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The Effect of Non-Linearity Between Credit Conditions and Economic Activity on Density Forecasts

Michal Franta*

Abstract

This paper examines the effect of non-linearities on density forecasting. It focuses on the relationship between credit markets and the rest of the economy. The possible non-linearity of this relationship is captured by a threshold vector autoregressive model estimated on the US data using Bayesian methods. Density forecasts thus account for the uncertainty in all model parameters and possible future regime changes. It is shown that considering non-linearity can improve the probabilistic assessment of the economic outlook. Moreover, three illustrative examples are discussed to shed some light on the possible practical applicability of density forecasts derived from non-linear models.

JEL Codes: C11, C32, E44.

Keywords: Density forecasting, nonlinearity, threshold autoregressive model.

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Nontechnical Summary

Density forecasts are defined as estimated probability densities of future values of a macroeconomic variable. So, a future development of a variable is not represented by a single number (point forecast) but by the whole distribution of possible values (density forecast). Density forecasts thus provide more information about the future outlook of a variable and not surprisingly have become an important tool of economic analysis, with many applications in economics and finance.

The estimation of density forecasts usually draws on linear models. However, a growing literature suggests that many economic relationships are inherently non-linear, and neglecting this fact can influence an economic analysis significantly. A prominent example of a non-linear relationship is the interaction between financial markets and the real economy during the recent financial crisis. The profound fall in economic activity has not been proportional to the original shock to the financial markets. Feedback effects have arisen between the financial markets and the real economy and affected the nature of the relationship.

Given the presumably non-linear relationship between credit conditions and economic activity, the aim of this paper is to examine density forecasting based on non-linear models. To that end a very simple non-linear model is estimated using Bayesian techniques and its forecasting ability is compared to its linear counterpart. The real economy is captured by output, the short-term interest rate, and inflation. The model is completed with a variable representing credit conditions. The data set contains US quarterly data and covers the period 1984–2012.

The results suggest that non-linear models can provide a more realistic tool for the probabilistic assessment of the macroeconomic outlook than linear models. Moreover, some practical issues are discussed with the aid of three illustrative examples. The first example focuses on density forecasting at the end of 2004 and describes the situation where non-linearity does not play an important role in density forecasting. It suggests that extending models to explicitly account for non-linearity will not necessarily give a sufficient gain for a majority of periods. On the other hand, the second example demonstrates that during stress events, the probabilistic assessment of the future provided by the non-linear model is more accurate. The example discusses the ex-ante probability of the global financial crisis estimated on data available in 2008Q2. Finally, the third example examines the likelihood of hitting the zero lower bound in the period 2008–2012. It implies that accounting for the uncertainty in model parameters is important to provide realistic assessment of likelihood of the zero lower bound events.

The analysis presented in the paper suggests that non-linear models are important when modeling stress events, and exploration of the effect of non-linearities on density forecasting is a promising topic for future economic research.

1. Introduction

A growing number of macroeconomic issues are being examined with the aid of density forecasts, i.e., the estimated probability densities of the future values of a random variable. For example, fan charts for inflation help the Bank of England communicate the direction and size of risks related to the inflation outlook (Britton et al., 1998). Next, predictive densities of macroeconomic variables allow for the assessment of the consistency and adverseness of macroeconomic scenarios underlying stress testing of the financial sector (Franta et al., 2013). Many applications of density forecasting can also be found in finance – for a selected survey see Tay and Wallis (2000).

Density forecasts are usually based on linear models. Basically, there are two reasons for this. First, the forecasting performance of linear models is often superior to that of non-linear models. Second, linear models are easy to deal with from the computational point of view. For example, as noted in Teräsvirta (2006) density forecasts based on non-linear models typically do not account for estimation uncertainty, as the inclusion of this type of uncertainty is computationally very demanding.

Imposing linearity on a macroeconomic relationship can, however, be misleading. A prominent example is the interaction between the financial markets and the real economy during the recent financial crisis. The aim of this paper is to examine the effect of non-linearity in the relationship between economic activity and credit markets on density forecasts. By building the analysis on a threshold vector autoregressive model and employing the Bayesian approach, it develops a simple framework able both to capture the non-linearity and to generate density forecasts in an intuitive and straightforward way. Moreover, the framework employed enables us to account for the estimation uncertainty.

How can density forecasts be affected by non-linearities and how much are they actually affected? Regimes identified within the modeling framework can differ in terms of the shock propagation mechanism and volatility of shocks. Therefore, density forecasts corresponding to different regimes differ as well. In addition, possible future regime changes need to be reflected in density forecasting. To address the positive part of the question, the performance of non-linear density forecasts is assessed in a standard way. The in-sample fit is assessed by means of the marginal likelihood of the model and the out-of sample fit by means of a pseudo out-of-sample forecasting performance exercise based on the Kullback-Leibler Information Criterion.

The model draws on the analysis introduced in Balke (2000), where the focus is on the role of credit in shock transmission in the US economy and where substantial differences in macroeconomic dynamics are detected for different ‘credit regimes’. Balke (2000) and the subsequent papers estimate the model by least squares, discretizing the range for the threshold variable driving the regime that the system is in. Here, similarly to Chen and Lee (1995) and Koop and Potter (2003), we use a Gibbs sampler with a Metropolis step to estimate the model. Therefore, the density forecasting takes into account not only the uncertainty related to the autoregressive parameters of the model and to the size of shocks, but also the uncertainty related to the value of the threshold and the delay of the threshold variable. The non-linear model and its linear counterpart are estimated on the US data.

The bottom line of the paper is that non-linear models can provide a more realistic tool for the probabilistic assessment of the macroeconomic outlook than linear models. On a general level, the result is confirmed by estimates of the marginal likelihood and by forecasting performance exercises for threshold VAR and VAR with constant parameters. Moreover, some practical issues are discussed with the aid of three illustrative examples. The first example focuses on density forecasting at the end of 2004 and describes the situation where non-linearity does not play an important role in density forecasting. It suggests that extending models to explicitly account for non-linearity will not necessarily give a sufficient gain for a majority of periods. On the other hand, the second example demonstrates that during stress events, the probabilistic assessment of the future provided by the non-linear model is more accurate. The example discusses the ex-ante probability of the global financial crisis estimated on data available in 2008Q2. Finally, the third example examines the likelihood of hitting the zero lower bound in the period 2008–2012. It shows that accounting for the uncertainty in model parameters is important to provide realistic assessment of likelihood of the zero lower bound events.

The structure of the paper is the following. The next section introduces the model and the dataset used for the analysis. Section 3 contains a discussion of the results, three illustrative examples, and some robustness checks. Finally, Section 4 concludes. Technical details of the estimation procedures, post-estimation diagnostics, and convergence diagnostics can be found in the appendices, which also contain some additional results.

2. Model

The relationship between credit markets and economic activity has been thoroughly examined, especially in the period following the recent Global Financial Crisis (GFC). The interaction between financial markets and the business cycle has proven to be crucial and many studies have reflected this fact. On the side of theory, for example, a lot of effort has been put into the extension of general equilibrium macroeconomic models for realistic modeling of financial frictions implying the so-called financial accelerator mechanism.[1] The relationship has been elaborated extensively by empirical studies, starting with McCallum (1991), who shows how credit rationing affects economic activity if a certain threshold is exceeded.[2]

Both the theoretical and empirical approaches suggest that the relationship between credit markets and economic activity is inherently non-linear. This non-linearity can stem, for example, from the asymmetric transmission of shocks during different phases of the business cycle and from periods of different levels of shock volatility. A possible channel through which the non-linearity is propagated is based on credit constraints of firms. Normally, an efficient financial market allows an investment project to be financed based on the expected rate of return. During stress events, however, informational asymmetries bring about the problem of availability of credit. The investment behavior of firms thus differs depending on the credit conditions.

[1] This strand of literature draws mainly on Bernanke and Gertler (1989) and Kiyotaki and Moore (1997). For an extensive survey of recent studies see Brázdik et al. (2011).

[2] Focusing on time-series models, various approaches have been employed, including Markov-switching models (e.g. Serwa, 2012, Hubrich and Tetlow, 2012) and panel VARs (e.g. Hristov et al., 2012).

One strand of the empirical literature that focuses on capturing non-linearities between credit markets and economic activity employs threshold vector autoregressions (TVARs). The seminal contribution in this vein is represented by Balke (2000), who identifies different credit regimes in the US economy and examines transmission within those regimes. Subsequent studies use the same methodology and address either the same question for different countries or more general questions dealing with the role of the financial sector in general.[3] As noted in Balke (2000), a TVAR model can capture regime switching, asymmetry, and multiple equilibria, being at the same time simple and intuitive.

The advantage of TVARs in examining non-linearity issues is that they are relatively parsimonious models, in contrast to, for example, time-varying parameter VARs, which consider a different set of autoregressive (AR) parameters and the elements of the residual covariance matrix for every period. The next advantage of the TVAR approach is the explicitness of the variable that drives the regime of the system. The interpretation of regimes is thus intuitive. This is in contrast to Markov-switching VARs, for which regime changes are driven by a non-observed state variable. On the other hand, a disadvantage of TVARs can be seen in the assumption of linearity within a particular regime, which can be inappropriate in the case of more complicated non-linear structures. Another problematic feature of TVARs is the assumed coincidence of switches in AR coefficients and volatility. The model can thus have difficulty capturing changes in volatilities.

Let's consider the following two-regime TVAR (p_1 , p_2):

$$y_t = x_t A_1 + \left(\tilde{x}_t A_2 - x_t A_1\right) I\left[y_{t-d}^{TR} \le r\right] + u_t, \tag{1}$$

where $y_t = \left[y_t^1, \ldots, y_t^M\right]$ is a row vector of endogenous variables, $x_t = \left[1, y_{t-1}, \ldots, y_{t-p_1}\right]$ and $\tilde{x}_t = \left[1, y_{t-1}, \ldots, y_{t-p_2}\right]$ are row vectors of length $1 + Mp_i$, and A_i are $\left(1 + Mp_i\right) \times M$ matrices of coefficients, $i = 1, 2$. Indicator $I\left[\cdot\right]$ equals one if a particular lagged value of the threshold variable, y_{t-d}^{TR}, lies below the threshold value r. The delay parameter $d \in \left\{1, 2, ..., d_0\right\}$ implies the lag of the threshold variable considered to identify the regime.

