RIGA TECHNICAL UNIVERSITY

Ginters BUSS

ROBUST TIME SERIES FORECASTING METHODS

Summary of doctoral thesis

Riga 2013

RIGA TECHNICAL UNIVERSITY
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Institute of computer control, automation and computer engineering

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ROBUST TIME SERIES FORECASTING METHODS

Summary of doctoral thesis

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**DOCTORAL THESIS
PROPOSED TO OBTAIN THE DEGREE OF DOCTOR
FROM RIGA TECHNICAL UNIVERSITY**

Doctoral thesis in engineering sciences is proposed to obtain the degree of Doctor from Riga Technical University and, in accordance with the decision of the Doctorate Board, the public defense shall be held in November 20, 2013, 14.30 at the Faculty of Computer Science and Information Technology, Meza 1/3, room 202.

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ORIGINALITY STATEMENT

I hereby declare that the work presented in this thesis is my own and has been proposed to obtain the degree of Doctor in engineering sciences at Riga Technical University. This thesis contains no material accepted for the award of any other degree or diploma at RTU or any other educational institution.

Ginters Buss ....(Signature)

Date: ....

The Doctoral thesis is written in English, consists of an introduction, three chapters, conclusions and bibliography. It contains 67 figures and 9 tables. The total number of pages is 136. The bibliography contains 92 references.

CONTENTS

1 GENERAL CHARACTERIZATION OF THE THESIS

1.1 Pertinence of the thesis

Forecasting is prevalent. Tourism industry forecasts the number of tourists (Athanasopoulos, Hyndman, Song and Wu, 2011). Energy industry forecasts the demand and price of energy (Raviv, Bouwman and van Dijk, 2013). Finance industry forecasts the prices for crude oil, grain, currency and securities (Asai, Caporin and McAleer, 2012). Policy makers make their decisions based on economic forecasts (Amisano and Geweke, 2013); their decisions affect many people's lives.

One of the most widespread forecasting tools is the Box-Jenkins (Box and Jenkins, 1970) autoregressive integrated moving average (ARIMA) model. However, Box-Jenkins methodology has its drawbacks. First, a modern forecaster is faced with lots of potentially useful data which ARIMA models cannot handle. Second, in many areas of forecasting, e.g. in economics, data are noisy. Thus, forecasting methods should be used that are robust against the noise. Third, data dynamics may be subject to sudden change. The forecasting methods should be able to forecast robustly during such changes in dynamics.

The increasing demand for forecasting methods that would be able to handle potentially large sets of data subject to noise and changes in dynamics makes the topic of the thesis pertinent.

1.2 Objective and task of the thesis

The main objective of the thesis thus is to develop robust forecasting methods that are able to work with noisy and high-dimensional data, with applications in macroeconomics.

In order to fulfill the objective of the thesis, the following tasks are proposed:

- develop a univariate asymmetric bandpass filter for end-point estimation problems,
- compare the performance of the developed asymmetric filter to the currently most popular alternative in macroeconomics,
- develop a method suitable for forecasting and signal extraction using high-dimensional and noisy data,
- assess the properties of the above method and compare with the currently best alternative in macroeconomics,
- investigate the robustness issues for Bayesian and factor forecasting models.

1.3 Object and subject of the thesis

The object of the thesis is forecasting process of noisy and high-dimensional time series.

The subject of the thesis is the set and the system of filter and model algorithms for short-term forecasting that are suitable to work with noisy and high-dimensional macroeconomic data.

1.4 Research methods

The following methods are used in the preparation of the thesis: mathematical statistics and probability theory, optimization theory, frequency domain analysis and filtration theory, computer visualization method, and algorithm theory.

1.5 Novelty of the thesis

The main novelties of the thesis are:

1. An asymmetric filter has been developed for frequency band extraction at the end-points of univariate series.
2. A method has been developed for signal extraction and forecasting using high-dimensional and noisy data sets.
3. Robustness issues of Bayesian and factor forecasting models have been investigated when the dynamics of the target change rapidly.

