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Three Essays on Applied Bayesian Econometrics

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Abstract

The dissertation consists of three papers which apply Bayesian econometric techniques to monitoring macroeconomic and macro-financial developments in the economy. Its aim is to illustrate how Bayesian methods can be employed in standard areas of economic research (estimating systemic risk in the banking sectors, nowcasting GDP growth) and also in a more original area (monitoring developments in sovereign bond markets).

The first essay addresses a task which analytical departments in central or commercial banks face very often - nowcasting foreign demand for a small open economy. On the example of the Czech economy, we propose an approach to nowcast foreign GDP growth rates for the Czech economy. For presentation purposes, we focus on three major trading partners: Germany, Slovakia and France. We opt for a simple method which is very general and which has proved successful in the literature: the method based on bridge equation models. A battery of models is evaluated based on a pseudo-real-time forecasting exercise. The results for Germany and France suggest that the models are more successful at backcasting, nowcasting and forecasting than the naive random walk benchmark model. At the same time, the various models considered are more or less successful depending on the forecast horizon. On the other hand, the results for Slovakia are less convincing, possibly due to the stability of the GDP growth rate over the evaluation period and the weak relationship between GDP growth rates and monthly indicators in the training sample.

In the second essay, we turn to monitoring developments in euro area sovereign bond markets. To study the period since October 2005 (when most data started to be available), with a particular focus on the financial and sovereign debt crises, we employ a factor model with time-varying loading coefficients and stochastic volatility, which allows for capturing changes in the pricing mechanism of bond yields. Our key contribution is exploring both the global and the local dimensions of bond yield determinants in individual euro area countries using a time-varying model. Using the reduced form results, we show

decoupling of periphery euro area bond yields from the core countries' yields following the financial crisis and the scope of their subsequent re-alignment. In addition, by means of the structural analysis based on identification via sign restrictions, we present time varying impulse responses of bond yields to EA and US monetary policy shocks and to confidence shocks.

The final essay analyses the evolution of the systematic risk of the banking industries in eight advanced countries using weekly data from 1990 to 2012. Time-varying betas are estimated using a Bayesian state-space model with stochastic volatility, whose results are contrasted with those of the standard M-GARCH and rolling-regression models. We show that both country-specific and global events affect the perceived systematic risk, while the impact of the latter differs considerably across countries. Finally, our results do not support fully the previous findings that equity prices did not reflect the build-up of systematic risk of the banking sector before the last financial crisis.

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Chapter 1

General Introduction

Bayesian econometric methods have become increasingly popular among economists in recent years. Their primary advantage stems from the possibility to incorporate prior beliefs on model structures in the estimation procedure. This merit is valuable particularly in macroeconomics, where often only a limited number of observations is available to the researcher.

As an example, vector autoregression models are heavily used in macroeconomics for forecasting but also structural analysis. These models suffer from the problem of overparameterization, as the number of coefficients in models grow very fast when additional variables are included. Bayesian VAR models overcome this problem by imposing prior information on the parameters. This information can originate from knowledge on the behaviour of inflation dynamics, for example, which tends to be stable between two periods (Doan et al., 1984) or approaches the inflation target in the medium-run (Villani, 2009). Predictions from these models tend to have more narrower credible intervals ("confidence bands") and smaller forecast errors, compared with standard VAR models. Since the models are usually simulated using Monte-Carlo techniques, it is straightforward to draw inferences around the quantities of interest, such as impulse response functions (Baumeister and Hamilton, 2015; Rubio-Ramirez et al., 2010) or forecasts, without the need to use bootstrapping or other complicated methods.

In the case of macroeconomic models built on micro-foundations (An and Schorfheide, 2007), one often has prior knowledge on several parameters, which stems either from economic theory or empirical studies. Imposing these onto the estimation leads to more meaningful estimates of parameters on which no information is available and often also to better predictions and more plausible impulse response functions.

Another reason for the popularity of Bayesian techniques in macroeconomics has been their ability to simulate state-space models (Carter and Kohn, 1994), which in classical econometrics rely on often unstable optimisation methods. These techniques allow researchers to estimate more complex unobserved processes (Stock and Watson, 2007), including stochastic volatility models Kim et al. (1998), time-varying coefficient models (Primiceri, 2005), or factor models (Bernanke et al., 2005).

In addition, the increase in computational power and the reduction of its costs in recent years have led many economists to embrace Bayesian techniques. Since posterior distributions in Bayesian econometric models can be rarely solved analytically, Markov Chain Monte Carlo methods (Chib and Greenberg, 1996, 1995; Casella and George, 1992) are used to simulate draws from posterior distributions and compute characteristics of posterior distributions (e.g., mean, mode, variance). These methods, although known for a long time, had been prohibitively computationally costly until recently (about 10 years). Finally, the publication of several relatively non-technical books and sources on the topic (Koop et al., 2010; Blake et al., 2012) made Bayesian techniques accessible to the broad public.

This dissertation illustrates the power of Bayesian econometric techniques in three areas of economic research. The overarching topic of the three essays is monitoring macroeconomic and macro-financial developments in the economy. The models used in the essays can, therefore, be used as one of the inputs for economic analysts and policymakers. The first paper applies Bayesian model averaging technique as a variable selection tool to nowcast GDP growth rates. The second paper studies the developments in euro area sovereign bond markets using a Bayesian factor model with time-varying loading coefficients and stochastic volatility. Finally, the third paper estimates a measure of systematic risk (CAPM betas) in banking sectors using a state space model, where state variables are simulated using Bayesian techniques.

The use of Bayesian techniques in the first paper is relatively standard in economic research, while their application is rather original in the subsequent two essays. The models and methods applied in all three essays encompass a broad spectrum of the Bayesian toolkit - a simple linear regression, VAR models, the time-varying parameter regression model, the model of stochastic volatility, Bayesian model averaging, factor models, and factor models with time-varying loadings. The appealing feature of Bayesian econometrics is that once several fundamental techniques are mastered, they can be combined to estimate rich models, for example, a factor-augmented vector autoregression model (FAVAR) with time-varying loadings and stochastic volatility presented in the second essay.

In the first essay (published as (Adam and Novotný, 2018)), we address a challenge that forecasters of a small economy very often face - nowcasting foreign demand growth. Successful forecasts of a small open economy need to take into account developments abroad, so a researcher needs to make reasonable assumptions about the external economic environment. These assumptions are often taken from external sources (such as Consensus Forecasts), which, however, provide outlooks only for yearly GDP growth rates. These annual numbers are disaggregated into a quarterly frequency by a mechanical procedure, which often does not take into account timely monthly indicators on current economic developments.

To overcome the gap between external yearly forecasts and available indicators on the economy, we introduce a semi-automatic approach to nowcasting foreign GDP growth rates for the Czech economy[1]. This approach is based on the bridge equation models (BEQ), which "bridge" information from monthly indicators (e.g. industrial production) into quarterly ones (GDP growth rates) using a simple linear regression model. The estimated linear relationship is subsequently used for nowcasting. Since a lot of monthly indicators are available, we reduce the space of possible models by grouping them into three categories: univariate models, more complex multivariate models, and finally models based on common components. In the first category, we average predictions of univariate models into five categories. One of the categories contains variables selected using Bayesian model averaging, which identifies the best possible candidates for explaining GDP growth.

The paper illustrates the suggested technique on backcasting, nowcasting and one-quarter ahead forecasting of GDP growth rates for Germany, Slovakia and France. The evaluation exercise takes into account 58 available time series, starting in January 1999. The calculated nowcasts are compared on an evaluation period starting in the first quarter of 2012. The models are re-estimated every quarter on currently available data, and the pseudo-real-time forecasting exercise takes into account the publication lags of the monthly indicators.

The forecasting exercise suggests that the performance of various competing

[1] Although the paper is written specifically for a small open economy, the techniques can also be used in other contexts, where many variables need to be nowcasted in a short time.

BEQ models is not constant and varies based on the forecasting horizon considered (i.e. backcast, nowcast and one-quarter-ahead forecast). In line with intuition, the forecasting ability of the models containing leading indicators is strongest at longer horizons, but diminishes for nowcasting and backcasting. At the same time, the power of the models containing industrial production is higher in the case of nowcasting and backcasting (compared to forecasting), especially in the third month, when the industrial production index is published for the first month of the current quarter.

The second essay (published as (Adam and Lo Duca, 2017)) studies the developments in the euro area sovereign bond markets, with a particular emphasis on the financial and sovereign debt crises. These two events demonstrated that understanding the pricing mechanism and the drivers of bond yields is essential to monitor risks, decide on policies and assess their effectiveness. A share of the literature suggests that at the peak of the sovereign debt crisis, euro area bond yields reflected fundamentals, in particular, the expected deterioration of the macro environment and fiscal positions. Another strand of literature suggests that risk aversion, panic and irrational investors' behaviour drove bond yields.

Against this backdrop, the essay presents a new model to assess the pricing mechanism of euro area sovereign bond yields from a dynamic perspective. It employs a factor model with time-varying loading coefficients and stochastic volatility to determine the drivers of sovereign bond yields in the euro area. The time variation in factor loading coefficients allows for capturing changes in the pricing mechanism of bond yields, consistent with the evidence emerging from other empirical studies. Exploring both the global and local dimensions of bond yield determinants in individual euro area countries is one of our key contributions. Specifically, our model studies the drivers of country-specific yields separating between (i) euro area core and periphery factors to assess integration, spill-overs and contagion within the euro area (ii) US and Emerging Market Economies (EMEs) market factors to assess spill-overs to the euro area from the rest of the world. Finally, time-varying impulse responses to monetary policy shocks and confidence shocks are identified via sign restrictions and studied.

The results support the view that the pricing mechanism of bond yields evolved during the European banking and sovereign crisis. The analysis identifies three distinct phases in euro area sovereign bond markets. In the first, initial phase, bond markets were almost fully integrated. In the second, when the crisis escalated, bond markets became disintegrated. In this phase, the pricing of euro area sovereign bonds depended on different factors and the transmission of monetary policy shocks became heterogeneous across countries. Lastly, in the third phase of partial re-integration, the pricing mechanism of bonds approached the pre-crisis conditions, according to loading coefficients and structural impulse responses.

Our results have implications for the debate on the impact of unconventional monetary policy on sovereign bond markets in the euro area. While the literature predominantly quantifies the impact of unconventional monetary policy on bond yields and it assesses the transmission channels (e.g. the signalling channel vs the portfolio balance channel), our results also shed light on the impact of policies on the pricing mechanism of yields. Specifically, we highlight a link between euro area unconventional policies, the way different factors are priced into bond yields and the reaction of bond yields to monetary policy shocks. We find that, when looking at loading coefficients and structural impulse responses, the announcement of Outright Monetary Transactions by the ECB was a game changer leading to gradual normalisation of the pricing mechanism of bond yields to the pre-crisis situation. Finally, another interesting finding shows that yields in troubled euro area countries became more responsive to EA monetary policy shocks during the crisis periods. This suggests that the ECB mix of unconventional monetary policy was particularly effective in those markets where monetary accommodation was needed.

The essay is valuable also from the methodological perspective since it extends the method by Chan and Jeliazkov (2009) to simulate draws from more complex models, such as the FAVAR model used in this paper. State variables in these models can follow a higher order VAR process so that the covariance matrix of shocks in the transition matrix is singular. This method is relatively straightforward to implement and computationally more efficient than the algorithms used routinely in the literature (e.g., (Carter and Kohn, 1994)).

The final essay (published as (Adam et al., 2012)) analyzes the evolution of systematic risk in the banking sectors. The inherent fragility of banks and the opacity of their businesses raise the question of whether markets can price the risk correctly. The excessive risk-taking by US banks before the market meltdown in 2007 is an example of a period when the correct evaluation of risk is questionable. Surprisingly, not even the ex-post literature provides any clear-cut answer to this question, so it remains unanswered whether markets were fully aware of the risks connected with mortgage loan securitization. As we show in this paper, the answer depends on how the systematic risk is estimated.

The paper extends the evidence from the current literature in several ways. First, it applies a Bayesian state-space model with stochastic volatility for the estimation of the CAPM betas of banking sectors. According to the CAPM theory, the betas should capture the systematic risk of the industry. It is now widely held that betas are not time-invariant, and methods such as the rolling-regression model, classic state-space models, and the GARCH model have so far been used frequently to estimate the evolution of betas. Still, these methods have several shortcomings, such as arbitrary choice of window size (in the case of rolling regression), assumed homoskedasticity of residuals (in both the rolling-regression and the state-space approaches), and a large amount of noise present in the estimates (estimation based on the GARCH model). In contrast, the model that we use links the advantages of both the state-space approach (estimating the beta as an unobservable process in a state-space model) and the approach based on the M-GARCH (multivariate generalized autoregressive conditional heteroskedasticity) model (allowing for heteroskedasticity of residuals).

We demonstrate how the estimates can be used by policymakers as an indicator of systematic risk. Some studies argue that in the US, the pre-crisis build-up of instability in the banking sector was not reflected in stock prices. Our analysis on the contrary shows that the banking sector risk in this seemingly calm period increased. In other words, the results do not support fully the previous findings that the systematic risk of the banking sector was significantly underestimated before the great financial crisis.

Next, we show that both country-specific and global events affect the perceived systematic risk, and the strength of the global factor differs considerably across countries. The previous literature has investigated the betas of financial sectors as a whole or has studied trends between sub-sectors in one individual country. On the other hand, the final essay explores potential global trends in the perceived riskiness of banking sectors. To evaluate the degree of co-movement, we estimate a global factor and calculate the percentage of the variation explained by the global factor for individual countries.

The results suggest that the banking sectors in some countries (the US, the UK, and Germany) share similar patterns in the evolution of their systemic risk; on the other hand, the sectors in other countries (Japan and Australia) look more isolated. The paper presents one of several possible explanations: the degree to which banking sectors are financially interconnected by cross-border exposures. It seems that the most influential financial centres exhibit the highest sensitivity to global developments and the degree to which the banking sector is internationalized can affect the sector's systemic risk.

To conclude, the thesis demonstrates how Bayesian econometric techniques can be employed in a broad spectrum of applications relevant to both economic research, but also to practitioners. Regarding economic research, the thesis shows applications in heavily studied areas - nowcasting, analyzing bond yields and estimating CAPM betas. For practitioners, the thesis suggests several tools useful for monitoring macroeconomic and macro-financial developments. As a result, these techniques can be used as one of the inputs for the economic analysis and also for policymakers.

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Chapter 2

Assessing the External Demand of the Czech Economy: Nowcasting Foreign GDP Using Bridge Equations

Abstract

We propose an approach to nowcasting foreign GDP growth rates for the Czech economy. For presentational purposes, we focus on three major trading partners: Germany, Slovakia and France. We opt for a simple method which is very general and which has proved successful in the literature: the method based on bridge equation models. A battery of models is evaluated based on a pseudo-real-time forecasting exercise. The results for Germany and France suggest that the models are more successful at backcasting, nowcasting and forecasting than the naive random walk benchmark model. At the same time, the various models considered are more or less successful depending on the forecast horizon. On the other hand, the results for Slovakia are less convincing, possibly due to the stability of the GDP growth rate over the evaluation period and the weak relationship between GDP growth rates and monthly indicators in the training sample.

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2.1 Introduction

GDP growth nowcasting has long been a topic of interest to both economic practitioners and academics. For forecasters, assessing the current state of the economy is of utmost importance, since the most recent observations are what drives forecasts to a significant extent, especially at the short ends of forecast horizons. Unfortunately, estimates of GDP growth are available with substantial lags, so estimates of the current (or even the last) GDP growth rates have to be produced. On a theoretical level, nowcasting has been of particular interest, since the techniques used face the challenge of extracting meaningful signals from a multitude of variables representing different parts of the economy. At the same time, these indicators are available with various lags and can be subject to significant measurement errors.

Forecasters of a small open economy face a challenge in that a successful forecast needs to take into account developments abroad. Very often, effective aggregates of foreign GDP growth, inflation rates and interest rates are constructed and assumptions are made about their future paths to produce forecasts for the domestic economy. In the case of the Czech Republic, the core forecasting model of the Czech National Bank assumes the paths of "effective" euro area aggregates of GDP and PPI inflation rates, which are constructed as trade-weighted averages of variables of the 17 most important euro area trading partners of the Czech Republic. These assumptions are taken from Consensus Forecasts (produced by Consensus Economics), which are published at monthly frequency. However, the forecasts are produced for yearly data and have to be disaggregated into quarterly frequency. Currently, the temporal disaggregation is based on a simple mechanistic approach which does not take into account timely data from the economy and available leading indicators.

This paper introduces an approach to producing nowcasts, backcasts and one-quarter-ahead forecasts of foreign GDP for the Czech economy, which drives foreign demand in the Czech National Bank's core forecasting model. The main aim of producing these estimates is to improve the current mechanistic approach to disaggregating the forecasted annual growth rates of GDP produced by external institutions which operate in the economies of interest. In addition, producing backcasts, nowcasts and one-quarter-ahead forecasts can provide a basis for making expert adjustments to the Consensus Forecast projections, which tend to reflect new information slowly.

The share of exports to the euro area in overall Czech exports is about 65%.

Since we face the challenge that many (17) countries enter the forecasting process at the Czech National Bank, we opt for one of the simplest, but also most successful, nowcasting methods, based on bridge equations. This approach "bridges" information from timely monthly indicators to quarterly GDP growth rates. For the sake of brevity, the paper presents the results for the three most important trading partners of the Czech Republic, Germany, Slovakia and France, which cover about 70% of exports to the euro area. The results are presented for a battery of models, starting with simple univariate bridge equation models, followed by more complex multivariate models and finishing with models containing principal components, which capture the co-movement among all relevant variables.

The results suggest that in the case of Germany and France, even most of the simplest models beat the naive forecasts at all horizons (i.e. when we consider backcasting, nowcasting and forecasting performance). The models containing leading indicators perform best at the one-quarter-ahead forecasting horizon in the case of Germany and to a smaller extent in the case of France. For shorter horizons (nowcasting and backcasting), the power of the models containing coincident indicators increases, especially in the third month of the quarter, when the industrial production index is published for the first month of the quarter. Finally, the model containing common components performs well at all horizons, especially in the case of nowcasting the current GDP growth rate. On the other hand, the results for Slovakia are not as successful. This stems primarily from low correlations of monthly indicators with GDP growth rates. In addition, GDP growth exhibited very low volatility over our evaluation period, so the naive forecast performs best.

2.2 Literature review

Short-term forecasting tools are used widely by policy institutions, since appropriate policy measures need to take into account timely information on macroeconomic developments. Specifically, data on GDP growth, which is published with a substantial time lag (typically 6 to 8 weeks), are observed closely by policymakers. Nowcasting of quarterly GDP growth has thus become very common at central banks. Traditional nowcasting methods used by central banks include bridge equation (BEQ) models and dynamic factor models (DFMs). These two groups of models are supplemented by other related models, e.g. OLS models with more explanatory variables, ARMAX models, mixed frequency VARs and MIDAS equations.

Feldkircher et al. (2015) apply both BEQ models and DFMs to Central and Eastern European countries. The models are estimated for the period from the first quarter of 2000 to the second quarter of 2008. Their evaluation period then ranges to the third quarter of 2014, covering the period since the Great Recession. They follow the standard practice when evaluating out-of-sample forecasting accuracy, which is measured by the root mean squared error (RMSE) with the latest available GDP growth figures (quasi out-of-sample forecasts). Their small-scale nowcasting models outperform a simple AR(1) model, but the model performance varies strongly across countries. Additionally, Huček et al. (2015) show that BEQ models and DFMs outperform ARMA models in the case of the Slovak economy. Moreover, BEQ models may offer an advantage over DFMs, since they are simple to construct and easy to understand.

Similarly, Antipa et al. (2012) forecast German GDP growth rates for the current quarter using factor and bridge models. They show that changing the bridge model equations by including newly available monthly information generally provides more precise forecasts and is preferable to maintaining the same equation over the horizon of the exercise. Importantly, the forecast errors of the BEQ models are smaller than those of the DFMs. Furthermore, the BEQ models not only provide very accurate forecasts, but are also straightforward to interpret. Indicators that appear to be unrelated or only loosely linked to the target variable can be neglected. The datasets are therefore relatively small and thus not costly to update. Second, BEQ model predictions allow for a better description of the forecast based on the evolution of the explanatory indicators. The ability to identify and interpret the drivers of forecasts is a useful feature, especially in periods characterized by significant or changing volatility.

This paper focuses on BEQ models due to their above-mentioned advantages over other types of models, particularly DFMs. BEQ models were introduced by Klein and Sojo (1989) as a regression-based system for GDP growth forecasting. BEQ models are essentially regressions relating quarterly GDP growth to one or a few monthly variables (such as industrial production or various survey indicators, especially leading ones) aggregated to quarterly frequency. The forecasting accuracy of bridge equations seems to rely on selecting the "right" higher frequency indicators conditional on the forecast horizon (Trehan, 1992). Since only partial monthly information is usually available for the target quarter, the monthly variables are forecasted using auxiliary models such as ARIMA models (Banbura et al., 2013). In order to exploit the information content from several monthly predictors, bridge equations are sometimes pooled (see, for example, (Kitchen and Monaco)). Since BEQ models are designed to be used on a monthly basis, the industrial production index is probably the most relevant and widely analysed high-frequency indicator.

The underlying structure of BEQ models is different from standard macroeconomic models, which are built around behavioural and causal relations between the variables. The gains of forecasts based on BEQ models relative to naive constant growth models are substantial, especially at very short horizons, and most of all for the current quarter, according to Baffigi et al. (2004). The high accuracy of forecasts at shorter horizons implies that these models should be used primarily to forecast growth in the current and previous quarters. In addition, it is straightforward to incorporate new data as soon as it is released. Early in the quarter, soft indicators have been found to be extremely important, especially since hard data (e.g. industrial production) is not yet available.

Furthermore, Giannone et al. (2008) propose a method which consists of bridging quarterly GDP with monthly data via regressing GDP growth rates on factors extracted from a large panel of monthly series with different publication lags. Angelini et al. (2011) show on euro area data that bridging via factors produces more accurate estimates than traditional bridge models. The factor model thus improves the pool of bridge equation models. They also show that survey data and other “soft” information are valuable for nowcasting. BEQ models for France, Germany, Italy and the euro area over the period from 1980 to 1999 are estimated by Baffigi et al. (2004). They conclude that BEQ models are far better than selected ARIMA and VAR models and a structural model. Moreover, over a forecasting horizon one- to two-steps ahead, the aggregation of forecasts by country performs better in forecasting euro area GDP and also offers information on the state of the single economies.

ECB staff use a set of bridge equations in their regular monitoring of economic activity in the euro area (Diron, 2008; Rünstler and Sédillot, 2003). In Germany, the higher volatility of GDP growth rates probably stems from the country’s reliance on the industrial sector and exports, which are sensitive to the global business cycle. Deutsche Bundesbank operates factor models and bridge equations for GDP growth forecasts. It updates its forecasts twice a month and concentrates on nowcasting the current quarter or backcasting the last quarter using all the available indicator-based information. In addition, one-quarter-ahead prediction (forecasting) is conducted (Bundesbank, 2013; Götz and Knetsch, 2019). Recently, Pinkwart (2018) argues that the forecast performance of BEQ models can be substantially improved in the case of Germany by combining the production side and the demand side projections. Mogliani et al. (2017) use a model which relies exclusively on business survey data in industry and services conducted directly by the Banque de France. Some soft indicators are even used by the French national statistics institute (INSEE) to compile its GDP figures. The National Bank of Slovakia regularly publishes its nowcast of the real economy in its monthly bulletin. To this end, it uses several approaches, including BEQ models. Incomplete monthly series of economic indicators are forecasted by ARMA models and then bridge equations are estimated by OLS for each explanatory variable. Finally, the average of the individual BEQ models is weighted by the AIC Huček et al. (2015); Tvrz (2016).

This paper concentrates on techniques for nowcasting foreign economic variables (specifically the GDP growth of the Czech Republic's main trading partners). The variety of BEQ models used ranges from simple univariate BEQ models to models based on common components. The main motivation is that a small open economy is substantially influenced by external developments.

On the other hand, the research into short-term forecasting at the Czech National Bank has so far focused exclusively on the Czech economy. Benda and Růžička (2007) evaluate nowcasts of Czech GDP growth using principal component analysis (PCA) and seemingly unrelated regression estimation (SURE) with monthly and quarterly explanatory variables. They show that these methods provide relatively accurate nowcasts and near-term forecasts of GDP fluctuations. Similarly, Arnoštová et al. (2011) forecast the quarterly GDP growth of the Czech economy up to three quarters ahead using six competing simple econometric models. Furthermore, Rusnák (2016) employs a dynamic factor model (DFM) to nowcast Czech GDP growth. Havránek et al. (2010) evaluate to what extent financial variables improve the forecasts of Czech GDP growth and inflation. More recently, the impact of financial variables on Czech macroeconomic developments is investigated by Adam and Plašil (2014) and Franta et al. (2016), who use various mixed-frequency data models to forecast Czech GDP growth. Babecká and Brůha (2016) present nowcast models for Czech external trade. This is a novel approach, since no nowcast model for trade has been described previously in the literature. They apply four empirical models: principal component regression, elastic net regression, the dynamic factor model and partial least squares.

2.3 Methodology and the design of the nowcasting and forecasting exercises

This paper employs the method based on bridge models (Rünstler and Sédillot, 2003; Baffigi et al., 2004; Diron, 2008). This method is one of the most straightforward, but also most general and successful, techniques used for nowcasting and, as a result, it is widely used in practice. Models from this class "bridge" information from timely monthly indicators into quarterly frequency. The method used to extract the information on the dynamics of a quarterly variable from monthly indicators is simple linear regression. This section describes the approach taken by the paper to forecasting GDP growth in a given quarter using one model. It subsequently describes the strategy used for the selection, aggregation and evaluation of several competing models.

2.3.1 The case of one model

Bridge models exploit statistical relations between monthly and quarterly indicators. For example, the coefficients of correlation between changes in GDP growth rates and quarterly averages of changes in several indicators exceed 0.7 in the case of Germany and France (Figures 2.1, 2.2 and 2.3). This relation is intuitive and reflected in the nature of the business cycle, which exhibits co-movements among many economic indicators (Burns and Mitchell, 1947).

Formally, in line with Antipa et al. (2012), let Y_t denote the quarter-on-quarter GDP growth rate and X_t denote the quarterly averages of q monthly explanatory variables (also referred to as indicators). The bridge model can be specified as:

$$Y_t = \alpha + \sum_{i=1}^{m} \beta_i Y_{t-1} + \sum_{j}^{q} \sum_{i}^{k} \delta_{j,i} X_{j,t-i} + \varepsilon_t, \tag{2.1}$$

where m is the number of autoregressive parameters and k is the number of explanatory variables and q is the maximum number of lags of explanatory

Throughout the paper, the term forecast can have two meanings – either a proper forecast of future GDP growth or a fitted value from a model, which could also denote a nowcast of GDP growth in the current quarter or even a backcast of GDP growth in the last quarter.

