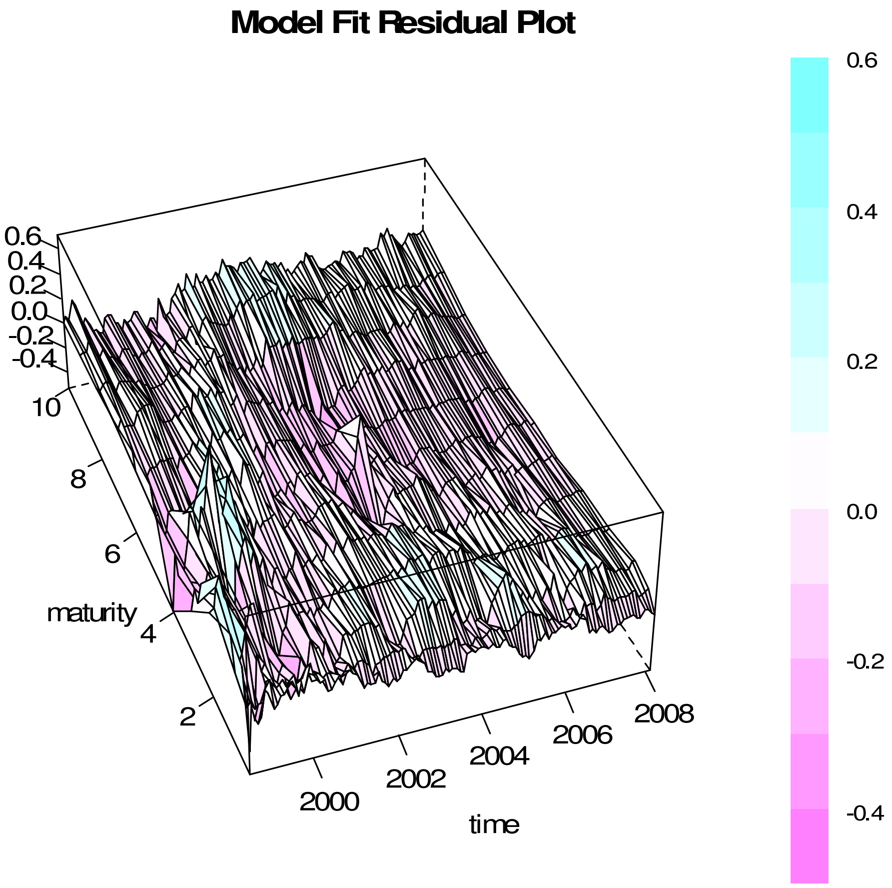


Table 7 - Model Fit Czech Republic

Model Fit for the Czech Republic Evaluating the Diebold Li Factor Decomposition of the Yield Curve Month end data from 1998:06 until 2008:1									
	3-month maturity			6-month maturity			12-month maturity		
	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual
Min.	1.4830	1.5100	-0.3530	1.4820	1.5090	-0.2534	1.4910	1.5170	-0.4174
1st Qu.	2.0420	2.1010	-0.0783	2.1820	2.1450	-0.0220	2.3460	2.3210	-0.0488
Median	3.0010	3.0650	-0.0290	3.0250	3.0600	0.0061	3.2030	3.1270	0.0548
Mean	4.0410	4.0690	-0.0287	4.0920	4.0910	0.0010	4.2040	4.1740	0.0300
3rd Qu.	5.2820	5.2400	0.0147	5.3530	5.3450	0.0302	5.4490	5.4640	0.1069
Max.	15.4300	15.7830	0.2143	15.4000	15.1670	0.2330	14.5510	14.2470	0.3040
	24-month maturity			36-month maturity			48-month maturity		
	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual
Min.	1.7320	1.7110	-0.3359	2.0280	2.0090	-0.5391	2.3200	2.3040	-0.5228
1st Qu.	2.8770	2.7450	0.0147	3.1090	3.0890	-0.0344	3.3100	3.3390	-0.0677
Median	3.5770	3.5120	0.0648	3.9350	3.9390	0.0088	4.1250	4.1520	-0.0259
Mean	4.4590	4.4100	0.0493	4.6580	4.6560	0.0022	4.8620	4.8730	-0.0110
3rd Qu.	5.7100	5.7640	0.1118	5.9950	6.0430	0.0536	6.1800	6.2240	0.0263
Max.	13.3540	13.2240	0.3980	12.5930	12.7880	0.2977	12.3100	12.6200	0.7011
	60-month maturity			72-month maturity			84-month maturity		
	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual
Min.	2.4720	2.5610	-0.3154	2.6950	2.7740	-0.2163	2.9220	2.9470	-0.4328
1st Qu.	3.4650	3.5310	-0.1097	3.6010	3.7210	-0.1053	3.7610	3.8200	-0.0650
Median	4.2130	4.2610	-0.0698	4.3000	4.3530	-0.0601	4.4160	4.4870	-0.0226
Mean	4.9940	5.0530	-0.0585	5.1370	5.1970	-0.0600	5.2840	5.3120	-0.0287
3rd Qu.	6.3000	6.3830	-0.0286	6.4980	6.5500	-0.0335	6.6790	6.6760	0.0182
Max.	12.7370	12.5700	0.3338	12.6940	12.5710	0.1310	12.6490	12.5910	0.1941
	96-month maturity			108-month maturity			120-month maturity		
	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual
Min.	3.0800	3.0870	-0.1331	3.3300	3.2020	-0.1282	3.2970	3.2960	-0.2255
1st Qu.	3.9460	3.9350	-0.0140	4.0270	4.0090	-0.0162	4.1470	4.0670	-0.0095
Median	4.6910	4.6270	0.0243	4.8570	4.7510	0.0362	4.9380	4.8540	0.0590
Mean	5.4270	5.4050	0.0216	5.5190	5.4800	0.0389	5.5860	5.5420	0.0441
3rd Qu.	6.7340	6.7500	0.0574	6.7760	6.8010	0.0798	6.8080	6.8930	0.1111
Max.	12.6550	12.6160	0.1574	12.6600	12.6410	0.2375	12.6640	12.6640	0.2411

3.3.2 Hungary

All the residuals for the Hungarian model are closely centred to zero. The highest mean deviation of the Diebold-Li model fit is -4.79 basis points for the 12-month yield segment, corresponding to -0.48% of the average yield level.

The maximum absolute value residual is -77.87 basis points for the 60-month category, which equals 5.54% of the actual yield level of November 1998 and 9.1% of the average yield level. The volatility of the 60-month residual is the highest with 17.26 basis points. The histogram reveals that the residuals are skewed to the left. In analogy to the Czech sample all of the major out layers are early in the sample and model fit seems to improve as time passes.

Reducing the sample period from January 2000 onwards reduces the maximum residual of the 60-month segment to below 30 basis points and is evenly distributed around the mean.

Figure 9 – Model Fit Residual Plot Hungary

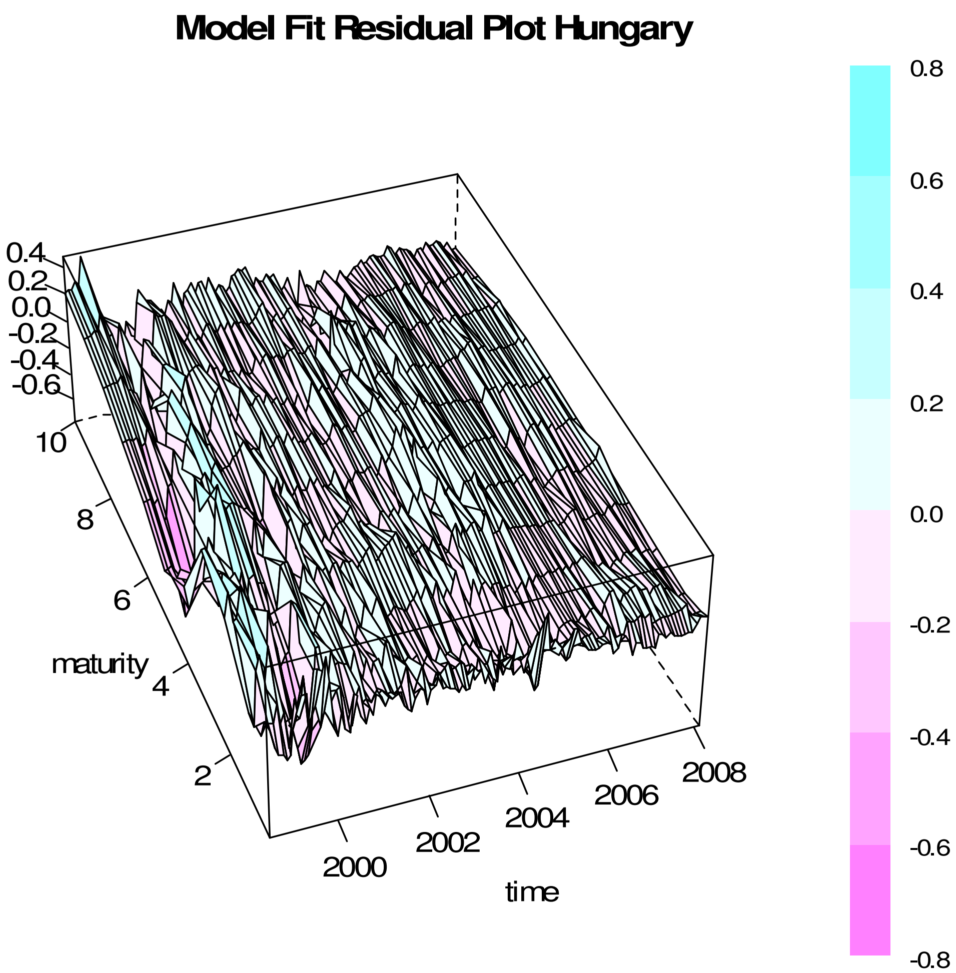


Table 8 – Model Fit Hungary

Model Fit for Hungary
Evaluating the Diebold Li Factor Decomposition of the Yield Curve
Month end data from 1998:06 until 2008:1

	3-month maturity			6-month maturity			12-month maturity		
	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual
Min.	5.8780	5.8720	-0.2384	5.8440	5.8100	-0.2800	5.6590	5.7150	-0.5898
1st Qu.	7.6340	7.6170	-0.0483	7.5810	7.6010	-0.0454	7.5400	7.6430	-0.1287
Median	9.8160	9.7290	0.0135	9.6880	9.6520	-0.0067	9.4410	9.5100	-0.0295
Mean	10.2180	10.1850	0.0323	10.1070	10.1210	-0.0139	9.9050	9.9530	-0.0479
3rd Qu.	11.5610	11.4770	0.0849	11.2590	11.4270	0.0293	10.9240	11.0180	0.0460
Max.	18.9900	19.1660	0.4330	18.9600	18.9940	0.2465	18.9500	18.6780	0.3301
	24-month maturity			36-month maturity			48-month maturity		
	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual
Min.	5.5780	5.6010	-0.2876	5.5600	5.5450	-0.2790	5.5430	5.5160	-0.3718
1st Qu.	7.4590	7.4940	-0.0558	7.3500	7.3250	-0.0117	7.2190	7.1900	-0.0637
Median	9.2190	9.1410	-0.0158	8.7570	8.7090	0.0195	8.2980	8.3960	0.0004
Mean	9.5680	9.5590	0.0090	9.2200	9.1800	0.0402	8.8540	8.8580	-0.0041
3rd Qu.	10.4280	10.4640	0.0368	10.0170	9.9590	0.0912	9.5180	9.5280	0.0380
Max.	18.3540	18.1500	0.4269	17.8940	17.7480	0.3930	17.2660	17.4450	0.4706
	60-month maturity			72-month maturity			84-month maturity		
	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual
Min.	5.5320	5.5010	-0.7787	5.4990	5.4920	-0.4003	5.4660	5.4880	-0.3765
1st Qu.	7.1280	7.1150	-0.0682	7.0380	6.9900	-0.0145	6.9290	6.9250	-0.0305
Median	8.1000	8.1260	0.0034	7.9620	7.9390	0.0197	7.8250	7.7860	0.0097
Mean	8.5660	8.5970	-0.0307	8.4040	8.3890	0.0150	8.2350	8.2240	0.0114
3rd Qu.	9.2110	9.1840	0.0593	8.9150	8.9260	0.0630	8.7550	8.7360	0.0530
Max.	16.7450	17.2150	0.3106	16.8020	17.0400	0.3112	16.8430	16.9040	0.3285
	96-month maturity			108-month maturity			120-month maturity		
	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual
Min.	5.4990	5.4850	-0.2270	5.4660	5.4830	-0.2877	5.4660	5.4820	-0.3344
1st Qu.	6.9110	6.8710	-0.0134	6.8100	6.8190	-0.0419	6.7580	6.7690	-0.0966
Median	7.6290	7.6580	0.0168	7.5280	7.5660	-0.0057	7.4500	7.4910	-0.0262
Mean	8.1070	8.0920	0.0158	7.9880	7.9850	0.0038	7.8660	7.8970	-0.0308
3rd Qu.	8.6330	8.5730	0.0496	8.4210	8.4380	0.0350	8.2100	8.2510	0.0257
Max.	16.8740	16.7980	0.2500	16.8980	16.7120	0.2953	16.9170	16.6430	0.4417

3.3.3 Poland

Similar to the countries before the model fits the Polish sample firmly. The maximum mean deviation of the latent factor model is 8.9 basis points for the 84-month yield segment, about 1.09% of the average yield level.

The maximum absolute value residual is -92.44 basis points for the 60-month category for August 1998, which is 6.1% of the actual yield. The histogram of the 60-month residual is skewed to the left. As in the case of Hungary does the tail to the left disappear when the sample is shortened to all data beginning January 2001. The 120-month segment shows the highest standard deviation of the residual with 23.63 basis points.

Figure 10 – Model Fit Residual Plot Poland

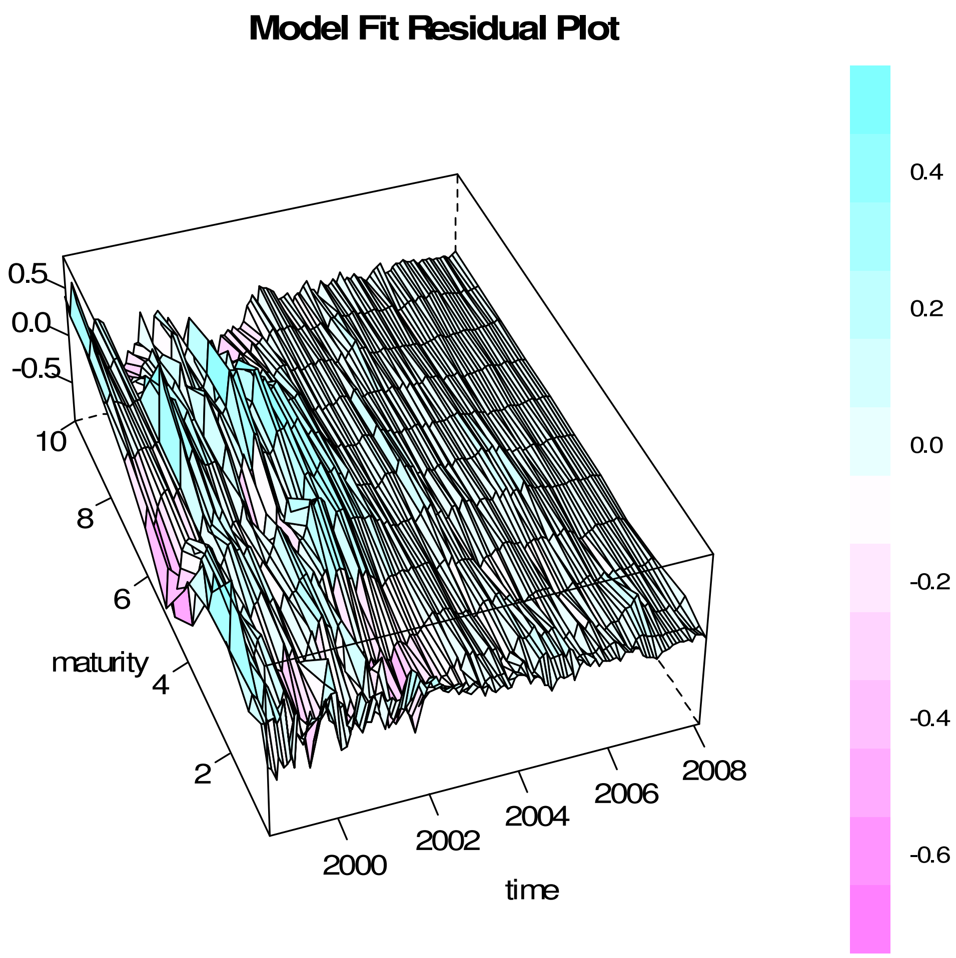


Table 9 - Model Fit Poland

Model Fit for Poland
Evaluating the Diebold Li Factor Decomposition of the Yield Curve
Month end data from 1998:06 until 2008:1

	3-month maturity			6-month maturity			12-month maturity		
	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual
Min.	3.7920	3.8260	-0.3520	3.9230	3.8770	-0.4084	3.9340	3.9350	-0.7276
1st Qu.	4.9020	4.9010	-0.0281	4.9040	4.9130	-0.0417	4.9150	4.9200	-0.1427
Median	6.4310	6.3460	0.0248	6.4420	6.4740	0.0012	6.8750	6.8190	-0.0211
Mean	9.6590	9.6090	0.0496	9.5500	9.5480	0.0024	9.3250	9.4010	-0.0759
3rd Qu.	14.5850	14.2850	0.1356	14.2270	14.2290	0.0443	13.5740	14.0260	0.0553
Max.	22.1500	22.3510	0.4162	21.7100	21.5820	0.2999	20.3260	20.3340	0.3263
	24-month maturity			**36-month maturity**			**48-month maturity**		
	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual
Min.	4.0410	4.0740	-0.5337	4.1960	4.2090	-0.2412	4.3540	4.3240	-0.5453
1st Qu.	5.0780	5.1070	-0.1373	5.2580	5.2360	-0.0405	5.3720	5.3480	0.0059
Median	7.0100	7.1020	-0.0357	7.0020	7.0700	0.0023	7.0580	7.0070	0.0490
Mean	9.0190	9.0730	-0.0542	8.7850	8.7670	0.0177	8.5810	8.5110	0.0702
3rd Qu.	13.1750	13.3850	0.0045	12.8520	12.8080	0.0494	12.0940	11.9750	0.1262
Max.	19.0450	18.6610	0.8208	18.2050	17.6570	0.5475	16.8610	17.0280	0.4621
	60-month maturity			**72-month maturity**			**84-month maturity**		
	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual
Min.	4.4340	4.4180	-0.9244	4.5040	4.4920	-0.4546	4.5750	4.5520	-0.2196
1st Qu.	5.4440	5.4320	-0.0624	5.4860	5.5030	-0.0090	5.5040	5.5180	-0.0090
Median	7.0260	6.9870	0.0091	7.0080	6.9850	0.0210	7.0160	7.0190	0.0181
Mean	8.2740	8.3040	-0.0310	8.1900	8.1410	0.0497	8.0990	8.0110	0.0885
3rd Qu.	11.0370	11.1960	0.0595	10.8360	10.7790	0.1209	10.6150	10.5810	0.1501
Max.	15.8160	16.6130	0.3543	15.9280	16.3270	0.4851	16.0080	16.1210	0.7937
	96-month maturity			**108-month maturity**			**120-month maturity**		
	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual	Actual Yield	Fitted Yield	Residual
Min.	4.5460	4.5990	-0.1660	4.5860	4.6380	-0.3708	4.6530	4.6510	-0.7393
1st Qu.	5.5130	5.5310	-0.0142	5.5430	5.5370	-0.0598	5.5590	5.5460	-0.2943
Median	7.0300	7.0160	0.0127	6.9410	7.0070	-0.0103	6.7690	6.9990	-0.0449
Mean	7.9450	7.9070	0.0384	7.7980	7.8230	-0.0250	7.6240	7.7550	-0.1305
3rd Qu.	10.2760	10.3180	0.0620	9.9560	10.0160	0.0207	9.7160	9.7780	0.0043
Max.	16.0680	15.9670	0.4794	16.1150	15.8470	0.3747	16.1530	15.7520	0.5458

4 Macro Dynamics

Besides modelling the yield curve, this thesis focuses on the dynamics of the yield curve and the causal macroeconomic links driving these dynamics. Especially in the chosen region with its small and open economies, influences from the macroeconomic environment are expected to be strong. It is therefore the goal to analyze the yield curve dynamics and the macroeconomic developments jointly and infer their relationship. To do this, macroeconomic factors have to be defined and entered into the model.

The latent three factors model described above in conjunction with macroeconomic variables, defined in the sequel, are combined in a standard recursive VAR model setting. This allows evaluating macro to yield as well as yield curve to macro factor relations. Diebold, Rudebusch and Aruoba (2006) inspired me to use this approach with some adaptations. To keep the model as parsimonious as possible a two-step estimation approach is used. In the first step, latent yield and macro factors are derived. In the second step, they are combined with the additional macro variables and the VAR model is estimated. The two-step approach keeps computational complexity to a minimum at good empirical properties.[3]

Interest rates are influenced by central bank policy. Monetary policy actions by the central bank are monitored and anticipated by fixed income market participants influencing the yield curve. Within their monetary framework the policy setters oversee the economic situation and react in anticipation of economic and financial market developments. The central bank base rate is therefore included in our dataset of macroeconomic variables as a proxy of monetary policy.

In small open economies with flexible exchange rates the impact of monetary policy shocks is revolving around exchange rate and interest rates effects. Increasing interest rates are associated with an appreciation of the exchange rate by interest rate parity arguments. For small open economies the exchange rate channel has been identified as crucial within macro economic policy

[3] See Bernanke, Boivin and Eliasz (2004)

identification.[4] Additionally, these economies are susceptible to external shocks impacting real economic developments internally. External monetary shocks for example have been shown to have a pervasive effect on emerging market economies.[5]

As it is the aim to model these complex interdependencies I include the nominal effective exchange rate and an international interest rate spread measure to proxy these effects. Moreover, the spread measure seems to be important as practitioners trade Central European bonds relative to benchmark bonds and spread levels are considered an important variable within investment decisions.

Additionally, the classical macroeconomic indicators of real economic activity and inflation will be included. To utilize broader macroeconomic information the first principal component of a group of variables explaining trends in real activity and inflation is included. The latent yield factors of the yield only model will be augmented with the above macro factors. Analysis will be according to standard VAR identification of recursive causal ordering. The fast responding market variables are ordered before the slower moving macro variables. The latent yield factors (Level, Slope, Curvature) are ordered first, followed by the spread (Spread) factor and the nominal effective exchange rate (NEER), to be succeeded by the first principal component of the real activity group (Real Activity) and the first principal component or the inflation group (Inflation). The central bank base rate (Base Rate), as the proxy of monetary policy, is ordered last as the national bank presumably monitors all the factors within their policy decision.

[4] See Cushman and Zha (1997)

[5] See for example Mackowiak (2007)

4.1 Macro Factor Definitions

In this section a detailed explanation of the included macro factors and variables follows:

4.1.1 Spread

Mackowiak (2007) shows that U.S. monetary policy shocks have a strong impact on emerging markets' (Latin America and East Asia) interest rates and the exchange rate. Testing this potential impact for the CEE-3 economies an interest spread measure to German benchmark interest rates is included in the model. Additionally there seems to be evidence that the spread pick up provided by emerging market bonds is an important investment argument and therefore changes should help in explaining yield curve behavior.
Spread is defined as the difference of the local level factor and the German level factor of the yield curve derived by the Diebold Li methodology. Thus positive values of Spread indicates a higher level of the first latent yield factor of the local yield curve relative to the German benchmark.

4.1.2 Nominal Effective Exchange Rate (NEER)

In CEE-3 the exchange rate channel has been identified to play a prominent role in the monetary transmission mechanism. Coricelli, Egert and MacDonald (2006) provide a good empirical assessment of the transition mechanism in Central and Eastern Europe. In these open economies the level of exchange rate can cause changes in prices, trade volumes and investments, thereby it is an important determinant in the model setting. Moreover, expectations of exchange rate developments will influence the dynamics of the yield curve, due to the fact that foreign portfolio investment is high in the researched fixed income markets.
In accordance, the J.P. Morgan Broad Effective Exchange Rate Index is added to the model. The index is a measure of the country's trade-weighted multilateral exchange rate against a broad group of trading partners. The NEER time series included in the model is the zero-mean and unit-variance normalized

year on year percentage change of the Index (Base year 2000 average is set equal to 100) as provided by Bloomberg.[6]

4.1.3 Real Activity

The textbook IS-LM model is one of the great building blocks of macroeconomic theory providing a link of interest rates to the real economy. In addition, real activity is effected by the exchange rate, credit and the asset price channel. On the other hand, real activity in relation to the output-gap is an important determinant of inflation dynamics, impacting interest rates via expectations and monetary policy. This makes real activity fundamental in capturing macroeconomic dynamics.

To utilize a broader macroeconomic dataset in the model I adapt the methodology of Ang and Piazzesi (2003). They build a group of macro variables explaining real activity by building a list of most variables that have been used in monthly VAR's in the economic literature. To reduce dimensionality the first principal component of the group is extracted and included in the model.

My real activity group contains a measure of Industrial Production (IP), a leading indicator of real activity (LEAD), a measure of unfilled job vacancies in the economy (VACAN), plus a measure of unemployment (UNEM) and of future employment (EMPL).

All time series of the group, except the sentiment indicator (EMPL), are reported in year on year percentage changes and have been separately normalized to have zero-mean and unit-variance before principal component analysis (PCA) is applied. The first principal component explaining most of the group's variance is derived as explained below and included in the model as the measure of real activity.

When using PCA one has the assumption that the data set used is restricted to a subspace of lower dimensionality, as in our case correlation patterns of macro economic variables explaining the level of real activity in the economy. PCA is a fairly simple statistical method to extract these structures at reduced dimensionality. Eigenvectors and eigenvalues of the covariance matrix of the variables will reveal useful information about patterns in the data. PCA is re-

[6] Ticker Information Czech Republic: JBXNCZK Index; Hungary: JBXNHUF Index; Poland: JBXNPLN Index

expressing the data as a linear combination of orthonormal basis vectors. The eigenvector with the highest eigenvalue reveals the most significant relationship between the data dimensions. Within PCA eigenvectors are therefore ordered by their eigenvalues from highest to lowest. Dimensionality can now be reduced by only including the most significant eigenvectors (principal components) to establish a projection of the original data set. This will lead to the loss of some information, but will be limited as long as the excluded eigenvectors are small. In addition, by dropping less significant principal components noise can be filtered out as it is idiosyncratic and lacks structure.

PCA projections of the data are therefore:

$$X = 1 * \overline{x}^T + TP^T + V, \qquad (4.1)$$

where the term $1 * \overline{x}^T$ denotes the original variable averages, X denotes the observations, $T = t_1, t_2, \ldots, t_k$ the latent variables or scores, $P = p_1, p_2 \ldots, p_k$ the transformation matrix consisting of the most significant eigenvectors of the covariance matrix and V the residuals of lost information due to dimensionality reduction. Alternatively to deriving P from the covariance matrix it can be calculated directly via singular value decomposition (SVD). For both calculation methods the data set has to be complete and balanced.

In the case where my data is complete and balanced the first principal component is derived by standard SVD methodology. In the other rare cases probabilistic PCA (PPCA) methodology, as implemented in the pcaMethods package of R, is used.

The pcaMethods package makes algorithms available to approximate PCA by different regression methods. [7] Missing values of the data set can be derived by projecting the principal component scores back into the original space based on the underlying correlation structure.

[7] See the pcaMethods package documentation at http://bioconductor.org/packages/1.9/bioc/html/pcaMethods.html for a more detailed explanation.

Missing values can be derived by:

$$\hat{X} = 1 * \overline{x}^{T} + TP^{T}, \tag{4.2}$$

as long as most of the important information is captured and the principal components make the residuals sufficiently small.

PPCA combines a probabilistic model with an expectation maximisation (EM) algorithm by assuming that the latent variables and noise are normally distributed. The likelihood function is defined in a way that outcomes distant from the training set will be assigned a lower probability and the best data fit can be estimated accordingly. It has been shown empirically, that the PPCA algorithm is able to handle up to 15% of missing data, before convergence breaks down.[8]

4.1.4 Inflation

One of the Central banks' major objectives is price stability. Inflation will be, therefore, addressed through monetary policy and other means available. Inflation and its expectations are also key determinants for the yield curve as they effect the real interest rate and risk premia. Furthermore, inflation is impacts the exchange rate, which in turn influences the credit channel and asset prices. Thus, inflation is an important fundamental measure to be included in the model.

A group of inflation measures including the consumer price index (CPI), producer price index (PPI) and a broad based commodity index (COM) in local currency has been set up. The first principal component of the group is derived and serves in the model as the measure of inflation. If the first principal component of the inflation group loads negatively on its component time series, the score is rotated by multiplication of negative 1. This makes interpretation straightforward as a high positive score of the first principal component is associated with high inflation dynamics.

[8] See pcaMethods documentation for more detail

4.1.5 Central Bank Base Rate

Monetary policy is transmitted into short- and long-term interest rates and these real interest rate developments will as a consequence impact aggregate demand and production of the economy. Policy setters watch and interpret economic developments closely and monetary policy actions provide an important feedback function to market participants.
This is why the central bank policy rate (Base Rate) is included in the model as a proxy of monetary policy. It is entered as the monthly year on year change of the policy rate normalized to have zero-mean and unit-variance.

In the appendix a more detailed account of the macro data for the various countries and the principal component analysis is provided.

5 Model Building and Forecasting

The main building block of this work is the autoregressive (AR) and the vector autoregressive (VAR) methodology.

AR models have the structure of a regression model with the weighted sum of one or more lags of the time series y_t.

AR(p):

$$y_t = c + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + e_t, \tag{5.1}$$

where y_t is the current variable and the explanatory variables are the i = 1 to p lags of the time series and e_t is the time t residual.

VAR models are the multivariate extensions of the AR models containing more than one time series.

The set of K endogenous variables $Y_t = (y_{1t}, \ldots, y_{kt}, \ldots, y_{Kt})^T$ is defined as an order p VAR process by the following convention.

VAR(p):

$$Y_t = A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + u_t, \tag{5.2}$$

where A_i are (K x K) coefficient matrices for lags i = 1, …, p and u_t is a K-dimensional white noise process. The coefficients of the VAR(p) process can be derived, for the given sample of endogenous variables, by least-squares methodology applied separately to each of the K variable equations.

In the given analysis the VAR methodology possesses a variety of advantageous properties. There is no differentiation between input and output variables. Every variable will be explained by all other variables and a specified number of lags of all other variables plus its own lags. Therefore, the researcher can stay agnostic about the direction of causal dependencies. Another advantage is that VAR models are able to capture bidirectional dependencies and the dynamic feedback of the variables. In setting this is a clear advantage as feedback relationships are expected to be strong between the macro economy and the yield curve in both directions. To investigate these interdependencies I use standard form VAR methodology.

Please note that the VAR methodology in standard form does not allow for contemporaneous feedback, as the right hand side of the VAR equation only contains pre-determined values. This shortcoming could be overcome by formulating a VAR model in structural form. As it is possible to use ordinary least squares methodology on each equation, for sake of simplicity, I stick to a VAR in standard form. Instead the problem is alleviated by ordering the variables in the model according to the theoretical speed of adjustment. Adapting the definition of Bernanke, Boivin and Eliasz (2005) of “fast-moving” and “slow-moving” variables I order the variables according to the sensitivity to contemporaneous economic news or shocks. Assuming a particular ordering is necessary to calculate the impulse responses and variance decompositions. Orthogonalised impulse responses are derived from a Choleski decomposition of the error variance-covariance matrix. Due to the calculation procedure, it follows that only a shock to the variable which is ordered first in the VAR(p)-process has an direct impact on all the remaining ones. Variables which have a lower order can only directly influence variables with an even lower order. This is why impulse responses are non-unique and financial theory should suggest an ordering.

Another weakness of the VAR approach, given by its a-theoretical nature and the large numbers of parameters included, is the difficulty of model interpretation. It is often complex to assess what impact a change in one variable has on the system, due to interconnectivity of equations and changing signs of coefficients in the lag structure. Therefore causality tests, impulse responses and variance decompositions have to be constructed to gain insight into system dynamics.

Next, I will formulate models as specified above, first for a yield only model and later for a yield-macro model, and pursue estimation for the in-sample period.

After estimation of the model coefficients, forecasts of the factors can be computed recursively. From these forecasts of the latent yield factors the yield curve representation can be calculated. Therefore in a second step yield forecasts are produced via the factor forecasts according to the following specification:

$$\hat{y}_{t+h/t}(\tau) = \hat{\beta}_{1,t+h/t} + \hat{\beta}_{2,t+h/t}\left(\frac{1-e^{-\lambda_t \tau}}{\lambda_t \tau}\right) + \hat{\beta}_{2,t+h/t}\left(\frac{1-e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau}\right), \quad (5.3)$$

and factor forecasts are according to a VAR(p) process

$$\hat{\beta}_{t+h/t} = \hat{c}_i + \hat{\Gamma}\hat{\beta}_t \,. \quad (5.4)$$

where $\hat{c}_i$ is the intercept column vector and $\hat{\Gamma}$ the coefficient matrix derived by ordinary least squares methodology on each equation separately as described above.

The AR(1) model can be interpreted as a restricted VAR(1), with every latent factor only depending on its own lags. Factor forecasts are therefore according to

$$\hat{\beta}_{i,t+h/t} = \hat{c}_i + \hat{\gamma}_i \hat{\beta}_{i,t}\,, \qquad i = 1,2,3 \quad (5.5)$$

keeping the estimation of the different factors independent from each other. As the AR model is a restricted case of a VAR model without feedback between the variables, my implementation of the AR model in R imposes zero restrictions on the regressors. This restricts the relationships between the latent factors (see appendix for R code).

Next, yield-only and yield-macro models will be estimated. The estimation results are given in the appendix but it should be noted that inference from the coefficient estimates is difficult. Neither tests for heteroscedasticity nor for autocorrelation of the residuals are performed. Violation of the assumptions underlying the linear regression model might render stated standard errors and R^2 incorrect. Another difficulty is the possible multicollinearity between explanatory variables of the Macro-Yield Model. Multicollinearity could be present between the Level and the Spread factor. With multicollinearity R^2 generally looks impressive but only few coefficient estimates will be significant due to high standard errors. Fortunately, the derived OLS estimates will be unbiased and consistent.

As my aim is to produce forecasts and inference of system dynamics is taken from impulse response analysis, the above difficulties are not of concern for this work.

Despite the possibility of wrong standard errors, I build restricted models where only coefficients at the 95% significance level (t-statistic >= 2) are included.

Smaller models have generally the tendency to produce better out-of-sample forecasts. Also the restricting procedure is somewhat arbitrary as it eliminates all insignificant explanatory variables from the original estimation. Removing explanatory variables one at a time and re-estimating the model will change standard errors and may turn previously insignificant variables into significant ones.

Guidance on the best order p of the model is drawn form the multivariate form of the Akaike information criterion (AIC) and the Schwarz criterion (SC). But as yields are calculated back from the factor forecast and models are frequently re-estimated on a changing window of data it is not clear that the information criteria relevant for explanation of the complete system will also lead to the best yield forecasts. I therefore estimate a wider range of models as implied by information criteria. Due to the limited sample size I limit the maximum lag structure at four. For every country a model with 1, 2 and 4 lags will be estimated. In the case of the Polish Yield-Only Model three lags is added as the AIC indicates this to be the optimal choice.

I proceed by producing out-of-sample forecasts with the methodology established above and assessing the quality of the forecasts.

5.1 Forecasting Results

This part of my work evaluates the out-of-sample forecasting performance of the Yield-Only AR(1) and the Un-/Restricted VAR(p) Models for the yield-only and the yield-macro setting. The in-sample period for model estimation runs from June 1998 to January 2006. Forecasting performance is evaluated within the out-of-sample period of February 2006 to January 2008. To evaluate the performance of the models the root mean squared errors (RMSE) for the out-of-sample period is calculated.

The root mean squared error for a given h-month ahead forecast is defined as:

$$RMSE(\tau)=\sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t(\tau)-\hat{y}_t(\tau))^2}\,, \tag{5.6}$$

where T is the total out-of-sample size, $y_t(\tau)$ the actual yield representation of maturity τ at out-of-sample time t and $\hat{y}_t(\tau)$ the corresponding model forecast.

Within the term-structure literature it is common to benchmark model performance against the random walk and the random walk has been shown difficult to outperform.

The random walk (without drift) assumes interest rates as a diffusion process moving up or down a certain amount at every time step at equal probability. If step intervals are assumed to be very small, according to the central limit theorem, the diffusion process will converge towards a normal distribution. Therefore interest rates will be normally distributed around the current interest level, which is equal to the mean of the distribution, making it the best estimate of future yields. In other words the random walk is a no-change forecast of the future term-structure:

$$\hat{y}_{t+h/t}(\tau)=y_t(\tau)\,. \tag{5.7}$$

To make the assessment of the forecasting and comparison of results straightforward I report the RMSE relative to random walk. Therefore reported values above 1 perform worse than the random walk and values below 1 out-perform the random walk. Forecasting performance is reported for the 2, 4, 6, 8, 10 and 12 months ahead-horizon. Note that due to the recursive nature of our forecasts the number of out-of-sample results declines with the number of the months ahead to be forecasted.

Further I benchmark the model forecasts to market based forecasts. Term-structure implied forward rates have a prominent role within fixed-income management, because they allow unbiased prediction of the future spot term-structure by the expectation hypothesis and no-arbitrage arguments. Forward rates are implied by the given spot term-structure and can be calculated. To see why the forward rate has to be an unbiased predictor see the following example adapted from Cuthbertson and Nitsche (2005)[9].

According to the expectation hypothesis the return of an investment in a long bond has to equal the expected return of a corresponding series of short-term investments where the reinvestment yields are uncertain.

If a long bond is held until maturity the return of the investment equals the yield to maturity. (Note that the yield to maturity convention widely used implicitly assumes that coupons can be reinvested at the yield to maturity)

Therefore the terminal value of the long bond will be:

$$TV = A_t (1 + y_t(\tau))^{(\frac{\tau}{12})}, \tag{5.8}$$

where A_t is the investment at time t, TV is the terminal value and $y_t(\tau)$ the appropriate yield of maturity τ (yields in annual rates and τ in month).

Alternatively one could invest in a sequence of short-term investments being rolled-over from period to period. The expected terminal value of the series is equal to:

$$E(TV) = A_t (1 + y_t(\tau_1))^{(\frac{\tau_1}{12})} (1 + E_t(y_t(\tau_2)))^{(\frac{(\tau_2 - \tau_1)}{12})} \ldots (1 + E_t(y_t(\tau_n)))^{(\frac{(\tau_n - \tau_{n-1})}{12})} \tag{5.9}$$

.

A risk neutral investor would be indifferent between the two investment options if they yield the same expected return:

$$(1 + y_t(\tau_T))^{(\frac{\tau_T}{12})} = (1 + y_t(\tau_1))^{(\frac{\tau_1}{12})} (1 + E_t(y_t(\tau_2)))^{(\frac{(\tau_2 - \tau_1)}{12})} \ldots (1 + E_t(y_t(\tau_{T-1})))^{(\frac{(\tau_{T-1} - \tau_{T-2})}{12})}. \tag{5.10}$$

[9] See Chapter 20 for a detailed explanation on term-structure theory

A real investor is risk averse and prefers an investment where there is no reinvestment risk. The reinvestment risk can be abolished by investing the proceeds at the maturity of the short bond at the time t given forward rate $f_t(\tau_1,\tau_2)$ and continue to do this for all remaining proceeds until the final maturity. Now the forward rates have to equal the expected future spot rates by no-arbitrage arguments. See the example below for clarification:
A two year investment at $y_t(24)$ must yield the same return as a one year investment at $y_t(12)$ followed by a forward investment from one year ahead until 2 years at $f_t(12,24)$. The forward rate $f_t(12,24)$ is known at time t and the forward investment is therefore riskless.

$$(1+y_t(24))^{\frac{24}{12}} = (1+y_t(12))^{\frac{12}{12}}(1+f_t(12,24))^{\frac{(24-12)}{12}} \tag{5.11}$$

This implies that

$$f_t(12,24) = \frac{(1+y_t(24))^2}{(1+y_t(12))} - 1\,. \tag{5.12}$$

To avoid the possibility of arbitrage (a riskless profit without capital allocation) the equality 4.11 has to hold. A violation of the equality would make it possible to earn a riskless profit by selling the over-priced side of the equation and investing in the under-priced side of the equation. Due to the fact that cash flows of the short and long investment will match each other at the terminal maturity, a positive difference of the transaction at time t (ignoring transaction costs and credit risk) is a riskless profit without capital allocation.
According to this methodology implied forward rates can be derived from the spot term-structure and by efficient market theory deviations of the forward rate from implied forward rates should not be consistent. Forward rates are therefore an unbiased prediction of the future yield curve.

Within my results I report relative RMSE of the forward implied spot yields[10] as the main competitor to the estimated auto- and vector autoregressive models. This choice is due to the widespread use of implied forward rates in the financial industry. Results are reported for the maturities of 3, 6, 12, 24, 36, 48, 60, 84 and 120 months.

5.1.1 Czech Republic

Averaging over all maturities only the Yield-Only AR(1) and Yield-Macro VAR(1) Model are able to out-perform the random walk for all reported forecast horizons. For the Yield-Only AR(1) Model performance improves with increasing forecast horizon. Reported RMSE for the 2-months forecast are 5% less compared to random walk and increasing to above 35% for the 12-months horizon. Performance of the Yield-Macro VAR(1) Model is between 8.1% for the 4-months forecast and 1.3% for the 10-months forecast better than the random walk forecast. These results are in line with the calculated information criteria in Table 10 and 11 both indicating a lag structure of one the best choice. Additionally the Restricted Yield-Only VAR(1) produces good forecasting results for the long maturity spectrum giving the best results for the 84 and 120 months maturities, for all forecast horizons.

Table 10 – Information Criteria Yield Only Model Czech Republic

Czech Republic Model Selection Yield Factor Only Model VAR(n)					
n	1	2	3	4	**selection**
AIC(n)	**-5.31415908**	-5.244877	-5.25879846	-5.26484699	**1**
SC(n)	**-5.02289135**	-4.73515846	-4.53062912	-4.31822685	**1**

Table 11 - Information Criteria Yield-Macro Model Czech Republic

Czech Republic Model Selection Yield-Macro Model VAR(n)					
n	1	2	3	4	**selection**
AIC(n)	**-14.6384125**	-14.6276944	-14.4532937	-14.2697981	**1**
SC(n)	**-12.8908061**	-11.3266601	-9.59883144	-7.86190795	**1**

Nevertheless, the Yield-Macro VAR(4) Model shows superior average performance for the 4 and 6-months forecasting horizons outperforming the Yield-Only AR(1) Model as the next best model by 7.2% and 3.8% relative to random walk forecasts.

[10] as calculated and provided by Bloomberg financial services implied forward rate function (FWCV) of the respective Zero Coupon Fair Market Yield Curve; Bloomberg Ticker information Czech Rebublic: F480; Hungary: F114; Poland: F119

Implied forward rates perform well in the given out-of-sample experiment for the Czech Republic. Only at the 2-month horizon the average performance for the total maturity spectrum is marginally below the random walk with 1.014. For all other forecasting horizons implied forward rates are out-performing the random walk by a considerable margin of up to 55.1% for the 12-month forecasting horizon. Forecasts based on implied forward rates are best for the 8, 10 and 12-months ahead horizon compared to the tested models. Average out-performance over all maturities for the above forecast horizons to the second best Yield-Only AR(1) Model is in the order of 6.2% to 9.9%. Implied forward rates show the tendency to forecast the shorter maturity spectrum better than longer rates for all h-ahead forecasts. This is probably due to shortcomings of the curve fitting techniques in the fair market yield curves methodology, which are the basis for the analysis. These problems have a bigger impact on implied forward rates than on spot rates itself.[11]

[11] See Tuckman(2002) Chapter 4 for a detailed discussion of the phenomenon

Table 12 - RMSE Czech Rep. 2, 4 and 6-month forecast relative to random walk

Root Mean Squared Error relative to Random Walk
Out-of-sample forecast Czech Republic 2006:02 - 2008:01

Maturity	AR(1)	VAR(1)	VAR(2)	VAR(4)	Res. VAR(1)	Res. VAR(2)	Res. VAR(4)	Macro VAR(1)	Macro VAR(2)	Macro VAR(4)	Res. Macro VAR(1)	Res. Macro VAR(2)	Res. Macro VAR(4)	Forward Rate
2-month ahead forecast														
3	0.898	0.935	1.345	1.097	0.899	1.341	1.495	**0.822**	1.071	1.126	1.181	0.953	1.637	1.097
6	1.071	1.182	1.717	1.370	1.148	1.634	1.837	**0.927**	1.299	1.226	1.551	1.109	1.910	1.062
12	1.192	1.406	1.890	1.484	1.376	1.695	1.880	1.114	1.466	1.264	1.768	1.270	1.926	**0.977**
24	1.085	1.441	1.900	1.453	1.424	1.539	1.770	1.197	1.574	1.221	1.792	1.293	1.917	**0.940**
36	**0.929**	1.201	1.559	1.246	1.164	1.285	1.529	1.037	1.273	1.085	1.486	1.016	1.554	0.988
48	**0.820**	1.033	1.377	1.090	1.014	1.151	1.364	0.926	1.215	1.030	1.309	0.959	1.405	0.969
60	**0.838**	0.945	1.191	1.030	0.905	1.062	1.263	0.887	1.094	1.022	1.136	0.890	1.222	1.001
84	**0.803**	0.915	1.172	1.027	0.869	1.085	1.259	0.883	1.135	0.986	1.129	0.927	1.211	1.023
120	**0.917**	1.079	1.480	1.254	1.010	1.520	1.680	0.994	1.278	0.959	1.442	1.056	1.413	1.067
Average	**0.950**	1.126	1.514	1.228	1.090	1.368	1.564	0.977	1.267	1.102	1.422	1.053	1.577	1.014
Max	1.192	1.441	1.900	1.484	1.424	1.695	1.880	1.197	1.574	1.264	1.792	1.293	1.926	**1.097**
4-month ahead forecast														
3	0.874	0.953	1.436	1.137	0.884	1.411	1.549	0.721	1.047	0.918	1.242	0.756	1.466	**0.687**
6	0.983	1.171	1.724	1.296	1.072	1.567	1.707	0.886	1.331	0.937	1.520	0.997	1.682	**0.674**
12	1.037	1.352	1.883	1.353	1.260	1.557	1.705	1.051	1.545	0.914	1.710	1.187	1.786	**0.669**
24	0.990	1.426	1.935	1.302	1.343	1.454	1.640	1.135	1.640	0.836	1.798	1.246	1.769	**0.774**
36	0.880	1.268	1.710	1.136	1.168	1.302	1.490	1.004	1.408	**0.724**	1.617	1.048	1.469	0.853
48	0.771	1.076	1.483	0.979	0.995	1.157	1.320	0.889	1.279	**0.710**	1.418	0.961	1.289	0.893
60	0.751	0.942	1.239	0.864	0.843	1.042	1.165	0.807	1.064	**0.715**	1.204	0.841	1.048	0.914
84	0.767	0.928	1.207	0.856	0.807	1.105	1.182	0.837	1.110	**0.760**	1.200	0.916	1.029	0.938
120	0.849	1.039	1.395	1.039	0.897	1.425	1.490	0.940	1.258	**0.742**	1.415	1.025	1.143	0.995
Average	0.878	1.128	1.557	1.107	1.030	1.336	1.472	0.919	1.298	**0.806**	1.458	0.997	1.409	0.822
Max	1.037	1.426	1.935	1.353	1.343	1.567	1.707	1.135	1.640	**0.937**	1.798	1.246	1.786	0.995
6-month ahead forecast														
3	0.793	0.944	1.409	1.053	0.818	1.353	1.378	0.729	1.115	0.698	1.176	0.796	1.413	**0.664**
6	0.873	1.121	1.628	1.161	0.971	1.447	1.477	0.876	1.359	0.725	1.398	0.995	1.594	**0.665**
12	0.930	1.301	1.803	1.221	1.150	1.459	1.509	1.038	1.583	0.741	1.589	1.187	1.714	**0.620**
24	0.932	1.431	1.943	1.228	1.283	1.440	1.534	1.148	1.770	0.774	1.765	1.313	1.768	**0.746**
36	0.818	1.264	1.733	1.058	1.115	1.280	1.378	1.002	1.576	**0.727**	1.616	1.138	1.522	0.857
48	**0.730**	1.091	1.523	0.927	0.949	1.179	1.256	0.892	1.441	0.752	1.445	1.038	1.352	0.926
60	**0.723**	0.950	1.274	0.843	0.802	1.066	1.119	0.800	1.214	0.793	1.242	0.891	1.136	0.930
84	0.777	0.940	1.246	0.867	**0.768**	1.159	1.168	0.839	1.301	0.946	1.263	0.965	1.170	0.946
120	0.862	1.038	1.391	1.026	**0.853**	1.469	1.441	0.967	1.475	1.039	1.451	1.068	1.323	1.026
Average	0.827	1.120	1.550	1.043	0.968	1.317	1.362	0.921	1.426	**0.799**	1.438	1.043	1.443	0.820
Max	**0.932**	1.431	1.943	1.228	1.283	1.469	1.534	1.148	1.770	1.039	1.765	1.313	1.768	1.026

Table 13 - RMSE Czech Rep. 8, 10 and 12-month forecast relative to random walk

Root Mean Squared Error relative to Random Walk
Out-of-sample forecast Czech Republic 2006:02 - 2008:01

Maturity	AR(1)	VAR(1)	VAR(2)	VAR(4)	Res. VAR(1)	Res. VAR(2)	Res. VAR(4)	Macro VAR(1)	Macro VAR(2)	Macro VAR(4)	Res. Macro VAR(1)	Res. Macro VAR(2)	Res. Macro VAR(4)	Forward Rate
8-month ahead forecast														
3	0.700	0.934	1.359	0.997	0.744	1.281	1.297	0.808	1.247	0.719	1.142	0.894	1.461	**0.500**
6	0.784	1.096	1.545	1.095	0.894	1.365	1.388	0.944	1.450	0.762	1.324	1.073	1.615	**0.497**
12	0.883	1.310	1.778	1.205	1.108	1.436	1.483	1.123	1.711	0.821	1.566	1.310	1.806	**0.569**
24	0.879	1.417	1.899	1.206	1.222	1.421	1.501	1.198	1.877	0.844	1.723	1.440	1.878	**0.709**
36	0.767	1.234	1.683	1.037	1.061	1.266	1.333	1.049	1.706	0.869	1.577	1.271	1.660	**0.759**
48	**0.713**	1.103	1.537	0.944	0.935	1.210	1.260	0.955	1.606	0.845	1.478	1.190	1.541	0.838
60	**0.710**	0.959	1.312	0.862	0.800	1.117	1.136	0.853	1.396	0.894	1.302	1.017	1.348	0.837
84	0.754	0.912	1.255	0.875	**0.744**	1.206	1.189	0.855	1.451	1.011	1.297	1.034	1.372	0.821
120	0.791	0.942	1.300	0.952	**0.775**	1.426	1.380	0.940	1.576	1.050	1.376	1.110	1.466	0.893
Average	0.776	1.101	1.519	1.019	0.920	1.303	1.330	0.969	1.558	0.868	1.421	1.149	1.572	**0.714**
Max	**0.883**	1.417	1.899	1.206	1.222	1.436	1.501	1.198	1.877	1.050	1.723	1.440	1.878	0.893
10-month ahead forecast														
3	0.659	0.903	1.317	0.928	0.704	1.249	1.230	0.832	1.355	0.683	1.097	0.981	1.528	**0.432**
6	0.739	1.064	1.507	1.033	0.848	1.337	1.318	0.969	1.565	0.722	1.283	1.178	1.699	**0.452**
12	0.840	1.284	1.764	1.159	1.063	1.431	1.421	1.151	1.862	0.823	1.542	1.446	1.934	**0.556**
24	0.850	1.406	1.934	1.178	1.194	1.439	1.440	1.246	2.117	0.918	1.749	1.665	2.103	**0.691**
36	0.731	1.199	1.694	0.981	1.024	1.270	1.250	1.078	1.934	0.912	1.577	1.497	1.867	**0.700**
48	**0.688**	1.071	1.571	0.894	0.909	1.231	1.193	0.996	1.879	0.964	1.506	1.441	1.804	0.809
60	**0.686**	0.906	1.335	0.785	0.772	1.126	1.061	0.881	1.673	1.001	1.322	1.251	1.594	0.781
84	0.719	0.824	1.247	0.764	**0.696**	1.197	1.112	0.852	1.709	1.073	1.292	1.272	1.630	0.756
120	0.689	0.801	1.212	0.795	**0.674**	1.349	1.261	0.876	1.725	0.993	1.300	1.315	1.654	0.853
Average	0.733	1.051	1.509	0.946	0.876	1.292	1.254	0.987	1.758	0.899	1.408	1.338	1.757	**0.670**
Max	**0.850**	1.406	1.934	1.178	1.194	1.439	1.440	1.246	2.117	1.073	1.749	1.665	2.103	0.853
12-month ahead forecast														
3	0.591	0.809	1.239	0.815	0.636	1.179	1.130	0.808	1.478	0.681	1.020	1.111	1.609	**0.328**
6	0.673	0.961	1.418	0.919	0.775	1.262	1.205	0.941	1.688	0.758	1.194	1.310	1.785	**0.357**
12	0.766	1.159	1.660	1.043	0.970	1.349	1.288	1.111	1.992	0.878	1.437	1.594	2.024	**0.407**
24	0.815	1.337	1.947	1.133	1.154	1.443	1.368	1.278	2.444	1.134	1.743	1.974	2.382	**0.600**
36	0.646	1.085	1.661	0.903	0.949	1.223	1.147	1.069	2.204	1.059	1.527	1.780	2.109	**0.542**
48	**0.607**	0.968	1.595	0.815	0.854	1.217	1.122	1.010	2.261	1.163	1.505	1.805	2.151	0.670
60	**0.582**	0.776	1.367	0.675	0.700	1.116	1.004	0.871	2.076	1.171	1.323	1.622	1.970	0.635
84	0.597	0.619	1.233	0.581	**0.572**	1.160	1.044	0.781	2.109	1.254	1.250	1.646	2.049	0.630
120	0.553	0.583	1.141	0.595	**0.533**	1.277	1.173	0.764	2.011	1.137	1.211	1.622	2.012	0.769
Average	0.648	0.922	1.473	0.831	0.794	1.247	1.165	0.959	2.029	1.026	1.357	1.607	2.010	**0.549**
Max	0.815	1.337	1.947	1.133	1.154	1.443	1.368	1.278	2.444	1.254	1.743	1.974	2.382	**0.769**

5.1.2 Hungary

The only model outperforming the random walk on an average over all maturities is the Yield-Only VAR(1) Model with 0.995 for the 2-months horizon and 0.834 for the 12-month horizon, even so it fails to be on average the best model for any forecasting horizon. For the shorter horizons of 2 and 4-months the Restricted Yield-Macro VAR(1) Model gives on average the best forecast for the whole maturity spectrum with a performance relative to random walk of 0.975 for 2-months and 0.949 for 4-months. For all other forecasting horizons the Restricted Yield-Only VAR(2) Model produces the best average forecasting results. Improvements over random walk run in the order of 10.6% for the 6-months horizon up to 37.5% for the 12-months horizon. For the Hungarian out-of-sample period the mentioned models out-perform the implied forward rates on average for all forecasting horizons. The improvement is in between a mere 0,3% for the 4-months period increasing to 23,4% for the 12-months horizon.