1.6 Practical applicability

1. Precise and timely estimate of business cycle conditions helps adopt the right decisions in monetary and fiscal policy that affect many people's lives;
2. The tighter link between the dependent and explanatory variables in the regularized filter methodology i) makes its estimates more robust against the presence of irrelevant explanatory variables thus making the variable pre-selection step easier, ii) makes forecasting easier, and iii) makes the decomposition of individual effects easier;
3. The results on the robustness of the Bayesian and factor methods helps to choose robust forecasting methods in real-time environment.

1.7 Approbation of the thesis

The approbation of the thesis has been achieved by presenting the results at 11 international scientific conferences and seminars (including 1 poster), by publishing 11 articles in international scientific journals or conference proceedings, by implementing the methods at the Central statistical bureau of Latvia for producing the official statistics of seasonally adjusted data and the flash release of Latvia's GDP since year 2009. The delivered models and filters are used for forecasting purposes at Latvijas Banka since 2011.

Publications:

1. Buss, G. (2010), "A Note on Now-/Forecasting with Dynamic Versus Static Factor Models along a Business Cycle", 10th International Vilnius Conference on Probability Theory and Mathematical Statistics: Abstracts of Communications, Vilnius, Lithuania, 28 June - 2 July, 2010, p 119.
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6. Buss, G. (2010), "Forecasts with Single-Equation Markov-Switching Model: an Application to the Gross Domestic Product of Latvia", Journal of Applied Economic Sciences, Vol 5, Issue 2, pp 49-59. (Indexed in: Scopus, RePEc, SciVerse, Scirus, Econlit, Google Scholar, Microsoft Academic Search)
7. Buss, G. (2010), "Forecasts with Single-Equation Markov-Switching Model: an Application to the Gross Domestic Product of Latvia", Acta Societatis Mathematicae Latviensis: Abstract of the 8th Latvian Mathematical Conference, Valmiera, Latvia, 9-10 April, 2010, p 17.

8. Buss, G. (2011), "An Application of Direct Filter Approach: New Economic Indicators for Latvia", Scientific Journal of RTU, 5th series, Computer Science, 48 vol, pp 75-81. (Indexed in: EBSCO, Google Scholar)
9. Buss, G. (2011), "A Band Pass Filter for Real-Time Signal Extraction", Abstracts of 16th International Conference on Mathematical Modelling and Analysis, Sigulda, Latvia, 25-28 May, 2011, p 22.
10. Buss, G. (2011), "Preliminary Results on Asymmetric Baxter-King Filter", Aplimat 2011: 10th International conference on applied mathematics: Proceedings, Bratislava, Slovakia, 1-4 February, 2011, pp 1499-1508. (Indexed in: Google Scholar)
11. Buss, G. (2012), "Introduction to regularized DFA", Scientific Journal of RTU, series 5, vol. 48, pp 48-56. (Indexed in: EBSCO, Google Scholar)

Conferences:

1. Buss, G. "Forecasts with single-equation Markov-switching model: an application to the gross domestic product of Latvia" 10th International Vilnius Conference on Probability Theory and Mathematical Statistics, Lithuania, Vilnius, 28. June - 2. July, 2010
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3. Buss, G. "Forecasts with single-equation Markov-switching model: an application to the gross domestic product of Latvia", 8th Latvian Mathematical Conference, Latvia, Valmiera, 9.-10. April, 2010
4. Buss, G. "Economic forecasts with Bayesian autoregressive distributed lag model: choosing optimal prior in economic downturn", 8th Latvian Mathematical Conference, Latvia, Valmiera, 9.-10. April, 2010
5. Buss, G. "Asymmetric Baxter-King Filter", 51. RTU International Scientific conference, Section: Computer Science, Subsection: Technologies of computer control, 11-15 October, 2010, Riga, Latvia
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7. Buss, G. "Asymmetric Baxter-King filter", 26th Annual congress of the European Economic Association and the 65th European meeting of the Econometric Society, 25-29 August, 2011, Oslo, Norway
8. Buss, G. "An application of direct filter approach: new economic indicators for Latvia", 52. RTU International Scientific conference, Section: Computer Science, Subsection: Technologies of computer control, 13 October, 2011, Riga, Latvia

