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The Impact of Financial Variables on Czech Macroeconomic Developments: An Empirical Investigation

Tomáš Adam and Miroslav Plašil *

Abstract

This paper investigates empirically to what extent financial variables can explain macroeconomic developments in the Czech Republic and how the results are sensitive to some (usually reasonable or routinely made) modeling choices. To this end, the dynamic model averaging/selection framework is applied to a universe of (potentially large) time-varying parameter VAR models, which allows one to assess the explanatory power of financial variables at each point in time. Based on a set of 27 competing models and an extensive ensemble of alternative specifications of those models, we find that financial variables were particularly relevant in explaining developments in the lead-up to and during economic downturns. By contrast, in tranquil times, models containing only traditional macroeconomic variables explained macroeconomic dynamics reasonably well. Within the broad set of financial variables considered, credit to the private sector, bank profitability, and leverage seem to be among the most relevant indicators.

Abstrakt

Tento článek zkoumá, do jaké míry pomáhají finanční proměnné vysvětlit makroekonomický vývoj v České republice a jak jsou výsledky citlivé na volbu apriorních nastavení, která jsou v empirické literatuře běžná. K tomuto účelu je využita metoda dynamického průměrování/výběru (potenciálně rozsáhlých) VAR modelů s časově proměnlivými parametry, která umožňuje určit, do jaké míry přispěly finanční proměnné k vysvětlení makroekonomického vývoje v jednotlivých obdobích. Na základě 27 modelů a široké škály jejich alternativních specifikací docházíme k závěru, že finanční proměnné přispívají k vysvětlení vývoje zejména těsně před recesemi a během nich. Naopak modely obsahující pouze tradiční makroekonomické proměnné dokázaly v klidných dobách vysvětlit makroekonomickou dynamiku uspokojivě. Z široké skupiny finančních proměnných patřily mezi relevantní ukazatele zejména úvěry soukromému sektoru, rentabilita bank a finanční páka bankovního sektoru.

JEL Codes: C32, C53, E44.
Keywords: Dynamic model averaging, macro-financial linkages, vector autoregression.

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Nontechnical Summary

Economic developments following the financial crisis of 2007—2008 brought about a reaction on both the theoretical and empirical front. The recent experience has shown that prevalent theoretical models containing traditional macroeconomic variables are not capable of fully describing, let alone forecasting, observed macroeconomic fluctuations. The research has thus shifted its focus to financial frictions and the role of financial variables in the economy. Similarly, empirical models assuming linearity have failed to forecast the severity of downturns in economic output. In response, non-linear models allowing for parameter instability and model switching have become widely embraced.

This empirical paper builds on the existing literature studying the interplay between macroeconomic and financial variables in the Czech economy. It uses a technique based on dynamic model averaging applied to a number of (potentially) large time-varying parameter VAR models. The technique assumes a large universe of candidate models, whose parameters vary over time, and estimates the probability that a particular model should be applied in a given time period. In other words, this method makes it possible to assess the explanatory potential of various models containing both macroeconomic and financial variables in explaining macroeconomic fluctuations at each point in time.

In order to evaluate the influence of financial factors on macroeconomic dynamics, we assume a large set of candidate models (27) containing macroeconomic and/or financial variables. At the same time, we investigate how the results are sensitive to various choices of parameters and settings that the researcher has to make before the estimation can start. One such choice, for example, is the choice of the target variable, i.e., the variable that should be explained as closely as possible (e.g. output growth, inflation, or both in our case).

Our estimation exercise suggests that the relationships between the variables are non-linear and that the parameters and models that govern these relationships both switch over time. The models' fit is dependent on the parameters chosen by the researcher. We show that models allowing for faster parameter adaptation provide a better fit of the variables of interest. This reflects both the transition that the Czech economy has undergone and the nature of crisis-like events, which can include abrupt and strong changes.

The explanatory power of financial variables was found to be strong in the lead-up to and during economic downturns. Additionally, macroeconomic dynamics become rather complex during these periods, as models with more than one financial variable are preferred to simpler alternatives. On the other hand, in tranquil times, the inclusion of financial variables seems to worsen the overall fit. These results proved to hold under various specifications. Regarding individual financial variables, the most relevant ones for explaining macroeconomic fluctuations include credit to the private sector, bank profitability, and leverage. By contrast, the indicator of systemic stress was not found to have a large explanatory power when compared to other financial indicators.

To sum up, this paper shows that although some financial variables were important for explaining macroeconomic fluctuations in the Czech economy, their explanatory power varied over time. It was strongest in the lead-up to and during the observed downturns in the economy. At the same time, the analysis does not reveal a single financial variable whose explanatory power is universally the highest. This might be explained by the varying nature of financial shocks.

1. Introduction

If experience is simply the name we give to our mistakes, then the recent financial crisis has made us more experienced and contributed to a considerable shift in economic thinking. The general lesson one can take away from the recent episode is that the financial realm can have unprecedentedly large effects on macroeconomic dynamics. Though the relationship between real and financial factors has long been recognized as being important (e.g. Bernanke and Blinder, 1988), the financial crisis and its effects have brought it back into the spotlight and forced policy makers to operate in a new intellectual environment.

The shift to the new paradigm has also prompted some new challenges in the area of statistics and modeling. This has led not only to the collection of new data, but also to a search for more sensible empirical macroeconomic assessment. The latter mainly reflects the incorporation of the financial sector into traditional macro models (both structural and atheoretical) and the use of a non-linear (e.g. time-varying) framework and a data-rich environment. The non-linear framework is of crucial importance, since financial crises, being episodic rather than systematic events, are almost impossible to describe using linear models. There is a growing consensus that financial and traditional macro variables are only loosely intertwined in normal times but if shocks to the real economy and the financial sector join forces and hit the economy at the same time, the negative effects can be considerable.

Drehmann et al. (2012) demonstrate that financial cycles are essentially quite independent of traditional business cycles as they are generally much longer and have higher amplitude. If, however, business cycle recessions coincide with the contractionary phase of the financial cycle, they tend to be much deeper. Similarly, Tetlow and Hubrich (2013) clearly reject a constant parameter model when studying the relation between the real economy and deteriorations in financial conditions in the US economy. Using a multivariate Markov-switching VAR model, they find that the negative output effects of a financial stress shock are much more pronounced and long-lasting in times of high financial stress than in normal times. Hartmann et al. (2013) and Holló et al. (2012) come to similar conclusions when studying the economy of the eurozone.

Based on data for the Czech economy, the present study aims to investigate how a range of financial variables are related to developments in traditional macro variables (in particular, GDP and inflation). Similarly to Tetlow and Hubrich (2013) and Havránek et al. (2012), we believe that empirical investigation of relations between the macroeconomy and the financial sector is a necessary precondition for any policy action or for the evolution of structural models. In particular, a better understanding of such interactions may have major implications for DSGE modeling of financial events and for macroprudential policy. The topic has already been analyzed for some time (e.g. Stock and Watson, 2003a; Espinoza et al., 2012; Havránek et al., 2012) but we are still far from having clearly articulated conclusions offering clear policy guidance. We believe this can be partially attributed to the application of different underlying models and modeling choices in the existing literature. While many practitioners are mainly interested in the economic message behind financial variables, we argue that the devil is in the detail and that the economic story is inseparable from thorough statistical investigation. Against this background, this paper wants to contribute to the ongoing discussion by elaborating upon several empirical and/or modeling issues that have so far (to the best of our knowledge) remained largely unexplored. First, we cast our analysis into the time-varying parameter framework, in which we allow both for changes in regression parameters and for changes in the volatility of shocks. This allows us to monitor the changing dynamics of the economic system and to account for potentially non-linear effects. Although studies going in this direction already exist (see Tetlow and Hubrich, 2013; Franta et al., 2011), they cannot provide an answer to some interesting research questions such as whether the complexity of the economic dynamics changes markedly over time. For technical reasons,[1] the literature above typically considers only one financial variable (at a time) in the model, which can be quite restrictive when one is investigating highly complex economic systems. One financial variable typically covers only a very narrow segment of the financial market and characterizes the financial sector in a very embryonic way. Using the methodology proposed by Koop and Korobilis (2013), we try to overcome this drawback and explore how the performance of a model depends on its complexity (i.e., whether a more complex environment characterized by a richly specified TVP-VAR provides a better description of the basic macroeconomic variables).

Second, while the recent literature acknowledges that the information content of individual financial variables is intrinsically time-varying, it does not explicitly account for model uncertainty and provides no operational guidance on which financial variables (if any) should be included in the model at time t. Therefore, we make a step in this direction and stick to the method first proposed by Raftery et al. (2010), which allows for dynamic change in the model dimension. This means that the estimation procedure might select a VAR model with financial variables as the 'correct' model in some periods while it may favor a model completely free of financial variables (or include only some of them) in other periods.

Third, large time-varying VARs are routinely estimated by Bayesian (MCMC) techniques, which in general are time-consuming. To avoid an excessive computational burden this usually implies that the researcher has to make some modeling decisions prior to the analysis without being able to fully evaluate their effect on the final results. These decisions include the choice of the number of lags in the VAR model and the nature and tightness of the prior distribution on the model parameters.[2] To shed some light on this issue we undertake an extensive exercise on how the results are sensitive to the researcher's choices and explore whether this may be a source of the rather mixed results across studies. This exercise is possible in our setting because the methodology proposed in Raftery et al. (2010) and Koop and Korobilis (2013) uses fast (but reasonable and quite exact) approximations, which replace tedious posterior sampling. On the other hand, the extensiveness of our analysis with respect to the researcher's prior decisions necessarily limits its scope in some other aspects. In particular, we are forced to restrict our attention to a single country and do not provide any international comparison, which potentially could be very interesting. We leave this area for future research. We note, however, that the presented results seem to point to quite general phenomena that may be of interest to a broader audience.

Finally, our paper differs from its closest relatives not only in terms of the methods used, but also in terms of the research question. It is important to highlight that our analysis should *not* be primarily seen as a forecasting exercise. While many authors focus mainly on the longer-term predictive content of financial variables[3] and/or on the construction of an indicator of financial conditions with the ambition of 'seeing a crisis coming,' our motivation is intrinsically different. We simply want to describe the interactions between macroeconomic and financial variables in different phases of the business cycle and show how the complexity of macroeconomic dynamics evolves over time. From the monetary and macroprudential policy perspective this means that we are interested not so much in the forecasting of crises and in preventive policy actions as in discovering how the 'do-as-usual' policy should accommodate changes in macroeconomic dynamics over the whole cycle.

[1] Traditional up-to-date tools such as the Bayesian time-varying parameter and Markov-switching VARs hit the sampling efficiency bound with growing complexity of the models.

[2] Of course, some pretesting is often carried out. However, testing in the time-varying VAR domain usually relies on a test for time-invariant counterparts, which is only a very rough approximation in some cases.

[3] See the literature review for details.