Table 14 – Information Criteria Yield Only Model Hungary

Hungary Model Selection Yield Factor Only Model VAR(n)					
n	1	2	3	4	**selection**
AIC(n)	-1.48319401	-1.39091817	-1.40365573	**-1.49740547**	**4**
SC(n)	**-1.18859615**	-0.87537192	-0.66716109	-0.53996243	**1**

Table 15 - Information Criteria Yield-Macro Model Hungary

Hungary Model Selection Yield-Macro Model VAR(n)					
n	1	2	3	4	**selection**
AIC(n)	-13.3104637	**-13.3470624**	-12.9523454	-12.8757705	**2**
SC(n)	**-11.5428766**	-10.0082866	-8.0423811	-6.39461764	**1**

Notice that for longer forecasting horizons the Yield-Only VAR(1) Model outperforms the Yield-Only AR(1) Model significantly up to an order of around 30%. This contradicts the argumentation of Diebold and Li(2006) of expected inferiority of VAR models compared to the AR model. This is in line with the finding of Mönch(2005). In his out-of-sample experiment he shows superior forecasting performance for the VAR(1) model for the American term-structure.

Table 16 - RMSE Hungary 2, 4 and 6-month forecast relative to random walk

Root Mean Squared Error relative to Random Walk
Out-of-sample forecast Hungary 2006:02 - 2008:01

Maturity	AR(1)	VAR(1)	VAR(2)	VAR(4)	Res. VAR(1)	Res. VAR(2)	Res. VAR(4)	Macro VAR(1)	Macro VAR(2)	Macro VAR(4)	Res. Macro VAR(1)	Res. Macro VAR(2)	Res. Macro VAR(4)	Forward Rate
2-month ahead forecast														
3	0.991	**0.913**	0.987	1.002	0.984	0.930	0.967	1.045	1.393	2.187	1.047	1.782	2.106	0.934
6	0.979	0.926	1.036	1.048	1.013	0.984	**0.919**	0.994	1.299	2.021	1.017	1.695	1.925	0.937
12	0.997	1.006	1.168	1.180	1.071	1.084	0.965	0.993	1.235	1.894	1.007	1.648	1.758	**0.959**
24	1.039	1.058	1.219	1.241	1.090	1.101	1.031	**0.953**	1.065	1.663	0.988	1.439	1.498	0.982
36	0.995	1.031	1.207	1.245	1.061	1.074	1.006	**0.924**	1.014	1.523	0.962	1.294	1.352	0.983
48	0.982	1.021	1.193	1.261	1.031	1.043	1.020	**0.942**	0.982	1.466	0.953	1.234	1.298	0.997
60	0.955	0.996	1.171	1.264	1.008	1.017	0.999	0.947	0.988	1.412	**0.937**	1.168	1.247	1.000
84	**0.932**	0.994	1.209	1.363	1.018	1.027	1.017	0.979	1.073	1.431	0.948	1.101	1.227	1.009
120	0.997	1.008	1.169	1.404	0.991	0.988	1.141	1.096	1.196	1.483	**0.915**	0.998	1.247	1.061
Average	0.985	0.995	1.151	1.223	1.030	1.027	1.007	0.986	1.138	1.676	**0.975**	1.373	1.517	0.985
Max	**1.039**	1.058	1.219	1.404	1.090	1.101	1.141	1.096	1.393	2.187	1.047	1.782	2.106	1.061
4-month ahead forecast														
3	0.975	**0.846**	0.930	1.003	0.964	0.873	0.907	1.070	1.553	2.433	1.086	1.998	2.234	0.883
6	0.942	**0.868**	0.993	1.051	0.946	0.912	0.884	0.998	1.462	2.190	0.985	1.856	2.012	0.882
12	0.971	0.957	1.125	1.165	0.998	1.008	0.934	0.997	1.426	2.056	0.958	1.815	1.849	**0.907**
24	1.042	1.055	1.237	1.275	1.044	1.071	1.043	1.010	1.314	1.882	0.968	1.716	1.626	**0.947**
36	1.000	1.041	1.234	1.290	1.020	1.050	1.035	0.967	1.175	1.668	**0.940**	1.527	1.421	0.954
48	0.996	1.039	1.248	1.340	0.998	1.033	1.081	0.976	1.113	1.647	**0.934**	1.485	1.380	0.977
60	0.948	1.000	1.212	1.337	0.953	0.985	1.068	0.949	1.018	1.525	**0.893**	1.341	1.272	0.978
84	0.918	0.990	1.222	1.415	0.944	0.969	1.102	0.976	0.966	1.460	**0.891**	1.197	1.204	0.988
120	1.004	1.025	1.198	1.492	0.931	0.939	1.279	1.143	0.975	1.483	**0.885**	1.071	1.227	1.055
Average	0.977	0.980	1.155	1.263	0.978	0.982	1.037	1.010	1.222	1.816	**0.949**	1.556	1.581	0.952
Max	**1.042**	1.055	1.248	1.492	1.044	1.071	1.279	1.143	1.553	2.433	1.086	1.998	2.234	1.055
6-month ahead forecast														
3	0.946	0.805	0.869	0.950	0.954	**0.795**	0.869	1.136	1.706	2.735	1.163	1.992	2.573	0.837
6	0.919	0.827	0.916	0.983	0.914	**0.822**	0.856	1.056	1.620	2.518	1.054	1.868	2.330	0.835
12	0.962	0.913	1.030	1.082	0.947	0.907	0.914	1.048	1.610	2.432	1.005	1.848	2.158	**0.867**
24	1.066	1.017	1.143	1.199	0.986	0.975	1.056	1.107	1.595	2.444	1.004	1.870	2.021	**0.913**
36	1.025	1.003	1.138	1.218	0.949	0.953	1.055	1.053	1.435	2.238	0.957	1.694	1.790	**0.910**
48	1.058	1.021	1.171	1.297	0.948	0.954	1.137	1.113	1.427	2.343	0.983	1.724	1.834	**0.937**
60	1.029	1.000	1.159	1.329	**0.912**	0.924	1.163	1.099	1.327	2.276	0.948	1.622	1.759	0.948
84	0.945	0.957	1.108	1.347	**0.855**	0.867	1.159	1.079	1.135	2.074	0.909	1.376	1.577	0.950
120	1.065	1.013	1.067	1.417	0.864	**0.851**	1.371	1.276	1.042	2.160	0.952	1.262	1.610	1.048
Average	1.002	0.951	1.067	1.202	0.925	**0.894**	1.065	1.108	1.433	2.358	0.997	1.695	1.961	0.916
Max	1.066	1.021	1.171	1.417	0.986	**0.975**	1.371	1.276	1.706	2.735	1.163	1.992	2.573	1.048

Table 17 - RMSE Hungary 8, 10 and 12-month forecast relative to random walk

Root Mean Squared Error relative to Random Walk
Out-of-sample forecast Hungary 2006:02 - 2008:01

Maturity	AR(1)	VAR(1)	VAR(2)	VAR(4)	Res. VAR(1)	Res. VAR(2)	Res. VAR(4)	Macro VAR(1)	Macro VAR(2)	Macro VAR(4)	Res. Macro VAR(1)	Res. Macro VAR(2)	Res. Macro VAR(4)	Forward Rate
8-month ahead forecast														
3	0.948	0.815	0.815	0.868	0.913	**0.752**	0.926	1.246	1.825	2.902	1.105	1.854	3.000	0.853
6	0.932	0.822	0.843	0.886	0.861	**0.760**	0.915	1.161	1.745	2.723	0.991	1.757	2.743	0.846
12	0.978	0.887	0.924	0.957	0.872	**0.817**	0.961	1.140	1.711	2.626	0.920	1.718	2.500	0.850
24	1.113	0.973	1.003	1.040	0.905	**0.862**	1.103	1.250	1.747	2.742	0.900	1.801	2.376	0.901
36	1.067	0.944	0.975	1.028	0.844	**0.823**	1.089	1.207	1.593	2.540	0.831	1.639	2.111	0.875
48	1.112	0.966	0.994	1.078	0.861	**0.827**	1.153	1.301	1.613	2.669	0.858	1.674	2.146	0.908
60	1.085	0.938	0.963	1.078	0.823	**0.790**	1.158	1.299	1.519	2.613	0.835	1.573	2.057	0.927
84	0.969	0.867	0.869	1.032	0.726	**0.711**	1.120	1.273	1.328	2.390	0.775	1.339	1.843	0.907
120	1.087	0.919	0.793	1.027	0.765	**0.722**	1.293	1.484	1.278	2.521	0.871	1.257	1.858	1.011
Average	1.032	0.903	0.909	0.999	0.841	**0.785**	1.080	1.262	1.595	2.636	0.899	1.623	2.293	0.897
Max	1.113	0.973	1.003	1.078	0.913	**0.862**	1.293	1.484	1.825	2.902	1.105	1.854	3.000	1.011
10-month ahead forecast														
3	1.005	0.864	0.796	0.811	1.001	**0.734**	1.010	1.307	1.718	2.912	1.296	1.825	3.522	0.846
6	0.989	0.844	0.796	0.809	0.927	**0.711**	0.983	1.183	1.603	2.692	1.181	1.691	3.159	0.811
12	1.051	0.886	0.852	0.860	0.920	**0.740**	1.025	1.108	1.519	2.553	1.120	1.617	2.814	0.815
24	1.216	0.950	0.895	0.908	0.955	**0.758**	1.157	1.198	1.497	2.631	1.133	1.687	2.555	0.874
36	1.174	0.895	0.831	0.855	0.864	**0.693**	1.124	1.184	1.364	2.465	1.033	1.555	2.240	0.818
48	1.196	0.909	0.834	0.874	0.867	**0.695**	1.155	1.265	1.342	2.503	1.042	1.531	2.185	0.880
60	1.147	0.868	0.784	0.843	0.819	**0.656**	1.124	1.268	1.246	2.413	0.988	1.419	2.042	0.896
84	1.051	0.781	0.661	0.745	0.727	**0.575**	1.062	1.329	1.145	2.332	0.900	1.281	1.887	0.863
120	1.174	0.856	**0.605**	0.705	0.828	0.663	1.189	1.594	1.146	2.480	1.010	1.244	1.820	0.993
Average	1.111	0.873	0.784	0.823	0.879	**0.692**	1.092	1.271	1.398	2.553	1.078	1.539	2.469	0.866
Max	1.216	0.950	0.895	0.908	1.001	**0.758**	1.189	1.594	1.718	2.912	1.296	1.825	3.522	0.993
12-month ahead forecast														
3	1.053	0.877	0.742	0.738	1.051	**0.699**	1.185	1.545	1.730	2.730	1.353	2.070	4.622	0.853
6	1.046	0.847	0.737	0.734	0.969	**0.665**	1.144	1.372	1.569	2.459	1.245	1.880	4.082	0.815
12	1.099	0.868	0.772	0.765	0.912	**0.670**	1.162	1.257	1.427	2.219	1.163	1.712	3.505	0.815
24	1.233	0.905	0.789	0.788	0.895	**0.669**	1.253	1.291	1.338	2.150	1.147	1.676	3.008	0.886
36	1.192	0.838	0.715	0.721	0.797	**0.601**	1.200	1.259	1.212	2.005	1.043	1.545	2.602	0.798
48	1.209	0.849	0.709	0.723	0.776	**0.604**	1.228	1.345	1.207	2.036	1.032	1.521	2.535	0.868
60	1.170	0.814	0.664	0.690	0.744	**0.578**	1.199	1.356	1.129	1.975	0.982	1.410	2.403	0.892
84	1.054	0.720	0.543	0.580	0.667	**0.515**	1.100	1.393	1.038	1.896	0.877	1.247	2.177	0.838
120	1.140	0.788	**0.521**	0.557	0.783	0.623	1.194	1.630	1.039	2.014	0.966	1.186	2.088	0.965
Average	1.133	0.834	0.688	0.699	0.844	**0.625**	1.185	1.383	1.299	2.165	1.090	1.583	3.002	0.859
Max	1.233	0.905	0.789	0.788	1.051	**0.699**	1.253	1.630	1.730	2.730	1.353	2.070	4.622	0.965

5.1.3 Poland

For the Polish out-of-sample results four models are able to out-perform the random walk on an average basis over all reported forecasting horizons. The Yield-Only VAR(1) Model, the Yield-Only VAR(3) Model, the Restricted Yield-Only VAR(1) Model and implied forward rate forecasts. The Yield-Only VAR(3) Model performs best on average for the forecasting periods of 4-months to 8-months ahead. Note that the Yield-Only VAR(3) Model is the only model superior to random walk for any single maturity for all forecasting horizons. Average performance reaches from 0.928 for the 2-months horizon, underperforming the the Restricted Yield-Only VAR(3) model by 4.2%, to 0.617 for the 6-months ahead period correspondent to an out-performance of 5.9% to the second best Restricted Yield-Only VAR(1) Model.

Table 18 – Information Criteria Yield Only Model Poland

Poland Model Selection Yield Factor Only Model VAR(n)					
n	1	2	3	4	**selection**
AIC(n)	-1.7047552	-1.92389433	**-1.9707416**	-1.94143747	**3**
SC(n)	-1.41348747	**-1.41417579**	-1.24257225	-0.99481732	**2**

Table 19 - Information Criteria Yield-Macro Model Poland

Poland Model Selection Yield-Macro Model VAR(n)					
n	1	2	3	4	**selection**
AIC(n)	-15.471349	-15.7687752	-15.637816	**-15.7812605**	**4**
SC(n)	**-13.7237425**	-12.4677409	-10.7833537	-9.37337028	**1**

Note that in the case of the Yield-Only Model the Akaike information criterion selects the clearly superior Yield-Only VAR(3) Model compared to the Yield-Only VAR(2) Model selected by the Schwarz criterion. The Yield-Only VAR(3) Model out-performs on average between 20.3% for the 2-months horizon up to 92% for the 12-months horizon relative to random walk forecasts.

Table 11 - RMSE Poland 2, 4 and 6-month forecast relative to random walk

Root Mean Squared Error relative to Random Walk
Out-of-sample forecast Poland 2006:02 - 2008:01

Maturity	AR(1)	VAR(1)	VAR(2)	VAR(3)	VAR(4)	Res. VAR(1)	Res. VAR(2)	Res. VAR(3)	Res. VAR(4)	Macro VAR(1)	Macro VAR(2)	Macro VAR(4)	Res. Macro VAR(1)	Res. Macro VAR(2)	Res. Macro VAR(4)	Forward Rate
2-month ahead forecast																
3	1.072	0.975	1.190	0.966	1.082	1.004	1.039	1.055	1.010	2.668	2.343	2.426	2.410	2.917	2.550	**0.948**
6	1.083	0.949	1.243	0.957	1.112	**0.926**	1.110	1.001	1.007	2.705	2.305	2.215	2.519	2.899	2.454	0.969
12	0.965	0.933	1.268	0.919	1.101	0.875	1.153	**0.859**	1.014	2.373	1.922	1.694	2.360	2.480	1.914	0.929
24	1.088	0.965	1.123	0.951	1.015	0.947	1.046	**0.897**	0.993	1.889	1.443	1.298	1.876	1.897	1.443	0.955
36	1.109	0.987	1.110	0.967	1.006	0.980	1.056	**0.900**	0.999	1.714	1.265	1.241	1.755	1.753	1.296	0.965
48	1.035	1.013	1.184	0.965	1.063	1.022	1.130	**0.854**	1.020	1.722	1.265	1.289	1.853	1.865	1.190	0.986
60	1.065	0.956	1.103	0.919	1.009	0.965	1.062	**0.825**	0.953	1.589	1.175	1.249	1.686	1.745	1.168	0.991
84	1.124	0.919	1.039	0.890	0.981	0.922	1.014	**0.808**	0.904	1.442	1.083	1.232	1.543	1.675	1.192	1.023
120	1.133	0.840	0.919	0.821	0.871	0.831	0.913	**0.774**	0.802	1.164	0.959	1.183	1.295	1.502	1.216	1.030
Average	1.075	0.949	1.131	0.928	1.027	0.941	1.058	**0.886**	0.967	1.919	1.529	1.536	1.922	2.081	1.603	0.977
Max	1.133	1.013	1.268	**0.967**	1.112	1.022	1.153	1.055	1.020	2.705	2.343	2.426	2.519	2.917	2.550	1.030
4-month ahead forecast																
3	1.023	0.903	1.267	**0.792**	1.015	0.890	1.039	0.965	0.982	2.956	2.697	2.554	2.048	3.165	2.820	0.909
6	1.034	0.927	1.363	**0.779**	1.034	0.854	1.117	0.938	1.022	3.033	2.709	2.456	2.237	3.201	2.858	0.937
12	0.903	0.914	1.376	**0.704**	1.039	0.815	1.144	0.770	1.020	2.755	2.382	2.049	2.254	2.886	2.515	0.870
24	1.015	0.884	1.188	**0.688**	0.929	0.856	1.024	0.765	0.923	2.258	1.880	1.496	1.947	2.318	2.026	0.921
36	1.020	0.856	1.094	**0.665**	0.869	0.850	0.967	0.723	0.871	1.948	1.581	1.224	1.761	2.057	1.721	0.931
48	1.028	0.891	1.155	**0.675**	0.934	0.897	1.037	0.693	0.908	1.922	1.526	1.234	1.812	2.125	1.656	0.955
60	1.087	0.859	1.098	**0.669**	0.915	0.865	0.995	0.683	0.870	1.784	1.399	1.185	1.697	2.041	1.561	0.964
84	1.165	0.812	1.032	**0.645**	0.896	0.811	0.943	0.649	0.814	1.614	1.259	1.182	1.569	2.013	1.460	1.003
120	1.197	0.753	0.908	**0.631**	0.809	0.735	0.843	0.632	0.729	1.322	1.048	1.128	1.339	1.865	1.305	1.013
Average	1.052	0.867	1.165	**0.694**	0.938	0.842	1.012	0.757	0.904	2.177	1.831	1.612	1.852	2.408	1.991	0.945
Max	1.197	0.927	1.376	**0.792**	1.039	0.897	1.144	0.965	1.022	3.033	2.709	2.554	2.254	3.201	2.858	1.013
6-month ahead forecast																
3	0.977	0.849	1.275	**0.780**	1.032	0.824	0.978	0.977	0.988	2.400	2.421	2.049	1.488	2.786	2.415	0.885
6	0.980	0.872	1.366	**0.758**	1.070	0.789	1.032	0.946	1.042	2.481	2.485	2.051	1.685	2.870	2.476	0.936
12	0.926	0.881	1.415	**0.667**	1.069	0.767	1.088	0.811	1.055	2.411	2.388	1.929	1.845	2.784	2.363	0.867
24	1.057	0.826	1.237	**0.630**	0.958	0.783	0.993	0.761	0.936	2.066	2.035	1.556	1.696	2.385	2.025	0.914
36	1.086	0.777	1.135	**0.577**	0.903	0.764	0.933	0.684	0.864	1.828	1.786	1.324	1.580	2.208	1.773	0.915
48	1.143	0.807	1.197	**0.563**	0.953	0.804	1.002	0.637	0.897	1.827	1.760	1.302	1.639	2.325	1.742	0.937
60	1.235	0.779	1.158	**0.555**	0.937	0.781	0.980	0.625	0.863	1.732	1.653	1.208	1.571	2.318	1.664	0.949
84	1.350	0.716	1.086	**0.521**	0.904	0.712	0.922	0.573	0.792	1.561	1.475	1.077	1.445	2.330	1.530	0.990
120	1.415	0.650	0.951	**0.501**	0.811	0.634	0.812	0.545	0.688	1.316	1.245	0.945	1.258	2.258	1.360	1.002
Average	1.130	0.795	1.202	**0.617**	0.960	0.762	0.971	0.729	0.903	1.958	1.916	1.493	1.578	2.474	1.928	0.933
Max	1.415	0.881	1.415	**0.780**	1.070	0.824	1.088	0.977	1.055	2.481	2.485	2.051	1.845	2.870	2.476	1.002

Table 12 - RMSE Poland 8, 10 and 12-month forecast relative to random walk

Root Mean Squared Error relative to Random Walk
Out-of-sample forecast Poland 2006:02 - 2008:01

Maturity	AR(1)	VAR(1)	VAR(2)	VAR(3)	VAR(4)	Res. VAR(1)	Res. VAR(2)	Res. VAR(3)	Res. VAR(4)	Macro VAR(1)	Macro VAR(2)	Macro VAR(4)	Res. Macro VAR(1)	Res. Macro VAR(2)	Res. Macro VAR(4)	Forward Rate
								8-month ahead forecast								
3	0.902	0.787	1.289	0.782	1.130	**0.738**	0.907	0.981	1.031	1.837	2.024	1.741	1.100	2.373	1.854	0.783
6	0.917	0.811	1.386	0.759	1.191	**0.711**	0.955	0.963	1.091	1.935	2.130	1.782	1.269	2.522	1.903	0.805
12	0.941	0.851	1.460	**0.706**	1.223	0.727	1.033	0.880	1.133	1.970	2.157	1.747	1.473	2.584	1.864	0.844
24	1.112	0.782	1.288	**0.672**	1.096	0.728	0.979	0.832	0.995	1.720	1.889	1.464	1.404	2.307	1.634	0.874
36	1.217	0.738	1.220	**0.628**	1.050	0.715	0.952	0.775	0.932	1.592	1.743	1.306	1.367	2.265	1.490	0.875
48	1.294	0.759	1.274	**0.591**	1.089	0.744	1.009	0.710	0.957	1.608	1.737	1.275	1.432	2.437	1.452	0.905
60	1.399	0.730	1.239	**0.580**	1.065	0.720	0.990	0.691	0.921	1.548	1.659	1.190	1.389	2.490	1.386	0.911
84	1.607	0.675	1.210	**0.549**	1.051	0.662	0.971	0.652	0.867	1.469	1.555	1.080	1.343	2.693	1.316	0.960
120	1.802	0.592	1.083	**0.518**	0.954	0.575	0.859	0.623	0.749	1.317	1.391	0.910	1.227	2.814	1.229	0.975
Average	1.244	0.747	1.272	**0.643**	1.094	0.702	0.962	0.790	0.964	1.666	1.809	1.388	1.334	2.498	1.570	0.881
Max	1.802	0.851	1.460	0.782	1.223	**0.744**	1.033	0.981	1.133	1.970	2.157	1.782	1.473	2.814	1.903	0.975
								10-month ahead forecast								
3	0.862	0.727	1.364	0.766	1.201	**0.661**	0.879	1.036	1.049	1.265	1.490	1.278	0.823	2.067	1.255	0.672
6	0.933	0.768	1.484	0.779	1.290	**0.658**	0.952	1.072	1.126	1.360	1.612	1.335	0.944	2.254	1.289	0.729
12	1.028	0.837	1.615	0.754	1.375	**0.694**	1.060	1.044	1.213	1.459	1.721	1.349	1.157	2.450	1.264	0.853
24	1.209	0.777	1.424	0.736	1.213	**0.704**	1.023	0.974	1.063	1.254	1.497	1.176	1.114	2.212	1.099	0.861
36	1.375	0.745	1.376	0.723	1.177	**0.703**	1.026	0.947	1.013	1.175	1.409	1.110	1.118	2.268	1.024	0.840
48	1.507	0.770	1.457	**0.685**	1.237	0.734	1.098	0.896	1.053	1.214	1.430	1.101	1.220	2.564	0.982	0.876
60	1.631	0.736	1.429	**0.664**	1.219	0.706	1.088	0.869	1.016	1.158	1.353	1.038	1.224	2.710	0.925	0.875
84	1.919	0.690	1.435	**0.646**	1.218	0.656	1.097	0.857	0.981	1.110	1.261	0.984	1.285	3.124	0.873	0.929
120	2.264	0.577	1.320	0.630	1.133	**0.557**	1.004	0.864	0.850	0.973	1.086	0.872	1.384	3.501	0.882	0.938
Average	1.414	0.736	1.434	0.709	1.229	**0.675**	1.025	0.951	1.040	1.219	1.429	1.138	1.141	2.572	1.066	0.841
Max	2.264	0.837	1.615	0.779	1.375	**0.734**	1.098	1.072	1.213	1.459	1.721	1.349	1.384	3.501	1.289	0.938
								12-month ahead forecast								
3	0.799	0.635	1.460	0.714	1.275	**0.527**	0.881	1.044	1.040	1.245	1.710	1.483	0.721	2.237	1.288	0.531
6	0.901	0.695	1.601	0.765	1.381	**0.549**	0.982	1.125	1.130	1.356	1.875	1.596	0.785	2.454	1.364	0.624
12	1.083	0.809	1.800	0.808	1.529	**0.636**	1.145	1.186	1.267	1.526	2.102	1.728	0.950	2.781	1.438	0.790
24	1.224	0.764	1.606	0.755	1.353	**0.662**	1.107	1.061	1.125	1.359	1.866	1.549	0.926	2.584	1.252	0.800
36	1.412	0.758	1.594	0.752	1.333	**0.685**	1.138	1.044	1.101	1.311	1.803	1.512	0.939	2.735	1.186	0.758
48	1.627	0.813	1.737	0.746	1.443	**0.744**	1.258	1.042	1.183	1.388	1.893	1.576	1.029	3.193	1.187	0.817
60	1.779	0.786	1.732	0.731	1.433	**0.720**	1.267	1.021	1.156	1.333	1.815	1.541	1.039	3.429	1.129	0.811
84	2.044	0.714	1.712	0.685	1.403	**0.639**	1.250	0.980	1.098	1.227	1.654	1.437	1.144	3.930	1.016	0.858
120	2.746	0.671	1.798	0.800	1.460	**0.596**	1.309	1.150	1.085	1.147	1.546	1.476	1.644	4.995	1.086	0.865
Average	1.513	0.738	1.671	0.751	1.401	**0.640**	1.149	1.073	1.132	1.321	1.807	1.544	1.020	3.149	1.216	0.762
Max	2.746	0.813	1.800	0.808	1.529	**0.744**	1.309	1.186	1.267	1.526	2.102	1.728	1.644	4.995	1.438	0.865

6 The Macroeconomy and the Yield Curve

6.1 Causality Tests of Macro Yield Curve Interaction

The assumption that yield-curve dynamics is driven by the macroeconomy and vice-versa will be explored in more detail. In this section I test Granger causality of the yield factors influencing the macro factors and the other way around. With the only exception of an almost 12% likelihood of Czech macro factors not impacting the yield curve, there is strong statistical evidence of a strong macro-yield and strong yield-macro link. Czech yield factors have only a 5.4% chance of not influencing the macroeconomy.

Table 13 - Yield-Macro Factor Causality Test Czech Republic Yield-Macro VAR(1)

Granger Causality Test	
	H0: Level Slope Curvature do not Granger-cause Spread NEER Real.Activity Inflation Base.Rate
p-value	0.0540
	H0: Spread NEER Real.Activity Inflation Base.Rate do not Granger-cause Level Slope Curvature
p-value	0.1198

In the case of Hungary probability for both directions is lower. There is a 4.37% chance of no yield-macro and only a 0.26% chance of no macro-yield relation.

Table 14 - Yield-Macro Factor Causality Test Hungary Yield-Macro VAR(2)

Granger Causality Test	
	H0: Level Slope Curvature do not Granger-cause Spread NEER Real.Activity Inflation Base.Rate
p-value	0.0437
	H0: Spread NEER Real.Activity Inflation Base.Rate do not Granger-cause Level Slope Curvature
p-value	0.0026

For the Polish model there is only a negligible chance of 0.02% of no macro-yield interaction and a chance of 1.21% of no yield-macro link.

Table 15 - Yield-Macro Factor Causality Test Poland Yield-Macro VAR(4)

Granger Causality Test	
	Granger causality H0: Level Slope Curvature do not Granger-cause Spread NEER Real.Activity Inflation Base.Rate
p-value	0.0121
	Granger causality H0: Spread NEER Real.Activity Inflation Base.Rate do not Granger-cause Level Slope Curvature
p-value	0.0002

The results above provide compelling evidence of strong macro-yield and yield-macro interaction for the researched countries.

6.2 System Dynamics

After providing strong evidence of bidirectional dependencies between the macroeconomy and the yield curve, I now uncover the system dynamics of these interdependencies. Shedding light on the relationship between macro factors and the yield curve is important as it improves understanding and decision making.

To interpret system dynamics orthogonal impulse response functions and forecast error variance decompositions are established.

Impulse response functions utilize the moving average representation of the VAR-process to interpret dynamics of the endogenous variables. The expected response of a positive one standard deviation shock of the researched variable towards the system is calculated and accumulated through time.[12] These estimated dynamic responses are shown in a graph for a 24-month period. Additionally, 90% confidence bands for the impulse responses are drawn from 100 bootstrap runs and printed in the graph.

Due to the unlikeliness of the variable shock to occur in isolation, orthogonal impulse responses are constructed. Choleski decomposition of the error variance-covariance matrix is used to preserve the expected contemporaneous correlation of the variables. The orthogonal impulse responses are, therefore, interpreted like in Mönch (2006) as being a “typical” shock response.

Error variance decompositions calculate the proportion of movement in a variable induced by the variable itself and by other variables of the system. Within the dynamic structure of a VAR, the shock to one variable will not only affect this variable directly, but will be transmitted to all other variables via system dynamics. Error variance decompositions calculate the percentage contribution of the various explanatory variables for the h-ahead forecast error variance. I report error variance decompositions up to a 12-month horizon. Note that orthogonal impulse responses are non-unique. Refer to chapter 4 for the arguments of the chosen ordering of the variables.

Both statistics are calculated for the highest lag order of the Unrestricted Yield-Only and Macro-Only Model as indicated by AIC and SC information criteria.

[12] See the R vars package documentation for detail

The choice of the higher order is due to the potentially richer structure of the response.
To enhance the readability of this section, impulse response plots and error variance decomposition tables and graphs are provided in the appendix. This is the base for the following analysis.
Next a brief summary and interpretation of the most relevant findings from impulse response and variance decomposition analysis follows. Variance decompositions are reported at the 12 months ahead horizon.

6.2.1 Czech Republic

6.2.1.1 Yield-Yield Dynamics

Surprise shocks of all three yield factors are very persistent only slowly declining over the 24 months period.
Level is little influenced by the other yield factors. 97.4% of the variation of Level depends on itself, while Slope and Curvature contribute to the rest in almost equal proportions. Impulse response analysis verifies this finding, as the response of Level to unit shocks of Slope and Curvature is dismal and not significant.
The dynamics of Slope are more dependent on the other yield factors, with Level contributing 19.8% and Curvature 12.6%. Curvature depends on Level with a variance contribution share of 12.2% and Slope contributes 3.8%. A typical increase of Level is accompanied by a steepening of the curve at increased convexity. While a flattening of the curve can be associated with growing convexity of the term structure, a shock to Curvature flattens the yield curve. The importance of Curvature is underscored by its low p-value in the causality test for not being causal to Level and Slope.

Table 16 – Yield-Only Factor Causality Test Czech Republic Yield-Macro VAR(1)

Granger Causality Test		
H0: Factor does not Granger-cause the remaining system		
Factor	**p-value**	**Rank**
Level	0.3150	2
Slope	0.7513	3
Curvature	0.0236	1

6.2.1.2 Macro-Yield Dynamics

Including macro factors to the model does not change the yield factor impulse responses significantly compared to the Yield-Only Model. The yield factor shock of Slope is estimated to be less persistent, but the significant areas of the two responses match each other closely.

The variation induced on Level by the macro variables is small, as 93.6% is self induced and 95.5% is explained by all three yield factors. In comparison to the yield-only variance decompositions the share of Slope explaining Level falls almost to zero. NEER is the most important macro variable explaining 2.1%. Note the fact that Base Rate's contribution is close to zero. Level shows the most significant response to a NEER shock by declining about 18 months. Even so none of the impulse responses for Level is significant. It seems that Level is most dependent on future inflation expectations as the responses to Inflation, NEER and Spread indicate.

Slope is more influenced by the macro variables. In the Yield-Macro Model the share of Slope explained by its own dynamics declines to 54.6% and all yield factors explain a total of 83.6%. By explaining 12.5% of the variance, Real Activity takes the highest portion of the macro variables and a Real Activity shock flattens the yield curve for almost 10 periods at marginal significance. NEER is second explaining 2%. The impulse response for Slope to a NEER shock is estimated to be hump-shaped positive for around 7 months. Thereafter the yield curve is steepening. The period from the 12th month to the 18th month is significant. Note that the steepening begins around the time when the shock to the exchange rate has declined to neutral and begins to depreciate.

Curvature is most influenced by macro variables, with 68.4% of the variation self induced and 79% explained by all yield factors. Spread is with 12.6% the most important macro influence. For the Czech Republic an increase of the average spread to the German benchmark yield curve significantly decreases the convexity of the yield curve. NEER with a share of 6.9% is also identified as influential for Curvature. The appreciation shock of the nominal effective exchange rate caused an immediate significant increase in the convexity of the curve for 5 periods. Note that the responses to Spread and NEER are complimentary because a Spread shock is associated with a depreciating currency. As the Curvature factor is often described as idiosyncratic, this is an interesting finding possibly linking Curvature to risk premia.

Note that a monetary policy shock in the Czech Republic has hardly any effect on the yield curve at all.

In general the macro-yield link for the Czech Republic, with macro variables contributing 21% to the variance of Curvature, 16.4% of Slope and a mere 4.5% for Level, might be interpreted as weak. But this is not verified in the Granger causality test, where NEER and Inflation rank first.

Table 17 - Yield-Macro Factor Causality Test Czech Republic Yield-Macro VAR(1)

Granger Causality Test		
H0: Factor does not Granger-cause the remaining system		
Factor	**p-value**	**Rank**
Level	0.0317	5
Slope	0.0993	8
Curvature	0.0192	4
Spread	0.0072	3
NEER	0.0003	1
Real Activity	0.0709	7
Inflation	0.0062	2
Base Rate	0.0633	6

6.2.1.3 Yield-Macro Dynamics

Due to its definition, Spread is highly influenced by the yield curve Level factor. Yield factors do explain 81.2%, with Level contributing 78.6%. A shock to Level is almost as strongly increasing Spread as Level itself and the nominal effective exchange rate is significantly depreciating.

Level explains 22.2% of NEER, making it the major contribution of all the yield factors, while all yield factors explain 26.9%. A typical Level factor shock is associated with a significant depreciation of NEER for at least 7 months and a significant increase in the Spread for more than 15 months.

Real Activity seems to be equally affected by Level and Slope with a variance contribution of 5.5% and 4.6%, while Curvature has only 0.6%. The impact of a Level shock on Real Activity is negative and significant for around 5 months. Impulse responses to a Slope shock are only significant for Real Activity, with the estimated response to be negative and u-shaped. An interesting finding is the long delayed negative response of Real Activity to a Curvature shock,

beginning in period 14 and declining further until the 24th month. The response is marginally significant from month 20.
Level contributes 12.4%, Curvature 9.1% and Slope 5.2% to the variance of Inflation. Inflation is estimated to increase hump-shaped in response to a Level shock, but it is only marginally significant form month 7 to month 11. The response estimation of a Slope shock for Inflation is negative and convex, but lacks significance. Shocking the Curvature factor and estimating the response of inflation gives a positive hump-shaped result for around 18 months, where periods 4 to 8 are marginally significant. Level conveys information about future inflation and there is evidence that the impact of the Level as well as the Curvature shock to Inflation is transmitted via a lower exchange rate.
Level is the yield factor having the highest variance contribution for Base Rate, with a mere 1.8% whereas all yield factors only contribute 2.6%. So it is not surprising that impulse responses for Base Rate to yield factor shocks are only short-lived and the link of the yield curve to monetary policy appears weak.

6.2.1.4 Macro-Macro Dynamics

Spread's variance contribution from macro variables is the highest for the Inflation factor and NEER with 3.4% and 3%, respectively. Spread is estimated to decline succeeding an NEER appreciation shock with marginal significance form the 12th month until around the 17th month, while a shock to Inflation is increasing Spread in a hump-shaped response without significance.
NEER's variance depends to 73.2% on macro dynamics, with Real Activity contributing 12.3% and Spread 9%. Surprise increases in Real Activity are associated with a hump-shaped appreciation of NEER with long significance. The above relation of Spread and NEER is confirmed, as a Spread shock depreciates NEER in a u-shaped response at marginal significance. Additionally, an Inflation shock appreciates NEER at high significance and Inflation contributes 3.7% of its variance. NEER is also estimated to appreciate in response to a monetary shock in a hump-shape non significant response. Therefore, the model does not encompass a price puzzle which is often

reported for VAR models analyzing monetary policy innovations in the Czech Republic.[13]

Real Activity is highly dependent on macro factors with all the yield factors only contributing 10.7% to its variation. NEER is identified to be most influential with a share of 12.2% and Spread is second with 6.6%. Indeed, a NEER shock reduces Real Activity significantly in a u-shaped response with a minimum in period 9. The Spread shock is estimated to increase Real Activity and is closely related to NEER which strongly depreciates in response. But both findings are only marginally significant. Additionally, a unit shock to inflation is significantly increasing Real Activity. The response to a monetary policy shock of Real Activity is hump-shaped positive until period 10 and negative thereafter. Only the first 4 months of the response are significant.

Inflation's variation is more dependent on NEER, contributing 34.5%, than on itself with 33.3%. The impulse response of Inflation to a NEER appreciation is strongly u-shaped negative with high significance. Contrary, a shock to Real Activity increases Inflation significantly hump-shaped. Again, the link to a monetary policy shock is weak. Inflation's non significant response to a monetary shock is not very pronounced, but estimated to be negative with a lag of around 6 months. The model does therefore not contain a price puzzle, as widely observed in other studies.[14]

Base Rate's variance highly depends on itself explaining 84.6%. Real Activity explains the highest share of the other macro variables with 8% and it is followed by NEER with 3.2%. Base Rate's response to a NEER appreciation is significantly negative. A shock to Inflation is estimated to increase the Base Rate, while a positive shock to Real Activity seems connected to an initially lower Base Rate. But none of the responses, except to NEER, are significant.

6.2.2 Hungary

6.2.2.1 Yield-Yield Dynamics

The Level shock is the least persistent, declining to neutral within only 6 months, while a shock to Curvature declines to neutral within 17 months. The

[13] See Corcelli et al. (2006) for a good summary of VAR literature in CEE
[14] Corcelli et al. (2006)

slope shock is very persistent and positive for all 24 months, only declining slowly.

Level contributes 85.9% to its own variation, Slope 9.7% and Curvature 4.4%. A Slope shock significantly increases Level and the response to a Curvature shock is estimated to be positive for around 6 months and negative thereafter. Only the initial positive response is significant.

Slope's variance is more dependent on Level, contributing 13%, than Curvature with a contribution of 1.9%. The initial response of the Slope factor to the Level shock is negative. It converges linearly to neutral in 7 months and is significant for around 4 months. The estimation follows to be slightly positive before declining to zero at the 15th month, non-significantly though. The Curvature shock seems to induce a positive response on the Slope factor. It increases for 2 months, then declines to zero around the 12th month and slightly negative for the rest of the time periods. But confidence bands are wide, making the complete response insignificant.

Curvature's variance is slightly more dependent on Level, contributing 15.9%, than on Slope with 14.4%. The impact on Curvature from a Level shock is negative and pronounced zigzag-shaped before returning to zero around month 7. The negative response of Curvature is significant for more than 5 periods. Later, no inference with significance can be drawn. Curvature has a strong positive reaction to the Slope shock fading with decreasing speed over the 24 months. The positive response is highly significant for around the first 3 months and marginally between months 20 and 24.

Table 18 – Yield-Only Factor Causality Test Hungary Yield-Only VAR(4)

Granger Causality Test		
H0: Factor does not Granger-cause the remaining system		
Factor	**p-value**	**Rank**
Level	0.0010	1
Slope	0.4954	3
Curvature	0.0524	2

6.2.2.2 Macro-Yield Dynamics

The inclusion of macro factors to the model alters the responses of the yield factors only marginally in comparison to the Yield-Only Model. The only noticeable difference is the Level response to a Slope shock, which is less pronounced, compared to the positive response in the Yield-Only Model.

Level's contribution to its own variance even increases compared to the Yield-Only Model, with 90.6%. The most important macro factor is Real Activity with a share of 6%. The other macro factors seem negligible contributing less than 1%. The Level factor is estimated to react positively to a Real Activity shock and it is marginally significant between the 10th and 12th month. The response to a NEER shock is positive for around 6 periods and negative thereafter. Level's estimated response to Inflation is an oscillation for around 5 months and is positive in the sequel until the 18th month and slightly negative then. Further, Level responds positively to a monetary policy shock for around 14 months before getting negative. All responses of Level to the macro factors, except Real Activity, are not significant.

Slope is more dependent on the macro factors, which contribute 16.6% of its variation. Inflation contributes the highest share with 6.4% and is succeeded by NEER with 5.1%. Slope reacts negatively for the complete 24 months, reaching a minimum around period 10, in response of an Inflation shock. The response is significant for a short period around the 4th month and from month 6 to 10. The response of Slope to a NEER shock is negative from the 3rd period, reaching a maximum at around month 8, and subsequently increasing to neutral in the 15th period and positive for the remaining time. The negative response is significant between the 4th and the 10th period. The impact of a monetary shock is estimated to be hump-shaped positive for around 12 periods, with a maximum at period 6, and u-shaped negative for the remaining time, with a minimum at around month 18. However, the estimated response is far from significant.

Curvature has, in the case of Hungary, the highest variance contribution from the macro factors with 25.9%. Inflation contributes 14.4%, Real Activity 5.9% and NEER 2.2%. In comparison with Curvature in the Czech Republic, Spread's contribution is low with only 2%. Curvature's initial negative response to an Inflation shock is highly significant between period 3 and 12, reaching a minimum around the 6th month. Thereafter the estimated negative response retreats towards neutral in period 18 and is slightly positive afterwards. On the contrary, Curvature has a strong initial response to Real Activity, reaching a maximum at around the 4th period, returning to neutral at around month 10 and it is negative and u-shaped thereafter. The strong initial positive response is significant between month 2 and 4.

The response of Curvature to a NEER shock is estimated to be positive for around 3 month before getting u-shaped negative with a minimum around period 5 and returning to neutral at period 10. Thereafter the response is hump-shaped positive with a maximum in month 17. However, this response is not significant. The response to a monetary shock is estimated to be negative, but confidence bands are wide.

Table 19- Yield-Macro Factor Causality Test Hungary Yield-Macro VAR(2)

Granger Causality Test		
H0: Factor does not Granger-cause the remaining system		
Factor	**p-value**	**Rank**
Level	0.0761	8
Slope	0.0006	2
Curvature	0.0020	4
Spread	0.0425	7
NEER	0.0089	6
Real Activity	0.0022	5
Inflation	0.0002	1
Base Rate	0.0008	3

6.2.2.3 Yield-Macro Dynamics

Spread's variation is 82% depending on the Level factor, 3.8% on the Slope factor and 1.1% on Curvature. Spread's response to a Level shock almost mirrors the shock at a slight delay. The estimated response to a shock of Slope is negative but not significant, while the response for Curvature is short and significantly positive.

The variance contribution of the yield factors to NEER is 22.6%. Slope contributes 9%, Level 8.3% and Curvature 5.3%. The estimated response of NEER to a Level shock is negative for around 16 months, the first 5 months with significance. NEER's response to Slope is negative for around 4 months, 2 months with significance, and positive thereafter. The estimated response of NEER to Curvature is slightly positive and hump-shaped for around 20 months at no significance.

The variance of Real Activity is most effected by Slope with 4.5%, followed by Level with 2.2% and Curvature 1.5%. The response of Real Activity to a Slope response is estimated u-shaped negative with a minimum at around the 12th

month. A shock to Level has almost no effect on Real Activity, while the response to Curvature is estimated to be hump-shaped positive for around 5 months and u-shaped negative, with a minimum at the 12^{th} month, thereafter. Due to wide confidence intervals, the yield factor responses for Real Activity are not significant.

Inflation has a variance contribution of 4.5% form Slope, 2.2% from Level and 1.5% from Curvature. A Level shock comes with higher Inflation for an estimated 7 months and the first three months are significant. The responses to a Level and Curvature shock are u-shaped negative with a short delay, but are lacking significance.

Base Rate's variance takes a contribution of 16.2% from the yield factors. Slope contributes 11%, Level 2.9% and Curvature 2.3%. Base Rate responds significantly positive to a Slope shock. The estimated response to a Level shock is also positive but not significant. In response to a Curvature shock, Base Rate reacts hump-shaped positive for around 10 months and slightly negative for the remaining time, without significance.

6.2.2.4 Macro-Macro Dynamics

The variance contribution of the other macro factors for Spread is highest for Real Activity with 3.8%. All other factors contribute less than 1%. None of Spread's impulse response functions to macro shocks, other than Spread itself, are significant.

NEER's variance takes a high contribution from other macro factors. Real Activity contributes 19.4%, Base Rate 13.9% and Spread 4.7%. NEER is estimated to depreciate in response to the Real Activity shock for the complete 24 months and it is significant up to month 9. Note the fact of Hungary's crawling-peg exchange rate system until 2001, influencing the above impulse response. NEER responds to Base Rate with a small initial depreciation for around 3 months and hump-shaped positive thereafter. The maximum is reached in period 13 and the response is significant from month 5 to month 14. Therefore, the model shows no exchange rate puzzle. NEER is estimated to depreciate in response to a Spread shock, but only at marginal significance.

Real Activity's variance contribution from NEER is 11.8% and 4.2% from Base Rate.

The impulse response of Real Activity to a NEER appreciation shock is significantly negative. The response to a monetary shock is hump-shaped positive for a period of 6 months and u-shaped negative with a minimum around the 15th month. The period between months13 and 16 is slightly significant.

Inflation is highly influenced by Real Activity, contributing 45.6% of the variance, while NEER contributes 25.9%. A Real Activity shock to Inflation is strong and hump-shaped for all months with significance from month 2 until around period 14. Appreciating NEER can be strongly associated with declining Inflation as the estimated response is negative for around 14 months, possessing significance until period 10. Subsequently, Inflation is rebounding. Inflation reacts marginally positive for 5 months to a monetary shock and is strongly u-shaped negative later, setting the minimum at around the 16th period. The deflationary effect is marginally significant between month 14 and 17. Therefore, the model contains no price puzzle, as often reported in other VAR studies.[15]

The variance of Base Rate is influenced by NEER with a contribution of 20.8%. Spread has a contribution of 3.4% and Inflation of 2.4%. Base Rate's response to an appreciation of NEER is clearly negative and significant up to period 13. The response of the Base Rate to a Inflation shock is estimated to be negative and u-shaped for almost the complete time interval, but not with significant confidence. The same is true for Spread.