9. Buss, G. "A new real-time indicator for the euro area GDP", Working Group on Forecasting, European Central Bank, 28-29 June, 2012, Tallinn, Estonia
10. Buss, G. "Introduction to regularized direct filter approach", 53. RTU International Scientific conference, Section: Computer Science, Subsection: Technologies of computer control, 13 October, 2012, Riga, Latvia
11. Buss, G. "Forecasting and signal extraction with regularized multivariate direct filter approach", 28th Annual congress of the European Economic Association and the 67th European meeting of the Econometric Society, 26-30 August, 2013, Gothenburg, Sweden

1.8 Structure and volume of the thesis

The thesis consists of an introduction, three chapters, conclusions and a bibliography. It contains 136 pages, 69 figures, 9 tables and 92 references. The structure of the thesis is the following:

*The **Introduction*** describes the pertinence of the thesis, the objective and tasks of the thesis, the object and the subject of the thesis, research methods used, its practical applicability, and the approbation of the thesis.

*The first chapter **"Asymmetric Baxter-King filter for end-point estimation"*** develops an extension of the symmetric Baxter-King band pass filter to an asymmetric Baxter-King filter. Band pass filters are useful whenever one wants to extract a signal defined by some frequency band burried by noise of other unwanted frequencies. The optimal correction scheme of the ideal filter weights is the same as in the symmetric version, i.e, cut the ideal filter at the appropriate length and add a constant to all filter weights to ensure zero weight on zero frequency. Since the symmetric Baxter-King filter is unable to extract the desired signal at the very ends of the series, the extension to an asymmetric filter is useful whenever the end-point estimation is needed. The section uses monte carlo simulation to compare the proposed filter's properties in extracting business cycle frequencies to the ones of the original Baxter-King filter and Christiano-Fitzgerald filter. Simulation results show that the asymmetric Baxter-King filter is superior to the asymmetric default specification of Christiano-Fitzgerald filter in real time signal extraction exercises.

*The second chapter **"Multivariate filter for high-dimensional and noisy datasets"*** develops a method for signal estimation and forecasting using high-dimensional and noisy datasets. Nowadays, data are abundant. Therefore, methods are demanded that are capable of effectively using potentially high-dimensional datasets. It is shown that the regularized filter is able to process high-dimensional data sets by controlling for effective degrees of freedom and that it is computationally fast. The section illustrates the features of the filter by tracking the medium-to-long-run component in GDP growth for euro area, including the replication of an established indicator's behavior, as well as producing more timely indicators. The regularized direct filter approach is found to be a promising tool for both concurrent estimation and forecasting using high-dimensional datasets, and a decent alternative to dynamic factor methodology.

The third chapter ***"Robustness of traditional methods and forecasting system overview"*** studies the robustness issues of the Bayesian and factor methodologies. It finds that the Bayesian Minnesota prior and the exact dynamic factors are not robust against a rapid change in the dynamics of the target variable. The chapter also summarizes the methods considered in the thesis and describes a forecasting system involving methods developed in the thesis.

Main conclusions

Bibliography

2 CONTENTS OF THE THESIS

2.1 Asymmetric Baxter-King filter for end-point estimation

This section develops an extension of the symmetric Baxter-King band pass filter to an asymmetric Baxter-King filter. Band pass filters are useful whenever one wants to extract a signal defined by some frequency band buried by noise of other unwanted frequencies. The optimal correction scheme of the ideal filter weights is the same as in the symmetric version, i.e, cut the ideal filter at the appropriate length and add a constant to all filter weights to ensure zero weight on zero frequency. Since the symmetric Baxter-King filter is unable to extract the desired signal at the very ends of the series, the extension to an asymmetric filter is useful whenever the end-point estimation is needed. The section uses monte carlo simulation to compare the proposed filter's properties in extracting business cycle frequencies to the ones of the original Baxter-King filter and Christiano-Fitzgerald filter. Simulation results show that the asymmetric Baxter-King filter is superior to the asymmetric default specification of Christiano-Fitzgerald filter in real time signal extraction exercises.