In line with Mariano and Murasawa (2003), quarterly growth rates are constructed by taking moving averages of monthly growth rates.

variables; β_i is an autoregressive parameters of lag i and $\delta_{j,i}$ is a regression coefficient of variable i at lag q. In all specifications, we opt for $m = 0$. This choice is common in the literature (Diron, 2008; Arnoštová et al., 2011) and is aimed at reducing the persistence of forecasts (and thus improving forecasting power when fundamentals change abruptly). In addition, the lagged GDP growth rate is not observed in the first two months of a given quarter and its extrapolation would add additional noise to the forecasts. Finally, one can argue that the lagged series is highly collinear with the monthly indicators, which leads to larger forecast sampling errors. Regarding the number of lags of each explanatory variable, parameters k were set based on an automatic selection procedure where the Akaike information criterion was minimized on the training sample (1999Q1–2011Q4).

Equation 2.1 is estimated using a simple ordinary least squares estimator. The estimated relationship can subsequently be used for the nowcasting and forecasting of a given quarter provided that the variables on the right-hand side (X_t) are known. This is rarely the case (with the exception of backcasting) and one hence needs to extrapolate observations of monthly indicators so that all observations are known in a given quarter. The literature uses simple AR, ARMA or VAR models for this task. For the sake of computational simplicity, we opt for AR models.

One can infer various sources of forecast errors. First, even if all the monthly indicators are known precisely (i.e. without any measurement errors), the GDP figures may not be estimated accurately (using bridge equations, or by other approaches). Next, since the models are estimated using simple OLS regressions, the choice of indicators matters and it is not clear what variables explain GDP growth rates best. In addition, the coefficients in Equation 2.1 are only estimated and are subject to statistical uncertainty. Finally, not all the monthly indicators are known in a given quarter and the missing figures are extrapolated, which very likely leads to further errors.

2.3.2 The evaluation of nowcasts and forecasts

In order to compare the performance of various competing models, we perform a pseudo-real-time out-of-sample forecasting exercise. For each month in a given quarter (denoted as M1, M2 and M3 in the paper), forecasts for three

Preliminary estimates suggested that the forecasting performance gain from using ARMA models compared to AR models is negligible. At the same time, the computational cost of selecting the optimal lag structure of AR and MA parameters was large.

horizons are considered: (i) a backcast (estimating GDP growth in the last quarter when the figure has not yet been published), (ii) a nowcast (estimating GDP growth in the given quarter), (iii) a forecast of GDP growth in the next quarter. It is assumed that the forecasts are made at the end of the month, so that all indicators which are published during the given month are known.

The models are estimated since the first quarter of 1999 (provided the data is available) and the evaluation period starts in the first quarter of 2012. For each month since January 2012, we take the following steps:

1. Missing observations are introduced at the tail of the sample according to the publication lag, in order to simulate "pseudo" real-time data vintages.

2. Observations from complete quarters are used in order to estimate the parameters in Equation 2.1.

3. The missing observations of monthly indicators are subsequently extrapolated using the AR models described in the previous subsection and aggregated to quarterly frequency. One should note that we extrapolate not only the missing observations due to the procedure described in the first step, but also the observations of the remaining months in the given and next quarters.

4. The estimated model is fitted in order to obtain a backcast, a nowcast and a forecast and the estimates are saved.

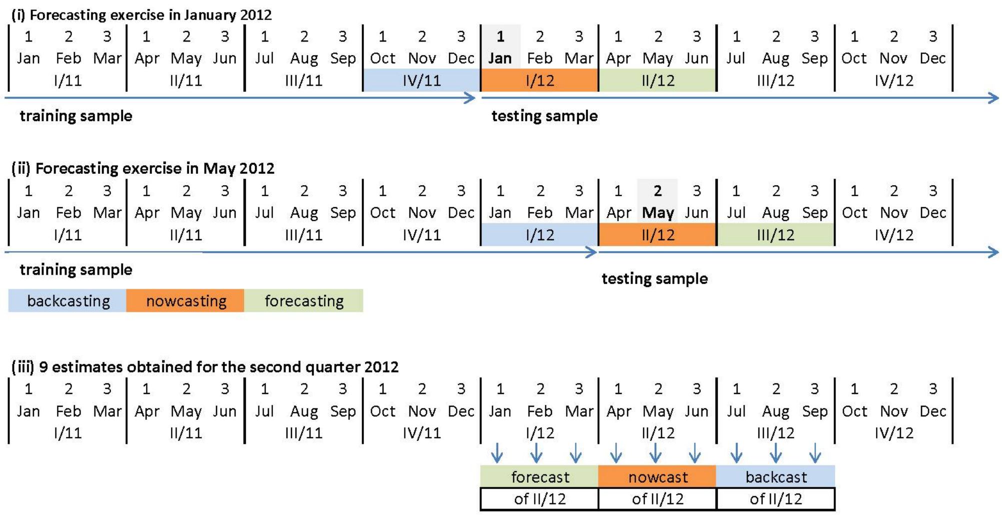
In other words, the forecast evaluation is performed recursively and the model is re-estimated every quarter. For each of the months considered, we obtain three sets of forecasts (a backcast, a nowcast and a forecast; panels (i) and (ii) in Figure 2.1) and for each quarter, we obtain nine sets of forecasts depending on the forecasting horizon (panel (iii) in Figure 2.1). For presentation purposes, we drop one of the horizons – the backcast in the third month, since the GDP figure for the last quarter is already published by then.

The models are compared based on the root mean square error for each forecast horizon. This is because one could expect the forecasting performance of each model to vary across the forecasting horizon and the month of the

All publication lags are described in Table 2.1 in the Appendix. The lags are denoted in months, i.e. 0 means that the data are available at the end of the given month at the latest; 1 means that the data are published by the end of the following month at the latest.

The order of the AR models is selected automatically based on the Akaike information criterion for each variable separately.

Figure 2.1: Timing scheme of the forecasting exercise



forecast. In the first month of a given quarter, when only leading indicators are available, one could expect these models to perform best for nowcasting. On the other hand, in the third month of a given quarter, when hard data from industry are available for the first month, models with industrial production may perform better.

In the presentation of the results, the benchmark model is a naive model based on a random walk forecast. This model assumes that GDP growth in the last, current and next quarters remains the same as the last published GDP growth figure.

2.3.3 Three types of models

The next section describes the variables considered in the forecasting exercise. In total, we have amassed 58 variables. In order to obtain results which are relatively easy to compare and present, we consider the following three groups of models for each country:

Univariate bridge equation models

In these models, only one variable is used as an indicator in the bridge equation (we also consider its lags, as described in Section 2.3.1). At the same time, we average the outcomes of these models (in line with Arnoštová et al. (2011), for example) and group them into the following categories:

1. BMA

2. correlations
3. leading indicators
4. financial variables
5. foreign variables

The BMA category includes indicators selected based on Bayesian model averaging, which accounts for the model uncertainty. Specifically, priors on regression parameters are set as non-informative and priors on probabilities are set as uniform. The posterior probabilities of the models are approximated using the simple Bayesian Information Criterion. The BMA category considers all variables whose posterior probabilities of inclusion exceed 0.1%.

Similarly, the correlations category contains 15 variables, which were selected based on their correlations with GDP growth rates. The probability threshold and the number of variables in the correlations category were chosen arbitrarily. However, this led to approximately the same number of indicators in each category, and variables from each important category (hard, soft, foreign indicators) were also selected.

Multivariate models

Multivariate models include multiple variables selected on the basis of economic intuition and also of their correlations with GDP growth. For each country, we consider (i) two models containing only a combination of two leading indicators; (ii) four models containing various coincident indicators (usually a combination of the industrial production index, the retail sales index and a measure of unemployment); (iii) two models containing both leading and coincident indicators. The precise model specifications are described in Appendix 2.D.

Models based on common components

The last model we consider is based on common components which capture the comovement among all the indicators relevant to a particular country. Since some of the observations are missing, especially at the start of the training sample, a method based on the EM algorithm (described by (Josse and Husson, 2012)) is used to extract the common components, estimate the loadings and

The R library by Raftery et al. (2018) was used for the computations.

impute the missing observations on the training sample. The iterative PCA algorithm starts by replacing missing observations with the initial values (such as the mean of the variable). It is followed by PCA of this provisional dataset and by imputing initially missing observations using the extracted common components and loadings. The process is then iterated until convergence is achieved.

The nowcasting procedure described above is modified slightly. First, the loadings of the principal components are obtained on the training sample using the method cited in the previous paragraph. Then, missing values are then imposed for each of the variables (based on their publication lags), which are then extrapolated using an AR process. Finally, the principal components are fitted based on the loadings estimated on the training sample, and the GDP growth forecast is subsequently obtained.

2.4 Data

2.4.1 The choice of countries

Seventeen euro area countries are currently used in the CNB's forecasting process (only Luxembourg and Malta are excluded from the total aggregate). GDP growth rates and measures of the inflation of these countries are weighted in order to generate "effective" euro area aggregates. The weights used for the aggregation are based on the trade weights of Czech exports. Nowcasting all 17 countries puts enormous demands on data processing, which is naturally prone to mistakes. In addition, when choosing the number of countries to include in the forecasting process, one faces a trade-off between covering a higher export share on the one hand and the ability to make expert judgments on the forecasts. This is partly because with 17 countries, the time-consuming process can lead to poor monitoring of individual countries. This is one of the advantages of BEQ models.

To reduce the computational burden of nowcasting the full aggregate, and in order to make the presentation of the results concise, we focus only on the three most important euro area countries weighted by their shares in Czech exports: Germany, France and Slovakia. We argue that, firstly, these three countries cover more than 70% of total Czech exports to the euro area (Figure

The package by Josse and Husson (2016) was used for the estimation.

The weight of Czech exports to the euro area in all Czech exports is about 65%.

2.2). This share increases to more than 83% when we include another two countries (Austria and Italy). Nevertheless, one could argue that including more countries is not necessary from the economic point of view, since the GDP growth rates of both Austria and Italy are highly correlated with German GDP growth (Figure 2.3).

2.4.2 Data used for the analysis

The dataset used in the nowcasting and forecasting exercises was obtained at the beginning of October 2018. In the terminology of the previous section, the exercise is performed in the third month (M3) of the third quarter of 2018. The data set starts in January 1999, i.e. at the inception of the euro area and the date when most of the time series start to be available. As stated in the previous section, the training sample spans 1999Q1–2011Q4 and the evaluation period is 2012Q1–2018Q3.

The downloaded variables represent various sectors of the economy and can be grouped into the following categories: (i) production and turnover in industry and construction, (ii) labour market variables, (iii) consumer and business surveys, (iv) external trade data, (iv) financial variables. In addition, since the economies studied in the paper are linked closely to the car industry, we use a variable on new passenger car registrations. Finally, as these economies are also very open, we use several indicators for the United States, which capture the global business cycle and foreign demand.

In total, 58 variables were downloaded from publicly available sources. Some of these variables are country-specific but the definitions are the same across countries (such as the industrial production index); some variables are country-specific and unique to a given country (such as the ZEW index indicator in the case of Germany). There are also some indicators which are shared by models in every country (such as US leading or financial indicators). The complete list of variables (along with their precise definitions) can be found in Table 2.1 in the Appendix. The data are downloaded in an automatic way using the APIs of the data providers (in the case of Eurostat, the ECB, Deutsche Bundesbank, Federal Reserve Economic Data (FRED) and Yahoo Finance) or directly from the ZEW and CESifo websites and can be routinely updated.

In the case of Slovakia, the case for including US variables is weaker, since the country trades mostly with other euro area member states. To address this feature of the Slovak economy, we included a German leading indicator in one of the multivariate models to capture the foreign demand channel (Model 2).

All the data, with the exception of financial variables, were seasonally adjusted by the publishing institutions. The nowcasting and forecasting exercises rely on stationary variables, i.e. we used log-differences or differences of variables that were non-stationary (I(1)).

Unfortunately, we were not able to obtain historical data vintages. As a result, the analysis is performed not in real time, but on the most recently available data. Nevertheless, as stated in the previous section, the analysis is performed on pseudo-real-time vintages, which take into account the publication lag of each time series (the lags are described in Table 2.1 in the Appendix).

2.5 Results

This section summarizes the results of the forecast evaluation exercise. All computations were performed in R, primarily using libraries in the Tidyverse collection. Charts were generated using the ggplot2 library.

The text uses various names for the forecast horizon: longer horizons denote proper forecasting of next-quarter GDP growth, while shorter horizons denote nowcasts and backcasts. The figures in this section summarize the root mean square errors of the forecasts at each horizon graphically. The precise figures can be found in Section 2.E in the Appendix. It is worth noting that the numbers on the horizontal axes of the figures denote the months in the quarters when the forecast is performed. As a result, the information sets (or data) available to the forecaster are the same for each month.

2.5.1 Germany

In the case of Germany (Figure 2.2), all the models considered based on bridge equations perform better than the naive random walk benchmark model. Regarding univariate models, the models based on leading indicators perform best at the long forecast horizon. However, their forecasting ability declines as the horizon of the forecast gets shorter both in absolute terms (slightly) and compared to some of the other competing models (considerably). The models based on BMA perform moderately well at longer horizons but improve when the horizon is shorter. The same holds for the models based on variables selected

R Core Team (2018)
Wickham (2017)
Wickham (2016)

based on the correlation coefficients and for the models containing industrial production indicators, especially in the case of backcasting. On the other hand, foreign variables do not necessarily improve nowcasting much compared to the benchmark model, but such models still perform better than those containing financial variables.

The evaluation exercise based on multivariate and common component models provide similar results to the univariate models. First, the models based on leading indicators perform best at the long end of the forecasting horizon, but their performance worsens for nowcasting and backcasting. Compared to the models based on leading indicators, those based on coincident and mixed indicators perform moderately worse at the longer end of the horizon, but their performance improves in the case of nowcasting and backcasting. The model based on common components performs relatively poorly at the longer end of the forecasting horizon, but its forecasting ability still beats that of the benchmark model. The performance of the common components model improves in the case of nowcasting and backcasting and is comparable to the best models from the other two groups.

2.5.2 Slovakia

The performance of the bridge models is considerably worse in the case of Slovakia (Figure 2.3). None of the models considered outperforms the random walk benchmark model, and the root mean square errors are more dispersed than in the case of Germany. The poor performance of the models for Slovakia can be explained by several factors. First, the volatility of GDP growth is very low in the case of Slovakia (Figure 2.1), which leads to very high performance of the benchmark model. Interestingly, the performance of the AR(2) model is worse than that of the random walk model, due to the stability of GDP growth rates. In addition, looking at the correlations between GDP growth rates and industrial production, the coefficient is significantly lower for Slovakia than for Germany and France (Figure 2.4, Table 2.5). Strikingly, the correlation coefficients between the two variables were even negative before the financial crisis (2.1). They subsequently turned positive, but were still lower than in the other two countries analysed. This signals issues with the measurement of GDP before the financial crisis.

We tried to eliminate the extreme GDP growth rates observed before the crisis, but this did not improve the performance of the models significantly.

Still, one can identify several features shared with the results for Germany. The models containing the industrial production index perform moderately well. Interestingly, however, the root mean square errors of the two multivariate models based on coincident indicators (coincident indicators 2 and 3) perform worse for nowcasting in the third month compared to the previous two months. As in the case of Germany, financial and foreign variables also do not add much information to the forecasts. The performance of the model based on common components can be assessed as consistently satisfactory.

2.5.3 France

In the case of France, almost all the models considered outperform the benchmark random walk model based on the random walk forecast. One major exception is the model containing financial variables, which performs worse in the case of the nowcast (in months 1 and 2) and the forecast (in month 3). This feature is similar to the cases of the two countries discussed previously.

The performance of all the other models considered is very similar at the long end of the forecasts. Looking at nowcasting, the performance of the models based on correlations and BMA improves, as does that of the multivariate models based on coincident and mixed indicators. The two models with mixed indicators perform best at the nowcasting horizon, both in absolute terms and compared to other models. Finally, the forecasts based on common components yield consistently satisfactory results.

2.5.4 Discussion of the Results

To sum up, the forecasting performance of the various competing models is not constant and varies based on the forecasting horizon considered. In line with intuition, the forecasting ability of the models containing leading indicators is strongest at longer horizons, but diminishes for nowcasting and backcasting. At the same time, the power of the models containing industrial production is increasing in the case of nowcasting and backcasting (compared to forecasting), especially in the third month, when the industrial production index is published for the first month of the current quarter. The ability of the industrial production index to explain GDP growth is highest in the case of Germany and France and lower in the case of Slovakia. This finding is not surprising in the case of Germany, as German economic output relies largely on industry (espe-

Figure 2.2: RMSE: Germany

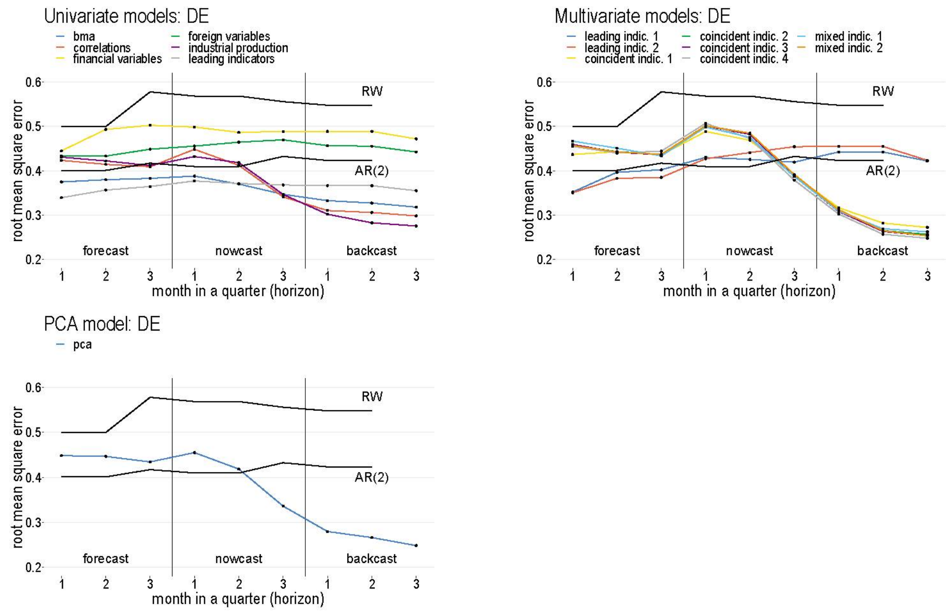


Figure 2.3: RMSE: Slovakia

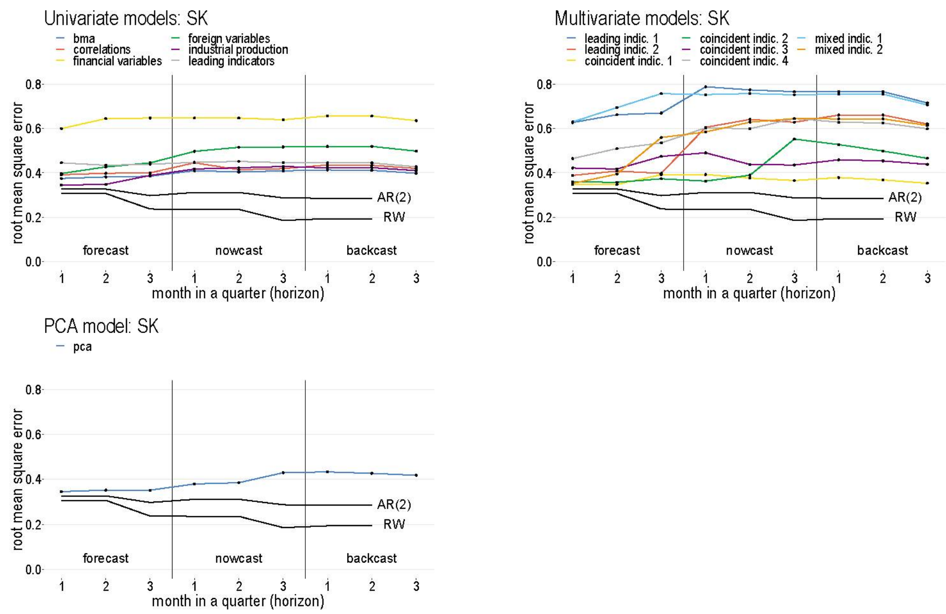
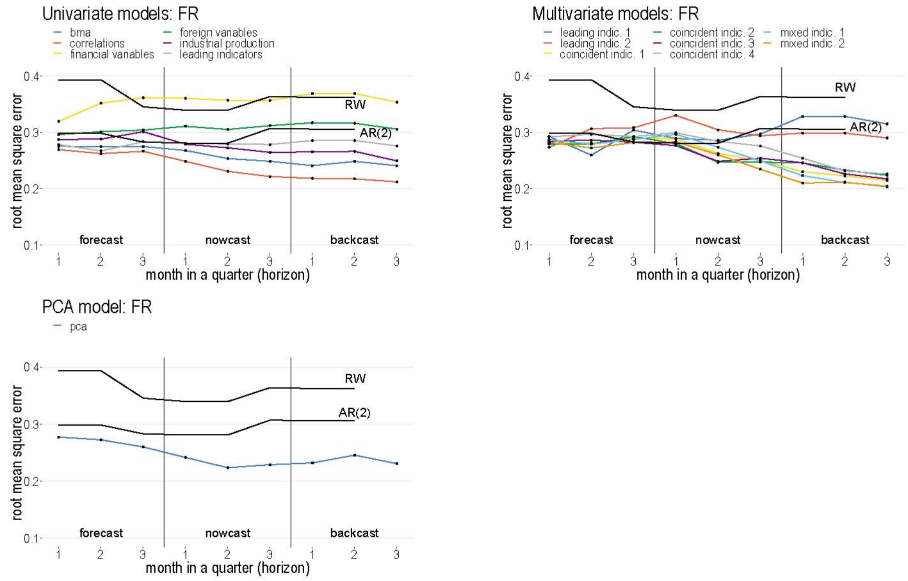


Figure 2.4: RMSE: France



cially manufacturing) and the industrial production index is one of the sources used to compute the GDP figures.

The models for Slovakia perform very poorly even when they are contrasted with the naive random walk model. This is due to the low volatility of GDP growth observed in recent years, especially after 2012, and the relatively high volatility of the monthly indicators. At the same time, the contemporaneous correlations between industrial production and GDP growth are small relative to the cases of Germany and France (Figure 2.2).

Overall, the forecasting performance of most of the models is highest for backcasting, followed by nowcasting and forecasting. This result is in line with the size of the information set available at the time of the forecast. The relatively poor performance of bridge models for forecasting stems from the extrapolation of monthly indicators, which sometimes involves producing more than ten monthly observations using simple AR models (the forecast horizon is nine months, plus the publication lag is up to two months). As a result, alternative models such as VAR or structural models might be useful for short-term forecasting.

On the other hand, bridge models exploit a significant amount of information from monthly indicators to produce nowcasts and backcasts. However, even these estimates are crucial for forecasting GDP growth many quarters ahead, since assessing the current state of the economy is critical in order to produce meaningful forecasts.

2.6 Conclusion

This paper introduced a new approach to nowcasting foreign GDP growth for the Czech economy. Although the current state of the Czech economy is assessed on a regular basis, no method for routinely nowcasting the foreign GDP growth of several countries has been proposed yet. To this end, the paper employed a relatively simple, but general and successful technique based on bridge models. These models extract information from timely monthly indicators to infer GDP growth rates in the past, current and even next quarters.

The method of bridge equations was employed to perform backcasts, nowcasts and short-term forecasts of GDP growth rates in three major trading partners of the Czech Republic: Germany, Slovakia and France. A pseudo-real-time forecasting exercise was performed for the three horizons for each of the three months in a given quarter for the whole evaluation period. The estimates were subsequently evaluated based on the root mean square errors for each forecast horizon.

The results for Germany and France confirmed economic intuition and the findings in the literature, in that the various models are more or less successful depending on the forecast horizon. Overall, most of the models considered in the paper outperform the benchmark model based on random walk forecasts. The models with industrial production indices are most successful for nowcasting and backcasting, notably when the industrial production index has already been published for a given quarter. On the other hand, the models containing leading indicators are more successful at the longer ends of forecasts, especially in the case of Germany, for which many soft indicators are constructed. In addition, the model containing common components capturing the overall dynamics shared by the monthly indicators performs well at all horizons, particularly in the case of nowcasting the current GDP growth rate.

On the other hand, the performance of the models for Slovakia is not as successful. Their poor performance stems from two major factors. The first is the very low volatility of GDP over the evaluation period, which is reflected in the highest performance of the random walk benchmark model. Second, the correlation coefficient between the industrial production index and GDP growth rates was negative before the crisis, signalling issues with the measurement of GDP in the first half of the sample.

The models based on bridge equations perform best for the nowcasting and backcasting horizons, but they can also be valuable for assessing the direction of GDP growth in the coming quarter. In addition, having accurate estimates of the last and current GDP growth rates enables one to impose more precise initial conditions in more complex models. As a result, the techniques in this paper can be considered the first step for future research into time series forecasting of external economic developments for the Czech economy.