6.2.3 Poland

6.2.3.1 Yield-Yield Dynamics

A Polish Level shock stays positively in the system for around 11 months, before getting negative. Significance lasts for around 6 months. Application of a unit shock to the Polish Slope factor is very persistent and only slightly declining until month 24 and it is significant for around 20 months. Again, a shock to Curvature is persistent for the whole 24 months, of which 9 months are significant.

[15] Corcelli et al. (2006)

The variance contribution to Level is 24.2% from Slope and 3.6% form Curvature. The estimated response of Level to a Slope shock is marginally negative for 4 months and it increases thereafter. After month 7 the positive response is significant. Level reacts positively to a Curvature shock, with significance beginning in period 9.

Slope's variance contribution is higher for Curvature with 21.9% as Level with 18.4%. The response of Slope to a Curvature shock is positive and pronounced and significant starting in month 3. A Level shock is negative for all of the 24 months, only with slight fluctuations, and significant for around 8 months.

The variance contribution split for Curvature is 24.3% from Slope and 14.4% from Level. The negative response of Curvature to a Level shock is significant for the time between the 5th and 16th month. Curvature reacts negatively for the first 2 months in response to a Slope shock, but it rapidly increases thereafter to reach a high at around the 7th month. In the sequel, the response is linearly declining to about half the maximum at month 24. But only the positive response between month 4 and 10 is significant.

Table 20 – Yield-Only Factor Causality Test Poland Yield-Only VAR(3)

Granger Causality Test		
H0: Factor does not Granger-cause the remaining system		
Factor	**p-value**	**Rank**
Level	0.0020	1
Slope	0.0510	3
Curvature	0.0314	2

6.2.3.2 Macro-Yield Dynamics

When comparing the Yield factor impulse response functions of the Macro-Yield Model to the Yield-Only Model, the Level shock response shows noteworthy differences. While the shock itself is almost unchanged, the estimated response of Slope changes distinctly, from purely negative to only negative for the first 7 months and positive thereafter. But it is noticeable that the significant part of the response closely matches the significant part of the Yield-Only response. The same effect is true for Curvature's response to the Level shock. Completely negative in the yield-only case the estimated response changes to be negative for 6 months and positive later on.

The share of variance induced on the Level factor by the macro factors is higher in comparison to the Czech Republic and Poland with 24.7%. NEER contributed 8.4%, Real Activity 4.9%, Spread 4.7%, Inflation 3.7% and Base Rate 3.1%. (Difference due to rounding) Level's response to NEER is positive for the first 6 months and negative thereafter. The negative period from month 8 to month 12 is significant. A Real Activity shock comes with an estimated initial reduction of the Level factor for around 8 months, with significance around the 5th month, and increases for the rest of the time periods. The response to an inflation shock is positive for 5 months, followed by a u-shaped negative response until period 10, and positive again for the time to follow. The response is significant until period 3 and marginally for some time of the last 4 months. The responses from Spread and Base Rate are not significant.

Slope's variance is, with a share of 41.1%, more dependent on the macro factors. Inflation contributes 24.2%, while Real Activity contributes 5.9% and NEER 5.6%. Slope increases strongly in response to an Inflation shock with long significance reaching its maximum at around month 10. Slope's response to Real Activity is estimated purely positive and it is significant from month 4 to 6. To a NEER shock Slope responds strongly negative for the whole time period but it is only marginally significant. Additionally, a monetary shock increases Slope significantly.

Curvature's variance share from macro factors is highest for NEER with 7.9% and Inflation with 7.8%. To a NEER shock Curvature responds pronounced and negative with a short delay and it is significant from period 8 to 12. The response to Inflation reveals a positive impact for almost the total time period with significance for around 4 months. Curvature responds positively to a Spread shock, with a short negative exception between months 3 and 7, without significance.

Table 21 - Yield-Macro Factor Causality Test Poland Yield-Macro VAR(4)

Granger Causality Test		
H0: Factor does not Granger-cause the remaining system		
Factor	**p-value**	**Rank**
Level	0.0596	8
Slope	0.0120	5
Curvature	0.0038	4
Spread	0.0028	3
NEER	0.0354	6
Real Activity	0.0005	2
Inflation	0.0557	7
Base Rate	0.0004	1

6.2.3.3 Yield-Macro Dynamics

Level contributes 59.8% to the variance of Spread and a Level shock remains almost unchanged in Spread's response.

NEER's variance is influenced by Curvature with a share of 10.2%, Slope 7.7% and Level 2.7%. NEER is estimated to react negatively to a Curvature shock for around 5 months and hump-shaped positive afterwards, having the maximum at around month 9. The region around the maximum is significant. NEER's response to Slope shows a slightly negative impact for around 10 months and it is positive for the remaining time. Only the positive response between periods 9 and 17 is significant. In response to a Level shock NEER is estimated to react negatively for around 8 months and positive for the remaining time, but this response is never significant.

Curvature explains 6.2% of Real Activity's variance, whereas Level 4.2% and Slope 1.9%. Real Activity's response to a Curvature shock is negative for around 9 months and positive for the time afterwards. The positive response between months 12 and 15 is slightly significant. Real Activity's response to the Level shock is initially negative and from the 4^{th} period on positive with wide confidence bands. The response of Real Activity to Slope is not distinct for the first 4 months and positive thereafter with significance form period 13 to 18.

Inflation's variance decompositions show a strong relation to Slope, contributing 24.9%. Curvature contributes 15.3% and Level 7.8%. Inflation increases with a Slope shock in a hump-shaped response with a maximum at around month 5 and returning to neutral in period 21. The first 8 months of the response are statistically significant. In response to Curvature, Inflation increases for an

estimated 14 months and the response is significant for at least 8 months. The impulse response to Level is not significant. Inflation is estimated to increase in response to a Level shock for all periods having a maximum around period 7.
Slope explains 31% of the variance of Base Rate, Curvature 19.7% and Level 2.3%. Base Rate increases in a hump-shaped reaction to a Slope shock with significance until period 9. After a short lag, Base Rate increases in response to a Curvature shock and it is estimated to return to neutral around period 17, before getting negative for the remaining periods. Significance runs from month 4 to 12. The response to Level is not significant but Base Rate is estimated to increase after a short almost neutral period from month 4 until period 19 and it is slightly negative thereafter.

6.2.3.4 Macro-Macro Dynamics

Macro factors' variance contribution for Spread is 10.2% from Real Activity, 4% from NEER and 2.7% from Inflation. Real Activity effects Spread negatively for an estimated 15 months and it is slightly positive thereafter. The negative response between period 4 and 7 is significant. Spread is estimated to increase in response to a NEER shock. The reaction is hump-shaped positive for 7 periods and it is negative for the remaining period without significance. Spread increases in response to an Inflation shock with significance for the first 3 months and from month 12 to 18.
NEER's variance is effected by Spread with 7.8%, Base Rate 7.6%, Inflation 7.5% and Real Activity 4.8%. A shock to Spread is connected to a depreciation of NEER for around 13 months and increasing thereafter. The first 4 months with depreciation are significant. A monetary shock appreciates NEER for 24 months with long periods of significance and the model therefore contains no exchange rate puzzle. NEER responds positively to Inflation with significance around the maximum from period 8 to 14. The response to Real Activity is estimated to be negative for the whole time period and it is significant from month 3 to 5.
Macro factors contributing to Real Activity's variance are NEER with 18.9%, Spread with 8.4%, Base Rate with 2.6% and Inflation with 2.3%. Real Activity increases in response to a NEER shock for an estimated 14 months and

declines thereafter, with most of the first 10 months carrying significance. Real Activity is estimated to decline in connection with a Spread shock for around 15 months and it is positive for the rest of the time. Real Activity's response is only marginally significant around the 5th month. The response of Real Activity to a monetary shock is estimated to be negative with a short exception around the 3rd period, but only the first 2 months are significant. An inflation shock is associated with higher Real Activity after a short lag of around 3 months and the estimated response is significant from month 16 to 22.

The variance contribution split of the macro factors for Inflation is 18.9% from NEER, 5.1% from Spread, 1.4% from Real Activity and 0.5% from Base Rate. Inflation is estimated to decline to the NEER shock and it is significant for around 15 months. Inflation in response to a Spread shock is estimated to be positive for all 24 months and the first three months are slightly significant. Inflation's response to Real Activity is negative for 6 months and later positive, with significance up to month 4. Inflation's response to a monetary shock is positive hump-shaped for around 7 months and increasingly negative thereafter. Only the first 2 months of the positive response are significant. Even though lacking significance, the model does not contain a price puzzle.

Base Rate's variance contribution via macro factors is 19.1% for Inflation, 11.3% from NEER, 3.2% from Spread and 2.5% from Real Activity. Inflation has a positive effect on Base Rate, estimated to last for 21 months. Significance lasts from month 3 to around period 10. Base Rate decreases in response to the currency appreciation with a short lag of around 3 months and the response is significant from around period 8 to month 18. In succession to a Spread shock, Base Rate is estimated to be lower for 8 months and positive in the following, but only the first 4 months of the negative response can be estimated with significance. Base Rate responds negatively to Real Activity for around 11 months before increasing hump-shaped in the remaining periods. The negative response is significant.

7 Summary and Conclusions

My thesis evaluates yield curve dynamics in conjunction with the macroeconomy for the small open economies of the Czech Republic, Hungary and Poland.

First, yield curve dynamics are approximated by three latent factors according to the Dielbold-Li exponential components methodology (Level, Slope and Curvatue). The Diebold-Li methodology fits interest rate dynamics generally well. The maximum mean residual of the model implied yields compared to the actual yields is -6 basis points (-1.7% of average yield level) for the Czech Republic, -4.79 basis points (-0.48% of average yield level) for Hungary and 8.9 basis points (1.09% of average yield level) for Poland. The performance is weaker for the early part of the samples, which is probably caused by low liquidity causing non systematic pricing errors. The Diebold-Li latent factor time series are included into the model as yield dynamics.

Secondly, macroeconomic variables expected to interact with yield dynamics are defined. Principal components methodology gives the possibility to use broader economic information at reduced complexity. Autoregressive and Vector-autoregressive Yield-Only and Yield-Macro Models of different lag-structures are specified and estimated. Subsequent to the estimation recursive out-of-sample forecasts are calculated.

The first principal component of the macroeconomic variables, containing information about the real activity of the economy, is able to explain 81.6% for the Czech Republic and 50.1% for Hungary. The share explained by the first principal component of the inflation group reaches from 59.3% for Hungary to 48.6% for the Czech Republic.

Forecasting performance is encouraging as models are able to outperform random walk forecasts, on average for all reported maturities, for all forecasting horizons, with improvements up to 38.3%. In Poland the Yield-Only VAR(3) Model is even superior to random walk for any single maturity for all forecasting horizons. Additionally, Hungarian and Polish models outperform implied forward rates on average for all horizons, while in the Czech Republic only the 4 and 6 months ahead forecasting horizon is outperformed.

Even so causality tests and impulse response analysis reveal strong bidirectional linkages of the yield curve and the macroeconomy, yield-only models have the tendency to outperform yield-macro models. The relatively short period of data availability might explain that phenomenon. As asymptotic methodology is used, the more complex macro-yield models are expected to suffer more from the short in-sample period.

The strong forecasting performance of the model encourages future work on defining trading and hedging strategies based on model forecasts, either on individual yield forecasts or on factor forecasts. The challenge remains to define strategies with significant outperformance that can be used in practice.

Another rewarding exercise might be estimating yield-only models on higher frequency yield data and testing forecasting performance. In my expectation this will work well as this thesis shows that yield-only models are successful in modelling yield curve dynamics. With shorter time intervals the model fit of the yield dynamics might improve and short-term idiosyncratic movement, independent from macro developments, could be captured.

Another improvement in forecasting performance might bring the use of even broader macroeconomic information to be summarized by dynamic factors. My approach pools economic time series into groups to facilitate economic interpretation and improve inference, perhaps at the cost of forecasting performance.

The Diebold-Li methodology does not impose no-arbitrage restrictions, which is untypical in finance. Incorporating those might be another direction of improvement. Still, if no-arbitrage holds for the original yield data, it should be approximately captured within the Diebold-Li factors. It is arguable that for the markets and time period analysed no-arbitrage might be violated due to illiquidity and market segmentation. Evidence from the empirical literature, if no-arbitrage restrictions improve out-of-sample forecasting performance, is mixed. Especially for emerging markets there is evidence that no-arbitrage can be violated.[16]

[16] For example Klein (2003)

Analyses of system dynamics reveal strong bidirectional links between the macroeconomy and the yield curve. Granger causality tests show strong evidence of macro variables influencing the yield curve. Probabilities for macro factors not Granger-causing Level, Slope and Curvature are 0.02% for Poland, 0.26% for Hungary and 11.98% for the Czech Republic. The macro-yield link for the Czech Republic can be confirmed by significant impulse responses of the yield factors due to macro variable shocks. Yield-macro links are confirmed by low probabilities of yield factors not Granger-causing macro variables (1.21% for Poland, 4.37% for Hungary and 5.4% in the Czech Republic). Ranking all factors according to their Granger causality, there is the general tendency of macro factors to possess lower probabilities of not Granger-causing the remaining system variables. This can be cautiously interpreted as a somewhat stronger macro-yield than yield-macro relationship. Variance decompositions show that with increasing forecasting horizon the importance of the macro factors is increasingly significant.

Clearly, the Level factor seems to carry predictive information about future inflation dynamics. In all three countries the Inflation factor is estimated to increase subsequent to a Level shock. Term spreads of the yield curve are considered to be a good leading indicator of future real activity of the economy. This is confirmed, as a Slope shock decreases the Real Activity factor for all three countries. Slope's shock is connected to tighter monetary policy, but inflation dynamics are distinct. While in the Czech Republic and Hungary the Inflation factor declines, it increases in Poland. This can be explained by the different response of the nominal effective exchange rate, which is estimated to appreciate for the Czech Republic and Hungary, while it slightly depreciates in Poland. Interestingly, a Curvature shock increases Slope. Accordingly, Real Activity should decline in response to the flattening of the yield curve. Indeed, the Curvature shock is followed by a reduction in Real Activity, apart from Poland where already the Slope-Real Activity is weak. This finding has to be taken with caution as not all impulse responses are significant, but this is in line with the result of Mönch (2006) for the American economy.

An increase of the average spread to the German benchmark yield curve decreases the convexity of the yield curve for all countries. As the Curvature factor is often described as idiosyncratic, this is another interesting finding. This assessment, additionally in connection with Curvature's response to the nominal effective exchange rate, might indicate a possible link between Curvature and risk premia. This could make a fertile direction of further research.

Within the small open economies of the CEE-3 the exchange rate channel is identified to be of outstanding importance for macro-macro dynamics. Variance decomposition analysis discloses that the nominal effective exchange rate is the most influential macro variable impacting on Real Activity in all three countries. Additionally, the nominal effective exchange rate is most influential for Inflation in the Czech Republic and Poland. In Hungary Real Activity takes the lead in determining inflation, but NEER's share is still high with 25.9%. An appreciation shock of the nominal effective exchange rate significantly reduces the Inflation factor and the monetary policy rate for all countries. Additionally, the Real Activity factor is significantly reduced in the Czech Republic and Hungary.

Last but not least, the evaluation of monetary policy contains for none of the Yield-Macro Models a price or exchange rate puzzle. Also, the response of the Real Activity factor to a monetary shock is negative after a lag period for the Czech Republic and Hungary and straight away negative for Poland. VAR studies with a focus on Central and Eastern Europe report all kind of puzzles and irrational output responses. Therefore, the implemented combination of factor analysis with VAR methodology seems to be effective in summarizing broader macroeconomic information to evaluate monetary policy consistently.

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9 Appendix - Macro Factor Details

9.1 Macro Data Czech Republic

9.1.1 Real Activity Czech Republic

The real activity group for the Czech Republic includes *Industrial Production YOY* change as calculated by the Czech Statistical Office and published by Bloomberg (Czech Statistical Office; CZIPITYY Index), the *OECD Czech Republic Leading Indicators Orig SA (seasonally adjusted)* (OECD; OECZA019 Index), *OECD Czech Republic Labor Market Indicators Unfilled Job Vacancies* (OECD; OECZL003 Index), *OECD Czech Republic Unemployment Registered* (OECD; OECZU003 Index) and *OECD Czech Republic Business Tendency Survey Manufacturing Employment Future SA* (OECD; OECZO034 Index).

Figure 11 – Graph Real Activity Time Series Czech Republic and first PC

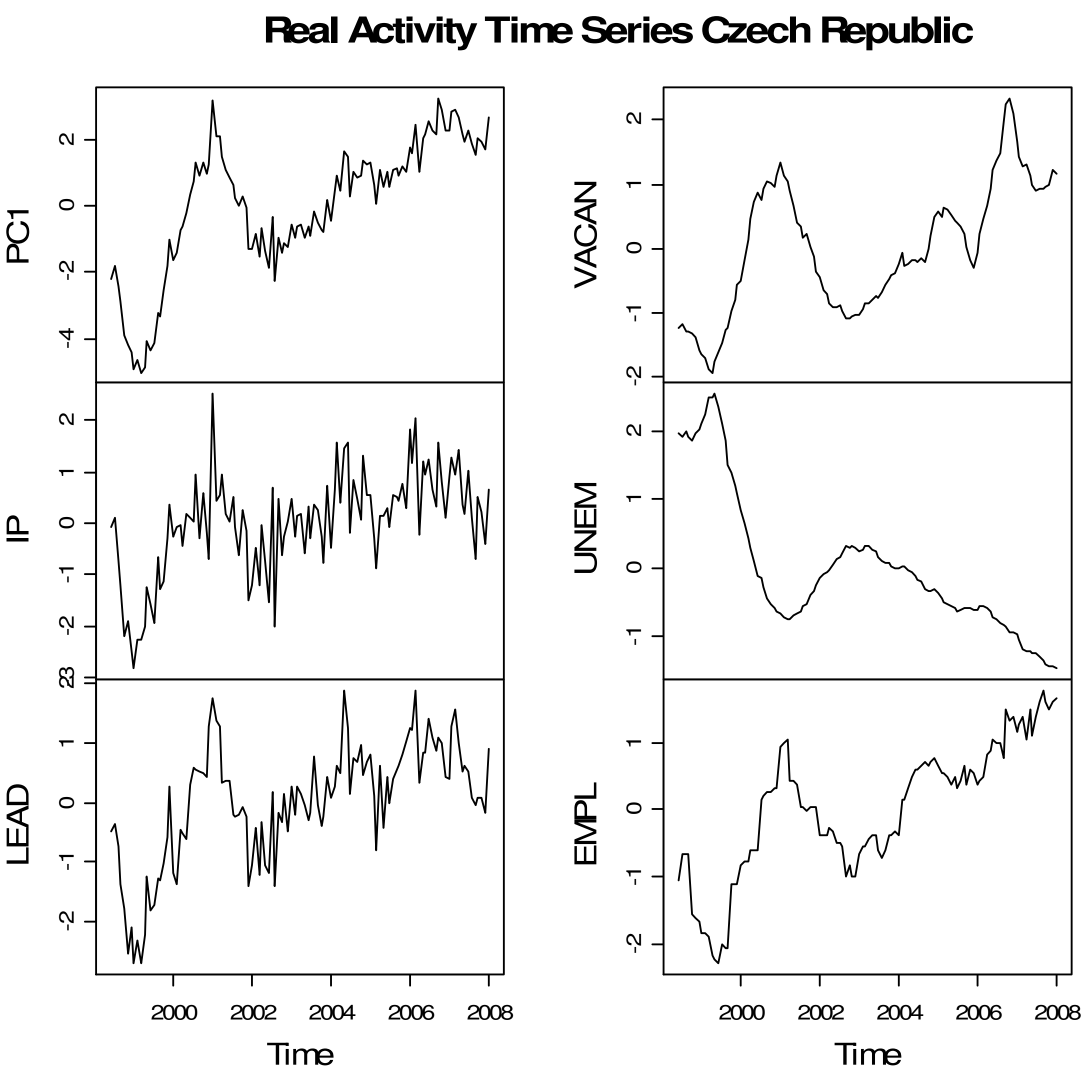


Table 22 - Principal Component Analysis of Real Activity Czech Republic

	Real Activity				
Principal Component	**1**	**2**	**3**	**4**	**5**
Proportion of Variance	0.8166	0.1144	0.0336	0.0196	0.0157
Cumulative Proportion	0.8166	0.9311	0.9647	0.9843	1.0000

Table 23 - Correlation Analysis of Real Activity Czech Republic

	Correlation Analysis Real Activity					
	PC1 of Real Activity	IP	LEAD	VACAN	UNEM	EMPL
PC1 of Real Activity	1.0000	0.8440	0.9098	0.8960	-0.9276	0.9380
IP	0.8440	1.0000	0.8878	0.6203	-0.6582	0.6697
LEAD	0.9098	0.8878	1.0000	0.7081	-0.7574	0.7663
VACAN	0.8960	0.6203	0.7081	1.0000	-0.8416	0.8680
UNEM	-0.9276	-0.6582	-0.7574	-0.8416	1.0000	-0.9184
EMPL	0.9380	0.6697	0.7663	0.8680	-0.9184	1.0000

9.1.2 Inflation Czech Republic

Inflation is represented by *Czech Republic CPI Nominal Change YoY* (Czech Statistical Office; CZCPYOY Index), *Czech Republic PPI Industrial Nominal Change YoY* (Czech Statistical Office; CZPPYOY Index) and the YOY change of the *Commodity Research Bureau Spot All Commodities Index* in Czech Koruna (Commodity Research Bureau; CRB CMDT Index).

Figure 12 – Graph Inflation Time Series Czech Republic and first PC

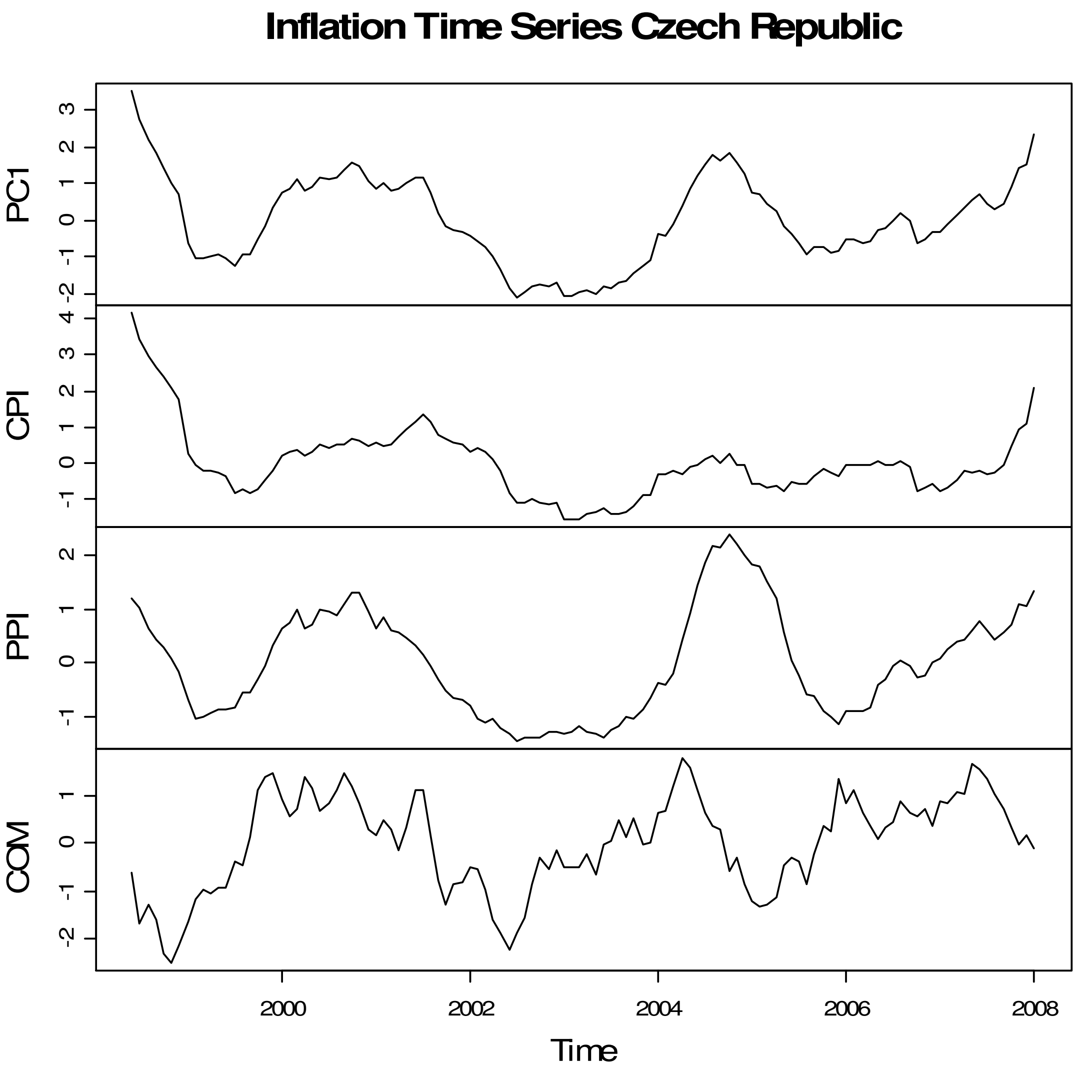


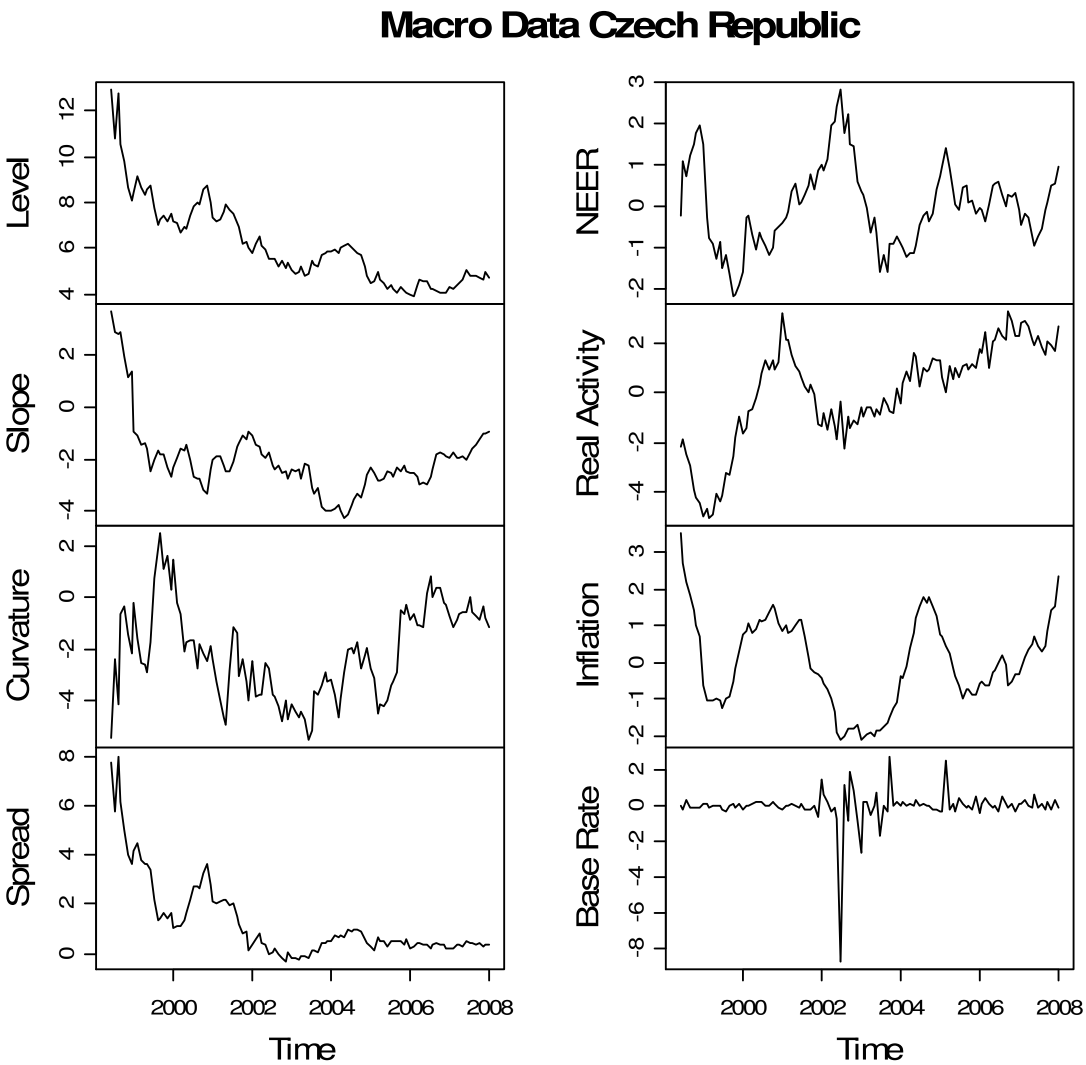
Table 24 – Principal Component Analysis of Inflation Czech Republic

Inflation			
Principal Component	**1**	**2**	**3**
Proportion of Variance	0.4864	0.3776	0.1360
Cumulative Proportion	0.4864	0.8640	1.0000

Table 25 – Correlation Analysis of Inflation Czech Republic

Correlation Analysis of Inflation				
	PC1 of Inflation	CPI	PPI	COM
PC1 of Inflation	1.0000	0.7978	0.8858	0.1951
CPI	0.7978	1.0000	0.4493	-0.1624
PPI	0.8858	0.4493	1.0000	0.2474
COM	0.1951	-0.1624	0.2474	1.0000

Figure 13 - Macro Data Czech Republic



9.2 Macro Data Hungary

9.2.1 Real Activity Hungary

Real Activity in Hungary consists of *Hungary Industrial Production SA YoY* (Hungarian Statistical Office; HUIPIYOY Index), *OECD Hungary Leading Indicators Orig SA* (OECD; OEHUA021 Index), *OECD Hungary Labor Market Indicators Unfilled Job Vacancies* (OECD; OEHUL004 Index), *OECD Hungary Unemployment Registered* (OECD; OEHUU003 Index) and *OECD Hungary Employment Manufacturing* (OECD; OEHUE003 Index).

Figure 14 – Graph Real Activity Time Series Hungary and first PC

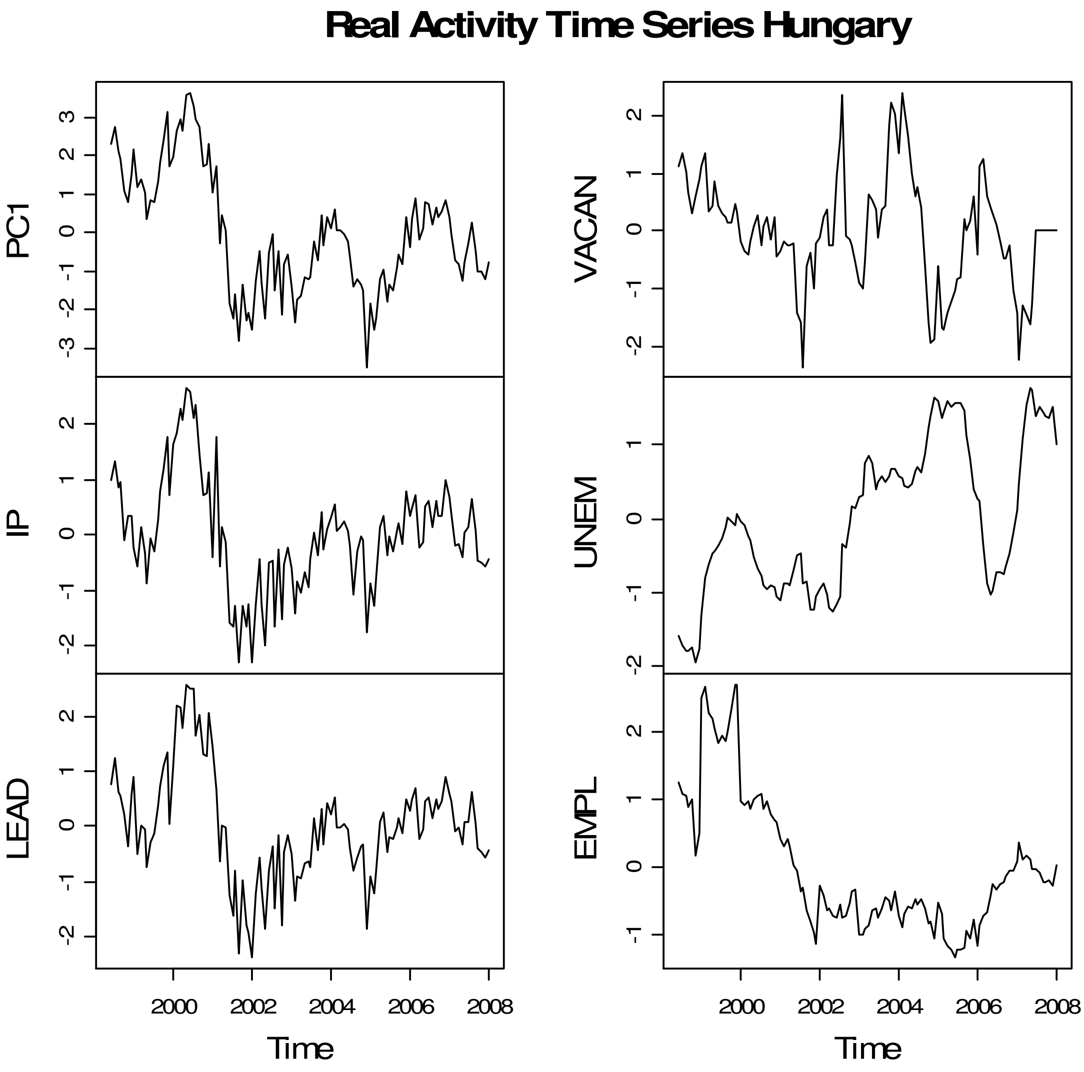


Table 26- Principal Component Analysis of Real Activity Hungary

Real Activity					
Principal Component	**1**	**2**	**3**	**4**	**5**
Proportion of Variance	0.5013	0.2343	0.1556	0.0978	0.0110
Cumulative Proportion	0.5013	0.7356	0.8912	0.9890	1.0000

Table 27- Correlation Analysis of Real Activity Hungary

Correlation Analysis Real Activity						
	PC1 of Real Activity	IP	LEAD	VACAN	UNEM	EMPL
PC1 of Real Activity	1.0000	0.8851	0.9001	0.3795	-0.4580	0.7333
IP	0.8851	1.0000	0.9442	0.1821	-0.1363	0.4491
LEAD	0.9001	0.9442	1.0000	0.1715	-0.1717	0.4817
VACAN	0.3795	0.1821	0.1715	1.0000	-0.2899	0.1840
UNEM	-0.4580	-0.1363	-0.1717	-0.2899	1.0000	-0.4058
EMPL	0.7333	0.4491	0.4817	0.1840	-0.4058	1.0000

9.2.2 Inflation Hungary

The Inflation group consists of *Hungary CPI YoY* (Hungarian Statistical Office; HUCPIYY Index), *Hungary PPI YoY* (Hungarian Statistical Office; HUPPIYY Index) and the YOY change of the *Commodity Research Bureau Spot All Commodities Index* in Hungarian Forint (Commodity Research Bureau; CRB CMDT Index).

Figure 15 – Graph Inflation Time Series Hungary and first PC

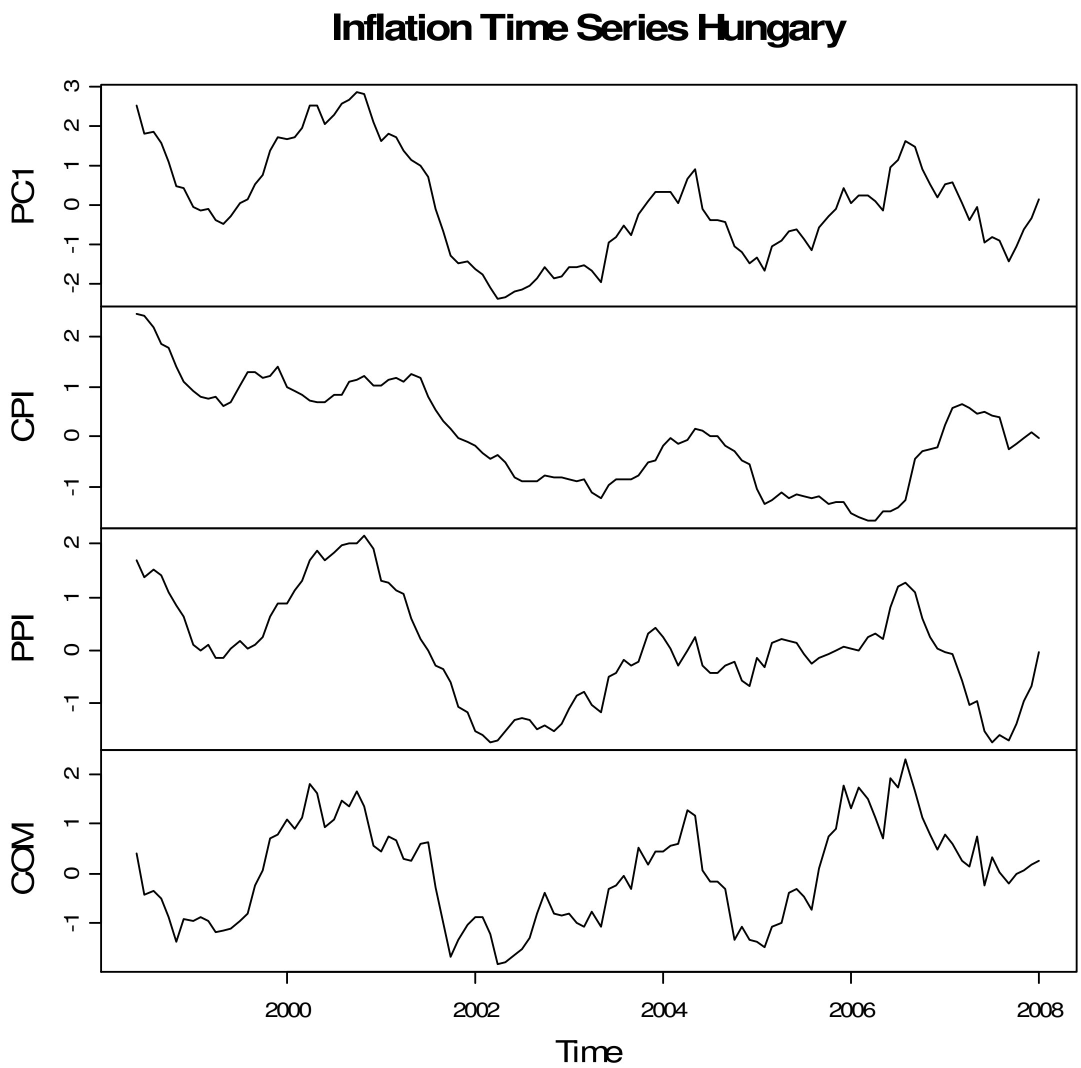


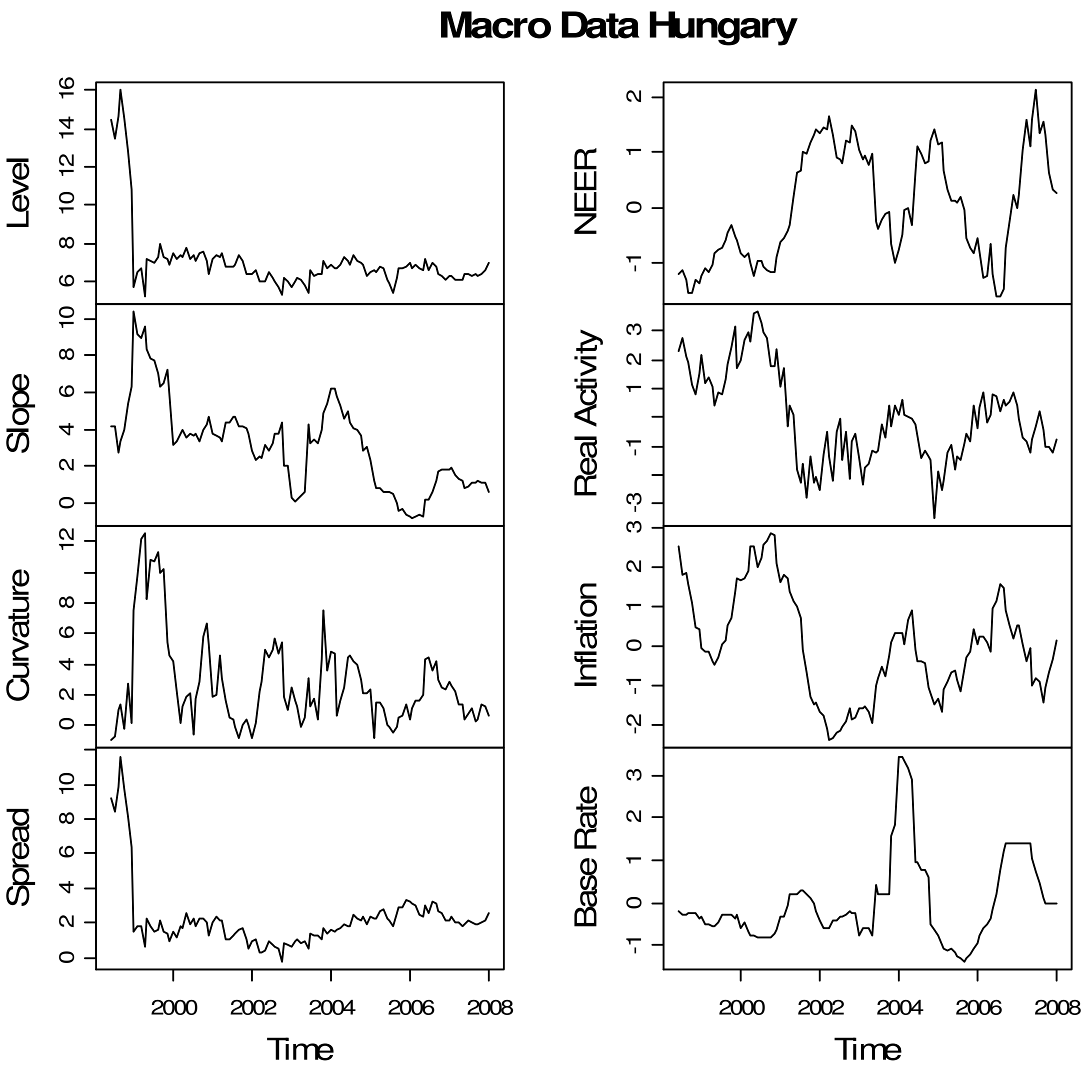
Table 28 - Principal Component Analysis of Inflation Hungary

Inflation			
Principal Component	**1**	**2**	**3**
Proportion of Variance	0.5927	0.3171	0.0902
Cumulative Proportion	0.5927	0.9098	1.0000

Table 29 – Correlation Analysis of Inflation Hungary

Correlation Analysis of Inflation				
	PC1 of Inflation	CPI	PPI	COM
PC1 of Inflation	1.0000	0.6060	0.9274	0.7421
CPI	0.6060	1.0000	0.4684	0.0500
PPI	0.9274	0.4684	1.0000	0.5898
COM	0.7421	0.0500	0.5898	1.0000

Figure 16 - Macro Data Hungary



9.3 *Macro Data Poland*

9.3.1 Real Activity Poland

The real activity group in Poland consists of *Poland Sold Industrial Output of Goods & Services at Current Prices YoY* (Polish Statistics Office; POISLYOY Index), *OECD Poland Leading Indicators SA Orig SA* (OECD; OEPOA017 Index), *OECD Poland Leading Indicators Unfilled Job Vacancies Orig SA* (OECD; OEPOA008 Index), *O E C D P o l a n d U n e m p l o y m e n t R e g i s t e r e d* (OECD; OEPOU003 Index) and *OECD Poland Business Tendency Survey Manufacturing Employment Future SA* (OECD; OEPOO041 Index).

Figure 17– Graph Real Activity Time Series Poland and first PC

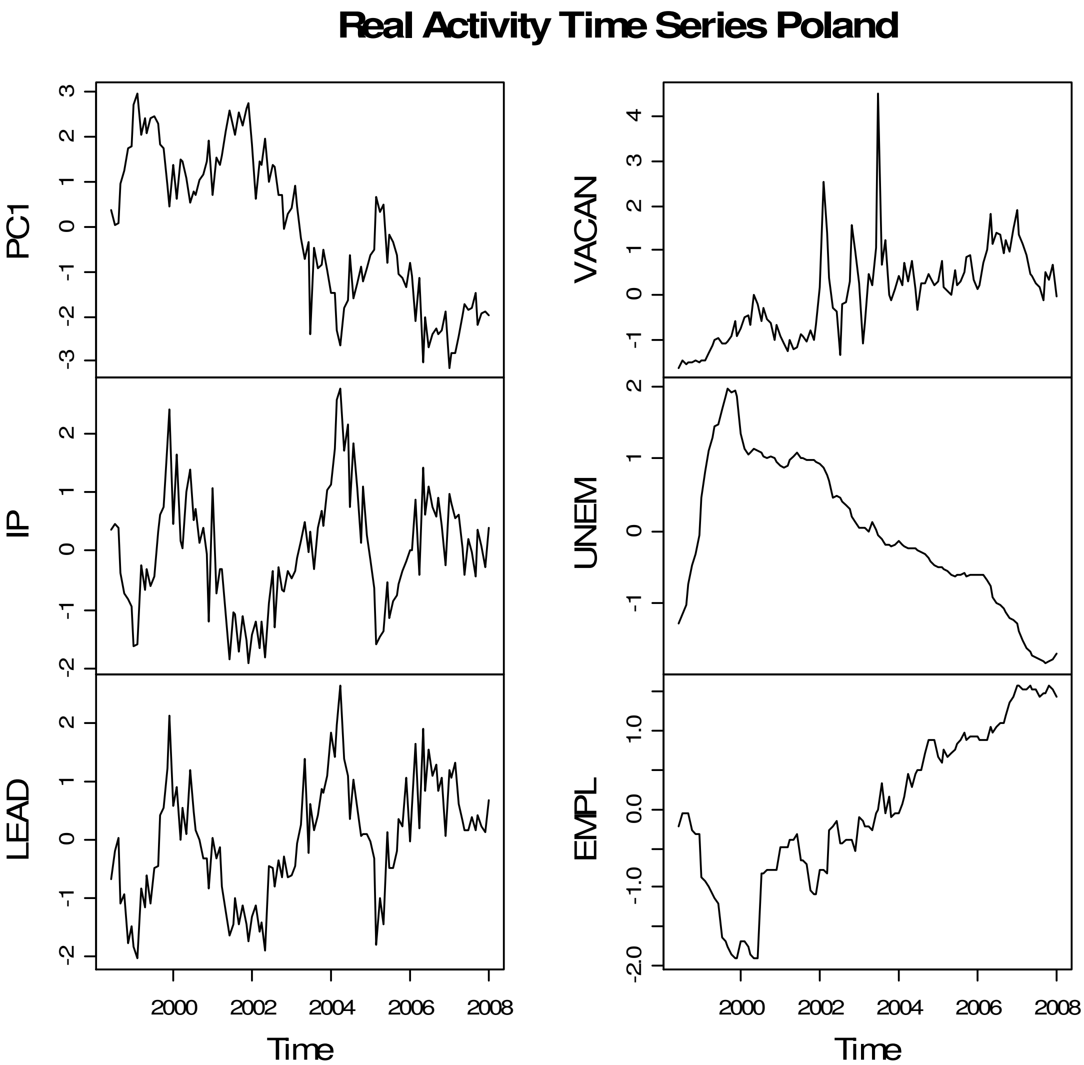


Table 30 - Principal Component Analysis of Real Activity Poland

Real Activity					
Principal Component	**1**	**2**	**3**	**4**	**5**
Proportion of Variance	0.5504	0.3044	0.1165	0.0168	0.0120
Cumulative Proportion	0.5504	0.8547	0.9712	0.9880	1.0000

Table 31 - Correlation Analysis of Real Activity Poland

Correlation Analysis Real Activity						
	PC1 of Real Activity	IP	LEAD	VACAN	UNEM	EMPL
PC1 of Real Activity	1.0000	-0.5802	-0.7563	-0.7309	0.8057	-0.8124
IP	-0.5802	1.0000	0.8871	0.2229	-0.1363	0.0894
LEAD	-0.7563	0.8871	1.0000	0.4377	-0.3084	0.2978
VACAN	-0.7309	0.2229	0.4377	1.0000	-0.4704	0.5431
UNEM	0.8057	-0.1363	-0.3084	-0.4704	1.0000	-0.9298
EMPL	-0.8124	0.0894	0.2978	0.5431	-0.9298	1.0000

9.3.2 Inflation Poland

The inflation group contains the following time series. *Poland CPI YoY* (Polish Statistics Office; POCPIYOY Index), *Poland PPI YoY* (Polish Central Bank; POPPIYOY Index) and the YOY change of *the Commodity Research Bureau Spot All Commodities Index* in Polish Zloty (Commodity Research Bureau; CRB CMDT Index).