To offer a flavor of the results, we found that financial variables start influencing macroeconomic dynamics in the late expansionary phase of the business cycle and become particularly important in recessions. Soon as the recessions deepen, the complexity of the relationship between the macroeconomy and financial variables tends to increase. By contrast, during tranquil times models with financial variables obtain less support from the data. In general, the performance of individual financial variables varies over time. However, even under these conditions there seem to be clear winners and losers. To name at least one winner, our analysis confirmed a prominent role of credit in macroeconomic dynamics during the last financial crisis, pointing to possible obstacles on the credit supply side throttling GDP growth. Finally, we found that conclusions relating to the role of financial variables are most affected by the prior degree of variation in the model coefficients. Other modeling choices, such as the number of lags, do have an impact on the overall fit of the model, but do not considerably alter the story about how financial variables affect macroeconomic dynamics.

The paper is structured as follows. Section 2 briefly discusses the related literature. Section 3 introduces the applied methodology and the estimation procedure, while Section 4 provides additional details on the data, candidate models, and analysis design. Section 5 provides a summary of the main results, and the final Section 6 concludes. The Appendix contains more detailed outcomes of the analysis and technical details on the estimation procedure.

2. Literature Review

Contrary to the popular view in recent years, there is a long tradition of incorporating the financial sector into macroeconomic models in economic research (Quadrini, 2011). Nevertheless, only since the financial meltdown of 2007 and 2008 have the interactions between the real economy and the financial sector started to be taken seriously by the mainstream of macroeconomic practitioners. The reason for the prompt embrace of the topic is that the recently observed macroeconomic fluctuations following the turmoil in financial markets cannot be reconciled with the standard New Keynesian models. Although these models assume frictions in the price-setting process, they still assume complete markets for contingent claims and that the assumptions of the Modigliani-Miller world hold. As a result, the financial structure of firms does not matter for macroeconomic fluctuations, and agents in the economy can insure themselves against adverse contingencies.

To overcome these unrealistic features, several models have been proposed, some of which were devised even before the financial crisis occurred. Before the financial meltdown, the literature focused mostly on the role of the financial sector as an amplifier of shocks stemming from the real economy. This was achieved by introducing agency problems, such as limited or costly enforcement of contracts and information asymmetries (e.g. Bernanke and Gertler, 1989; Bernanke et al., 1999; Kiyotaki and Moore, 1997). In short, a negative productivity shock leads to a deterioration in the creditworthiness of borrowers via a change in their net worth or the value of collateral. This subsequently increases the costs of financing an investment (or tightens credit constraints) and leads to lower investment in the economy and more severe downturns than without the introduced imperfections.

Particularly in recent years, the literature has been exploring another dimension of the interaction between the financial and the real sector: the role of the financial sector as a shock originator. In this case, disruptions in the financial sector (financial shocks) affect credit constraints and lead to lower flows of funds from lenders to borrowers, which has repercussions for the real economy. References for how these shocks originate and propagate can be found in Quadrini (2011) and Brunnermeier et al. (2012), for example.

Turning to the empirical literature, several papers study whether including financial variables in empirical models can help predict macroeconomic variables and what their effects are. The results, however, are not unequivocal. In general, the conclusion of this strand of literature is that some financial variables do help predict macroeconomic variables, but their forecasting power varies over time. In addition, some variables help predict only inflation or only GDP growth.

One of the first attempts was by Stock and Watson (1999), who considered, among other variables, the role of stock prices, interest rates and their spreads, and money and credit aggregates. They found that forecasts based on the Phillips curve generally outperformed those based on other variables, including financial variables. A more recent article by Stock and Watson (2003b) explores the role of asset prices, which are by definition forward looking, on a panel of seven advanced countries. They conclude that the forecasting power of some financial variables is significant, but is not stable across countries, time, and variables. They suggest that combining forecasts from relatively poor models could lead to superior models, but econometric models at that time lacked this ability.

Another approach to assessing the predictive content of financial variables is by Forni et al. (2003), who take averages of financial variables as an explanatory variable of euro area inflation and industrial production. They conclude that financial variables help in forecasting inflation but not industrial production. In addition, the empirical evidence is mixed with respect to model specification, sample choice, and forecast horizon.

An approach closer to the original suggestion of Stock and Watson (2003b), consisting in the combination of forecasts, is taken by Koop and Korobilis (2012), who propose a method based on the dynamic model averaging by Raftery et al. (2010). This method is able to combine time-varying models by assigning time-varying weights to each of them. Thus, the parameters of each model vary over time, as does the weight of each model in the resulting aggregate model. In their empirical application, they include, among other variables, 3m Treasury bill rates, spreads between 10-year and 3-month interest rates, the M1 monetary aggregate, and a stock market index. They conclude that even the best predictors change over time. Among financial variables, the best predictors were 3m Treasury bill rates and interest rate spreads. As an extension, Koop and Korobilis (2013) study the switching of three VAR models (with respect to model size). The middle model includes borrowings of depository institutions from the Fed, the S&P 500 index, and the M2 money stock, and the large model also includes 10-year Treasury yields.

The literature referenced so far examines the power of individual variables for predicting macroeconomic variables. But there is also a different strand of literature which examines the explanatory power of the financial conditions, as captured by a financial conditions index (FCI) aggregating many financial variables (a review of indices can be found in Hatzius et al. (2010), for example). To sum up, the construction of FCIs faces a difficulty in the choice of explanatory variables as well as the problem that their explanatory power changes over time and that the effect of the aggregate financial conditions on the macroeconomy can be time-varying. All of these problems are tackled by Koop and Korobilis (2014), who propose a FAVAR with time-varying coefficients to capture how the financial conditions influence the economy. That is, the financial conditions are modeled as a latent factor, whose loadings as well as its effect on the economy are time-varying. In addition, the paper considers dynamic model averaging, i.e., the variables used for the construction of the FCI index can switch over time.

Regarding the Czech economy, the literature studying the effects of the financial sector on the macroeconomy is not very extensive. Ryšánek et al. (2012) study the implications of financial frictions for the Czech economy. Their model suggests a faster reaction of monetary policy during

2009 compared to the model without frictions. This is consistent with the finding that the effect of financial frictions is more pronounced when interest rate spreads are increasing, which supports the use of non-linear forecasting models containing financial variables.

Empirically, Havránek et al. (2010) conclude, based on a fixed-parameter VAR model, that financial variables generally improve the forecasting performance of the model, but the improvement varies across periods and also with respect to the forecasted variable. The exception is the stock market, which always improves the forecast of both GDP and inflation. Non-linear interactions between domestic macroeconomic variables, financial variables (credit, NPLs), and exogenous variables in a threshold VAR model are studied by Konečný and Babecká-Kucharčuková (2013). In this model, the threshold value of credit spreads between the rate on newly issued loans and the money market rate is endogenously estimated. The authors find that the responses of real variables are procyclical and do not vary much across regimes given by the value of the threshold variable; on the other hand, the responses of financial variables to real shocks do differ across regimes.

3. Modeling Framework and Estimation Methodology

In this paper, we study interactions between the macroeconomy and financial variables within the VAR framework. From the perspective of economic theory, the model allows the researcher to stay purely on statistical ground, while keeping in touch with theoretical underpinnings. The VAR model has long been used as a starting point for monetary policy analyses and its link to more theory-founded models is intensified by the fact that a reduced form of a large variety of DSGE models can be cast into the VAR form. In addition, VAR models have proved to be successful in forecasting exercises.

Following the recent standard in the VAR literature as set out in Primiceri (2005), we use the time-varying parameter VAR with a time-varying covariance matrix. Allowing for changes in the VAR parameters and in the error covariance structure has been shown to be important for empirical assessment of the Czech economy (see Franta et al., 2014).

Given that the Czech Republic is a small and very open economy likely to be affected by foreign shocks (be they in the form of foreign demand, foreign inflation or commodity prices), we control for external developments by including exogenous variables in the VAR model. Exogeneity implies that foreign variables can influence domestic variables, while the opposite does not hold. The resulting reduced-form VAR-X model can be written as

$$y_t = c_t + \sum_{i=1}^{p} A_{i,t} y_{t-i} + \sum_{j=1}^{q} B_{i,t} x_{t-j} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma_t) \tag{3.1}$$

where y_t and x_t are vectors of endogenous and exogenous variables, respectively, c_t is a vector of constants, and $A_{i,t-i}$ and $B_{i,t-i}$ are matrices of parameters.

In the canonical macro VAR models for open economies, vector y_t usually includes a measure of real economic activity (GDP, industrial production or unemployment), a measure of price developments (CPI or PPI inflation), a measure of the monetary policy stance (proxied by a short-term money market rate), and the exchange rate. To analyze the links between the macroeconomy and the financial sector, vector y_t is further enriched by financial variables. We examine the role of financial variables which have appeared in previous studies of the Czech economy (Havránek et al., 2010; Franta et al., 2011) and enlarge this set by some yet unexplored ones. The financial variables are listed and described in full in Section 4.

As Havránek et al. (2010), for example, have stressed, there is *a priori* large uncertainty about which set of financial variables best characterizes developments in the financial sector. Moreover, the relevance of individual financial variables or combinations thereof may vary over time, for example as a result of different economic conditions over the business cycle and different underlying financial shocks. To tackle the uncertainty and the choice of relevant variables explicitly, we use the approach proposed in Koop and Korobilis (2013), which combines the merits of (potentially large) time-varying parameter (TVP) VAR models with the Bayesian model averaging (selection) framework. The model averaging is done recursively, which means that the estimation procedure allows for different models to be selected in every period (based on the posterior model probability criterion).

In more formal terms, we consider a system of N time-varying VAR models switching over time and filter their posterior probabilities in a Markov-switching manner. The complete set of models considered in our analysis is again presented in greater detail in Section 4.

Estimation of the described system of equations is infeasible without recourse to approximations that eliminate the need for computationally demanding MCMC sampling. Following Koop and Korobilis (2013), we solve this problem by using three different forgetting factors, which greatly simplify estimation of the variances in the measurement and transition equations of the Kalman filter as well as the calculation of transition probabilities between candidate models (see Appendix A for all the technical details). This approach allows us to quickly estimate all the (time-varying) parameters for a given set of candidate models and compute their posterior model probabilities. These time-varying probabilities are then taken as the basis for the empirical assessment of the impact that financial variables have on macroeconomic dynamics and their complexity.

4. Data, Candidate Models, and Analysis Design

4.1 Data and Models

To model the Czech economy, we use monthly data from 1999:1 to 2012:12. Since our focus is not directly on forecasting, we use the revised data set available in May 2013. The monthly data was chosen in order to exploit the highest available frequency due to a rather limited number of observations. The 1999 starting point was chosen for two main reasons: first, it coincides with the creation of the euro area (its data are used as exogenous variables), and second, Czech financial variables do not have too long a history, so we had to strike a balance between data availability, data quality, and methodological consistency over time. The year 1999 seems to be a reasonable compromise between these requirements, although it is important to note that data at the beginning of the sample may still have dubious information content or may be marked by one-off effects related to the financial crisis in the late 1990s. Some caution is thus in order.