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2.A Data used for the analysis

Table 2.1: Data used for the analysis

	ticker	keys	lags	DE	SK	FR	EA19	US
Eurostat								
GDP growth								
GDP qoq growth SCA	gdp_qoq	namq_10_gdp: Q.CLV_PCH_PRE.SCA.B1GQ.	5	x		x		
GDP qoq growth SA	gdp_qoq	namq_10_gdp: Q.CLV_PCH_PRE.SA.B1GQ.	5		x			
production in industry								
industry total	ip_total	sts_inpr_m: M.PROD.B-D.SCA.PCH_PRE.	2	x	x	x		
manufacturing	ip_manufacturing	sts_inpr_m: M.PROD.C.SCA.PCH_PRE.	2	x	x	x		
electricity, gas, steam and air conditioning supply	ip_energy	sts_inpr_m: M.PROD.D.SCA.PCH_PRE.	2	x	x	x		
mining and quarrying	ip_mining_quarrying	sts_inpr_m: M.PROD.B.SCA.PCH_PRE.	2	x	x	x		
intermediate goods industry	ip_intermediate	sts_inpr_m: M.PROD.MIG_ING.SCA.PCH_PRE.	2	x	x	x		
capital goods industry	ip_capital_goods	sts_inpr_m: M.PROD.MIG_CAG.SCA.PCH_PRE.	2	x	x	x		
durable consumer goods industry	ip_durables	sts_inpr_m: M.PROD.MIG_DCOG.SCA.PCH_PRE.	2	x	x	x		
non-durable consumer goods industry	ip_nondurables	sts_inpr_m: M.PROD.MIG_NDCOG.SCA.PCH_PRE.	2	x	x	x		
production in construction								
production in construction	construction	sts_copr_m: M.PROD.F.SCA.PCH_PRE.	2	x	x	x		
deflated turnover in retail trade								
retail trade, except of motor vehicles and motorcycles	retail_excl_vehicles	sts_trtu_m: M.TOVV.G47.SCA.PCH_PRE.	2	x	x	x		
retail trade of non-food products (except fuel)	retail_nonfood	sts_trtu_m: M.TOVV.G47_NFOOD_X_G473.SCA.PCH_PRE.	2	x	x	x		
turnover in industry								
mining and quarrying	it_mining_quarrying	sts_intv_m: M.TOVT.B.SCA.PCH_PRE.	2	x	x	x		
manufacturing	it_manufacturing	sts_intv_m: M.TOVT.C.SCA.PCH_PRE.	2	x	x	x		
turnover in industry; domestic market								
mining and quarrying	it_dom_mining_quarrying	sts_intvd_m: M.TOVD.B.SCA.PCH_PRE.	2	x	x	x		
manufacturing	it_dom_manufacturing	sts_intvd_m: M.TOVD.C.SCA.PCH_PRE.	2	x	x	x		
turnover in industry; non-domestic market								
mining and quarrying	it_nondom_mining_quarrying	sts_intvnd_m: M.TOVE.B.SCA.PCH_PRE.	2	x	x	x		
manufacturing	it_nondom_manufacturing	sts_intvnd_m: M.TOVE.C.SCA.PCH_PRE.	2	x	x	x		
labour market								
unemployment rate total	unrate_total	une_rt_m: M.SA.TOTAL.PC_ACT.T.	1	x	x	x		

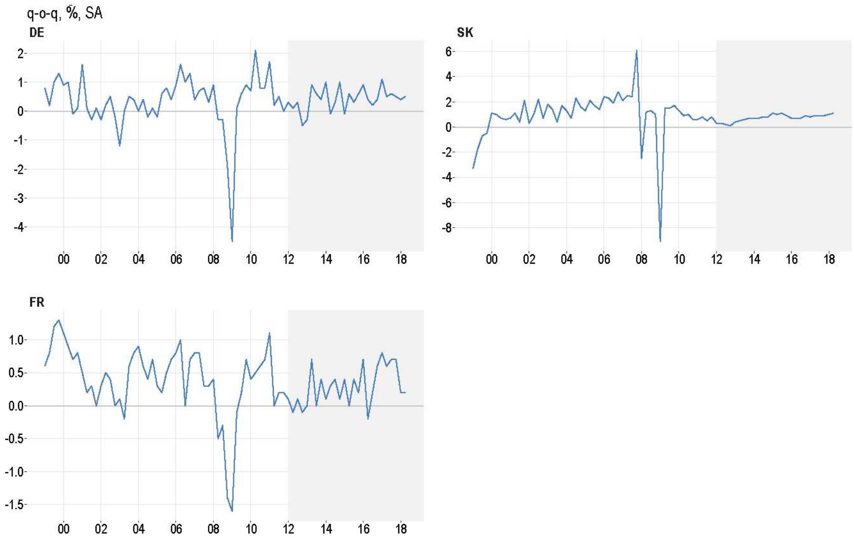
	ticker	keys	lags	DE	SK	FR	EA19	US
unemployment rate, 25 years and over	unrate_25over	une_rt_m: M.SA.Y25-74.PC_ACT.T.	1	x	x	x		
unemployment rate, under 25 years	unrate_25under	une_rt_m: M.SA.Y_LT25.PC_ACT.T.	1	x	x	x		
consumer and business surveys								
consumer confidence indicator	ecs_consumer_confidence	ei_bsco_m: M.BS-CSMCI.SA.BAL.	0	x	x	x		
consumer unemployment expectations	ecs_consumer_exp_unem	ei_bsco_m: M.BS-UE-NY.SA.BAL.	0	x	x	x		
industry confidence indicator	ecs_industry_confidence	ei_bsin_m_r2: M.BS-ICI.SA.BAL.	0	x	x	x		
industry employment expecations	ecs_industry_exp_employment	ei_bsin_m_r2: M.BS-IEME.SA.BAL.	0	x	x	x		
services confidence indicator	ecs_services_confidence	ei_bsse_m_r2: M.BS-SCI.SA.BAL.	0	x	x	x		
services employment expectations	ecs_services_exp_employment	ei_bsse_m_r2: M.BS-SEEM.SA.BAL.	0	x	x	x		
retail confidence indicator	ecs_retail_confidence	ei_bsrt_m_r2: M.BS-RCI.SA.BAL.	0	x	x	x		
retail employment expectations	ecs_retail_exp_employment	ei_bsrt_m_r2: M.BS-REM.SA.BAL.	0	x	x	x		
construction confidence indicator	ecs_construction_confidence	ei_bsbu_m_r2: M.BS-CCI-BAL.SA.	0	x	x	x		
construction employment expectations	ecs_construction_exp_empl	ei_bsbu_m_r2: M.BS-CEME-BAL.SA.	0	x	x	x		
external trade								
exports outside of the EU, current value	exports_ex_eu	ext_st_28msbec: M.EXP.TRD_VAL_SCA.EXT_EU28.TOTAL.	2	x	x	x		
exports, current value	exports_world	ext_st_28msbec: M.EXP.TRD_VAL_SCA.WORLD.TOTAL.	2	x	x	x		
ECB								
car registrations								
new passenger car registration mom, sa	car_registrations	STS.M.I8.Y.CREG.PC0000.3.PER	2				x	
Buba								
orders received								
industry, constant prices	orders_industry	BBDE1.M.DE.Y.AEA1.A2P300000.F.C.I15.A	2	x				
intermediate goods, constant prices	orders_intermediates	BBDE1.M.DE.Y.AEA1.A2P310000.F.C.I15.A	2	x				
capital goods, constant prices	orders_capital_goods	BBDE1.M.DE.Y.AEA1.A2P320000.F.C.I15.A	2	x				
consumer goods, constant prices	orders_consumer_goods	BBDE1.M.DE.Y.AEA1.A2P350000.F.C.I15.A	2	x				
Fred								
foreign variables								
Industrial production: manufacturing	us_manufacturing	IPMAN	1					x
Industrial production index	us_ip_total	INDPRO	1					x
University of Michigan: consumer sentiment	us_umcsent	UMCSENT	0					x
Motor vehicle retail sales: domestic autos	us_dom_cars	DAUTOSA	1					x
Retail sales	us_retail	RETAILSMSA	2					x
OECD consumer confidence indicator for the US	us_oecd_consop	CSCICP03USM665S	2					x
OECD business confidence indicator for the US	us_oecd_business_surveys	BSCICP03USM665S	2					x
Other								
leading indicators - Germany								
ifo business climate, industry and trade	ifo_industry_climate		0	x				
ifo business situation, industry and trade	ifo_industry_situation		0	x				
ifo business expectations, industry and trade	ifo_industry_expectations		0	x				

	ticker	keys	lags	DE	SK	FR	EA19	US
ifo business climate, manufacturing	ifo_manufacturing_climate		0	x				
ifo business situation, manufacturing	ifo_manufacturing_situation		0	x				
ifo business expectations, manufacturing	ifo_manufacturing_expectations		0	x				
ZEW indicator of economic sentiment, Germany	zew_sentiment		0	x				
ZEW indicator of economic situation, Germany	zew_situation		0	x				
financial variables								
DAX performance index	dax	yahoo: ^GDAXI	0	x				
CAC 40	cac40	yahoo: ^FCHI	0			x		
Euro Stoxx 50	stoxx50	yahoo: ^STOXX50E	0				x	
S&P 500 Index	sp500	yahoo: ^GSPC	0					x

Note:
Data sources are printed in bold. Keys column denotes the name of the database (in the case of Eurostat) and other identification dimensions / tickers.
Column lags denotes the publication lag in weeks (i.e., zero indicates that the variable is published by the end of a given month).
Variables in the Other category were downloaded from the websites of publishing institutions (CESifo or Center for European Economic Research, ZEW) or from Yahoo Finance (financial variables).

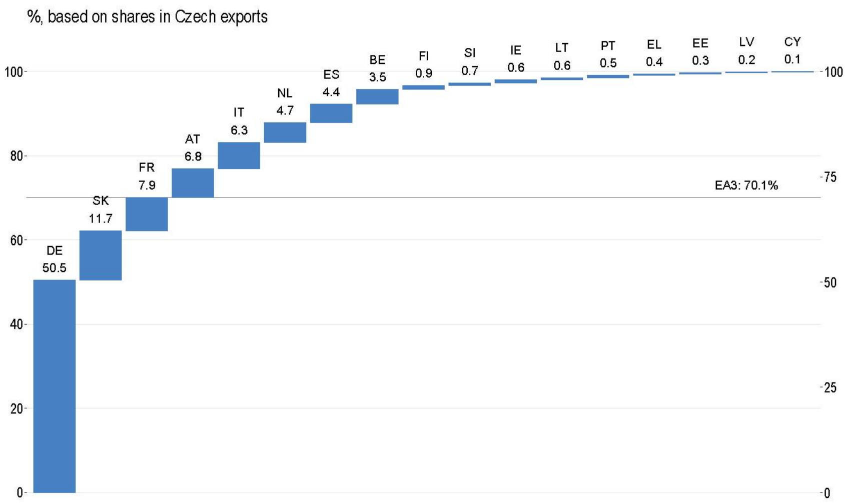
2.B Major trading partners of the Czech Republic: stylized facts

Figure 2.1: GDP growth rates in the considered countries



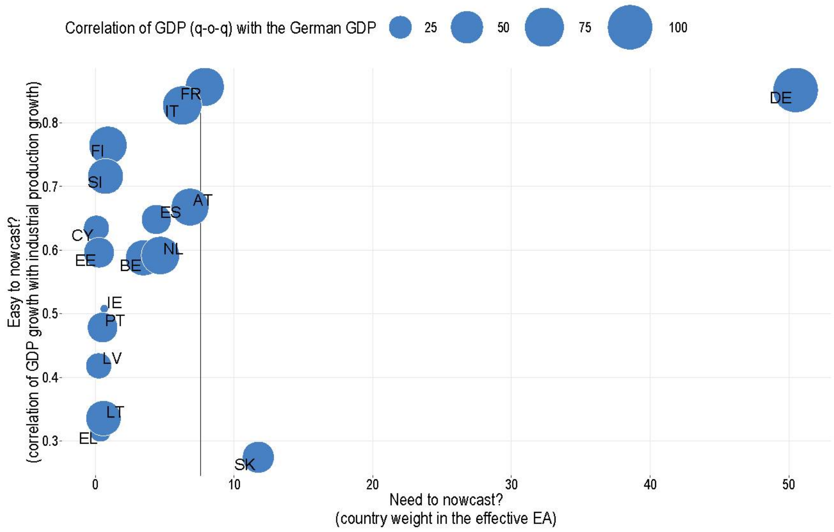
Source: Eurostat

Figure 2.2: EA country weights based on the Czech export shares (2018 Q1)



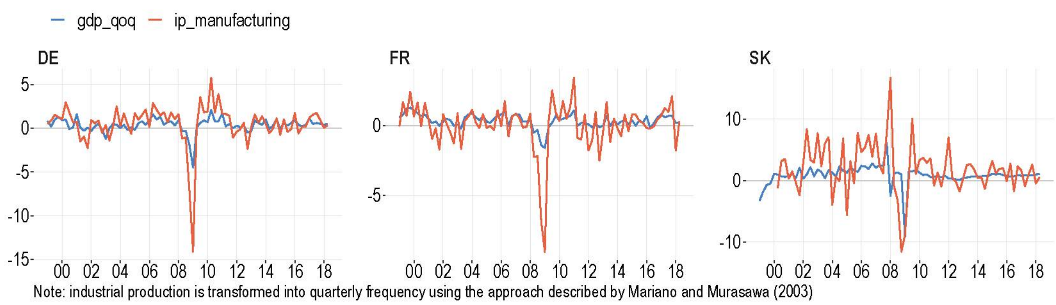
Source: Eurostat, CZSO

Figure 2.3: EA country weights based on the Czech export shares, correlations of gdp growth rates with industrial production growth



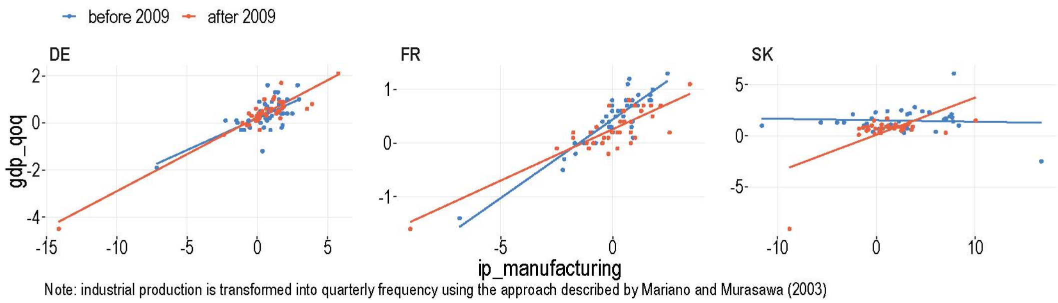
Source: Eurostat

Figure 2.4: GDP and industrial production growth rates



Source: Eurostat

Figure 2.5: GDP and industrial production growth rates



Source: Eurostat

Table 2.1: Correlation coefficients between GDP growth rates and industral production growth rates

	before 2009	after 2009
DE	0.68	0.94
FR	0.90	0.85
SK	-0.06	0.62

Source: Eurostat

2.C Monthly indicators in univariate models (BMA, correlations)

Figure 2.1: Variables selected based on BMA and correlations: Germany

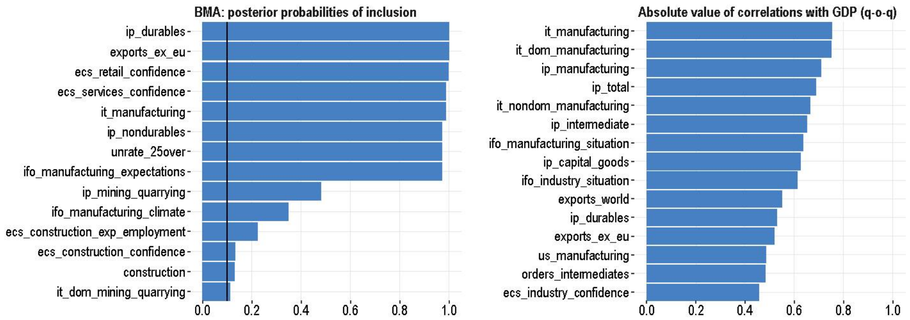


Figure 2.2: Variables selected based on BMA and correlations: Slovakia

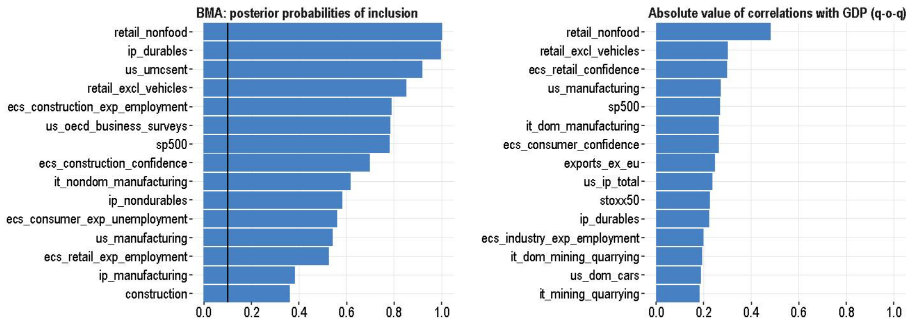
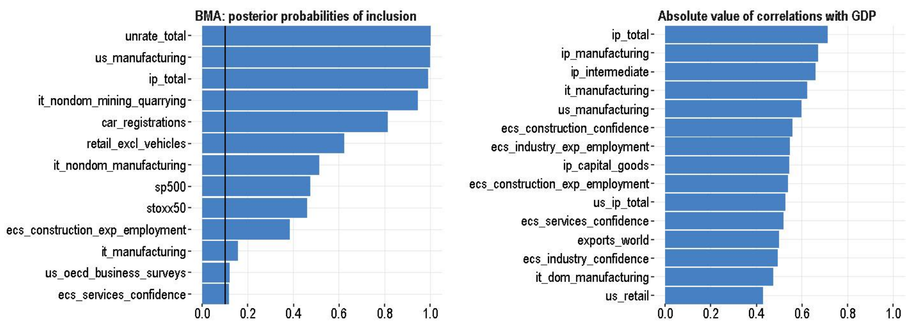


Figure 2.3: Variables selected based on BMA and correlations: France



2.D Multivariate model equations

2.D.1 Germany

Models with leading indicators:

- Model 1: gdp_qoq ~ ecs_industry_exp_employment + ecs_industry_exp_employment_lag + ifo_manufacturing_expectations_lag
- Model 2: gdp_qoq ~ ifo_manufacturing_expectations + ifo_manufacturing_expectations_lag + zew_sentiment

Models with coincident indicators:

- Model 3: gdp_qoq ~ ip_total + retail_nonfood
- Model 4: gdp_qoq ~ ip_manufacturing + retail_nonfood
- Model 5: gdp_qoq ~ ip_manufacturing + orders_industry_lag + retail_nonfood
- Model 6: gdp_qoq ~ ip_manufacturing + retail_nonfood + unrate_25over

Models with leading and coincident indicators:

- Model 7: gdp_qoq ~ ifo_manufacturing_expectations + ip_manufacturing
- Model 8: gdp_qoq ~ ifo_manufacturing_expectations + ip_manufacturing + retail_nonfood

2.D.2 Slovakia

Models with leading indicators:

- Model 1: gdp_qoq ~ ecs_consumer_exp_unemployment + ecs_consumer_exp_unemployment_lag + ecs_construction_exp_employment
- Model 2: gdp_qoq ~ ecs_consumer_exp_unemployment + ifo_manufacturing_expectations

Models with coincident indicators:

- Model 3: gdp_qoq ~ ip_manufacturing + ip_manufacturing_lag + retail_excl_vehicles
- Model 4: gdp_qoq ~ ip_durables + ip_durables_lag + retail_nonfood
- Model 5: gdp_qoq ~ ip_manufacturing_lag + retail_excl_vehicles + unrate_total + unrate_total_lag
- Model 6: gdp_qoq ~ ip_total + ip_total_lag + retail_excl_vehicles + us_manufacturing

Models with leading and coincident indicators:

- Model 7: gdp_qoq ~ ip_total_lag + retail_excl_vehicles_lag + ecs_consumer_exp_unemployment_lag
- Model 8: gdp_qoq ~ ip_total_lag + retail_excl_vehicles_lag + ecs_construction_exp_employment

2.D.3 France

Models with leading indicators:

- Model 1: gdp_qoq *sim* ecs_industry_exp_employment + ecs_construction_exp_employment
- Model 2: gdp_qoq *sim* ecs_industry_confidence + ecs_services_confidence

Models with coincident indicators:

- Model 3: gdp_qoq ∼ ip_total + ip_total_lag + retail_excl_vehicles
- Model 4: gdp_qoq ∼ ip_manufacturing + ip_manufacturing_lag + retail_excl_vehicles
- Model 5: gdp_qoq ∼ ip_manufacturing + ip_manufacturing_lag + unrate_total
- Model 6: gdp_qoq ∼ ip_total + us_manufacturing_lag

Models with leading and coincident indicators:

- Model 7: gdp_qoq ∼ ip_total + ip_total_lag + ecs_industry_exp_employment
- Model 8: gdp_qoq ∼ ip_total + ip_total_lag + retail_nonfood + ecs_industry_exp_employment

2.E Root mean square errors

Table 2.1: Root mean square errors: Germany

model	Backcast			Nowcast			Forecast		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
benchmark models									
AR(2)	0.423	0.423	NA	0.401	0.401	0.417	0.410	0.410	0.432
random walk	0.548	0.548	NA	0.500	0.500	0.578	0.568	0.568	0.556
common component model									
pca	0.280	0.266	0.248	0.448	0.447	0.434	0.455	0.418	0.336
economic models									
coincident indicators 1	0.317	0.282	0.272	0.437	0.443	0.436	0.488	0.469	0.389
coincident indicators 2	0.312	0.265	0.257	0.457	0.443	0.437	0.501	0.485	0.391
coincident indicators 3	0.308	0.264	0.254	0.459	0.442	0.436	0.501	0.482	0.387
coincident indicators 4	0.303	0.257	0.248	0.455	0.440	0.444	0.507	0.473	0.379
leading indicators 1	0.442	0.442	0.422	0.352	0.397	0.402	0.430	0.426	0.419
leading indicators 2	0.455	0.455	0.424	0.350	0.383	0.385	0.427	0.441	0.454
mixed indicators 1	0.309	0.269	0.263	0.467	0.451	0.433	0.498	0.475	0.387
mixed indicators 2	0.312	0.265	0.253	0.457	0.442	0.437	0.501	0.485	0.392
pairwise models									
bma	0.333	0.327	0.318	0.375	0.380	0.383	0.388	0.370	0.347
correlations	0.310	0.306	0.298	0.423	0.414	0.409	0.448	0.412	0.341
financial variables	0.489	0.489	0.472	0.445	0.493	0.502	0.499	0.487	0.489
foreign variables	0.457	0.455	0.442	0.433	0.433	0.449	0.456	0.464	0.470
industrial production	0.302	0.283	0.276	0.431	0.422	0.412	0.432	0.418	0.347
leading indicators	0.366	0.366	0.355	0.339	0.357	0.365	0.377	0.371	0.368

Table 2.2: Root mean square errors: Slovakia

	Backcast			Nowcast			Forecast		
model	M1	M2	M3	M1	M2	M3	M1	M2	M3
benchmark models									
AR(2)	0.285	0.285	NA	0.327	0.327	0.297	0.312	0.312	0.287
random walk	0.193	0.193	NA	0.307	0.307	0.237	0.236	0.236	0.186
common component model									
pca	0.433	0.427	0.418	0.346	0.352	0.352	0.380	0.385	0.430
economic models									
coincident indicators 1	0.379	0.368	0.353	0.348	0.347	0.392	0.392	0.376	0.365
coincident indicators 2	0.527	0.498	0.466	0.359	0.357	0.373	0.363	0.389	0.552
coincident indicators 3	0.459	0.454	0.438	0.422	0.417	0.474	0.490	0.438	0.435
coincident indicators 4	0.628	0.625	0.599	0.464	0.509	0.535	0.602	0.599	0.645
leading indicators 1	0.766	0.766	0.715	0.627	0.662	0.669	0.788	0.774	0.766
leading indicators 2	0.661	0.661	0.620	0.389	0.408	0.398	0.605	0.641	0.628
mixed indicators 1	0.755	0.755	0.706	0.630	0.694	0.757	0.753	0.757	0.752
mixed indicators 2	0.643	0.643	0.614	0.352	0.394	0.559	0.584	0.628	0.645
pairwise models									
bma	0.413	0.412	0.398	0.375	0.381	0.385	0.410	0.404	0.409
correlations	0.435	0.434	0.420	0.391	0.398	0.400	0.445	0.414	0.419
financial variables	0.656	0.656	0.635	0.599	0.644	0.647	0.647	0.647	0.639
foreign variables	0.519	0.519	0.498	0.397	0.427	0.445	0.497	0.515	0.517
industrial production	0.422	0.423	0.410	0.345	0.348	0.388	0.417	0.423	0.429
leading indicators	0.445	0.445	0.427	0.445	0.434	0.439	0.447	0.451	0.446

Table 2.3: Root mean square errors: France

	Backcast			Nowcast			Forecast		
model	M1	M2	M3	M1	M2	M3	M1	M2	M3
benchmark models									
AR(2)	0.306	0.306	NA	0.298	0.298	0.283	0.281	0.281	0.307
random walk	0.362	0.362	NA	0.393	0.393	0.345	0.339	0.339	0.364
common component model									
pca	0.232	0.246	0.231	0.277	0.272	0.260	0.242	0.224	0.229
economic models									
coincident indicators 1	0.230	0.223	0.215	0.280	0.281	0.290	0.288	0.263	0.250
coincident indicators 2	0.246	0.233	0.224	0.279	0.279	0.293	0.280	0.247	0.247
coincident indicators 3	0.246	0.226	0.217	0.284	0.286	0.282	0.277	0.249	0.254
coincident indicators 4	0.254	0.231	0.226	0.292	0.297	0.293	0.299	0.284	0.276
leading indicators 1	0.328	0.328	0.315	0.293	0.260	0.304	0.289	0.286	0.297
leading indicators 2	0.299	0.299	0.290	0.273	0.307	0.308	0.330	0.305	0.294
mixed indicators 1	0.223	0.211	0.205	0.287	0.279	0.287	0.297	0.274	0.249
mixed indicators 2	0.210	0.212	0.203	0.282	0.272	0.282	0.283	0.260	0.235
pairwise models									
bma	0.241	0.248	0.241	0.275	0.275	0.275	0.268	0.254	0.249
correlations	0.218	0.218	0.212	0.269	0.262	0.266	0.249	0.231	0.222
financial variables	0.369	0.369	0.354	0.320	0.352	0.362	0.360	0.357	0.357
foreign variables	0.317	0.316	0.306	0.296	0.301	0.304	0.311	0.305	0.312
industrial production	0.265	0.266	0.249	0.287	0.288	0.301	0.279	0.273	0.264
leading indicators	0.286	0.286	0.276	0.278	0.267	0.283	0.281	0.280	0.278

Chapter 3

Modeling Euro Area Bond Yields Using a Time-Varying Factor Model

Abstract

In this paper, we study the dynamics and drivers of sovereign bond yields in euro area countries using a factor model with time-varying loading coefficients and stochastic volatility, which allows for capturing changes in the pricing mechanism of bond yields. Our key contribution is exploring both the global and the local dimensions of bond yield determinants in individual euro area countries using a time-varying model. Using the reduced form results, we show decoupling of periphery euro area bond yields from the core countries' yields following the financial crisis and the scope of their subsequent re-integration. In addition, by means of the structural analysis based on identification via sign restrictions, we present time varying impulse responses of bond yields to EA and US monetary policy shocks and to confidence shocks.

This paper was co-authored by Marco Lo Duca (ECB). It was published in ECB working Paper Series as a paper No 2012/February 2017. The authors would like to thank for helpful discussions and valuable feedback to: Giorgio Primiceri, Fabio Canova, Roberto De Santis, Giulio Nicoletti, Mahir Binici, Marek Jarocinski, Joshua Chan, participants to the INFINITI 2016 Conference, and to participants to internal seminars of the European Central Bank.

3.1 Introduction

Sovereign bond markets have increasingly drawn the attention of policy makers and academics in recent years. As the global financial crisis and the European banking and sovereign crises demonstrated, understanding the pricing mechanism and the drivers of bond yields is essential to monitor risks, decide on policies and assess their effectiveness.

First, sovereign bonds are benchmark financial instruments used for pricing of a large variety of financial assets, including bank loans and derivatives. As a consequence, sovereign bond yields have implications for the broader macro financial environment and the transmission of monetary policy.