Figure 18 – Graph Inflation Time Series Poland and first PC

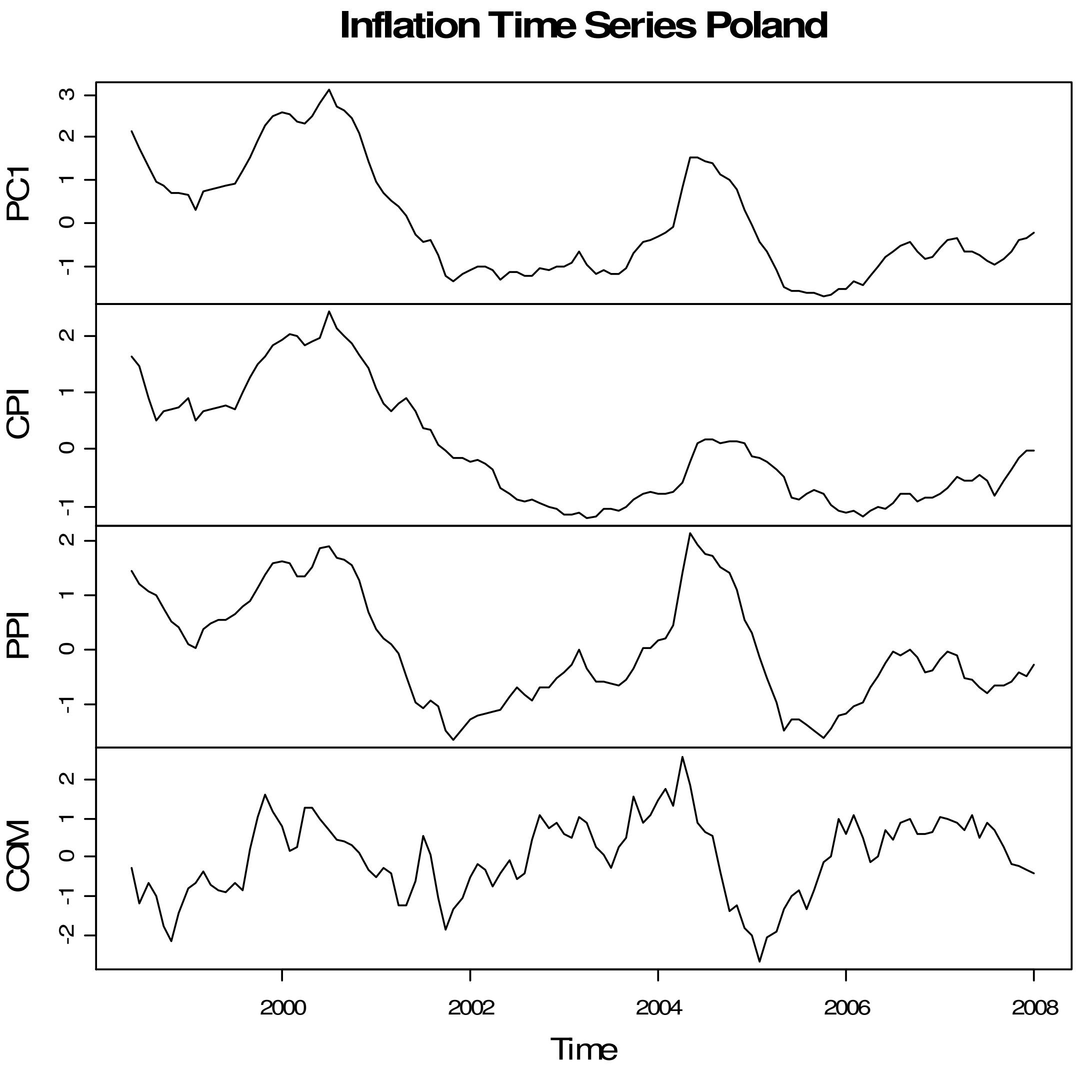


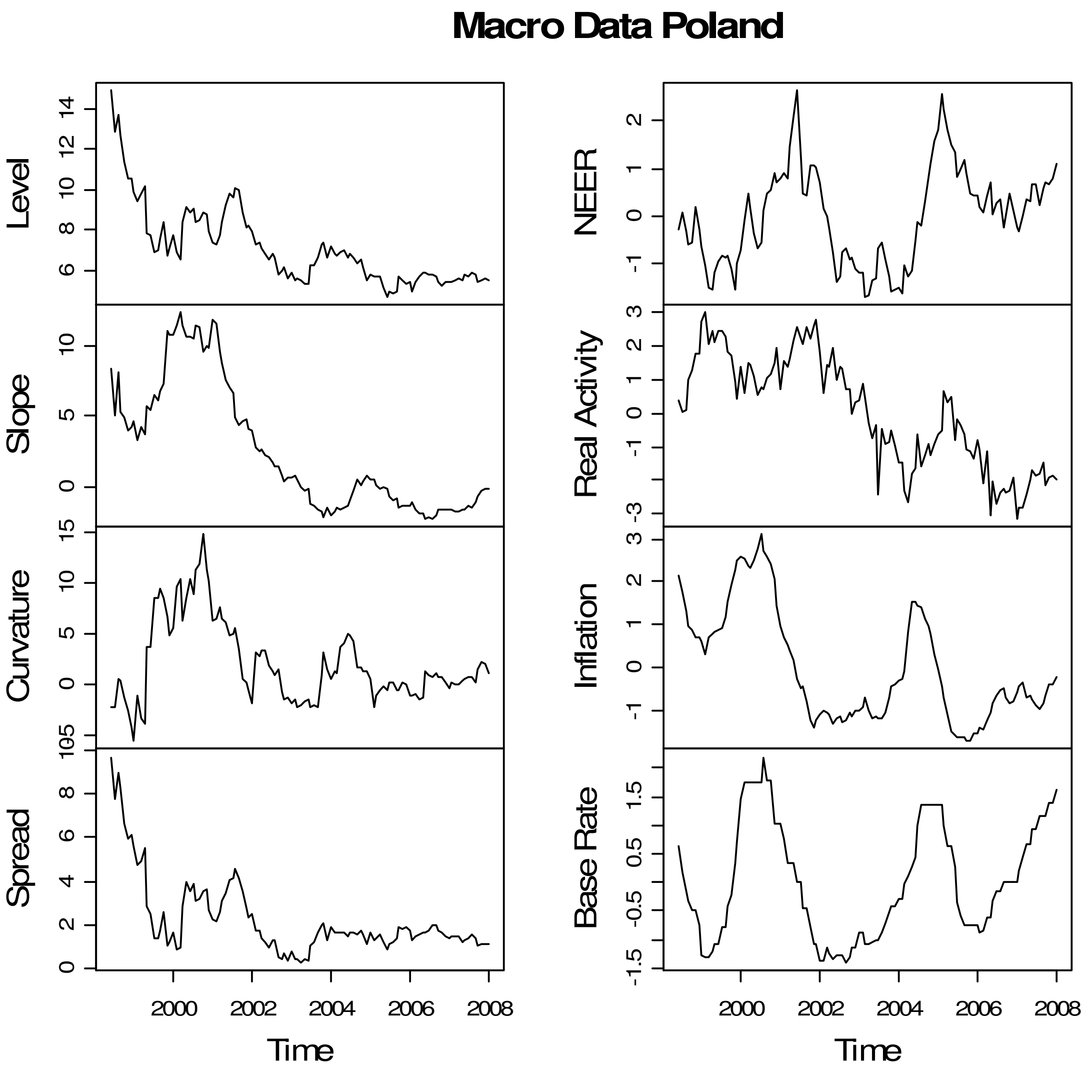
Table 32 - Principal Component Analysis of Inflation Poland

Inflation			
Principal Component	**1**	**2**	**3**
Proportion of Variance	0.5705	0.3587	0.0708
Cumulative Proportion	0.5705	0.9292	1.0000

Table 33 – Correlation Analysis of Inflation Poland

Correlation Analysis of Inflation				
	PC1 of Inflation	CPI	PPI	COM
PC1 of Inflation	1.0000	0.9070	0.9358	0.1144
CPI	0.9070	1.0000	0.7064	-0.1372
PPI	0.9358	0.7064	1.0000	0.2200
COM	0.1144	-0.1372	0.2200	1.0000

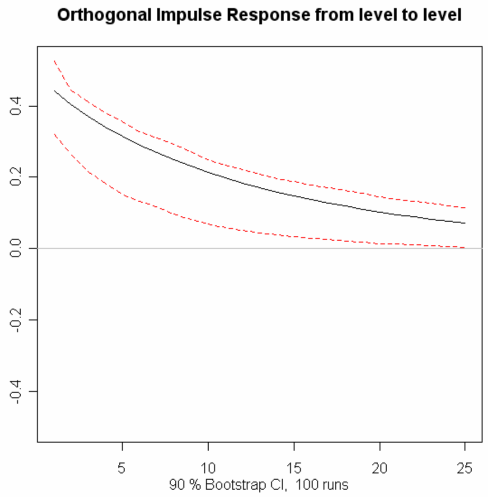
Figure 19 - Macro Data Poland

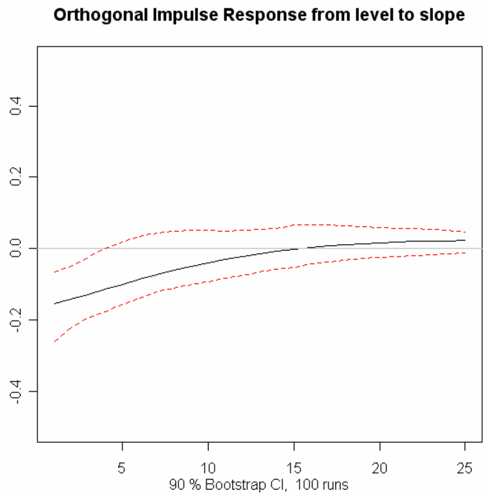


10 Appendix - Impulse Responses

10.1 Impulse Responses Yield-Only Model Czech Republic

Figure 20 - Impulse Response Czech Republic Yield-Only VAR(1) - Level





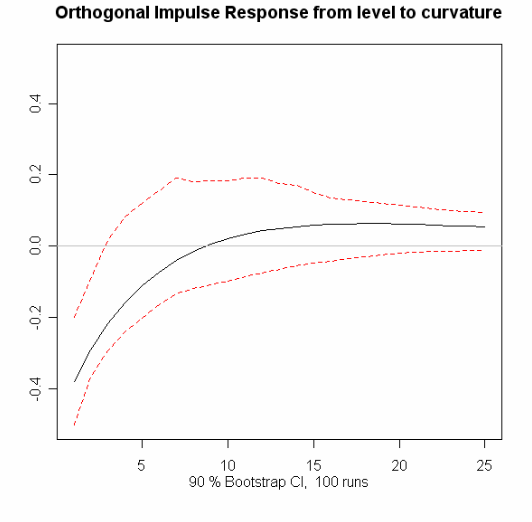

Orthogonal Impulse Response from level to curvature
0.4
0.2
0.0
-0.2
-0.4
5
10
15
20
25
90 % Bootstrap CI, 100 runs

Figure 21 - Impulse Response Czech Republic Yield-Only VAR(1) - Slope

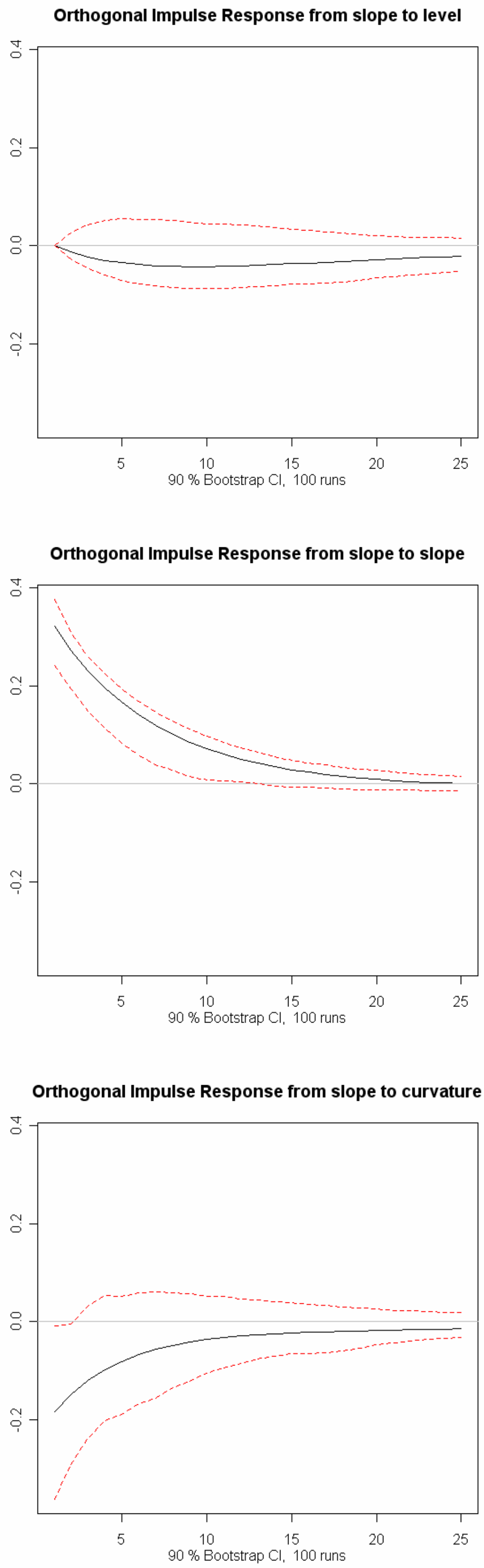
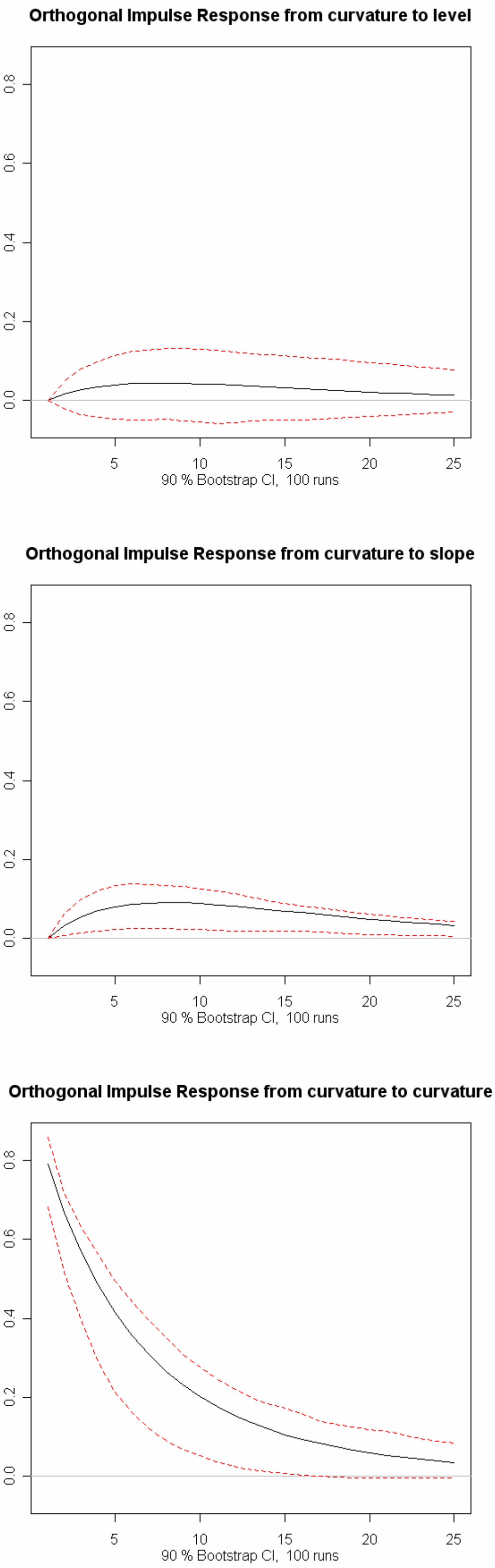


Figure 22 - Impulse Response Czech Republic Yield-Only VAR(1) - Curvature



10.2 Impulse Responses Yield-Macro Model Czech Republic

Figure 23 - Impulse Response Czech Republic Yield-Macro VAR(1) - Level

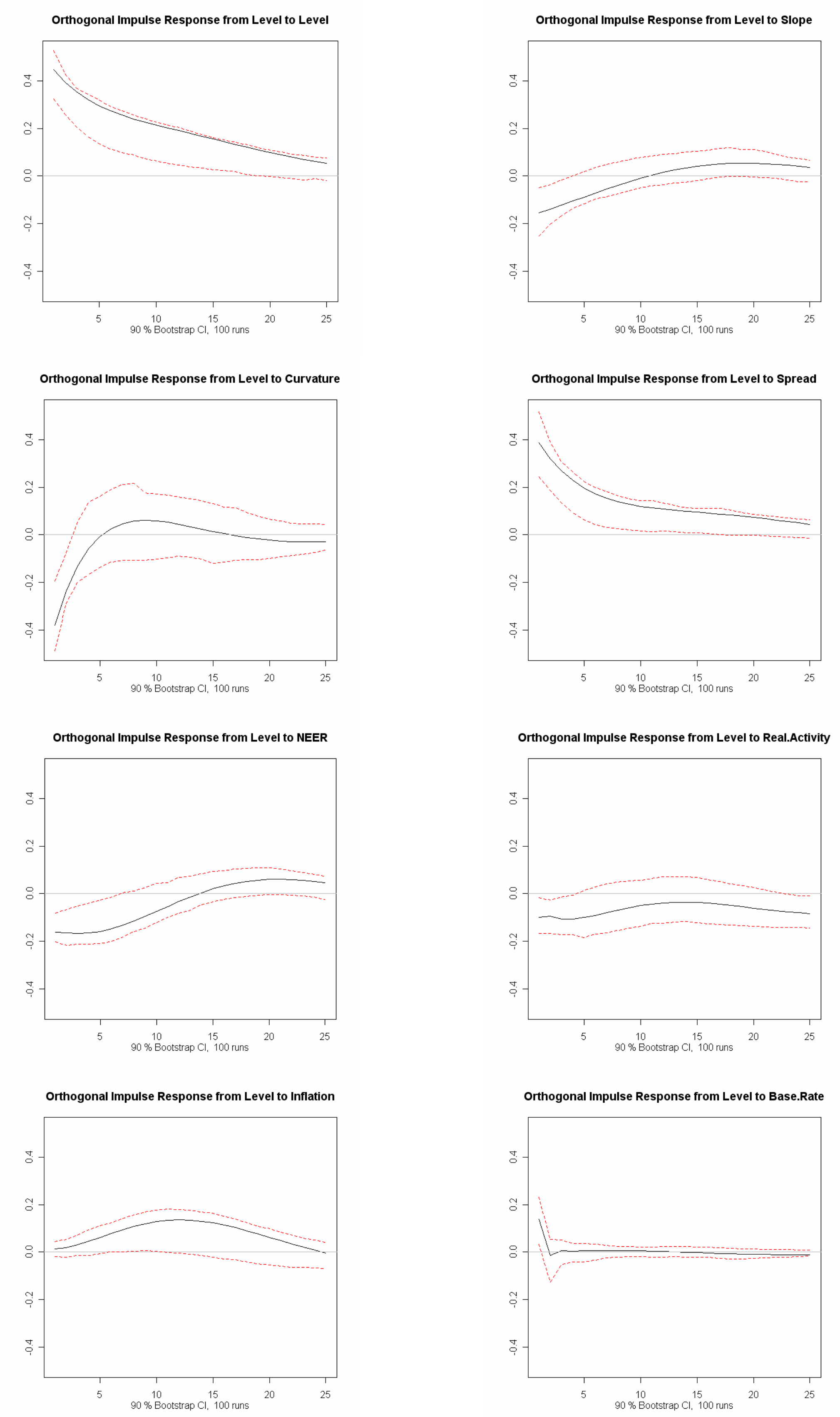


Figure 24 - Impulse Response Czech Republic Yield-Macro VAR(1) - Slope

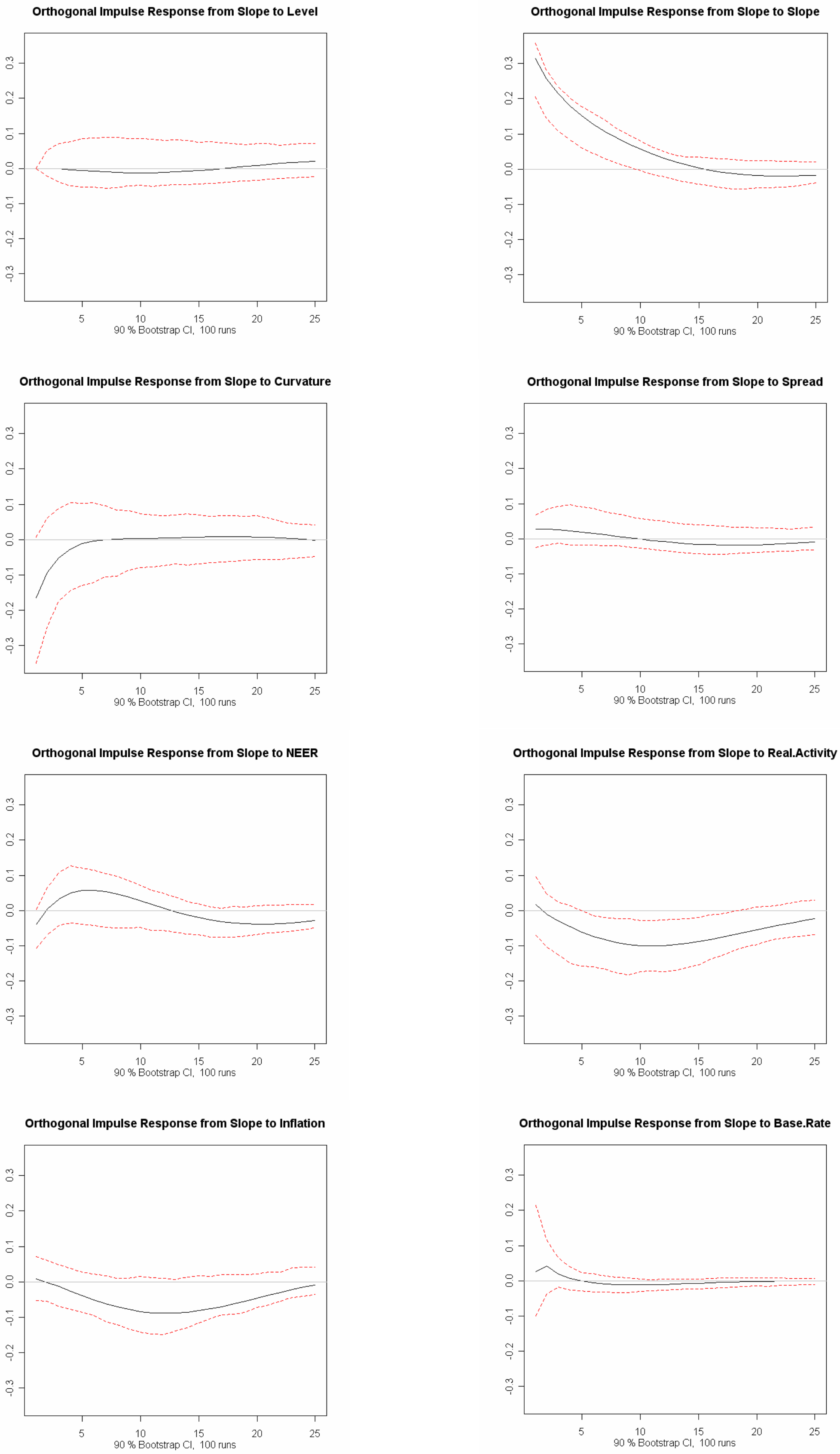


Figure 25 - Impulse Response Czech Republic Yield-Macro VAR(1) - Curvature

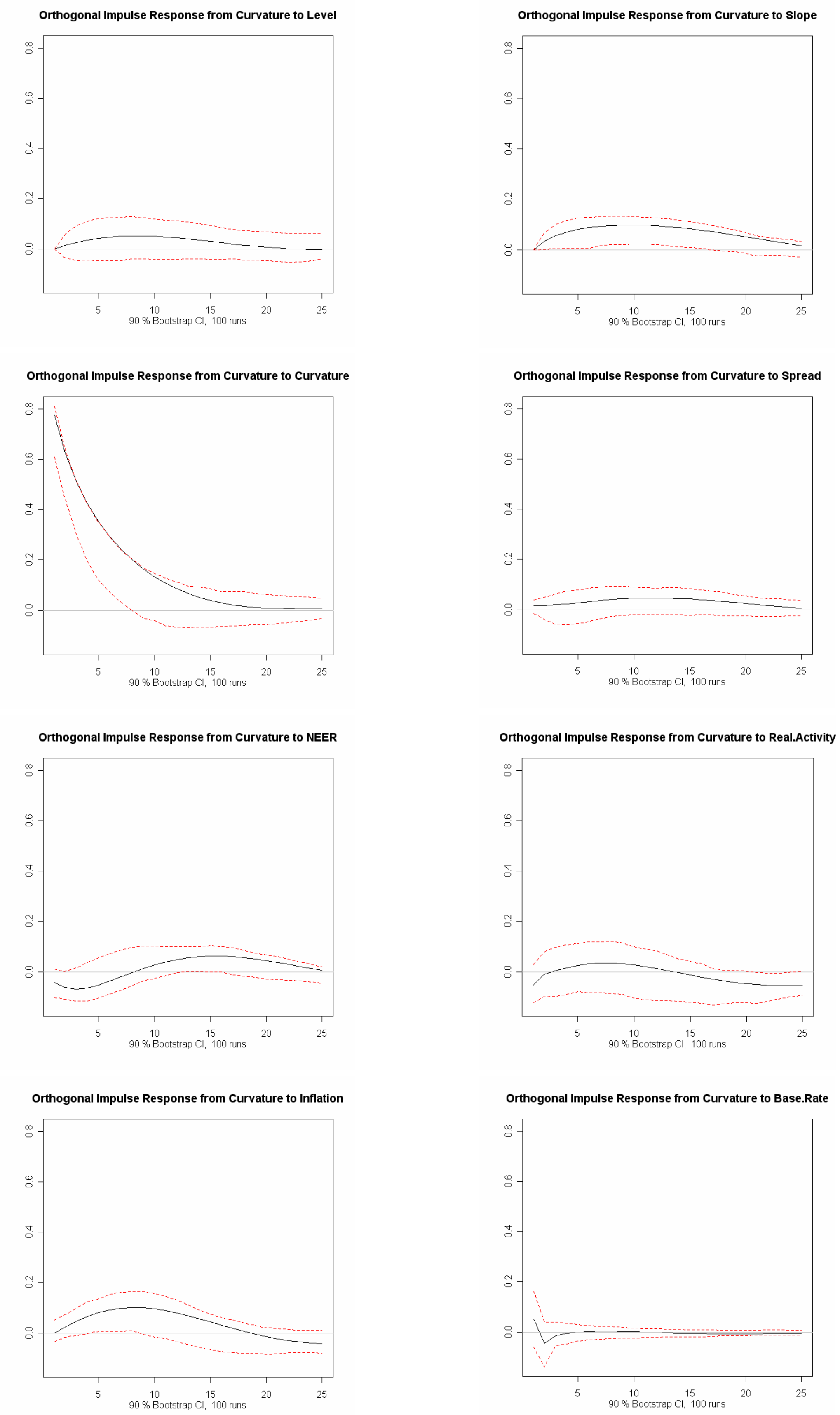


Figure 26 - Impulse Response Czech Republic Yield-Macro VAR(1) - Spread

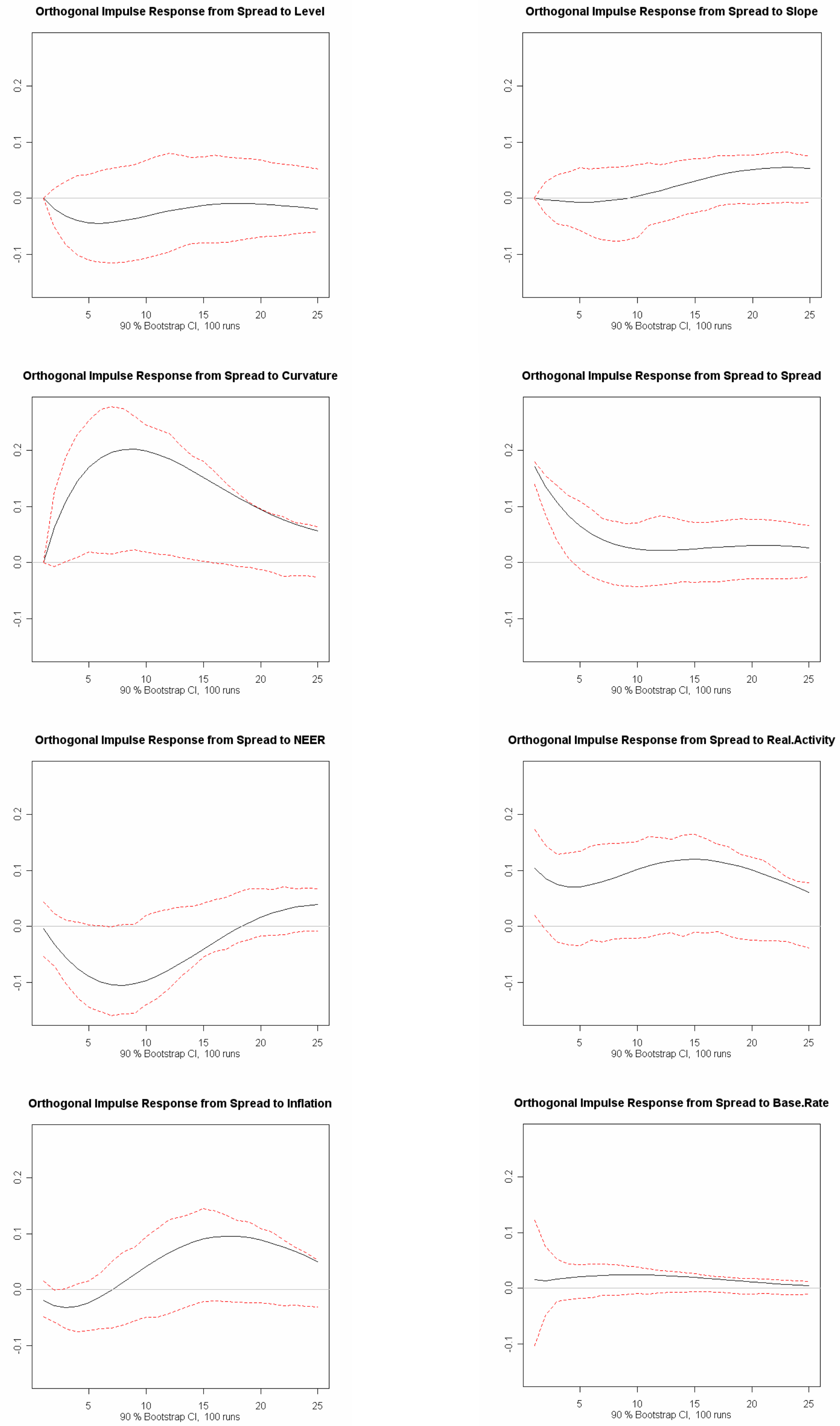


Figure 27 - Impulse Response Czech Republic Yield-Macro VAR(1) - NEER

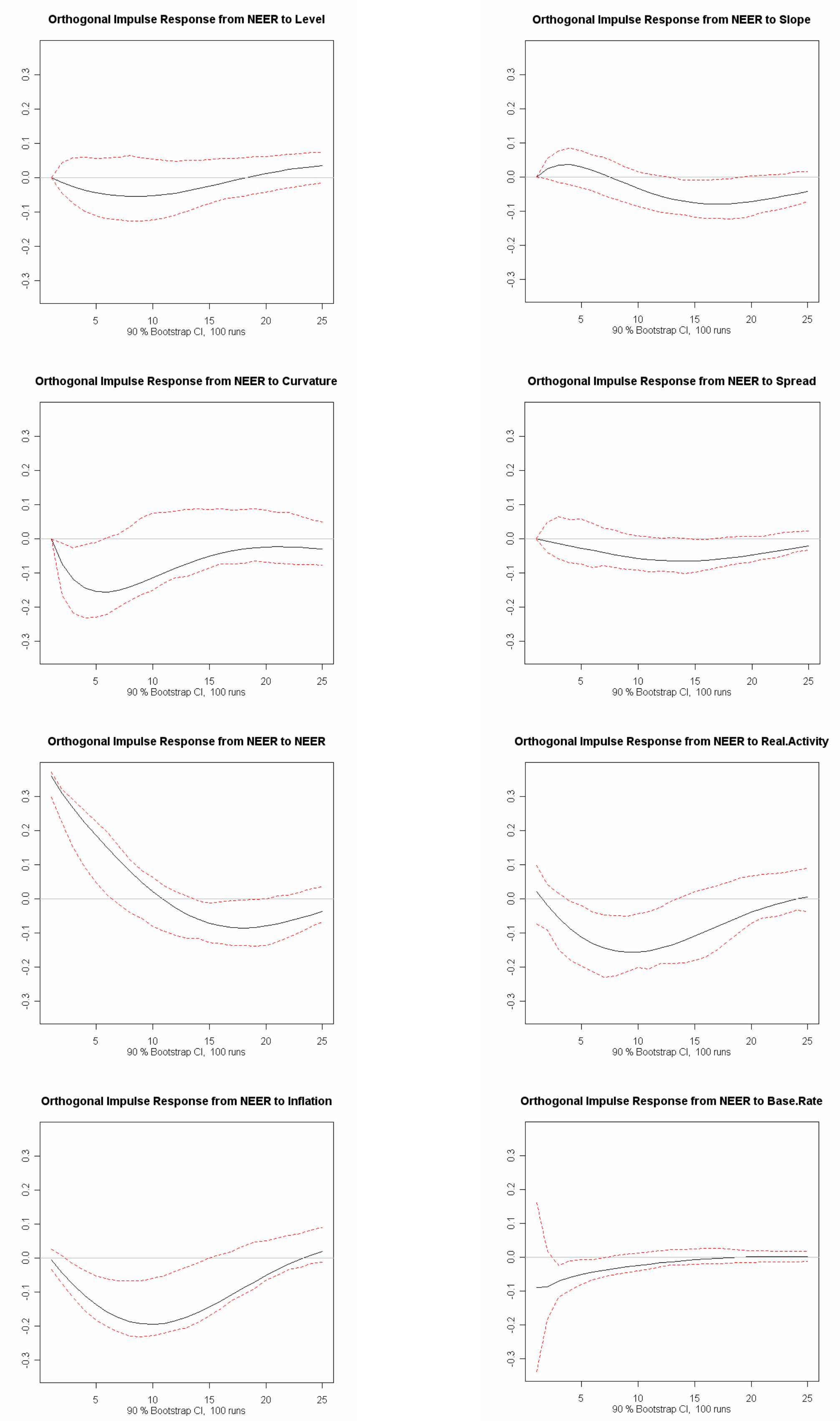


Figure 28 - Impulse Response Czech Republic Yield-Macro VAR(1) - Real Activity

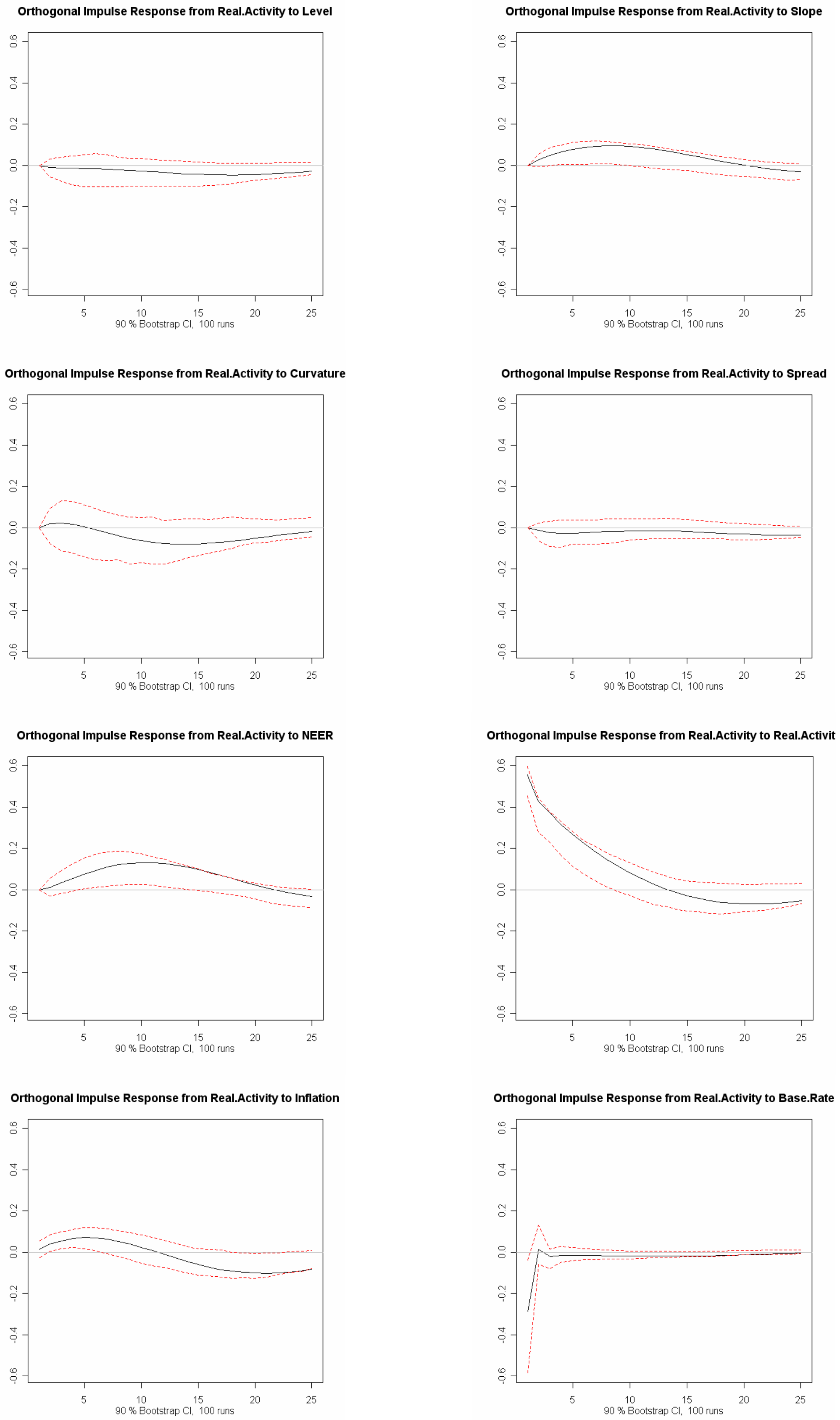


Figure 29 - Impulse Response Czech Republic Yield-Macro VAR(1) - Inflation

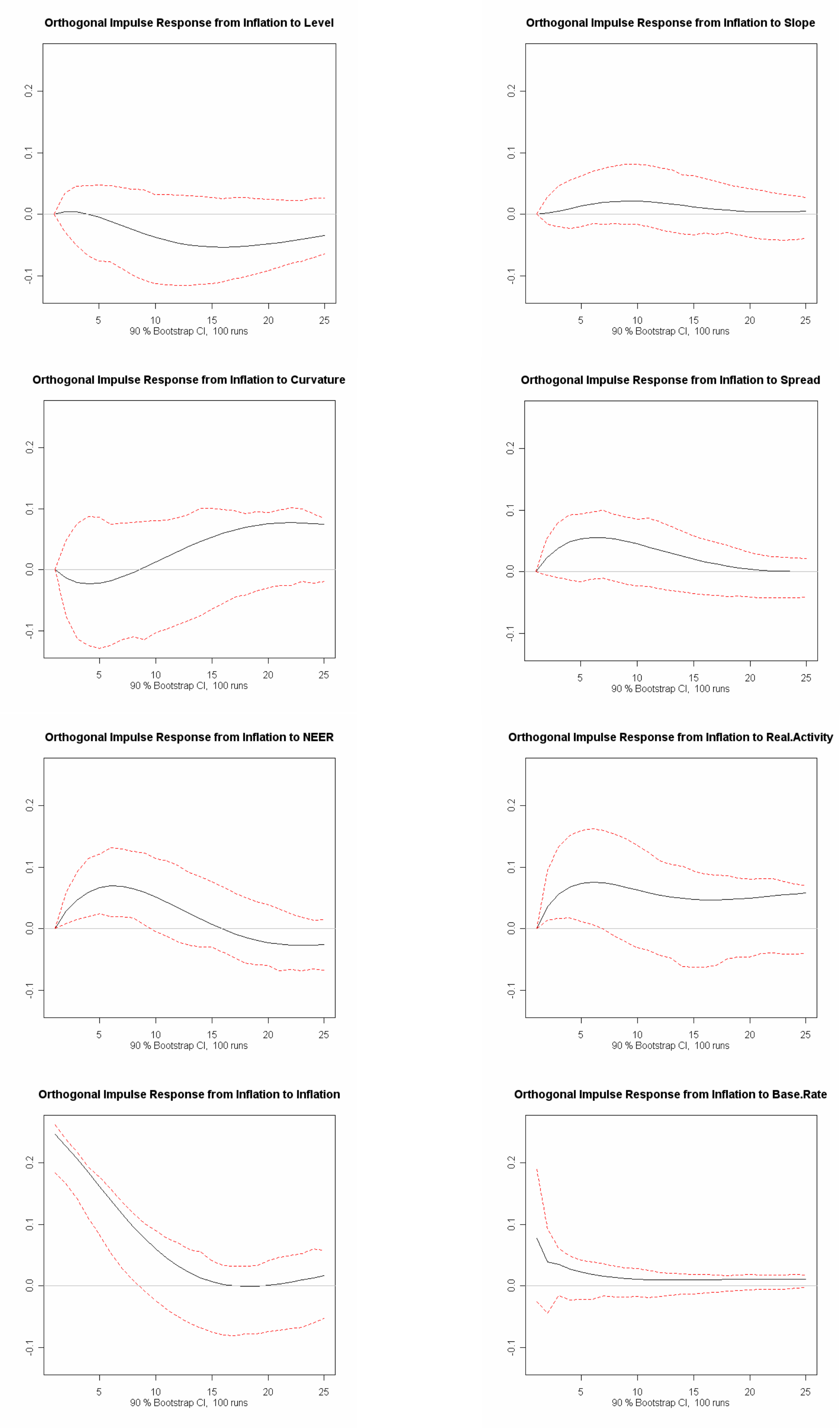
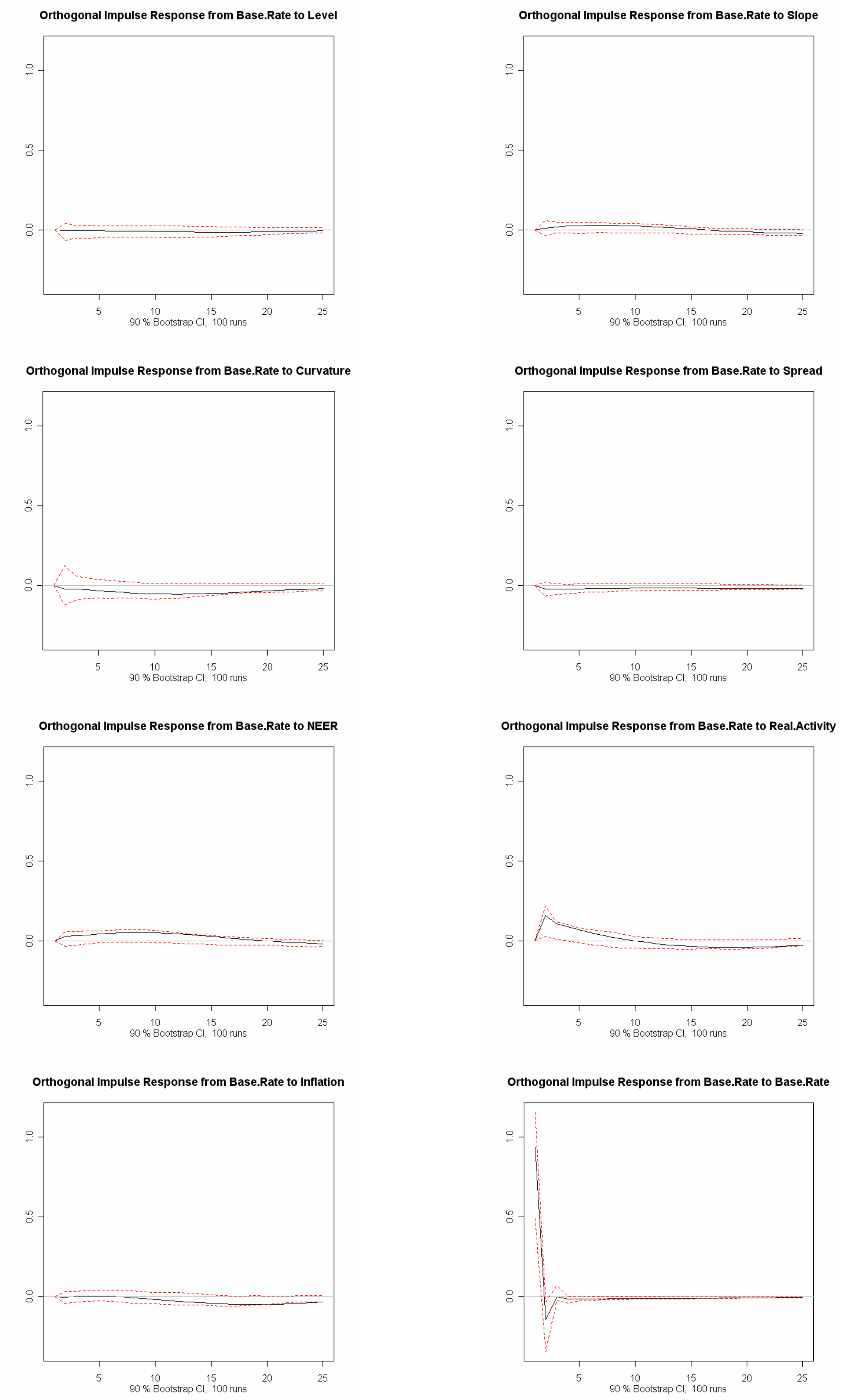


Figure 30 - Impulse Response Czech Republic Yield-Macro VAR(1) - Base Rate



10.3 Impulse Responses Yield-Only Model Hungary

Figure 31 - Impulse Response Hungary Yield-Only VAR(4) - Level

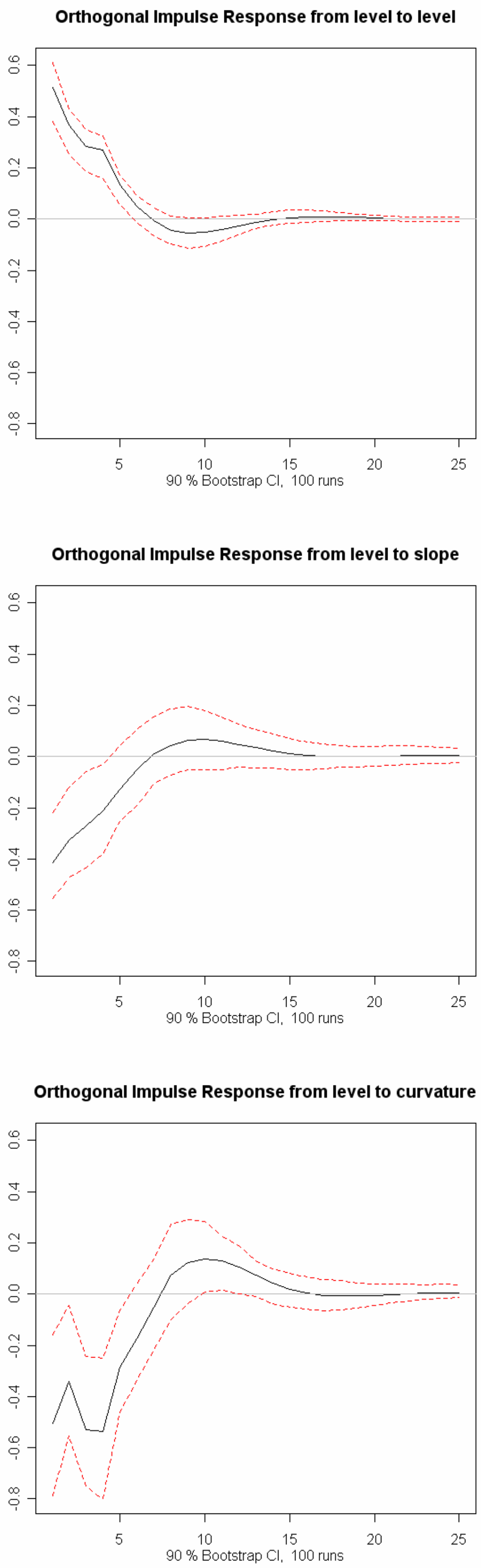


Figure 32 - Impulse Response Hungary Yield-Only VAR(4) - Slope

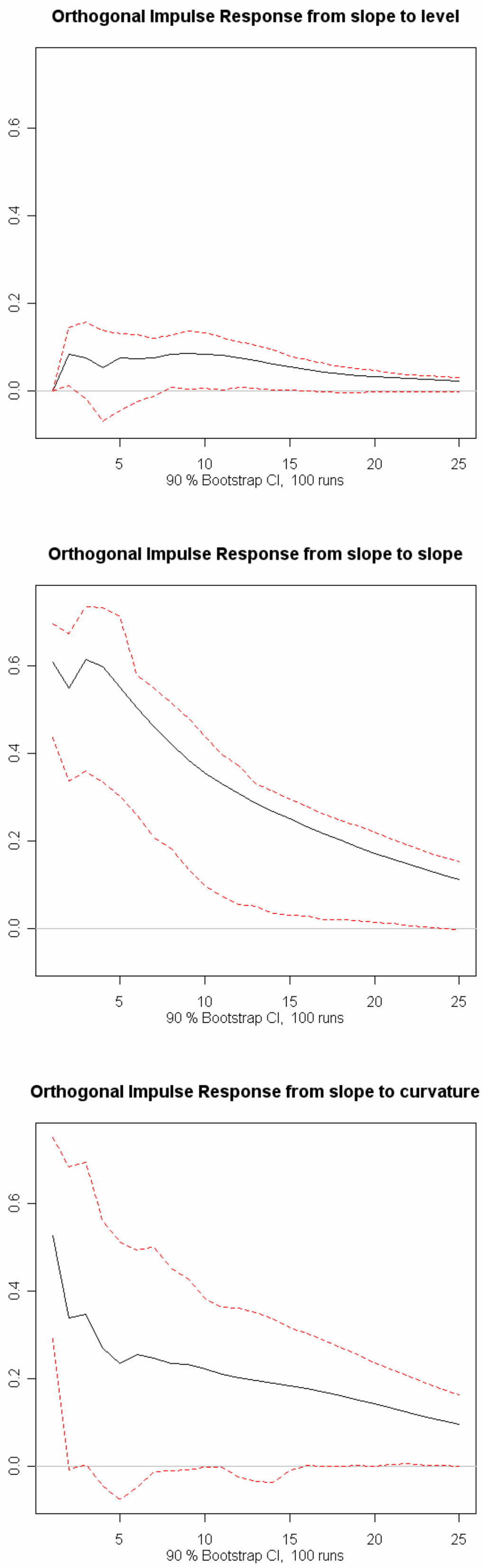
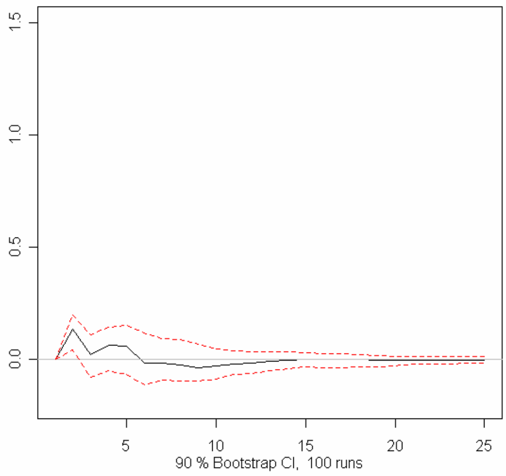
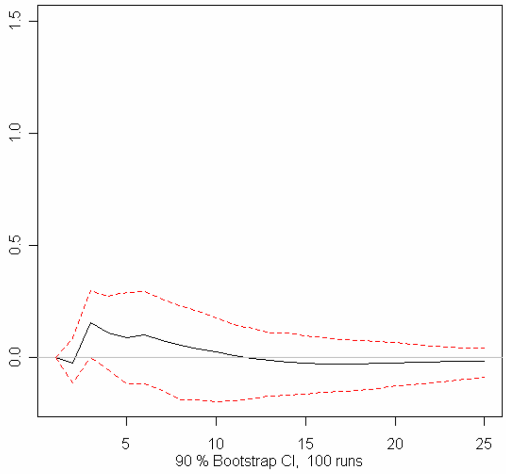