Stacking row vectors y_t, x_t, and u_t for $t = 1, \ldots, T$ according to the indicator function into Y_i, X_i, and U_i we can rewrite the model in matrix form:

$$\begin{aligned} Y_1 &= X_1 \mathrm{A}_1 + U_1 \qquad \mathrm{y}_{t-d}^{TR} > r \\ Y_2 &= X_2 \mathrm{A}_2 + U_2 \qquad \mathrm{y}_{t-d}^{TR} \le r \end{aligned}, \tag{2}$$

[3] Atanasova (2003) and Calza and Sousa (2006) focus on the role of credit markets in economic activity in the UK and the euro area, respectively. Holló et al. (2012) and Van Roy (2012) construct their own financial stress indicator and examine its effect on the real economy in the euro area and Germany, respectively.

where the elements of the column vector U_1 are distributed as $N(0,\Sigma_1)$ and the elements of U_2 are distributed as $N(0,\Sigma_2)$. We therefore allow for regime-dependent volatilities.[4]

2.1 Data

The vector of endogenous variables includes GDP and CPI inflation (seasonally adjusted annualized q-o-q growth), the federal funds rate, and a measure of the credit market conditions. The sample covers the period 1984Q1–2012Q3. We follow the relevant literature and choose the start of the sample to be 1984Q1, which corresponds to the beginning of the 'Great Moderation.' The choice of the credit market conditions measure is a tricky task. The predictive ability of a measure can change over time. For example, Friedman and Kuttner (1993) and others show a robust relationship between the difference between the interest rate on commercial paper and Treasury bills and future economic activity in the United States during the 1970s and 1980s. However, as noted by Faust et al. (2012), this relationship disappeared in the 1990s. So, we follow recent literature (Ferraresi et al., 2013, Atanasova, 2003) and consider the spread between the BAA-rated corporate bond yield and the 10-year treasury constant maturity rate. As a robustness check, we also test an alternative measure considered also in Balke (2000) and Ferraresi et al. (2013) – the first difference of the mix of bank loans and commercial paper in total firm external finance.[5]

The threshold variable, y_t^{TR}, is a transformed version of the respective credit conditions measure. The transformation employed is primarily intended to 'smooth' the measure and thus avoid too frequent changes of regime. Again we follow the literature and take the moving average of the BAA spread (MA(2)) and the mix variable (MA(6)). Graphs of the endogenous variables and threshold variables can be found in Appendix A.

3. Results

The Gibbs sampler with a Metropolis step is run for 100,000 iterations, discarding the first 50,000 to minimize the influence of the initial values of the parameters. Every 10th draw is taken to get independent draws. The estimation procedure, prior distributions, and initial values of the model parameters are described in Appendix B. Note that the prior on the AR coefficients is the same for the two regimes and thus reflects the prior belief of no threshold effect.

Density forecasts are constructed by stochastically simulating the iterated forecasts and taking the summary statistics of the resulting empirical distributions. More precisely, draws from the conditional posterior distributions of the parameter subsets obtained in the Gibbs sampler after the burn-in period are used to compute iterated forecasts for a horizon of up to seven quarters. Then the centered 68% and 95% of the posterior distributions for a particular variable, period, and forecasting horizon describe the density forecasts. Importantly, the simulated forecasts take into account regime changes i.e., whenever the forecast of the threshold variable indicates a regime change for a given threshold,

[4] The assumption of regime-dependent volatility is not usual in the literature employing TVARs to examine the relationship between credit and economic activity. However, as suggested in the case of monetary policy regimes in Sims and Zha (2006), neglecting changes in volatility can incorrectly suggest changes in coefficients.

[5] This measure is the ratio of the total amount of loans in the liabilities of non-financial corporate and non-corporate firms to the sum of the total amount of loans plus the amount of commercial paper issued by non-financial corporate firms.

the set of model parameters corresponding to the regime is used for the computation of the next quarter forecast.

A measure that suggests whether the non-linear model is preferred to its linear version is the marginal likelihood. Details on the marginal likelihood estimation can be found in Appendix C. The marginal likelihood is a measure closely related to the model's out-of-sample prediction performance (Geweke, 2001). Table 1 reports the marginal likelihood for various lags for the constant-parameter VAR (CVAR) and threshold VAR (TVAR) models and suggests that TVARs provide a superior fit to CVARs. Furthermore, comparing the marginal likelihoods of low-order TVARs with higher-order CVARs suggests that the TVAR model is considerably more parsimonious.

Table 1: Marginal Likelihood

		Threshold VAR			
	p_2	1	2	3	4
p_1	1	-604.26	-617.79	-626.78	-632.92
	2	-609.21	-619.59	-629.70	-636.14
	3	-613.47	-626.08	-634.04	-640.27
	4	-598.53	-611.93	-625.64	-637.60
		Constant VAR			
p		1	2	3	4
		-793.61	-763.49	-741.91	-700.61

Note: The marginal likelihood is computed on the full sample; details of the estimation can be found in Appendix C.

Table 1 also provides some guidance on the number of lags for the TVAR model in the two regimes, p_1 and p_2, and for the CVAR model, p. Nevertheless, other aspects need to be taken into account when setting the number of lags. Most importantly, the problem of over-parameterization limits the number of lags from above, as a regime can at minimum contain 15% of the estimation sample (16 observations) due to our assumption imposed on the maximum (minimum) value of the threshold – see Appendix B.

A more subtle analysis of the forecasting performance and thus of the model selection can be carried out using the Kullback-Leibler Information Criterion (KLIC) (Vuong, 1989). The KLIC is a measure of the distance between densities and allows us to examine the forecasting performance for a particular variable and forecasting horizon. The criterion implies that for a given endogenous variable, x_t, and forecasting horizon, h, the model with the highest expected logarithmic score, $E\left[\log f_{t+h,t}\left(x_{t+h}\right)\right]$, is preferred. As shown by Fernandez-Villaverde and Rubio-Ramirez (2004) the model chosen according to the KLIC is the model with the highest posterior probability.

The expected logarithmic score is estimated using the average logarithmic score – the average log of the density for a realization of the endogenous variable, $\bar{x}_{t+h}$, taken for the period covering the last 40 observations (2002Q4–2012Q3). All available periods constitute the set A and the size of the set is N:

$$\frac{1}{N}\sum_{t\in A}\ln f_{t+h,t,i}\left(\bar{x}_{t+h}\right). \tag{3}$$

Regarding the TVAR and CVAR comparison based on the average logarithmic score, one point is worth emphasizing. It could be argued that in general TVARs include more parameters and thus provide wider density forecasts, as density forecasting also captures parameter uncertainty. Wider density forecasts are then more likely to cover the ex-post realized values of the endogenous variables, so the better forecasting performance of TVARs is simply a result of more parameters being included in such models. However, it is important to realize that the average logarithmic score penalizes too wide density forecasts. Intuitively, if an ex-ante realized value lies close to the median of two density forecasts, the wider density forecast adds less to the average logarithmic score. Therefore, the forecasting performance exercise for TVARs and CVARs is informative.

Table 2 reports the estimated expected logarithmic score for the TVAR model with different numbers of lags. It shows that different numbers of lags are preferable for different variables and forecasting horizons.[6] However, the differences are not large. For further analysis we consider the TVAR(4,4) model, as it performs the best in the vast majority of cases. Similarly, the CVAR(4) model is chosen based on the average logarithmic score (Table 3).

Table 2: TVAR – Average Logarithmic Score

	Output growth	Inflation	FF rate	Credit conditions		Output growth	Inflation	FF rate	Credit conditions
$p_1, p_2 = 1$					$p_1, p_2 = 3$				
Horizon : 1	-1.13	-1.00	**-0.92**	-0.89	Horizon : 1	-1.10	**-0.99**	-0.96	**-0.84**
2	-1.20	-1.01	-1.09	-0.96	2	-1.17	-0.99	-1.07	**-0.88**
3	-1.37	-0.98	-1.21	-0.97	3	-1.37	-0.97	-1.15	-0.90
4	-1.40	-0.94	-1.32	-0.98	4	-1.37	-0.96	-1.25	-0.89
5	-1.46	-0.99	-1.44	-0.97	5	-1.42	-1.00	-1.35	-0.88
6	-1.53	**-1.00**	-1.51	-0.96	6	-1.49	-1.04	-1.46	-0.88
7	-1.60	-1.06	-1.63	-0.95	7	-1.55	**-1.04**	-1.56	-0.86
$p_1, p_2 = 2$					$p_1, p_2 = 4$				
Horizon : 1	-1.11	-1.03	-0.94	-0.88	Horizon : 1	**-1.08**	-1.00	-0.95	-0.85
2	-1.18	-1.01	-1.06	-0.93	2	**-1.15**	**-0.97**	**-1.01**	-0.88
3	**-1.34**	-1.00	-1.15	-0.97	3	-1.38	**-0.95**	**-1.07**	**-0.89**
4	-1.38	-0.96	-1.26	-0.98	4	**-1.37**	**-0.92**	**-1.14**	**-0.86**
5	-1.42	-1.03	-1.35	-0.97	5	**-1.38**	**-0.99**	**-1.22**	**-0.84**
6	-1.49	-1.04	-1.43	-0.98	6	**-1.44**	-1.03	**-1.29**	**-0.84**
7	-1.56	-1.08	-1.55	-0.97	7	**-1.51**	-1.04	**-1.38**	**-0.81**

Note: The highest value for a particular variable and horizon is in bold. The average logarithmic score is computed on the period 2002Q4–2012Q3.

A comparison of the average logarithmic scores for the TVAR and CVAR models in Table 2 and Table 3 suggests that the forecasting performance of the best model for a particular horizon and variable is very similar, with a slight preference for the TVAR model. So, accounting for non-

[6] For the sake of simplicity, we only considered cases of the same number of lags in both regimes, as such assumption does not affect the exposition significantly.

linearity does not improve the forecasting ability of the VAR modeling framework much, and in general the linear approach seems to be sufficient. The negligible increase in forecasting performance may be due to over-fitting and misspecification of the TVARs as well as to the general absence of non-linear effects.