We use standard macro variables to capture developments in the real economy: real activity is captured by annual GDP growth disaggregated into monthly frequency using the Chow-Lin technique, with industrial production used as an auxiliary indicator variable. Price developments are measured using annual CPI inflation,[4] interest rates using the short-term interbank rate (3M PRIBOR), and exchange rate fluctuations using annual growth in the CZK/EUR exchange rate. Similarly, real and price developments in the Czech Republic's main trading partners are captured by the monthly euro area GDP and HICP inflation measures. In addition, we use oil prices as a proxy for commodity prices.

The choice of financial variables reflects the fact that the Czech financial sector is primarily bank-based. The list is still far from being exhaustive, but its size is somewhat limited by data availability and quality. In particular, it was not possible to include any relevant measure of interest rate spread (say, the difference between interest rates on new loans and the interbank rate) as the time series concerned were too short. Moreover, unlike Havránek et al. (2010) we also exclude the measure of banking-sector liquidity as the Czech banking sector remained largely liquid over the entire sample and changes in this indicator may reflect factors other than financial shocks. Our set of financial variables thus contains credit to the private sector, growth in non-performing loans, non-performing loan coverage (the ratio of loan loss provisions to the volume of non-performing loans), returns on equity of the banking sector, leverage of the banking sector, monetary aggregate M2, the Prague stock market index (PX), and the euro area composite indicator of systemic stress (CISS). As shown in Adam and Benecká (2013), the indicator of financial stress constructed for the Czech financial system is highly correlated with the one constructed for the euro area. However, due to its limited sample length, we use the original index in our analysis.

The first five financial variables describe developments in the banking sector from both the risk accumulation and risk materialization perspectives. The contribution of monetary aggregates to improving forecasting models is frequently analyzed, as is the role of stock market indices, so it is quite natural to include them in our analysis. We also included the indicator of systemic stress (CISS) as it is becoming a popular choice in the empirical literature (see Holló et al., 2012; Hartmann et al., 2013, among others). The CISS captures volatilities on different financial markets and combines them into a single composite indicator using a simple aggregation algorithm. As such it represents a measure of the overall uncertainty (stress) on markets, and changes in its level may indicate uncertainty shocks to the economy. In this light, inclusion of the CISS may also help answer the interesting question of whether financial developments or pure uncertainty shocks matter more for macroeconomic fluctuations (though it can sometimes be difficult to separate the two).

A comprehensive list of the variables and their initial transformations is presented in Table C.1. While the definitions of all the variables are quite standard, our measure of credit deserves closer attention. We opt for a rather unconventional indicator defined as the gap between the log level of credit at time t and the minimum of the credit level during the previous 12 months. This one-sided measure, which is similar in construction to the unemployment recession gap advocated by Stock and Watson (2010), searches for local credit expansion extremes and mutes phases of negative growth. As such it gauges the build-up phase of the credit cycle and its way back to the trough. We prefer this measure to the credit growth series as the latter is plagued by banks' efforts to clear their balance sheets of bad loans provided in the 1990s and by the transfer of those loans to a special-purpose agency. As a result, the credit growth series exhibits a slump which cannot be accounted for by the economic environment.

A candidate VAR model can be formed as any subset of the variables discussed above, but we take a more targeted approach as it better serves our purposes. We consider four models containing only

[4] We do not use net inflation (i.e., inflation excluding administrative prices) because the official time series is not long enough.

Table 1: List of Candidate Models

macroeconomic variables	
1	gdp_cr, infl_cr
2	gdp_cr, infl_cr, pribor
3	gdp_cr, infl_cr, czkeur
4	gdp_cr, infl_cr, pribor, czkeur
one financial variable	
5	gdp_cr, infl_cr, pribor, czkeur, credit
6	gdp_cr, infl_cr, pribor, czkeur, leverage
7	gdp_cr, infl_cr, pribor, czkeur, npl
8	gdp_cr, infl_cr, pribor, czkeur, roe
9	gdp_cr, infl_cr, pribor, czkeur, coverage
10	gdp_cr, infl_cr, pribor, czkeur, ciss
11	gdp_cr, infl_cr, pribor, czkeur, m2
12	gdp_cr, infl_cr, pribor, czkeur, px
two financial variables	
13	gdp_cr, infl_cr, pribor, czkeur, credit, roe
14	gdp_cr, infl_cr, pribor, czkeur, credit, leverage
15	gdp_cr, infl_cr, pribor, czkeur, roe, leverage
16	gdp_cr, infl_cr, pribor, czkeur, npl, coverage
more than two financial variables	
17	gdp_cr, infl_cr, pribor, czkeur, npl, coverage, ciss
18	gdp_cr, infl_cr, pribor, czkeur, credit, roe, m2
19	gdp_cr, infl_cr, pribor, czkeur, credit, roe, px
20	gdp_cr, infl_cr, pribor, czkeur, credit, leverage, m2
21	gdp_cr, infl_cr, pribor, czkeur, credit, leverage, px
22	gdp_cr, infl_cr, pribor, czkeur, credit, leverage, roe
23	gdp_cr, infl_cr, pribor, czkeur, credit, roe, m2, px
24	gdp_cr, infl_cr, pribor, czkeur, credit, roe, leverage, m2
25	gdp_cr, infl_cr, pribor, czkeur, credit, roe, leverage, px
26	gdp_cr, infl_cr, pribor, czkeur, credit, leverage, roe, m2, px
27	gdp_cr, infl_cr, pribor, czkeur, credit, leverage, roe, m2, px, coverage, npl,ciss

traditional macro variables, then a suite of models additionally containing one or more financial variables, and finally the model containing all the variables. As to the models with one to three financial variables, some effort was made to form models with respect to either risk accumulation or materialization characteristics, but this distinction cannot always be made. The list of competing models is shown in Table 1. The choice of the model universe is arguably subjective, but we believe it is representative enough for the research questions at hand.

4.2 Analysis Design

Before we proceed to the presentation of our results, we outline the design of our exercise. Based on the posterior model probabilities, our ultimate goal is to assess the changing performance of selected models over time. This is chiefly driven by a desire to find out what model best describes actual economic developments in a given period, as this should help distill the stylized facts about macroeconomic dynamics in different phases of the business cycle. Such facts can in turn be used in the construction of better-grounded theoretical models.

However, we would also like to control for some modeling choices made by the researcher and find out to what extent these prior choices affect the final results. Our perception is that many existing studies do not pay sufficient attention to this issue and that the justification and robustness of the results are often not fully presented. In our analysis, we pay particular attention to the choice of the number of lags in the VAR model, the tightness of the prior on the autoregressive parameters β (regulated through the shrinkage parameter γ, see Section A.3), and the prior variability in coefficients β (determined by λ_{min} and L, see eq. A.7). Moreover, through the choice of predictive density we also control for potentially different preferences of individual researchers, as they may not be equally interested in all the variables included in the model.

As from the Bayesian perspective the model is fully defined by the tandem of the likelihood and the prior, we can think of different technical settings as definitions of various models. This implies that each of the 27 candidate models described in Section 4 can enter the analysis in dozens of mutations that reflect alternative modelers' choices or views about the priors. As a result, the original model universe inflates dramatically, eventually reaching several thousand models. Since a full description of these models is very extensive, we postpone the discussion of the choices along each dimension to Appendix B (where the model dimensions are given by the number of lags, the tightness of the prior, the variability of the coefficients, and the choice of predictive density).

5. Empirical Findings

5.1 The Impact of Modeling Choices on the Results

We first explore the general impact of modeling choices on the diversity of the results obtained. Readers interested purely in the economic message (stripped of technical details) may want to skip this subsection and proceed directly to the following one. However, we stress again that the process of model construction is an integral part of the economic story-telling.

Our exercise suggests that the results are most affected by the choice of priors related to the amount of variation in the coefficients. Conditional on this choice, the researcher can observe various posterior model probabilities and thus obtains qualitatively different empirical evidence. Based on the MSE and likelihood measures of the global model's performance, it is apparent that models allowing for higher variation uniformly outperform their relatively stable counterparts (see Table 2). This holds true for all three alternative specifications of the predictive density.

Our finding may mirror two phenomena in particular. First, as the Czech Republic belongs to the group of transition countries converging toward the advanced economies, observed (one-off) structural changes may be better captured by more dynamic models, especially at the beginning of the sample, where structural changes still played a considerable role. However, in recent years, when the pace of convergence has slowed, the preference for greater variation in the coefficients may point to a rather different and more general phenomenon related to the non-linear pattern of (financial) crises. As the previous literature suggests, crises are rare and episodic events with quite fast materialization of risks and an almost immediate influence on the economic conditions. This may explain why constant-parameter models or models only allowing for gradual changes in coefficients provide an inferior description of the data when the economic dynamics are marked by an unfolding crisis.

These results have serious implications for the elicitation of priors in VAR models aiming at the modeling of crises, particularly in situations where the sample is quite short and priors assume a predominant role. It is common practice to set the prior variation in the coefficients using a training sample.[5] However, if the training sample covers relatively tranquil periods, the model may not adapt well to the considerable but episodic changes in economic dynamics induced by crises. As a result, the outcomes of such a model can become severely distorted. Eventually, our results suggest that the issue should be cautiously tackled and the robustness of the results should always be demonstrated. Moreover, a time-varying data-driven approach such as ours seems to be a preferable option, as it allows for little change in stable times and for abrupt parameter accommodation otherwise.

Table 2: The Measures of the Best Models' Fit

(a) lamba = 0.96, L = 1.1

	4 lags			6 lags			9 lags		
density	**model**	**gamma**	**criterion**	**model**	**gamma**	**criterion**	**model**	**gamma**	**criterion**
criterion: likelihood									
GDP	1	0.10	-92.04	1	0.10	-93.64	1	0.10	-96.43
avg			-108.68			-112.24			-115.17
Inflation	11	0.10	-111.22	11	0.10	-108.99	2	0.10	-101.10
avg			-120.26			-117.60			-110.69
GDP, inflation	1	0.10	-200.94	1	0.10	-201.29	1	0.10	-202.55
avg			-224.26			-224.97			-242.81
criterion: MSE									
GDP	6	0.10	0.17	6	0.10	0.17	6	0.10	0.18
avg			0.22			0.22			0.22
Inflation	11	0.10	0.23	24	0.10	0.24	26	0.10	0.21
avg			0.27			0.30			0.26

(b) lambda = 0.9, L = 1.3

	4 lags			6 lags			9 lags		
density	**model**	**gamma**	**criterion**	**model**	**gamma**	**criterion**	**model**	**gamma**	**criterion**
criterion: likelihood									
GDP	1	0.10	-90.42	1	0.10	-91.97	1	0.10	-94.18
avg			-105.69			-109.54			-112.62
Inflation	11	0.10	-109.02	11	0.05	-106.70	2	0.10	-99.98
avg			-116.41			-114.25			-110.00
GDP, inflation	1	0.10	-194.70	1	0.10	-195.23	2	0.10	-193.33
avg			-215.50			-217.55			-219.94
criterion: MSE									
GDP	6	0.10	0.17	6	0.10	0.17	21	0.10	0.17
avg			0.20			0.20			0.20
Inflation	11	0.10	0.22	24	0.10	0.23	26	0.10	0.21
avg			0.25			0.28			0.25

Note: The measures of the best models' fit (likelihood, MSE) for two sets of hyperparameters determining the 'smoothness' of parameters (a,b). Column 'Model' shows which model has the best fit and column gamma shows its corresponding gamma (tightness) parameter. Rows 'avg' denote the averages of the criterion over the best 50 models. The MSE criterion is not available for the bivariate criterion (GDP, inflation) for interpretation reasons.