2.1.1 Deriving the filter

Consider the following orthogonal decomposition of the zero-mean covariance stationary stochastic process, x_t:

$$x_t = y_t + \tilde{x}_t. \tag{2.1}$$

The process, y_t, has power only in frequencies (measured in radians) belonging to the interval $\{[a_1, a_2] \cup [-a_2, -a_1]\} \subset (-\pi, \pi)$, where $0 < a_1 < a_2 < \pi$. The process, $\tilde{x}_t$, has power only in the complement of this interval in $(-\pi, \pi)$. By the spectral representation theorem,

$$y_t = b(L)x_t, \tag{2.2}$$

where the ideal band pass filter, $b(L)$, is

$$b(L) = \sum_{h=-\infty}^{\infty} b_h L^h, \quad L^h x_t = x_{t-h}, \tag{2.3}$$

with

$$\begin{aligned} b_h &= \frac{\sin(ha_2) - \sin(ha_1)}{\pi h}, \quad h = \pm 1, \pm 2, \ldots \\ b_0 &= \frac{a_2 - a_1}{\pi}, \quad a_1 = \frac{2\pi}{p_u}, \quad a_2 = \frac{2\pi}{p_l}, \end{aligned} \tag{2.4}$$

and $p_u, p_l \in (2, \infty)$ define the upper and lower bounds of the wave length of interest. With b_h's specified as in (2.4), the frequency response function of the ideal filter at frequency ω is

$$\begin{aligned} \beta(\omega) &= 1 \quad \text{for } \omega \in [a_1, a_2] \cup [-a_2, -a_1] \\ &= 0 \quad \text{otherwise.} \end{aligned} \tag{2.5}$$

Fig. 2.1 shows the amplitude of the ideal bandpass filter with cut-off wave lengths 18 and 96 months and the absolute value of the discrete Fourier transform of Latvia's gross domestic product (interpolated to monthly frequency).

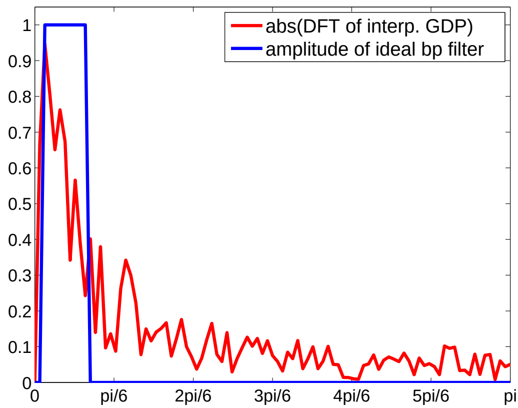


Fig. 2.1. The absolute value of the discrete Fourier transform of Latvia's gross domestic product (interpolated to monthly frequency) and the amplitude of the ideal bandpass filter with cut-off wave lengths 18 and 96 months.

Baxter and King (1999) have proposed to obtain a symmetric, fixed length approximation to the ideal filter, (2.3) and (2.4), by minimizing

$$Q = \int_{-\pi}^{\pi} \delta(\omega)\delta(-\omega) d\omega$$

s.t.

$$\begin{aligned} \hat{\beta}(0) &= \sum_{k=-K}^{K} \hat{b}_k = 0 \\ \hat{b}_k &= \hat{b}_{-k}, \end{aligned} \tag{2.6}$$

where $\delta(\omega) = \beta(\omega) - \hat{\beta}(\omega)$ is the discrepancy between the exact and the approximate filter amplitudes at frequency ω, and the constraint $\hat{\beta}(0) = 0$ is to ensure zero weight on the trend frequency, in line with the assumption $a_1 > 0$. The solution to (2.6) is a truncation of the ideal filter symmetrically at length K, and addition of a constant $(-\sum_{k=-K}^{K} b_k)/(2K+1)$ to all filter weights to ensure $\hat{\beta}(0) = 0$. Baxter and King (1999) suggest the value of K to be about 3 years, i.e, K=12 for quarterly data, and K=36 for monthly data. The symmetry of the filter together with the condition $\hat{\beta}(0) = 0$ implies that the filter renders stationary time series that is integrated of oder 2 (I(2)) or less. Thus, the symmetric BK filter has trend-reduction property and, therefore, it can be applied to nonstationary, up to I(2) series.