Figure 33 - Impulse Response Hungary Yield-Only VAR(4) - Curvature

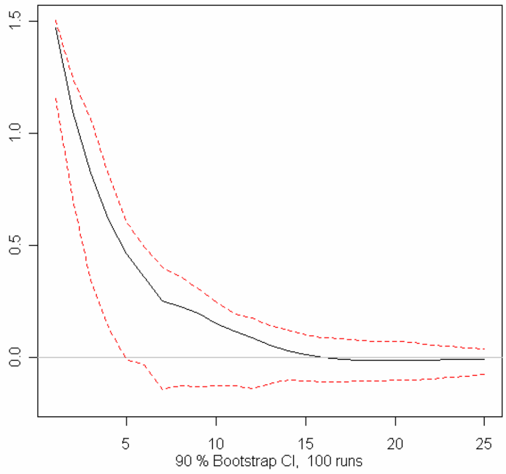
Orthogonal Impulse Response from curvature to level



Orthogonal Impulse Response from curvature to slope



Orthogonal Impulse Response from curvature to curvature



10.4 Impulse Responses Yield-Macro Model Hungary

Figure 34 - Impulse Response Hungary Yield-Macro VAR(2) - Level

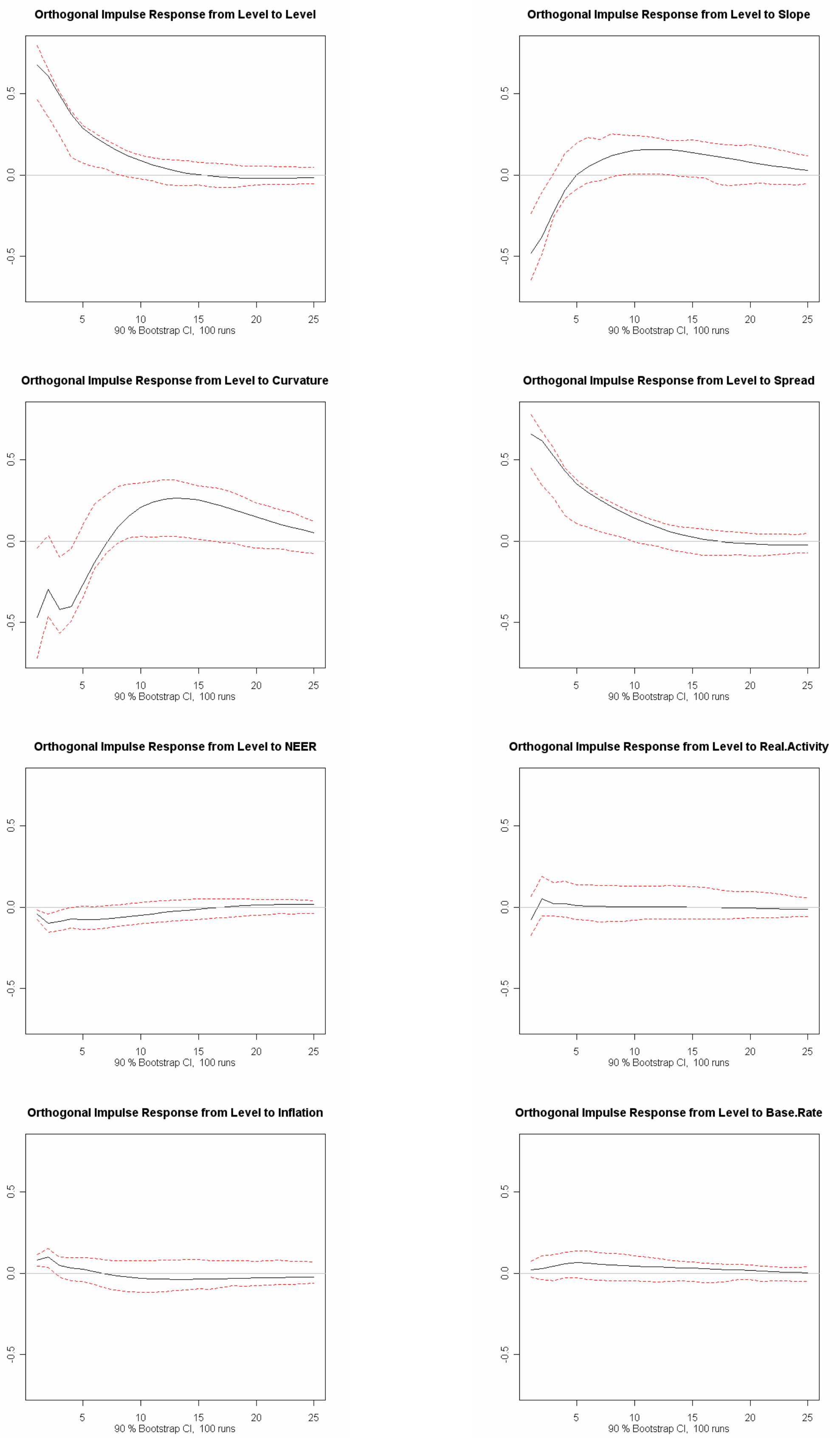


Figure 35 - Impulse Response Hungary Yield-Macro VAR(2) - Slope

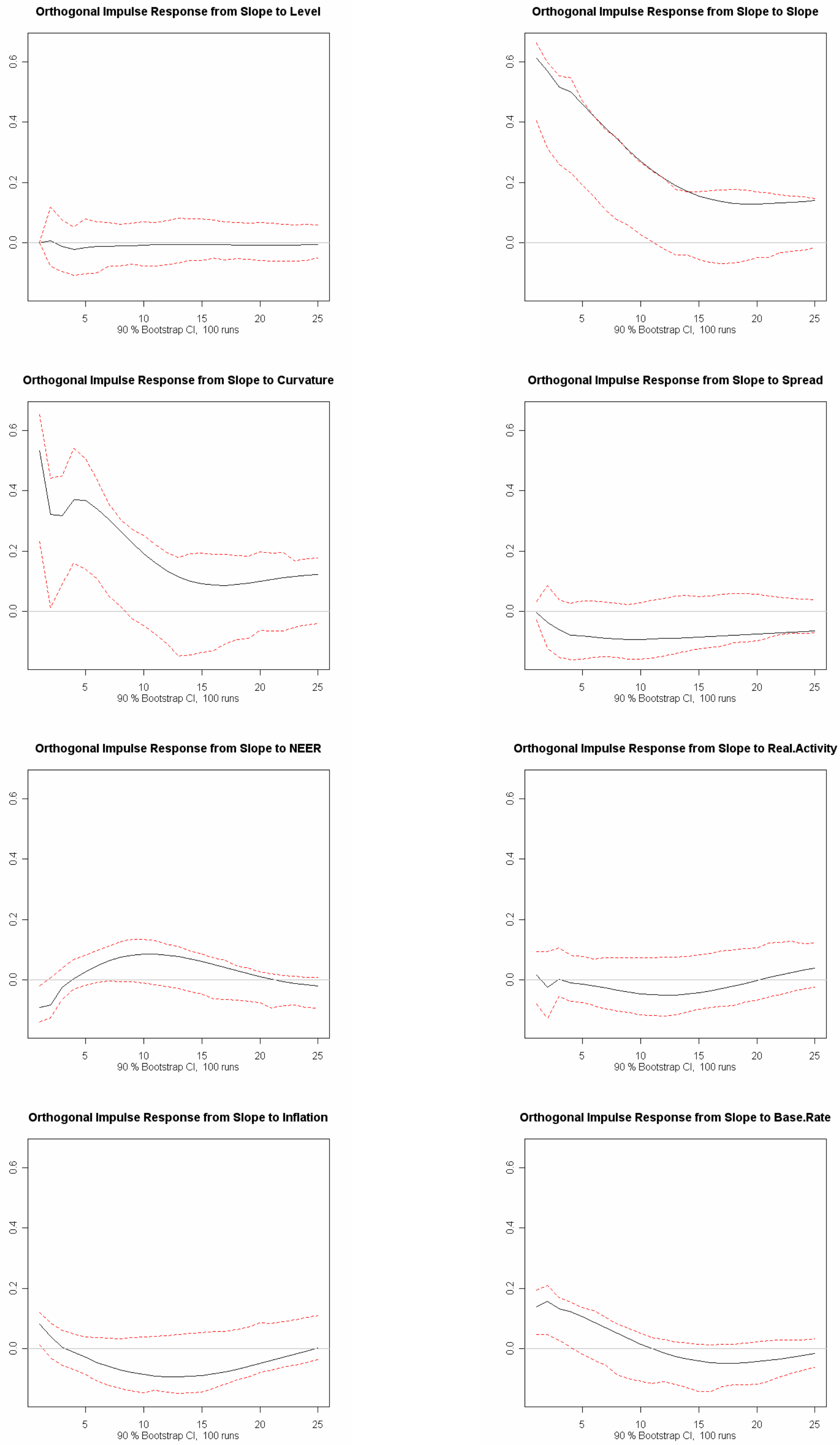


Figure 36 - Impulse Response Hungary Yield-Macro VAR(2) - Curvature

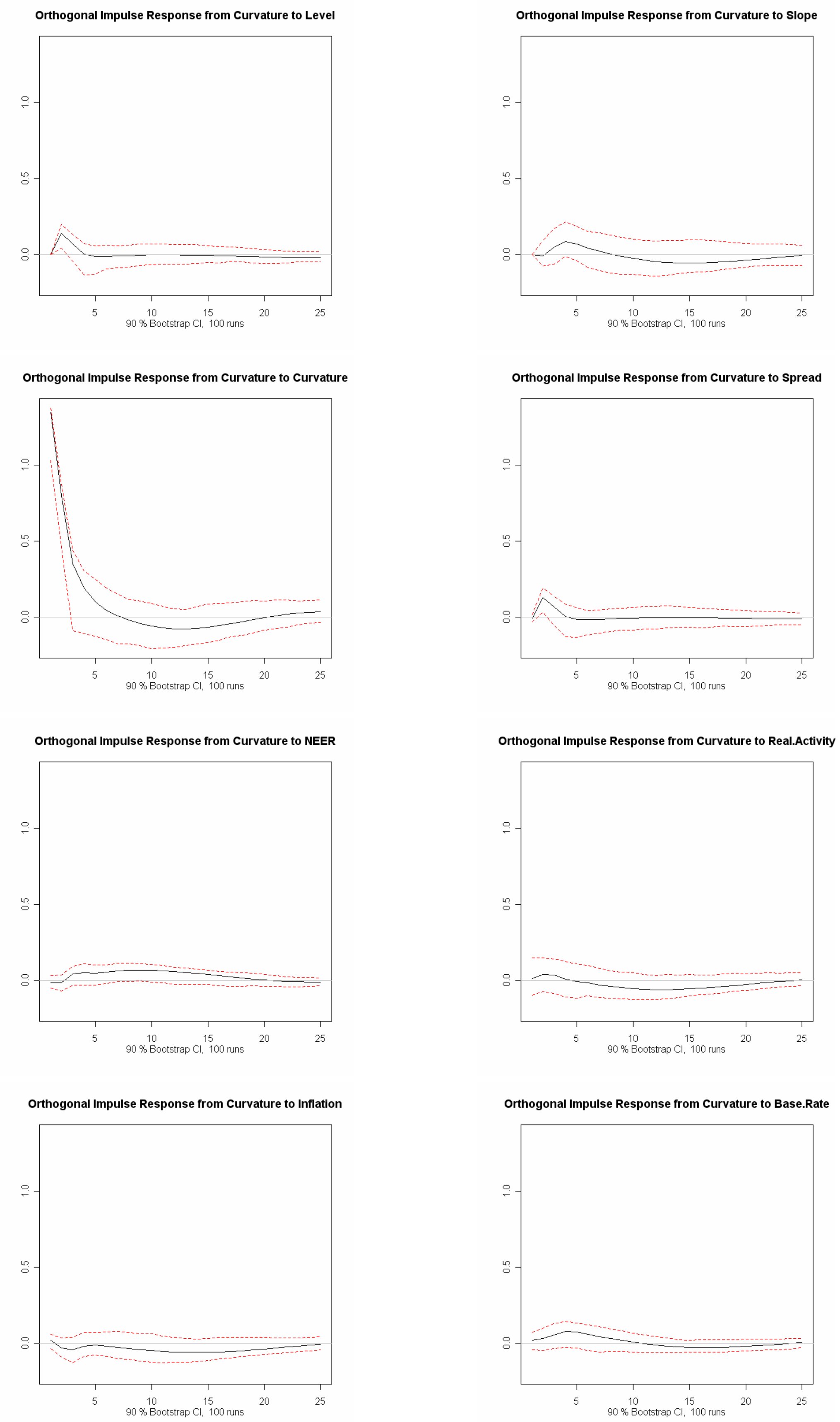


Figure 37 - Impulse Response Hungary Yield-Macro VAR(2) - Spread

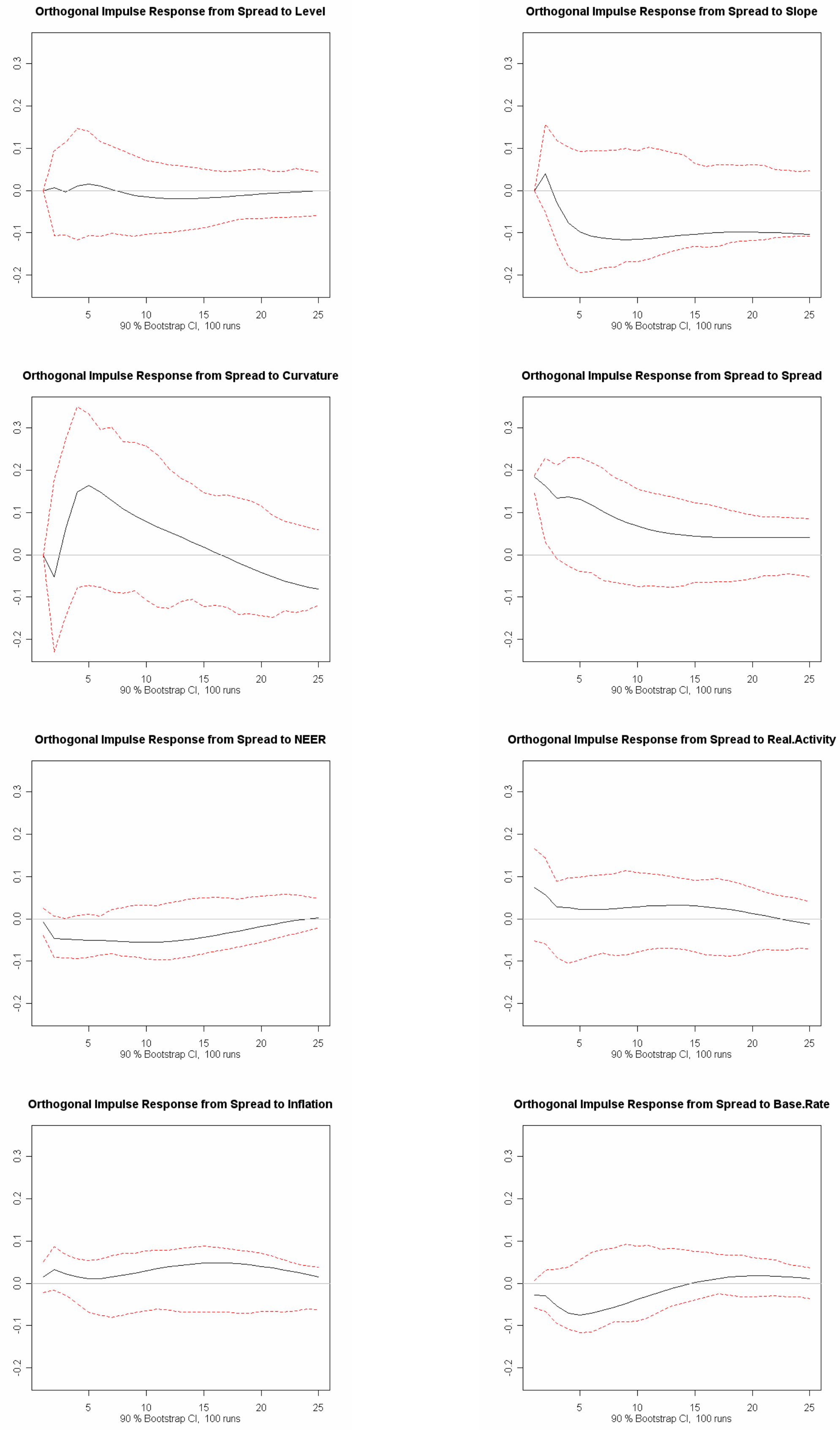


Figure 38 - Impulse Response Hungary Yield-Macro VAR(2) - NEER

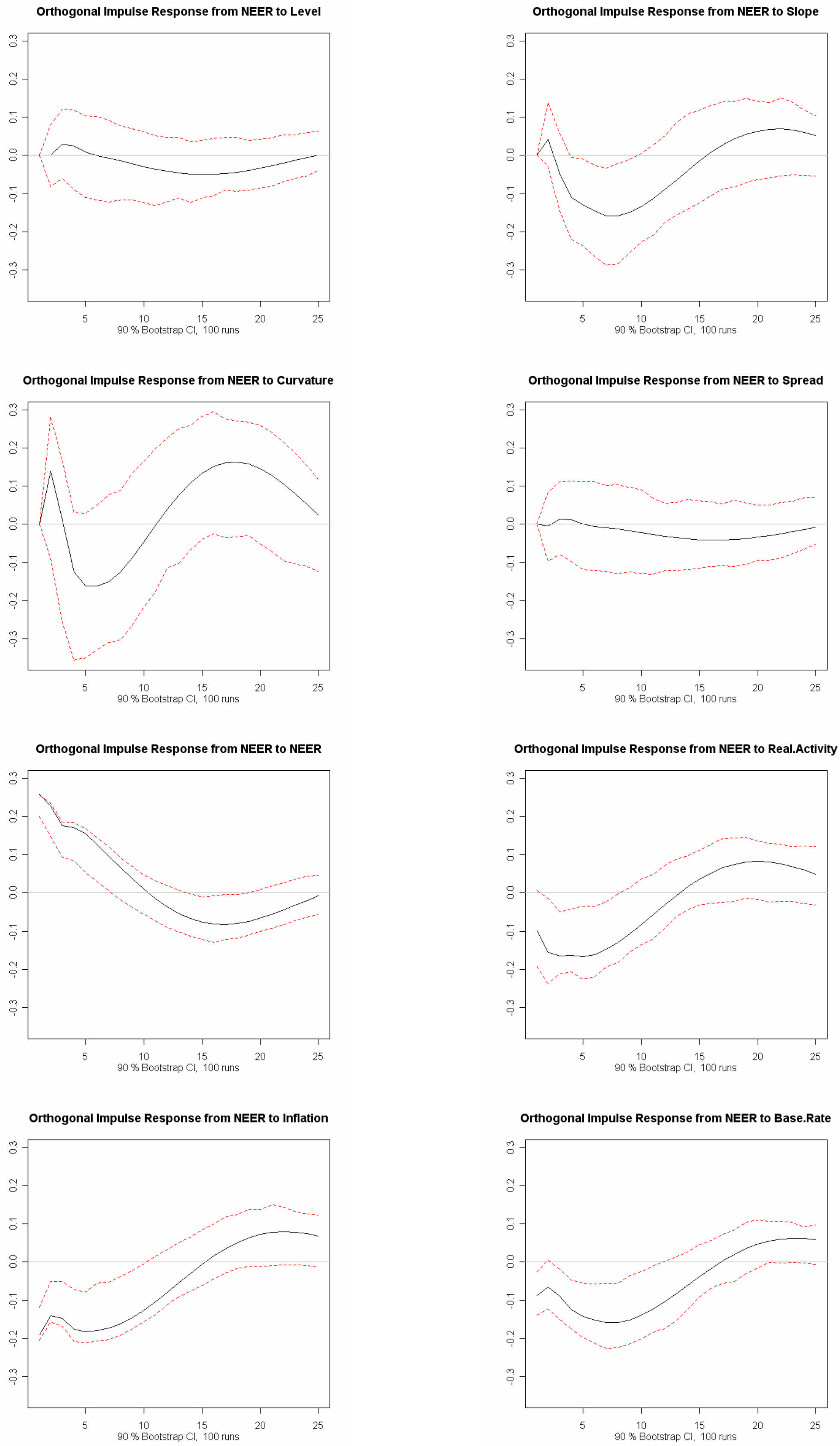


Figure 39 - Impulse Response Hungary Yield-Macro VAR(2) - Real Activity

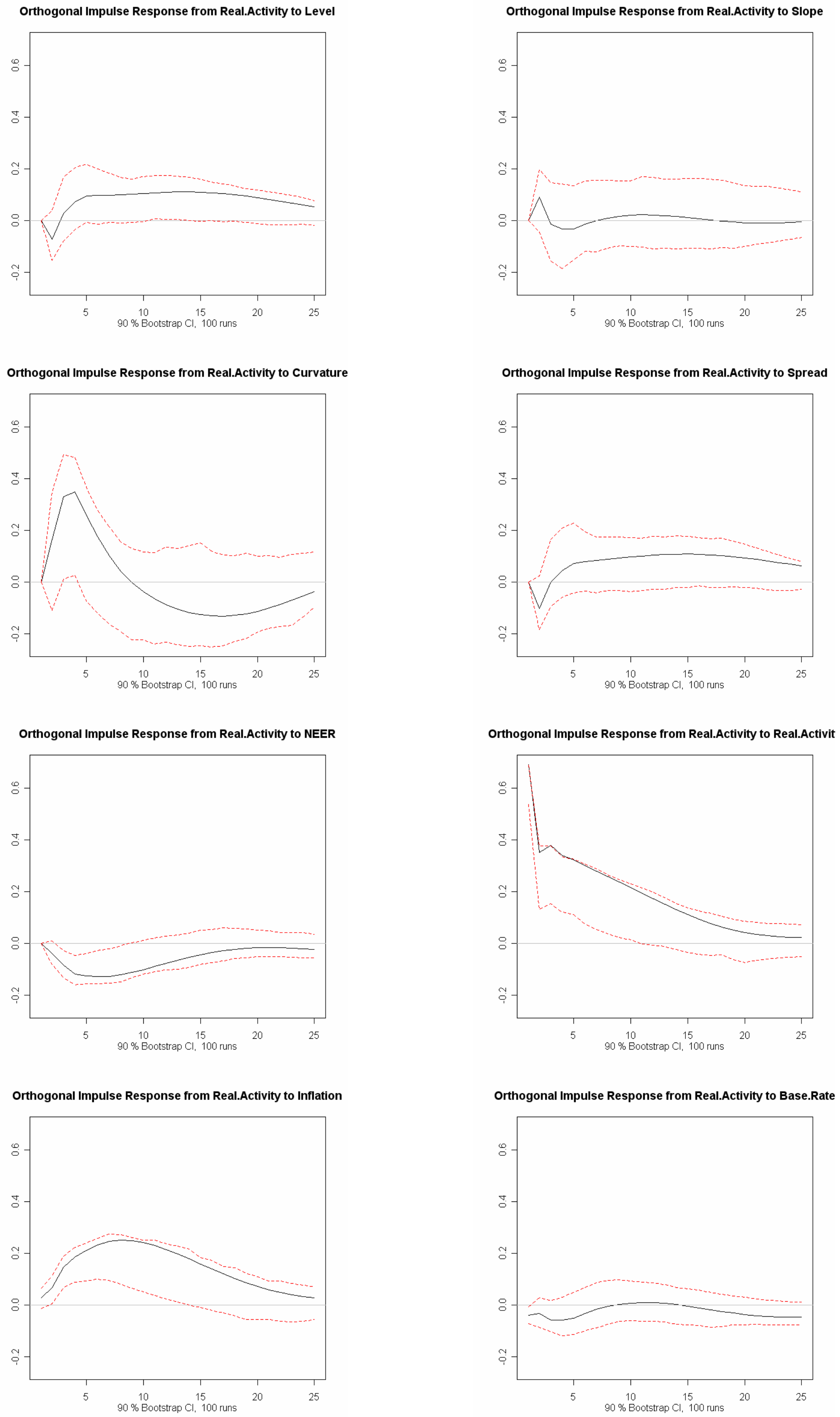


Figure 40 - Impulse Response Hungary Yield-Macro VAR(2) - Inflation

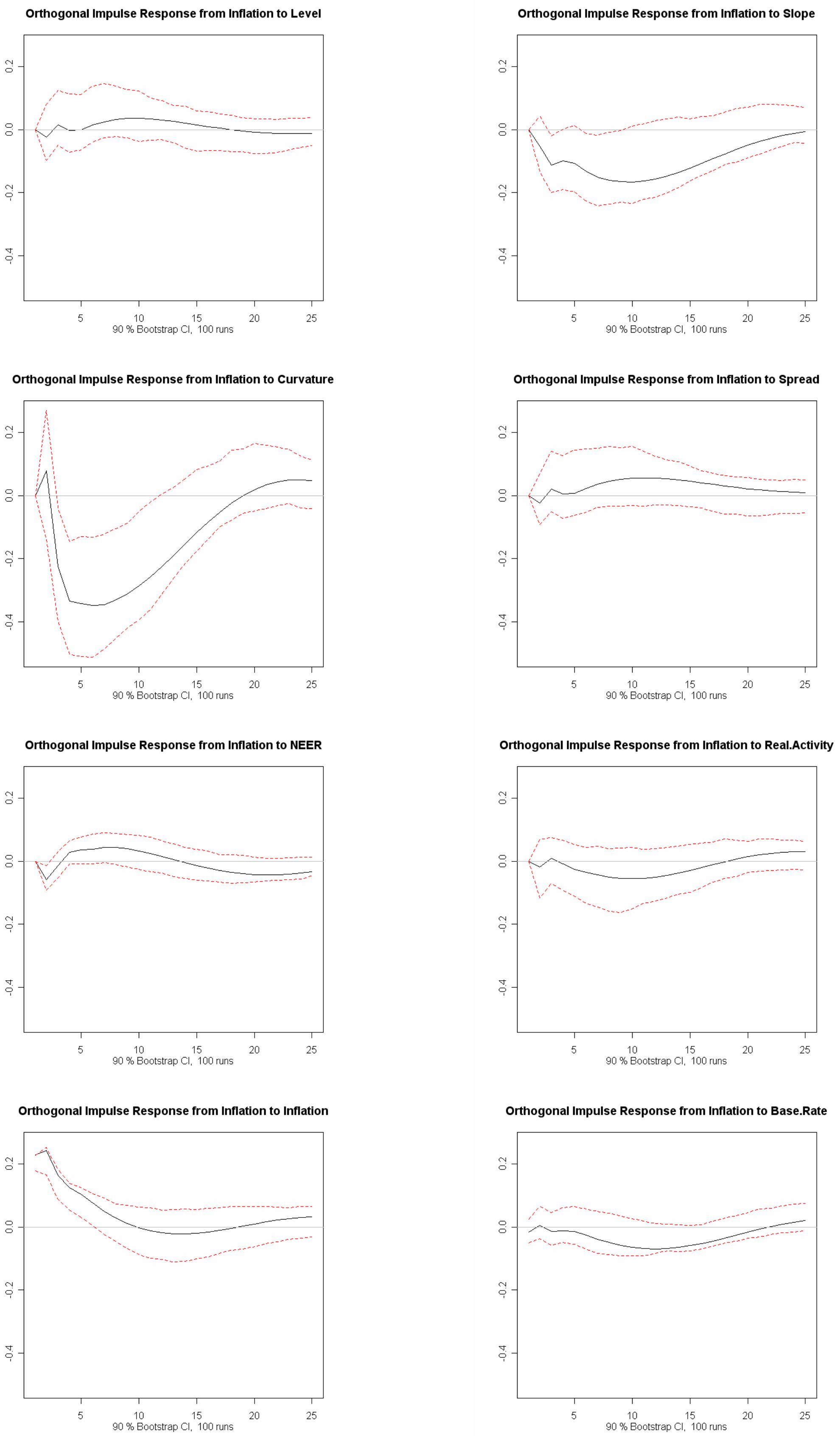
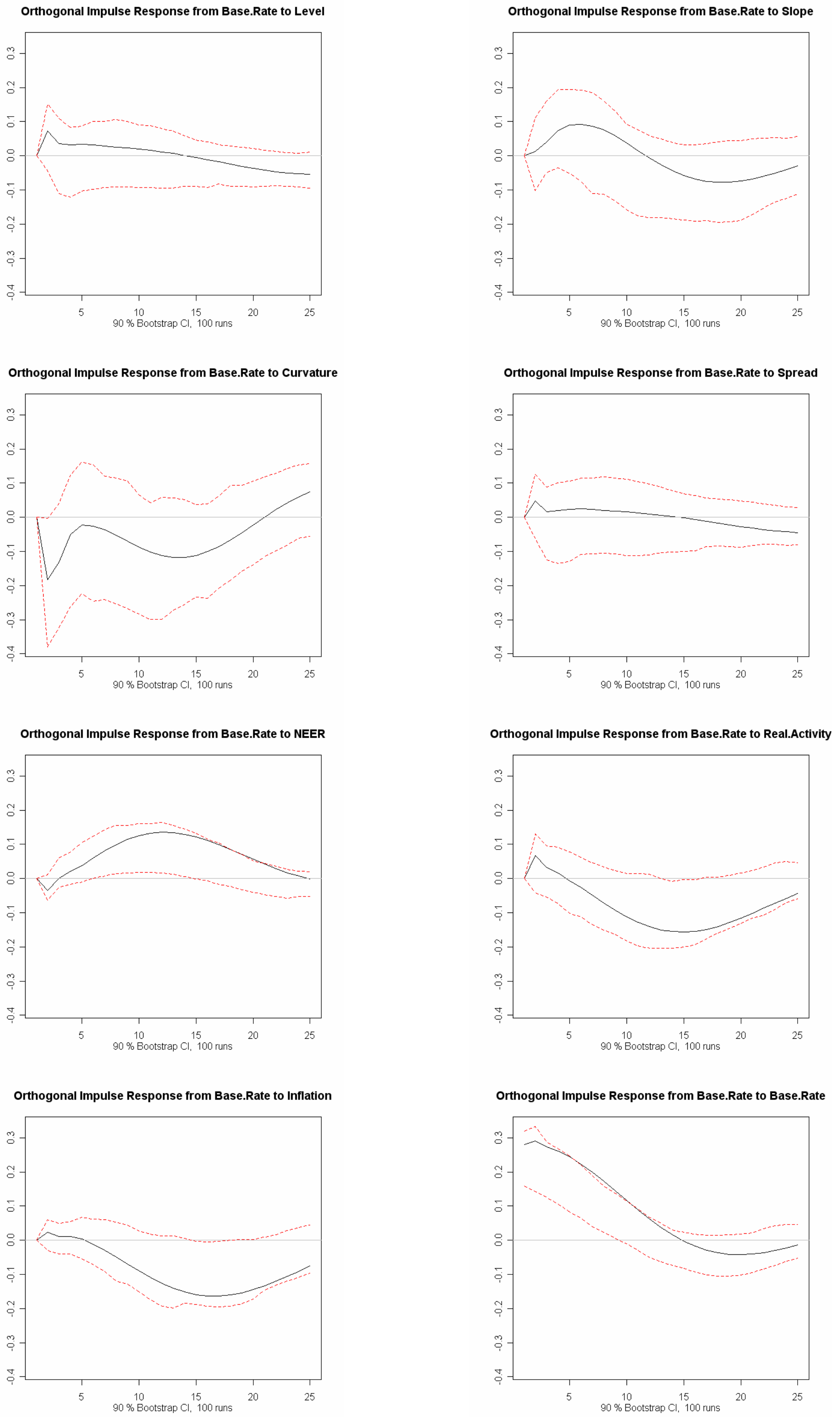


Figure 41 - Impulse Response Hungary Yield-Macro VAR(2) - Base Rate



10.5 Impulse Yield-Only Model Poland

Figure 42 - Impulse Response Poland Yield-Only VAR(3) - Level

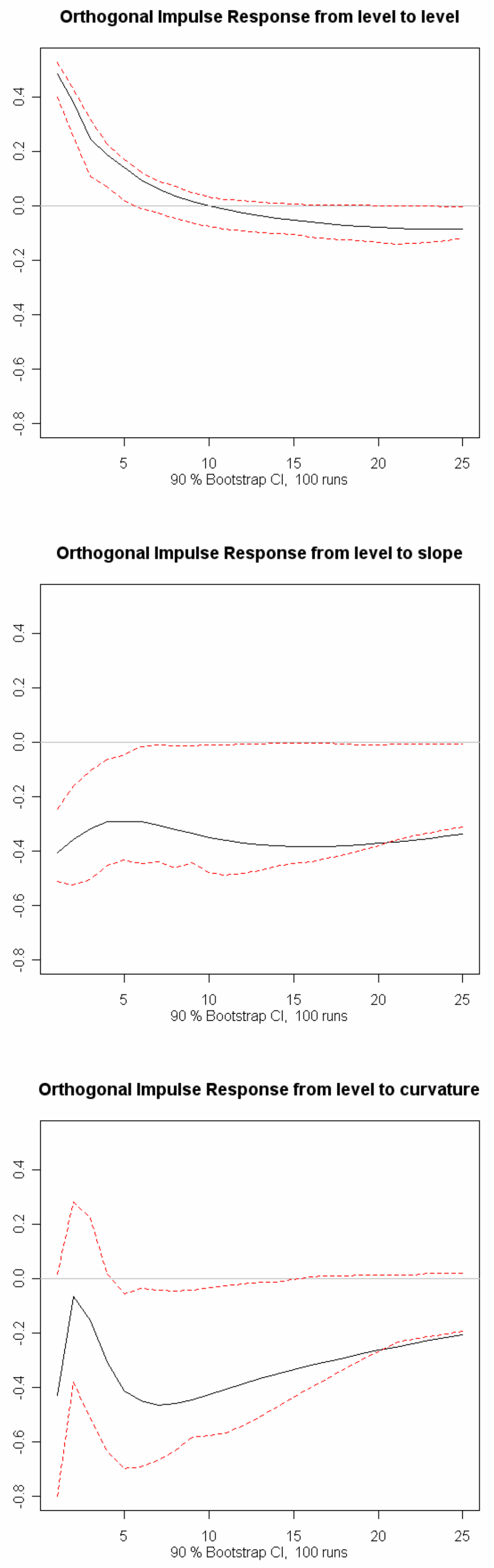


Figure 43 - Impulse Response Poland Yield-Only VAR(3) - Slope

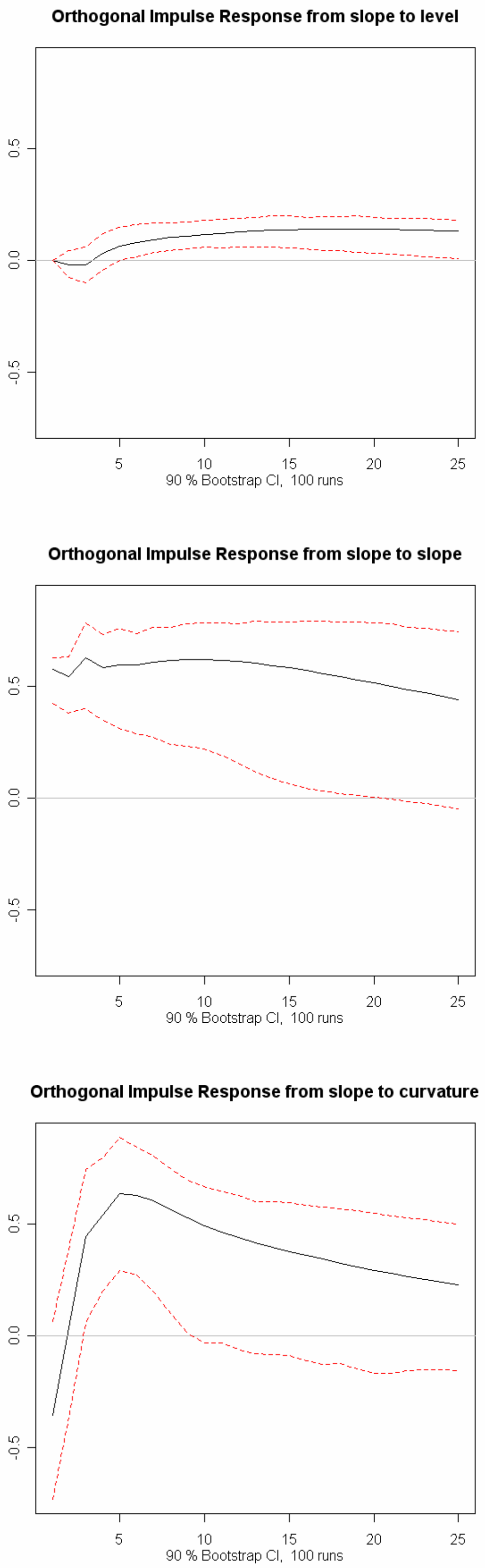
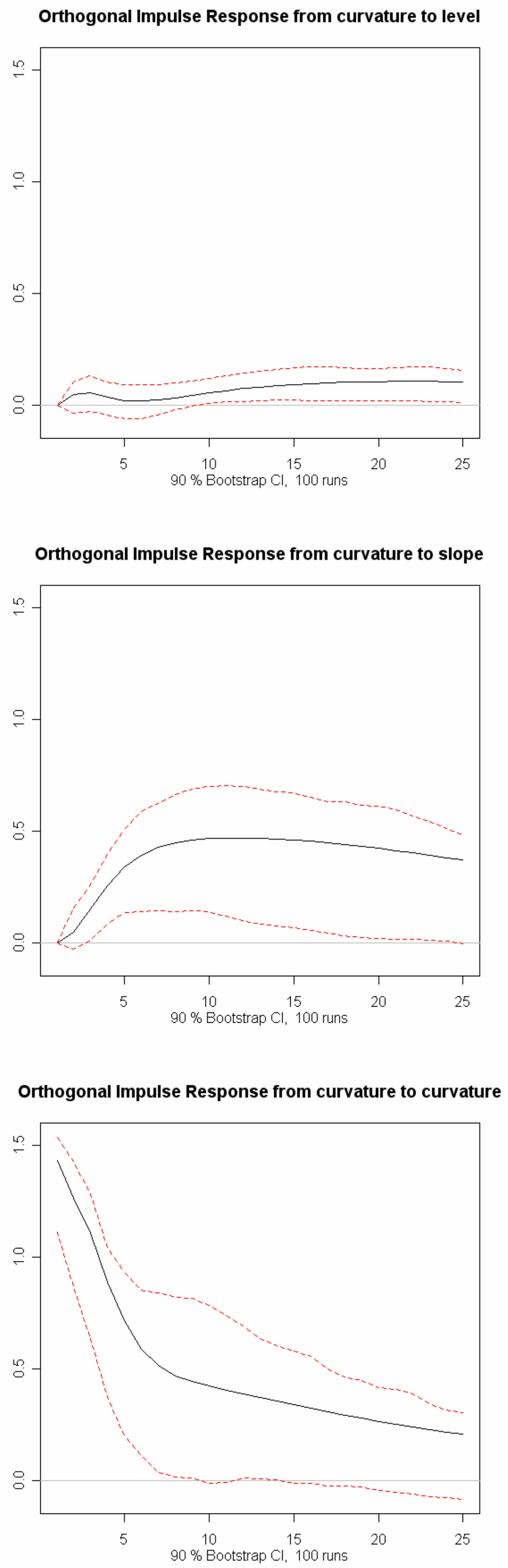