Second, as short term rates hit the zero lower bound across advanced economies, central banks resorted to unconventional monetary policies, including large purchases of sovereign bonds, with the aim of providing stimulus by lowering long term yields. This led the academic and policy communities to step up the efforts to analyse bond markets to assess the effectiveness, the transmission channels and international spill-overs of unconventional monetary policy ((Gagnon et al., 2011), (D'Amico and King, 2013), (Wright, 2012), (Leombroni et al., 2018), (Joyce et al., 2011) for the UK; (Hancock and Passmore, 2011), (Stroebel et al., 2012), (Hattori et al., 2016), (Rosa, 2012), (Gilchrist et al., 2014), (Neely et al., 2010), (Chen et al., 2012), (Fratzscher et al., 2013), (Rogers et al., 2014), (Bowman et al., 2015), (Christensen and Rudebusch, 2012), (Bauer and Neely, 2014), (Krishnamurthy and Vissing-Jorgensen, 2011), (Bauer and Rudebusch, 2014)).

Finally, the European sovereign and banking crisis showed the importance of understanding signals from bond markets in order to assess the underlying pricing factors and design appropriate policy responses ((De Santis, 2012), (De Santis, 2015), (De Grauwe and Ji, 2013), (Beirne and Fratzscher, 2013)). On the one hand, a number of contributions suggest that, at the peak of the sovereign debt crisis, euro area bond yields reflected fundamentals, in particular the expected deterioration of the macro environment and of fiscal positions. On the other hand, a number of other contributions suggest that risk aversion, panic and irrational investors' behaviour drove bond yields.

Overall, the evidence presented on the European crisis supports the view that the pricing mechanism of sovereign bond yields might change over time, consistent with the existence of multiple equilibria and market imperfections.

Against the background of the importance of understanding the drivers of bond yields, especially in a crisis/post crisis environment, this study contributes to the policy debate and the academic literature by presenting a new model to assess the pricing mechanism of euro area sovereign bond yields from a dynamic perspective. In particular, we use a factor model with time varying loading coefficients and stochastic volatilities to assess the drivers of sovereign bond yields in euro area countries. The time variation in factor loading coefficients allows for capturing changes in the pricing mechanism of bond yields, consistent with the evidence emerging from other empirical studies. Exploring both the global and local dimensions of bond yield determinants in individual euro area countries is one of our key contributions. Specifically, our model studies the drivers of country specific yields separating between (i) Euro area core and periphery factors to assess integration, spill-overs and contagion within the euro area (ii) US and Emerging Market Economies (EMEs) market factors to assess spill-overs to the euro area from the rest of the world. Finally, time varying impulse responses to monetary policy shocks and confidence shocks are identified via sign restrictions and studied.

From a financial stability perspective, the model presented in this article allows for the detection of anomalies or rapid changes in the pricing mechanism of bonds. For example, the model can detect early signs of de-coupling among euro area bond markets when idiosyncratic volatilities increase and when the role of the loading coefficient of the "core" euro area factor decreases. It can detect early signs of contagion when the loading coefficient of the "periphery" euro area factor increases. It can also be used to monitor the intensity of the spill-overs from the rest of the world by looking at the loading coefficients on the external variables. Relevant benchmarks for assessing the level of anomalies in the pricing mechanism are provided by loading coefficients, volatilities and shape of impulse responses in the pre-crisis and crisis periods. From a monetary policy perspective, the model provides useful information on whether the pricing mechanism changes in response to policy actions.

From an academic perspective, this study improves on the existing literature ((Boysen-Hogrefe, 2013), (D'Agostino and Ehrmann, 2013)) by adding external factors (US and EMEs) and other variables into a dynamic factor model with time varying loading coefficients for euro area bond yields. Furthermore, the study presents new evidence based on time varying impulse responses to discuss how the transmission of EA and US monetary policy shocks has evolved during the crisis. In addition, from the econometric point of view, the study shows how a recently proposed precision-based simulator of state-space models by

Chan and Jeliazkov (2009) can be used to sample factors in a FAVAR model after a correction of singularity in the transition matrix.

The empirical analysis presented in the paper shows that there is substantial time variation in the loading coefficients of factors and in the impulse responses of yields to different shocks. This supports the view that the pricing mechanism of bond yields is not stable across periods, suggesting the existence of multiple equilibria where the pricing factors for bonds differ. In particular, the model captures well the unfolding of the European sovereign and banking crisis as of 2010 and the subsequent re-integration of markets after 2012. As of 2010, when the crisis escalated, idiosyncratic volatilities in a number of euro area countries spiked, bond yields in the periphery gradually became more sensitive to the euro area ”periphery” factor and less sensitive to the ”core” factor. At the same time the impulse responses of bond yields in some countries changed shape, suggesting changes in the transmission of monetary policy shocks. After 2012, the pricing mechanism gradually approached the situation prevailing in the pre-crisis periods.

The results of the analysis have implications for the debate on the impact of unconventional monetary policy on sovereign bond markets in the euro area. Specifically, our results suggest a link between euro area unconventional policies, the way different factors are priced into bond yields and the reaction of bond yields to monetary policy shocks. A notable finding is that the announcement of Outright Monetary Transactions by the ECB appears to have led to the gradual normalisation of the pricing mechanism of bond yields towards the pre-crisis situation. Another interesting finding is that the ECB mix of unconventional monetary policy gained particular traction in those markets experiencing distress where accommodation was needed.

The remainder of the paper is organised as follows. The next section presents the model and the data used for the empirical analysis. The subsequent two sections discuss the results and their implications for financial stability surveillance and for the analysis of monetary policy. The final section concludes.

3.2 Methodology and data

3.2.1 Model setup

To study the dynamics of bond yields, we use a FAVAR model with time-varying loadings. In our benchmark model, first differences of bond yields of N euro area countries are assumed to be driven by two euro area factors, dynamics of bond yields in the United States and in emerging markets, by changes in USD/EUR exchange rate and finally by country-specific idiosyncratic shocks. The five driving factors in turn evolve according to a VAR(p) process, which allows us to study interactions between the factors themselves and also responses of each euro area government bond yields to these factors.

More formally, let $y_{i,t}$ denote bond yield of country i ($i = 1, ...N$) at time t, i_t^{us}, i_t^{eme} denote the US and emerging market factors, s_t denote the USD/EUR exchange rate and $\lambda_{i,j,t}$ denote loading of i-th country on j-th factor at time t. This notation leads to the following measurement equation:

$$y_{i,t} = \lambda_{i,1,t}f_{1,t} + \lambda_{i,2,t}f_{2,t} + \lambda_{i,3,t}i_t^{us} + \lambda_{i,4,t}i_t^{eme} + \lambda_{i,5,t}s_t + v_{i,t}, \tag{3.1}$$

$$v_{i,t} \sim N(0, \sigma^2_{v_{i,t}}) \tag{3.2}$$

We assume that the loadings on the five factors driving euro area bond yields are time-varying. This allows us to study how the pricing mechanism changes over time. Another approach to allow for time-varying parameters in the FAVAR is taken by Mumtaz et al. (2011), who allow for changing parameters in the VAR part of the model. We opt for the first specification, since our emphasis is on the identification of drivers (factors) driving bond yields in each euro area country.

In line with the literature (e.g., Primiceri (2005)) and in order to reduce dimensionality of the model, we assume that time-varying loadings follow a random walk process:

$$\lambda_{i,j,t} = \lambda_{i,j,t-1} + \epsilon_{i,j,t}, \quad \epsilon_{i,j,t} \sim N(0, \sigma^2_{\epsilon_{i,j}}), \tag{3.3}$$

where shocks $\epsilon_{i,j,t}$ are uncorrelated across equations, explanatory variables and time (indices i, j, t, respectively).

In addition to loadings, idiosyncratic shocks to the measurement equation are allowed to be time-varying and follow a random walk stochastic volatility process:

$$\log \sigma^2_{v_{i,t}} = \log \sigma^2_{v_{i,t-1}} + \epsilon_{v_t}, \quad \epsilon_{v_t} \sim N(0, \sigma_{\epsilon^2_v}) \tag{3.4}$$

The common factors and "exogenous" variables evolve according to a standard VAR process:

$$Y_t = \Phi(L) Y_t + e_t, e_t \sim N(0, \Sigma), \tag{3.5}$$

where $Y_t = \{f_{1,t}, f_{2,t}, i^{us}_t, i^{eme}_t, s_t\}$, $\Phi(L)$ is a multivariate lag polynomial (which includes an intercept in each VAR equation) and Σ is a general covariance matrix, i.e., we allow for non-zero correlation between shocks to the VAR equations.

Identification of factors

The factors $f_{1,t}$ and $f_{2,t}$ are identified using the strategy suggested by Bernanke et al. (2005) by assuming restrictions on the first two rows of matrix L_t, which stacks the row vectors $(\lambda_{i,1,t}, \lambda_{i,2,t}, \lambda_{i,3,t}, \lambda_{i,4,t}, \lambda_{i,5,t})$ across index i. Specifically, we assume that $\lambda_{i,j,t} = 1$ for $i = j$ and $\lambda_{i,1,t} = 0$ otherwise, for $i = 1, 2$.

This identification strategy allows us to interpret the common factors, when ordering of variables is chosen properly. In our case, we choose the first two bond yield series to represent bond yields of Belgium and Greece, respectively. This means that bond yield dynamics of Belgium is contemporaneously unaffected by movements in the second factor, bond yields in the US and emerging markets. Similarly, in other words, movements in Greek government bond yields are contemporaneously driven only by the second factor and idiosyncratic shocks. As a result of this identification, we can loosely interpret the first euro area factor as the core factor ($\lambda^{core}_{i,t} \equiv \lambda_{i,1,t}$) and the second euro area factor as the periphery factor ($\lambda^{periphery}_{i,t} \equiv \lambda_{i,2,t}$).

One may argue why German yields were not chosen to be ordered first, instead of Belgian. We do not opt for this possibility, since due to safe haven effects observed in the recent years, it is not reasonable to assume that $\lambda^{periphery}_{DE,t}$ would be always zero. Instead, one can expect $\lambda^{periphery}_{DE,t}$ to be often negative.

Table 3.1: Sign restrictions on responses (on impact) to structural shocks

	EA core	EA periphery	US	EME	USD/EUR
EA monetary policy shock	+	+		+	+
US monetary policy shock			+	+	-
Risk aversion shock			-	+	-

Note: The plus sign in the USD/EUR column denotes the appreciation of euro vis-a-vis the US dollar.

In addition, a robustness check for this alternative identification strategy did not yield substantially different results.

Identification of structural shocks

In order to identify structural shocks in the model and draw impulse responses, we use an identification scheme based on contemporaneous sign restrictions (see Table 3.1). We focus on three structural shocks. The tightening EA monetary policy shock is characterized by an increase in the euro area core and periphery factors, by an appreciation of the euro vis-a-vis the US dollar and by an increase in bond yields in emerging markets. This set of sign restrictions is motivated by standard assumptions on the impact of monetary policy on quasi-risk free yields, as captured by the core factor, and on the exchange rate . In addition, we impose that the periphery factor, which prices in sovereign risk in troubled euro area countries, and emerging market yields, which prices in other risk factors, increase with monetary policy tightening, consistent with the findings on the impact on monetary policy on risk (Fratzscher et al. (2016), Bekaert et al. (2013)). Similarly to the euro area monetary policy shock, the tightening US monetary policy shock is characterized by an increase in the US and EME yields and by an appreciation of the US dollar. Finally, the risk aversion shock (or negative shock to market confidence) leads to higher yields

It is worth noting that the first factor estimated using the baseline setup is mostly correlated with changes in yields in Finland (91%) and Germany (90%), while the correlation coefficients with changes in yields in Belgium is 75%. The second factor is mostly correlated with yields in Italy (43%), Greece (38%) and Spain (37%). This confirms that the chosen normalization of factors does not predetermine the shape of the estimated factors and also motivates the names of the factors (core / periphery). The correlations are also depicted in Figure.

Yields are expected to increase and the exchange rate to appreciate in response to monetary tightening in emerging markets, US dollar appreciation and lower US yields, reflecting safe haven flows. For the risk aversion shock, we leave responses in the euro area core and periphery factors unrestricted. We discuss the identified structural shocks and potential alternative approaches in Section 5.

Estimation

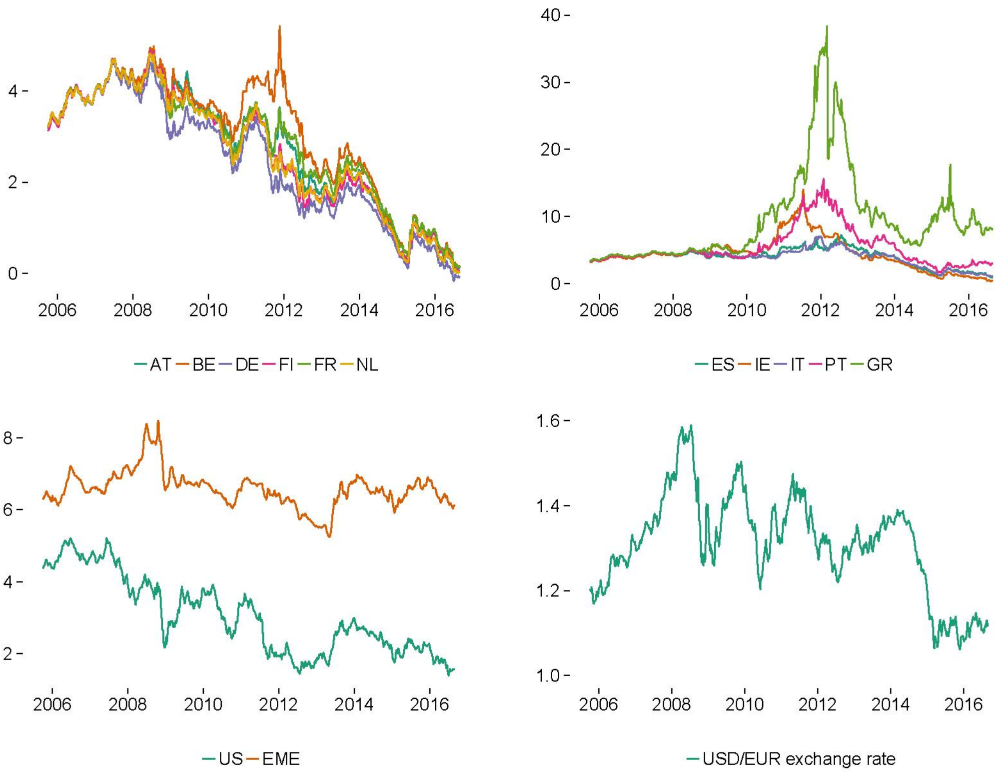
The model is estimated using Bayesian techniques, where posterior distributions of parameters are approximated by the Gibbs sampler. Technical details of the estimation are provided in the Appendix. Worth to note is that the dimension of the model is large, both in terms of the number of observations and parameters. The unobserved variables (factors, factor loadings and stochastic volatilities of idiosyncratic shocks) are usually estimated using simulation algorithm, such as that proposed by Carter and Kohn (1994). In contrast, we use a relatively recent precision-based simulator suggested by Chan and Jeliazkov (2009), which significantly reduces the computational burden in that it avoids the Kalman filtering step used in the standard algorithms. We run the Gibbs sampler 55,000 times and discard the first 50,000 draws as a burn-in sample. The subsequent 5,000 draws of parameters are used to compute posterior quantities.

3.2.2 Data

We use weekly data on 10 year government bond yields for the analysis, starting in October 2005 and ending at the end of August 2016. The data are plotted in Figure 3.1. We difference the data to achieve stationarity required for the factor analysis and subsequently standardize them for computational purposes.

We use a common standardization, i.e., demeaning and dividing by a standard deviation.

Figure 3.1: Sovereign bond yields and euro/dollar exchange rate (USDEUR)



Source: Datastream

3.3 Results

The model described in the previous section yields several outputs, which we study subsequently.

3.3.1 Reduced-form results: estimated factors, idiosyncratic volatilities and loading coefficients

The raw estimated factors are not very informative on their own, since they are estimated on stationary time series and therefore capture co-movements of weekly bond yield changes, which can be very noisy. To obtain a more informative insight from the factors, we focus on their cumulative sums (Figure 3.2), which show general directions of bond yield movements. A number of stylised facts are worth noting. First, the euro area core factor displays a similar

Table 3.2: Descriptive statistics for sovereign bond yields and euro/dollar exchange rate (USDEUR)

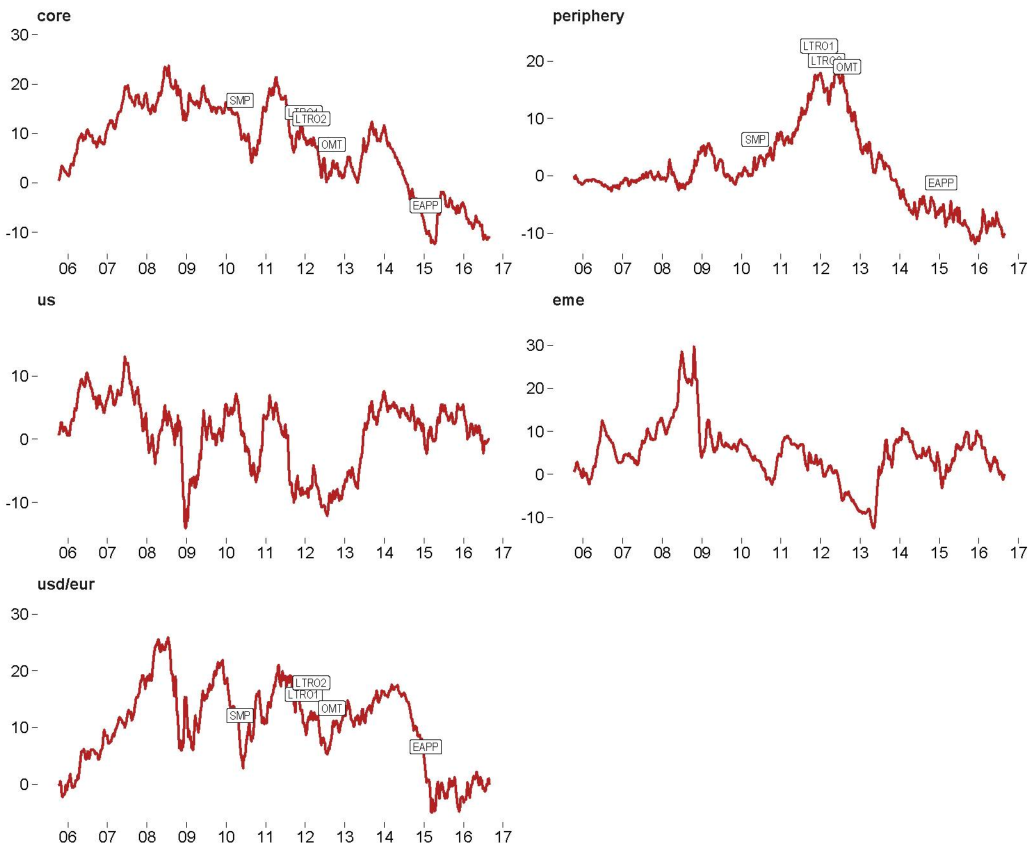
		Levels					Differences				
Variable	n	min	max	mean	median	sd	min	max	mean	median	sd
AT	559	0.24	4.84	2.83	3.24	1.27	-0.28	0.39	-0.01	-0.01	0.08
BE	559	0.37	5.41	3.11	3.58	1.28	-0.65	0.57	0.00	-0.01	0.10
DE	559	0.00	4.64	2.48	2.67	1.30	-0.30	0.27	-0.01	-0.01	0.08
EME	559	5.24	8.48	6.59	6.58	0.51	-0.48	0.44	0.00	-0.01	0.08
ES	559	1.20	7.25	3.99	4.10	1.27	-1.22	0.62	0.00	0.00	0.14
FI	559	0.22	4.89	2.71	2.93	1.28	-0.31	0.30	0.00	-0.01	0.08
FR	559	0.39	4.81	2.87	3.22	1.19	-0.27	0.35	-0.01	-0.01	0.08
GR	559	3.39	38.35	9.61	7.65	6.97	-19.60	5.11	0.01	0.01	1.11
IE	559	0.68	14.02	4.51	4.32	2.40	-1.89	1.59	0.00	-0.02	0.21
IT	559	1.19	7.05	4.00	4.25	1.23	-1.00	0.57	0.00	-0.01	0.12
NL	559	0.23	4.82	2.72	2.92	1.28	-0.25	0.28	-0.01	-0.01	0.08
PT	559	1.65	15.60	5.43	4.44	2.81	-2.26	1.91	0.00	0.00	0.29
US	559	1.44	5.21	3.08	2.88	1.05	-0.41	0.31	0.00	-0.01	0.10
USDEUR	559	1.06	1.59	1.31	1.32	0.11	-0.06	0.10	0.00	0.00	0.02

Source: Datastream

pattern to core euro area countries' bond yields, as observed in Figure ??. Second, the euro area periphery factor captures well the evolution of sovereign tensions across the euro area. In particular, the periphery factor started to follow an upward trend in 2010 reaching a peak in 2012. It stabilised in early 2012, following the three year ECB long-term refinancing operations (LTROs) and reverted in the second part of the year after the ECB announced the possibility of Outright Monetary Transactions (OMT). After the summer of 2012, the periphery factor followed a generally declining trend. This evidence suggests a role of ECB policies in bringing the pricing mechanism of bond yields to "normal" times. Another interesting finding is that the downward trend in the periphery factor did not revert during the summer 2015, the period of large uncertainty related to the extension of the macroeconomic adjustment programme in Greece. This suggests that the latter episode of turmoil remained largely contained. A last finding is that one can observe a decoupling of the euro area core factor from US yields after 2013, when monetary policy in the euro area and in the US started diverging.

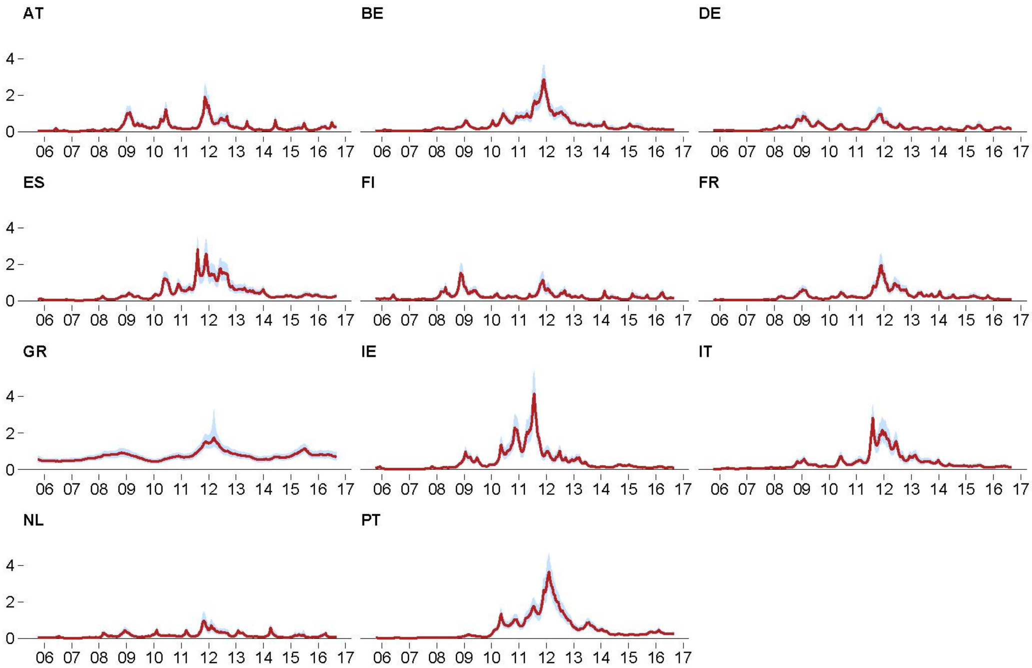
Turning to the stochastic volatility of idiosyncratic shocks (Figure 3.3), it was generally elevated during the peak of the financial crisis of 2008, reflecting the turmoil in financial markets. Another generally observed peak coincides with the beginning of 2012, i.e. around the peak of the sovereign debt crisis.

Figure 3.2: Cumulative sums of estimated factors and exogenous variables



Note: exogenous variables used for the analysis were stationarized and standardized, subsequently.

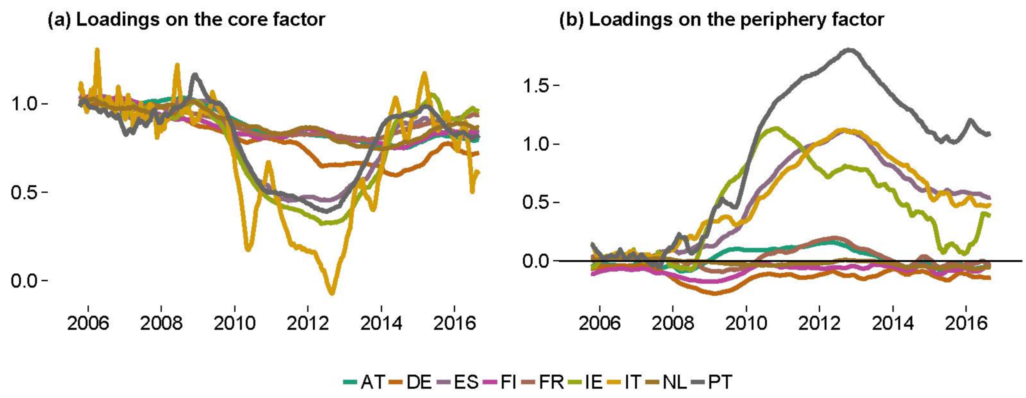
Figure 3.3: Stochastic volatility of idiosyncratic shocks to bond yields: posterior median, 16th and 84th quantiles.



Interestingly, stochastic volatility in Greece evolves relatively smoothly compared to other countries. This reflects the high standard deviation of changes in Greek bond yields on which the model is estimated and additionally its loading on the periphery factor, which explains Greek bond movements relatively well on average. Nevertheless, stochastic volatility of idiosyncratic shocks of Greek bonds was elevated during the summer 2015, reflecting the uncertainty around the extension of the adjustment programme.

Turning to factor loadings (Figures 3.4 and 3.9 - 3.11), there are a number of interesting findings. First, at the beginning of the sample, loadings on both the core and the periphery factors were homogeneous, reflecting the integration of the euro area bond markets. Second, following the financial crisis of 2008, loadings of all countries on the core factor generally declined. Third, the loadings of IT, PT, IE, ES started decoupling from the loadings of other countries in 2009. Their loadings on the core factor declined significantly, while the loading on the periphery factor substantially increased. Consistently with the dynamics of the periphery factor, the decoupling reached its peak in 2012, after which countries became again more homogeneous (as measured by the similarity of loading coefficients). It is worth noting that the reversal in the

Figure 3.4: Evolution of loadings of bond yields on factors



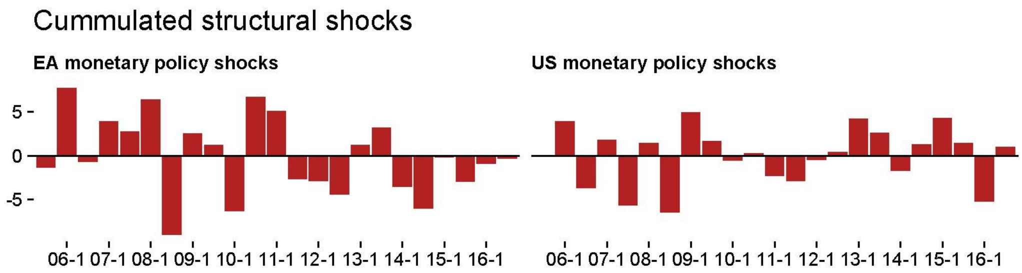
dispersion among loading coefficients coincides with the announcement of the OMT programme in summer 2012 (denoted in figures in the Appendix). The OMT brought about a change in the pricing mechanism of sovereign bonds, leading to "re-integration" between the periphery and the core of the euro area. Nevertheless, at the end of the sample, loadings on the core factor were still lower than at the beginning of the sample, while loadings on the periphery factor were higher (particularly in the case of Portugal, Spain, and Italy). Interestingly, the loadings of Germany and Finland on the periphery factor are generally negative, which reflects their safe haven status. The safe haven status of these two countries is further reflected by periods of large positive loadings on the exchange rate (Figure 3.9), which signals that depreciation of the euro tends to be associated with declining yields in Germany and Finland on average.