Since the symmetric BK filter can not be used to extract the desired frequencies at the very end (for the first and the last K observations) of the input series, a natural extension of the Baxter and King (1999) filter is to allow the approximate filter to be asymmetric, to be able to use the filter in real time. In order to optimally approximate an ideal symmetric linear filter in a Baxter-King sense, the problem is to minimize

$$Q = \int_{-\pi}^{\pi} \delta(\omega)\delta(-\omega)d\omega$$

s.t.

$$\hat{\beta}(0) = \sum_{h=-p}^{f} \hat{b}_h = 0. \tag{2.7}$$

The condition $\hat{\beta}(0)$ ensures zero weight on zero frequency, thus this asymmetric filter also has a trend-reduction property, however, it alone, without symmetry, is not sufficient to render I(2) process stationary. Thus, the ability of the asymmetric BK filter of real time signal extraction comes at a cost of losing the power to eliminate two unit roots from the input series.

It is shown that if there is no constraint on $\hat{\beta}(0)$, the optimal approximate (in Baxter-King sense) filter is simply derived by truncation of the ideal filter's weights. If there is a constraint on $\hat{\beta}(0) = \sum_{h=-p}^{f} \hat{b}_h = 0$, the required adjustment is

$$\theta = \frac{-\sum_{h=-p}^{f} b_h}{p+f+1}, \tag{2.8}$$

which yields the same optimal weight adjustment scheme as in the symmetric Baxter-King filter case.

Fig. 2.2 illustrates coefficients of 51-observation long symmetric BK filter and one-sided asymmetric BK filter targeting business cycle frequencies. The outputs of BK and ABK filters applied on a sample data are shown in Fig. 2.3. Clearly, only the ABK filter can be used at the end point of time series.

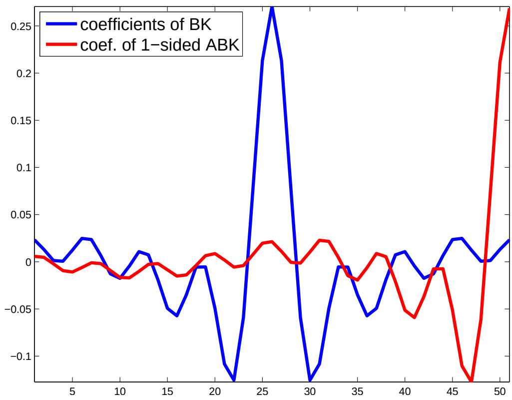


Fig. 2.2. Coefficients of 51-observation long symmetric BK filter and one-sided asymmetric BK filter targeting business cycle frequencies.

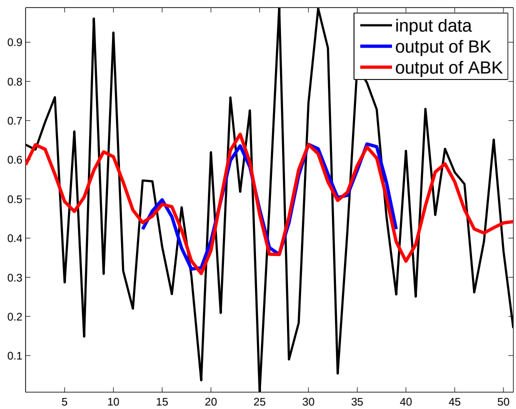


Fig. 2.3. The outputs of 51-observation long symmetric BK filter and asymmetric BK filter applied on a sample data.

Fig. 2.4 shows a flowchart for using the Baxter-King filter. In order to use the filter, the user has to choose a one-dimensional input series and the upper and lower bounds on the length of the cycle one wants to extract. In macroeconomics, these bounds typically are defined by the length of business cycle, i.e., between 1.5-8 years. In other fields, these might be different.

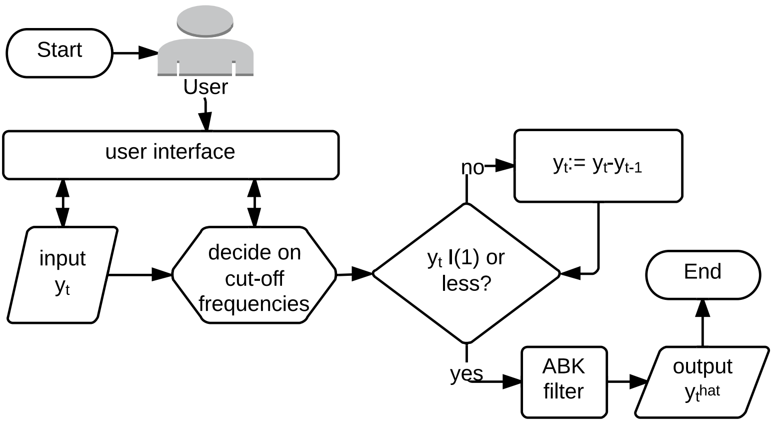


Fig. 2.4. A flowchart of the univariate asymmetric filter algorithm

The input series must be at most first-order integrated, otherwise differentiation is needed. Most seasonally adjusted macroeconomic series are up to I(1), so, typically, no data transformation is required.