Figure 44 - Impulse Response Poland Yield-Only VAR(3) - Curvature



10.6 Impulse Responses Yield-Macro Model Poland

Figure 45 - Impulse Response Poland Yield-Macro VAR(4) - Level

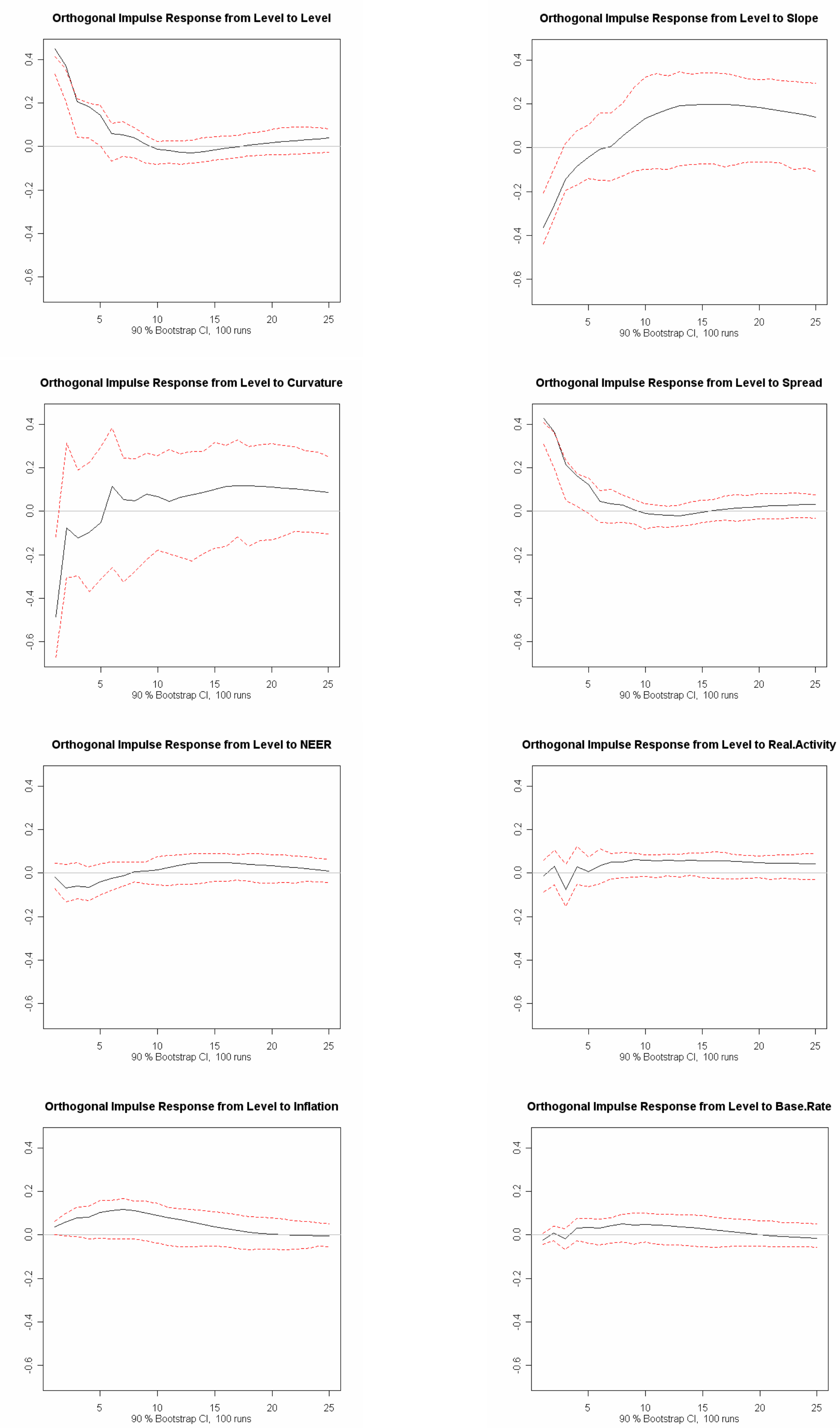


Figure 46 - Impulse Response Poland Yield-Macro VAR(4) - Slope

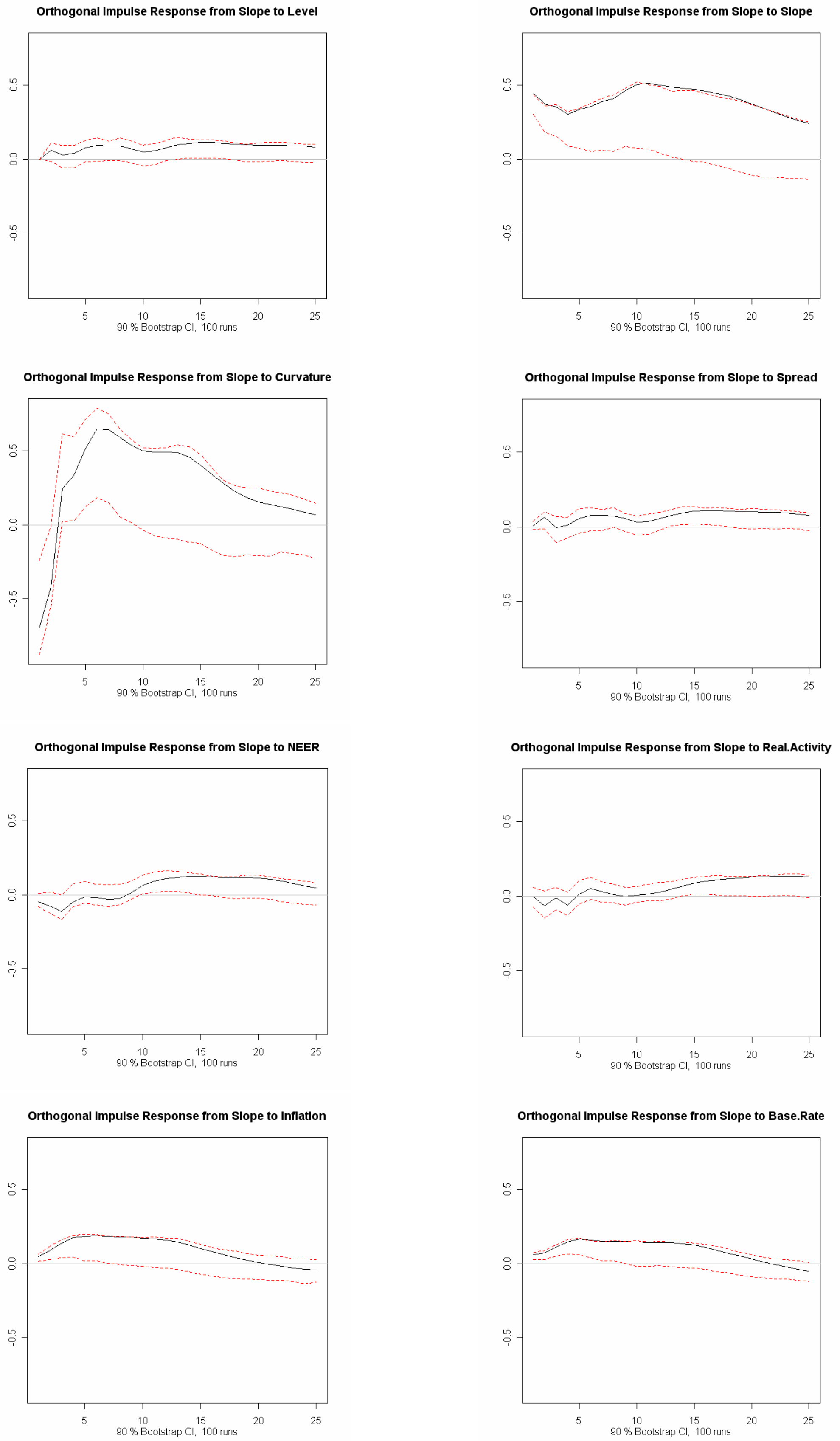


Figure 47 - Impulse Response Poland Yield-Macro VAR(4) - Curvature

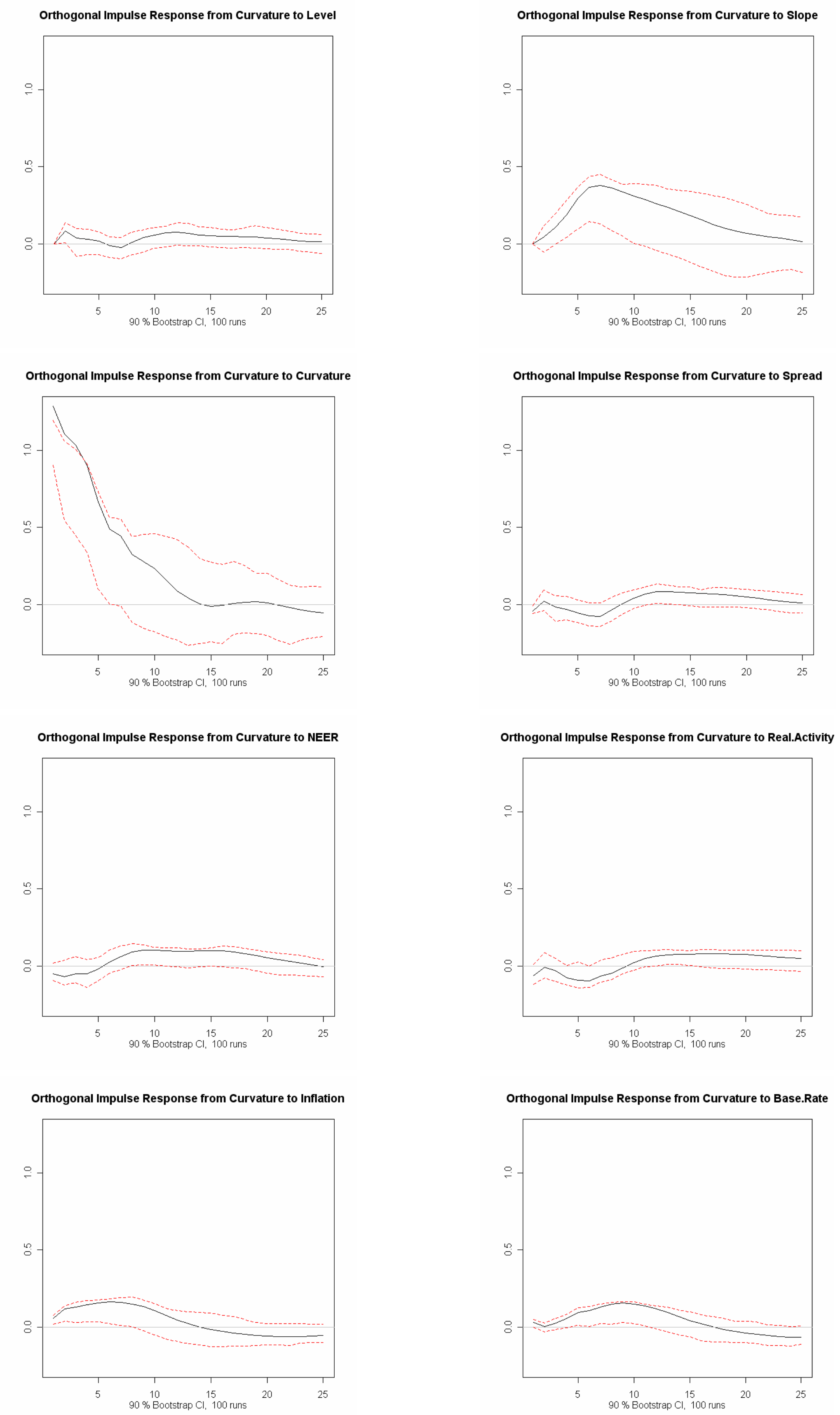


Figure 48 - Impulse Response Poland Yield-Macro VAR(4) - Spread

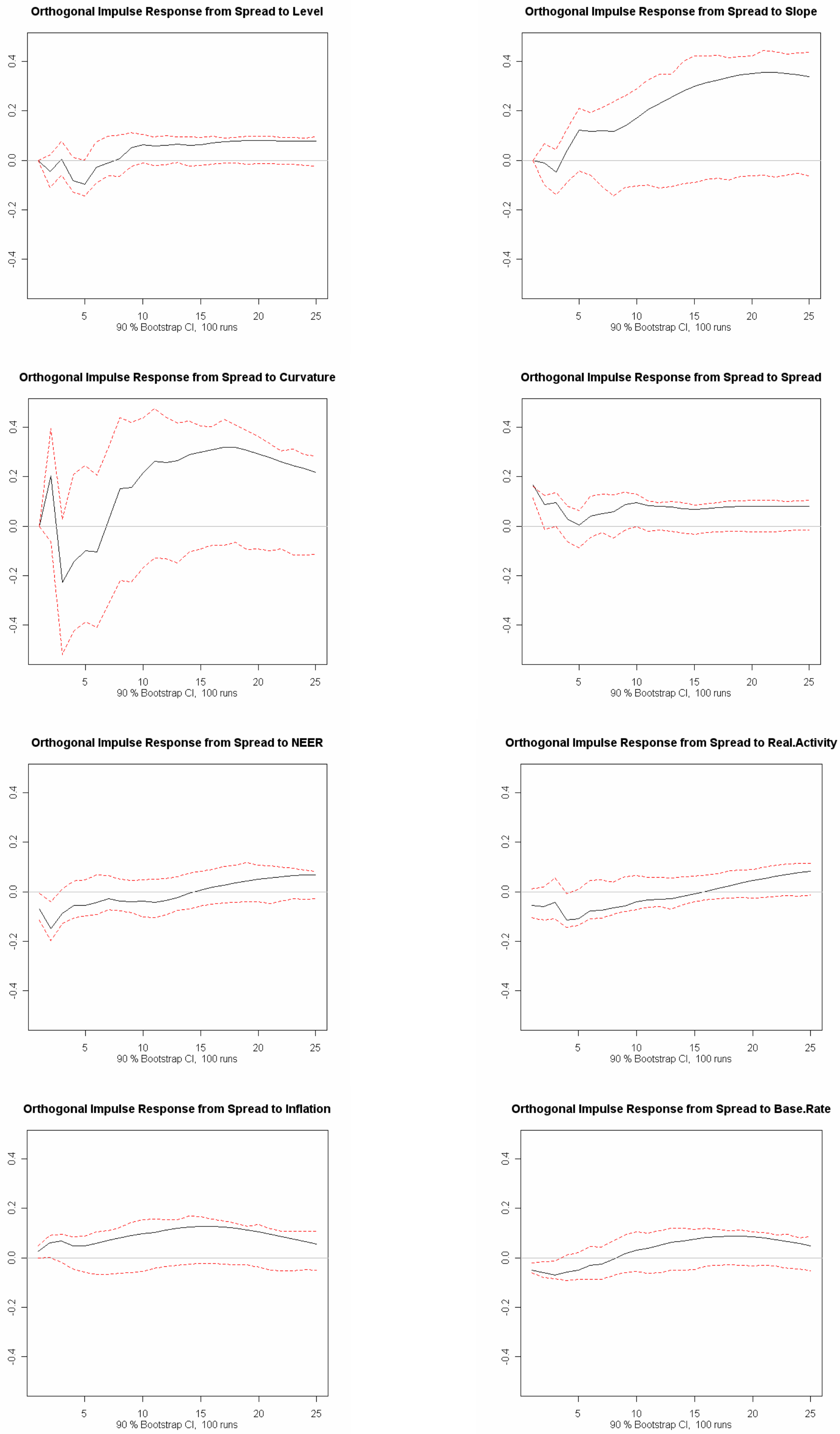


Figure 49 - Impulse Response Poland Yield-Macro VAR(4) - NEER

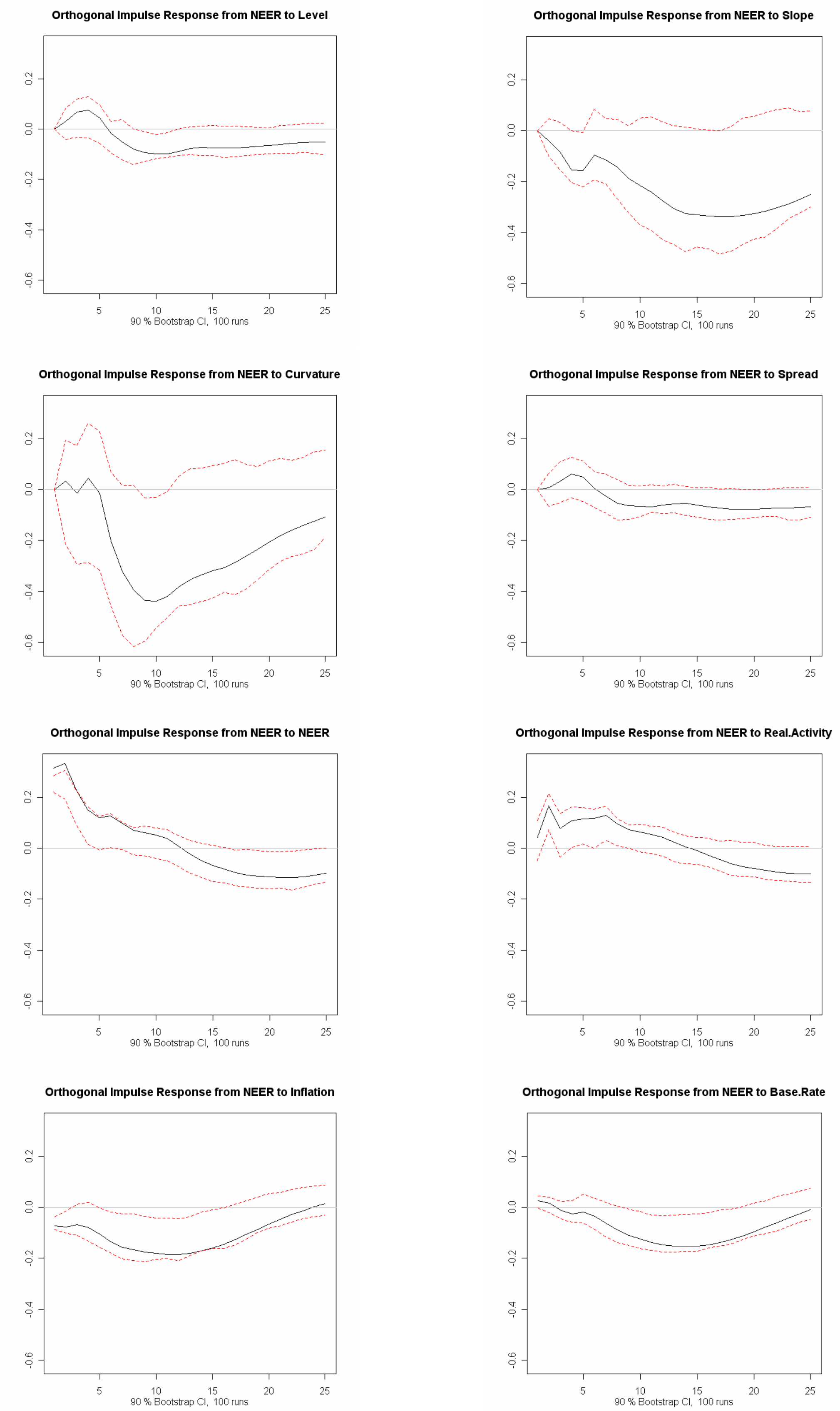


Figure 50 - Impulse Response Poland Yield-Macro VAR(4) - Real Activity

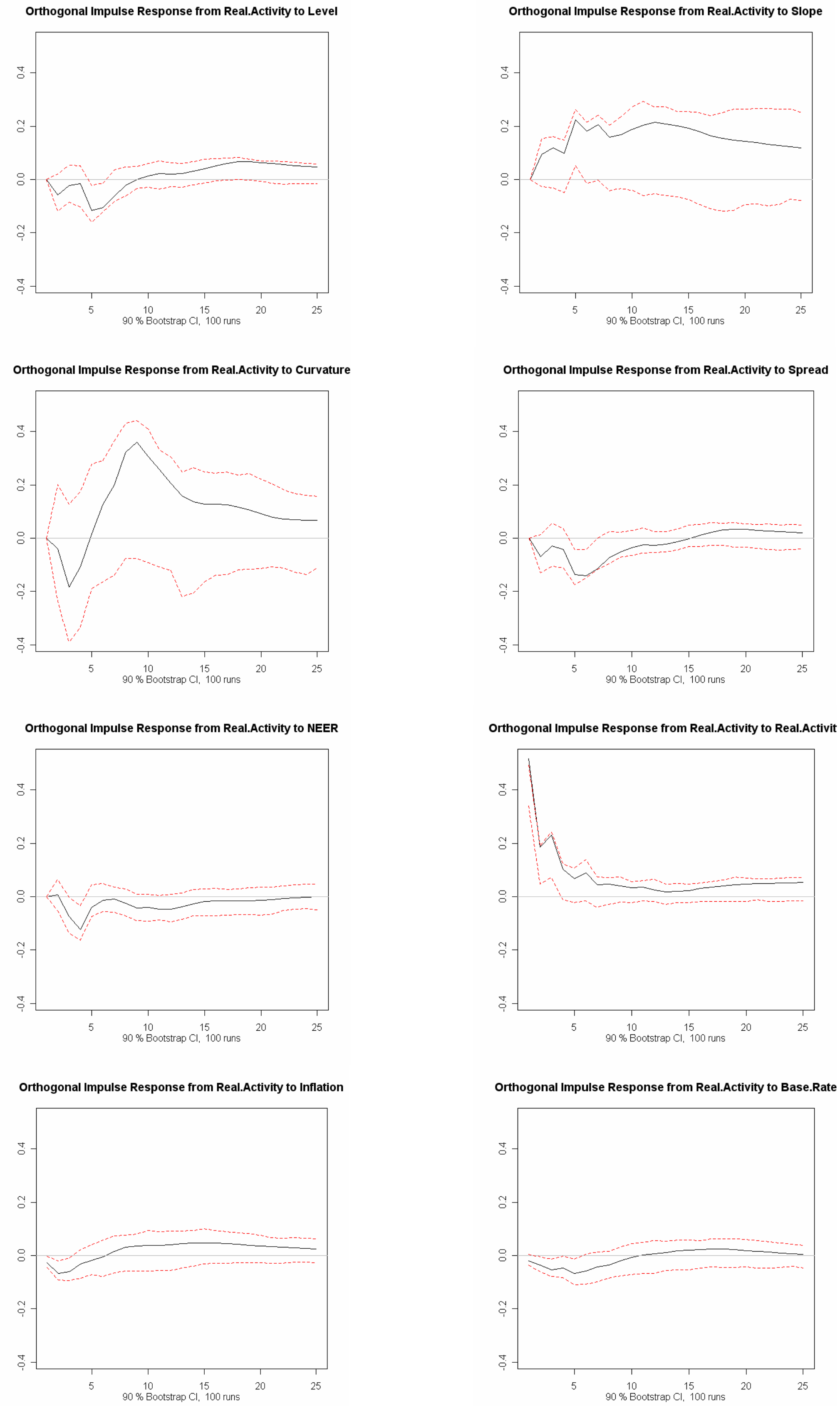


Figure 51 - Impulse Response Poland Yield-Macro VAR(4) - Inflation

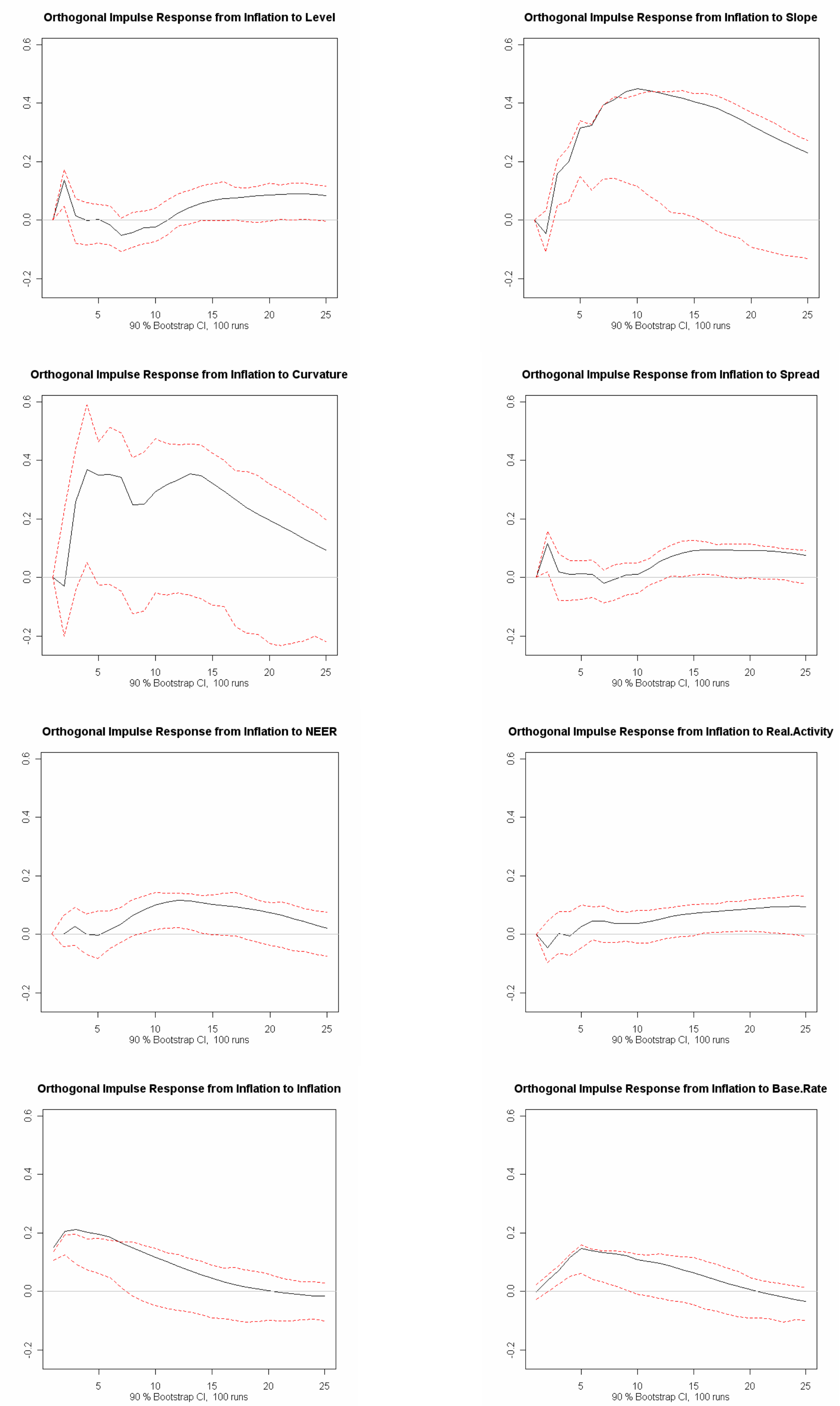
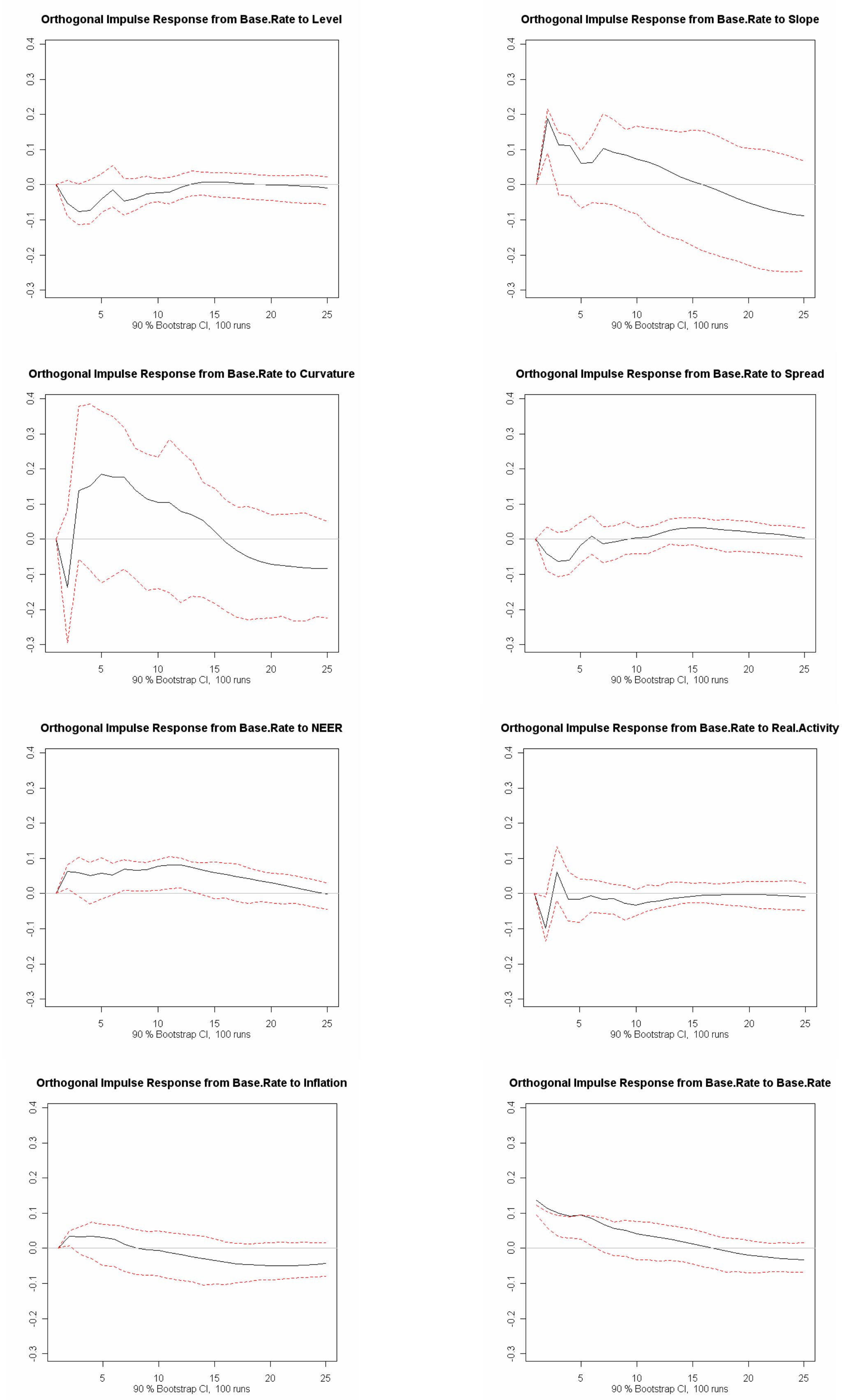


Figure 52 - Impulse Response Poland Yield-Macro VAR(4) - Base Rate

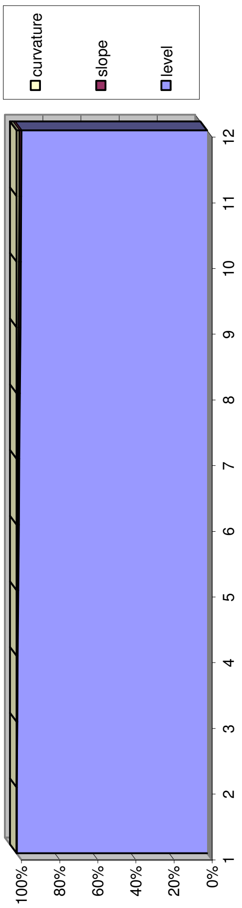


11 Appendix - Forecast Error Variance Decompositions

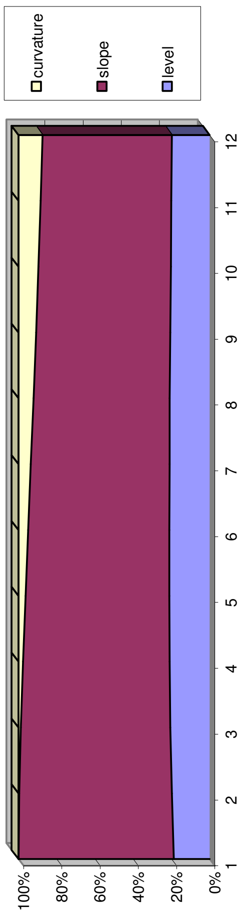
11.1 Yield-Only FEVD Czech Republic

Table 34 - Yield-Only FEVD Czech Republic VAR(1)

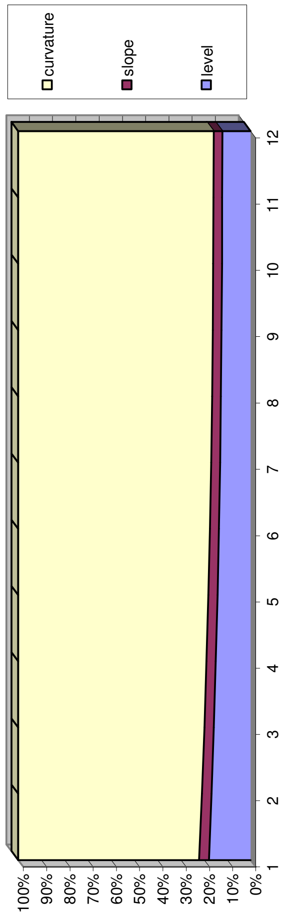
	LEVEL		
n ahead	level	slope	curvature
1	1.0000	0.0000	0.0000
2	0.9989	0.0004	0.0007
3	0.9968	0.0013	0.0019
4	0.9942	0.0025	0.0034
5	0.9912	0.0038	0.0050
6	0.9882	0.0052	0.0066
7	0.9853	0.0066	0.0081
8	0.9825	0.0080	0.0095
9	0.9800	0.0093	0.0107
10	0.9776	0.0106	0.0118
11	0.9755	0.0118	0.0127
12	0.9737	0.0128	0.0135



	SLOPE		
n ahead	level	slope	curvature
1	0.1877	0.8123	0.0000
2	0.1979	0.7978	0.0042
3	0.2050	0.7823	0.0126
4	0.2094	0.7667	0.0239
5	0.2115	0.7515	0.0370
6	0.2118	0.7372	0.0510
7	0.2108	0.7241	0.0651
8	0.2089	0.7122	0.0789
9	0.2064	0.7015	0.0921
10	0.2037	0.6920	0.1043
11	0.2009	0.6836	0.1155
12	0.1982	0.6762	0.1257



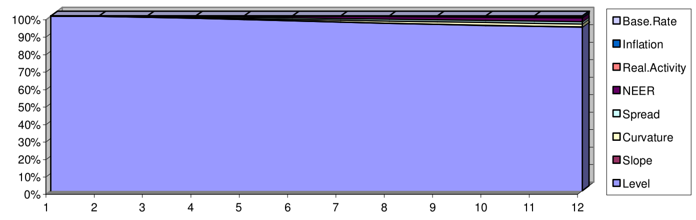
	CURVATURE		
n ahead	level	slope	curvature
1	0.1799	0.0421	0.7780
2	0.1689	0.0411	0.7900
3	0.1590	0.0402	0.8008
4	0.1503	0.0396	0.8101
5	0.1429	0.0391	0.8180
6	0.1368	0.0387	0.8245
7	0.1320	0.0384	0.8296
8	0.1282	0.0382	0.8336
9	0.1255	0.0380	0.8364
10	0.1237	0.0379	0.8384
11	0.1225	0.0379	0.8396
12	0.1220	0.0378	0.8402



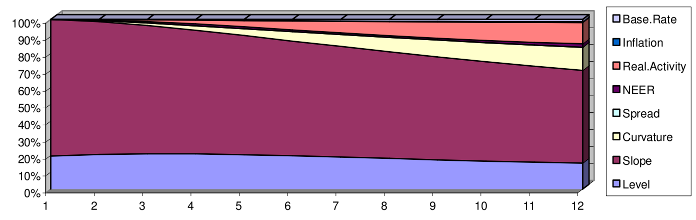
11.2 Yield-Macro FEVD Czech Republic

Table 35 - Yield-Macro FEVD Czech Republic VAR(1) – Level, Slope, Curvature, Spread

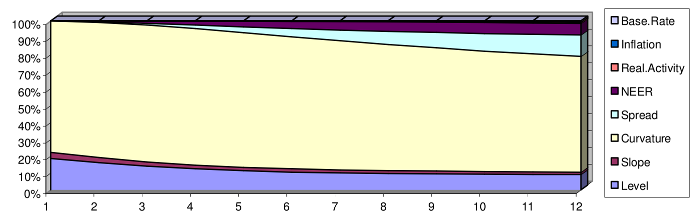
n ahead	LEVEL							
	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.9977	0.0000	0.0005	0.0010	0.0006	0.0002	0.0000	0.0000
3	0.9932	0.0000	0.0015	0.0029	0.0019	0.0004	0.0001	0.0000
4	0.9873	0.0000	0.0031	0.0051	0.0038	0.0006	0.0001	0.0000
5	0.9805	0.0001	0.0051	0.0072	0.0062	0.0009	0.0001	0.0000
6	0.9733	0.0001	0.0074	0.0090	0.0088	0.0011	0.0003	0.0001
7	0.9661	0.0002	0.0097	0.0104	0.0115	0.0014	0.0006	0.0001
8	0.9591	0.0003	0.0118	0.0114	0.0141	0.0017	0.0013	0.0001
9	0.9526	0.0005	0.0138	0.0121	0.0165	0.0022	0.0023	0.0002
10	0.9466	0.0006	0.0155	0.0124	0.0184	0.0027	0.0035	0.0002
11	0.9412	0.0007	0.0168	0.0125	0.0199	0.0035	0.0051	0.0003
12	0.9364	0.0008	0.0178	0.0125	0.0210	0.0043	0.0068	0.0004



n ahead	SLOPE							
	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.1956	0.8044	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.2055	0.7817	0.0054	0.0000	0.0029	0.0036	0.0000	0.0009
3	0.2093	0.7549	0.0151	0.0001	0.0066	0.0116	0.0001	0.0022
4	0.2083	0.7273	0.0275	0.0002	0.0093	0.0232	0.0003	0.0039
5	0.2040	0.7004	0.0413	0.0003	0.0105	0.0371	0.0008	0.0056
6	0.1975	0.6748	0.0559	0.0004	0.0104	0.0523	0.0014	0.0074
7	0.1897	0.6505	0.0706	0.0004	0.0098	0.0679	0.0021	0.0090
8	0.1815	0.6274	0.0853	0.0004	0.0093	0.0829	0.0028	0.0104
9	0.1734	0.6055	0.0994	0.0004	0.0096	0.0966	0.0036	0.0115
10	0.1658	0.5846	0.1129	0.0004	0.0113	0.1084	0.0043	0.0123
11	0.1593	0.5648	0.1252	0.0005	0.0147	0.1179	0.0048	0.0128
12	0.1539	0.5461	0.1363	0.0008	0.0197	0.1250	0.0052	0.0130



n ahead	CURVATURE							
	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.1870	0.0351	0.7780	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.1620	0.0289	0.8006	0.0032	0.0045	0.0003	0.0002	0.0003
3	0.1409	0.0248	0.8096	0.0103	0.0128	0.0006	0.0004	0.0005
4	0.1248	0.0220	0.8072	0.0208	0.0230	0.0007	0.0007	0.0008
5	0.1135	0.0201	0.7967	0.0337	0.0333	0.0006	0.0008	0.0012
6	0.1059	0.0187	0.7815	0.0479	0.0427	0.0006	0.0009	0.0017
7	0.1010	0.0177	0.7639	0.0626	0.0507	0.0009	0.0009	0.0024
8	0.0977	0.0168	0.7458	0.0772	0.0569	0.0015	0.0009	0.0031
9	0.0954	0.0162	0.7283	0.0910	0.0616	0.0025	0.0009	0.0040
10	0.0937	0.0157	0.7120	0.1039	0.0649	0.0040	0.0009	0.0049
11	0.0922	0.0153	0.6972	0.1155	0.0672	0.0058	0.0011	0.0058
12	0.0909	0.0149	0.6840	0.1258	0.0685	0.0079	0.0014	0.0067



n ahead	SPREAD							
	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.8322	0.0041	0.0013	0.1623	0.0000	0.0000	0.0000	0.0000
2	0.8326	0.0049	0.0016	0.1573	0.0002	0.0006	0.0017	0.0012
3	0.8316	0.0055	0.0022	0.1514	0.0006	0.0018	0.0050	0.0019
4	0.8291	0.0058	0.0031	0.1456	0.0015	0.0030	0.0094	0.0025
5	0.8254	0.0060	0.0044	0.1400	0.0029	0.0041	0.0141	0.0030
6	0.8210	0.0060	0.0060	0.1349	0.0049	0.0049	0.0189	0.0034
7	0.8159	0.0059	0.0080	0.1302	0.0076	0.0055	0.0231	0.0037
8	0.8103	0.0057	0.0104	0.1260	0.0110	0.0058	0.0268	0.0040
9	0.8044	0.0055	0.0130	0.1222	0.0150	0.0060	0.0296	0.0042
10	0.7982	0.0053	0.0157	0.1188	0.0196	0.0062	0.0317	0.0044
11	0.7920	0.0052	0.0184	0.1158	0.0246	0.0063	0.0331	0.0045
12	0.7858	0.0052	0.0211	0.1132	0.0298	0.0063	0.0339	0.0047

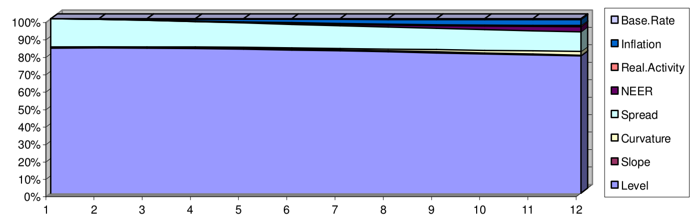
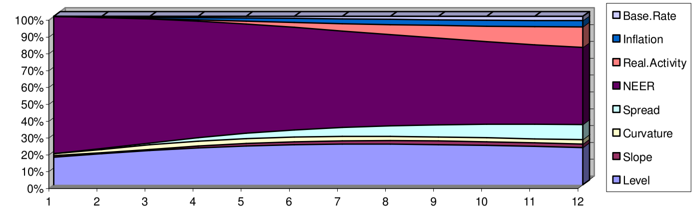
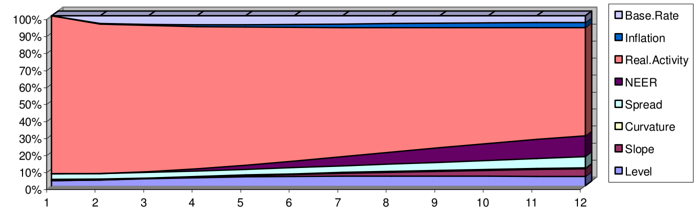


Table 36 - Yield-Macro FEVD Czech Republic VAR(1) – NEER, Real Activity, Inflation, Base Rate

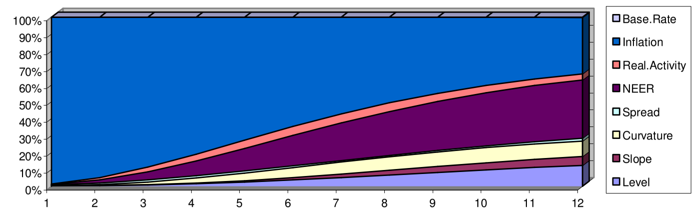
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
	NEER							
1	0.1641	0.0098	0.0123	0.0001	0.8138	0.0000	0.0000	0.0000
2	0.1849	0.0055	0.0205	0.0036	0.7790	0.0004	0.0027	0.0035
3	0.2042	0.0068	0.0267	0.0104	0.7360	0.0031	0.0074	0.0053
4	0.2196	0.0104	0.0297	0.0197	0.6915	0.0086	0.0130	0.0075
5	0.2307	0.0143	0.0300	0.0306	0.6486	0.0173	0.0187	0.0098
6	0.2378	0.0176	0.0287	0.0421	0.6086	0.0289	0.0239	0.0123
7	0.2410	0.0200	0.0267	0.0535	0.5725	0.0430	0.0284	0.0149
8	0.2410	0.0213	0.0248	0.0640	0.5405	0.0590	0.0318	0.0175
9	0.2384	0.0218	0.0236	0.0731	0.5129	0.0758	0.0342	0.0200
10	0.2339	0.0216	0.0234	0.0806	0.4899	0.0926	0.0358	0.0222
11	0.2281	0.0211	0.0243	0.0862	0.4712	0.1085	0.0365	0.0241
12	0.2219	0.0205	0.0261	0.0900	0.4568	0.1226	0.0365	0.0256



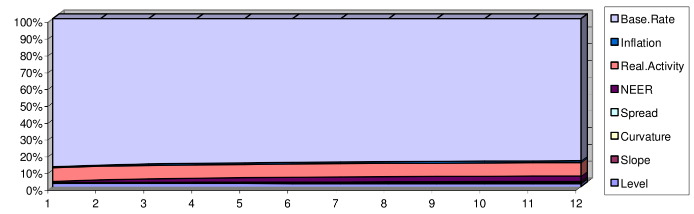
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
	REAL ACTIVITY							
1	0.0300	0.0009	0.0079	0.0324	0.0013	0.9274	0.0000	0.0000
2	0.0338	0.0008	0.0049	0.0323	0.0014	0.8792	0.0023	0.0453
3	0.0413	0.0018	0.0038	0.0323	0.0054	0.8588	0.0060	0.0507
4	0.0476	0.0040	0.0035	0.0328	0.0133	0.8365	0.0103	0.0521
5	0.0522	0.0073	0.0037	0.0341	0.0245	0.8124	0.0147	0.0511
6	0.0552	0.0117	0.0043	0.0362	0.0382	0.7865	0.0186	0.0493
7	0.0568	0.0168	0.0049	0.0391	0.0535	0.7597	0.0220	0.0471
8	0.0574	0.0225	0.0055	0.0430	0.0693	0.7327	0.0248	0.0449
9	0.0572	0.0285	0.0060	0.0477	0.0848	0.7061	0.0270	0.0428
10	0.0566	0.0345	0.0062	0.0532	0.0991	0.6807	0.0287	0.0409
11	0.0558	0.0402	0.0063	0.0594	0.1118	0.6571	0.0300	0.0394
12	0.0550	0.0456	0.0062	0.0661	0.1223	0.6355	0.0310	0.0383



n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
	INFLATION							
1	0.0032	0.0009	0.0000	0.0058	0.0007	0.0027	0.9867	0.0000
2	0.0047	0.0005	0.0047	0.0100	0.0172	0.0144	0.9484	0.0000
3	0.0086	0.0014	0.0154	0.0126	0.0480	0.0278	0.8862	0.0001
4	0.0152	0.0039	0.0296	0.0132	0.0886	0.0400	0.8092	0.0002
5	0.0248	0.0081	0.0450	0.0122	0.1340	0.0489	0.7267	0.0003
6	0.0371	0.0137	0.0594	0.0105	0.1796	0.0535	0.6460	0.0002
7	0.0514	0.0201	0.0716	0.0087	0.2220	0.0542	0.5718	0.0002
8	0.0667	0.0271	0.0808	0.0078	0.2591	0.0519	0.5064	0.0002
9	0.0823	0.0340	0.0871	0.0081	0.2899	0.0479	0.4503	0.0003
10	0.0974	0.0407	0.0907	0.0097	0.3142	0.0433	0.4034	0.0007
11	0.1114	0.0468	0.0919	0.0127	0.3324	0.0389	0.3647	0.0012
12	0.1239	0.0523	0.0913	0.0170	0.3450	0.0355	0.3331	0.0020



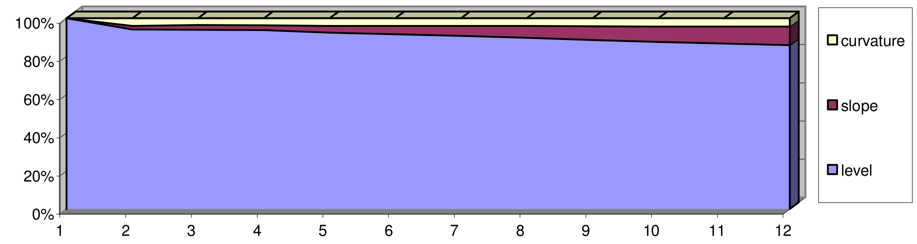
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
	BASE RATE							
1	0.0190	0.0006	0.0027	0.0002	0.0082	0.0823	0.0060	0.8810
2	0.0186	0.0023	0.0046	0.0004	0.0156	0.0798	0.0073	0.8714
3	0.0185	0.0026	0.0048	0.0007	0.0203	0.0796	0.0084	0.8651
4	0.0184	0.0027	0.0048	0.0010	0.0237	0.0794	0.0090	0.8610
5	0.0184	0.0026	0.0048	0.0014	0.0261	0.0794	0.0095	0.8579
6	0.0184	0.0027	0.0048	0.0018	0.0279	0.0793	0.0098	0.8554
7	0.0183	0.0027	0.0048	0.0024	0.0292	0.0793	0.0100	0.8532
8	0.0183	0.0028	0.0048	0.0029	0.0302	0.0794	0.0102	0.8513
9	0.0183	0.0030	0.0047	0.0035	0.0310	0.0795	0.0103	0.8497
10	0.0183	0.0031	0.0047	0.0040	0.0315	0.0797	0.0104	0.8483
11	0.0183	0.0032	0.0047	0.0046	0.0319	0.0799	0.0104	0.8470
12	0.0183	0.0033	0.0047	0.0051	0.0321	0.0801	0.0105	0.8459



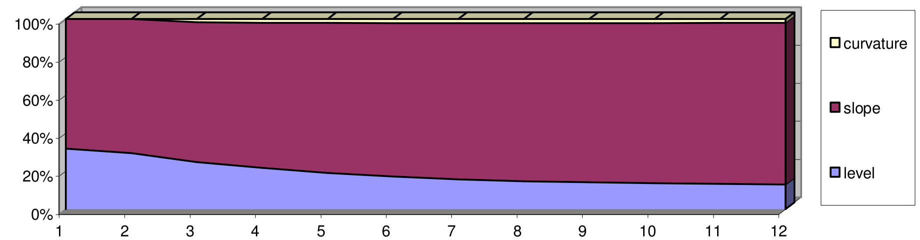
11.3 Yield-Only FEVD Hungary

Table 37 - Yield-Only FEVD Hungary VAR(4)

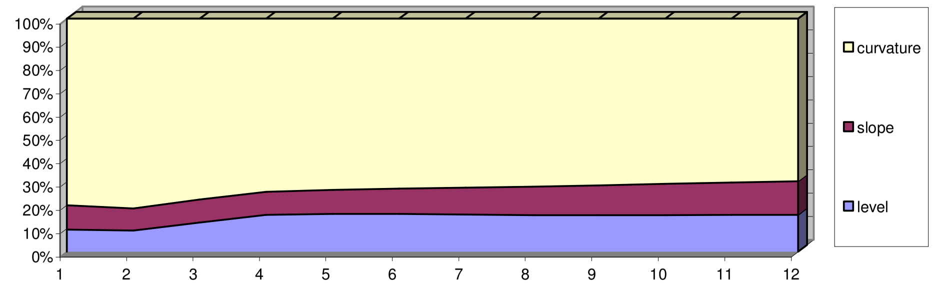
	LEVEL		
n ahead	level	slope	curvature
1	1.0000	0.0000	0.0000
2	0.9417	0.0169	0.0414
3	0.9400	0.0249	0.0351
4	0.9367	0.0263	0.0370
5	0.9250	0.0345	0.0405
6	0.9167	0.0428	0.0405
7	0.9079	0.0514	0.0407
8	0.8972	0.0615	0.0413
9	0.8856	0.0716	0.0428
10	0.8753	0.0812	0.0436
11	0.8663	0.0898	0.0439
12	0.8588	0.0973	0.0439



	SLOPE		
n ahead	level	slope	curvature
1	0.3180	0.6820	0.0000
2	0.2946	0.7047	0.0007
3	0.2484	0.7348	0.0168
4	0.2167	0.7639	0.0194
5	0.1916	0.7884	0.0200
6	0.1717	0.8064	0.0219
7	0.1576	0.8202	0.0222
8	0.1482	0.8301	0.0218
9	0.1418	0.8371	0.0211
10	0.1373	0.8423	0.0204
11	0.1336	0.8467	0.0197
12	0.1304	0.8504	0.0191



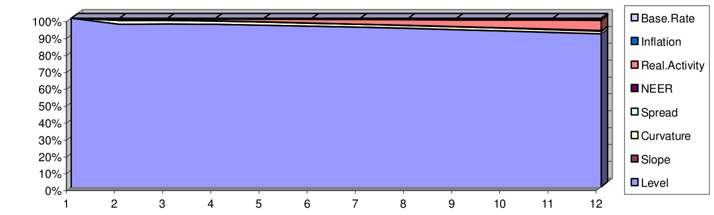
	CURVATURE		
n ahead	level	slope	curvature
1	0.0954	0.1035	0.8011
2	0.0905	0.0957	0.8138
3	0.1260	0.0992	0.7748
4	0.1588	0.0992	0.7420
5	0.1629	0.1025	0.7346
6	0.1619	0.1091	0.7290
7	0.1593	0.1163	0.7245
8	0.1574	0.1225	0.7200
9	0.1571	0.1286	0.7143
10	0.1578	0.1340	0.7082
11	0.1586	0.1389	0.7025
12	0.1588	0.1435	0.6977



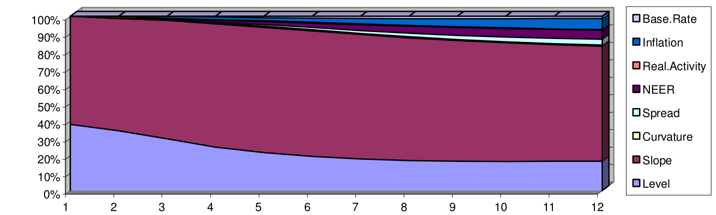
11.4 Yield-Macro FEVD Hungary

Table 38 - Yield-Macro FEVD Hungary VAR(2) – Level, Slope, Curvature, Spread

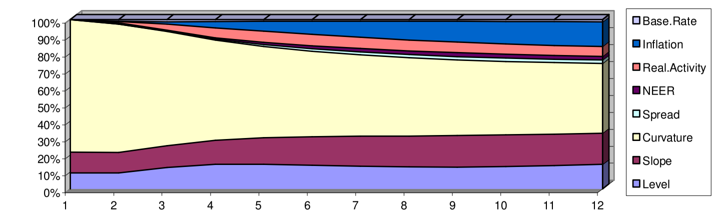
	LEVEL							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.9648	0.0000	0.0223	0.0001	0.0000	0.0061	0.0006	0.0061
3	0.9655	0.0001	0.0216	0.0001	0.0008	0.0054	0.0007	0.0059
4	0.9636	0.0005	0.0191	0.0001	0.0012	0.0088	0.0006	0.0060
5	0.9581	0.0006	0.0179	0.0003	0.0012	0.0150	0.0006	0.0064
6	0.9522	0.0007	0.0171	0.0004	0.0011	0.0210	0.0007	0.0069
7	0.9459	0.0007	0.0167	0.0004	0.0011	0.0269	0.0011	0.0072
8	0.9391	0.0008	0.0163	0.0004	0.0012	0.0330	0.0017	0.0075
9	0.9317	0.0008	0.0160	0.0004	0.0015	0.0393	0.0025	0.0077
10	0.9236	0.0009	0.0158	0.0006	0.0020	0.0460	0.0033	0.0079
11	0.9152	0.0009	0.0156	0.0008	0.0029	0.0528	0.0039	0.0079
12	0.9064	0.0009	0.0155	0.0010	0.0039	0.0599	0.0045	0.0079



	SLOPE							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.3794	0.6206	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.3434	0.6432	0.0001	0.0015	0.0017	0.0075	0.0025	0.0002
3	0.2972	0.6785	0.0018	0.0018	0.0028	0.0059	0.0107	0.0013
4	0.2504	0.7054	0.0058	0.0048	0.0094	0.0054	0.0145	0.0043
5	0.2172	0.7184	0.0074	0.0090	0.0166	0.0053	0.0183	0.0079
6	0.1950	0.7200	0.0074	0.0132	0.0244	0.0048	0.0242	0.0108
7	0.1806	0.7140	0.0070	0.0173	0.0325	0.0044	0.0313	0.0130
8	0.1722	0.7041	0.0065	0.0210	0.0395	0.0041	0.0385	0.0141
9	0.1681	0.6924	0.0061	0.0245	0.0449	0.0039	0.0456	0.0144
10	0.1668	0.6805	0.0060	0.0277	0.0486	0.0038	0.0524	0.0141
11	0.1674	0.6692	0.0062	0.0306	0.0506	0.0038	0.0586	0.0136
12	0.1690	0.6590	0.0066	0.0333	0.0512	0.0038	0.0640	0.0131



	CURVATURE							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.0946	0.1227	0.7827	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0947	0.1199	0.7580	0.0009	0.0060	0.0085	0.0019	0.0102
3	0.1262	0.1279	0.6752	0.0018	0.0051	0.0358	0.0148	0.0132
4	0.1451	0.1414	0.5910	0.0065	0.0080	0.0581	0.0379	0.0120
5	0.1461	0.1562	0.5382	0.0114	0.0126	0.0662	0.0583	0.0110
6	0.1401	0.1685	0.5040	0.0149	0.0169	0.0677	0.0776	0.0104
7	0.1334	0.1774	0.4798	0.0172	0.0203	0.0663	0.0955	0.0102
8	0.1295	0.1831	0.4613	0.0186	0.0222	0.0641	0.1110	0.0102
9	0.1293	0.1859	0.4463	0.0194	0.0228	0.0620	0.1236	0.0107
10	0.1325	0.1864	0.4335	0.0198	0.0225	0.0603	0.1333	0.0117
11	0.1380	0.1854	0.4223	0.0200	0.0218	0.0593	0.1401	0.0130
12	0.1448	0.1834	0.4124	0.0199	0.0215	0.0590	0.1443	0.0146



	SPREAD							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.9268	0.0000	0.0002	0.0731	0.0000	0.0000	0.0000	0.0000
2	0.8981	0.0014	0.0187	0.0672	0.0000	0.0114	0.0006	0.0025
3	0.9014	0.0040	0.0176	0.0653	0.0002	0.0086	0.0008	0.0021
4	0.8967	0.0078	0.0150	0.0688	0.0003	0.0087	0.0007	0.0021
5	0.8876	0.0112	0.0137	0.0731	0.0002	0.0112	0.0006	0.0023
6	0.8783	0.0147	0.0129	0.0764	0.0002	0.0141	0.0009	0.0025
7	0.8691	0.0184	0.0124	0.0784	0.0003	0.0172	0.0016	0.0026
8	0.8597	0.0222	0.0120	0.0796	0.0003	0.0207	0.0026	0.0028
9	0.8502	0.0260	0.0117	0.0804	0.0005	0.0245	0.0039	0.0028
10	0.8403	0.0297	0.0115	0.0809	0.0007	0.0287	0.0053	0.0029
11	0.8303	0.0332	0.0113	0.0811	0.0011	0.0332	0.0068	0.0029
12	0.8202	0.0367	0.0111	0.0813	0.0016	0.0381	0.0082	0.0029

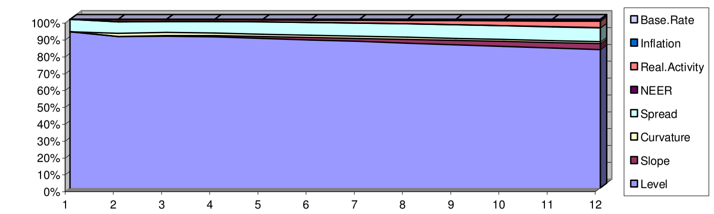
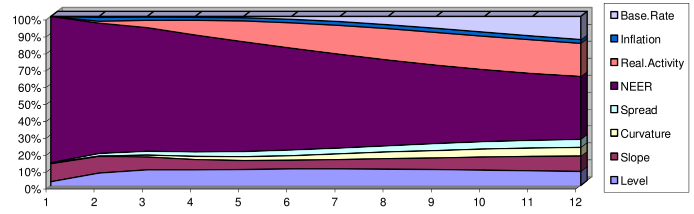
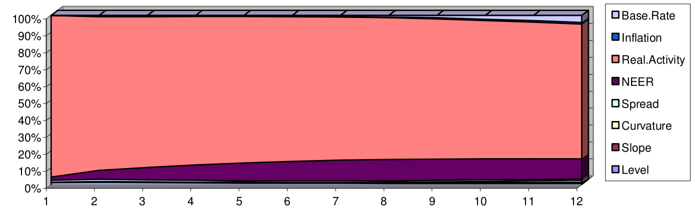


Table 39 - Yield-Macro FEVD Hungary VAR(2) – NEER, Real Activity, Inflation, Base Rate

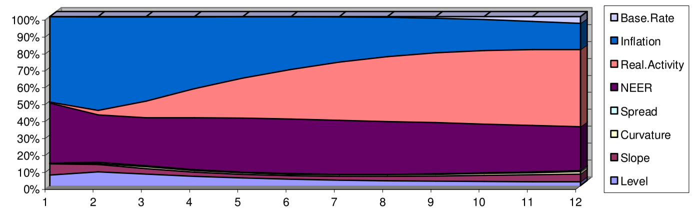
	NEER							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.0227	0.1058	0.0039	0.0007	0.8668	0.0000	0.0000	0.0000
2	0.0731	0.0977	0.0035	0.0142	0.7709	0.0101	0.0225	0.0079
3	0.0921	0.0764	0.0111	0.0221	0.7319	0.0425	0.0181	0.0059
4	0.0922	0.0604	0.0186	0.0269	0.6906	0.0878	0.0172	0.0064
5	0.0947	0.0522	0.0228	0.0304	0.6491	0.1227	0.0181	0.0099
6	0.0976	0.0512	0.0279	0.0333	0.6018	0.1502	0.0196	0.0184
7	0.0979	0.0551	0.0337	0.0360	0.5520	0.1714	0.0217	0.0322
8	0.0964	0.0618	0.0392	0.0386	0.5045	0.1859	0.0234	0.0503
9	0.0938	0.0696	0.0439	0.0411	0.4617	0.1942	0.0242	0.0715
10	0.0905	0.0774	0.0478	0.0433	0.4250	0.1975	0.0242	0.0943
11	0.0868	0.0844	0.0507	0.0453	0.3952	0.1970	0.0234	0.1172
12	0.0830	0.0899	0.0526	0.0469	0.3725	0.1940	0.0223	0.1388