The results furthermore indicate that whereas the number of lags has some influence on the global performance of models (see Table 2), the choice of the number of lags has a surprisingly low impact on the assessment of the relative performance of the model vis-á-vis other models as measured by the posterior model probabilities. With the exception of the univariate marginal density of inflation, where the posterior model probabilities vary slightly with the change in the number of lags, all the other results offer quite a similar story (see the next subsection). In general, the optimal lag length seems to depend on the choice of predictive density: while for GDP and the bivariate marginal density of GDP and inflation the data are best captured by only 4 lags, in the case of inflation a choice of 9 lags tends to be favored in terms of the likelihood. We read these results as showing that the optimal lag length is closely related to the research question. If the researcher is only interested in the relative performance of models with and without financial variables, the number of lags does not pose a major problem. If, however, the models are to be used for forecasting purposes, the

[5] Note that even under this approach, the researcher controls the amount of variation in the coefficients *subjectively*, as the prior distribution based on the training sample is typically scaled by a scaling factor (often denoted by τ) chosen by the researcher.

researcher should be mindful of the ultimate purpose of the model, as a universally optimal lag length for forecasting different variables does not seem to exist. As a corollary, global criteria such as the AIC or BIC do not necessarily lead to the selection of the optimal lag length if the researcher is largely interested in the prediction of a single variable (while being quite indifferent to the others).

Interestingly, we did not find any systematic switching pattern in the parameters γ driving the degree of shrinkage in the VAR coefficients. Even more importantly, the value of 0.1 implying the lowest degree of shrinkage dominates in almost all periods and for all candidate models. This is a little strange, since one would expect the degree of shrinkage to become larger as the dimension of the VAR increases. This is at least common practice in the literature on large VARs (see Koop and Korobilis, 2013), where shrinkage is introduced to avoid overfitting. One possible explanation for our result is that we work with monthly data. Since the response of the variables to the initial shock usually exceeds a period of one month, the inclusion of higher lags is crucial to capture the economic dynamics, and the coefficients on higher lags cannot automatically be shrunk to zero. While for quarterly data it is usually reasonable to assume that more distant quarters are a priori less relevant, this is not necessarily the case for monthly data in macroeconomic applications. Since the results suggest that the choice of γ tends to be empirically uninteresting in terms of comparing the models, we factor them out from the subsequent analysis by summing the posterior model probabilities along this dimension. This means that we eventually obtain posterior model probabilities for all 27 candidate models which are unconditional on the initial prior on the VAR coefficients. Doing this and keeping the number of lags fixed at the length determined above we can now assess the relative performance of each candidate model.

5.2 Interplay of Macroeconomic and Financial Variables

Since the most interesting conclusions can be drawn when one maps the evolution of the posterior model probabilities onto past economic events, we first make a little digression and review the key facts about the Czech economy. After a banking and economic crisis in the late 1990s, the Czech economy experienced a gradual recovery and returned to growth and a relatively stable environment. These favorable economic conditions (which we later refer to as 'normal' times) lasted roughly until 2009, when the world-wide effects of the financial crisis spilled over into the Czech economy and caused a deep recession. The few years leading up to the crisis can be considered a boom, with economic growth recording a historically fast pace. This period coincided with the peak of the financial cycle, with year-on-year credit growth above 20%. The downturn starting in 2009 heralded a W-shaped recession and, after a mild recovery in 2010 and 2011, the economy slid back into slowdown (fueled by the sovereign debt crisis in the EU). Similarly to the situation in developed countries, the recent economic performance is marked by low aggregate demand and a low inflation environment. These phenomena are being accompanied by a rather limited scope for traditional monetary policy, as policy rates have hit the zero lower bound, opening up a debate about unconventional monetary policy.

As far as the financial sector is concerned, it has been dominated by the banking sector since the transformation of the Czech economy in the 1990s. The banking sector itself has undergone dramatic restructuring, especially after the banking crisis in 1997/1998, which resulted in the closure of several small and mid-sized banks. After the crisis, a successful effort was made to find strategic foreign investors for the major Czech banks. This led to stabilization of the banking sector and banks managed to build up sufficient capital cushions over the following years. The well-capitalized Czech banking sector then weathered the latest financial crisis without serious difficulties. This can also be attributed to its very low exposures to problematic regions and to the mainly local deposit funding of Czech banks. Nevertheless, the economic downturn starting in 2009 still resulted in sizable credit losses and elevated levels of credit risk. In response to these developments, banks temporarily restricted the flow of credit into the sound part of the economy and may have contributed to a deeper and longer decline in GDP. However, the subdued credit supply was soon followed by a corresponding decline in credit demand. Muted credit activity (driven mainly by the demand side) has been observed ever since, with the exception of a minor upsurge during the modest economic recovery in 2010 and 2011. Recently, low credit growth in combination with a low interest rate environment has been putting downward pressure on bank profitability and may stimulate search-for-yield behavior.

Armed with a rudimentary knowledge of Czech economic *realia*, we can take a closer look at the path of the posterior model probabilities. Although it might be tempting to offer an explanation for every single blip in the posterior model probability, we refrain from doing so and only focus on the main features of the macroeconomic dynamics. We prefer to take a bird's-eye view rather than looking through a microscope as we believe that a more distant perspective can provide more general and less idiosyncratic outcomes which may be of interest to a broader audience. To reduce visual 'clutter' in the results, we group the 27 candidate models into four categories: the first category contains models which do not contain any financial variable ('traditional macro models'), the second category is formed by adding one financial variable at a time ('1 financial variable'), the third category encompasses models with two financial variables ('2 financial variables'), and the fourth category contains all the rest ('$>$ 2 financial variables'). Apart from making the presentation of the results clearer, the grouping helps determine how the complexity of the model needs to be changed in different periods to best capture movements in GDP growth and/or inflation. Figure 1 depicts the models with the maximum posterior model probability in each period both globally (black bars) and within each category (blue bars) and Figure 2 shows the evolution of the posterior model probabilities over time, where the probabilities were summed along the categories (periods with negative GDP growth are shaded gray).[6]

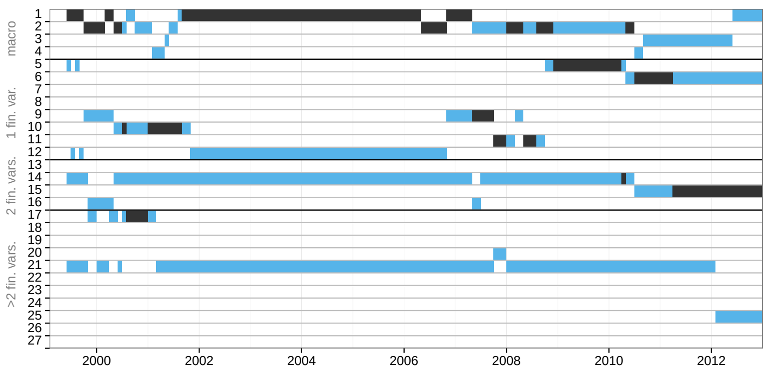
The most general observation is that there is a clear tendency in the model-switching behavior no matter which choice of predictive density is used to derive the posterior model probabilities. The switching takes place between the model categories as well as between the individual models within each category. While this supports the inclusion of financial variables in the model in quite a high number of periods, the contribution of individual financial variables seems to be only temporary and does not stretch over too long a horizon. This means that financial variables themselves take turns in receiving the best model 'award,' indicating a need to consider a larger set of financial quantities when modeling the economy across time. In this light it can be argued that the traditional strategy, which consists in isolated analysis of the VARs with one financial variable at a time (see e.g. Havránek et al., 2012) and in the subsequent assessment of global properties, might provide a slightly distorted picture. On the other hand, it can also be seen that the most complex model (i.e., that containing all the explanatory variables) is never selected. This may be caused either by hitting the estimation efficiency bound, where the number of parameters is too high to get any reasonable estimates, or by the fact that the macroeconomic dynamics are indeed only poorly characterized by such variable-rich VARs. Either way, it should probably discourage the use of excessively complex TVP-VAR models in empirical work, especially when the data sample is relatively short.

Moving from general observations to more specific conclusions, one can immediately see that in 'normal' times, models without financial variables outperform those with financial variables by an

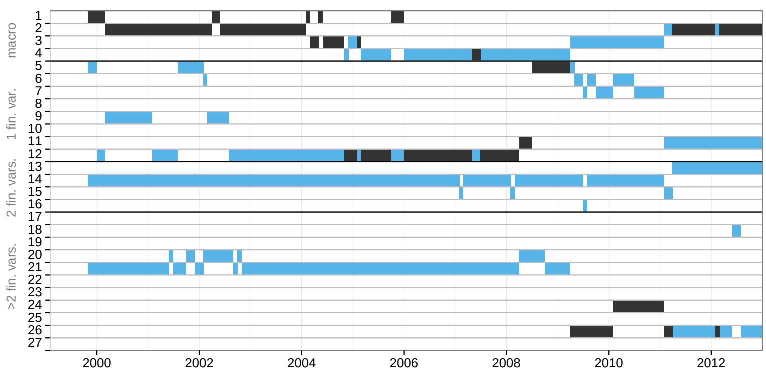
[6] Since even the worst model always has some probability mass, categories containing more models than the others would *ceteris paribus* display a higher posterior probability by construction. This holds true even if all the models perform equally well. For this reason we divide the posterior probability of each category by its cardinality and scale it to sum to one. This can be seen as a form of penalty for categories containing a higher number of models. Charts with unpenalized posterior probabilities can be found in the Appendix.