The next section describes results from monte carlo simulation to assess the performance of the proposed filter.

2.1.2 Comparing filter performance by monte carlo simulation

This subsection assesses the performance of the proposed filter to extract business cycle frequencies (corresponding to wave length between 1.5 and 8 years) in comparison to the asymmetric Christiano-Fitzgerald (CF) filter which is optimized for an input signal following a random walk (RW) process (Christiano and Fitzgerald, 2003).

Consider the following data generating process (DGP):

$$y_t = \mu_t + c_t, \tag{2.9}$$

where

$$\mu_t = \mu_{t-1} + \epsilon_t \tag{2.10}$$

$$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + \eta_t \tag{2.11}$$

$$\epsilon_t \sim nid(0, \sigma_\epsilon^2),\ \eta_t \sim nid(0, \sigma_\eta^2). \tag{2.12}$$

Equation (2.9) defines a series, y_t, as the sum of a permanent component (stochastic trend), μ_t, and a cyclical component, c_t. The trend, μ_t, in this case is specified as a random walk process. The dynamics of the cyclical component, c_t, is specified as a second order autoregressive (AR(2)) process so that the peak of the spectrum of c_t could be at zero frequency or at business cycle frequencies. Disturbances, ϵ_t and η_t, are assumed to be uncorrelated.

Data are generated from (2.9) with $\phi_1 = 1.2$ and different values for ϕ_2 to control the location of the peak in the spectrum of the cyclical component. I also vary the ratio of standard deviations of the disturbances, $\sigma_\epsilon/\sigma_\eta$, to change the relative importance of components of y_t. Such DGP can create series with spectral characteristics typical to macroeconomic variables, such as gross domestic product and inflation (Watson, 1986; Guay and St-Amant, 2005).

Particularly, 10,000 samples of length 401 are created, with the first 200 observations of each sample dropped off as burn-in. The vector $[\phi_1, \phi_2]$ is set to five different values, as shown in Table 2.1.

Table 2.1.

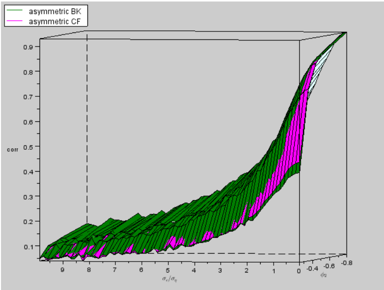
Five different values of $[\phi_1, \phi_2]$ for the DGP

ϕ_1	ϕ_2	Fundamental period of the cycle (yrs)
1.2	-0.25	$\approx \infty$
1.2	-0.35	$\gg 8$
1.2	-0.44	8.2
1.2	-0.5	3.5
1.2	-0.8	1.9

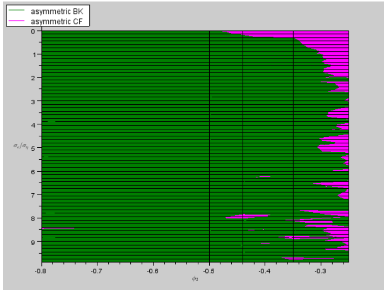
The value of $\sigma_\epsilon/\sigma_\eta$ is set to change from 0 to 9.9 with step size 0.15 (Watson (1986) estimated this ratio for the U.S. GNP to be 0.75).

The performance of filters is assessed by comparing the estimated correlation of the true cyclical component at time t with the estimated cyclical component at time t, $\hat{\rho}(c_t, \hat{c}_t)$.