3.3.2 Structural form results

Regarding the structural analysis, it is worth checking the evolution of structural shocks in order to assess the plausibility of the imposed sign restrictions. To facilitate the identification of periods of "prevailing" monetary accommodation, Figure 3.5 plots semi-annually cumulated euro area and US monetary policy shocks. In the euro area, significant loosening of monetary policy occurs in the second half of 2008 and 2011, in the first half of 2010 and during 2012

On July 26 2012, the ECB president hinted to the imminent adoption unconventional monetary policy measure during his speech in London. The OMT was finally announced in August 2012.

Figure 3.5: Semiannually cumulated structural shocks

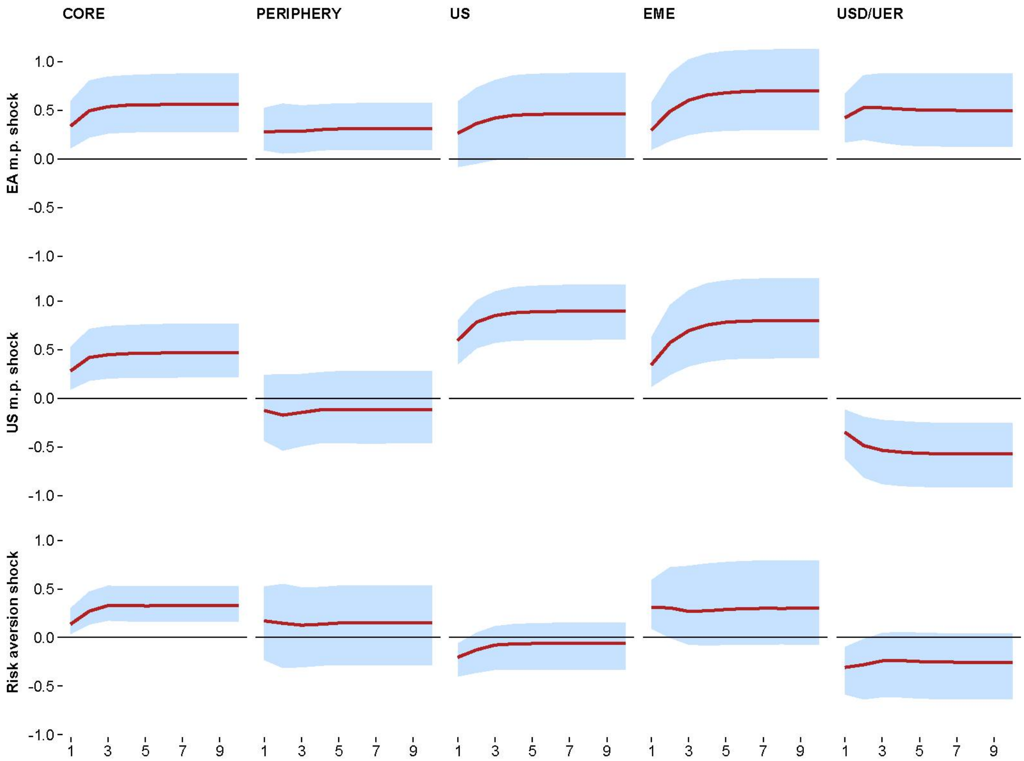


and 2014. All of these periods coincide with important monetary policy actions. The detected accommodation in the second half of 2008 corresponds to aggressive rate cuts and provision of liquidity in the aftermath of the collapse of Lehman Brothers. Accommodation in 2010 and 2011 corresponds to the introduction and the re-activation of the Security Market Program (SMP). Easing in 2012 reflects the unprecedented provision of long term loans via the three year long term refinancing operations and the announcement of Outright Monetary Transactions (OMT). Finally, accommodation in 2014 reflects the progressive building up of expectations and the final announcement of the Extended Asset Purchase Program (EAPP). Turning to the US monetary policy shocks, one can observe loosening in the second half of 2008, and 2011 in response to the introduction of different rounds of bond purchases. On the other hand, the model correctly captures the announcement of tapering of bond purchases in 2013 and the build-up of expectations of monetary policy tightening in 2015.

To validate our identification scheme, we also check the largest identified shocks. For euro area the largest accommodative monetary policy shocks occurred in the weeks when the SMP (May 2010) and the EAPP (January 2015) were announced. The largest accommodative US monetary policy shocks coincided with the initial announcement of the LSAP programme (November 2008) and its expansion to government securities (March 2009). On the other hand, one of the largest tightening shock for the US was in June 2013, when the "tapering" of the QE programme by the Fed was anticipated.

Figure 3.6 depicts responses to the identified shocks described in the methodology section (euro area and the US monetary policy shocks, respectively, and the risk aversion shock). The shocks are priced in quickly, reflecting the fast behaviour of financial markets. In addition, the speed of responses is lowest in emerging market economies.

Figure 3.6: Cumulative impulse responses to structural shocks: posterior median, 16th and 84th quantiles. x-axis: weeks



The responses to the euro area (tightening) monetary policy shock are significant for the core and periphery factors, as well as for the exchange rate, leading to an appreciation of the euro vis-a-vis the US dollar. The same shock leads to positive responses of the US (not specified by the sign restrictions) and emerging market yields, although the reaction is statistically insignificant in the first two weeks in case of the United States. A tightening US monetary policy shock leads to a significant positive response in emerging markets and to a significant appreciation of the dollar vis-a-vis the euro. The same shock leads to a positive, significant, response in the euro area core factor, which is not implied by the sign restrictions. Finally, increasing risk aversion, which by definition leads to the appreciation of the dollar accompanied by rising yields in the EMEs and declining yields in the United States, leads to a decrease in yields in the core and an increase in the periphery, although the responses in the periphery are insignificant. This can be explained by a various nature of the risk aversion shocks (global vs local, for example).

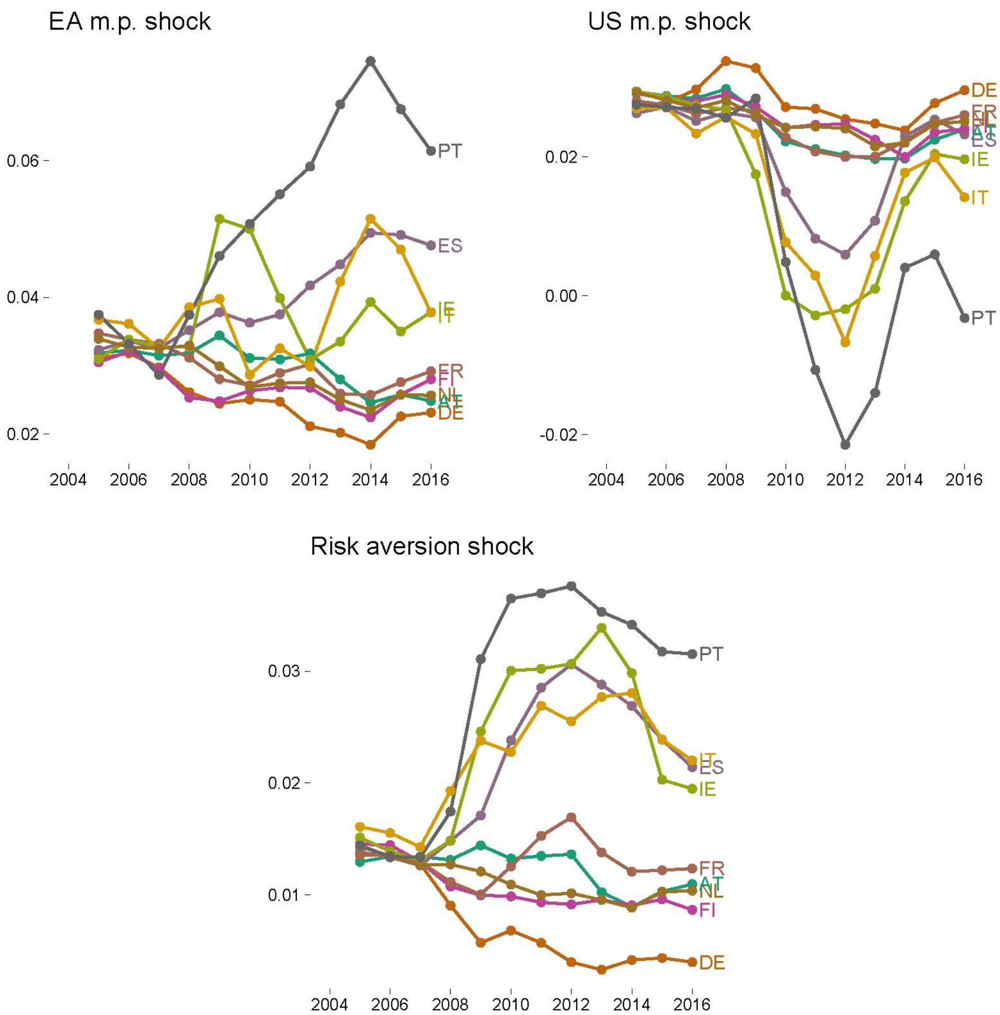
The impulse response functions presented so far have been computed using the VAR equation of the FAVAR model based on the assumption of constant coefficients. These results can be transformed using time-varying loadings into time-varying impact responses of each country to each structural shock, which are depicted in Figures 3.7. The time varying impulse responses provide interesting insights on how the transmission of monetary policy has evolved during recent years, reflecting market conditions and different policy mixes.

The results suggest that at the beginning of the sample, the responses of sovereign yields to all shocks were relatively homogeneous across countries, consistent with a high degree of financial integration in Europe. Focusing on the euro area monetary policy shock, the responses of PT, ES, IT and IE started decoupling from the other countries in 2008. Overall, between 2008 and 2014 impulse responses remained dispersed across euro area countries. At the end of the sample, responses were homogenous again across the euro area, with the exception of PT, IT and ES. The latter result suggests at least partial normalisation of the transmission mechanism of monetary policy to bond yields in the euro area.

Interestingly, bond yields in troubled euro area countries (PT, IT, IE and ES) became more sensitive to euro area monetary policy as the crisis escalated. This finding apparently contradicts the narrative that the transmission mechanism of monetary policy in the euro area became impaired during the crisis. While this may indeed be the case for the transmission of conventional monetary policy via short term rates, other forms of unconventional monetary policy were introduced during the crisis specifically to overcome the lack of "grip" of conventional monetary policy. By relying on the identification scheme based on sign restrictions on the movement of factors and the exchange rate, our approach captures the impact of the overall mix of monetary policy on bond yields. Against this backdrop, the finding that yields in troubled euro area countries react more to the mix of monetary policy is not surprising. This supports the view that new forms of monetary policy were most effective where they were needed, i.e. in bond markets of troubled euro area countries.

Turning to US monetary policy shocks, the responses of euro area bond yields were also homogeneous at the beginning of the sample, suggesting strong integration in European sovereign bond markets. Similarly to the responses to euro area monetary policy shocks, the dispersion of responses increased significantly starting from 2010, when the euro area banking and sovereign crisis escalated, and peaked in 2012. At the end of the sample, responses were homogenous again across the euro area, with the exception of IE, IT and PT. It

Figure 3.7: Impact coefficients to the euro area and US monetary policy shocks - annual averages

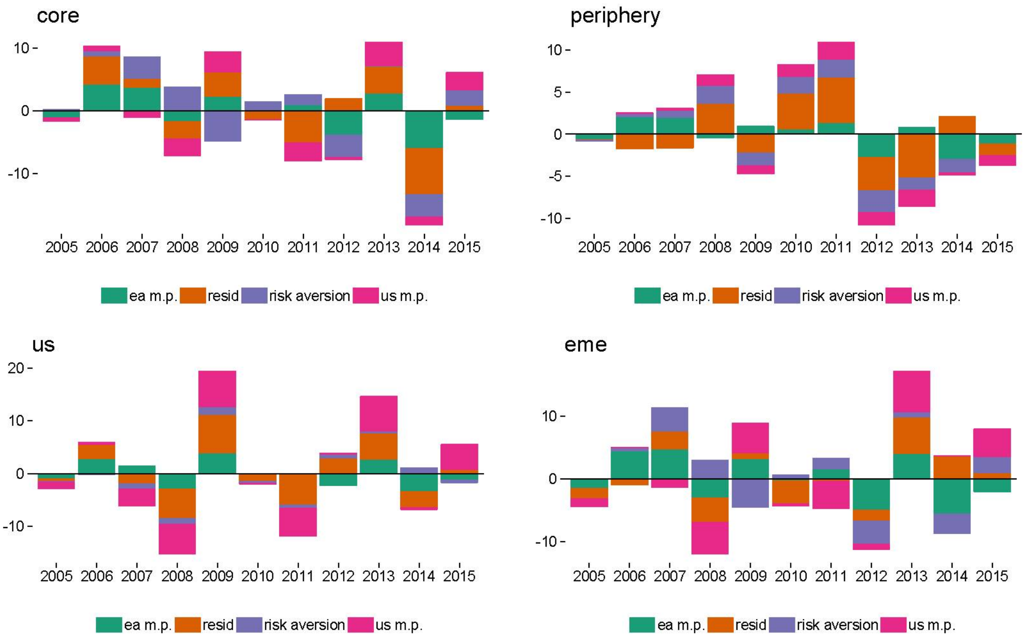


is worth noting how countries largely driven by the periphery factor during the acute phase of the European crisis (PT, IT, IE, ES) were "isolated" from the US monetary policy shocks. The higher and more stable impact coefficients of the euro area other countries could be related to substitutability of their bonds with US Treasuries in portfolios of global bond investors. The impulse response analysis suggests that this substitutability was lost by troubled euro area countries after the financial crisis of 2008. At the same time, yields of these countries started to react more sensitively to risk aversion shocks and this sensitivity diminished somewhat only after 2012.

The impulse response analysis described so far suggests how yields of each country react over time to shocks of the same size. In order to assess the drivers of changes in bond yields, one can employ an historical decomposition (plotted in Figure 3.8). The results show that the euro area core factor was driven to a large extent by euro area monetary policy shocks, which led to declines in yields particularly in 2008, 2012 and 2014, i.e. years when the ECB either cut interest rates or announced programmes to further ease monetary conditions. Furthermore, one can observe the opposite effect of expectations of tightening the US monetary policy in 2013 and 2015. Changes in the periphery factor were largely driven by unexplained shocks, which plausibly capture the local risk aversion and worsening fundamentals, i.e. effects we are not able to identify using our relatively parsimonious model. On the other hand, loosening of the euro area monetary policy in 2012, 2014 and 2015 was successful in driving down the periphery factor.

Regarding the US factor, one can observe that changes in the euro area monetary policy had relatively small impact on its changes. In addition, the model identifies significant loosing in 2008 and 2011 and tightening in 2013 and 2015. Finally, the US monetary policy had a significant loosening effect on EME yields in 2011 and 2012, reflecting portfolio rebalancing effect of unconventional monetary policy. On the other hand, the tapering announcement in 2013 and expectations of tightening the US monetary policy in 2015 contributed to an increase in EME bond yields.

Figure 3.8: Historical decomposition of annual changes in bond unobserved factors, bond yields in the US and EMEs.



3.4 Discussions of the results

3.4.1 Implications for financial stability surveillance

The results discussed in the previous section support the view that the pricing mechanism of bond yields evolved during the European banking and sovereign crisis. First, a new pricing (periphery) factor associated to the euro area troubled countries emerged during the acute phase of the crises. Second, loading coefficients of bond yields on the different factors changed substantially during the crisis. Specifically, the loading coefficients of troubled countries on the periphery factor increased, while those on the core factor decreased. The opposite was true for other euro area countries. Third, the reaction of yields to US and Euro area monetary policy shocks also evolved according to market conditions.

The results support the view of three distinct phases in euro area sovereign bond markets between 2006 and early 2016. In an initial phase of almost full integration, only one pricing factor mattered for euro area sovereign bond yields (i.e. the core factor). Also, loading coefficients and impulse responses to shocks where homogeneous across sovereign bond markets in this period. In the second phase, when the crisis escalated, bond yields decoupled: some bond yields remained tightly linked to the core factor, while others became linked to the periphery factor. During this phase, also the transmission of monetary policy was heterogeneous across countries. Lastly, in the third phase of partial re-integration of bond markets, the pricing mechanism appeared to approach the pre-crisis conditions according to loading coefficients and impulse responses.

Concerning potential explanations of the above findings, as discussed in ((Lo Duca, 2012)), there are several reasons why the determinants of asset prices could change across periods. First, during turbulent periods, information asymmetries could prevent the market to clear at a given price ((Stiglitz and Weiss, 1981)). Second, heterogeneous investors have different allocation strategies, therefore pricing changes across periods are reflecting the mix of active investors. The latter is likely to have changed substantially during the crisis, especially for sovereign bonds in troubled euro area countries. In particular, evidence suggests that the pool of active investors in these bond markets shrank and liquidity got much thinner. Third, during periods of market turbulence, investors might face binding constraints as, for example, margin calls, or the need to sell certain assets to preserve the risk profile of their portfolios. In this context, investment decisions are either increasingly influenced by certain events, as rating actions, or become increasingly related to the dynamic of certain variables as, for example, the price or the volatility of certain benchmark assets. As pointed by Adrian et al. (2010), this can generate self-enforcing de-leveraging cycles that increase the sensitivity of prices and flows to common factors. Fourth, the information set that investors use to price assets might change over time. This might have been the case during the European banking and sovereign crisis when ex-ante unlikely fears of euro break up started being priced into sovereign bonds (Draghi (2012), De Santis (2015)). Another explanation is provided by Leombroni et al. (2018), who claim that monetary policy communication affects risk premia. Before the crisis, these risk premia were affected uniformly in the euro area countries, while after the crisis, a more significant risk premium materialized for the periphery countries due to a pessimistic communication, which drove a wedge between yields of the core and periphery countries..

The above results suggest a framework to assess the gravity of distress in bond markets based on the model presented in this paper. First, spiking idiosyncratic volatilities are a first sign of market turbulence. Although, as demonstrated by the 2015 Greek episode, a spike in the idiosyncratic volatility in one market does not necessarily transmit to other markets. Idiosyncratic volatilities could be benchmarked to average levels in the pre-crisis and in the crisis periods. Second, looking at the pricing of the periphery and the core factors across bond markets is important to assess the degree of integration and spill-overs across countries. Significant turbulence would be detected when the loading on the periphery factor increases in one country. A dangerous situation of contagion would emerge when the loading coefficient of the periphery factor increases in more countries. Generally, the dispersion of the loading coefficients for each factor could be benchmarked to the levels observed during the acute phase of the crisis.

3.4.2 Impact of monetary policy on the pricing mechanism of sovereign bond yields

Our results have implications for the debate on the impact of unconventional monetary policy on bond markets. While the literature predominantly quantifies the impact of unconventional monetary policy on bond yields and it assesses the transmission channels (e.g. signalling channel vs portfolio balance channel), our results shed light on the impact of policies on the pricing mechanism of yields. Specifically, our results suggest an intriguing link between euro area unconventional policies, the way different factors are priced into bond yields and the reaction of bond yields to monetary policy shocks. While it is extremely difficult to formally test the link between unconventional monetary policy and changes in the pricing mechanism of sovereign bond yields, a number of stylised facts appear to support the view that the announcement of Outright Monetary Transactions by the ECB was a game changer leading to a turning point in several indicators of markets stress. Conversely, several other unconventional monetary policy actions, including the Security Market Programme (SMP), other purchases programmes and liquidity injections, while having visible positive effects (Fratzscher et al. (2016)), only temporarily halted the escalation of the crisis. Specifically, the OMT announcement coincides (i) with turning points in the cumulated dynamics of the periphery factor which started decreasing the second half of 2012, (ii) with a gradual normalisation of the loading coefficients of bond yields on the core and periphery factors towards pre-crisis levels and (iii) with gradual normalisation of the reaction of euro area bond yields to monetary policy shocks.

Another interesting finding relates to the dynamic response of sovereign yields to euro area monetary policy shocks. In particular, over time, yields in troubled euro area countries became more responsive to EA monetary policy shocks. At the same time, the response of yields in other euro area countries did not display substantial changes. This suggests that ECB mix of unconventional monetary policy was particularly effective in those markets in distress where risk premia rose and where accommodation was needed.

3.4.3 Robustness analysis

We check the robustness of our findings along several dimensions. Regarding the reduced form analysis, we test alternative assumptions to identify the core and periphery factors. In our benchmark specification, we identify the signs and magnitudes of the factors by assuming that changes in the Belgian sovereign yields on the core factor have loading equal to one and zero elsewhere. Symmetrically, the Greek sovereign bond yield loads only on the periphery factor by the coefficient equal to one. In the robustness check, we replace the Belgian bond yields by German bond yields, while we replace the Greek bond yields with Portuguese yields. The results are substantially unaffected by this change . Generally the results are broadly stable as long as the core factor is identified by mean of a non-troubled euro area sovereign bond yield and the periphery factor by one euro area troubled country. While the shape of the factors might slightly change across specifications, the key results about time variation in loading coefficients and impulse response functions remain stable.

Regarding the identification of structural shocks and the related impulse responses, we perform two additional robustness checks. In the first one, we want to check how restrictive our assumption on fixed coefficients in the VAR part of the model is (i.e., $\Phi(L), \Sigma$ in Equation 3.2.1). Our motivation for this is that one may expect that the transmission mechanism has changed due to the introduction of non-standard measures of monetary policy. Therefore, we estimate (endogenously in one model) two sets of system matrices $(\Phi(L), \Sigma)$, where the first set is used for filtering the state variables in the first part of the sample (up to the end of 2010) and the second set is used for the filtering in the remaining sample. The resulting factors are highly correlated with the baseline results (with correlation coefficients of the two factors of 0.99, 0.93, respectively). Also the impulse responses that we obtain in this setting confirm the findings of our benchmark specification.

The correlation between the first factors (core factor) in the two different specifications is 0.98, while the correlation between the second factors (periphery factor) is 0.9.

Second, we extend the model to include an additional exogenous variables which helps identifying shocks. We note that demand shocks might results in similar effects to US monetary policy shocks in the set of variables that we include in the model and use for identification. Essentially, a demand shock in the US might push US yields and the US dollar up, the same conditions that we use for identifying US monetary policy shocks. In order to disentangle between the two type of shocks, we include US breakeven inflation among the variables in the model. While a demand shock would push inflation up, a tightening monetary policy shock would push it down. The results in this setting confirm a large part of our benchmark specification. However, this alternative model specification identifies monetary policy tightening in the US in 2009, which is not very plausible. In order to keep the model parsimonious, we decided to drop the measure of break-even inflation from the baseline model.

3.5 Conclusion

The paper studies movements in euro area sovereign bond yields using a factor model with time-varying loadings, which capture potential changes in the pricing mechanism of bond yields. Impulse responses to three structural shocks (EA monetary policy, US monetary policy and risk aversion) are also analysed over time. The structural identification strategy based on sign restrictions yields overall plausible results when assessed against key monetary policy actions during the period under review.

The results support the view that the pricing mechanism of bond yields evolved during the European banking and sovereign crisis. The analysis identifies three distinct phases in euro area sovereign bond markets. First, an initial phase when bond markets were almost fully integrated. A second phase of dis-integration in bond markets when the crisis escalated. In this phase the pricing of euro area sovereign bonds depended on different factors and the transmission of monetary policy shocks became heterogeneous across countries. Lastly, a third phase of partial re-integration, when the pricing mechanism of bonds approached the pre-crisis conditions, according to loading coefficients and structural impulse responses.

In our view, this is less of a problem in the euro area, where a demand shock would most likely lead to a decrease in risk and therefore to a decrease in the periphery factor, which is the opposite of a tightening monetary policy shock.

Measured as 10-year breakeven inflation rate, downloaded from Federal Reserve Economic Data (ticker T10YIE).

The above results suggest a framework to assess the gravity of distress in bond markets based on the model presented in this paper. The framework could rely on benchmarking idiosyncratic volatilities, loading coefficients and impulse responses to the averages observed during the pre-crisis and during the crisis periods. Spiking idiosyncratic volatilities would be a first sign of market turbulence. The pricing of the periphery and the core factors across bond markets could be used to assess the degree of integration and spill-overs across countries. Generally, the dispersion of the loading coefficients for each factor and of the impact coefficients of impulse responses to structural shocks could be informative of anomalies in the pricing of bonds.

Our results have implications for the debate on the impact of unconventional monetary policy on sovereign bond markets in the euro area. While the literature predominantly quantifies the impact of unconventional monetary policy on bond yields and it assesses the transmission channels (e.g. the signalling channel vs the portfolio balance channel), our results also shed light on the impact of policies on the pricing mechanism of yields. Specifically, our results suggest a link between euro area unconventional policies, the way different factors are priced into bond yields and the reaction of bond yields to monetary policy shocks. We find that the announcement of Outright Monetary Transactions by the ECB was a game changer leading to a gradual normalisation of the pricing mechanism of bond yields to the pre-crisis situation, when looking at loading coefficients and structural impulse responses. Finally, another interesting finding shows that yields in troubled euro area countries became more responsive to EA monetary policy shocks during the crisis periods. This suggests that ECB mix of unconventional monetary policy was particularly effective in those markets where accommodation was needed.

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3.A Estimation of the FAVAR with time-varying loadings and stochastic volatility

The model given by Equations 3.2, 3.3 gives rise to the following blocks of parameters:

- Factors $f_{1,t}$, $f_{2,t}$
- Time-varying factor loadings $\lambda_{i,j,t}$, $i = 1, \ldots, N$, $j = 1, 2, 3, 4$
- Idiosyncratic shocks volatilities $\sigma^2_{v,t}$
- VAR model parameters B and Σ

3.A.1 Gibbs sampling

The marginal posterior distributions and their quantiles are approximated using the Gibbs sampler by drawing parameters from their conditional posterior distributions, most of which are standard in the literature. Time-varying loadings were sampled by applying the algorithm by Chan and Jeliazkov (2009); the VAR model parameters were drawn from their conditional posterior distributions which are standard in the Bayesian VAR literature. Variances of the idiosyncratic shocks were sampled using the approach by Kim et al. (1998). What deserves a deeper explanation is sampling of factor themselves.