Table 3: CVAR – Average Logarithmic Score

		Output growth	Inflation	FF rate	Credit conditions			Output growth	Inflation	FF rate	Credit conditions
$p=1$						$p=3$					
Horizon :	1	-1.11	**-1.00**	**-0.94**	-0.99	Horizon :	1	**-1.07**	-1.03	-1.10	-0.88
	2	-1.21	**-1.04**	**-1.08**	-1.08		2	**-1.16**	-1.10	-1.24	-0.89
	3	-1.36	**-1.04**	-1.21	-1.13		3	**-1.34**	-1.12	-1.34	-0.92
	4	-1.43	-0.97	-1.32	-1.07		4	**-1.42**	-1.03	-1.45	-0.85
	5	**-1.48**	-1.00	-1.44	-1.00		5	-1.48	-1.00	-1.56	-0.78
	6	**-1.53**	**-1.01**	-1.49	-0.92		6	-1.55	-1.06	-1.64	-0.73
	7	**-1.61**	-1.09	-1.59	-0.86		7	-1.62	-1.13	-1.76	-0.68
$p=2$						$p=4$					
Horizon :	1	-1.10	-1.03	-1.08	-0.96	Horizon :	1	-1.10	-1.01	-1.09	**-0.87**
	2	-1.21	-1.05	-1.22	-0.98		2	-1.19	-1.07	-1.14	**-0.89**
	3	-1.36	-1.07	-1.31	-1.00		3	-1.36	-1.08	**-1.18**	**-0.89**
	4	-1.44	-1.04	-1.44	-0.94		4	-1.43	**-0.94**	**-1.28**	**-0.83**
	5	-1.49	-1.03	-1.52	-0.88		5	-1.48	**-0.96**	**-1.34**	**-0.77**
	6	-1.54	-1.05	-1.61	-0.84		6	-1.54	-1.02	**-1.42**	**-0.72**
	7	-1.62	-1.14	-1.72	-0.80		7	-1.62	**-1.06**	**-1.49**	**-0.67**

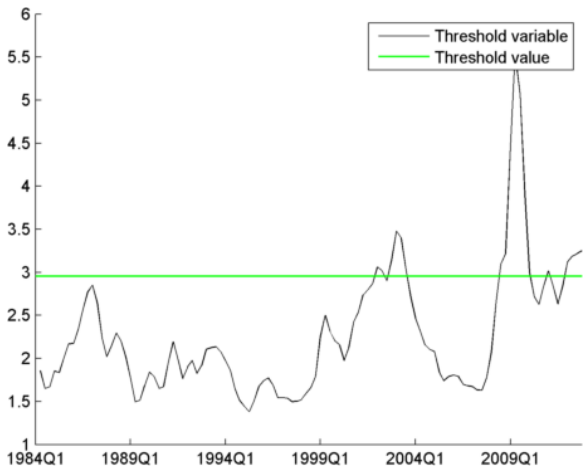
Note: The highest value for a particular variable and horizon is in bold. The average logarithmic score is computed on the period 2002Q4–2012Q3.

Considering TVAR(4,4) and CVAR(4), only each fourth comparison for a particular forecasting horizon and variable results in a preference for the CVAR model. Restricting the forecasting performance exercise to the sub-period before the GFC, i.e., 2002Q4–2008Q2 (see the tables in Appendix F), yields CVAR(4) to be preferable already in each second comparison. This suggests that stress events such as the GFC represent circumstances where the TVAR model provides a more accurate probabilistic outlook for the variables. Such hypothesis is explored more deeply in the following three illustrative examples. The first example discusses the case where the non-linearity has no effect. The second example relates to the ex-ante probability of the GFC. Finally, the third example concerns the probability of hitting the zero lower bound – a topical macroeconomic issue. We start, however, with the benchmark estimation carried out on the full data sample.

3.1 Benchmark Estimation

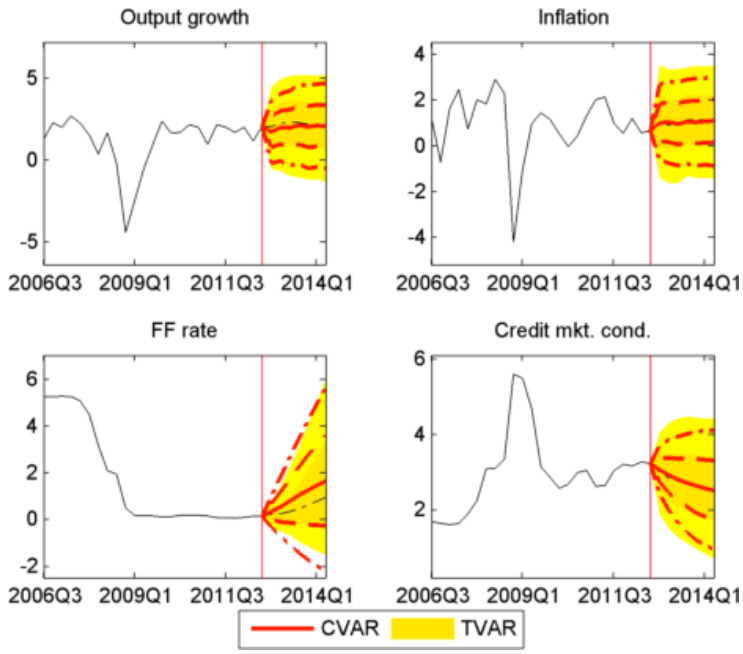
As the benchmark estimation we estimate the TVAR(4,4) and CVAR(4) models on the full sample covering the period 1984Q1–20012Q3. The convergence of the Gibbs sampler is discussed in Appendix D. Posterior distributions of selected model parameters are presented in Appendix E. The mean of the posterior distribution of the threshold is estimated at 2.95. Not surprisingly, regime 1 covers the period of tight credit conditions during the GFC and the period after the 2001 recession (Figure 1).

Figure 1: Threshold Variable and Estimated Threshold



The density forecasts presented in Figure 2 demonstrate that for the benchmark estimation the non-linear model produces wider distributions of future values of endogenous variables than the linear model. The only exception is the density forecast of the federal funds rate, which does not differ between the two models. Furthermore, it can be observed that the density forecasts based on the TVAR model are not symmetric.

Figure 2: Density Forecasts From the CVAR(4) and TVAR(4,4) Models



Note: For the CVAR, the red curves indicate the median and the centered 68% and 95% of the density forecasts. For the TVAR, the median is denoted by the black dot-dash line and the centered 68% and 95% of the density forecasts are indicated by dark and light yellow.

The sample skewness for a particular forecasting horizon and variable is presented in Table 4. The table shows that the density forecasts based on TVAR(4,4) are not symmetric. The opposite is true for the CVAR(4) model, which clearly exhibits symmetry of density forecasts. The ability of the model to provide asymmetric density forecasts can play a significant role in the performance of the TVAR model during stress events.

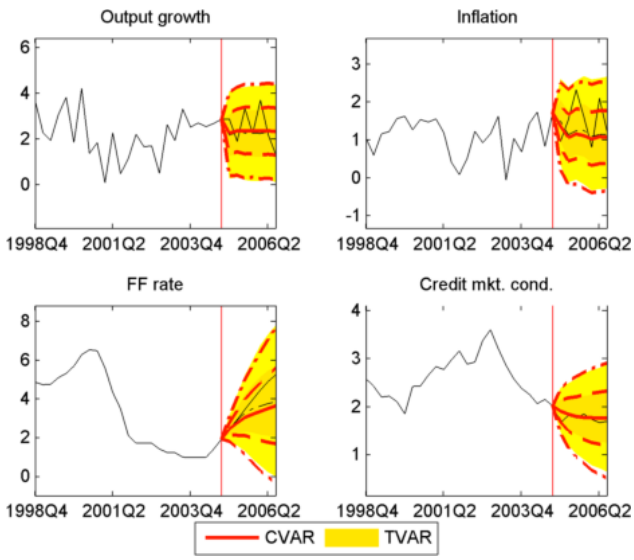
Table 4: Sample Skewness – Full Sample

	TVAR(4,4)				CVAR(4)			
Horizon:	Output growth	Inflation	FF rate	Credit conditions	Output growth	Inflation	FF rate	Credit conditions
1	-0.27	-0.02	-0.13	0.08	0.04	0.03	-0.02	0.00
2	-0.14	-0.02	0.96	0.08	0.01	-0.02	-0.02	0.00
3	-0.29	-0.04	1.24	0.14	-0.03	0.02	0.00	-0.02
4	-0.31	-0.23	1.13	0.16	0.01	-0.04	0.00	-0.03
5	-0.19	-0.16	0.99	0.10	0.02	0.00	0.00	-0.03
6	-0.10	-0.27	0.96	0.06	0.01	0.00	0.00	0.01
7	-0.10	-0.59	0.91	0.07	0.02	-0.02	-0.01	0.03

3.2 Non-Linearity Without Any Effect

As noted, for example, in Clements et al. (2004), non-linear models outperform linear models in out-of-sample forecasting only if the evaluation period 'contains non-linear features.' So, an improvement cannot be expected in the assessment of the future uncertainty related to the outlook for endogenous variables if non-linearity does not enter the simulation of the density forecasts.

Figure 3: Density Forecasts From the CVAR(4) and TVAR(4,4) Models Estimated on 1984Q1–2004Q4

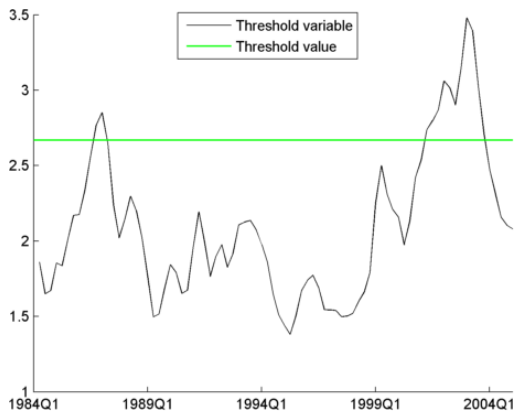


Note: For the CVAR, the red curves indicate the median and the centered 68% and 95% of the density forecasts. For the TVAR, the median is denoted by the black dot-dash line and the centered 68% and 95% of the density forecasts are indicated by dark and light yellow. Observed data are denoted by a solid black line.