Figure 1: Best Models

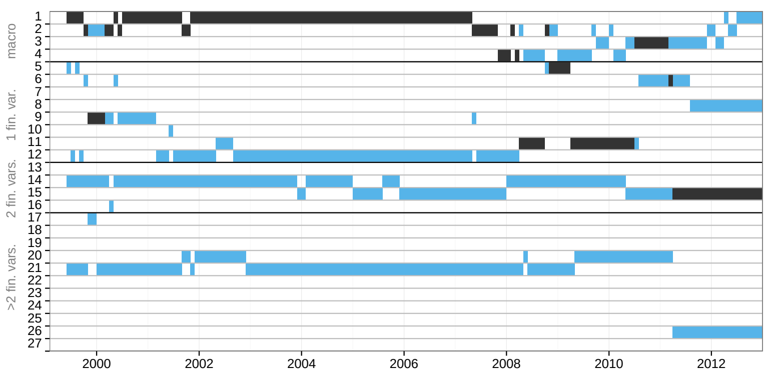
(a) GDP (4 lags)



(b) Inflation (9 lags)



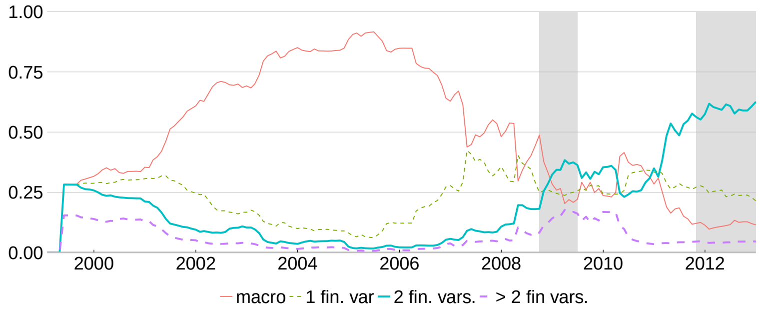
(c) GDP, inflation (4 lags)



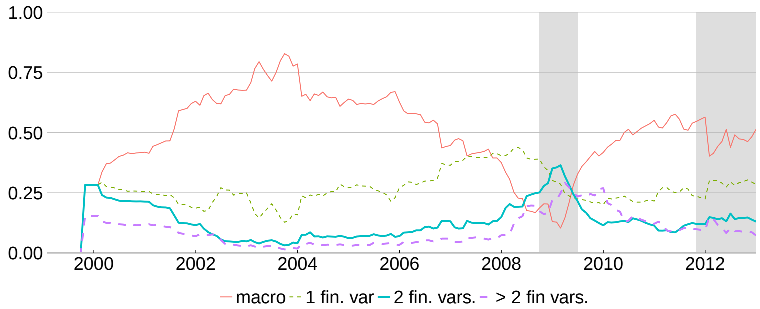
Note: Best models ($\lambda_{min} = 0.9, L = 1.3$): black (darker) squares represent models with the (absolutely) highest probabilities in the given time period. Blue (lighter) squares represent models with the highest probabilities in each category. macro = models with macroeconomic variables only. The list of variables in each model can be found in Table 1.

Figure 2: Posterior Model Probabilities

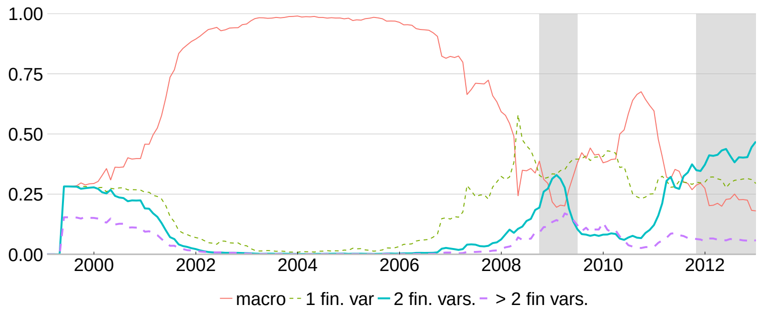
(a) GDP (4 lags)



(b) Inflation (9 lags)



(c) GDP, inflation (4 lags)



Note: The lines represent updated (posterior) conditional probabilities summed over each category of models. $\lambda_{min} = 0.9, L = 1.3$; macro = models with macroeconomic variables only. The shaded areas in the figures indicate negative GDP growth in the given period.

impressive margin. The posterior model probabilities show that financial variables are little related to movements in traditional variables in tranquil periods, and this seems to revert only in the very late expansionary phase of the business cycle. Quite importantly, nothing seems to suggest that financial variables convincingly help explain movements in GDP and inflation too long before a crisis/recession occurs.

On the other hand, the economic dynamics in the downturn of the business cycle are very likely to be explained by more complex relations between variables. In both 2009 and 2012, the complexity of the relations tended to increase with the severity of the recession. Traditional macroeconomic VARs consistently lose their efficiency and become less appealing. This underscores the nature of (financial) crises, which can be characterized by negligible interplay between traditional macro variables and financial factors in normal times and by a largely negative synergy when the crisis unfolds. These results can have a huge impact on monetary policy conduct during crises, as it appears that in crises the traditional models exhibit the largest failure to describe economic dynamics, while the need for policy actions in such periods is the most urgent. This suggests that we need not only more intensive study of the policy options, but also new underlying models that provide a more faithful economic picture and better guidance for policy decisions during recessions.

Although the general message about the fluctuating performance of traditional macroeconomic VARs holds true across all predictive density specifications, the choice of predictive density still leads to important nuances. In the scenario where the researcher is mainly interested in the predictive density of GDP growth, the posterior ‘category’ probability of VAR models without financial variables starts to decline gradually in 2005, and between 2007 and the advent of the recession exhibits roughly the same performance as the category of models with one financial variable. However, none of the financial variables appears to gain a convincingly predominant role indicating a systematic influence in this period. During the crisis the posterior model probability of more complex models increases and credit and bank leverage become — either separately or in combination — particularly important determinants. The need for greater complexity is somewhat muted during the subsequent short recovery, but it becomes pressing again as the economy dips back into recession. During the renewed recession, bank profitability (RoE) and leverage are the key financial variables which help to better explain GDP growth.

The course of the posterior model probabilities based on the predictive density of inflation exhibits similar features to that based on GDP growth, with the exception of the recession in 2012, when the basic macroeconomic VARs still work better than their counterparts with financial variables. Differences also exist in terms of the financial variables that are favored by the model selection procedure. The model with the stock price index gets the highest support in the pre-crisis period (say 2004—2008), while with the advent of the crisis it is replaced by the model containing the credit variable. Credit is later complemented by other variables, resulting in the selection of models with very high complexity. The explanatory power of the stock price index with respect to the inflation rate may seem quite surprising. However, this result has been observed in earlier studies on the Czech economy (Havránek et al., 2012). The posterior category probabilities based on the bivariate predictive density also bear conspicuous resemblance to the previous results. However, the predominance of traditional macro models in tranquil times is even more pronounced. The use of bivariate density leads to the selection of different models than in the previous two cases. Nevertheless, they again include credit, leverage, and return on equity. Unlike before, M2 also has some explanatory potential for mutual developments in GDP growth and inflation, especially between 2008 and 2009 (i.e., at the tipping point between the peak of the cycle and recession).

Overall, our analysis revealed that except for tipping points and the ensuing recessions, the impact of financial variables on GDP growth and inflation is rather limited. Although from time to time a model with financial variables is favored even in tranquil periods, this selection does not exhibit any systematic pattern and is rather haphazard in nature. On the contrary, the role of some financial variables during economic downturns seems to be particularly important. This documents the presence of highly non-linear effects. Our results confirm the existence of a strong link between credit developments and the path of GDP growth and inflation during the Great Recession, but other financial variables (leverage, RoE) also turned out to provide some explanatory gains for macroeconomic dynamics during (or slightly before) economic slowdowns. Some financial variables remained of little use over the whole time span, the most prominent member of this group being the indicator of systemic stress (CISS). This is quite striking, as the CISS and similar indicators are commonly thought to be a reasonable choice when one wants to incorporate links to the financial sector into the model (e.g. Holló et al., 2012). However, this may point to the fact that the course of financial variables actually matters more for macroeconomic dynamics than their second moments (i.e., their volatility or associated 'uncertainty') .

While in our hands the ability of the CISS to provide a better fit breaks down in the face of other financial variables, this does not mean it is automatically irrelevant in other econometric frameworks. For example, it still may serve as a good threshold indicator for modeling a change in parameters. Since episodes of elevated financial stress are quite well correlated with periods of deep recession, the previously established result in the literature that the economic environment dramatically changes when in a high-stress state is not in stark contradiction with our findings. Anyway, regardless of what methodology is used, our exercise highlights an urgent need for further development of non-linear models and corresponding economic theory.

6. Conclusions

In this paper, we assessed to what extent the financial side of the economy relates to the evolution of traditional macroeconomic variables. We analyzed this question within the dynamic model averaging/selection framework applied to large time-varying VAR models. We also explored thoroughly how the results vary due to various plausible priors that the researcher can choose.

Although we only analyzed a single economy — the Czech Republic — we believe our findings might be of interest to a much broader audience. However, we realize that a more thorough cross-country analysis would still be needed to reach more universal conclusions. Unlike some previous studies, our interest in financial variables is driven not by their longer-term forecasting potential, but rather by their immediate influence on economic dynamics. Identification of periods when financial variables help to better capture macroeconomic developments not only uncovers changes in dynamics, but also highlights episodes when traditional macro models may fail to deliver a fair picture of the economy and thus may potentially provide inadequate guidance for monetary policy decisions.

Our analysis revealed substantial evidence that economic dynamics are driven by non-linear patterns of two kinds: the first relates to the observed variation in the model coefficients, while the second relates to the time-varying model dimension. Placing our main research interest on the latter, we found that in normal times, models without financial variables perform reasonably well and can beat their counterparts containing financial characteristics by a considerable margin. In recessions, however, models containing financial variables gain some advantage over those without them. Once the economy shifts to the recessionary phase of the business cycle, the interplay between macroeconomic and financial variables has a significant impact on the economy. Moreover, in periods of economic slowdown these links seem to get rather complex, as models with more than one financial variable are preferred to simpler alternatives. Nevertheless, given the limited sample length, which only covers two recent economic recessions, some caution is still necessary for generalizing the results.

When studying the role of individual financial variables, credit, returns on equity, and bank leverage turned out to bear significant information on developments in both GDP growth and inflation during recessions. Some other financial variables (especially M2 and the stock price index) also contributed to a better fit in some periods. However, their influence is somewhat less systematic and thus perhaps less convincing. On the other hand, some variables failed to live up to their good reputation. Most notably, the indicator of systemic stress (CISS) surprisingly loses the game when it is confronted with other financial variables. This may highlight the fact that financial developments rather than the general uncertainty (read volatility) associated with financial turmoil chiefly drive macroeconomic dynamics.

The observed impact of financial variables suggests a need to translate these features into better-founded theoretical concepts. In particular, the theory should provide more elaborate insights into the economic nature of episodic events such as crises and recessions and explain the role of the financial sector in them. At the same time, we should better understand how the economy moves from one state of operation to another. As recessions generally require the adoption of the most relevant policy measures, the pursuit of a faithful picture of the economy in a recession becomes all the more pressing for policy conduct to hit the intended target.

As for the degree of variation in the coefficients, we found that models allowing for slow gradual changes capture the dynamics of the Czech economy worse than those with faster adaptation to the new conditions. While this partially reflects the transition character of the Czech economy and the presence of structural breaks at the beginning of the sample, it also signals that non-linear effects can be quite swift and strong. The number of lags in a model does not significantly alter its relative performance vis-á-vis its competitors, but still has a marked impact on its performance in absolute terms. The optimal lag length also depends on the researcher's preferences with respect to the main variables of interest, i.e., on the choice of the form of the predictive density. To sum up, the results of our exercise imply that some prior choices should perhaps be made more carefully and justified more explicitly in empirical practice.