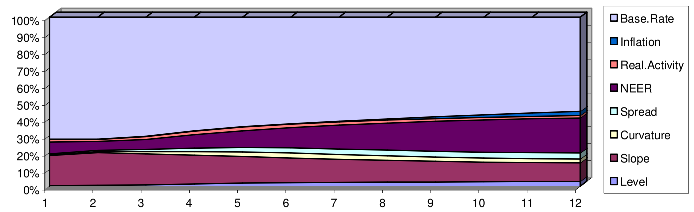
	REAL ACTIVITY							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.0120	0.0006	0.0002	0.0111	0.0201	0.9559	0.0000	0.0000
2	0.0134	0.0013	0.0023	0.0133	0.0522	0.9102	0.0005	0.0068
3	0.0111	0.0011	0.0033	0.0115	0.0739	0.8921	0.0005	0.0066
4	0.0100	0.0010	0.0028	0.0105	0.0903	0.8790	0.0005	0.0059
5	0.0089	0.0010	0.0025	0.0097	0.1044	0.8672	0.0010	0.0052
6	0.0081	0.0012	0.0025	0.0092	0.1154	0.8563	0.0020	0.0053
7	0.0074	0.0016	0.0030	0.0088	0.1225	0.8466	0.0033	0.0067
8	0.0070	0.0023	0.0040	0.0087	0.1261	0.8372	0.0048	0.0099
9	0.0066	0.0033	0.0053	0.0086	0.1267	0.8278	0.0065	0.0151
10	0.0063	0.0044	0.0070	0.0087	0.1251	0.8180	0.0082	0.0223
11	0.0060	0.0056	0.0088	0.0089	0.1220	0.8075	0.0097	0.0314
12	0.0058	0.0069	0.0107	0.0092	0.1183	0.7963	0.0108	0.0419



	INFLATION							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.0614	0.0665	0.0033	0.0023	0.3536	0.0073	0.5057	0.0000
2	0.0820	0.0427	0.0065	0.0062	0.2816	0.0267	0.5516	0.0027
3	0.0682	0.0312	0.0116	0.0064	0.2838	0.0981	0.4985	0.0023
4	0.0550	0.0243	0.0100	0.0056	0.3055	0.1721	0.4253	0.0022
5	0.0452	0.0212	0.0085	0.0047	0.3189	0.2363	0.3634	0.0018
6	0.0375	0.0213	0.0078	0.0041	0.3223	0.2946	0.3106	0.0017
7	0.0318	0.0235	0.0079	0.0038	0.3195	0.3442	0.2665	0.0028
8	0.0279	0.0268	0.0085	0.0038	0.3122	0.3834	0.2317	0.0057
9	0.0254	0.0310	0.0096	0.0041	0.3015	0.4129	0.2048	0.0108
10	0.0238	0.0356	0.0112	0.0046	0.2882	0.4339	0.1842	0.0184
11	0.0229	0.0404	0.0131	0.0054	0.2737	0.4478	0.1683	0.0285
12	0.0224	0.0450	0.0151	0.0064	0.2587	0.4557	0.1559	0.0408

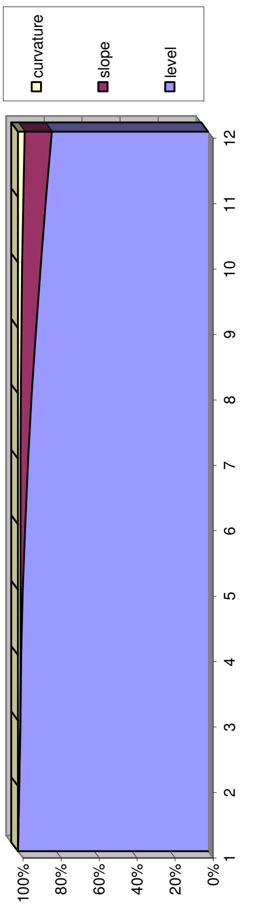


	BASE RATE							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.0037	0.1781	0.0028	0.0073	0.0695	0.0151	0.0024	0.7211
2	0.0051	0.1943	0.0057	0.0072	0.0520	0.0123	0.0013	0.7222
3	0.0088	0.1829	0.0127	0.0133	0.0587	0.0182	0.0014	0.7040
4	0.0139	0.1692	0.0222	0.0209	0.0783	0.0212	0.0014	0.6729
5	0.0189	0.1565	0.0272	0.0266	0.0990	0.0216	0.0015	0.6486
6	0.0220	0.1456	0.0284	0.0305	0.1200	0.0202	0.0023	0.6310
7	0.0237	0.1362	0.0278	0.0328	0.1410	0.0184	0.0042	0.6160
8	0.0249	0.1281	0.0267	0.0340	0.1605	0.0169	0.0069	0.6020
9	0.0259	0.1214	0.0254	0.0345	0.1773	0.0158	0.0104	0.5892
10	0.0269	0.1162	0.0243	0.0346	0.1909	0.0152	0.0145	0.5775
11	0.0278	0.1124	0.0235	0.0344	0.2010	0.0148	0.0190	0.5670
12	0.0288	0.1100	0.0231	0.0340	0.2079	0.0145	0.0237	0.5581

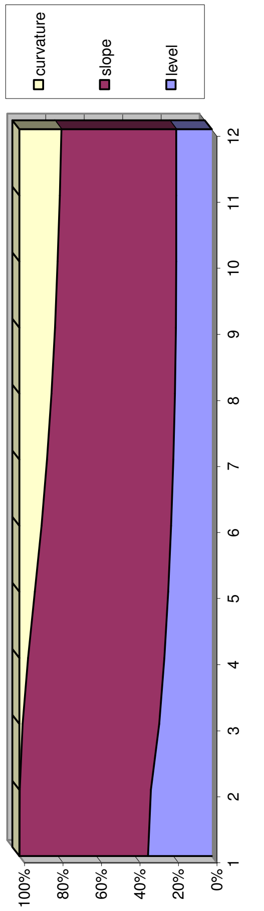


11.5 Yield-Only FEVD Poland

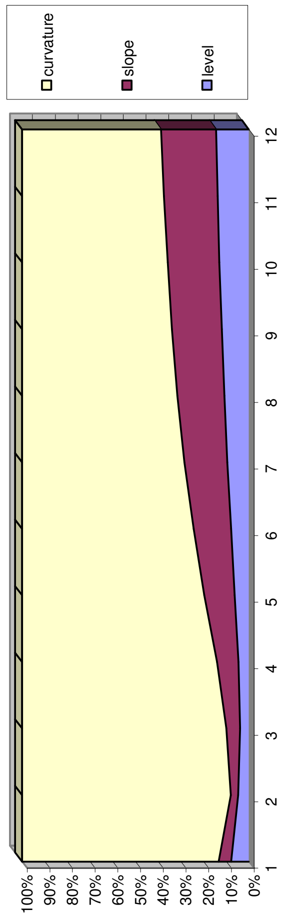
Table 40 - Yield-Only FEVD Poland VAR(3)



	LEVEL		
n ahead	level	slope	curvature
1	1.0000	0.0000	0.0000
2	0.9928	0.0012	0.0059
3	0.9862	0.0019	0.0120
4	0.9827	0.0041	0.0132
5	0.9748	0.0119	0.0133
6	0.9624	0.0243	0.0134
7	0.9463	0.0398	0.0139
8	0.9268	0.0579	0.0153
9	0.9042	0.0777	0.0181
10	0.8789	0.0987	0.0224
11	0.8513	0.1204	0.0284
12	0.8222	0.1421	0.0357



	SLOPE		
n ahead	level	slope	curvature
1	0.3306	0.6694	0.0000
2	0.3163	0.6813	0.0024
3	0.2721	0.7106	0.0173
4	0.2471	0.7069	0.0460
5	0.2262	0.6925	0.0813
6	0.2102	0.6745	0.1153
7	0.1986	0.6573	0.1441
8	0.1910	0.6418	0.1672
9	0.1864	0.6283	0.1852
10	0.1842	0.6165	0.1993
11	0.1835	0.6061	0.2104
12	0.1839	0.5968	0.2193

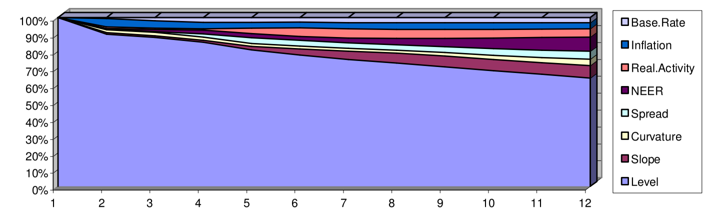


	CURVATURE		
n ahead	level	slope	curvature
1	0.0779	0.0545	0.8676
2	0.0475	0.0328	0.9198
3	0.0391	0.0605	0.9004
4	0.0463	0.0942	0.8595
5	0.0619	0.1340	0.8041
6	0.0787	0.1653	0.7560
7	0.0946	0.1894	0.7160
8	0.1084	0.2066	0.6849
9	0.1200	0.2195	0.6605
10	0.1294	0.2292	0.6414
11	0.1372	0.2369	0.6259
12	0.1437	0.2430	0.6132

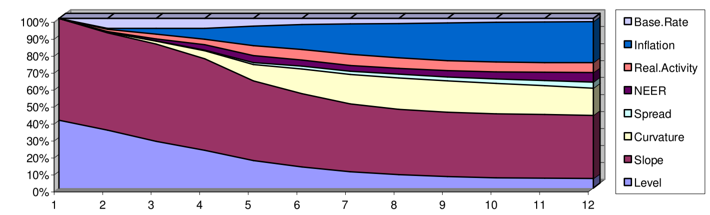
11.6 Yield-Macro FEVD Poland

Table 41 - Yield-Macro FEVD Poland VAR(4) – Level, Slope, Curvature, Spread

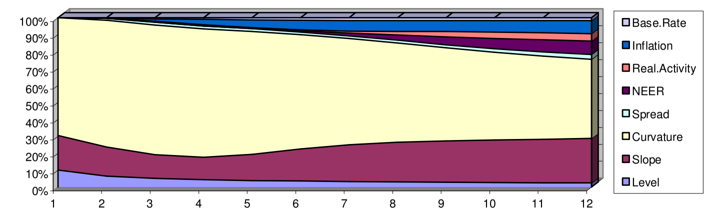
	LEVEL							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.8998	0.0090	0.0182	0.0053	0.0024	0.0088	0.0492	0.0074
3	0.8817	0.0097	0.0192	0.0046	0.0128	0.0088	0.0433	0.0197
4	0.8528	0.0119	0.0191	0.0179	0.0231	0.0083	0.0385	0.0283
5	0.8072	0.0211	0.0178	0.0336	0.0247	0.0321	0.0347	0.0287
6	0.7779	0.0350	0.0174	0.0336	0.0241	0.0505	0.0337	0.0278
7	0.7523	0.0473	0.0176	0.0325	0.0277	0.0553	0.0369	0.0304
8	0.7305	0.0584	0.0173	0.0315	0.0373	0.0543	0.0386	0.0321
9	0.7080	0.0642	0.0196	0.0346	0.0503	0.0527	0.0385	0.0322
10	0.6857	0.0657	0.0242	0.0396	0.0633	0.0512	0.0382	0.0320
11	0.6637	0.0679	0.0309	0.0432	0.0754	0.0503	0.0370	0.0316
12	0.6411	0.0738	0.0380	0.0471	0.0839	0.0490	0.0365	0.0305



	SLOPE							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.4008	0.5992	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.3420	0.5736	0.0036	0.0002	0.0027	0.0149	0.0035	0.0595
3	0.2753	0.5731	0.0168	0.0028	0.0108	0.0279	0.0340	0.0591
4	0.2226	0.5393	0.0476	0.0040	0.0319	0.0311	0.0650	0.0585
5	0.1625	0.4705	0.0949	0.0131	0.0404	0.0574	0.1162	0.0450
6	0.1251	0.4312	0.1454	0.0175	0.0360	0.0620	0.1460	0.0368
7	0.0973	0.3995	0.1736	0.0195	0.0335	0.0661	0.1775	0.0330
8	0.0803	0.3836	0.1865	0.0206	0.0342	0.0624	0.2026	0.0298
9	0.0688	0.3776	0.1856	0.0225	0.0381	0.0595	0.2213	0.0266
10	0.0618	0.3769	0.1783	0.0258	0.0428	0.0582	0.2327	0.0236
11	0.0579	0.3761	0.1693	0.0305	0.0484	0.0581	0.2387	0.0210
12	0.0560	0.3731	0.1599	0.0360	0.0557	0.0588	0.2416	0.0189



	CURVATURE							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.1002	0.2048	0.6950	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0634	0.1731	0.7471	0.0107	0.0003	0.0004	0.0002	0.0049
3	0.0502	0.1408	0.7637	0.0179	0.0002	0.0068	0.0131	0.0074
4	0.0426	0.1333	0.7565	0.0179	0.0005	0.0074	0.0321	0.0097
5	0.0377	0.1545	0.7251	0.0170	0.0005	0.0066	0.0452	0.0133
6	0.0352	0.1897	0.6741	0.0165	0.0054	0.0078	0.0556	0.0157
7	0.0319	0.2169	0.6281	0.0149	0.0164	0.0114	0.0628	0.0176
8	0.0295	0.2344	0.5864	0.0160	0.0308	0.0210	0.0638	0.0181
9	0.0279	0.2442	0.5498	0.0171	0.0463	0.0317	0.0650	0.0180
10	0.0265	0.2505	0.5187	0.0201	0.0603	0.0379	0.0683	0.0178
11	0.0251	0.2563	0.4910	0.0247	0.0713	0.0412	0.0726	0.0177
12	0.0242	0.2628	0.4673	0.0287	0.0793	0.0425	0.0779	0.0173



	SPREAD							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.8613	0.0002	0.0086	0.1299	0.0000	0.0000	0.0000	0.0000
2	0.8373	0.0105	0.0060	0.0929	0.0001	0.0132	0.0355	0.0046
3	0.8241	0.0091	0.0057	0.1010	0.0027	0.0132	0.0313	0.0129
4	0.8146	0.0086	0.0073	0.0949	0.0105	0.0158	0.0290	0.0193
5	0.7769	0.0143	0.0121	0.0872	0.0143	0.0498	0.0269	0.0183
6	0.7319	0.0238	0.0209	0.0848	0.0135	0.0824	0.0254	0.0173
7	0.6963	0.0323	0.0304	0.0848	0.0139	0.1009	0.0247	0.0167
8	0.6752	0.0403	0.0316	0.0876	0.0181	0.1068	0.0240	0.0163
9	0.6562	0.0440	0.0308	0.0976	0.0240	0.1081	0.0234	0.0158
10	0.6379	0.0444	0.0328	0.1093	0.0301	0.1070	0.0229	0.0154
11	0.6197	0.0450	0.0392	0.1169	0.0360	0.1047	0.0236	0.0150
12	0.5978	0.0477	0.0484	0.1219	0.0402	0.1020	0.0271	0.0148

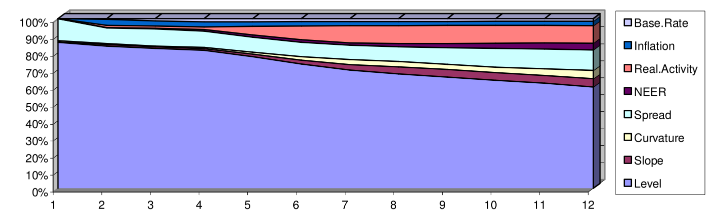
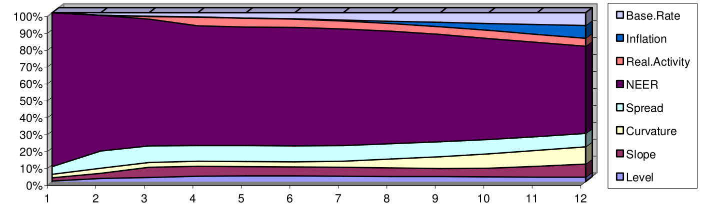
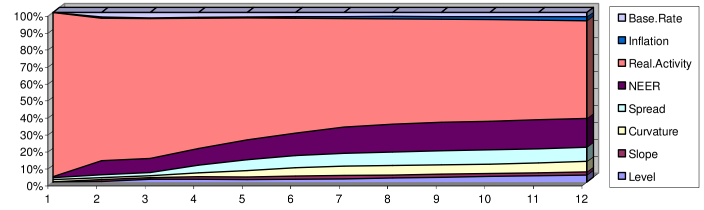


Table 42 - Yield-Macro FEVD Poland VAR(4) – NEER, Real Activity, Inflation, Base Rate

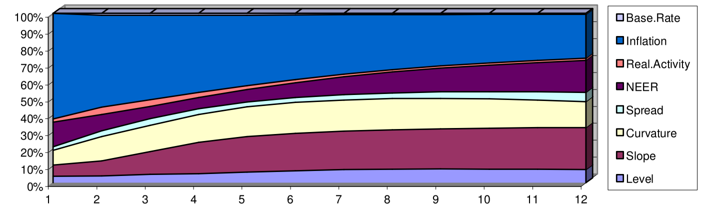
	NEER							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.0030	0.0199	0.0217	0.0440	0.9115	0.0000	0.0000	0.0000
2	0.0195	0.0311	0.0281	0.1020	0.8041	0.0001	0.0000	0.0151
3	0.0253	0.0600	0.0285	0.0981	0.7487	0.0160	0.0021	0.0212
4	0.0324	0.0576	0.0307	0.0932	0.7083	0.0512	0.0018	0.0248
5	0.0344	0.0546	0.0299	0.0951	0.7010	0.0519	0.0017	0.0314
6	0.0339	0.0527	0.0301	0.0943	0.7012	0.0497	0.0022	0.0359
7	0.0327	0.0523	0.0370	0.0917	0.6894	0.0476	0.0047	0.0446
8	0.0311	0.0509	0.0520	0.0901	0.6653	0.0464	0.0128	0.0514
9	0.0295	0.0484	0.0698	0.0879	0.6346	0.0474	0.0252	0.0571
10	0.0279	0.0523	0.0843	0.0848	0.5978	0.0473	0.0414	0.0641
11	0.0271	0.0628	0.0948	0.0815	0.5570	0.0477	0.0585	0.0705
12	0.0272	0.0770	0.1023	0.0777	0.5176	0.0476	0.0748	0.0759



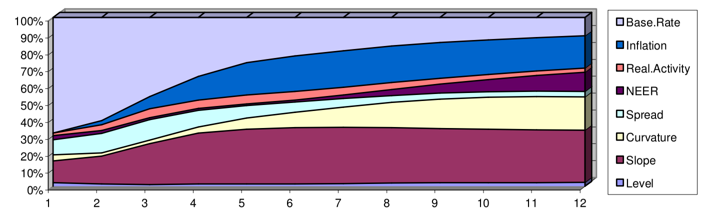
	REAL ACTIVITY							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.0006	0.0000	0.0135	0.0111	0.0065	0.9683	0.0000	0.0000
2	0.0030	0.0116	0.0106	0.0187	0.0818	0.8410	0.0060	0.0272
3	0.0165	0.0099	0.0109	0.0200	0.0821	0.8243	0.0050	0.0313
4	0.0165	0.0160	0.0221	0.0451	0.0984	0.7684	0.0046	0.0288
5	0.0153	0.0153	0.0371	0.0646	0.1168	0.7181	0.0057	0.0271
6	0.0164	0.0190	0.0506	0.0703	0.1328	0.6768	0.0089	0.0251
7	0.0198	0.0193	0.0548	0.0757	0.1536	0.6409	0.0119	0.0240
8	0.0232	0.0188	0.0563	0.0800	0.1630	0.6216	0.0136	0.0235
9	0.0285	0.0183	0.0550	0.0831	0.1670	0.6086	0.0153	0.0242
10	0.0333	0.0180	0.0547	0.0840	0.1697	0.5979	0.0172	0.0253
11	0.0374	0.0181	0.0571	0.0839	0.1706	0.5877	0.0197	0.0256
12	0.0416	0.0188	0.0619	0.0835	0.1695	0.5757	0.0232	0.0257



	INFLATION							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.0383	0.0666	0.0870	0.0196	0.1467	0.0192	0.6225	0.0000
2	0.0403	0.0891	0.1433	0.0354	0.0958	0.0424	0.5441	0.0097
3	0.0498	0.1338	0.1550	0.0405	0.0724	0.0397	0.4988	0.0100
4	0.0538	0.1842	0.1659	0.0340	0.0670	0.0297	0.4552	0.0102
5	0.0634	0.2093	0.1759	0.0298	0.0736	0.0223	0.4163	0.0095
6	0.0706	0.2219	0.1823	0.0289	0.0881	0.0174	0.3824	0.0085
7	0.0768	0.2283	0.1846	0.0306	0.1063	0.0145	0.3518	0.0071
8	0.0799	0.2334	0.1841	0.0335	0.1238	0.0135	0.3257	0.0061
9	0.0810	0.2382	0.1798	0.0378	0.1405	0.0132	0.3041	0.0053
10	0.0805	0.2424	0.1723	0.0429	0.1573	0.0132	0.2864	0.0048
11	0.0793	0.2460	0.1629	0.0486	0.1738	0.0134	0.2714	0.0046
12	0.0776	0.2487	0.1531	0.0551	0.1890	0.0138	0.2582	0.0045



	BASE RATE							
n ahead	Level	Slope	Curvature	Spread	NEER	Real.Activity	Inflation	Base.Rate
1	0.0224	0.1280	0.0361	0.0890	0.0231	0.0163	0.0001	0.6849
2	0.0133	0.1655	0.0191	0.1160	0.0173	0.0334	0.0250	0.6104
3	0.0113	0.2415	0.0197	0.1227	0.0114	0.0520	0.0725	0.4689
4	0.0140	0.3019	0.0353	0.0989	0.0115	0.0484	0.1408	0.3492
5	0.0141	0.3240	0.0653	0.0760	0.0090	0.0527	0.1901	0.2688
6	0.0143	0.3339	0.0902	0.0606	0.0112	0.0513	0.2097	0.2288
7	0.0165	0.3326	0.1201	0.0503	0.0204	0.0462	0.2173	0.1965
8	0.0196	0.3272	0.1494	0.0415	0.0354	0.0410	0.2168	0.1691
9	0.0207	0.3214	0.1732	0.0357	0.0532	0.0354	0.2119	0.1483
10	0.0219	0.3162	0.1891	0.0327	0.0721	0.0310	0.2048	0.1322
11	0.0227	0.3120	0.1970	0.0313	0.0923	0.0275	0.1977	0.1194
12	0.0230	0.3099	0.1973	0.0320	0.1128	0.0250	0.1909	0.1092



12 Appendix – R Code

12.1 Function to derive Diebold Li Factors

```
di.li.factor.function <- function ( yield.data, start.date = 0, set.frequency = 12,
                                    tau =  c(3,6,12,2*12,3*12,4*12,5*12,6*12,7*12,8*12,9*12,10*12),
                                    lambda = 0.0609)

# derives the diebold li factors from yield cross section in dataframe yield.data
# and returns factor, tau is a vector containing the maturity segments of the yield curve in
#month; start is the starting date of the time series in year + month/12; frequency = 12 for
#monthly data; tau is the vector of the maturity structure of the yield data passed in yield.data;
#lambda is fixed at 0.0609

{
dimvar <- dim(yield.data)                    # writes dimension of yield matrix in variable dimvar(number of
                                             # rows, number of colums)

di.li.factor <- mat.or.vec(dimvar[1],3)      # initializes matrix (number of rows, number of
                                             # colums)

di.li.loading.1 <- mat.or.vec(length(tau),1)
di.li.loading.2 <- mat.or.vec(length(tau),1)
di.li.loading.3 <- mat.or.vec(length(tau),1)

for (loading.count in 1:length(tau))

          # establishes the factor loadings in maturity tau
          {
          di.li.loading.1[loading.count] <- 1

          di.li.loading.2[loading.count] <-
          (1-exp( -lambda*tau[loading.count]))/(lambda*tau[loading.count])

          di.li.loading.3[loading.count] <-
          (1-exp(-lambda *tau[loading.count]))/( lambda *tau[loading.count])-exp(-
          lambda *tau[loading.count])
          }

yield.curve <- mat.or.vec(length(tau),1)

time.count <- 0
maturity.count <- 0

for (time.count in 1:dimvar[1])

          {
          for (maturity.count in 1:length(tau))

                    #building yield curve vector
                    {
                    yield.curve[maturity.count] <-
                                                            yield.data[time.count,
                                                                        maturity.count]

                    }

        #The lm function derives the regression model explaining the
        #yield.curve vector by the di.li.loading vectors without a constant

        di.li.factor.lm <- lm ( yield.curve ~ -1 +di.li.loading.1
                                                                    +di.li.loading.2
                                                                    +di.li.loading.3)

        #regression coefficients of the regression are written in to the
        #di.li.factor matrix

        di.li.factor[time.count,] <- di.li.factor.lm$coef

        }
```

```
#colums of di.li.factors are labeled according to their interpretation

colnames(di.li.factor) <- c( "level" , "slope" , "curvature")

#time series is build by function ts

di.li.factor <- ts(di.li.factor, start = start.date,
                              frequency = set.frequency)

# di.li.factor multiple time series is returned

return (di.li.factor)

}
```

12.2 Function to calculate Diebold – Li Model residuals

```
di.li.factor.resid.function <- function ( yield.data, start.date = 0,
                                          set.frequency = 12,
                                          tau = c(3,6,12,2*12,3*12,4*12,5*12,6*12,
                                          7*12,8*12,9*12,10*12),lambda = 0.0609)

# derives the diebold li factors from yield cross section of yield data
# and calculates model fit and residuals to actual yield data

{
# dimvar is vector containing dimension of yield.data (length(t),
# length (tau))
dimvar <- dim(yield.data)

# matrix um original
di.li.factor <- mat.or.vec(dimvar[1],3 + length(tau) *3 )

# loading vectors are defined
di.li.loading.1 <- mat.or.vec(length(tau),1)
di.li.loading.2 <- mat.or.vec(length(tau),1)
di.li.loading.3 <- mat.or.vec(length(tau),1)

# for-loop calculates parametric loadings according Diebold Li formula
for (loading.count in 1:length(tau))

          {
          di.li.loading.1[loading.count] <- 1

          di.li.loading.2[loading.count] <-
          (1-exp( -lambda*tau[loading.count]))/(lambda*tau[loading.count])

          di.li.loading.3[loading.count] <-
          (1-exp(-lambda *tau[loading.count]))/( lambda *tau[loading.count])-exp(-
          lambda *tau[loading.count])
          }

# defines yield curve representation vector
yield.curve <- mat.or.vec(length(tau),1)

time.count <- 0
maturity.count <- 0

for (time.count in 1:dimvar[1])

          {
          for (maturity.count in 1:length(tau))

                    {
                    # writes time t representation of yield curve in vector
                    yield.curve[maturity.count] <-
                                                        yield.data[time.count,
                                                                   maturity.count]

                    }
          # ols.data ist matrix of yield curve and loadings in column form

          ols.data <- cbind(yield.curve,di.li.loading.1,
                                        di.li.loading.2,di.li.loading.3)

         di.li.factor.lm <- lm ( yield.curve ~ -1 +di.li.loading.1
                                                           +di.li.loading.2
                                                           +di.li.loading.3)



        # writes ols coefficients in first three columns
          di.li.factor[time.count,] <- di.li.factor.lm$coef
```

```
# model.fit contains the original yield curve, the ols fitted yield curve and
residuals in column form

model.fit <- data.frame(ols.data[,1],fitted.value=predict(di.li.factor.lm),
                        residual = resid(di.li.factor.lm))


                   for (maturity.count in 1:length(tau))

                   {
                   # writes original yield.curve in matrix
                   di.li.factor[time.count, maturity.count*3+1] <-
                                                      model.fit[maturity.count,1]
                   # writes fitted.value in matrix
                   di.li.factor[time.count, maturity.count*3+2] <-
                                                      model.fit[maturity.count,2]
                   # writes residual in matix
                   di.li.factor[time.count, maturity.count*3+3] <-
                                                      model.fit[maturity.count,3]

                   }



          }
# names the columns of matrix
colnames(di.li.factor) <- c( "level" , "slope" , "curvature", "Y3" , "Fit.Y3",
"Resid.Y3", "Y6", "Fit.Y6", "Resid.Y6", "Y12", "Fit.Y12", "Resid.Y12", "Y24",
"Fit.Y24", "Resid.Y24", "Y36" , "Fit.Y36" , "Resid.Y36", "Y48", "Fit.Y48",
"Resid.Y48", "Y60", "Fit.Y60", "Resid.Y60" ,   "Y72" , "Fit.Y72" , "Resid.Y72" ,
"Y84", "Fit.Y84", "Resid.Y84" , "Y96" , "Fit.Y96" , "Resid.Y96", "Y108" , "Fit.Y108"
, "Resid.Y108" , "Y120" , "Fit.Y120" , "Resid.Y120")

# converts matrix into time series
di.li.factor <- ts(di.li.factor, start = start.date, frequency = set.frequency)

# returns time series
return (di.li.factor)

}
```

12.3 Yield-Only AR(1) Forecast Function

```
di.li.factor.forecast.AR.function <- function ( di.li.fact.data, end.in.sample ,
                                  end.out.of.sample, max.lag = 1 , n.ahead.max = 12)

# yield factors are forecasted by AR(1)model
# end.in.sample defines end in-sample period (year+(month/12))
# end.out.of.sample defines end out-of-sample period
# max.lag defines the maximum lag length of model
# n.ahead.max is maximum forecast time h

{
# matrix to take the result defined (number of periods, three factors and confidence level
# for every n.ahead forecast)

di.li.forecast.n.ahead <- mat.or.vec((end.out.of.sample * 12 - end.in.sample * 12),
                                                                  6*n.ahead.max)
# restriction vectors defined, feedback is restricted within factor structure
#(lags of level only explain level)

res.1 <- mat.or.vec(1,3)
res.1 <- c(1,1,1)
res.2 <- mat.or.vec(3,3)
diag(res.2) <- 1
res <- cbind(res.2,res.1)

# sets index to -5 as starting value
index <- -5

# loop iterates h month ahead forecasts
for (n.ahead.count in 1: n.ahead.max)
        {
        index <- index + 6
        # loop iterates number of out-of-sample period
        for ( fcst.count in 1: (end.out.of.sample * 12 - end.in.sample * 12))
                {
                if (n.ahead.count > fcst.count)
                        {
                        # assignes NA for non available forecasts
                        di.li.forecast.n.ahead[fcst.count,index]          <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 1]      <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 2]      <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 3]      <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 4]      <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 5]      <- NA

                        }
                        else
                        # else calculate n.ahead month AR(p) forecast
                        {

                        # VAR (p) is estimated for in-sample period (see vars R package
                        # for detail)
                        var <- VAR(window ( di.li.fact.data, end = (end.in.sample+
                                                                  (fcst.count-
                                                      n.ahead.count)/12) ),
                                                      p = max.lag , type = "const")
                        # VAR(p) is restricted to AR(p)
                        var.res <- restrict(var, method = "manual", resmat = res)

                        # n.ahead forecast calculated
                        var.fcst <- predict (var.res, n.ahead = n.ahead.count)

                        # writes factor forecasts and confidence intervals into result matrix
                        # level factor
                        di.li.forecast.n.ahead[fcst.count,index] <-
                                                      var.fcst$fcst$level[n.ahead.count,1]
                        di.li.forecast.n.ahead[fcst.count,index+1] <-
                                                      var.fcst$fcst$level[n.ahead.count,4]
                        # slope factor
                        di.li.forecast.n.ahead[fcst.count,index +2] <-
                                                      var.fcst$fcst$slope[n.ahead.count,1]
                        di.li.forecast.n.ahead[fcst.count,index +3] <-
```

```
                                                            var.fcst$fcst$slope[n.ahead.count,4]


                                  # curvature factor
                                  di.li.forecast.n.ahead[fcst.count,index +4] <-
                                                            var.fcst$fcst$curvature[n.ahead.count,1]

                                  di.li.forecast.n.ahead[fcst.count,index +5] <-
                                                            var.fcst$fcst$curvature[n.ahead.count,4]

                                  }

                        }
        }

# converts matrix into time series
di.li.forecast.n.ahead <- ts(di.li.forecast.n.ahead , start =  (end.in.sample + 1/12),
frequency = 12 )
# labels columns of time series
colnames(di.li.forecast.n.ahead) <- rep (c( "forecastlevel" ,"CI level", "forecast slope"
,"CI slope", "forecast curvature", "CI curvature"),((index+5)/6))
# returns the result
return(di.li.forecast.n.ahead)

}
```

12.4 Yield-Only VAR(p) Forecast Function

```
di.li.factor.forecast.VAR.function <- function ( di.li.fact.data, end.in.sample ,
end.out.of.sample, max.lag = 1 , n.ahead.max = 12)

# yield factors are forecasted by VAR(p) model
# end.in.sample defines end in-sample period (year+(month/12))
# end.out.of.sample defines end out-of-sample period
# max.lag defines the maximum lag length of model
# n.ahead.max is maximum forecast time h

{

di.li.forecast.n.ahead <- mat.or.vec((end.out.of.sample * 12 - end.in.sample * 12),
                                                                            6*n.ahead.max)
index <- -5

for (n.ahead in 1: n.ahead.max)
        {
        index <- index + 6
        for ( fcst.count in 1: (end.out.of.sample * 12 - end.in.sample * 12))
                {
                if (n.ahead > fcst.count)
                        {
                        di.li.forecast.n.ahead[fcst.count,index]           <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 1]        <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 2]        <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 3]        <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 4]        <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 5]        <- NA

                        }
                        else
                        {


                        var <- VAR(window ( di.li.fact.data, end = (end.in.sample+
                                                                    (fcst.count-n.ahead)/12)
                                                              ),
                                                              p =  max.lag, type = "const")
                        var.fcst <- predict (var, n.ahead = n.ahead)

                        di.li.forecast.n.ahead[fcst.count,index] <-
                var.fcst$fcst$level[n.ahead,1]
                        di.li.forecast.n.ahead[fcst.count,index+1] <-
                                                              var.fcst$fcst$level[n.ahead,4]

                        di.li.forecast.n.ahead[fcst.count,index +2] <-
                                                              var.fcst$fcst$slope[n.ahead,1]
                        di.li.forecast.n.ahead[fcst.count,index +3] <-
                                                              var.fcst$fcst$slope[n.ahead,4]


                        di.li.forecast.n.ahead[fcst.count,index +4] <-
                                                              var.fcst$fcst$curvature[n.ahead,1]

                        di.li.forecast.n.ahead[fcst.count,index +5] <-
                                                              var.fcst$fcst$curvature[n.ahead,4]

                        }

                }
        }
di.li.forecast.n.ahead <- ts(di.li.forecast.n.ahead , start =  (end.in.sample + 1/12),
frequency = 12 )
colnames(di.li.forecast.n.ahead) <- rep (c( "forecastlevel" ,"CI level", "forecast slope"
,"CI slope", "forecast curvature", "CI curvature"),((index+5)/6))
return(di.li.forecast.n.ahead)

}
```

12.5 Restricted Yield-Only VAR(p) Forecast Function

```
di.li.factor.forecast.ResVAR.function <- function ( di.li.fact.data, end.in.sample ,
end.out.of.sample, max.lag = 1 , n.ahead.max = 12)

# function produces factor forecasts by VAR(p) model where coefficients are significant at
# the 95% level (t-statistics >=2)

{

di.li.forecast.n.ahead <- mat.or.vec((end.out.of.sample * 12 - end.in.sample * 12),
                                                                               6*n.ahead.max)

index <- -5

for (n.ahead in 1: n.ahead.max)
        {
        index <- index + 6
        for ( fcst.count in 1: (end.out.of.sample * 12 - end.in.sample * 12))
                {
                if (n.ahead > fcst.count)
                        {
                        di.li.forecast.n.ahead[fcst.count,index]            <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 1]        <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 2]        <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 3]        <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 4]        <- NA
                        di.li.forecast.n.ahead[fcst.count,index + 5]        <- NA

                        }
                        else
                        {

                        var <- VAR(window ( di.li.fact.data, end = (end.in.sample+
                                                                (fcst.count-n.ahead)/12)
                                                             ),
                                                             p = max.lag , type = "const"

                        # variables with significance level below the 95% CI
                        #(t-statistics >= 2)are eliminated from model

                        res.var <-restrict ( var, method = "ser", thresh = 2)

                        var.fcst <- predict (res.var, n.ahead = n.ahead)

                        di.li.forecast.n.ahead[fcst.count,index] <-
                                                             var.fcst$fcst$level[n.ahead,1]
                        di.li.forecast.n.ahead[fcst.count,index+1] <-
                                                             var.fcst$fcst$level[n.ahead,4]

                        di.li.forecast.n.ahead[fcst.count,index +2] <-
                                                             var.fcst$fcst$slope[n.ahead,1]
                        di.li.forecast.n.ahead[fcst.count,index +3] <-
                                                             var.fcst$fcst$slope[n.ahead,4]


                        di.li.forecast.n.ahead[fcst.count,index +4] <-
                                                             var.fcst$fcst$curvature[n.ahead,1]

                        di.li.forecast.n.ahead[fcst.count,index +5] <-
                                                             var.fcst$fcst$curvature[n.ahead,4]

                        }

                }
        }
di.li.forecast.n.ahead <- ts(di.li.forecast.n.ahead , start =  (end.in.sample + 1/12),
frequency = 12 )
colnames(di.li.forecast.n.ahead) <- rep (c( "forecastlevel" ,"CI level", "forecast slope"
,"CI slope", "forecast curvature", "CI curvature"),((index+5)/6))
return(di.li.forecast.n.ahead)

}
```

12.6 Yield-Macro VAR(p) Forecast Function

```
di.li.factor.forecast.MACRO.function <- function ( macro.data, end.in.sample ,
                                          end.out.of.sample, max.lag = 1 , n.ahead.max = 12)

# yield factors together with macro factors are forecasted by VAR(p) model
# end.in.sample defines end in-sample period (year+(month/12))
# end.out.of.sample defines end out-of-sample period
# max.lag defines the maximum lag length of model
# n.ahead.max is maximum forecast time h

{
colnames(macro.data) <- c("level","slope","curvature","spread","NEER","real.activity",
                          "inflation","base.rate")

di.li.forecast.n.ahead <- mat.or.vec((end.out.of.sample * 12 - end.in.sample * 12),
                                                                          6*n.ahead.max)
index <- -5

for (n.ahead in 1: n.ahead.max)
       {
       index <- index + 6
       for ( fcst.count in 1: (end.out.of.sample * 12 - end.in.sample * 12))
              {
              if (n.ahead > fcst.count)
                     {
                     di.li.forecast.n.ahead[fcst.count,index]           <- NA
                     di.li.forecast.n.ahead[fcst.count,index + 1]       <- NA
                     di.li.forecast.n.ahead[fcst.count,index + 2]       <- NA
                     di.li.forecast.n.ahead[fcst.count,index + 3]       <- NA
                     di.li.forecast.n.ahead[fcst.count,index + 4]       <- NA
                     di.li.forecast.n.ahead[fcst.count,index + 5]       <- NA

                     }
                     else
                     {


                     var <- VAR(window (macro.data, end = (end.in.sample+
                                                          (fcst.count-n.ahead)/12)
                                                   ),
                                                          p = max.lag ,
                                                           type = "const")
                     var.fcst <- predict (var, n.ahead = n.ahead)

                     di.li.forecast.n.ahead[fcst.count,index] <-
                                                   var.fcst$fcst$level[n.ahead,1]
                     di.li.forecast.n.ahead[fcst.count,index+1] <-
                                                   var.fcst$fcst$level[n.ahead,4]

                     di.li.forecast.n.ahead[fcst.count,index +2] <-
                                                   var.fcst$fcst$slope[n.ahead,1]
                     di.li.forecast.n.ahead[fcst.count,index +3] <-
                                                   var.fcst$fcst$slope[n.ahead,4]


                     di.li.forecast.n.ahead[fcst.count,index +4] <-
                                                   var.fcst$fcst$curvature[n.ahead,1]

                     di.li.forecast.n.ahead[fcst.count,index +5] <-
                                                   var.fcst$fcst$curvature[n.ahead,4]

                     }

              }
       }
di.li.forecast.n.ahead <- ts(di.li.forecast.n.ahead , start =  (end.in.sample + 1/12),
frequency = 12 )
colnames(di.li.forecast.n.ahead) <- rep (c( "forecastlevel" ,"CI level", "forecast slope"
,"CI slope", "forecast curvature", "CI curvature"),((index+5)/6))
return(di.li.forecast.n.ahead)

}
```

12.7 Restricted Yield-Macro VAR(p) Forecast Function

```
di.li.factor.forecast.RES.MACRO.function <- function ( macro.data, end.in.sample ,
                                                        end.out.of.sample, max.lag = 1 ,
                                                        n.ahead.max = 12)

# yield factors are forecasted by VAR(p) model
# end.in.sample defines end in-sample period (year+(month/12))
# end.out.of.sample defines end out-of-sample period
# max.lag defines the maximum lag length of model
# n.ahead.max is maximum forecast time h

{
colnames(macro.data) <- c("level","slope","curvature","spread","NEER",
                           "real.activity","inflation","base.rate")
di.li.forecast.n.ahead <- mat.or.vec((end.out.of.sample * 12 - end.in.sample * 12),
                                      6*n.ahead.max)
index <- -5

for (n.ahead in 1: n.ahead.max)
{
     index <- index + 6
     for ( fcst.count in 1: (end.out.of.sample * 12 - end.in.sample * 12))
          {
          if (n.ahead > fcst.count)
                {
                di.li.forecast.n.ahead[fcst.count,index]     <- NA
                di.li.forecast.n.ahead[fcst.count,index + 1] <- NA
                di.li.forecast.n.ahead[fcst.count,index + 2] <- NA
                di.li.forecast.n.ahead[fcst.count,index + 3] <- NA
                di.li.forecast.n.ahead[fcst.count,index + 4] <- NA
                di.li.forecast.n.ahead[fcst.count,index + 5] <- NA

                }
          else
          {

          var <- VAR(window (macro.data, end = (end.in.sample+
                                                 (fcst.count-n.ahead)/12) ),
                            p = max.lag , type = "const")

         # variables with significance level below the 95% CI
         #(t-statistics >= 2)are eliminated from model

         res.var <- restrict(var, method ="ser", thresh = 2)

         var.fcst <- predict (res.var, n.ahead = n.ahead)

         di.li.forecast.n.ahead[fcst.count,index] <- var.fcst$fcst$level[n.ahead,1]
         di.li.forecast.n.ahead[fcst.count,index+1] <- var.fcst$fcst$level[n.ahead,4]

         di.li.forecast.n.ahead[fcst.count,index +2] <-
                                              var.fcst$fcst$slope[n.ahead,1]
         di.li.forecast.n.ahead[fcst.count,index +3] <-
                                              var.fcst$fcst$slope[n.ahead,4]


         di.li.forecast.n.ahead[fcst.count,index +4] <-
                                          var.fcst$fcst$curvature[n.ahead,1]

         di.li.forecast.n.ahead[fcst.count,index +5] <-
                                           var.fcst$fcst$curvature[n.ahead,4]

         }
     }
}
di.li.forecast.n.ahead <- ts(di.li.forecast.n.ahead , start =  (end.in.sample +
1/12), frequency = 12 )
colnames(di.li.forecast.n.ahead) <- rep (c( "forecastlevel" ,"CI level", "forecast
slope" ,"CI slope", "forecast curvature", "CI curvature"),((index+5)/6))
return(di.li.forecast.n.ahead)

}
```

12.8 Function to calculate Yields from Diebold Li Factor Forecasts

```
di.li.factor.yield.forecast.function <- function ( data,
                                                tau = c(3,6,12,2*12,3*12,4*12,5*12,6*12,
                                                7*12,8*12,9*12,10*12), lambda = 0.0609,
                                                start= 0 , n.ahead.max = 12)

# data is Diebold Li factor forecast object, function calculates yields based on
# factors forecasted; start is first forecast (2006+1/12 = Feb 2006)

{
dimdata <- dim(data)

di.li.loading.1 <- mat.or.vec(length(tau),1)
di.li.loading.2 <- mat.or.vec(length(tau),1)
di.li.loading.3 <- mat.or.vec(length(tau),1)
yield.forecast     <- mat.or.vec(dimdata[1], length(tau)* n.ahead.max)


for (loading.count in 1:length(tau))

          {
          di.li.loading.1[loading.count] <- 1

          di.li.loading.2[loading.count] <-
          (1-exp( -lambda*tau[loading.count]))/(lambda*tau[loading.count])

          di.li.loading.3[loading.count] <-
          (1-exp(-lambda *tau[loading.count]))/( lambda *tau[loading.count])-exp(-
          lambda *tau[loading.count])
          }


index.fact <- -5
index.col <- -(length(tau)) # -15

for (n.ahead in 1: n.ahead.max)

          {
          index.col <- index.col + (length(tau))

          index.fact <- index.fact + 6

          for (maturity.count in 1:length(tau))

                    {

                    for (time.count in 1:dimdata[1])

                              {
                              yield.forecast[time.count, index.col + maturity.count]
<- data[time.count,index.fact]* di.li.loading.1[maturity.count] +
data[time.count,index.fact+2]* di.li.loading.2 [maturity.count]+
data[time.count,index.fact+4]* di.li.loading.3 [maturity.count]
                              }


                    }
          }
yield.forecast <- ts(yield.forecast,start=start,frequency=12)
colnames(yield.forecast) <- rep ( tau, n.ahead.max)
return(yield.forecast)

}
```

12.9 Function to calculate Random Walk Yield Forecasts

```
random.walk.forecast.function <- function (yield.data , end.in.sample ,
                                           end.out.of.sample , n.ahead.max = 12,
                                           tau =  c(3,6,12,2*12,3*12,4*12,5*12,6*12,
                                                    7*12,8*12,9*12,10*12))

# derives random walk forecasts yield forecasts

{
dimdata <- dim(yield.data)
number.of.total.forecasts <- (end.out.of.sample*12 -end.in.sample*12)
rm.yield.forecast <- mat.or.vec(number.of.total.forecasts, length(tau)* n.ahead.max)

index.col <- -(length(tau)) # -15

for (n.ahead in 1: n.ahead.max)

        {
        index.col <- index.col + (length(tau))


        for (maturity.count in 1:length(tau))

                {

                        for (fcst.count in 1: number.of.total.forecasts)

                        {
                                if (n.ahead > fcst.count)
                                {
                                rm.yield.forecast[fcst.count , index.col +
                        maturity.count] <- NA
                                }
                                else
                                {

                                rm.yield.forecast[fcst.count , index.col +
                                                  maturity.count] <-
                                                        yield.data[(dim(yield.data)[1])-
                                                                number.of.total.forecasts-
                                                                n.ahead + fcst.count,
                                                                maturity.count]
                                }
                        }
                }
        }



rm.yield.forecast  <- ts ( rm.yield.forecast ,
                           start = end.in.sample + 1/12, frequency = 12)

colnames(rm.yield.forecast) <- rep ( tau, n.ahead.max)

return(rm.yield.forecast)

}
```

12.10 Function to calculate RMSE

```
RMSE.function <- function (forecast.data , yield.data , end.in.sample ,
end.out.of.sample , n.ahead.max = 12, tau =  c(3,6,12,2*12,3*12,4*12,5*12,6*12,
7*12,8*12,9*12,10*12))

# function calculates RMSE; summing up the time t squared error of object
# forecast.data and yield.data; divided by sample size; square root taken
{
RMSE <- mat.or.vec(1,dim(forecast.data)[2])
name.vec <- mat.or.vec(1,dim(forecast.data)[2])
yield <- window(yield.data, start = end.in.sample +1/12)


for (n.ahead in 0: (n.ahead.max-1))
        {
                for (count in 1:length(tau))

                {

                name.vec[1, n.ahead * length(tau)+count] <- paste("RMSE", n.ahead+1,
                               tau[count])
                }
        }


colnames(RMSE) <- name.vec

out.of.sample.period.length <- dim(forecast.data)[1]


for (n.ahead in 1: n.ahead.max)
        {


        for (maturity.count in 1:length(tau))

                {
                square.sum <- 0
                rmse.count <- 0
                for (rmse.step in 1: out.of.sample.period.length)

                        {
                        if (n.ahead > rmse.step)
                                {
                                }
                                else
                                {
                                rmse.count <- rmse.count + 1

                                square.sum  <- square.sum +
                        (forecast.data[rmse.step,(n.ahead -1)*
                        length(tau)+maturity.count]-yield[rmse.step,maturity.count])^2
                                }

        RMSE[1, (n.ahead -1)* length(tau)+maturity.count]<-
                                                   (square.sum /rmse.count) ^0.5
                        }
                }
        }
return(RMSE)

}
```

13 Appendix – Model estimation results

13.1 Czech Republic

13.1.1 Yield-Only Model Czech Republic

Table 43 - Regression result Czech Republic Yield-Only VAR(1)

Estimation period: 1998:6 - 2006:1

```
$level

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
    Min       1Q   Median       3Q      Max
-1.38008 -0.26556 -0.01168  0.22083  2.54236

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
level.l1      0.89972    0.04016  22.403   <2e-16 ***
slope.l1     -0.01567    0.04611  -0.340   0.7348
curvature.l1  0.03771    0.03093   1.219   0.2261
const         0.62542    0.36340   1.721   0.0888 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4871 on 87 degrees of freedom
Multiple R-Squared: 0.9949,     Adjusted R-squared: 0.9947
F-statistic:  4262 on 4 and 87 DF,  p-value: < 2.2e-16



$slope

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
    Min       1Q   Median       3Q      Max
-1.78771 -0.20441  0.01323  0.29146  0.67873

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
level.l1      0.04700    0.03160   1.487   0.1405
slope.l1      0.84323    0.03628  23.243   <2e-16 ***
curvature.l1  0.01728    0.02434   0.710   0.4796
const        -0.65542    0.28594  -2.292   0.0243 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3833 on 87 degrees of freedom
Multiple R-Squared: 0.9783,     Adjusted R-squared: 0.9773
F-statistic: 982.4 on 4 and 87 DF,  p-value: < 2.2e-16


$curvature

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
    Min       1Q   Median       3Q      Max
-2.28399 -0.73815 -0.07097  0.53512  2.72587

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
level.l1      0.19983    0.07790   2.565  0.01203 *
```

```
slope.l1     -0.05354    0.08943  -0.599  0.55093
curvature.l1  0.76557    0.06000  12.759  < 2e-16 ***
const        -1.97960    0.70491  -2.808  0.00615 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9448 on 87 degrees of freedom
Multiple R-Squared: 0.908,      Adjusted R-squared: 0.9037
F-statistic: 214.6 on 4 and 87 DF,  p-value: < 2.2e-16
```

13.1.2 Yield-Macro Model Czech Republic

Table 44- Regression result Czech Republic Yield-Macro VAR(1)