Conditional on other parameters of the model, factors can be routinely extracted as an unobserved variable in a state space model, which can be written in the following way:

The observation equation relates the observed variables to unobserved state variables:

$$\underbrace{\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{N,t} \\ i_t^{us} \\ i_t^{eme} \end{bmatrix}}_{y_t} = \underbrace{\begin{bmatrix} \lambda_{1,1} & \lambda_{1,2} & \lambda_{1,3} & \lambda_{1,4} \\ \lambda_{2,1} & \lambda_{2,2} & \lambda_{2,3} & \lambda_{2,4} \\ \vdots & \vdots & \vdots & \vdots \\ \lambda_{N,1} & \lambda_{N,2} & \lambda_{N,3} & \lambda_{N,4} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{H_t} \underbrace{\begin{bmatrix} f_{1,t} \\ f_{2,t} \\ \tilde{i}_t^{us} \\ \tilde{i}_t^{eme} \end{bmatrix}}_{\beta_t} + \underbrace{\begin{bmatrix} e_{1,t} \\ e_{2,t} \\ \vdots \\ e_{N,t} \\ e_{us,t} \\ e_{eme,t} \end{bmatrix}}_{e_t} \tag{3.6}$$

In this appendix, we focus on the case of a VAR(1) process, however higher order processes can be incorporated by re-defining the F matrix.

where

$$R = \mathbf{cov}(e_t) = \mathbf{diag}\{\sigma_{1,t}, \sigma_{2,t}, \dots \sigma_{N,t}, 0, 0\} \tag{3.7}$$

The transition equation describes the dynamics of state variables:

$$\underbrace{\begin{bmatrix} f_{1,t} \\ f_{2,t} \\ \widetilde{i}_t^{us} \\ \widetilde{i}_t^{eme} \end{bmatrix}}_{\beta_t} = \underbrace{\begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix}}_{\mu} + \underbrace{\begin{bmatrix} \phi_{11,1} & \phi_{12,1} & \phi_{13,1} & \phi_{14,1} \\ \phi_{21,1} & \phi_{22,1} & \phi_{23,1} & \phi_{24,1} \\ \phi_{31,1} & \phi_{32,1} & \phi_{33,1} & \phi_{34,1} \\ \phi_{41,1} & \phi_{42,1} & \phi_{43,1} & \phi_{44,1} \end{bmatrix}}_{F} \underbrace{\begin{bmatrix} f_{1,t-1} \\ f_{2,t-1} \\ \widetilde{i}_{t-1}^{us} \\ \widetilde{i}_{t-1}^{eme} \end{bmatrix}}_{\beta_{t-1}} + \underbrace{\begin{bmatrix} v_{1,t} \\ v_{2,t} \\ v_{us,t} \\ v_{eme,t} \end{bmatrix}}_{v_t} \tag{3.8}$$

$$\mathbf{cov}(v_t) = \Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}, \tag{3.9}$$

where Σ_{ii} is a 2x2 block of matrix Σ.

Note that exogenous variables (i_t^{us} and i_t^{eme}) are both in the observation and transition equations and the relationship between them is achieved by imposing ones in Equation 3.6 and zero variances in Equation 3.7.

The unobserved factors can be relatively easily sampled, for example, using the algorithm by Carter and Kohn (1994), which is, however, prohibitively slow for our purposes. Therefore we use the ideas from the algorithm by Chan and Jeliazkov (2009), whose variant adjusted for our purposes is described subsequently.

First, in order to correct for singularity of matrix R we reduce the number of our state variables only to the number of factors. As a result, we can write our observation equation as:

$$\widetilde{y}_t = \begin{bmatrix} y_{1,t} - \lambda_{1,3} i_t^{us} - \lambda_{1,4} i_t^{eme} \\ y_{2,t} - \lambda_{2,3} i_t^{us} - \lambda_{2,4} i_t^{eme} \\ \vdots \\ y_{N,t} - \lambda_{N,3} i_t^{us} - \lambda_{N,4} i_t^{eme} \end{bmatrix} = \begin{bmatrix} \lambda_{1,1,t} & \lambda_{1,2,t} \\ \lambda_{2,1,t} & \lambda_{2,2,t} \\ \vdots & \vdots \\ \lambda_{N,1,t} & \lambda_{N,2,t} \end{bmatrix} \begin{bmatrix} f_{1,t} \\ f_{2,t} \end{bmatrix} + \underbrace{\begin{bmatrix} e_{1,t} \\ e_{2,t} \\ \vdots \\ e_{N,t} \end{bmatrix}}_{e_t} \tag{3.10}$$

and the transition equation as:

$$\begin{bmatrix} f_{1,t} \\ f_{2,t} \end{bmatrix} = \widetilde{\mu}_t + \begin{bmatrix} \phi_{11,1} & \phi_{12,1} \\ \phi_{21,1} & \phi_{22,1} \end{bmatrix} \begin{bmatrix} f_{1,t-1} \\ f_{2,t-1} \end{bmatrix} + \widetilde{v}_t \tag{3.11}$$

where

$$\mathbf{cov}(\widetilde{v}_t) = \widetilde{\Sigma} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21} \tag{3.12}$$

and

$$\widetilde{\mu}_t = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} + \Sigma_{12}\Sigma_{22}^{-1} \begin{bmatrix} v_{1,t} \\ v_{2,t} \end{bmatrix} \tag{3.13}$$

,

which follows from the properties of conditional normal distributions.
Let

$$L_t = \begin{bmatrix} \lambda_{1,t,1} & \lambda_{1,t,2} \\ \lambda_{2,t,1} & \lambda_{2,t,2} \\ \vdots & \\ \lambda_{N,t,1} & \lambda_{N,t,2} \end{bmatrix} \tag{3.14}$$

and

$$\widetilde{f}_t = (f_{1,t}, f_{2,t})^T \tag{3.15}$$

We can rewrite the measurement equation as

$$\begin{bmatrix} \widetilde{y}_1 \\ \widetilde{y}_2 \\ \vdots \\ \widetilde{y_T} \end{bmatrix} = \begin{bmatrix} L_1 & 0 & 0 & 0 \\ 0 & L_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & L_T \end{bmatrix} \begin{bmatrix} \widetilde{f}_1 \\ \widetilde{f}_2 \\ \vdots \\ \widetilde{f_T} \end{bmatrix} + \begin{bmatrix} \widetilde{e}_1 \\ \widetilde{e}_2 \\ \vdots \\ \widetilde{e_T} \end{bmatrix} \tag{3.16}$$

or, in line with Chan and Jeliazkov (2009), as

$$y = G\eta + \epsilon \tag{3.17}$$

The stacked version of the transition equation can be written as:

$$H\eta = Z\gamma + \nu \tag{3.18}$$

where

$$H = \begin{bmatrix} I_2 & & & & \\ -\widetilde{F} & I_2 & & & \\ & -\widetilde{F} & I_2 & & \\ & & \ddots & \ddots & \\ & & & -\widetilde{F} & I_2 \end{bmatrix} \tag{3.19}$$

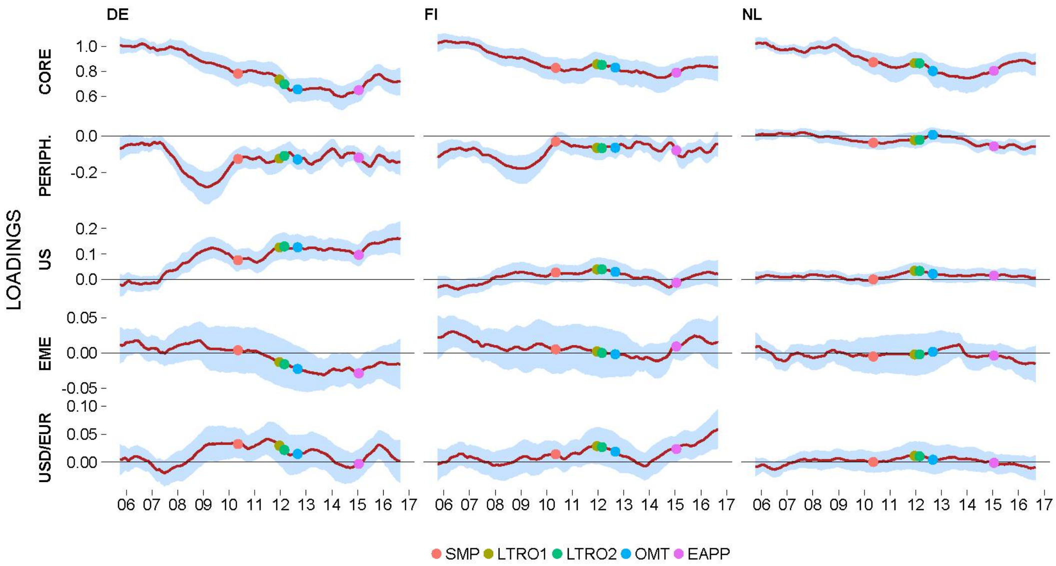
and

$$Z\gamma = \begin{bmatrix} \widetilde{a}_1 \\ \widetilde{a}_2 \\ \widetilde{a}_1 \\ \widetilde{a}_2 \\ \vdots \end{bmatrix} \tag{3.20}$$

This specification of the model is now in line with (Chan and Jeliazkov, 2009) and their algorithm can be used to sample the unobserved factors.

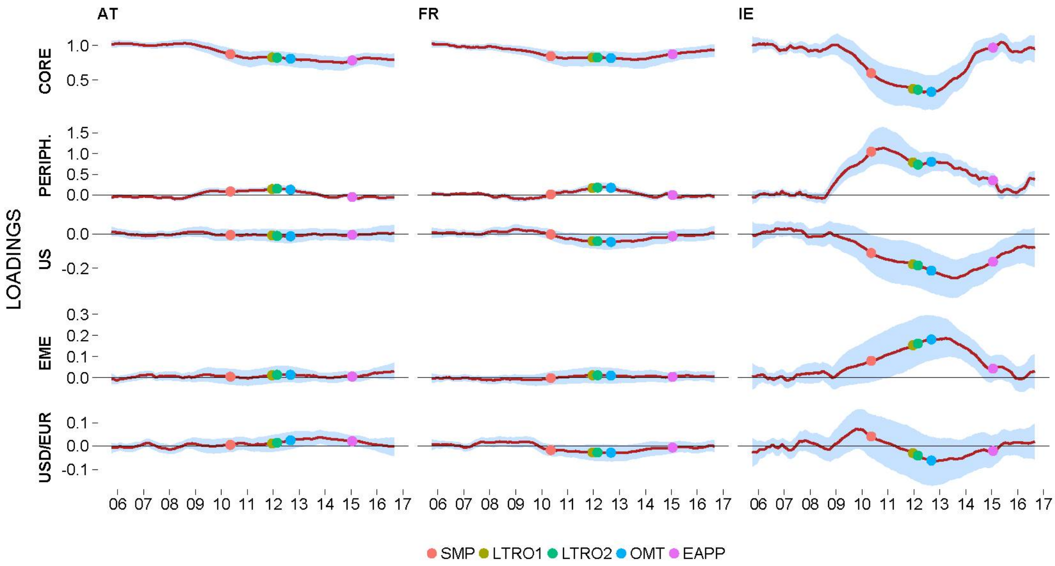
3.B Time-varying loadings on factors and exogenous varibales

Figure 3.9: Evolution of loadings of bond yields on factors



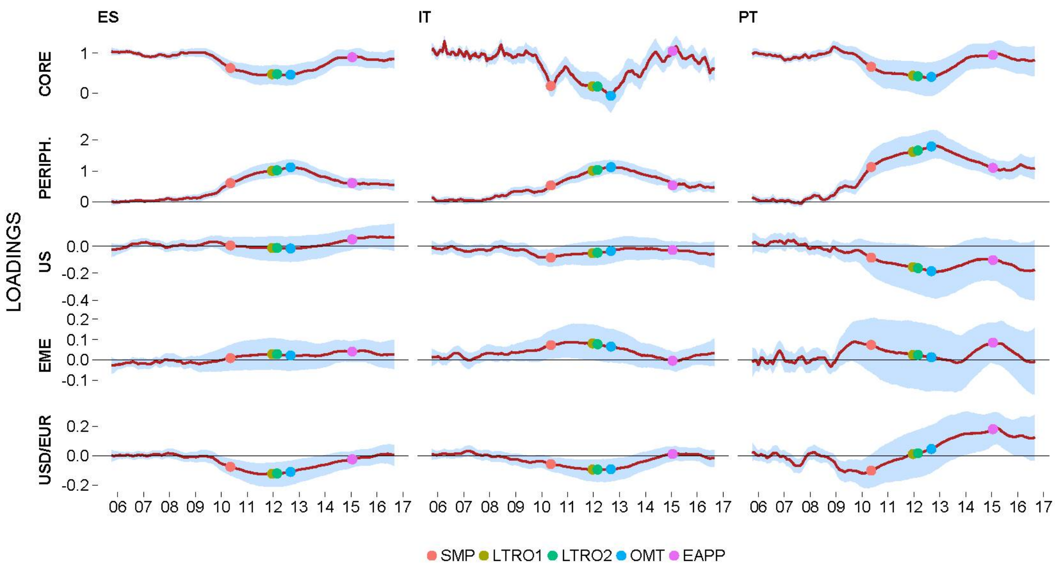
Note: posterior median, 16th and 84th quantiles.

Figure 3.10: Evolution of loadings of bond yields on factors



Note: posterior median, 16th and 84th quantiles.

Figure 3.11: Evolution of loadings of bond yields on factors



Note: posterior median, 16th and 84th quantiles.

3.C Time-varying impact responses to structural shocks

Figure 3.12: Posterior median responses (on impact) of bond yields to structural shocks over time.

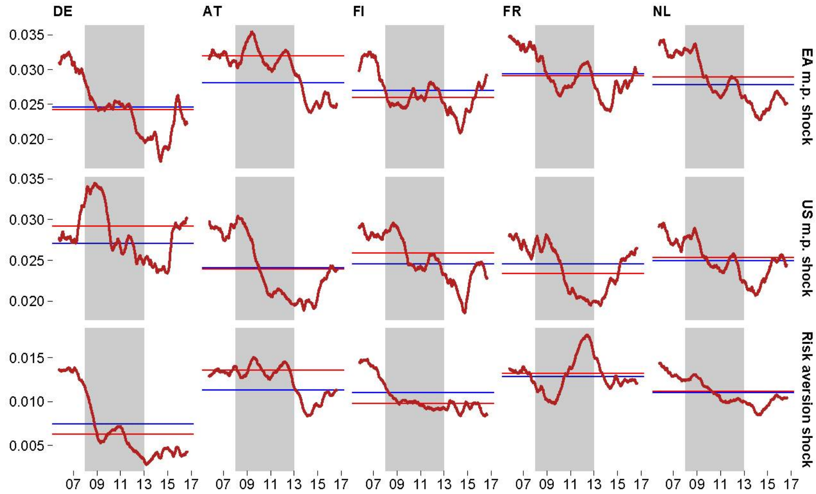
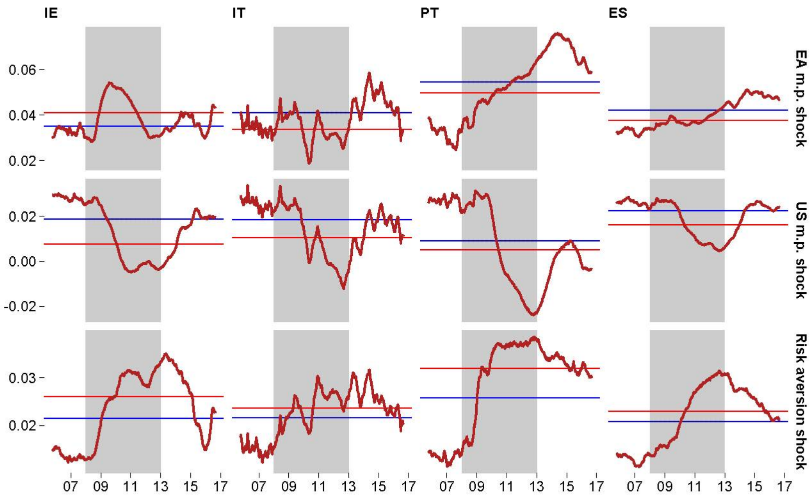
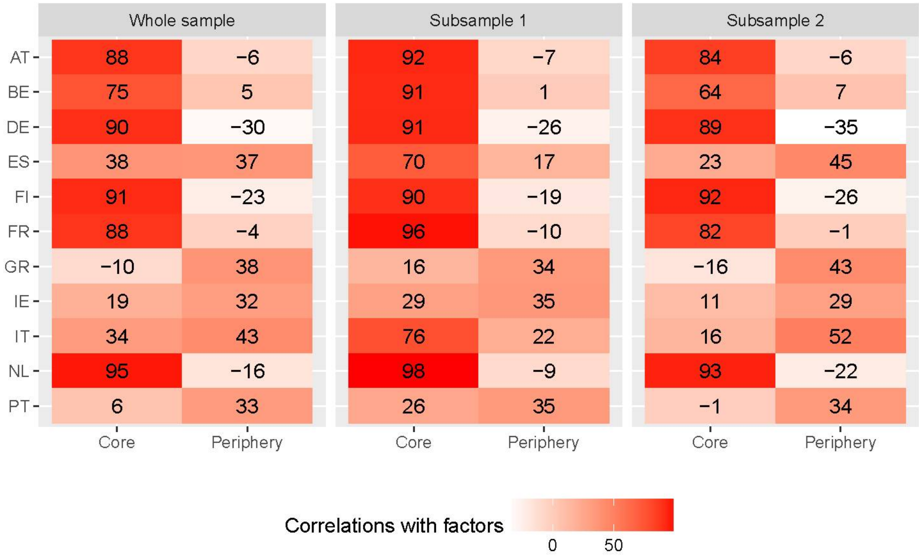


Figure 3.13: Posterior median responses (on impact) of bond yields to structural shocks over time.



3.D Correlations with factors

Figure 3.14: Correlations of each country with factors.



Note: Subsample 1: October 2005 - December 2010. Subsample 2: January 2011 - August 2015.

Chapter 4

Time-Varying Betas of Banking Sectors

Abstract
This paper analyzes the evolution of the systematic risk of the banking industries in eight advanced countries using weekly data from 1990 to 2012. Time-varying CAPM betas are estimated at a country level by means of a Bayesian state-space model with stochastic volatility, whose results are contrasted with those of the standard M-GARCH and rolling-regression models. By estimating a common factor driving the estimated betas, we show that both country-specific and global events affect the perceived systematic risk, while the impact of the latter differs considerably across countries. Finally, our results do not support the previous findings that the systematic risk of the banking sector was underestimated before the last financial crisis.

4.1 Introduction

Systematic risk has been among the most studied issues in the financial literature, particularly when the systematic risk of banking sectors is considered. The inherent fragility of banks and the opacity of their businesses raise the question of whether markets are able to price the risk correctly. The excessive risk-taking by US banks before the market meltdown in 2007 is an example of

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a period when the correct evaluation of risk is questionable. Surprisingly, not even the ex-post literature provides any clear-cut answer to this question, so it is not clear whether markets were aware of the risks connected with mortgage loan securitization. As we show in this paper, the results depend on how the systematic risk is estimated.

The paper extends the evidence from the current literature in several ways. First, it applies a Bayesian state-space model with stochastic volatility for the estimation of the CAPM betas of banking sectors on a country level in eight advanced economies. According to the CAPM theory (e.g., (Sharpe, 1964), (Lintner, 1975), (Mossin, 1966)), the betas should capture the systematic risk of the industry. It is now widely held that betas are not time-invariant, and methods such as the rolling-regression model, classic state-space models, and the GARCH model have so far been used frequently to estimate the evolution of betas. Still, these methods have several shortcomings, such as arbitrary choice of window size (in the case of rolling regression), assumed homoskedasticity of residuals (in both the rolling-regression and the state-space approaches), and a large amount of noise present in the estimates (estimation based on the GARCH model). On the other hand, the model that we use links the advantages of both the Kalman filter approach (estimating the beta as an unobservable process in a state-space model) and the approach based on the M-GARCH model (allowing for heteroskedasticity of residuals).

Next, the paper presents the results for three methods—the rolling-regression model, the GARCH model, and the state-space model with stochastic volatility—and, on the example of US banking betas in the pre-crisis period, shows how these estimates can be useful for policymakers. This period was characterized by a build-up of instability in the banking sector, which was not reflected in stock prices according to some studies. Nevertheless, our analysis shows that the banking sector risk in calm periods could still be priced in if the estimation techniques used in this paper were employed.

Third, we analyze the time-varying betas of banking sectors across different advanced countries. The previous literature has investigated the betas of financial sectors as a whole or has studied trends between sub-sectors in one individual country. On the other hand, our estimation, based on a factor extracted from country-level estimates, allows us to look at potential global trends in the perceived riskiness of banking sectors. To evaluate the degree of co-movement, we estimate a global factor and calculate the percentage of the variation explained by the global factor for individual countries. The results suggest that the banking sectors in some countries (the US, the UK, and Germany) share similar patterns in the evolution of their systemic risk; on the other hand, the sectors in other countries (Japan and Australia) look more isolated. The paper presents one of many possible explanations: the degree to which the countries are financially interconnected. Thus, we compare our results with previous findings on international banking and the transmission of financial stress. It seems that the most influential financial centres exhibit the highest sensitivity to global developments and the degree to which the banking sector is internationalized can be reflected in the sector's systemic risk.

We believe that our proposed estimation method could enhance the analyses by equity capital investors, bank managers as well by financial supervisors. This innovative approach can be applied to the banking sector as a whole or individual banks' data. Hence, it can be used to estimate the cost of capital more accurately or to identify the determinants of systemic risk. It may also help in the identification of instability accumulation in tranquil times, as this phenomenon remains a crucial issue for financial stability.

4.2 Systematic risk and the banking sector

The concept of the capital asset pricing model (CAPM) has been under the relentless attention of both academicians and practitioners for almost 50 years. One of the most important implications of this model is that we can use the contribution of an asset to the variance of the market portfolio (the asset's beta) as a measure of the asset's systematic risk. This risk is determined by general market conditions and cannot be diversified away.

The assessment of systematic risk is vital both for academic research when testing asset-pricing models and market efficiency, and for investment decisions such as portfolio choice, capital budgeting, and performance evaluation. In recent years, it has also become used for financial stability purposes to estimate the cost of equity (Barnes and Lopez, 2006) or even to measure the level of financial stress.

Our study is unique in that it compares time-varying betas in banking sectors across different countries. Betas of banking sectors have usually been

While CAPM betas are used to monitor systematic risk of banking sectors purely based on asset prices, more complex methods are used to measure systemic risk of banking sectors, which use fundamental indicators of banks ((Tobias and Brunnermeier, 2016; Chan-Lau and Sy, 2007; Babecky et al., 2013)) estimated in the literature as a part of sectoral analyses in the financial industry. For example, Mergner and Bulla (2008) estimate the time-varying betas of a financial sector (including insurance companies) in a pan-European portfolio. A similar exercise is performed by Groenewold and Fraser (1999) on Australian sectors. Estimation is performed on an individual stock level by Lie et al. (2000), who estimate the time-varying betas of 15 financial sector companies in Australia on daily data. They use the GARCH model and the Kalman filter, which generates better results based on in-sample MAE and MSE.

Another pure banking-sector analysis is by King (2009), who estimates the costs (required rate of return) of capital in six developed countries using rolling regression. The author claims that the costs declined in all countries except in Japan until 2005 when they started to rise. The decline in costs reflects both a declining beta and a declining risk-free rate. He also suggests that a low beta may point to mispricing of banking shares.

More recently, Caporale (2012) performs tests for structural breaks in a market model of the US banking sector. He identifies three structural breaks — 1960M12, 1989M09, and 2000M03, after which banking betas were at historic lows (the sample ended in 2008). He suggests that the risk was mispriced (i.e., the systematic risk was underestimated), as the banks took the highest leverage and risk in this time, while the expected risk was low. On the other hand, Bhattacharyya and Purnanandam (2011) look at the evidence of excessive risk-taking of US banks in the pre-crisis period on an individual bank level. They conclude that financial markets were able to identify banks engaged in risky operations before the meltdown.

Another stream of literature investigates the determinants of systematic risk. In particular, several studies examine the question of whether more leveraged banks bear a higher systematic risk. While Yang and Tsatsaronis (2012) show a positive correlation between leverage and beta on a sample of 50 banks from OECD countries, di Biase and Elisabetta (2012) do not find a strong link in the Italian sector. Also, the cost of equity (which is determined based on beta) is still a key issue mainly for banking sector supervision and financial stability purposes. A recent paper by Yang and Tsatsaronis (2012) extends this stream by showing that leverage and business cycles influence the systematic component of banking risk, so bank equity financing is cheaper in booms and dearer during recessions. Altunbas et al. (2010) identify several determinants of individual bank riskiness, accounting for banking sector characteristics such as GDP, housing prices, and the yield curve.

The CAPM measure of systemic risks could be linked to other concept for measuring systemic risks such as the CoVaR or distance to default approaches, as well as the more standard Probit/Logit models of banking crises. The work of Segoviano and Goodhart (2009) could be also relevant because it highlights the role of banking structures on the formation of systemic risk—contrasting a system of universal banks against a system of specialized banks.

The impact of banking globalization on banking sector risk has not been investigated in this context thoroughly. Individual bank data from Germany were studied by Buch et al. (2012), who show that internationalization increases the riskiness of banks. Similarly, Cetorelli and Goldberg (2012) show that banking globalization is leading to faster transmission of global shocks, so increased financial linkages between banking sectors worldwide increase their vulnerability to financial shocks.

4.3 Approaches to the estimation of systematic risk

For the purposes of this paper (estimating betas of the banking sectors), we consider the standard CAPM result, summarized in the following equation:

$$E(\tilde{R}_i) = \beta_i E(\tilde{R}_m) \tag{4.1}$$

where β is the CAPM beta of asset i, $\tilde{R}_i = R_i - r_f$ is the excess return on asset i (r_f is the return on the risk-free asset) and $\tilde{R}_m = R_m - r_f$ is the excess return on the market portfolio. This equation asserts that in equilibrium, the returns on an asset depend linearly only on the returns on the market portfolio (thus, it is a one-factor model). This model should hold ex-ante, but it can be estimated only on historical data, so the following market model regression is used for the estimation:

$$\tilde{R}_{it} = \alpha_i + \beta_i \tilde{R}_{mt} + \epsilon_{it}, \epsilon_{it} \sim N(0, \sigma_i^2). \tag{4.2}$$

The original model implies an equilibrium relation, which should be stable or time-invariant. However, the stability of this relation has been challenged several times in the literature and there is now a consensus that β_i is not constant. For instance, Fabozzi and Francis (1978) claim that betas may be random coefficients, which could explain the large variance of betas estimated using OLS, the poor performance in estimating the returns on assets, and the rejection of the CAPM in many stock markets. Despite these findings, no consensus has been found on the method for estimating time-varying betas. Usually, the Kalman filter or a GARCH model are used (e.g., (Faff et al., 2000), (Mergner and Bulla, 2008), (Lie et al., 2000)) with differing results.