As an example, Figure 3 presents the density forecasts for the two models estimated on the 1984Q1–2004Q4 sub-sample. The differences between the density forecasts based on linear and non-linear models are negligible. The reason can be observed in Figure 4, where the threshold variable and the estimated threshold are shown. The threshold variable in 2004 is so far from the threshold (2.67) that the density forecasts are hardly influenced at all by the possibility of regime changes. Moreover, the vector autoregression in the prevailing regime is apparently close to the estimated CVAR model. The sample skewness shows that all the density forecasts are symmetric.[7]

[7] The results for sample skewness are available upon request.

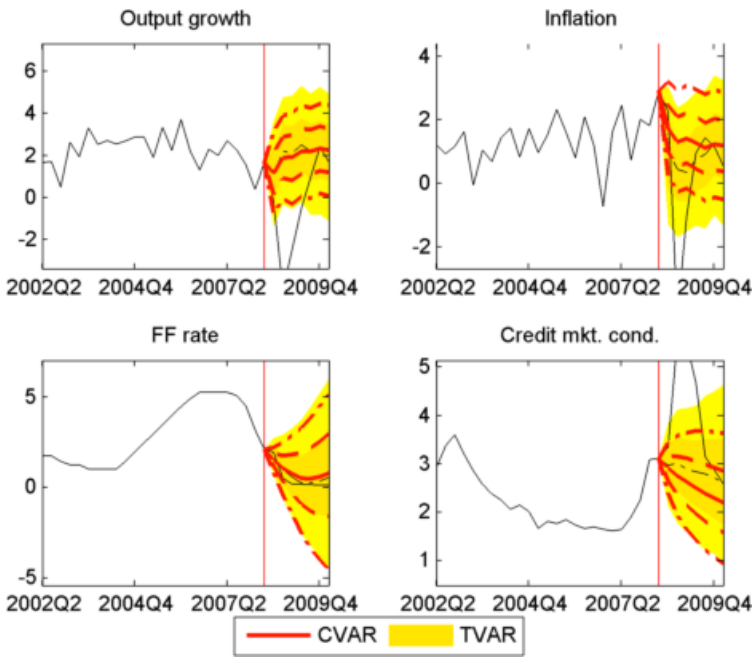
Figure 4: Threshold Variable and Estimated Threshold, 1984Q1–2004Q4



3.3 Probability of the GFC

The motivation for examining the density forecasts produced by non-linear models lies partially in the question of whether accounting for the non-linearity between credit markets and economic activity would have helped produce a more accurate probabilistic assessment of the future before the realization of the GFC. To answer this question, the model is estimated on the sub-sample covering the period 1984Q1–2008Q2. The following figure shows the density forecasts and ex-post observed values of the endogenous variables. Again, asymmetric density forecasts are produced by the TVAR model.

Figure 5: Density Forecasts From the CVAR(4) and TVAR(4,4) Models Estimated on 1984Q1–2008Q2



Note: For the CVAR, the red curves indicate the median and the centered 68% and 95% of the density forecasts. For the TVAR, the median is denoted by the black dot-dash line and the centered 68% and 95% of the density forecasts are indicated by dark and light yellow. Observed data are denoted by a solid black line.

Table 5 provides a probabilistic assessment of the ex-post observed values of the endogenous variables covering the GFC. An accurate measure should be based on joint density forecasts. However, for our purposes it is sufficient to look at distributions marginalized in the dimension of the variable and forecasting horizon.

Table 5: Cumulative Distribution Function of Marginalized Distributions at Ex-post Observed Values of Endogenous Variables.

TVAR(4,4)				
Forecasting period	Output growth	Inflation	FF rate	Credit conditions
2008Q3	0.152	0.877	0.746	0.827
2008Q4	<0.001	<0.001	0.276	0.999
2009Q1	0.002	0.067	0.365	0.999
2009Q2	0.016	0.584	0.483	0.996
2009Q3	0.187	0.709	0.472	0.690
2009Q4	0.529	0.457	0.451	0.582
2010Q1	0.345	0.273	0.426	0.48
CVAR(4)				
2008Q3	0.09	0.77	0.89	0.952
2008Q4	<0.001	<0.001	0.225	0.999
2009Q1	<0.001	0.002	0.301	0.999
2009Q2	0.009	0.357	0.41	0.999
2009Q3	0.131	0.663	0.426	0.894
2009Q4	0.522	0.459	0.408	0.820
2010Q1	0.292	0.211	0.383	0.722

Note: The models are estimated on the 1984Q2–2008Q2 sub-period. The marginalized distributions are evaluated on the data for 2008Q3–2010Q1.

The numbers in Table 5 provide the probabilities of observing the value of a particular variable at a particular forecasting horizon less than or equal to the ex-post observed values. For example, based on the data to 2008Q2 the estimated probability of observing inflation in 2009Q1 less than or equal to the ex-post observed value (0.95%) is 0.067 for the TVAR model and 0.002 for the CVAR model.

From Figure 5 and Table 5 it follows that for some horizons the non-linear model suggests a non-zero probability of an ex-post observed outcome that the linear model estimates as a zero-probability event. It has to be stated, however, that this is not the case for all the zero-probability events suggested by the linear model.

3.4 Probability of Hitting the ZLB

Another issue that can be resolved using density forecasts is the likelihood of hitting the zero lower bound on the nominal interest rate. By employing stochastic simulations, Chung et al. (2012) estimate the probabilities of hitting the ZLB and staying at the ZLB for at least one, four, and eight quarters. Their stochastic simulations are based on a battery of models – structural models (the FRB/US model, the Smets-Wouters model, and the Estimated Dynamic Optimization-Based Model used by the Board of Governors) and statistical models (TVP-VAR, the Laubach-Williams model, and the GARCH model).

The aim of this subsection is to complement the results from Chung et al. (2012) and estimate the probability of hitting the ZLB with stochastic simulations based on the TVAR(4,4) and CVAR(4) models. Similarly to Chung et al. (2012) for the TVP-VAR and GARCH models we do not impose the ZLB. Moreover, we stick to the suggested forecasting horizon of 5 years. In addition, we follow Chung et al. (2012) and estimate the models on the sample 1968Q1–2007Q4. The starting date for the forecasting is 2008Q1. The results are reported in Table 6.

Table 6: Estimated Probability of ZLB Events

			Results from Chung et al. (2012) – Tables 2 and 3					
Lasting at least:	TVAR	CVAR	FRB/US*	EDO	SW	LW	TVP-VAR	GARCH*
1 quarter	0.10	0.11	0.03	0.02	0.13	0.09	0.07	0.20
4 quarters	0.12	0.11	0.01	<0.01	<0.01	0.05	0.02	0.09
8 quarters	0.03	0.03	<0.01	<0.01	<0.01	0.01	<0.01	0.02

Note: (*) The asterisk denotes models that do not account for uncertainty about the parameters and latent variables.

The table suggests that the TVAR model predicts a probability of long-lasting ZLB events (four and eight quarters) that is higher than the models considered in Chung et al. (2012). For the ZLB to be hit for at least one quarter, the estimated probabilities are close to the Laubach-Williams model and Smets-Wouters model. So, underestimation of the probability of hitting the zero lower bound by the current macroeconomic models discussed by Chung et al. (2012) is not an issue in the TVAR and CVAR models. On the other hand, the non-linear version of VAR seems not to add anything in this respect.

Finally, note that Chung et al. (2012) do not impose the ZLB on the TVP-VAR and GARCH models. As the zero lower bound constraint does not represent the focus of this paper it is not accounted for in the TVAR and CVAR models either. However, the treatment of the ZLB in density forecasting is discussed in detail in Franta et al. (2013) and would be implemented for non-linear density forecasts analogously.

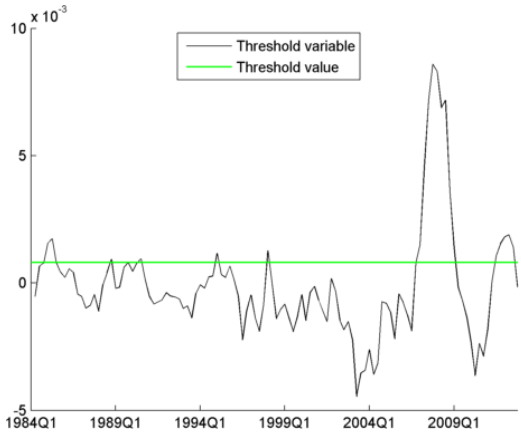
3.5 Some Modeling and Robustness Issues

The main modeling issue concerns the threshold parameter r. For very low initial values of the parameter the posterior distribution exhibits bimodality, suggesting the existence of more than two regimes. However, the TVAR(4,4) model imposes two regimes. From the computational point of view, more than two regimes represents an obstacle, as regimes with a very low number of observations can occur. Therefore, the assumption of two regimes is retained and instead the prior distribution on the threshold parameter is modified to cover only a part of its range. Details are given in Appendix B.

A robustness check is carried out with respect to the length of the data sample. The original period starting in 1984 is extended to start in 1960. The results of the benchmark estimation are not significantly affected. The results are also robust to the choice of hyperparameters of the prior variance of AR coefficients. In addition to the original values from Canova (2007), the values introduced in Kadiyala and Karlsson (1997) that imply more shrinkage are tested.

Finally, an alternative credit conditions measure and its transformation in the threshold variable are tested. The estimated threshold value is shown in Figure 6. In accordance with the original credit conditions measure, the alternative variable identifies the period around 2009 as regime 1. Nevertheless, the variable suggests more regime changes than the original variable based on the BAA spread.

Figure 6: An Alternative Threshold Variable and Estimated Threshold, 1984Q1–2012Q3.