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Appendix

Appendix A: Modeling Framework and Estimation Methodology

This section describes in detail the estimation methodology outlined in Section 3 and draws on Koop and Korobilis (2013). The first part describes the estimation procedure, where we consider a single time-varying parameter (TVP) VAR model. The subsequent parts give a detailed account of how the probabilities of each model are filtered recursively and how the choice of priors on the initial values of the state variables can be made.

A.1 The Case of a Single Model

Estimation of the parameters in a single TVP model with forgetting factors is quite similar to the traditional state space model estimation, which is mainly based on Kalman filter recursions (see Raftery et al., 2010; Koop and Korobilis, 2013). We assume an almost identical setting as Koop and Korobilis (2013). However, to account for the specific features of a small open economy we also include exogenous variables in the model (representing external demand, oil price, and foreign inflation shocks).

Let Y be a $T \times M$ matrix of endogenous variables and Z be a $T \times k$ matrix of explanatory variables which includes a column of ones (representing the intercept) and the lagged values of the endogenous and exogenous variables. To shrink the model universe, we only consider situations where $p = q$, i.e., the numbers of lags of endogenous and exogenous variables included in the model are always equal. Let y_t denote an $M \times 1$ vector containing observations at time t and $X_t = I_M \otimes Z_t$ be a matrix of explanatory variables at time t. Let β_t be a $k \times 1$ vector of regression coefficients, where $k = 1 + k_1 + k_2$, k_1 is the number of coefficients on the exogenous explanatory variables, and $k_2 = p * M$ is the number of coefficients on the lagged endogenous variables.

The TVP VAR we want to estimate can be rewritten as follows:

$$y_t = X_t \beta_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma_t) \tag{A.1}$$

$$\beta_{t+1} = \beta_t + u_t, \quad u_t \sim N(0, Q_t) \tag{A.2}$$

That is, the model parameters evolve according to a random walk and the shocks to the state variables and observation errors are both heteroskedastic. First, let us assume that the evolution of Σ_t is known and focus on filtering parameters β_t.

The steps involved are closely related to Kalman filtering and consist of two familiar steps — a prediction step and an updating step. Both steps are conditional on the initial distribution of the parameters at time $t = 0$, $\beta_{0|0}$ and $\Sigma_{0|0}$, which in our context play the role of priors in the Bayesian VAR. More will be given on the choice of the priors later on, but let us assume that the initial distribution of the regression coefficients is:

$$\beta_{0|0} \sim N(b_{0|0}, V_{0|0}) \tag{A.3}$$

In the prediction step, we predict the value of β_t given the information set at $t-1$. For that purpose, simple recursive updating based on Equation A.2 is applied. Therefore, the predicted distribution of parameter $\beta_t|y^{t-1}$ is:

$$\beta_t|y^{t-1} \sim N(\beta_{t|t-1}, V_{t|t-1}) \tag{A.4}$$

In the standard Kalman filter, the following equation is applied to estimate the state uncertainty.

$$V_{t|t-1} = V_{t-1|t-1} + Q_t \tag{A.5}$$

However, this step requires estimation of the state error variance, Q_t, which is not feasible in our context, where we need to estimate hundreds of models. Instead, we adopt the method of forgetting factors and simplify the prediction step by

$$V_{t|t-1} = \frac{1}{\lambda} V_{t-1|t-1} \tag{A.6}$$

where λ is the forgetting (or discount) factor, which gives the weight on the past observations. Since the equation implies that $Q_t = (\lambda^{-1} - 1)V_{t-1|t-1}$, we can see that $\lambda = 1$ implies no shocks to the parameters of the model and thus the constant coefficients model. On the other hand, small λ implies large shocks Q_t and thus a large weight would be given on the prediction error (new observations). As a result, model parameters β_t would fluctuate a lot.

From the discussion of the interpretation of parameter λ, it is apparent that the choice of λ affects the results. In the literature, it is set close to one (0.96—0.99). We employ the extension by Koop and Korobilis (2013), in that we estimate the forgetting factors recursively:

$$\lambda_t = \lambda_{min} + (1 - \lambda_{min})L^{f_t} \tag{A.7}$$

where $f_t = -NINT(\tilde{\varepsilon}'_{t-1}\tilde{\varepsilon}_{t-1})$ (NINT denotes the nearest integer) and $\tilde{\varepsilon}_t = y_t - \beta_{t|t-1}X_t$ is the one-step ahead prediction error. As a result, high prediction errors imply a lower forgetting factor, meaning that a higher weight will be attributed to new observations and the estimated evolution of $\beta_{t|t-1}$ will be more volatile.

The updating step is based on the standard Kalman updating equation, which involves weighting the predicted value $\beta_{t|t-1}$ and the prediction error by the Kalman gain.

The procedure described so far has been based on the assumption that the covariance matrix of the observation errors, Σ_t, is known. To estimate it, we adopt the widely used exponentially weighted moving average (EWMA) estimator:

$$\widehat{\Sigma}_t = \kappa \widehat{\Sigma}_{t-1} + (1-\kappa)\widehat{\varepsilon}_t \widehat{\varepsilon}_t{}' \tag{A.8}$$

The parameter κ can again be interpreted as a forgetting factor, in the sense that $1-\kappa$ determines the weight given to the new observations. We arbitrarily set parameter κ to 0.96. However, some pretesting did not show oversensitivity of the results to a choice within the range of 0.94–0.98.

A.2 Model Switching

The procedure for filtering model probabilities draws heavily on the Hamilton filter, but again, an approximation using a forgetting factor is used to remove the need to estimate the parameters of the transition matrix used in the Markov-switching models.

Let $\pi_{0|0,j}$ be the probability of model j at time $t=0$ and assume that it is known. We set it, in line with the usual practice, as $1/N$, where N is the number of models. This means that the same prior probability is assigned to each model.

The prediction step is

$$\pi_{t|t-1,j} = \frac{\pi^{\alpha}_{t-1|t-1,j}}{\Sigma^{J}_{l=1}\pi^{\alpha}_{t-1|t-1,l}} \tag{A.9}$$

where the transition matrix multiplication is replaced by simple ‘discounting’ of the probabilities towards the prior probability at the rate affected by α.

The updating step is identical to the one used in the Markov-switching models and can be derived using Bayes’ theorem:

$$\pi_{t|t,j} = \frac{\pi_{t|t-1,j}\,p_j(y_t|y^{t-1})}{\Sigma^{J}_{l=1}\pi_{t|t-1,l}\,p_l(y_t|y^{t-1})} \tag{A.10}$$

where $p_j(y_t|y^{t-1})$ is the likelihood of model j given the parameters $\beta_{t-1|t-1}$, which is based on the multivariate normal density function.

The interpretation of the forgetting factor α is clear from

$$\pi_{t|t-1,j} \propto \prod_{i=1}^{t-1}\left[p_j(y_{t-1}|y^{t-i-1})\right]^{\alpha^i} \tag{A.11}$$

which means that model j is assigned a higher probability if it has forecasted well in the recent past. The weighting of more recent versus past observations is given by the forgetting factor α. If α is equal to one, each historical predictive likelihood is assigned the same weight. On the other hand, lower α implies that the past forecasting performance is assigned a lower weight and the posterior model probability is mainly dependent on the most recent forecasting performance. To sum up, we can expect that a high forgetting factor α will lead to more stable probabilities of the models over time, whereas a low α will lead to more frequent model switching. Throughout the analysis we use a value of 0.95 as our benchmark. We believe that higher values do not allow us to capture pronounced but only temporary effects of financial variables on the macroeconomic dynamics.[7]

When evaluating the likelihood of model j in the updating step, we can use either the joint density of all the endogenous variables, or the marginal density of a subset of endogenous variables (which is multivariate normal again, due to the properties of the multivariate normal distribution). This allows us to assign posterior model probabilities based on the predictive likelihood of only a subset of variables. In what follows, we evaluate the models based on the prediction likelihood ('forecasting performance') of either one variable (GDP or inflation) or two variables (both GDP and inflation).

A.3 Selection Among Priors

The filtering described so far can be used to select models which differ with respect not only to the choice of endogenous variables, but also to the choice of priors on β_0. In line with Koop and Korobilis (2013) we use a simplified Minnesota prior: $\beta_0 \sim N(\beta_{0|0}, \mathrm{Var}(\beta_0))$. The mean value b_0 is set to a vector of zeros, whereas covariance matrix $\mathrm{Var}(\beta_0)$ is diagonal with $\frac{\gamma}{r^2}$ for coefficients on lag $r = 1, \ldots, p$ and $\underline{a}$ for exogenous variables, where $\underline{a}$ is a large positive constant.

It can be observed that the priors on the models differ only in terms of the choice of the γ parameter, which determines the tightness of the prior. The specification of the prior is fully automatic otherwise.

A.4 Summary: Estimation and Interpretation of (Hyper)parameters

To conclude the section on our methodology, we can interpret the estimation procedure as being a modified version of the standard Kalman and Hamilton filtering procedures. In order to avoid overparameterization of the model, the procedure employs approximations based on forgetting factors, which are summarized in Table A.1.

The forgetting factors $(\lambda, \kappa, \alpha)$ and the tightness of the Minnesota prior are the only parameters that need to be set. Subsequently, the estimation is fully automatic, without any need for prior information. In the next sections we comment on the results disregarding the first two years (24 observations), which are used as an initialization period.

[7] We also estimated the posterior model probabilities with $\alpha = 0.99$. These results are not reported in full due to space constraints, but they are available upon request.

Table A.1: Summary and Interpretation of the Parameters Used in the Model

Forgetting factor	... affects ...	and a higher value implies
λ	the volatility of estimated coefficients β_t	a lower weight on the prediction error, thus estimated β_t is less volatile
κ	the volatility of measurement error shocks Σ_t	a lower weight on the recent measurement error relative to the past estimate, thus smoother changes in volatility
α	the volatility of estimated $\pi_{t\|t-1,j}$	a higher weight on the past forecasting performance, thus estimated $\pi_{t\|t-1,j}$ is smoother

Appendix B: Analysis Design

Section 4.2 made the case for careful study of the sensitivity of the results to the modeling choices made by the researcher. In this section, we describe our choices of various parameters in our estimation exercise.

In our analysis, we pay particular attention to the choice of the number of lags in the VAR model, the tightness of the prior on the autoregressive parameters β (regulated through the shrinkage parameter γ, see Section A.3), and the prior variability in coefficients β (determined by λ_{min} and L, see eq. A.7). As from the Bayesian perspective the model is fully defined by the tandem of the likelihood and the prior, we can think of different priors as definitions of different models. This analytical setting implies that each of the 27 candidate models described in Section 4 can enter the analysis in dozens of mutations that reflect alternative modelers' views on the priors. As a result, the original model universe inflates dramatically, eventually reaching several thousand models. We briefly discuss the choices considered along the respective dimensions.