In order to draw credible conclusions from our analysis, we employ three approaches to estimating betas and compare their results. The first approach is based on a simple rolling-regression model. The second approach is based on the M-GARCH model introduced by Bollerslev (1990), which is based on estimating the conditional covariances between the returns on the market portfolio and the asset under consideration. The third approach is based on a Bayesian state-space model with stochastic volatility, which estimates betas as an unobserved component and allows for time-varying variance of shocks.

4.3.1 Rolling regression

As a starting point, we employ a method based on rolling-regression estimates, where time-varying betas are estimated by OLS on a moving window of a given number of observations. The drawback of this method is its sensitivity to the choice of window size and the sensitivity of OLS to outliers. As this method is used only as a benchmark against which we compare the other two methods, the size of the window is chosen informally.

4.3.2 M-GARCH

First, let us assume without loss of generality that $\tilde{R}_{jt} = \varepsilon_{jt}$, where $j = i, M$, and the error terms are assumed to be $(\varepsilon_{it}, \varepsilon_{Mt})' = H_t^{1/2} z_t$, and $z_{jt} \sim N(0,1)$ are uncorrelated. Since $\varepsilon_{jt}|\Psi_{t-1} \sim N(0, H_t)$, the equation 4.3 represents a conditional covariance matrix between the banking sector returns and the market returns:

$$H_t = \begin{pmatrix} h_{ii,t} & h_{iM,t} \\ h_{Mi,t} & h_{MM,t} \end{pmatrix} \tag{4.3}$$

Following the analysis by Rippel and Jánský (2011), we opt for a GARCH(1,1) process, which leads to the M-GARCH model described by the vector Equation 4.4. The same equation can be rewritten in a more compact way (Equation 4.6) using a *vech* operator that stacks in one column all non-redundant elements of a symmetric matrix that are either on or below the diagonal (Hamilton, 1994).

$$\begin{pmatrix} h_{ii,t} \\ h_{iM,t} \\ h_{MM,t} \end{pmatrix} = \begin{pmatrix} c_{11} \\ c_{12} \\ c_{22} \end{pmatrix} + \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \times \begin{pmatrix} \varepsilon^2_{i,t-1} \\ (\varepsilon_{i,t-1})(\varepsilon_{M,t-1}) \\ \varepsilon^2_{M,t-1} \end{pmatrix} + \quad (4.4)$$

$$\begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix} \times \begin{pmatrix} h_{ii,t-1} \\ h_{iM,t-1} \\ h_{MM,t-1} \end{pmatrix} \quad (4.5)$$

$$(\text{vech})H_t = C + A(\text{vech})\varepsilon + B(\text{vech})H_{t-1} \quad (4.6)$$

A disadvantage of the multivariate M-GARCH model is its overparameterization. For example, the M-GARCH(1,1) model has 21 unknown coefficients and the number is growing at a polynomial rate as the number of time series involved rises (Pagan, 1996). Some authors, such as Bollerslev (1990), suggest setting all coefficients above and below the diagonal to zero. This simplification leads to a substantially reduced form of the general equation and it allows us to describe the model by equations 4.7, 4.9 and 4.8 with only seven coefficients. The correlation between the returns of a banking sector and the market, denoted ρ, is by Bollerslev (1990) assumed to be constant. This simplification leads to the following system of equations:

$$h_{ii,t} = c_{11} + a_{11}\varepsilon^2_{i,t-1} + b_{11}h_{ii,t-1} \quad (4.7)$$

$$h_{MM,t} = c_{22} + a_{33}\varepsilon^2_{M,t-1} + b_{33}h_{MM,t-1} \quad (4.8)$$

$$h_{iM,t} = \rho\sqrt{h_{ii,t}h_{MM,t}} \quad (4.9)$$

Having estimated the three equations above, the time-varying beta can be easily calculated. The standard CAPM model calculates the β as a ratio of covariance between an asset and the market and the market volatility. Since the variance-covariance matrix in the M-GARCH model is time dependent, the time-varying beta can be calculated using the respective conditional covariance matrix H_t. In other words, a time-varying beta calculated using an M-GARCH model has a form described by the following equation:

$$\beta_{it} = \frac{cov_t(\tilde{R}_{it}, \tilde{R}_{Mt})}{var_t(\tilde{R}_{Mt})} = \frac{h_{iM,t}}{h_{MM,t}} \tag{4.10}$$

4.3.3 Bayesian state space model with stochastic volatility

The drawback of the previous approach is that it contains a lot of noise because the betas can change substantially every period, which is not plausible. To overcome this problem, we model the betas as an unobservable process which follows a random walk. We assume the following state-space model (note that the analyzed asset's index i is omitted):

$$\widetilde{R}_t = \alpha_t + \beta_t \widetilde{R}_{mt} + u_t, \qquad u_t \sim N(0, \sigma_t^2), \qquad t = 1, 2, ..., T \tag{4.11}$$

$$B_t = \begin{pmatrix} \alpha_t \\ \beta_t \end{pmatrix} = \begin{pmatrix} \alpha_{t-1} \\ \beta_{t-1} \end{pmatrix} + \begin{pmatrix} v_{\alpha,t} \\ v_{\alpha,t} \end{pmatrix}, \qquad \begin{pmatrix} v_{\alpha,t} \\ v_{\alpha,t} \end{pmatrix} \sim N(\mathbf{0}, \Sigma) \tag{4.12}$$

$$\log \sigma_t = \log \sigma_{t-1} + \eta_t, \qquad \eta_t \sim N(0, W) \tag{4.13}$$

This state-space model is similar to those used in the literature. However, those models, estimated using the Kalman filter, assume that the residuals u_t are homoskedastic, i.e., σ_t is fixed. This can bring bias into the results (i.e., the betas can be overestimated or underestimated, depending on the value of σ_t), because σ_t is used in the Kalman filtering and presumably varies over time. Therefore, we assume a variant of stochastic volatility, i.e., the volatility is modelled as a latent process σ_t which is not a simple function of the past or current values of the observables, as is the case with a GARCH process, for example. We assume the simplest version of the stochastic volatility process, where the volatility follows a geometric random walk.

This kind of model is usually estimated using Bayesian inference, which overcomes the problem of failure to find local maxima, as is the case with the MLE approach. In addition, Bayesian methods in this context are relatively easy to implement and can be extended to find the posterior distributions of parameters in very complex models. The major difference between the MLE and Bayesian approaches to state-space modeling is that the latter assumes that the parameters of the state/observational equations (i.e., the variances of the error terms) are not fixed parameters to be estimated, but are random variables. Also, the state variables (B_t and σ_t) are regarded as random variables as well. The estimation starts by assuming the prior distributions of the hyper-parameters and the starting values of the state variables, and solving for the posterior densities of all these variables (by means of Bayes' theorem). Because the joint posterior density function is intractable in this case, a simulation using Markov chain Monte Carlo methods is performed. Its details are described in the Appendix 4.B

4.4 Time-varying betas of the banking sectors

4.4.1 Data used for the analysis

We estimate the time-varying betas of the banking industries in eight advanced countries—the United States, the United Kingdom, Germany, France, Switzerland, Japan, Hong Kong, and Australia. The countries were chosen based on their market capitalization and the number of banks operating in the country. The major stock market indices were used as the indices representing the market portfolio. In some cases, banking sector indices are published by stock exchanges, but to ensure consistency we opted for banking sector indices constructed by Thomson Reuters. Finally, the risk-free rates of most countries were chosen as those recommended by Datastream (available on its intranet, for example), while the risk-free rate of Hong Kong was chosen based on the literature. All the data were downloaded from Datastream and are summarized in Table 4.1. The normalized stock indices are plotted in Figure 4.2 in Appendix 4.C.

Weekly data spanning January 1990 to February 2011 are used for the analysis. The exceptions are Germany and France, whose data start in January 1999, when the Euribor rate was introduced. The sample could have been extended by using the national money market rates before 1999, but we wanted to ensure consistency of the results, so this extension was skipped.

4.4.2 Results: systemic risk of the banking sectors

We estimated the time-varying betas of each banking sector using the three approaches mentioned in the previous section—the rolling-regression model, the multivariate GARCH model, and finally the state-space model with stochastic volatility. Figure 4.3 in Appendix 4.D presents the results from the rolling

Table 4.1: Data used for the analyss

Country	Risk-Free Rate	Stock Market Index
United Kingdom	UK Interbank 3M	FTSE 100
France	Euribor 3M	CAC 40
Germany	Euribor 3M	DAX 30
Switzerland	Swiss Liquidity Financing Rate 1M	SMI
United States	US 3M T-Bill	NYSE COMPOSITE
Japan	3M Interbank	NIKKEI 225
Hong Kong	HKD Depo 1M	Hang Seng
Australia	Dealer bill 90 day rate	ALL ORDS

Source: Thomson Reuters Datastream

regression with a window spanning 50 observations, which corresponds to approximately one year. This approach has two major drawbacks—there is no means of estimating the optimal size of the window, and the technique is sensitive to outliers. Therefore, the technique would yield different results depending on the size of a chose window.

Next, Figures 4.4 and 4.5 in Appendix 4.E presents estimates using the multivariate GARCH. The drawback of this method is that the resulting time series contains a large amount of noise, which causes them to be very erratic. Since each new observation affects the volatility of both the market and the indices and, therefore, the betas, changes between two consecutive observations should be interpreted cautiously.

Finally, Figures 4.6 and 4.7 in Appendix 4.F present the posterior medians and two posterior quantiles of the latent processes of the betas and the stochastic volatility simulated using the Gibbs sampler. The burn-in sample has 8,000 iterations, and the following 2,000 iterations were used to form the quantiles. One can observe that the most substantial differences between this approach and the former two occur at times of increased volatility, which is because the last method filters out the noise brought about by every new observation. The ability of this method to filter out noise from the signals is why we introduced this third method.

All three approaches strongly support the idea of the time-varying nature of the beta, and several important features are apparent. First, we do not observe any steady decline in the banking sector beta after 1990. This finding is in contrast with King (2009), who concludes that the bank betas trended downward for most countries over a 20-year period, with a substantial increase only in the latest period. He used bank level estimates that are lower than the equity sub-index estimates we employ. The differences are unusually large in the case of the UK and increased during the recent crisis period (mainly due to a different weighting and sample). Still, our focus is not on the cost of capital, but on investors' reasoning (perceived riskiness) and global factors for the most important banking groups.

Second, our beta estimates indicate that the banking sector risk in quiet times could still have been reflected in asset prices. As for the period after 2005, it is often argued in the literature that market expectations of banking risk in the US were low while bank leverage and risk-taking were rising during the housing market credit boom. Still, our findings are not consistent with the notion that this instability build-up was mispriced. The US banking beta started to rise as early as July 2006 from levels close to 0.6, growing steadily to 1.5 two years later when the financial crisis had fully developed. Similarly, the sovereign debt crisis was expected to hit mainly the French banking sector, so its beta remained at elevated levels (more than 1.6) in most of 2010. In the first months of 2011, the beta for the French banking sector started to rise again, reaching 2.5 at the end of 2011.

Third, the reaction of the markets to the recent crises also differed substantially. While the dot-com bubble in 2000 increased the perceived riskiness of the American banking sector and lowered it for other countries, the global financial crisis increased the betas of many banking sectors all around the world at the same time. The same pattern, i.e., synchronized increase in the systematic risk, although to a lesser extent, can be found in the data for the more recent euro area sovereign debt crisis. This may be due to the systemic nature of the crisis, as the transmission of shocks was facilitated by the international banking network. The growth of banking sector linkages between several countries (such as the US, the UK, and Germany) could have contributed to the higher perceived riskiness of their banking sectors.

To explore the similarities among the movements of banking sector betas across countries more precisely, we estimate a global factor of systematic risk and assess its synchronization with the individual countries' betas.

4.4.3 Extension: exploring the global development of systemic risk

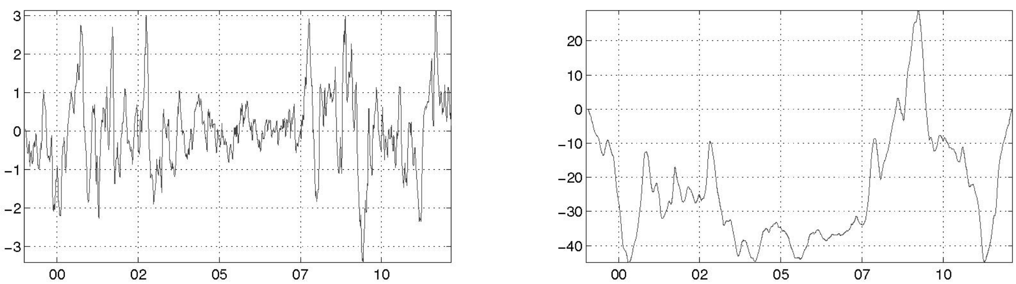
As we have pointed out, some banking sectors share similar patterns in the evolution of their systematic risk. That is, in most of the studied countries, their betas generally declined until 2005, after which they started to rise. Australia and Japan were exceptions, and the systematic risk of their banking sectors looks isolated to a large extent from global developments. Therefore, it seems that changes in the perceived riskiness of some banking sectors are more sensitive to global shocks in some countries than in others. To quantify the hypothesis that the systematic risk of some banking sectors is more isolated from global developments, we extract a common (global) factor to all the betas and compute the proportion of the variation of each beta explained by the global factor. If more variation is explained, the banking sector is more sensitive to global developments.

For further analysis, we use posterior medians estimated using Bayesian inference as described above (the transition equation is $\beta_t = \beta_{t-1} + v_t$). This is because this method filters out noise and outliers that are present in the results obtained by the GARCH and rolling-regression models. Since we have assumed that the process of betas follows a random walk, it is not surprising that the hypothesis of a unit root is not rejected by the Dickey-Fuller test. To achieve stationarity, we first differenced the original time series and then normalized them, so the value of the transformed series has the interpretation of the deviation from the mean, where the unit of measurement is the standard deviation of the estimated sample.

The dynamic factor model, described in the Appendix ??, was estimated using the MLE approach and the Kalman filter, and the estimated global factor is plotted along with its cumulative sum in Figure 4.1. The magnitude of the factor is not directly interpretable, but one can observe that the sharp decline in the beta after the dot-com bubble in 2000 was followed by a period when the average beta for our sample rose and moved around unity. At the beginning of 2003, the betas of the banking sectors in several countries fell sharply again. The trend reversed only in 2007 when the financial crisis spread globally. The sovereign debt crisis had a smaller impact than the financial crisis, but the betas in several countries (France, UK, and Germany, among others) still rose substantially.

To quantify the extent to which the global factor explains the dynamics

Figure 4.1: The global factor of the systematic risk of the banking sector and its cumulative sum



of each beta, we estimate a regression over the whole period and another two regressions over two sub-periods: 1999–2006 and 2006–February 2012 . Next, in order to check the robustness of the results, we estimate another two factors, one for each sub-period, and estimate Equation 4.20 over the sub-periods. This step is done to make sure that the results do not change when matrix P is estimated using the split sample. If the results are to be robust, R2 should not differ much. Unfortunately, there is no statistical test to test for the equality of the two approaches, since different dependent variables are used, so the differences are assessed only informally.

The results are reported in Table 4.2. The highest percentage of the variation explained by the global factor both across sub-samples and over the whole sample is for the United Kingdom, while its value increased over time as well. It is followed by the United States, France, and Germany. On the other hand, the beta for Japan seems unrelated to global developments.

4.4.4 Systematic risk and global banking

One potential explanation for the level of sensitivity to global developments is the extent to which countries are financially interconnected. Ideally, internationalization per se is a diversification strategy reducing a bank's risk, which depends on the correlation between domestic and foreign assets and the volatility of foreign markets. However, Buch et al. (2009), for example, found that

The choice of 2006 was driven by two reasons in addition to a robustness check. First, we wanted to include in the second sub-period the onset of the crisis in the US. Then, according to Garratt et al. (2011), a substantial shift in international banking occurred in 20006Q1 when Switzerland moved away from the most important financial centers in the sense of financial stress transmission. This structure remained broadly unchanged until recently. For further explanation see the remaining text.

Table 4.2: Banking sector systematic risk: percentage of the variation explained by the global factor

Factor	Time period	US	UK	DE	FR	JP	CH	HK	AU
Factor 1	1999-2012Feb	0.27	0.38	0.19	0.31	0.01	0.17	0.23	0.13
	1999-2006	0.15	0.32	0.15	0.32	0.01	0.14	0.24	0.14
	2006-2011	0.37	0.44	0.24	0.32	0.01	0.22	0.22	0.13
Factor 2	1999-2006	0.11	0.3	0.16	0.31	0.02	0.13	0.28	0.19
Factor 3	2006-2012Feb	0.39	0.46	0.23	0.32	0.01	0.2	0.22	0.12

Note: The first part of the table shows the results when the global factor is estimated for the whole period. The second part shows the results when two factors are estimated for the two sub-periods.

internationalization increases the risk of German banks, although the results depend strongly on the type and the size of the bank.

Also, the global financial crisis has shown that international integration exposes banks to additional risk, especially through the global banking network. Internationalization has dominated banking in the last ten years, with the amount of global international claims having increased by 400% since 2000, mainly in advanced countries. Cetorelli and Goldberg (2012) show how globally active banks contribute to the international propagation of shocks. A global bank responds to a domestic liquidity shock by adjusting its funds internationally. The financial stability dimension of global banking has led to several attempts to limit these activities (BIS, 2009).

Therefore, an interesting question arises whether investors are aware of cross-country banking sector linkages when pricing risk. There is still no simple measure of the degree to which a country's banking sector is internationally integrated. One possible simple measure is the volume of loans from non-resident banks as a percentage of GDP (presented in Table 4.3). Switzerland, Hong Kong, and the UK have had a dominant position in international lending during the last ten years, while Japan and Australia have remained rather isolated. Another important development is the rise in offshore activities, which are related to operations of hedge funds and shadow banking. The country ranking is similar.

More sophisticated measures are based on the BIS bilateral claims database, taking into account both debtor and creditor positions. Garratt et al. (2011) use this dataset to identify important financial centers. Using an information

Table 4.3: Banking sector external relations: cross country comparison

		Loans from non-resident banks (amt. outstanding / GDP)	Offshore bank deposits / domestic bank deposits
United Kingdom	1999	83.3%	10.5%
	2004	112.3%	23.5%
	2009	204.7%	21.1%
Germany	1999	24.50%	6.3%
	2004	30.1%	9.2%
	2009	35.7%	8.7%
United States	1999	13.90%	9%
	2004	17.8%	13.1%
	2009	33.8%	23%
Hong Kong, China	1999	172%	11.7%
	2004	90.3%	15.6%
	2009	129.7%	38.6%
France	1999	27.4%	5.7%
	2004	35.9%	9.8%
	2009	72%	12%
Switzerland	1999	101.3%	18.6%
	2004	137.9%	29.4%
	2009	284.4%	61.8%
Japan	1999	15%	0.5%
	2004	12.4%	1.2%
	2009	11.5%	2.4%
Australia	1999	14%	4.5%
	2004	12.6%	5.1%
	2009	26.8%	4.1%

Source: Beck et al. (2009)

map equation, they divide banking groups from 21 countries into a structure which shows a map of financial stress contagion. They conclude that the most influential centers became smaller but more contagious. As for the structure, the most prestigious centers in 2000 were the UK, the US, Germany, and Japan. In 2006, Japan and Switzerland ceased to be dominant while France became dominant. In 2009, the most influential centers were the US, the UK, France, and Germany, in line with our beta findings. Any identification of the determinants of the pricing of perceived risk is beyond the scope of this paper, but one can conclude that the most influential financial centers exhibit the highest sensitivity of betas to the global factor.

4.5 Conclusion

In this paper, we estimated the time-varying betas of the banking sectors in eight advanced countries. We showed that the systematic risk of the industries varies considerably over time using three approaches—a rolling-regression model, an M-GARCH model, and a Bayesian state-space model. The choice of method can have a substantial impact on the assessment of whether markets can price the risk correctly. Our approach, based on Bayesian inference, provides some new evidence, and, contrary to some previous literature, we do not find strong evidence of declining systematic risk before the recent financial and sovereign crises; according to the literature, such a decline would have signalled the mispricing of risk.

Finally, we investigated the cross-country differences in banking sector betas. The systematic risk of banking sectors is primarily determined by domestic factors, but some countries share a degree of co-movement in their banking sector betas. The subsequent discussion showed that the growth of international banking linkages and faster transmission of financial shocks could have contributed to more significant comovement in some countries.

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Appendix

4.A Estimating CAPM betas in a Bayesian state-space framework

As we have noted in the main body of the text, we use a relatively standard approach for estimating a states space model with stochastic volatility. This approach is described well in a multivariate setting in (Primiceri, 2005) or (Koop and Korobilis, 2010). Here, we only review our choice of the priors and the Gibbs sampling.

Choice of priors

Before the vector of parameters can be sampled from their joint posterior distribution, prior distributions and their hyperparameters must be chosen. For our purposes, the priors were set broadly in line with Primiceri (2005). That is, we have chosen a training sample of size t_0, on which the starting values of time varying parameters were estimated. The OLS estimates on the training sample have been used as a reference value for the priors:

$$\begin{pmatrix} \alpha_0 \\ \beta_0 \end{pmatrix} \sim N\left(\begin{pmatrix} \widehat{\alpha}_{OLS} \\ \widehat{\beta}_{OLS} \end{pmatrix}, 3\,.\,\widehat{\Sigma}_{OLS}\right) \tag{4.14}$$

$$\log \sigma_0 \sim N(\log \hat{\sigma}_{OLS}, 1) \tag{4.15}$$

$$\Sigma \sim IW(t_o\,.\,k_Q^2 . \hat{\Sigma}_{OLS}, t_0) \tag{4.16}$$

$$W \sim IG(4\,.\,k_W^2, 4) \tag{4.17}$$

The means of the initial values of state variables $(\alpha_0, \beta_0, \log \sigma_0)$ were set at their OLS values, but with a larger variance. The prior on the error variance of B (the distribution of Σ) has been set to belong to the inverse-Wishart family, with the scale parameter set as a fraction of the OLS variance of estimates of B. The degrees of freedom parameter was chosen as t_0. This is in line with the interpretation of the inverse-Wishart distribution parameters: sum of squared errors and the number of observations. It is worth noting that the choice of the inverse-Wishart distribution implies that covariance matrix Σ is not diagonal, i.e. shocks to α_t and β_t may be correlated (this is not the case in some studies using the Kalman filter). Finally, the prior on the variance of the error term to the volatility process, W was chosen as a noninformative conjugate prior from the inverse-gamma distribution.

Gibbs sampling

The state-space model in this subsection is a relatively complex one and we simulate it by drawing from its joint posterior density function. The variables of interest are not only variances Σ and W, but also state variables. Together, we sample from the joint posterior distribution of the following vector of random variables: $\Omega = \left\{B^T, \sigma^T, \Sigma, W\right\}$.

Draws from joint posterior density functions in the state-space models are done by means of the Gibbs sampler, which draws in turns from the conditional posterior densities of each block of random variables. If the sampling is performed a sufficient number of times, the distribution of draws generated using the Gibbs sampler converges to draws from the joint posterior density. The conditional sampling is done in the following five steps:

1. Initialize B^T, σ^T, Σ, W
2. Draw B^T from $p(B^T|y^T, \sigma^T, \Sigma, W)$
3. Draw σ from $p(\sigma^T|y^T, B^T, \Sigma, W)$
4. Draw Σ from $p(\Sigma|B^T, \sigma^T, W)$
5. Draw W from $p(W|B^T, \sigma^T, \Sigma)$

The blocks are initialized at their OLS values and then a large number of repetitions n of steps 2-5 are performed. In order to skip draws before the Markov chain converges, we omit the first n_1 burn-in observations. The remaining $n - n_1$ observations are used for the analysis.

Step 2 is performed using a variant of the Bayesian simulation smoother of state-space models, proposed by Carter and Kohn (1994). In this step, we obtain draws from the posterior density of the vector B^T. Conditional on draws B^T and variance hyperparameters, we can obtain the estimates of residuals u^T and apply the algorithm by Kim et al. (1998) combined with the previous algorithm to obtain draws of a latent stochastic volatility process. The steps

The symbol x^T denotes $x_1, x_2, ..., x_T$

are summarized in the appendix of (Primiceri, 2005). Step 3 is a standard one of drawing the covariance matrix in a SURE model when we assume a conjugate inverse Wishart prior. Finally, Step 4 is a standard one of drawing the variance in a linear regression model, assuming a conjugate inverse gamma prior.

4.B Estimating the global factor

One approach to extracting a global component of banking sector betas is the principal components analysis, which is widely used in similar settings. However, as we want to allow for the autocorrelation of shocks to the global factor, we estimate it as an unobserved component f in the following dynamic factor model:

$$\beta_t = Pf_t + u_t, \quad u_t \sim MN(0, \Sigma_u) \tag{4.18}$$

$$f_t = Af_{t-1} + \nu_t, \quad \nu_t \sim AR(1) \tag{4.19}$$

where β_t stacks the estimated betas transformed to achieve stationarity (this is described in the text).

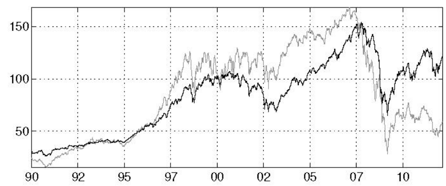
The proportion of variation explained by the global factor is estimated by estimating the following linear regression:

$$\beta_{it} = a_i + b_i\hat{f}_t + \eta_{it} \tag{4.20}$$

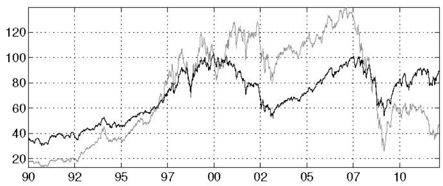
and examining R^2. If R^2 is higher, we claim that the global factor explains the sector beta better.

4.C Banking and stock market indices

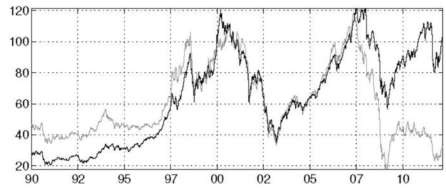
Figure 4.2: Stock market (dark line) and banking sector indices, weekly values.