4. Conclusions

This paper examined density forecasts for a simple non-linear model and compared them with the density forecasts produced by its linear counterpart. To that end, we focused on a macroeconomic relationship that is presumably highly non-linear – the relationship between credit markets and economic activity. The macroeconomic dynamics between credit markets and the rest of the economy were captured by a threshold vector autoregression of output, inflation, the short-term interest rate, and a measure of the credit conditions.

The results suggest that accounting for non-linearity can improve estimates of the uncertainty of the macroeconomic outlook. More precisely, during 'normal times' the threshold VAR seems not to improve the forecasting performance significantly and thus its use is not sufficiently justified. The extra effort of modeling non-linearities is not necessarily worth it and a linear model usually suffices. Non-linearity does not matter even in the second moments. However, in periods of tight credit conditions, when non-linearities presumably play a significant role, the threshold VAR model is a more suitable tool for forecasting the probabilistic outlook for the economy.

To illustrate the above-mentioned issues, the paper discusses three examples – a situation where non-linearity does not play any significant role, the ex-ante probability of the Global Financial Crisis, and the likelihood of zero lower bound events.. A possible explanation for why the TVAR model improves forecasting performance arises. It seems that the TVAR model can produce asymmetric densities more easily than a constant-parameter VAR.

The result that the TVAR model is appropriate for modeling 'stress events' naturally implies a possible use of the model. Realistic modeling of stress events is a key element of stress testing of the financial sector. An advantage of the TVAR model is that the threshold variable that drives the regime of the system is endogenous. The explicit regime driver allows us to impose a particular regime in the future. This can be done, for example, by soft-conditioning as introduced in Waggoner and Zha (1999). Such a procedure could be useful in the formulation of macroeconomic scenarios used in stress testing of the financial sector.

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Appendix A: Data

This appendix presents endogenous variables (Fig. A1), an alternative credit conditions variable (Fig. A2), and benchmark and alternative threshold variables (Fig. A3). For details on the data see Subsection 2.1.

Figure A1: Endogenous Variables in the Benchmark Specification, 1960Q1–2012Q3

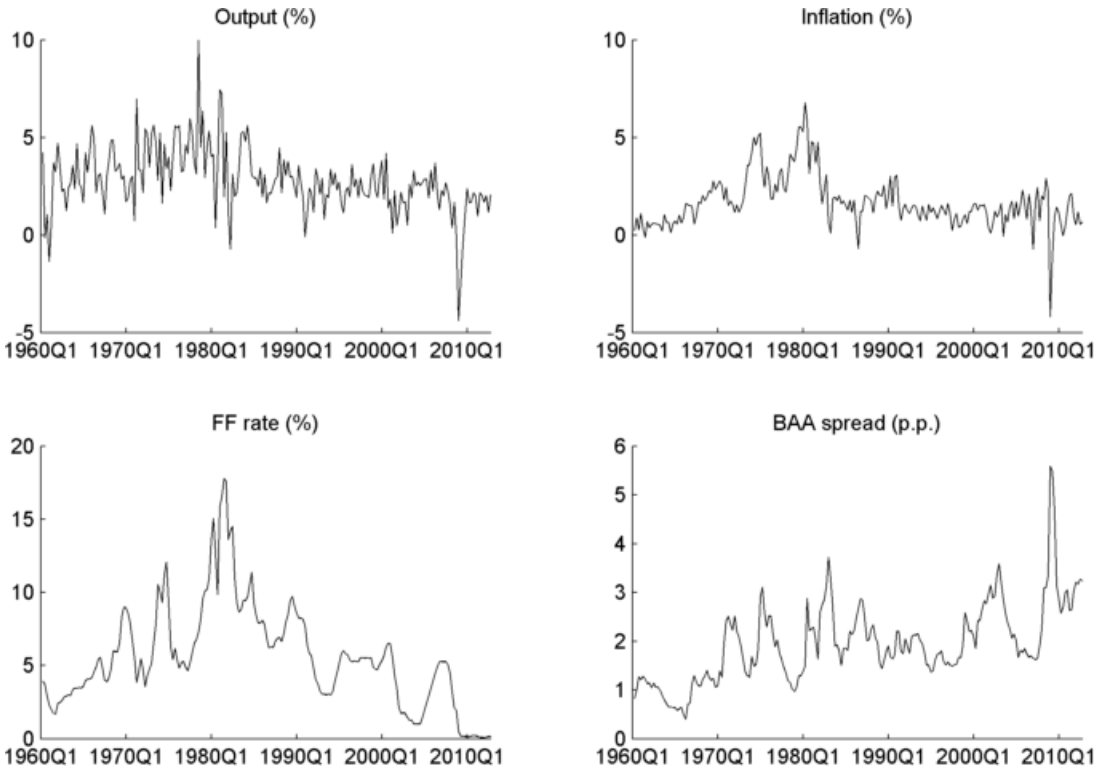


Figure A2: Mix Variable, 1960Q1–2012Q3

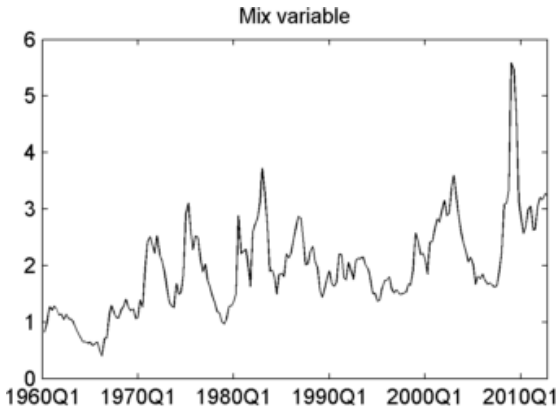
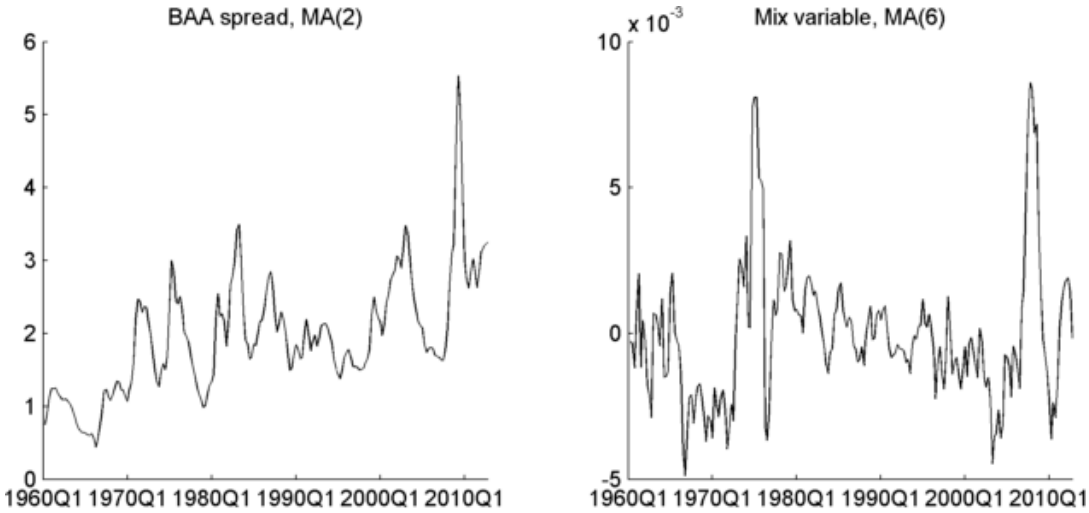


Figure A3: Threshold Variables, 1960Q1–2012Q3



Appendix B: Bayesian Estimation

B.1 Priors

For the AR coefficients and residual variance–covariance matrix, the normal-inverse Wishart prior is assumed (see, for example, Karlsson, 2012):

$$\alpha_i \sim N\left(\alpha_i^{PR}, V_i^{PR}\right) \text{ and } \Sigma_i \sim invW(0.1 * I_M, M+1) \quad i = 1, 2, \tag{B1}$$

where α_i is a vector created by stacking the columns of A_i. We set $\alpha_i^{PR} = 0_{(1+p_i M)M \times 1}$ and V_1^{PR}, V_2^{PR} such that the diagonal element equals ϕ_0 / l^2 for the coefficient on the lags of the LHS variable at lag l. For the coefficients on the lags of variables different from the LHS variable $(m \neq n)$ the prior variance is set to $\phi_0 \phi_1 \sigma_{i,m}^2 / (l^2 \sigma_{i,n}^2)$, and $\phi_0 \phi_2$ for the coefficients on the intercepts. $\sigma_{i,m}^2$ is the standard error of an AR(1) process for a particular variable *m* estimated on the whole sample. The hyperparameters are set to $\phi_1 = 0.2, \phi_2 = 0.5$, and $\phi_3 = 10^5$. The specification of the prior variance of the AR coefficients and hyperparameter values is taken from Canova (2007). The residual variance matrix follows an inverse Wishart distribution with five degrees of freedom and the scale matrix equal to a rescaled identity matrix. The priors on the AR coefficients and the residual variance-covariance matrix are independent.

The prior for parameter *r*, $pr(r)$, is considered to be uniform on $\left[r_{q=0.15}, r_{q=0.85}\right]$, where r_q denotes the respective quantile of the threshold variable.[8] As the preliminary analysis suggests the possibility of more than two regimes, the values of the threshold are restricted in the benchmark estimation to the upper half of the range, i.e., $\left[r_{q=0.50}, r_{q=0.85}\right]$.

Finally, the prior for the delay parameter follows a multinomial distribution with probability of a particular delay equal to $1/d_0$. Parameter d_0 is set to 3.

[8] As an alternative, the beta distribution on the same interval with the shape parameters β_a, β_b is considered. The results are not significantly affected. The beta distribution is chosen to impose less weight on the extremes without excluding the end points of the interval.