Given the monthly data frequency, we consider three different lag lengths — 4, 6, and 9 months. Although one may argue that in some cases 3 quarters is too short to fully capture all the effects, the inclusion of higher lags would lead to a high computational burden and potential problems with overparameterization. We played around a bit with other lag lengths, but after running a few experiments we did not find that lower or higher lag lengths markedly changed the general message of our results.[8]

The tightness of the prior on coefficients β is fully regulated through the single parameter γ. Following Koop and Korobilis (2013), we use quite a wide grid for γ: $[10^{-5}, 10^{-3}, 5^{-3}, 0.01, 0.05, 0.1]$ to allow for different degrees of parameter shrinkage, which may help (at least partially) overcome any problems with overparameterization. As the switching mechanism allows us to favor different models (and thus priors) in every period, we can virtually update the amount of shrinkage in a time-varying fashion.

As to the degree to which coefficients β are allowed to wander across time, we consider two sets of parameters λ_{min} and L: $\{\lambda_{min} = 0.96; \mathrm{L} = 1.1\}$ and $\{\lambda_{min} = 0.9; \mathrm{L} = 1.3\}$. The first set defines a fairly stable VAR with smooth parameter transition and quite low sensitivity to the large prediction errors, while the second set corresponds to a more dynamic environment where the coefficients adapt rapidly to the new conditions once the data indicate any deviation from the current state. We refer to this dimension as the model stability dimension.

In theory, models with different numbers of variables, lags, and parameter priors can all be put into a single common set of models and compared with each other by means of posterior model probabilities. However, in order to reduce the complexity and facilitate interpretation of the results, we treat the tightness of prior γ on the one hand and the lag length and parameters λ_{min} and L on the other differently in the estimation. To keep things manageable we divide the whole set into six subsets along the lag length dimension and the model stability dimension. This means that for each combination of lag length and model stability we estimate 162 models (27 models times 6 different values of γ), whose performance can be compared at any point in time. Direct comparison between models with different numbers of lags and stability features in time-varying fashion is no longer

[8] For our preferred VAR specifications we tried to estimate models with 2 and 12 lags. As these specifications did not exhibit better performance in terms of likelihood than those included in the analysis we leave them out of our considerations.

possible, but the models can still be compared in terms of their global predictive performance as measured by the likelihood of the model or the mean squared error (MSE). Effectively, this means that we allow for a time-varying pattern in coefficients β as well as in the model dimension, but we keep other things fixed once we have found the optimal lag length and optimal values for λ_{min} and L.

Model assessment over time is based on the posterior model probabilities. As demonstrated in Section A.2, the posterior model probabilities crucially depend on the predictive densities of the variables of interest. Different predictive densities may thus give rise to different posterior model probabilities. We consider three alternative scenarios where the posterior model probability is determined with respect to the marginal predictive density of *i)* inflation, *ii)* GDP growth or *iii)* the bivariate (marginal) density of inflation and GDP growth. This reflects researchers' potentially different preferences when it comes to analyzing the impacts of financial variables on the economy. When one is interested only in the predictive content of a single variable, univariate densities should be preferred. On the other hand, when one wants to obtain optimal and model-consistent predictions for multiple variables simultaneously, multivariate predictive distributions may be a preferable option. We limit our attention to the inflation rate and GDP, as these variables have arguably been subject to the greatest scrutiny in the previous empirical literature on this topic. For better illustration, the complete design of the analysis is depicted in Figure B.1.

Figure B.1: The Design of the Analysis

	choice	interpretation	values
same across models and set-ups	κ	persistence of volatility of measurement shocks	0.96
	α	model probability persistence	0.95
same across set-ups	number of lags		4, 6, 9
	L, λ_{min}	volatility of estimated coefficients	$\lambda_{min} = 0.96, L = 1.1$ $\lambda_{min} = 0.9, L = 1.3$
	criterion variable		GDP, inflation, GDP and inflation
variable across models	model variables	explanatory variables	1-27
	γ	tightness of the prior	10e-5, 10e-3, 5e-3, 0.01, 0.05, 0.1

Note: Summary of the design of the analysis: choice and interpretation of the parameters

For the assessment of the global performance of the models, we consider two measures — the predictive likelihood summed over the observations and the mean squared predictive error (MSE). The MSE is based on the predicted errors, i.e., on the non-updated coefficients $(\beta_t|y^{t-1})$. The advantage of the likelihood measure is that it uses the whole distribution of the predictive density, not only a point estimate, as is the case with the MSE. In addition, the likelihood measure does not penalize large forecasting errors as severely as the MSE does. This could underestimate the model's performance due to a few large forecasting errors in a limited number of periods. For these reasons, when the measures show a preference for different models, we incline toward the likelihood measure as the preferred indicator of a model's performance.

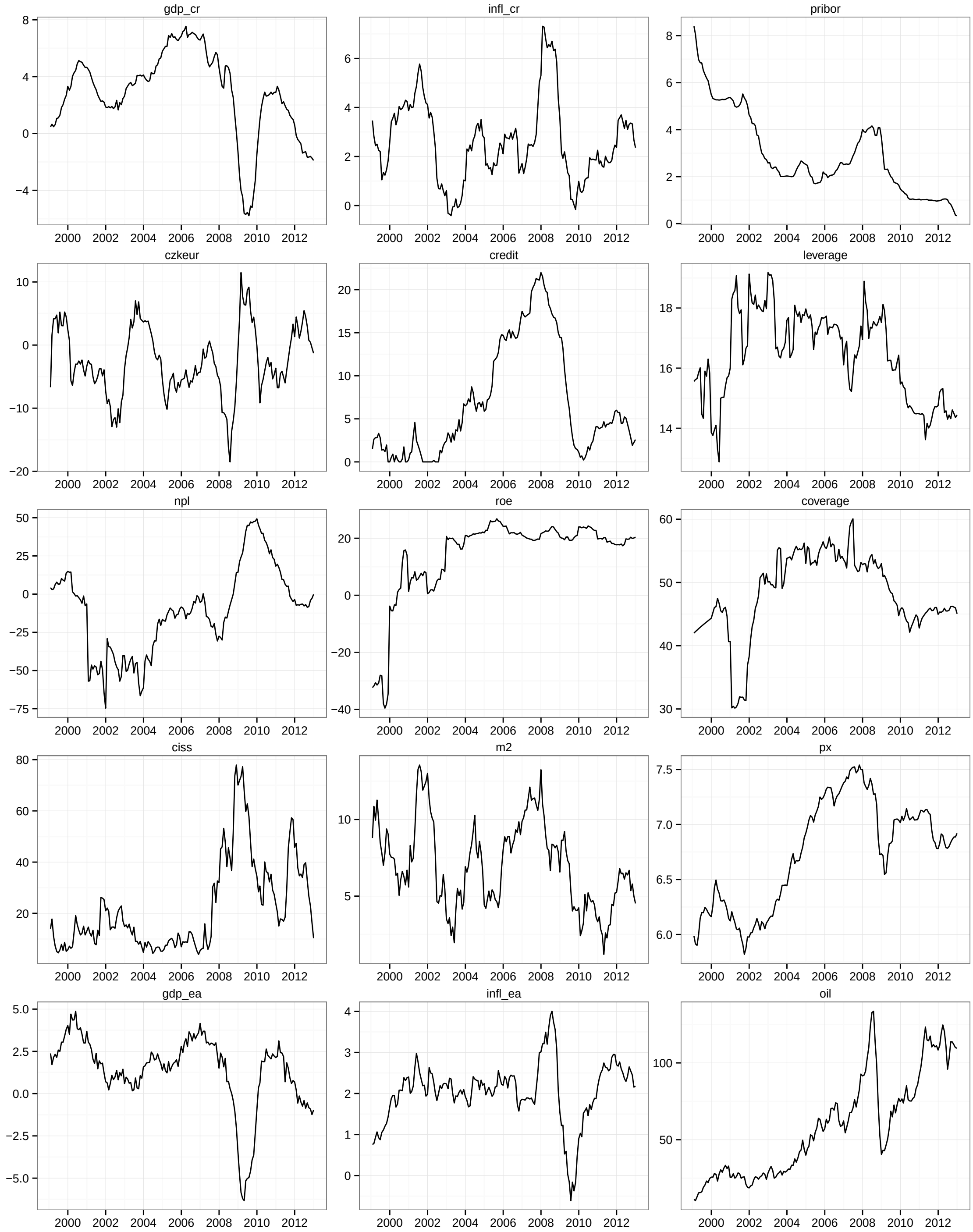
Appendix C: List of Variables

Table C.1: Variables Used in the Analysis

name	description
gdp_cr	GDP disaggregated into monthly frequency (Chow-Lin method, industrial production as indicator variable), y-o-y growth
infl_cr	annual CPI inflation
pribor	3-month money market rate (PRIBOR)
czkeur	annual percentage change of CZK/EUR exchange rate
credit	credit expansion gap: difference between log of credit in period *t* and minimum of log of credit during last 12 months
leverage	leverage of banking sector (Tier 1 capital/total assets)
npl	annual growth of non-performing loans
roe	return on equity of banking sector
coverage	non-performing loan coverage (loan loss provisions/non-performing loans)
ciss	Composite Indicator of Systemic Stress (Holló et al., 2012)
m2	annual growth rate of M2
px	annual growth rate of Prague stock exchange index (PX 50)
gdp_ea	euro area GDP, same construction as for Czech GDP
infl_ea	euro area HICP inflation rate
oil	Brent crude oil price in US dollars

Source: Czech Statistical Office, CNB's ARAD database, ECB SDW, Datastream

Figure C.1: Variables Used in the Analysis.