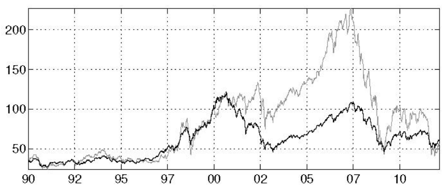
(a) United States



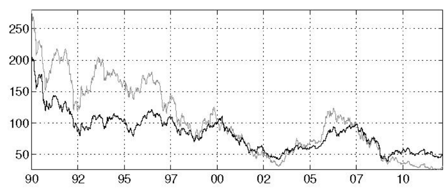
(b) United Kingdom



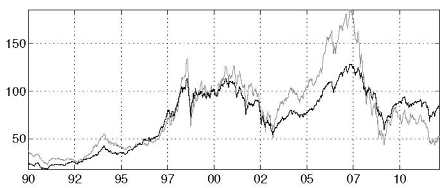
(c) Germany



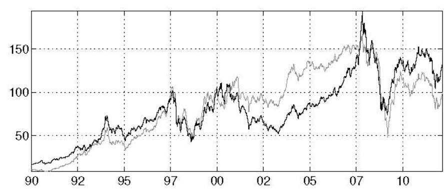
(d) France



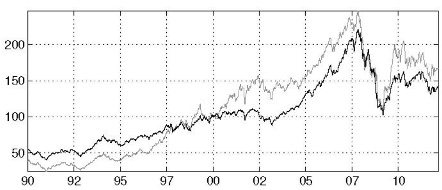
(e) Japan



(f) Switzerland



(g) Hong Kong

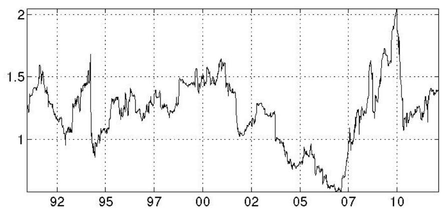


(h) Australia

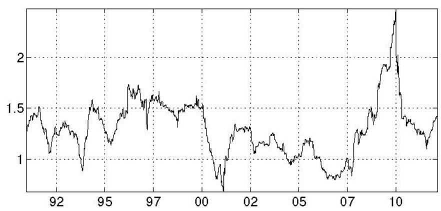
Note: Weekly averages, the values were normalized so that their values are 100 in the first week of 2000.
Source: Thomson Reuters Datastream.

4.D Betas estimated using rolling regressions

Figure 4.3: Rolling regression estimates of banking betas over windows of 50 observations



(a) United States



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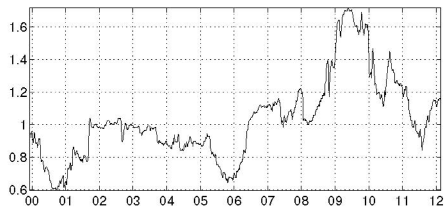
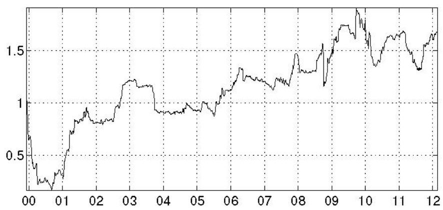
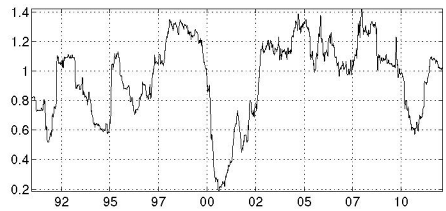


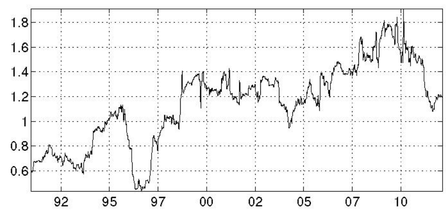
(c) Germany



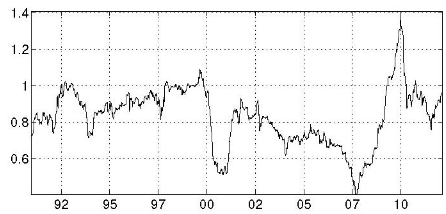
(d) France



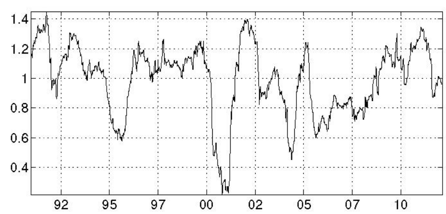
(e) Japan



(f) Switzerland



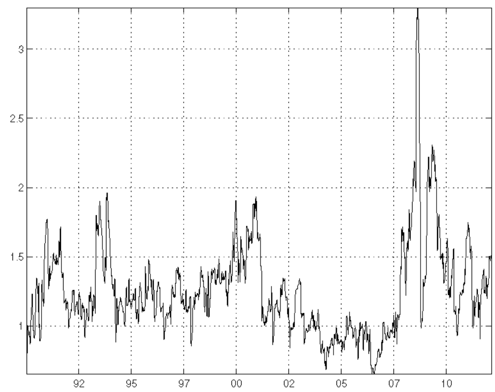
(g) Hong Kong



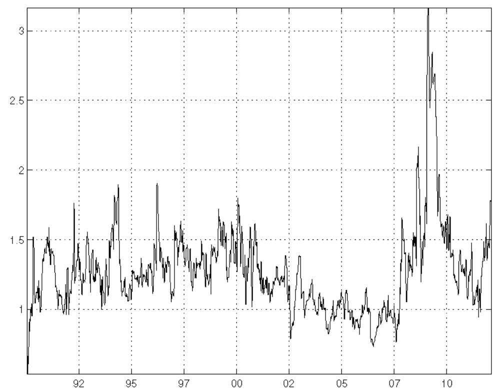
(h) Australia

4.E Banking Sector Betas - estimation using M–GARCH model

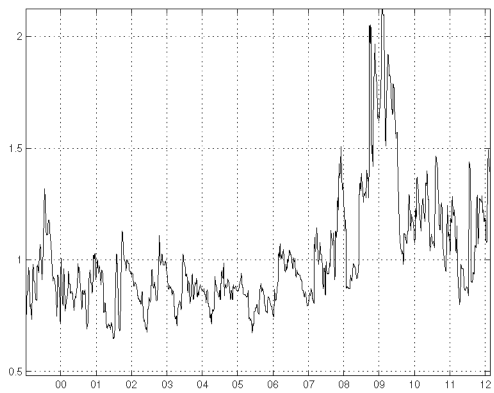
Figure 4.4: Betas estimated using M-GARCH model



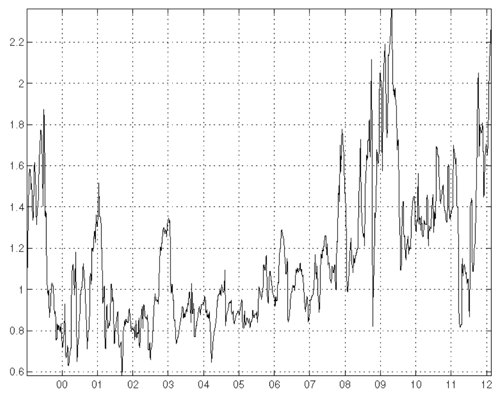
(a) United States



(b) United Kingdom

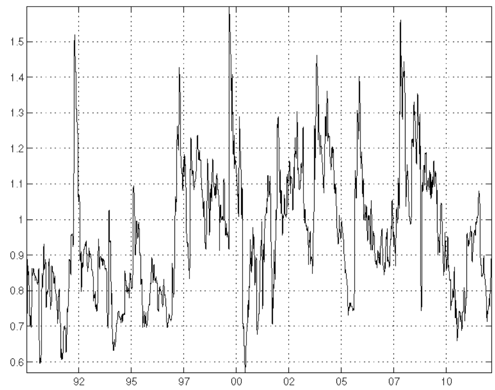


(c) Germany

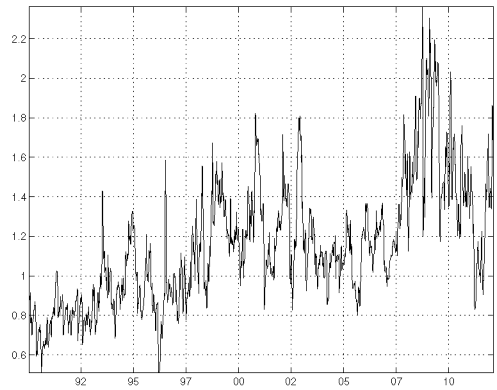


(d) France

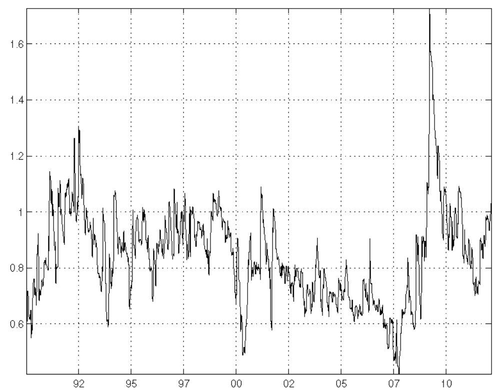
Figure 4.5: Betas estimated using M-GARCH model



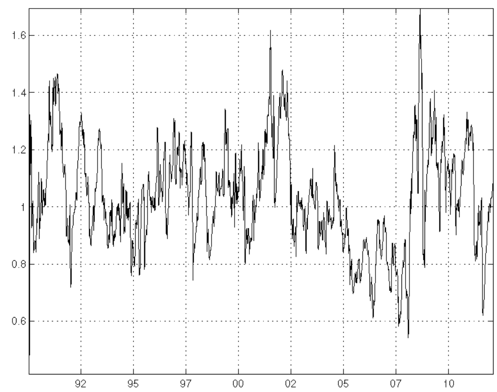
(a) Japan



(b) Switzerland



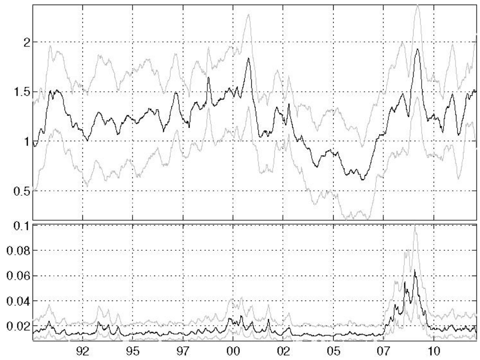
(c) Hong Kong



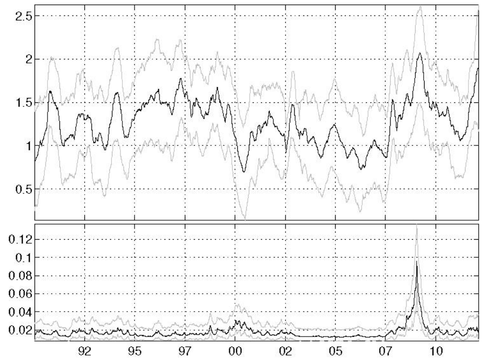
(d) Australia

4.F Banking Sector Betas - estimation using Bayesian state space model with stochastic volatility

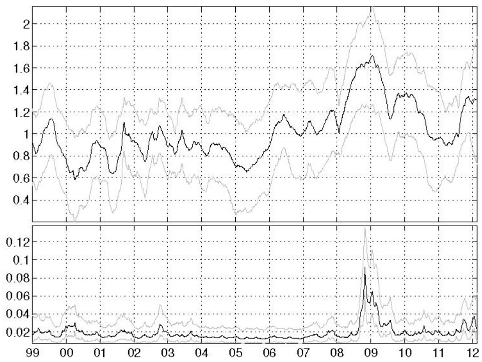
Figure 4.6: Posterior medians, 5-th and 95-th percentiles of betas (upper panels) and stochastic volatility (lower panels)



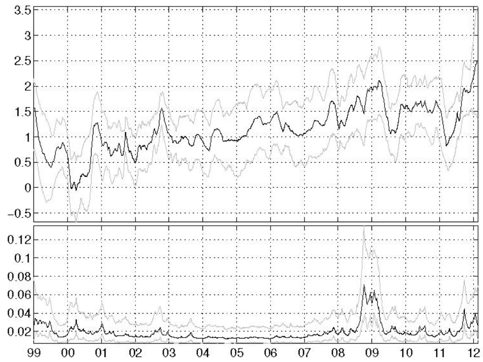
(a) United States



(b) United Kingdom

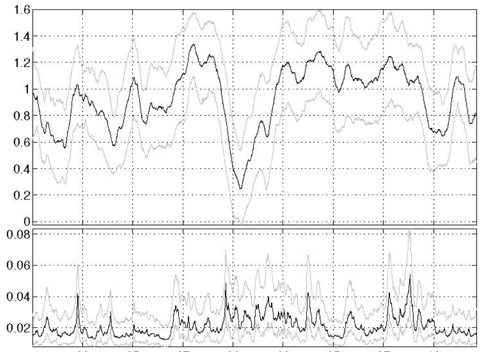


(c) Germany

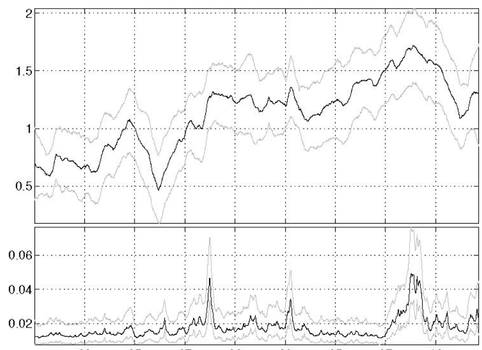


(d) France

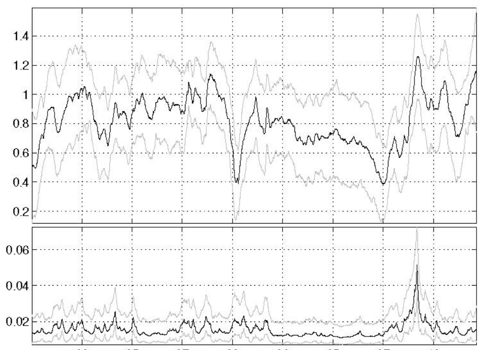
Figure 4.7: Posterior medians, 5-th and 95-th percentiles of betas (upper panels) and stochastic volatility (lower panels)



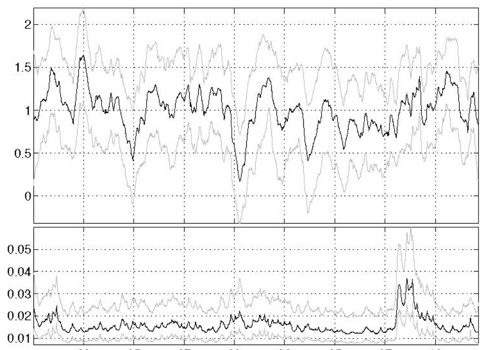
(a) Japan



(b) Switzerland



(c) Hong Kong



(d) Australia

Appendix A

Response to Opponents' Reports

I would like to express my gratitude to all the referees for their detailed comments and useful suggestions. I believe they helped to improve the dissertation, and several recommendations will be helpful also in my future research.

The comments by the referees are typeset in roman; my response is in italics.

A.1 Martin Feldkircher, PhD

Starting with the nowcasting contribution, an interesting evaluation would be to see by how much GDP forecasts for the Czech economy improve by having better forecasts of external demand. Moreover, as central banks start to provide more and more often not only the point forecast but the surrounding uncertainty (see e.g., the inflation report of the CNB), I think it would be worth looking at density measures of forecast evaluation, such as log-predictive scores. These would ensure that models are selected that yield both a precise mean forecast that is not surrounded by a large degree of forecast uncertainty caused by overfitting. In case, in future work, alternative models such as VARs are considered for short-term forecasting (p. 28) one might consider having specifications with stochastic volatility, as there is a large literature that demonstrate that that accounting for time variation in variances significantly improves forecasts (Cogley and Sargent, 2005; Clark and Ravazzolo, 2015; Carriero et al., 2016; Chan and Eisenstat, 2018).

Thank you very much for this comment. Regarding the first part, I plan to investigate this topic further in a future research paper. We will examine how forecasts of the Czech economy are improved by having better estimates of external demand. I also want to investigate what variables yield the most signi-

ficant improvement of forecasts - is it a headline GDP growth? Other potential candidates are components of GDP, such as investment, consumption, or even exports, as Czech exporters often export intermediate products. Regarding the first essay, its focus is solely on nowcasting GDP growth; therefore, we did not include the suggested analysis yet.

Regarding the density measures and stochastic volatility, we will bear this suggestion in mind in future research, when we might look only at a small number of competing models. In the current set-up, comparing density measures of forecasts would not be feasible due to a large number of evaluated models. Since the uncertainty stems from various sources (from the auxiliary ARMA models and then from the sole bridge equation) and frequencies are mixed, computing density measures would be computationally very demanding.

Second, the paper on euro area bond yields finds evidence for a decoupling of euro area core and periphery bond yields, starting with the period of the sovereign debt crisis. More specifically, bond yields in the periphery became more sensitive to a periphery factor and less to the core factor. This finding could be in line with results of a recent study by Leombroni et al. (2018) that attributes the decoupling to ECB communication. More precisely, in their work, they show that communication by the ECB has affected core and periphery bond yields in a similar way until up to the crisis after which the effect has ceased for periphery bond yields. Here, an additional risk premium materialized that affected periphery bond yields more than core yields driving a wedge between the two.

Thank you for this comment. I have added the mentioned paper in the literature review and the discussion of the results.

A.2 Risto Herrala, PhD

If the author(s) plan to further submit the papers for academic journal publication (as I think they should) it may be useful to keep in mind that papers may need to be revised before each submission to take into account the latest comments and also match the editorial policies of the selected journals.

From my own experience, it may be useful to before each submission run through a checklist of certain stylistic and clarifying tips, which I'll detail below for the author's benefit:

As regards the tables and charts, it helps the referees if they are presented in a 'self explanatory' fashion: below each table and chart the authors should insert a note of explanation about the table/chart: the precise content and the data source. In most essays, this is already done, but not consistently. Double headings should be removed for the purposes of journal submission (fig 2.4 on p. 38; fig 3.5 on p 58;..).

Also please check before submission to academic journals that all parameters and variables are always defined even if they are standard in the literature or otherwise seem self explanatory (ie β and δ in connection with Eq (2.1) p 18;. ..; Eq 4.2 p90 (is σ variance or std err?) ...; Eq 5.1 p 121; Eq 5.3 on p 122;...). The purpose of this tedious practice is twofold: it greatly helps the reader, and it also forces to author to use notation economically which may help avoid mistakes.

Thank you very much for careful reading of the thesis and for this comment. I particularly liked the suggestion at the end that limiting the number of equations helps to avoid mistakes and typos. I will bear this in mind also in my future research.

As regards references, the paper demonstrates excellent awareness of the literature. Nevertheless, in some places, referencing could be sharpened before journal submission, in particular the motivation of the Bayesian state-space-model should be more specific than that it is similar to those used in the literature.

Thank you for this suggestion. I will keep this in mind. I might also add/remove some references, depending on the focus of the journal, where we will submit the papers.

Tight focusing would be typically appreciated in many journals as opposed to demonstration of skill which is the focus of a doctoral thesis. This applies in particular to the fourth essay which amply demonstrates the econometric skill of the author without, in the end, producing much in terms of interesting results. One commonly used practice to increase focus is to focus on the one approach that he considers most interesting, and discussing the other approaches is a robustness section. In many joumals, referees may expect to see explicit discussion of robustness of the results.

Thank you for this comment. I agree and admit that this is especially the case of the fourth essay. We wrote it at the beginning of my PhD studies when I was focusing mostly on econometrics; therefore, the focus on discussing the results was slightly lower. I believe that over time, I managed to put more emphasis on discussing the results and putting them into context rather than on discussing econometric techniques.

A.3 Doc. Dr. Ing. Martin Melecký, Ph.D.

I would like to thank to doc. Melecký for careful reading of the thesis and providing me with a marked hard copy of the dissertation.

- Essay 1

Tomas could clarify whether the uncertainty surrounding the forecasts of monthly variables using an auxiliary model is considered when computing the overall confidence bands for the forecast of the external demand (foreign GDP growth). Furthermore, the role of time-varying (trade-based) weights on trade-partners' GDP in forecasting aggregate foreign demand for an open (Czech) economy could be discussed.

This comment is a similar one to the comment by Martin Feldkircher. In the paper, we do not focus on how the forecasts of external demand improve forecasting of the Czech economy, but on how to nowcast foreign GDP growth. This applies also to time-varying weights of trading partners. As I wrote in the response to the comment by Dr. Feldkircher, selecting optimal variables (including the optimal weights) which help to forecast the Czech economy will be addressed in another research paper.

Tomas could explain why he switches between using AIC and BIC variable selection criteria. For consistency, one indicator should be used. For small samples, it is well known that BIC performs better.

In the selection of optimal number of lags in bridge equations, we use consistently the Akaike information criterion. Bayesian Information Criterion (mentioned on p. 21) is used as an approximation of the marginal likelihood of regression models used in the BMA variable selection procedure. Computing all marginal likelihoods by simulations would pose an enormous computational costs, therefore their approximation based on the BIC is used.

Has the author attempted to collect real-time data using different publication vintages rather than relying on "pseudo" real-time experiments? Do revisions play an important role in the model's forecasting performance?

Unfortunately, we were not able to collect vintages of all indicators for all countries. This is discussed at the end of Section 2.4. I agree that data revisions might play a role. To overcome at least some problem with forecast evaluation, we use pseudo-real-time vintages, which take into account the publication lag of *each time series. A similar approach is taken, for example, by Feldkircher et al. (2015).*

The pros and cons of evaluating forecasting performance using RMSE could be discussed. The forecasting literature uses numerous other performance criteria, and the author's choice could be better justified — see, for instance, the work of Francis Diebold.

We took the approach based on RMSE, which is common in the literature on nowcasting (e.g., Feldkircher et al. (2015), Rusnák (2016) use also MSE/RMSE to evaluate model performance). I believe RMSE does not suffer from drawbacks especially in our case when GDP growth was not particularly volatile on the testing sample (therefore, the penalisation of a significant error in one observation does not outweigh small errors in the remaining observations). In addition, more sophisticated tests, such as Diebold-Mariano test are complicated by two factors - (i) nowcasts stem from combined models (ARMA and regressions), (ii) we have a mixed frequency, in that we combine monthly and quarterly observations, therefore it is not clear what the forecast horizon would be.

- Essay 2

Chapter 3 "Modeling Euro Area Bond Yields Using a Time-Varying Factor Model." The introduction discusses the potentially important role of asset purchase programs deployed by the central banks around the world for the pricing of government bonds. Yet, the model does not take this potential time-varying determinant(s) into account. Note that not only the mere volume could matter—measured, for instance, as the share of total bank assets—but also the extension of the programs from sovereign bonds to corporate bonds. Similarly, the stock variables such as the level of indebtedness could matter and who holds the debt. Both the indebtedness of Belgium and Greece are well above 100 percent of GDP and could have crossed a sustainable (sensitive) threshold—see the work of Reinhart and Rogoff. Yet, the debt of Belgium is held mostly by citizens while that of Greece mostly by foreigners. For instance, the Netherlands could have been a better choice for the country ordered first. Moreover, the role of private sector indebtedness and overall external indebtedness could be reflected upon. There are various implicit and explicit contracts between the private and public sector that give rise to contingent liabilities. The indebtedness of the private sector is not entirely independent of that of the government. Consider all the recapitalizations that took place in the Eurozone (Ireland, Spain) and elsewhere—including the U.S. TARP. Because the structural identification of shocks as residuals hinges on properly specified models, omitting potentially important variables is a credibility risk for the analysis.

Thank you for this comment. Since this model is empirical (not based on a theoretical model built on micro foundations), one could always argue that some variable is omitted. I believe that omitting variables related to debt (of the private or the public sector) is not a crucial problem for several reasons. (i) country-specific variables are "covered" by various loadings and intercepts in each equation - similarly to fixed effects in panel data models; (ii) debt variables are not changing dramatically on a weekly frequency, on which the model is built; (iii) the model contains idiosyncratic shocks, whose volatility is time-varying, so idiosyncratic changes in indebtedness should be reflected as a country-specific shock.

Regarding the volume of asset purchases - the model identifies monetary policy shocks, which are identified as shocks leading to changes in factors and exchange rates. Therefore linking those to the volume of asset purchases would be a different exercise.

...For instance, the Netherlands could have been a better choice for the country ordered first.

Theoretically, the choice of the country should be irrelevant for the shape of the factor (it affects only its magnitude and sign) and thus for the structural analysis. We discuss the choice of countries for the identification of factors on p. 50. We performed a robustness check by switching Belgium for Finland, and the results were unchanged.

- Essay 3

"Financial Stress and Its Non-Linear Impact on CEE Exchange Rates." I really like this chapter—that is, its clear and intuitive insight delivered by the simple analytical model and the power of cutting-edge estimation underpinning the interesting findings. Let me raise some questions that Tomas could reflect on during his defense. One, the simple theoretical model does not seem to produce regime switches. Could other models such as smooth-transition VARs be an equally good choice for testing the analytical model's predictions?

We have considered the threshold VAR model as a candidate model for the analysis, but in the end, we opted for a regime-switching model. The reason is *that we believe changes in risk aversion are not directly related to the level of financial stress, and they are unobserved (the Markov switching model assumes an unobserved latent process). In addition, one may argue that there is path dependency, i.e., investors may react to a rise in the level of stress in a different way when stress has been at elevated levels for a long time than they do when it rises by the same amount in calm times, for example. Substantial or prolonged increased volatility of asset prices may alter the risk aversion of traders or even change the credit constraints, which are unobserved. In other words, to link the empirical and the theoretical model in the paper, the volatility of an asset is captured by a financial stress indicator and the regime (linked to risk aversion) is an unobserved process.*

Two, could the need for regime "switches" be a result of a possible incomplete specification bias?

This may be true; however, we would still need a non-linear model to capture responses of a different sign. In the empirical part, we explicitly assume that risk aversion is unobserved (and thus omitted), so its changes are captured by the Markov switching model.

Three, how much does the possibility of (supposedly) unlimited short-selling by investors affect the results?

We mention the possibility of short-selling only in the stylized theoretical model. Its assumption is needed to ensure that the optimum weights are continuous. For the conclusions of the paper, it is essential only that if risk aversion changes (not continuously, i.e., it jumps), we obtain a jump in optimum weights, which leads to sales or purchases of the satellite currency.

- Essay 4

The chapter could clarify right from the start that the systemic risk is gauged at the country level, but that global systemic risk could be another variable of interest.

Thank you for this comment. I have modified the abstract and the introduction.

The CAPM measure of systemic risks could be linked to other concept for measuring systemic risks such as the CoVaR or distance to default approaches, as well as the more standard Probit/Logit models of banking crises. The work of Segoviano and Goodhart (2009) could be also relevant because it highlights the role of banking structures on the formation of systemic risk—contrasting a system of universal banks against a system of specialized banks.

Thank you for this comment. I have added a footnote in the literature review.

In view of chapter 2 and problems with T-bill markets as well as the money markets, one would like to see a full discussion of the DataStream's approach to constructing the risk-free rates for countries.

I agree that after the financial crisis, it is difficult to define what a risk-free rate is. For example, several studies show that money market rates contained credit risk or liquidity risk premia, which is not consistent with a definition of a risk-free rate. To make the analysis feasible, we used a list of risk-free rates provided by Thomson Reuters Datastream and use these rates (their list is in Table 5.1).

The transition to section 5.4.3. could be clarified including by restating equation 5.12. (its upper row) using the factors as determinants. The notation in Appendix 5.B should be clarified and linked to the betas directly. It is not clear what y refers to here.

Thank you for this comment. I have clarified the notation in Appendix 5.B and repeated the transition equation in section 5.4.3.