B.2 Gibbs Sampler

The likelihood function takes the following form (see, for example, Kadiyala and Karlsson, 1997):

$$L\left(\mathrm{A}_1,\mathrm{A}_2,\Sigma_1,\Sigma_2,r,d\mid Y\right)\propto\left|\Sigma_1\right|^{-\frac{n_1}{2}}\left|\Sigma_2\right|^{-\frac{n_2}{2}}\exp\left\{-\frac{1}{2}tr\left[\sum_{i=1}^{2}\left(Y_i-X_i\mathrm{A}_i\right)'\Sigma_i^{-1}\left(Y_i-X_i\mathrm{A}_i\right)\right]\right\}=$$

$$=\left|\Sigma_1\right|^{-\frac{n_1}{2}}\left|\Sigma_2\right|^{-\frac{n_2}{2}}$$

$$\exp\left\{-\frac{1}{2}\sum_{i=1}^{2}\left(\alpha_i-\alpha_i^{OLS}\right)'\left(\Sigma_i^{-1}\otimes X_i'X_i\right)\left(\alpha_i-\alpha_i^{OLS}\right)-\frac{1}{2}tr\left[\sum_{i=1}^{2}\Sigma_i^{-1}\left(Y_i-X_i\mathrm{A}_i^{OLS}\right)'\left(Y_i-X_i\mathrm{A}_i^{OLS}\right)\right]\right\}$$

$$=N\left(\alpha_i\mid\alpha_i^{OLS},\Sigma_i\otimes\left(X_i'X_i\right)^{-1}\right)\times iW\left(\Sigma_i\mid\left(Y_i-X_i\mathrm{A}_i^{OLS}\right)'\left(Y_i-X_i\mathrm{A}_i^{OLS}\right),n_i-1+p_im-1\right)$$

where $n_1=\sum_{t=1}^{T-p}I_{\left\{y_t^{TR}\le r\right\}}$ and $n_2=T-p-n_1$ are parameters dependent on the threshold value *r*.

The Gibbs sampler formulated in terms of the conditional posterior distributions of parameter subsets is as follows:

1) AR coefficients:

$$\alpha_i\mid\Sigma_i,r,d,Y\sim N\left(\alpha_i^{POST},\left(\left(V_i^{PR}\right)^{-1}+\Sigma_i^{-1}\otimes X_i'X_i\right)^{-1}\right)\qquad\text{(B2)}$$

where $\alpha_i^{POST}=\left(\left(V_i^{PR}\right)^{-1}+\Sigma_i^{-1}\otimes X_i'X_i\right)^{-1}\left[\left(V_i^{PR}\right)^{-1}\alpha_i^{PR}+\left(\Sigma_i^{-1}\otimes X_i'X_i\right)\alpha_i^{OLS}\right]$

2) Residual variance matrix:

$$\Sigma_i^{-1}\mid\alpha_i,Y,r,d\sim W\left(\left[\left(Y_i-X_i\mathrm{A}_i^{OLS}\right)'\left(Y_i-X_i\mathrm{A}_i^{OLS}\right)+\left(\mathrm{A}_i-\mathrm{A}_i^{OLS}\right)'X_i'X_i\left(\mathrm{A}_i-\mathrm{A}_i^{OLS}\right)\right]^{-1},n_i\right)\qquad\text{(B3)}$$

3) Threshold value:

The conditional posterior probability of the threshold *r* is:

$$p\left(r\mid\mathrm{A}_1,\mathrm{A}_2,\Sigma_1,\Sigma_2,d,Y\right)\propto\left|\Sigma_1\right|^{-\frac{n_1}{2}}\left|\Sigma_2\right|^{-\frac{n_2}{2}}\exp\left\{-\frac{1}{2}tr\left[\sum_{i=1}^{2}\left(Y_i-X_i\mathrm{A}_i\right)'\Sigma_i^{-1}\left(Y_i-X_i\mathrm{A}_i\right)\right]\right\}\times pr\left(r\right).\qquad\text{(B4)}$$

The draw of the threshold is carried out similarly to Koop and Potter (2003). Since the conditional posterior for the threshold is not identified, a Metropolis algorithm is employed. The proposed value of the threshold is drawn and the log of its conditional posterior probability is compared to the log of the conditional posterior probability for the original value of the threshold parameter. If the difference is larger than the logarithm of a draw from a standard uniform, then the proposed value is taken.

4) Delay parameter:

The conditional posterior follows a multinomial distribution with probability

$$p\left(d \mid \mathrm{A}_1, \mathrm{A}_2, \Sigma_1, \Sigma_2, r, Y\right) = \frac{L\left(\mathrm{A}_1, \mathrm{A}_2, \Sigma_1, \Sigma_2, r, d \mid Y\right)}{\sum_{d=1}^{d_0} L\left(\mathrm{A}_1, \mathrm{A}_2, \Sigma_1, \Sigma_2, r, d \mid Y\right)}. \tag{B5}$$

B.3 Initial Values

The initial values of the threshold value and the delay parameter are taken as a draw from the respective prior distribution. The initial covariance matrix equals the OLS estimate of a draw from a standard uniform covariance matrix of the model.

Appendix C: Marginal Likelihood

The marginal likelihood for the threshold VAR is computed according to Chib (1995) and Chib and Jeliazkov (2001). The Bayes rule yields the posterior distribution of the model parameters $\Theta \equiv \{A_1, A_2, \Sigma_1, \Sigma_2, r, d\}$:

$$p(\Theta \mid Y) = \frac{\mathrm{Lik}(Y \mid \Theta) \times p(\Theta)}{\mathrm{MLik}(Y)}. \tag{C1}$$

Thus,

$$\ln(\mathrm{MLik}(Y)) = \ln(\mathrm{Lik}(Y \mid \Theta)) + \ln(p(\Theta)) - \ln(p(\Theta \mid Y)). \tag{C2}$$

The previous formula is usually evaluated at a high density point under the posterior. A posterior mean of the parameter vector is considered. Since the delay parameter can attain only integer values, the mode of the sampled posterior distribution of the delay parameter is taken. The parameter vector used for the evaluation of the marginal likelihood is denoted as Θ^*. In the following we denote $A \equiv \{A_1, A_2\}$ and $\Sigma \equiv \{\Sigma_1, \Sigma_2\}$.

1) Log-likelihood of data at Θ^*:

$$\ln\left(\mathrm{Lik}\left(Y \mid \Theta^*\right)\right) = -\frac{(n_1+n_2)M}{2} + \frac{n_1}{2}\ln\left|\Sigma_1^{*-1}\right| + \frac{n_2}{2}\ln\left|\Sigma_2^{*-1}\right| - \frac{1}{2}tr\left[\sum_{i=1}^{2}\left(Y_i - X_i \mathrm{A}_i^*\right)' \Sigma_i^{*-1}\left(Y_i - X_i \mathrm{A}_i^*\right)\right] \tag{C3}$$

2) Joint prior at Θ^*:

$$\begin{aligned} A_i &\sim N\left(A_i^{PR}, V_i^{PR}\right) \quad \Sigma_i \sim iW\left(S^{PR}, v^{PR}\right) \qquad \text{for } i = 1,2 \\ r &\sim U\left(r_{q=0.1}, r_{q=0.9}\right) \qquad d \sim Multinomial\left(1, 1/d_0\right) \end{aligned} \tag{C4}$$

3) Posterior density of parameters at Θ^*:

$$p\left(\Theta^* \mid Y\right) = p\left(A^* \mid \Sigma^*, r^*, d^*, Y\right) p\left(\Sigma^* \mid r^*, d^*, Y\right) p\left(r^* \mid d^*, Y\right) p\left(d^* \mid Y\right), \tag{C5}$$

where $p\left(A^* \mid \Sigma^*, r^*, d^*, Y\right) = p\left(A_1^* \mid \Sigma^*, r^*, d^*, Y\right) p\left(A_2^* \mid \Sigma^*, r^*, d^*, Y\right)$, as the conditional posterior distribution for A_i is independent of A_i for $i \neq j$. The two terms of the last formula represent the full conditional posterior density ordinate of the AR parameters, which follow a normal distribution, with parameters computed in the same way as in the Gibbs sampler (see B2).

The term $p\left(\Sigma^* \mid r^*, d^*, Y\right)$ is approximated by the following sum:

$$\frac{1}{K}\sum_{k=1}^{K} p\left(\Sigma_1^* \mid r^*, d^*, A_1^{(k)}, Y\right) p\left(\Sigma_2^* \mid r^*, d^*, A_2^{(k)}, Y\right), \tag{C6}$$

where a reduced conditional density ordinate of covariance matrix Σ_i^* is computed in a separate reduced Gibbs MCMC run carried out for fixed r^* and d^*.

As the full conditional density is unknown for r^*, the procedure from Chib and Jeliazkov (2001) is employed to estimate $p\left(r^* \mid d^*, Y\right)$ using the following ratio:

$$\frac{\sum_{k=1}^{K} \alpha\left(r^{(k)}, r^* \mid A^{(k)}, \Sigma^{(k)}, d^*, Y\right) q\left(r^{(k)}, r^* \mid A^{(k)}, \Sigma^{(k)}, d^*, Y\right)}{\sum_{k=1}^{K} \alpha\left(r^*, r^{(k)} \mid A^{(k)}, \Sigma^{(k)}, d^*, Y\right)}, \tag{C7}$$

where

$$\alpha\left(r, r' \mid A^{(k)}, \Sigma^{(k)}, d^*, Y\right) = \min\left\{1, \frac{\mathrm{Lik}\left(Y \mid A^{(k)}, \Sigma^{(k)}, r', d^*\right) p\left(r'\right)}{\mathrm{Lik}\left(Y \mid A^{(k)}, \Sigma^{(k)}, r, d^*\right) p\left(r\right)} \frac{q\left(r', r \mid A^{(k)}, \Sigma^{(k)}, d^*, Y\right)}{q\left(r, r' \mid A^{(k)}, \Sigma^{(k)}, d^*, Y\right)}\right\} \tag{C8}$$

and $q\left(r, r' \mid \cdots\right)$ denotes the proposal density for the transition from r to r'. The proposal densities take a simple form of uniform or beta distributions (see B4).