Source: Czech Statistical Office, CNB's ARAD database, ECB SDW, Datastream

Appendix D: Posterior Model Probabilities

Figure D.1: GDP, $\lambda_{min} = 0.96, L = 1.1$

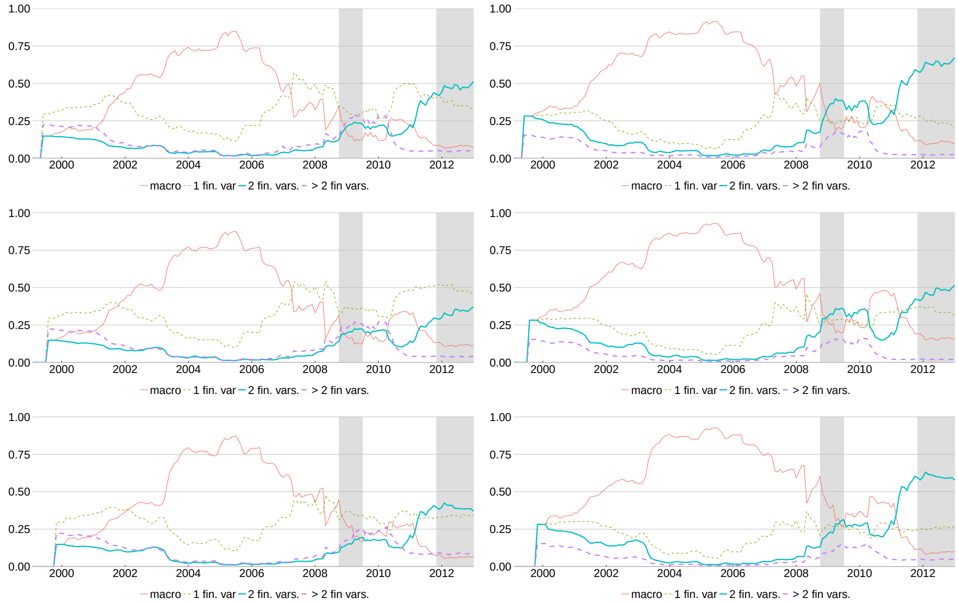
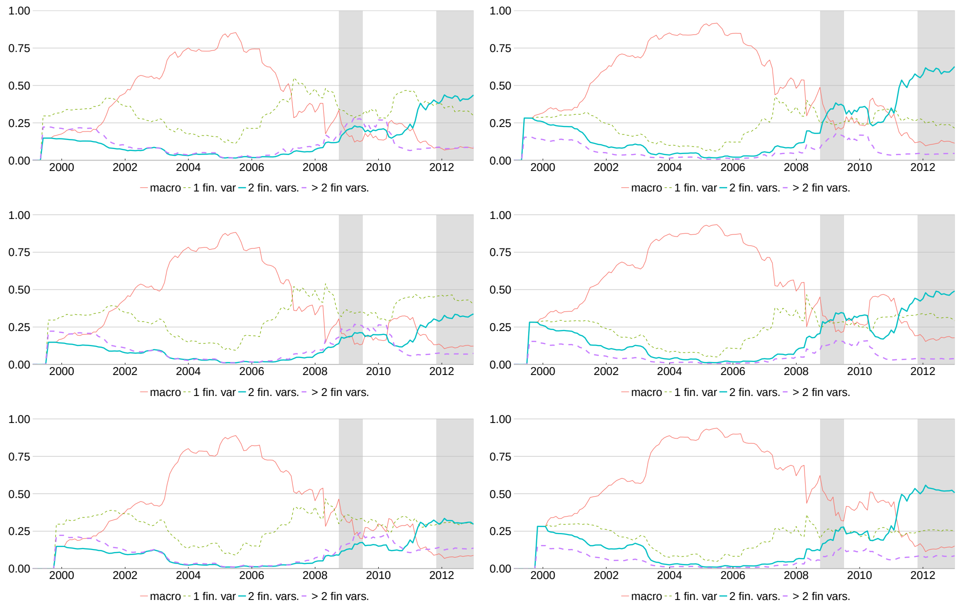


Figure D.2: GDP, $\lambda_{min} = 0.9, L = 1.3$



Note: Probabilities based on the likelihood evaluated for GDP growth only. The shaded areas in the figures indicate negative GDP growth in the given period. Figures on the right plots depict standardized probabilities (described in the text).

Figure D.3: Inflation, $\lambda_{min} = 0.96, L = 1.1$

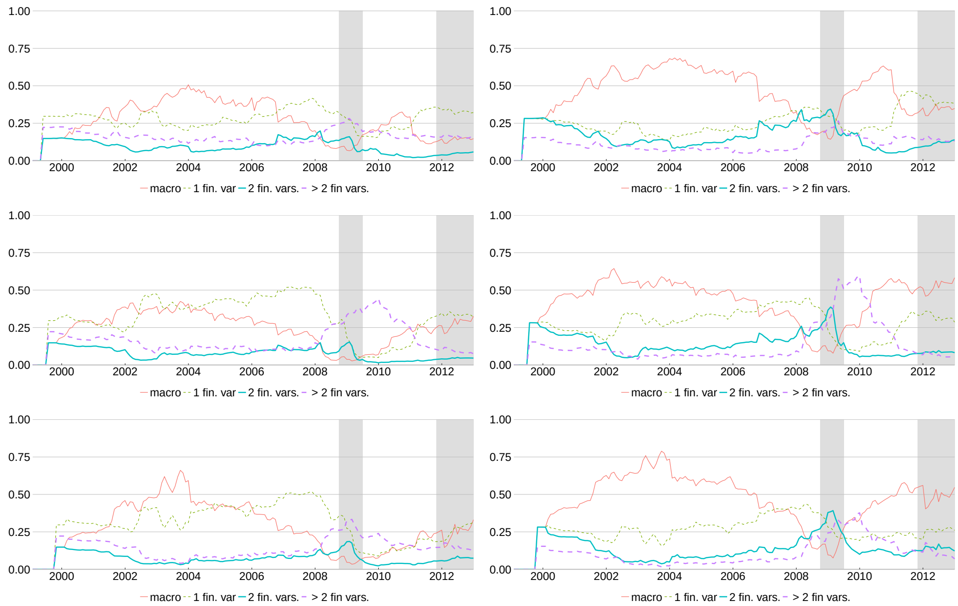
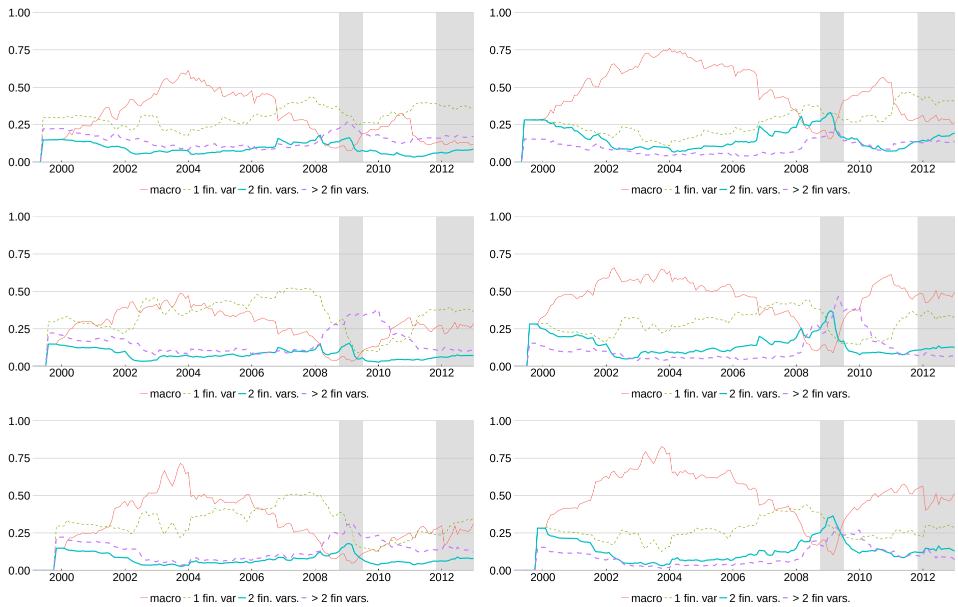


Figure D.4: Inflation, $\lambda_{min} = 0.9, L = 1.3$



Note: Probabilities based on the likelihood evaluated for inflation only. The shaded areas in the figures indicate negative GDP growth in the given period. Figures on the right plots depict standardized probabilities (described in the text).

Figure D.5: GDP, Inflation, $\lambda_{min} = 0.96, L = 1.1$

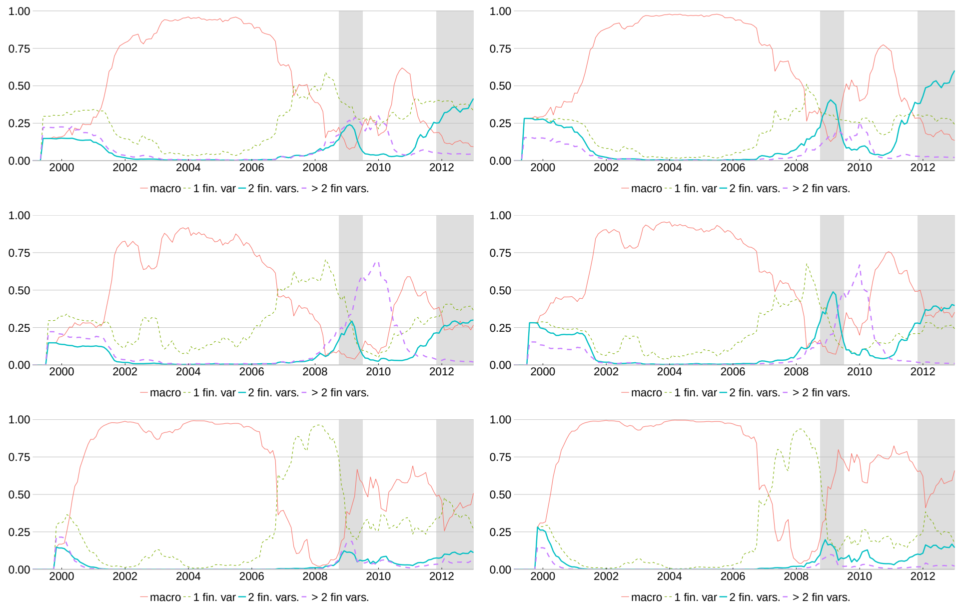
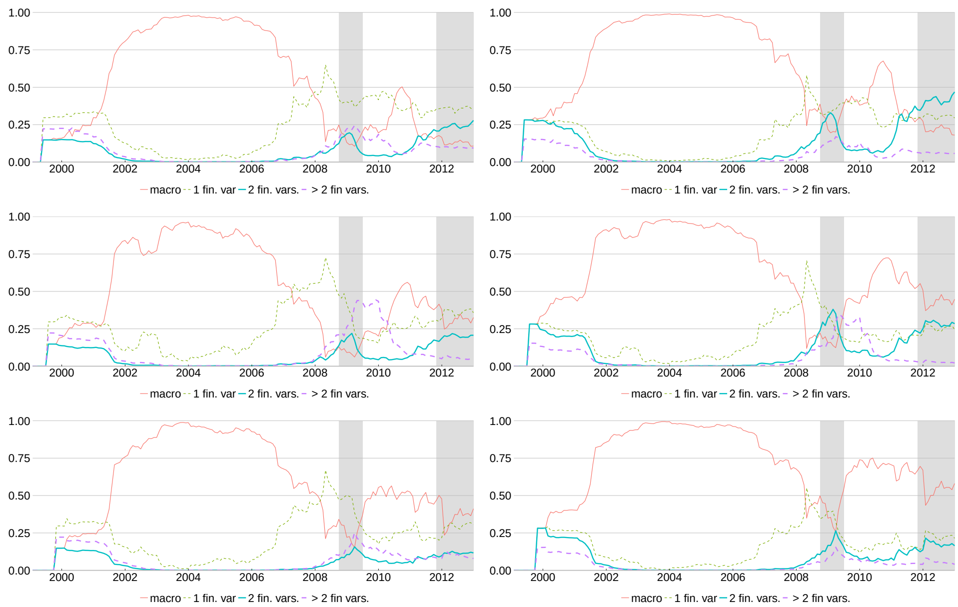


Figure D.6: GDP, Inflation, $\lambda_{min} = 0.9, L = 1.3$



Note: Probabilities based on the likelihood evaluated for GDP growth and inflation. The shaded areas in the figures indicate negative GDP growth in the given period. Figures on the right plots depict standardized probabilities (described in the text).

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