Estimation period: 1998:6 - 2006:1

```
$Level

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-1.33088 -0.24517 -0.00976  0.19529  2.51867

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
Level.l1         0.963817   0.096915   9.945 9.59e-16 ***
Slope.l1         0.023158   0.067607   0.343    0.733
Curvature.l1     0.032516   0.038284   0.849    0.398
Spread.l1       -0.096134   0.104878  -0.917    0.362
NEER.l1         -0.031283   0.066291  -0.472    0.638
Real.Activity.l1 0.003820   0.055736   0.069    0.946
Inflation.l1     0.004485   0.081365   0.055    0.956
Base.Rate.l1     0.006410   0.049751   0.129    0.898
const            0.417480   0.546455   0.764    0.447
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4985 on 82 degrees of freedom
Multiple R-Squared: 0.995,      Adjusted R-squared: 0.9944
F-statistic:  1809 on 9 and 82 DF,  p-value: < 2.2e-16


$Slope

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-1.71676 -0.19914  0.01422  0.26735  0.73696

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
Level.l1         0.11238    0.07425   1.514   0.1340
Slope.l1         0.82777    0.05180  15.981   <2e-16 ***
Curvature.l1     0.04548    0.02933   1.551   0.1249
Spread.l1       -0.02614    0.08035  -0.325   0.7458
NEER.l1          0.08159    0.05079   1.606   0.1120
Real.Activity.l1 0.05737    0.04270   1.343   0.1828
Inflation.l1    -0.02007    0.06234  -0.322   0.7483
Base.Rate.l1     0.01307    0.03812   0.343   0.7326
const           -0.97062    0.41866  -2.318   0.0229 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3819 on 82 degrees of freedom
Multiple R-Squared: 0.9797,     Adjusted R-squared: 0.9775
F-statistic: 440.3 on 9 and 82 DF,  p-value: < 2.2e-16


$Curvature

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-2.24622 -0.64648 -0.03745  0.49491  2.52689
```

```
Coefficients:
               Estimate Std. Error t value Pr(>|t|)
Level.l1       -0.092105   0.182849  -0.504    0.616
Slope.l1        0.001541   0.127554   0.012    0.990
Curvature.l1    0.701983   0.072231   9.719 2.69e-15 ***
Spread.l1       0.221308   0.197873   1.118    0.267
NEER.l1        -0.236693   0.125071  -1.892    0.062 .
Real.Activity.l1 -0.088252  0.105158  -0.839    0.404
Inflation.l1    0.051906   0.153512   0.338    0.736
Base.Rate.l1   -0.048054   0.093866  -0.512    0.610
const          -0.496158   1.030998  -0.481    0.632
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9405 on 82 degrees of freedom
Multiple R-Squared: 0.9141,     Adjusted R-squared: 0.9046
F-statistic:  96.9 on 9 and 82 DF,  p-value: < 2.2e-16


$Spread

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-1.21743 -0.18083 -0.01032  0.18017  2.67955

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
Level.l1       -0.02051    0.09283  -0.221    0.826
Slope.l1        0.03928    0.06476   0.607    0.546
Curvature.l1    0.01009    0.03667   0.275    0.784
Spread.l1       0.82198    0.10046   8.182 3.04e-12 ***
NEER.l1        -0.02923    0.06350  -0.460    0.646
Real.Activity.l1 -0.02623   0.05339  -0.491    0.625
Inflation.l1    0.10137    0.07794   1.301    0.197
Base.Rate.l1   -0.01754    0.04766  -0.368    0.714
const           0.41559    0.52344   0.794    0.430
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4775 on 82 degrees of freedom
Multiple R-Squared: 0.9544,     Adjusted R-squared: 0.9494
F-statistic: 190.7 on 9 and 82 DF,  p-value: < 2.2e-16


$NEER

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
      Min        1Q    Median        3Q       Max
-1.128197 -0.259662 -0.005956  0.280309  1.003019

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
Level.l1        0.11475    0.08285   1.385   0.1698
Slope.l1        0.14052    0.05780   2.431   0.0172 *
Curvature.l1   -0.03118    0.03273  -0.953   0.3436
Spread.l1      -0.20605    0.08966  -2.298   0.0241 *
NEER.l1         0.84988    0.05667  14.997   <2e-16 ***
Real.Activity.l1  0.03228   0.04765   0.677   0.5000
Inflation.l1    0.11889    0.06956   1.709   0.0912 .
Base.Rate.l1    0.02825    0.04253   0.664   0.5084
const          -0.20870    0.46716  -0.447   0.6562
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4262 on 82 degrees of freedom
Multiple R-Squared: 0.8639,     Adjusted R-squared: 0.849
F-statistic: 57.85 on 9 and 82 DF,  p-value: < 2.2e-16
```

```
$Real.Activity

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.44446 -0.34663 -0.08014  0.36755  2.11801 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
Level.l1       -0.026992   0.113784  -0.237  0.81307    
Slope.l1       -0.111902   0.079375  -1.410  0.16238    
Curvature.l1    0.004452   0.044948   0.099  0.92134    
Spread.l1      -0.050149   0.123133  -0.407  0.68486    
NEER.l1        -0.067179   0.077830  -0.863  0.39057    
Real.Activity.l1  0.847617   0.065438  12.953  < 2e-16 ***
Inflation.l1    0.084927   0.095528   0.889  0.37659    
Base.Rate.l1    0.167686   0.058411   2.871  0.00521 ** 
const          -0.008129   0.641573  -0.013  0.98992    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.5853 on 82 degrees of freedom
Multiple R-Squared: 0.9177,     Adjusted R-squared: 0.9086 
F-statistic: 101.6 on 9 and 82 DF,  p-value: < 2.2e-16 


$Inflation

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.64976 -0.14437  0.01957  0.16026  0.44863 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
Level.l1        0.092519   0.043424   2.131 0.036120 *  
Slope.l1       -0.051254   0.030293  -1.692 0.094451 .  
Curvature.l1    0.025999   0.017154   1.516 0.133464    
Spread.l1      -0.063685   0.046992  -1.355 0.179073    
NEER.l1        -0.108536   0.029703  -3.654 0.000454 ***
Real.Activity.l1  0.046843   0.024974   1.876 0.064257 .  
Inflation.l1    0.895786   0.036457  24.571  < 2e-16 ***
Base.Rate.l1   -0.000978   0.022292  -0.044 0.965113    
const          -0.573567   0.244850  -2.343 0.021578 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.2234 on 82 degrees of freedom
Multiple R-Squared: 0.971,      Adjusted R-squared: 0.9679 
F-statistic: 305.5 on 9 and 82 DF,  p-value: < 2.2e-16 


$Base.Rate

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max 
-7.82981 -0.15724  0.02498  0.20202  2.58103 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)  
Level.l1       -0.27423    0.21887  -1.253   0.2138  
Slope.l1        0.08929    0.15268   0.585   0.5603  
Curvature.l1   -0.08398    0.08646  -0.971   0.3343  
Spread.l1       0.11224    0.23685   0.474   0.6368  
NEER.l1        -0.30881    0.14971  -2.063   0.0423 *
Real.Activity.l1 -0.06873    0.12587  -0.546   0.5866  
Inflation.l1    0.23501    0.18375   1.279   0.2045  
Base.Rate.l1   -0.15114    0.11236  -1.345   0.1823  
const           1.54148    1.23409   1.249   0.2152  
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.126 on 82 degrees of freedom
Multiple R-Squared: 0.08309,    Adjusted R-squared: -0.01755
F-statistic: 0.8256 on 9 and 82 DF,  p-value: 0.5944
```

13.2 Hungary

13.2.1 Yield-Only Model Hungary

Table 45 - Regression result Hungary Yield-Only VAR(4)

Estimation period: 1998:6 - 2006:1

```
$level

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.58447 -0.31138 -0.03016  0.34438  1.32312 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
level.l1      0.91206    0.11239   8.115  7.2e-12 ***
slope.l1      0.11598    0.10007   1.159  0.25015    
curvature.l1  0.08664    0.03981   2.176  0.03267 *  
level.l2     -0.16075    0.16121  -0.997  0.32191    
slope.l2     -0.04173    0.13457  -0.310  0.75734    
curvature.l2 -0.14557    0.05079  -2.866  0.00539 ** 
level.l3      0.15022    0.15850   0.948  0.34627    
slope.l3     -0.11600    0.13419  -0.864  0.39010    
curvature.l3  0.08600    0.05138   1.674  0.09835 .  
level.l4     -0.22806    0.10551  -2.161  0.03385 *  
slope.l4      0.13352    0.09351   1.428  0.15748    
curvature.l4 -0.04348    0.04045  -1.075  0.28579    
const         1.92834    0.29566   6.522  7.2e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.5658 on 75 degrees of freedom
Multiple R-Squared: 0.9945,     Adjusted R-squared: 0.9935 
F-statistic:  1036 on 13 and 75 DF,  p-value: < 2.2e-16 


$slope

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.02122 -0.37963 -0.05081  0.29243  3.70517 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
level.l1      0.06335    0.16407   0.386  0.70051    
slope.l1      0.90636    0.14609   6.204 2.76e-08 ***
curvature.l1 -0.01716    0.05811  -0.295  0.76865    
level.l2      0.22061    0.23534   0.937  0.35156    
slope.l2      0.08031    0.19646   0.409  0.68386    
curvature.l2  0.14302    0.07414   1.929  0.05751 .  
level.l3     -0.15698    0.23138  -0.678  0.49957    
slope.l3     -0.01860    0.19591  -0.095  0.92461    
curvature.l3 -0.13767    0.07501  -1.835  0.07042 .  
level.l4      0.09491    0.15403   0.616  0.53965    
slope.l4     -0.09964    0.13652  -0.730  0.46773    
curvature.l4  0.02365    0.05905   0.401  0.68984    
const        -1.14482    0.43162  -2.652  0.00975 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.8259 on 75 degrees of freedom
Multiple R-Squared: 0.9705,     Adjusted R-squared: 0.9654 
```

```
F-statistic: 189.7 on 13 and 75 DF,  p-value: < 2.2e-16


$curvature

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max 
-3.77836 -0.97536 -0.06983  1.14347  4.42757 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
level.l1     -0.0370384  0.3629309  -0.102    0.919    
slope.l1     -0.0223394  0.3231678  -0.069    0.945    
curvature.l1  0.7033902  0.1285527   5.472 5.65e-07 ***
level.l2     -0.3005150  0.5205910  -0.577    0.565    
slope.l2      0.2821255  0.4345725   0.649    0.518    
curvature.l2 -0.0008897  0.1640045  -0.005    0.996    
level.l3     -0.0748410  0.5118286  -0.146    0.884    
slope.l3     -0.1918869  0.4333526  -0.443    0.659    
curvature.l3  0.0179274  0.1659299   0.108    0.914    
level.l4      0.4784346  0.3407296   1.404    0.164    
slope.l4      0.1718254  0.3019797   0.569    0.571    
curvature.l4 -0.0549493  0.1306116  -0.421    0.675    
const        -0.4340727  0.9547666  -0.455    0.651    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 1.827 on 75 degrees of freedom
Multiple R-Squared: 0.8595,     Adjusted R-squared: 0.8352 
F-statistic:  35.3 on 13 and 75 DF,  p-value: < 2.2e-16
```

13.2.2 Yield-Macro Model Hungary

Table 46- Regression result Hungary Yield-Macro VAR(2)

Estimation period: 1998:6 - 2006:1

```
$Level

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max 
-3.54951 -0.33610 -0.02000  0.22418  2.21165 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)  
Level.l1        0.79892    0.47106   1.696   0.0941 .
Slope.l1       -0.07504    0.14764  -0.508   0.6128  
Curvature.l1    0.10779    0.05432   1.984   0.0510 .
Spread.l1       0.13402    0.44952   0.298   0.7664  
NEER.l1         0.12282    0.46352   0.265   0.7918  
Real.Activity.l1 -0.03269  0.12781  -0.256   0.7988  
Inflation.l1   -0.07877    0.36367  -0.217   0.8291  
Base.Rate.l1    0.30455    0.28203   1.080   0.2838  
Level.l2       -0.16491    0.50671  -0.325   0.7458  
Slope.l2        0.07070    0.14094   0.502   0.6175  
Curvature.l2   -0.10023    0.05177  -1.936   0.0567 .
Spread.l2       0.05600    0.48152   0.116   0.9077  
NEER.l2         0.22747    0.45749   0.497   0.6205  
Real.Activity.l2 0.20480   0.12191   1.680   0.0973 .
Inflation.l2    0.18405    0.34136   0.539   0.5914  
Base.Rate.l2   -0.24506    0.28404  -0.863   0.3911  
const           2.15894    1.20505   1.792   0.0773 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.7561 on 73 degrees of freedom
Multiple R-Squared: 0.9913,     Adjusted R-squared: 0.9893 
F-statistic: 490.2 on 17 and 73 DF,  p-value: < 2.2e-16 


$Slope

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
      Min        1Q    Median        3Q       Max 
-2.168912 -0.424764 -0.008126  0.338742  3.359469 

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
Level.l1        -0.030423   0.528960  -0.058  0.95429    
Slope.l1         0.909504   0.165792   5.486 5.64e-07 ***
Curvature.l1    -0.002354   0.060996  -0.039  0.96932    
Spread.l1        0.163260   0.504774   0.323  0.74729    
NEER.l1         -0.054986   0.520498  -0.106  0.91616    
Real.Activity.l1 -0.011982  0.143518  -0.083  0.93369    
Inflation.l1    -0.191733   0.408372  -0.470  0.64011    
Base.Rate.l1    -0.066966   0.316691  -0.211  0.83312    
Level.l2         0.841984   0.568993   1.480  0.14324    
Slope.l2        -0.084458   0.158265  -0.534  0.59521    
Curvature.l2     0.004667   0.058128   0.080  0.93623    
Spread.l2       -0.863285   0.540703  -1.597  0.11468    
NEER.l2         -0.957939   0.513724  -1.865  0.06624 .  
Real.Activity.l2 -0.233689  0.136899  -1.707  0.09207 .  
Inflation.l2    -0.107755   0.383322  -0.281  0.77942    
Base.Rate.l2     0.031564   0.318955   0.099  0.92144    
const           -3.782217   1.353164  -2.795  0.00663 ** 
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.849 on 73 degrees of freedom
Multiple R-Squared:  0.97,      Adjusted R-squared: 0.963
F-statistic: 138.6 on 17 and 73 DF,  p-value: < 2.2e-16


$Curvature

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-3.51985 -0.79392  0.06338  0.91906  4.40088

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
Level.l1          0.7050     1.0544   0.669    0.506
Slope.l1          0.3056     0.3305   0.925    0.358
Curvature.l1      0.5475     0.1216   4.503 2.49e-05 ***
Spread.l1        -0.5062     1.0062  -0.503    0.616
NEER.l1           0.1907     1.0375   0.184    0.855
Real.Activity.l1  0.1531     0.2861   0.535    0.594
Inflation.l1      0.1741     0.8140   0.214    0.831
Base.Rate.l1     -0.9130     0.6313  -1.446    0.152
Level.l2         -0.8920     1.1342  -0.786    0.434
Slope.l2          0.2101     0.3155   0.666    0.508
Curvature.l2     -0.1188     0.1159  -1.025    0.309
Spread.l2         0.6511     1.0778   0.604    0.548
NEER.l2          -0.9679     1.0240  -0.945    0.348
Real.Activity.l2  0.2680     0.2729   0.982    0.329
Inflation.l2     -1.1588     0.7641  -1.517    0.134
Base.Rate.l2      0.6076     0.6358   0.956    0.342
const             0.7845     2.6973   0.291    0.772
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.692 on 73 degrees of freedom
Multiple R-Squared: 0.8828,     Adjusted R-squared: 0.8556
F-statistic: 32.36 on 17 and 73 DF,  p-value: < 2.2e-16


$Spread

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-3.35858 -0.33056  0.02849  0.24330  2.35478

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
Level.l1         -0.015486   0.475010  -0.033   0.9741
Slope.l1         -0.139012   0.148883  -0.934   0.3535
Curvature.l1      0.108228   0.054775   1.976   0.0519 .
Spread.l1         0.920971   0.453291   2.032   0.0458 *
NEER.l1           0.002771   0.467411   0.006   0.9953
Real.Activity.l1 -0.063573   0.128881  -0.493   0.6233
Inflation.l1     -0.132927   0.366721  -0.362   0.7180
Base.Rate.l1      0.233897   0.284391   0.822   0.4135
Level.l2         -0.248839   0.510960  -0.487   0.6277
Slope.l2          0.087314   0.142123   0.614   0.5409
Curvature.l2     -0.095072   0.052199  -1.821   0.0727 .
Spread.l2         0.185469   0.485555   0.382   0.7036
NEER.l2           0.324519   0.461328   0.703   0.4840
Real.Activity.l2  0.235967   0.122936   1.919   0.0588 .
Inflation.l2      0.233010   0.344226   0.677   0.5006
Base.Rate.l2     -0.143865   0.286424  -0.502   0.6170
const             1.781805   1.215151   1.466   0.1469
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7624 on 73 degrees of freedom
```

```
Multiple R-Squared: 0.9394,     Adjusted R-squared: 0.9253
F-statistic: 66.62 on 17 and 73 DF,  p-value: < 2.2e-16


$NEER

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
      Min        1Q    Median        3Q       Max
-1.038533 -0.100872  0.008711  0.110997  0.590596

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
Level.l1          0.147855   0.154765   0.955   0.3426
Slope.l1          0.016900   0.048508   0.348   0.7285
Curvature.l1      0.000437   0.017846   0.024   0.9805
Spread.l1        -0.207112   0.147689  -1.402   0.1650
NEER.l1           0.706355   0.152289   4.638 1.51e-05 ***
Real.Activity.l1 -0.039622   0.041991  -0.944   0.3485
Inflation.l1     -0.161200   0.119483  -1.349   0.1815
Base.Rate.l1     -0.135327   0.092659  -1.460   0.1484
Level.l2         -0.070081   0.166478  -0.421   0.6750
Slope.l2         -0.034404   0.046306  -0.743   0.4599
Curvature.l2      0.031302   0.017007   1.841   0.0698 .
Spread.l2         0.114675   0.158201   0.725   0.4708
NEER.l2           0.160594   0.150307   1.068   0.2888
Real.Activity.l2 -0.075136   0.040054  -1.876   0.0647 .
Inflation.l2      0.258283   0.112154   2.303   0.0241 *
Base.Rate.l2      0.213889   0.093321   2.292   0.0248 *
const            -0.378492   0.395914  -0.956   0.3422
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2484 on 73 degrees of freedom
Multiple R-Squared: 0.9435,     Adjusted R-squared: 0.9304
F-statistic: 71.77 on 17 and 73 DF,  p-value: < 2.2e-16


$Real.Activity

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-1.82291 -0.38697  0.01612  0.43818  1.41186

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
Level.l1         -0.3137196  0.4307607  -0.728  0.46876
Slope.l1         -0.2358921  0.1350136  -1.747  0.08481 .
Curvature.l1      0.0044673  0.0496724   0.090  0.92858
Spread.l1         0.2223870  0.4110645   0.541  0.59015
NEER.l1          -1.3473752  0.4238697  -3.179  0.00217 **
Real.Activity.l1  0.3204174  0.1168748   2.742  0.00769 **
Inflation.l1     -0.1683053  0.3325596  -0.506  0.61432
Base.Rate.l1     -0.0312342  0.2578989  -0.121  0.90394
Level.l2          0.9399404  0.4633617   2.029  0.04616 *
Slope.l2          0.2270674  0.1288838   1.762  0.08229 .
Curvature.l2     -0.0111886  0.0473368  -0.236  0.81381
Spread.l2        -0.8911106  0.4403235  -2.024  0.04666 *
NEER.l2           0.4013077  0.4183531   0.959  0.34060
Real.Activity.l2  0.2584017  0.1114842   2.318  0.02326 *
Inflation.l2      0.0009451  0.3121598   0.003  0.99759
Base.Rate.l2     -0.1075425  0.2597425  -0.414  0.68006
const            -3.1369696  1.1019546  -2.847  0.00573 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6914 on 73 degrees of freedom
Multiple R-Squared: 0.866,      Adjusted R-squared: 0.8347
F-statistic: 27.74 on 17 and 73 DF,  p-value: < 2.2e-16
```

```
$Inflation

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.618072 -0.192537 -0.002629  0.169285  0.703323 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
Level.l1        -0.15905    0.18387  -0.865  0.38987    
Slope.l1        -0.01655    0.05763  -0.287  0.77479    
Curvature.l1    -0.03312    0.02120  -1.562  0.12261    
Spread.l1        0.16260    0.17546   0.927  0.35714    
NEER.l1          0.32644    0.18093   1.804  0.07532 .  
Real.Activity.l1  0.05060    0.04989   1.014  0.31379    
Inflation.l1     1.06450    0.14195   7.499 1.23e-10 ***
Base.Rate.l1     0.11688    0.11008   1.062  0.29184    
Level.l2         0.09515    0.19779   0.481  0.63190    
Slope.l2        -0.01273    0.05501  -0.231  0.81766    
Curvature.l2     0.01784    0.02021   0.883  0.38006    
Spread.l2       -0.14696    0.18795  -0.782  0.43679    
NEER.l2         -0.42951    0.17857  -2.405  0.01870 *  
Real.Activity.l2  0.13270    0.04759   2.789  0.00675 ** 
Inflation.l2    -0.30879    0.13325  -2.317  0.02329 *  
Base.Rate.l2    -0.13404    0.11087  -1.209  0.23056    
const            0.55378    0.47037   1.177  0.24289    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.2951 on 73 degrees of freedom
Multiple R-Squared: 0.9646,     Adjusted R-squared: 0.9564 
F-statistic: 117.1 on 17 and 73 DF,  p-value: < 2.2e-16 


$Base.Rate

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.47745 -0.12413 -0.01017  0.09061  1.59050 

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
Level.l1          0.054845   0.227599   0.241   0.8103    
Slope.l1          0.025960   0.071337   0.364   0.7170    
Curvature.l1      0.008954   0.026245   0.341   0.7340    
Spread.l1        -0.009255   0.217193  -0.043   0.9661    
NEER.l1           0.234466   0.223958   1.047   0.2986    
Real.Activity.l1 -0.022718   0.061753  -0.368   0.7140    
Inflation.l1      0.110947   0.175713   0.631   0.5297    
Base.Rate.l1      1.003027   0.136265   7.361 2.22e-10 ***
Level.l2          0.183304   0.244825   0.749   0.4564    
Slope.l2         -0.075661   0.068098  -1.111   0.2702    
Curvature.l2      0.002075   0.025011   0.083   0.9341    
Spread.l2        -0.233625   0.232652  -1.004   0.3186    
NEER.l2          -0.567412   0.221044  -2.567   0.0123 *  
Real.Activity.l2 -0.068606   0.058904  -1.165   0.2479    
Inflation.l2     -0.187850   0.164935  -1.139   0.2585    
Base.Rate.l2     -0.106587   0.137239  -0.777   0.4399    
const            -1.062792   0.582235  -1.825   0.0720 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.3653 on 73 degrees of freedom
Multiple R-Squared: 0.8965,     Adjusted R-squared: 0.8724 
F-statistic: 37.19 on 17 and 73 DF,  p-value: < 2.2e-16 
```

13.3 Poland

13.3.1 Yield-Only Model Poland

Table 47 - Regression result Poland Yield-Only VAR(3)

Estimation period: 1998:6 - 2006:1

```
$level

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-1.538168 -0.275822  0.006704  0.288671  1.278300

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
level.l1      0.810044   0.117762   6.879 1.27e-09 ***
slope.l1     -0.015694   0.076222  -0.206 0.837397
curvature.l1  0.033393   0.033848   0.987 0.326862
level.l2     -0.157430   0.140369  -1.122 0.265453
slope.l2     -0.001142   0.084308  -0.014 0.989231
curvature.l2 -0.015774   0.044578  -0.354 0.724388
level.l3      0.142958   0.102922   1.389 0.168737
slope.l3      0.064419   0.069967   0.921 0.360010
curvature.l3 -0.011356   0.033703  -0.337 0.737054
const         1.206859   0.302531   3.989 0.000147 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5436 on 79 degrees of freedom
Multiple R-Squared: 0.9953,     Adjusted R-squared: 0.9947
F-statistic:  1682 on 10 and 79 DF,  p-value: < 2.2e-16


$slope

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-1.87470 -0.30549 -0.03836  0.25696  3.25353

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
level.l1      0.09382    0.17250   0.544   0.5881
slope.l1      0.96519    0.11166   8.644 4.82e-13 ***
curvature.l1  0.03117    0.04958   0.629   0.5314
level.l2      0.20280    0.20562   0.986   0.3270
slope.l2      0.20782    0.12350   1.683   0.0964 .
curvature.l2  0.04364    0.06530   0.668   0.5059
level.l3     -0.23144    0.15077  -1.535   0.1288
slope.l3     -0.25338    0.10249  -2.472   0.0156 *
curvature.l3 -0.00611    0.04937  -0.124   0.9018
const        -0.42739    0.44316  -0.964   0.3378
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7963 on 79 degrees of freedom
Multiple R-Squared: 0.9824,     Adjusted R-squared: 0.9802
F-statistic: 441.8 on 10 and 79 DF,  p-value: < 2.2e-16


$curvature

Call:
```

```
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
      Min         1Q     Median         3Q        Max
-4.0928388 -0.9241832  0.0007199  0.7327267  4.7538300

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
level.l1      1.18654    0.37105   3.198  0.00199 **
slope.l1      0.59471    0.24016   2.476  0.01541 *
curvature.l1  0.88801    0.10665   8.327 2.01e-12 ***
level.l2     -0.66951    0.44228  -1.514  0.13407
slope.l2      0.16612    0.26564   0.625  0.53355
curvature.l2 -0.06224    0.14046  -0.443  0.65891
level.l3     -0.51708    0.32429  -1.595  0.11481
slope.l3     -0.58997    0.22045  -2.676  0.00905 **
curvature.l3 -0.10614    0.10619  -1.000  0.32059
const         0.36474    0.95321   0.383  0.70301
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.713 on 79 degrees of freedom
Multiple R-Squared: 0.8993,     Adjusted R-squared: 0.8865
F-statistic: 70.51 on 10 and 79 DF,  p-value: < 2.2e-16
```

13.3.2 Yield-Macro Model Poland

Table 48- Regression result Poland Yield-Macro VAR(4)

Estimation period: 1998:6 - 2006:1

```
$Level

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-0.95888 -0.27917 -0.01788  0.29053  0.98857

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
Level.l1        1.45867    0.41668   3.501 0.000928 ***
Slope.l1        0.19198    0.14570   1.318 0.193082
Curvature.l1    0.02624    0.04869   0.539 0.592100
Spread.l1      -0.55056    0.42113  -1.307 0.196544
NEER.l1         0.35736    0.21286   1.679 0.098859 .
Real.Activity.l1 -0.09124  0.13265  -0.688 0.494420
Inflation.l1    0.94563    0.40937   2.310 0.024668 *
Base.Rate.l1   -0.35842    0.41115  -0.872 0.387134
Level.l2       -0.83591    0.49589  -1.686 0.097522 .
Slope.l2       -0.10493    0.14332  -0.732 0.467205
Curvature.l2   -0.04621    0.05601  -0.825 0.412874
Spread.l2       0.59680    0.49045   1.217 0.228859
NEER.l2        -0.43944    0.33343  -1.318 0.192983
Real.Activity.l2 -0.02059  0.12995  -0.158 0.874666
Inflation.l2   -2.04623    0.71517  -2.861 0.005957 **
Base.Rate.l2   -0.48484    0.47884  -1.013 0.315720
Level.l3        0.84950    0.46701   1.819 0.074356 .
Slope.l3       -0.02100    0.09541  -0.220 0.826572
Curvature.l3    0.01140    0.04772   0.239 0.812024
Spread.l3      -0.70451    0.47244  -1.491 0.141617
NEER.l3         0.33492    0.32610   1.027 0.308902
Real.Activity.l3 -0.03816  0.12894  -0.296 0.768368
Inflation.l3    1.58146    0.72272   2.188 0.032921 *
Base.Rate.l3    0.91265    0.53309   1.712 0.092530 .
Level.l4       -0.39866    0.39604  -1.007 0.318525
Slope.l4        0.11150    0.09307   1.198 0.236035
Curvature.l4   -0.03957    0.03656  -1.082 0.283836
Spread.l4       0.37589    0.39825   0.944 0.349377
NEER.l4        -0.07561    0.22962  -0.329 0.743180
Real.Activity.l4 -0.27594  0.11977  -2.304 0.025033 *
Inflation.l4   -0.47032    0.43098  -1.091 0.279906
Base.Rate.l4   -0.39322    0.39226  -1.002 0.320520
const          -0.23401    1.07069  -0.219 0.827801
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5124 on 55 degrees of freedom
Multiple R-Squared: 0.997,      Adjusted R-squared: 0.9952
F-statistic: 556.3 on 33 and 55 DF,  p-value: < 2.2e-16


$Slope

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-1.42048 -0.28337 -0.06196  0.27897  2.12305

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
Level.l1      -0.470901   0.514021  -0.916 0.363607
```

```
Slope.l1        0.635358   0.179732   3.535 0.000836 ***
Curvature.l1    0.033931   0.060059   0.565 0.574395
Spread.l1       0.559739   0.519512   1.077 0.285991
NEER.l1        -0.262136   0.262590  -0.998 0.322520
Real.Activity.l1  0.171782  0.163632   1.050 0.298399
Inflation.l1   -0.243819   0.504994  -0.483 0.631143
Base.Rate.l1    1.029596   0.507197   2.030 0.047208 *
Level.l2        0.531363   0.611727   0.869 0.388826
Slope.l2        0.049823   0.176799   0.282 0.779148
Curvature.l2    0.001553   0.069088   0.022 0.982150
Spread.l2      -0.709042   0.605023  -1.172 0.246279
NEER.l2         0.400425   0.411318   0.974 0.334560
Real.Activity.l2  0.146578  0.160301   0.914 0.364503
Inflation.l2    1.620926   0.882240   1.837 0.071573 .
Base.Rate.l2   -1.073841   0.590703  -1.818 0.074527 .
Level.l3       -0.485802   0.576106  -0.843 0.402740
Slope.l3       -0.118370   0.117701  -1.006 0.318969
Curvature.l3   -0.010268   0.058863  -0.174 0.862161
Spread.l3       0.576229   0.582799   0.989 0.327127
NEER.l3        -0.501241   0.402281  -1.246 0.218047
Real.Activity.l3 -0.090277  0.159055  -0.568 0.572629
Inflation.l3   -1.359375   0.891549  -1.525 0.133056
Base.Rate.l3   -0.478251   0.657621  -0.727 0.470161
Level.l4       -0.114616   0.488554  -0.235 0.815389
Slope.l4        0.136116   0.114811   1.186 0.240893
Curvature.l4    0.081969   0.045100   1.817 0.074590 .
Spread.l4      -0.023079   0.491286  -0.047 0.962702
NEER.l4         0.315281   0.283258   1.113 0.270526
Real.Activity.l4  0.351510  0.147753   2.379 0.020856 *
Inflation.l4    0.809907   0.531661   1.523 0.133400
Base.Rate.l4    0.311623   0.483896   0.644 0.522260
const           3.202195   1.320811   2.424 0.018647 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.632 on 55 degrees of freedom
Multiple R-Squared: 0.9922,     Adjusted R-squared: 0.9875
F-statistic: 212.5 on 33 and 55 DF,  p-value: < 2.2e-16


$Curvature

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-4.06248 -0.71660 -0.01063  0.81708  3.40884

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
Level.l1         0.70127    1.41621   0.495    0.622
Slope.l1         0.59842    0.49519   1.208    0.232
Curvature.l1     0.88324    0.16547   5.338 1.84e-06 ***
Spread.l1        0.63867    1.43134   0.446    0.657
NEER.l1         -0.06144    0.72348  -0.085    0.933
Real.Activity.l1  0.10488   0.45083   0.233    0.817
Inflation.l1    -0.51674    1.39134  -0.371    0.712
Base.Rate.l1     0.07839    1.39741   0.056    0.955
Level.l2         1.64154    1.68541   0.974    0.334
Slope.l2         0.25056    0.48711   0.514    0.609
Curvature.l2    -0.19892    0.19035  -1.045    0.301
Spread.l2       -2.68297    1.66694  -1.610    0.113
NEER.l2         -0.18487    1.13325  -0.163    0.871
Real.Activity.l2 -0.24664   0.44166  -0.558    0.579
Inflation.l2     1.75821    2.43072   0.723    0.473
Base.Rate.l2     2.19149    1.62749   1.347    0.184
Level.l3        -0.98061    1.58727  -0.618    0.539
Slope.l3        -0.16208    0.32428  -0.500    0.619
Curvature.l3     0.11422    0.16218   0.704    0.484
Spread.l3        1.40914    1.60571   0.878    0.384
NEER.l3          0.61782    1.10835   0.557    0.580
Real.Activity.l3  0.20802   0.43822   0.475    0.637
Inflation.l3    -1.41038    2.45637  -0.574    0.568
Base.Rate.l3    -2.39620    1.81186  -1.323    0.191
Level.l4        -1.11106    1.34605  -0.825    0.413
```

```
Slope.l4       -0.49622  0.31632  -1.569   0.122
Curvature.l4   -0.17708  0.12426  -1.425   0.160
Spread.l4       0.82432  1.35357   0.609   0.545
NEER.l4        -1.09733  0.78042  -1.406   0.165
Real.Activity.l4  0.37434  0.40709  0.920  0.362
Inflation.l4   -1.16327  1.46481  -0.794   0.431
Base.Rate.l4    2.10751  1.33322   1.581   0.120
const          -1.48159  3.63906  -0.407   0.685
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.741 on 55 degrees of freedom
Multiple R-Squared: 0.9275,     Adjusted R-squared: 0.884
F-statistic: 21.32 on 33 and 55 DF,  p-value: < 2.2e-16


$Spread

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-0.90502 -0.27110  0.02798  0.26880  0.94099

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
Level.l1          0.766265  0.425289   1.802   0.0771 .
Slope.l1          0.134688  0.148706   0.906   0.3690
Curvature.l1     -0.008174  0.049692  -0.164   0.8700
Spread.l1         0.091258  0.429832   0.212   0.8326
NEER.l1           0.184070  0.217261   0.847   0.4005
Real.Activity.l1 -0.124179  0.135385  -0.917   0.3630
Inflation.l1      0.755585  0.417820   1.808   0.0760 .
Base.Rate.l1     -0.198922  0.419643  -0.474   0.6374
Level.l2         -0.864799  0.506129  -1.709   0.0932 .
Slope.l2         -0.164194  0.146279  -1.122   0.2665
Curvature.l2     -0.022418  0.057162  -0.392   0.6964
Spread.l2         0.613285  0.500582   1.225   0.2257
NEER.l2          -0.310417  0.340315  -0.912   0.3657
Real.Activity.l2  0.025279  0.132629   0.191   0.8495
Inflation.l2     -1.811846  0.729944  -2.482   0.0161 *
Base.Rate.l2     -0.389789  0.488734  -0.798   0.4286
Level.l3          0.462128  0.476657   0.970   0.3365
Slope.l3          0.041314  0.097383   0.424   0.6730
Curvature.l3      0.003911  0.048702   0.080   0.9363
Spread.l3        -0.357135  0.482194  -0.741   0.4621
NEER.l3           0.340230  0.332838   1.022   0.3112
Real.Activity.l3 -0.043858  0.131599  -0.333   0.7402
Inflation.l3      1.651257  0.737647   2.239   0.0293 *
Base.Rate.l3      1.043605  0.544100   1.918   0.0603 .
Level.l4         -0.303055  0.404218  -0.750   0.4566
Slope.l4          0.151638  0.094992   1.596   0.1161
Curvature.l4     -0.024142  0.037315  -0.647   0.5203
Spread.l4         0.364349  0.406478   0.896   0.3740
NEER.l4          -0.054910  0.234361  -0.234   0.8156
Real.Activity.l4 -0.258570  0.122248  -2.115   0.0390 *
Inflation.l4     -0.604490  0.439883  -1.374   0.1750
Base.Rate.l4     -0.616294  0.400364  -1.539   0.1295
const            -0.072858  1.092808  -0.067   0.9471
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5229 on 55 degrees of freedom
Multiple R-Squared: 0.9749,     Adjusted R-squared: 0.9598
F-statistic: 64.73 on 33 and 55 DF,  p-value: < 2.2e-16


$NEER

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
       Min         1Q     Median         3Q        Max
-0.6359541 -0.1607866  0.0005274  0.1825289  0.7613728
```

```
Coefficients:
                Estimate Std. Error t value Pr(>|t|)
Level.l1         0.01506    0.28095   0.054   0.9574
Slope.l1        -0.15080    0.09824  -1.535   0.1305
Curvature.l1    -0.03480    0.03283  -1.060   0.2937
Spread.l1       -0.28462    0.28395  -1.002   0.3206
NEER.l1          1.08637    0.14352   7.569 4.41e-10 ***
Real.Activity.l1 -0.01235   0.08944  -0.138   0.8907
Inflation.l1     0.05597    0.27601   0.203   0.8400
Base.Rate.l1     0.33474    0.27722   1.208   0.2324
Level.l2        -0.19038    0.33435  -0.569   0.5714
Slope.l2         0.06645    0.09663   0.688   0.4946
Curvature.l2     0.05643    0.03776   1.495   0.1408
Spread.l2        0.41488    0.33069   1.255   0.2149
NEER.l2         -0.24245    0.22481  -1.078   0.2855
Real.Activity.l2 -0.07812   0.08762  -0.892   0.3765
Inflation.l2     0.34447    0.48220   0.714   0.4780
Base.Rate.l2    -0.24232    0.32286  -0.751   0.4561
Level.l3         0.39565    0.31488   1.256   0.2142
Slope.l3         0.11975    0.06433   1.861   0.0680 .
Curvature.l3    -0.03047    0.03217  -0.947   0.3477
Spread.l3       -0.41640    0.31854  -1.307   0.1966
NEER.l3         -0.16642    0.21987  -0.757   0.4523
Real.Activity.l3 -0.03920   0.08693  -0.451   0.6538
Inflation.l3    -0.94352    0.48729  -1.936   0.0580 .
Base.Rate.l3    -0.19133    0.35943  -0.532   0.5967
Level.l4        -0.28041    0.26703  -1.050   0.2983
Slope.l4        -0.06768    0.06275  -1.079   0.2855
Curvature.l4     0.02531    0.02465   1.027   0.3091
Spread.l4        0.29071    0.26852   1.083   0.2837
NEER.l4          0.22205    0.15482   1.434   0.1572
Real.Activity.l4  0.12339   0.08076   1.528   0.1323
Inflation.l4     0.70333    0.29059   2.420   0.0188 *
Base.Rate.l4     0.18336    0.26448   0.693   0.4910
const            0.43768    0.72191   0.606   0.5468
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3455 on 55 degrees of freedom
Multiple R-Squared: 0.9396,     Adjusted R-squared: 0.9033
F-statistic: 25.91 on 33 and 55 DF,  p-value: < 2.2e-16


$Real.Activity

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-1.80918 -0.21616  0.03209  0.26323  0.93832

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
Level.l1         0.55274    0.42907   1.288  0.20306
Slope.l1         0.08170    0.15003   0.545  0.58824
Curvature.l1     0.02300    0.05013   0.459  0.64816
Spread.l1       -0.43125    0.43366  -0.994  0.32436
NEER.l1          0.58641    0.21919   2.675  0.00981 **
Real.Activity.l1  0.32719   0.13659   2.395  0.02003 *
Inflation.l1     0.10194    0.42154   0.242  0.80981
Base.Rate.l1    -0.88191    0.42338  -2.083  0.04191 *
Level.l2        -0.82781    0.51063  -1.621  0.11071
Slope.l2        -0.16305    0.14758  -1.105  0.27406
Curvature.l2    -0.06575    0.05767  -1.140  0.25919
Spread.l2        0.55457    0.50504   1.098  0.27695
NEER.l2         -0.74322    0.34334  -2.165  0.03477 *
Real.Activity.l2  0.23524   0.13381   1.758  0.08431 .
Inflation.l2    -0.21399    0.73644  -0.291  0.77247
Base.Rate.l2     1.28688    0.49308   2.610  0.01165 *
Level.l3         0.58700    0.48090   1.221  0.22744
Slope.l3         0.04177    0.09825   0.425  0.67242
Curvature.l3     0.01583    0.04914   0.322  0.74857
Spread.l3       -0.53144    0.48649  -1.092  0.27942
NEER.l3          0.54146    0.33580   1.612  0.11259
```

```
Real.Activity.l3 -0.05973   0.13277  -0.450  0.65454
Inflation.l3      0.55276   0.74421   0.743  0.46080
Base.Rate.l3     -0.44092   0.54894  -0.803  0.42531
Level.l4         -0.12419   0.40781  -0.305  0.76187
Slope.l4          0.14227   0.09584   1.484  0.14339
Curvature.l4     -0.02392   0.03765  -0.635  0.52788
Spread.l4         0.28995   0.41010   0.707  0.48253
NEER.l4           0.07756   0.23645   0.328  0.74414
Real.Activity.l4 -0.02396   0.12334  -0.194  0.84668
Inflation.l4     -0.12710   0.44380  -0.286  0.77566
Base.Rate.l4     -0.51312   0.40393  -1.270  0.20932
const            -1.16284   1.10253  -1.055  0.29617
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5276 on 55 degrees of freedom
Multiple R-Squared: 0.9232,     Adjusted R-squared: 0.8771
F-statistic: 20.03 on 33 and 55 DF,  p-value: < 2.2e-16


$Inflation

Call:
lm(formula = y ~ -1 + ., data = datamat)

Residuals:
     Min       1Q   Median       3Q      Max
-0.36481 -0.09105 -0.02162  0.08803  0.58341

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
Level.l1         -0.194532  0.167509  -1.161   0.2505
Slope.l1          0.078737  0.058571   1.344   0.1844
Curvature.l1      0.039353  0.019572   2.011   0.0493 *
Spread.l1         0.338760  0.169299   2.001   0.0503 .
NEER.l1           0.058405  0.085573   0.683   0.4978
Real.Activity.l1 -0.034049  0.053324  -0.639   0.5258
Inflation.l1      1.410167  0.164568   8.569 1.04e-11 ***
Base.Rate.l1      0.289848  0.165286   1.754   0.0851 .
Level.l2          0.216975  0.199350   1.088   0.2812
Slope.l2          0.027543  0.057615   0.478   0.6345
Curvature.l2     -0.023140  0.022514  -1.028   0.3086
Spread.l2        -0.263837  0.197165  -1.338   0.1864
NEER.l2          -0.018133  0.134040  -0.135   0.8929
Real.Activity.l2  0.053082  0.052239   1.016   0.3140
Inflation.l2     -0.663154  0.287505  -2.307   0.0249 *
Base.Rate.l2     -0.510559  0.192499  -2.652   0.0104 *
Level.l3          0.023180  0.187742   0.123   0.9022
Slope.l3         -0.038856  0.038356  -1.013   0.3155
Curvature.l3     -0.008670  0.019182  -0.452   0.6531
Spread.l3        -0.006756  0.189923  -0.036   0.9718
NEER.l3          -0.104020  0.131095  -0.793   0.4309
Real.Activity.l3  0.017251  0.051833   0.333   0.7405
Inflation.l3      0.100923  0.290538   0.347   0.7296
Base.Rate.l3      0.207996  0.214306   0.971   0.3360
Level.l4         -0.013728  0.159210  -0.086   0.9316
Slope.l4         -0.061290  0.037415  -1.638   0.1071
Curvature.l4      0.001639  0.014697   0.112   0.9116
Spread.l4        -0.026980  0.160100  -0.169   0.8668
NEER.l4          -0.029508  0.092308  -0.320   0.7504
Real.Activity.l4 -0.026805  0.048150  -0.557   0.5800
Inflation.l4     -0.013238  0.173258  -0.076   0.9394
Base.Rate.l4      0.041968  0.157692   0.266   0.7911
const            -0.344974  0.430426  -0.801   0.4263
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.206 on 55 degrees of freedom
Multiple R-Squared: 0.9864,     Adjusted R-squared: 0.9782
F-statistic: 120.5 on 33 and 55 DF,  p-value: < 2.2e-16


$Base.Rate

Call:
lm(formula = y ~ -1 + ., data = datamat)
```

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.48288 -0.06039  0.00909  0.06226  0.35516

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
Level.l1        0.0075233  0.1321305   0.057   0.9548
Slope.l1       -0.0331239  0.0462006  -0.717   0.4764
Curvature.l1   -0.0260141  0.0154384  -1.685   0.0977 .
Spread.l1      -0.0151000  0.1335419  -0.113   0.9104
NEER.l1         0.1048267  0.0674994   1.553   0.1262
Real.Activity.l1 -0.0132372  0.0420621  -0.315   0.7542
Inflation.l1    0.2891422  0.1298101   2.227   0.0300 *
Base.Rate.l1    0.7175405  0.1303764   5.504 1.00e-06 ***
Level.l2        0.0574321  0.1572461   0.365   0.7163
Slope.l2        0.0838961  0.0454465   1.846   0.0703 .
Curvature.l2    0.0153844  0.0177593   0.866   0.3901
Spread.l2      -0.0679885  0.1555228  -0.437   0.6637
NEER.l2        -0.1150547  0.1057304  -1.088   0.2813
Real.Activity.l2 -0.0600171  0.0412059  -1.457   0.1509
Inflation.l2   -0.0993747  0.2267821  -0.438   0.6630
Base.Rate.l2   -0.1507539  0.1518418  -0.993   0.3251
Level.l3        0.1402309  0.1480896   0.947   0.3478
Slope.l3       -0.0003809  0.0302552  -0.013   0.9900
Curvature.l3   -0.0063244  0.0151309  -0.418   0.6776
Spread.l3      -0.0724113  0.1498100  -0.483   0.6308
NEER.l3         0.1440573  0.1034074   1.393   0.1692
Real.Activity.l3  0.0165184  0.0408856   0.404   0.6878
Inflation.l3    0.3602124  0.2291751   1.572   0.1217
Base.Rate.l3    0.0139361  0.1690432   0.082   0.9346
Level.l4       -0.1256897  0.1255840  -1.001   0.3213
Slope.l4       -0.0547933  0.0295126  -1.857   0.0687 .
Curvature.l4    0.0033869  0.0115931   0.292   0.7713
Spread.l4       0.0004413  0.1262864   0.003   0.9972
NEER.l4        -0.0033277  0.0728121  -0.046   0.9637
Real.Activity.l4 -0.0262876  0.0379804  -0.692   0.4918
Inflation.l4   -0.2420695  0.1366647  -1.771   0.0821 .
Base.Rate.l4    0.0576320  0.1243868   0.463   0.6450
const          -0.1721383  0.3395180  -0.507   0.6142
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1625 on 55 degrees of freedom
Multiple R-Squared: 0.9853,     Adjusted R-squared: 0.9765
F-statistic: 111.8 on 33 and 55 DF,  p-value: < 2.2e-16
```

Curriculum Vitae

LEBENSLAUF

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PERSÖNLICHE ANGABEN

Familienstand:	ledig
Staatsangehörigkeit:	deutsch
Geburtsdatum:	25.02.1973
Geburtsort:	Waiblingen / Rems-Murr-Kreis (D)

TÄTIGKEITEN

Seit November 2005	UNIQA Finanz-Service GmbH, Wien (A) Fixed Income Emerging Markets Asset Management und Betreuung UNIQA Schwestergesellschaften in Bulgarien, Liechtenstein, Polen, Slowakei, Schweiz und Tschechien Back-up Fondsmanagement UNIQA Eastern European Debt Fund
Oktober 2003 – Mai 2005	Institut für Strategische Kapitalmarktforschung, Wien (A) Portfoliomanagement Programm (Stipendiaten managen Portfolios unter der Supervision von DI Pühringer, Prof. Dockner und Prof. Zechner) Portfolio: Medium Risk
Juli 2004 – Sept. 2004	MTU Maintenance Co. Ltd., Wanzai (VR China) Accounting Dept., Operative Planung und Cash-flow Management
Oktober 2003 – Juli 2004	Wirtschaftsuniversität Wien (A) Meisterklasse Osteuropa (Zweisemestriges Projekt/Zusatzausbildung) Institut für Unternehmensführung (Prof. Dr. Speckbacher) „Powers Reseved in CEE“ – Modell zur Bestimmung des optimalen Dezentralisierungsgrades internationaler Unternehmen
Juli 2003 – Okt. 2003	EPCOS China Co. Ltd., Zhuhai (VR China) Finance & Reporting, Foreign Exchange Management
Juli 2002 – Okt. 2002	HVB Bank Hungary Rt., Budapest (H) Structured Finance, Treasury and Controlling
August 1994 – Juni 1996	Simpson College Indianola, Iowa (USA) Assistant for Gesture-Recognition-Research bei Prof. Garry Newell (algorithmische und neuronale Handschrifterkennung)

AUSBILDUNG / STUDIUM

Seit März 1999	Betriebswirtschaftliches Zentrum der Universität Wien (A) Studiengang: Internationale Betriebswirtschaftslehre Schwerpunktfächer: Corporate Finance, Banking, Int. Rechnungslegung Mündl. Abschlussprüfung: mit gutem Erfolg bestanden Diplomarbeit: „ The dynamics of interest rates in the Czech Republic, Hungary and Poland: A Vector Autoregressive Latent Yield and Macro Factor Approach"
Juli 1998 – März 1999	Willy Hagen Kaffee & Tee GmbH, Heilbronn (D) Trainee im Ausbildungsprogramm Marketing der Fachhochschule Pforzheim
Oktober 1996 – Juni 1998	Ruprechts-Karls-Universität Heidelberg (D) Studiengang: Medizinische Informatik
September 1994 – Juni 1996	Simpson College Indianola, Iowa (USA) Major: Computer Information Systems Minor: Economics
Juli 1993 – September 1994	Zivildienstleistender bei der Arbeiterwohlfahrt Schorndorf (D) Mobiler Sozialer Dienst
September 1990 – Mai 1993	Technisches Gymnasium an der Gewerblichen Schule Waiblingen (D) 19.05.1993 Abschluß Allgemeine Hochschulreife

COMPUTERKENNTNISSE

Microsoft Office:	Word, Excel, PowerPoint, Outlook (professionell) Access (intermediate)
Finanzdaten Provider:	Bloomberg, Reuters, EcoWin, Datastream, Morningstar
Statistik/Ökonometrie:	SPSS, R, Eviews
Programmierung:	Icon, C++, Pascal, Ada

SPRACHEN

Deutsch:	Muttersprache
Englisch:	fließend (verhandlungssicher)
Französisch:	Schulkenntnisse
Ungarisch:	Grundkenntnisse
Russisch:	Grundkenntnisse

EHRENAMTLICHE TÄTIGKEITEN

1997 – 1998	Vorstand des Allgemeinen Studierendenausschusses (ASTA)
1994 – 1996	Vice-president of the International Student Organization of Simpson College
1995 – 1996	Representative for Student Senate of Simpson College
1989 – 1994	Stellvertretender Vorsitzender des Stadtjugendrings Schorndorf

AUSLANDSERFAHRUNG / SOMMERUNIVERSITÄTEN

August 2001	Sommeruniversität am Kharkov Polytechnical Institute, Ukraine Sprache und Kultur
Juli 2001	Sommeruniversität an der Pécsi Tudományegyetem, Pécs, Ungarn Sprache und Kultur
August 2000	Solovki Heritage Museum, Rußland Arbeit zur historischen Erhaltung des Klosters und Gulag
August 1999	Civil Service International, Belfast, Nord Irland Organisation von Kontakten zwischen Protestanten und Katholiken

INTERRESSEN / HOBBIES

Sport (Marathon 2:49, Radfahren, Skifahren, Fußball, Eishockey)
Politik, Geschichte, Kochen, Lesen

Eidesstattliche Erklärung

Ich erkläre hiermit an Eides statt, dass ich die vorliegende Arbeit selbständig und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sind als solche kenntlich gemacht.

Die Arbeit wurde bisher in gleicher oder ähnlicher Form keiner anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht.

Wien, im September 2008

Gunnar Brechtken