Finally, the marginal density $p\left(d^* \mid Y\right)$ is estimated using the original chain produced by the Gibbs sampler:

$$\frac{1}{K}\sum_{k=1}^{K} p\left(d^* \mid A^{(k)}, \Sigma^{(k)}, r^{(k)}, Y\right). \tag{C9}$$

Appendix D: Convergence Diagnostics[9]

Two measures of autocorrelation are used to assess the Gibbs sampler convergence. The first measure is the simple autocorrelation of a chain of draws at a lag equal to 10. A more general measure of a chain's autocorrelation is the inefficiency factor, defined as follows:

$$1+2\sum_{k=1}^{\infty}\rho_k\,, \tag{D1}$$

where ρ_k represents the autocorrelation of the chain at lag *k*. Low autocorrelation values and inefficiency factor values less than 20 suggest independent draws from the conditional posteriors and thus efficiency of the sampling algorithm.

The next measure is based on Raftery and Lewis (1992) and suggests how many draws should be taken from the conditional posteriors within the Gibbs sampler to obtain a stationary joint distribution.[10]

Table D1 reports the convergence diagnostics for the threshold value *r* and the delay parameter *d*.

Table D1: Convergence Diagnostics

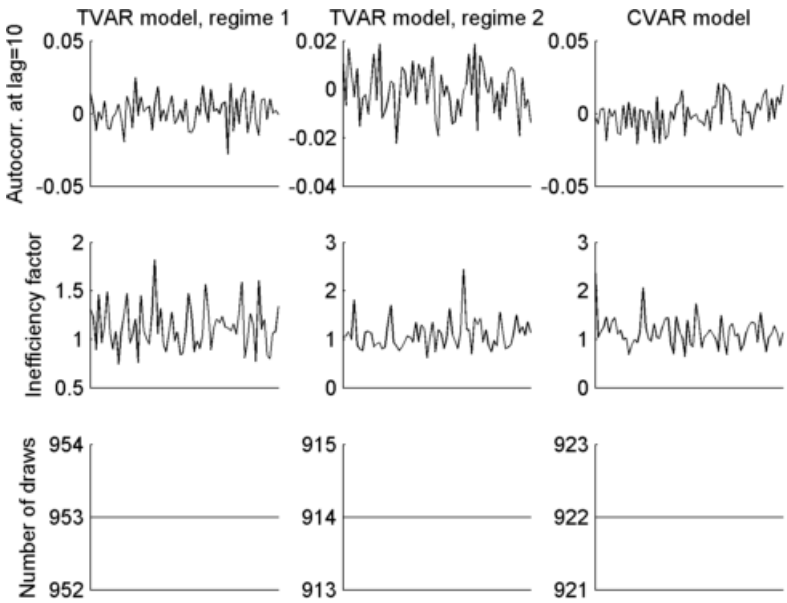
Parameter	Autocorr. at lag=10	Inefficiency factor	Number of runs
Threshold *r*	0.0115	0.4179	2246
Delay par. *d*	0.0128	1.7658	8770

The following figures present the statistics for the AR coefficients (in the two regimes of the TVAR model and for the CVAR model). The parameters are stacked along the x-axis. The y-axis presents the value of the particular statistic. The presented statistics suggest that the chain of draws generated within the Gibbs sampler converges to the posterior distribution.

[9] The Econometric Toolbox (LeSage, 1999) for Matlab is used.

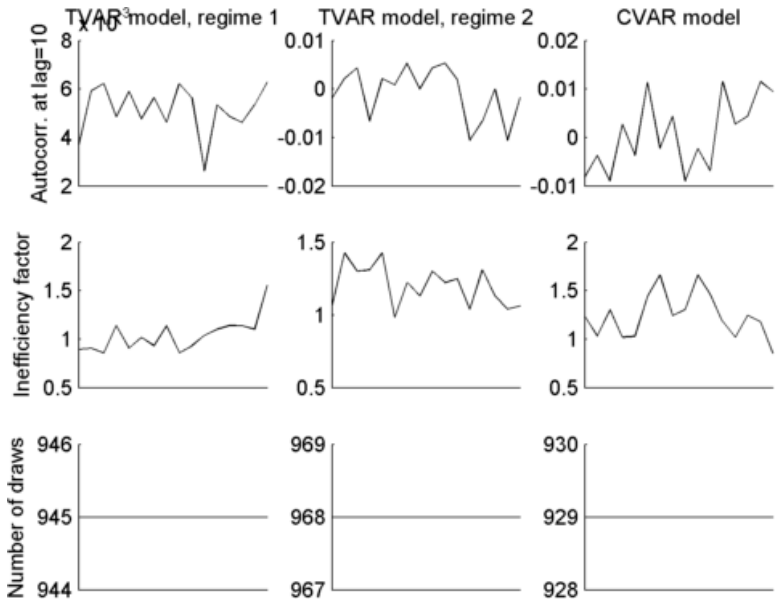
[10] The usual diagnostics parameters are used: for the 0.025th and 0.975th quantiles of a marginal posterior distribution, an accuracy of 0.025 is required to be achieved with a probability of 0.95.

Figure D1: Convergence Diagnostics for the AR Coefficients



Note: The parameters are stacked on the x-axis; for the TVAR model there are 36 AR parameters in each regime; the CVAR includes 52 AR parameters.

Figure D2: Convergence Diagnostics for the Elements of the Covariance Matrices

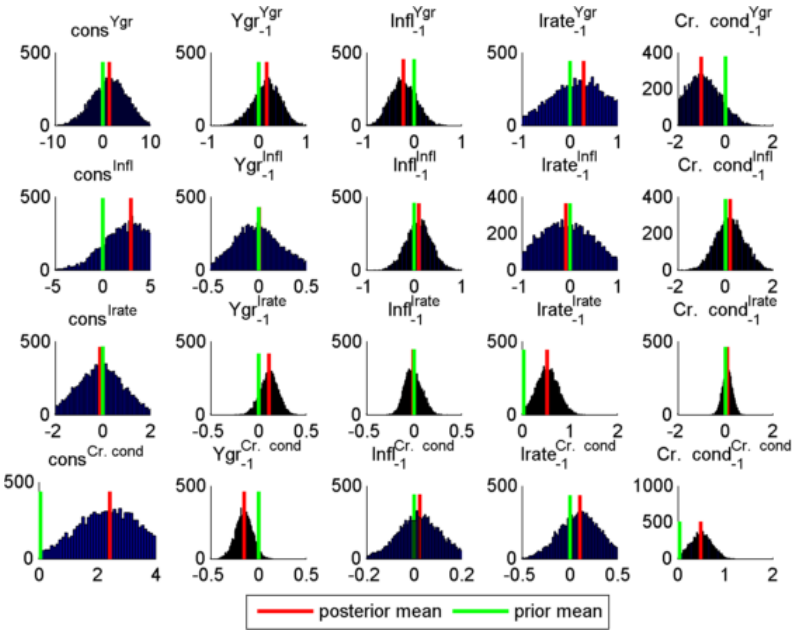


Note: The parameters are stacked on the x-axis; for the TVAR model there are 16 elements of the residual covariance matrix in each regime; the CVAR includes 16 elements of the residual covariance matrix.

Appendix E: Estimation Diagnostics

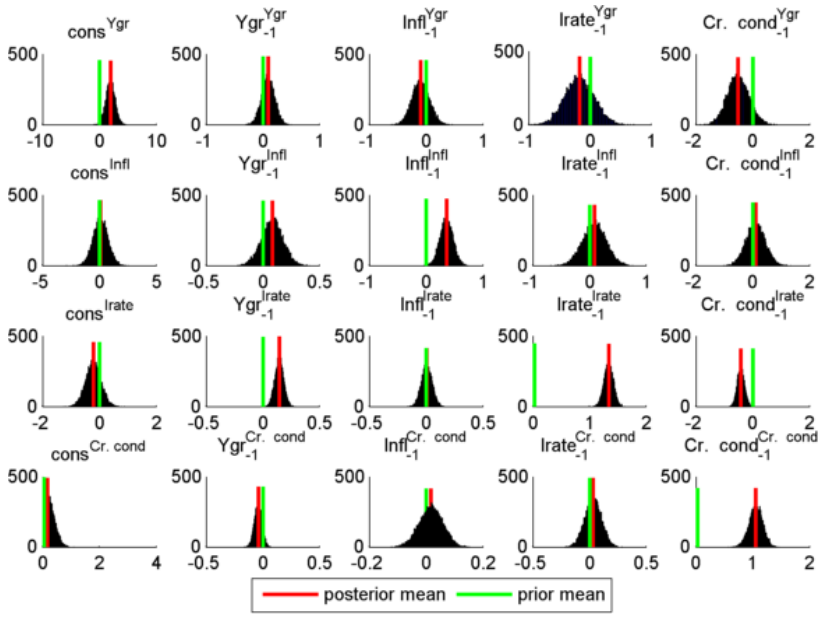
The following figures show the posterior distributions of selected model parameters of the TVAR(4,4) model estimated on the full sample. Complete results for all the model parameters and both the TVAR (4,4) and CVAR(4) models are available upon request. For convenience of comparison, the corresponding distributions in Figures E1 and E2 are presented over the same range.

Figure E1: Posterior Distribution of Selected AR Parameters, TVAR(4,4), Regime 1



Note: The superscript in the graph label indicates the left-hand side variable, and the subscript denotes the lag.

Figure E2: Posterior Distribution of Selected AR Parameters, TVAR(4,4), Regime 2



Note: The superscript in the graph label indicates the left-hand side variable, and the subscript denotes the lag.

Figures E1 and E2 show the posterior distributions of the intercept and first lag of the endogenous variables in the TVAR(4,4) model. The figures also indicate the prior and posterior mean of the respective distribution. The distributions of the parameters estimated in the first regime exhibit in general higher variances, as implied by the low number of observations in regime 1. The posterior means of the selected parameters between the two regimes usually differ in size and even in sign in some cases. For example, the coefficient at the first lag of the credit measure in the equation for the federal funds rate is positive with a mean close to zero in regime 1 and negative in regime 2.

Figure E3: Posterior Distribution of the Elements of the Covariance Matrix, TVAR(4,4), Regime 1

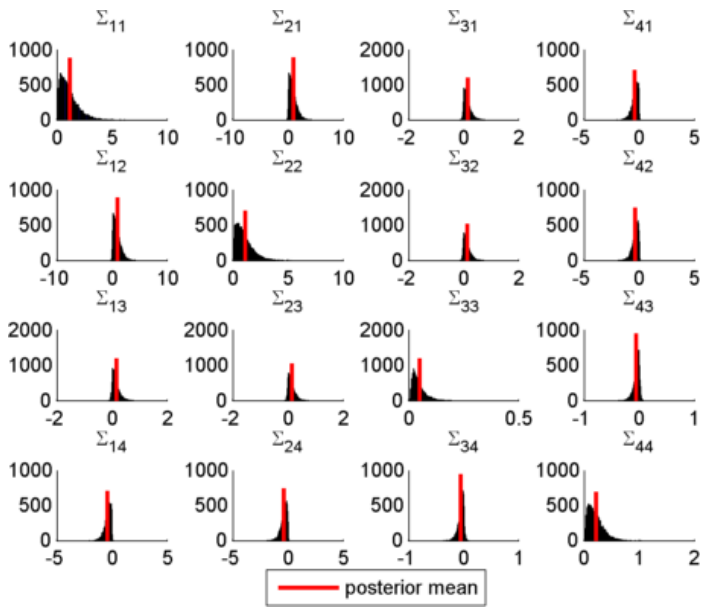
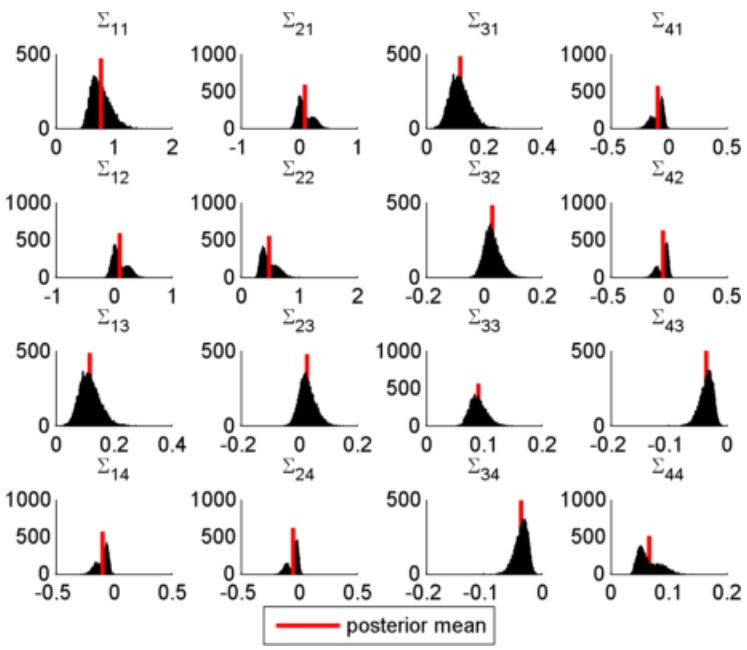


Figure E4: Posterior Dstribution of the Elements of the Covariance Matrix, TVAR(4,4), Regime 2



Similarly to the presented distributions of the AR parameters, the posterior distributions of the elements of the covariance matrices are estimated more precisely for regime 2 (Figures E3 and E4).

Finally, Figures E5 and E6 show the posterior distributions of the threshold and delay parameters. For the threshold, the chain of draws is also presented (left panel).

Figure E5: Posterior Distribution of the Threshold Value, TVAR(4,4).

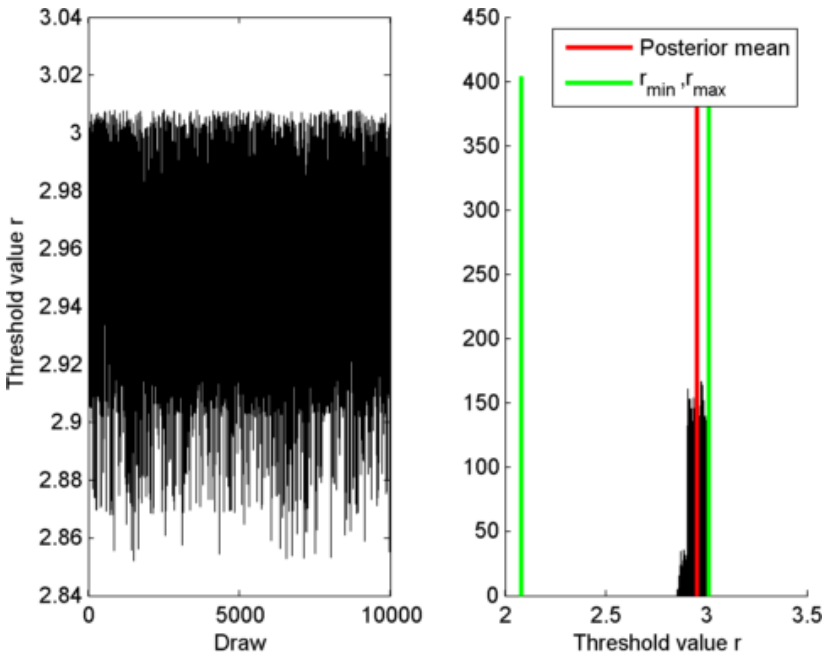
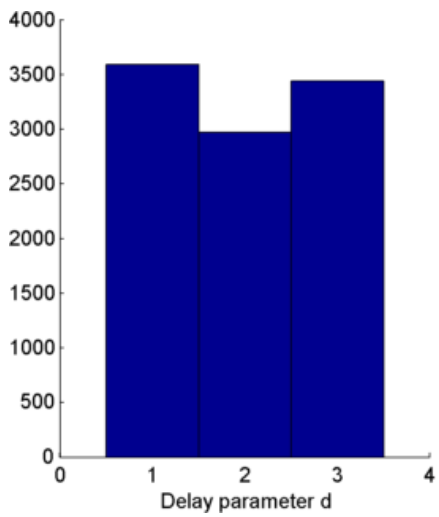


Figure E6: Posterior Distribution of the Delay Parameter, TVAR(4,4)



Appendix F: Average Logarithmic Score on Subsample

Table F1: TVAR – Average Logarithmic Score (1984Q1–2008Q2)

$p_1, p_2 = 1$	Output growth	Inflation	FF rate	Credit conditions	$p_1, p_2 = 3$	Output growth	Inflation	FF rate	Credit conditions
Horizon : 1	-0,93	-1,05	-1,02	-1,00	Horizon : 1	-0,93	-1,03	-1,04	**-0,98**
2	-0,88	**-0,91**	-0,97	-1,16	2	-0,80	-0,94	-1,01	-1,13
3	-0,89	**-0,85**	-0,91	-1,26	3	-0,81	-0,89	-0,94	-1,22
4	-0,89	**-0,78**	-0,76	-1,34	4	-0,83	-0,82	-0,78	-1,29
5	-0,92	-0,76	-0,67	-1,40	5	-0,85	-0,78	-0,70	-1,32
6	-0,93	-0,76	-0,63	-1,44	6	-0,84	-0,75	-0,67	-1,36
7	-0,95	-0,74	-0,59	-1,47	7	-0,86	-0,70	-0,64	-1,40
$p_1, p_2 = 2$					$p_1, p_2 = 4$				
Horizon : 1	-0,93	-1,13	**-1,01**	-1,02	Horizon : 1	**-0,89**	**-1,03**	-1,08	-0,99
2	-0,88	-0,97	**-0,96**	-1,19	2	**-0,78**	-0,94	-0,98	**-1,13**
3	-0,85	-0,90	-0,88	-1,31	3	**-0,78**	-0,87	**-0,86**	**-1,20**
4	-0,85	-0,82	-0,74	-1,40	4	**-0,82**	-0,79	**-0,70**	**-1,24**
5	-0,87	-0,80	-0,66	-1,44	5	**-0,83**	**-0,75**	**-0,62**	**-1,26**
6	-0,89	-0,78	-0,63	-1,51	6	**-0,83**	**-0,73**	**-0,57**	**-1,30**
7	-0,89	-0,76	-0,60	-1,55	7	**-0,84**	**-0,69**	**-0,55**	**-1,32**

Note: The highest value for a particular variable and horizon is in bold. The average logarithmic score is computed on the period 2002Q4–2008Q2.

Table F2: CVAR – Average Logarithmic Score (1984Q1–2008Q2)

$p = 1$	Output growth	Inflation	FF rate	Credit conditions	$p = 3$	Output growth	Inflation	FF rate	Credit conditions
Horizon : 1	-0,97	-1,04	**-1,01**	-0,88	Horizon : 1	**-0,95**	-1,09	-1,17	**-0,85**
2	-0,89	**-0,88**	**-0,96**	-0,97	2	-0,86	-0,96	-1,16	**-0,93**
3	-0,93	**-0,87**	**-0,89**	-1,02	3	**-0,85**	-0,93	-1,11	**-0,97**
4	-0,90	-0,76	**-0,74**	-1,06	4	-0,85	-0,85	-0,99	**-0,99**
5	-0,94	-0,79	**-0,63**	-1,08	5	-0,86	-0,78	-0,91	**-0,99**
6	-0,94	-0,75	**-0,58**	-1,09	6	-0,88	-0,76	-0,87	**-1,02**
7	-0,99	-0,76	**-0,55**	-1,09	7	-0,92	-0,75	-0,83	**-1,04**
$p = 2$					$p = 4$				
Horizon : 1	-0,99	-1,13	-1,13	-0,89	Horizon : 1	-0,96	**-1,03**	-1,22	-0,86
2	-0,92	-0,97	-1,12	-0,97	2	**-0,85**	-0,91	-1,11	-0,95
3	-0,91	-0,93	-1,04	-1,02	3	-0,85	-0,87	-1,01	-0,99
4	-0,89	-0,87	-0,92	-1,06	4	**-0,84**	**-0,76**	-0,86	-1,02
5	-0,91	-0,83	-0,83	-1,07	5	**-0,86**	**-0,74**	-0,78	-1,02
6	-0,94	-0,80	-0,78	-1,10	6	**-0,88**	**-0,71**	-0,71	-1,04
7	-0,97	-0,82	-0,74	-1,13	7	**-0,91**	**-0,68**	-0,68	-1,05

Note: The highest value for a particular variable and horizon is in bold. The average logarithmic score is computed on the period 2002Q4–2008Q2.

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