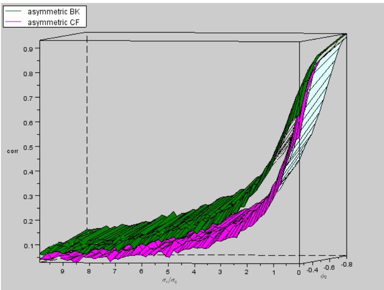
Now, let us compare the performance of the asymmetric filters at the end of the sample, where the fixed-length symmetric filters can not be applied. Fig. 2.5 shows the estimated correlation of the true and estimated cycles at observation 12, 6 and 1 from the end of the sample, calculated across the 10,000 replications, and averaged over both symmetric ends.



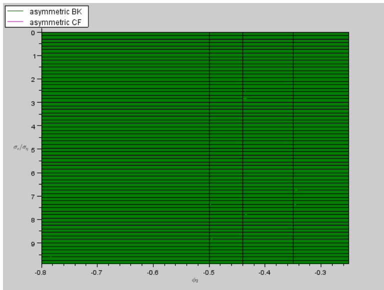
(a) Correlation at obs. 12



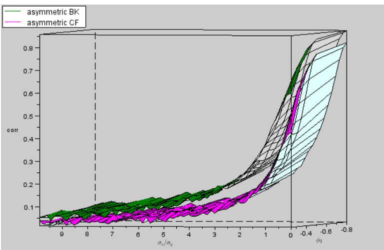
(b) view at 2.5(a) from the top



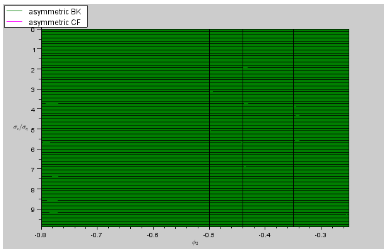
(c) Correlation at obs. 6



(d) view at 2.5(c) from the top



(e) Correlation at obs. 1



(f) view at 2.5(e) from the top

Fig. 2.5. Estimated correlation of the true and extracted cycles at time t, $\hat{\rho}(c_t, \hat{c}_t)$, by asymmetric BK and CF filters at observations number 12, 6 and 1, counting from the end of the series

Fig. 2.5 shows the filters give close result at points closer to the center of the sample. Indeed, at the center of the sample, where the asymmetric filters become symmetric, the correlation graph looks similar to Fig. 2.5(a), thus not shown here. As the estimation point approaches the end of the sample, filters become more asymmetric, and the difference in their performance becomes more obvious. Thus, the asymmetric filters perform roughly equally well at points that are at least about 3 years (for quarterly data) away from the end of the sample. Otherwise, the asymmetric BK filter becomes increasingly superior to the asymmetric CF filter for any cycle length and for any share of permanent component in the input signal considered in the simulation.

Specifically, and as a summary, for `typical' macroeconomic series ($\sigma_\epsilon/\sigma_\eta = 3/4$, cycle length: 3.5 years), the ratio of correlations given by the ABK and CF filters is shown in Fig. 2.6, where the horizontal axis represents the point of signal extraction and T denotes the sample length.

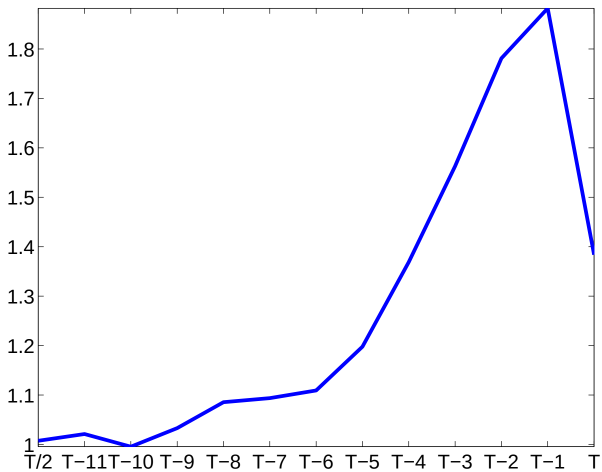


Fig. 2.6. The ratio of correlations given by the ABK and CF filters for `typical' macroeconomic series ($\sigma_\epsilon/\sigma_\eta = 3/4$, cycle length: 3.5 years)

It shows that in the middle of the sample, $T/2$, both ABK and CF filters perform equally, i.e., the ratio of correlations is about unity. However, when the point of extraction moves to the end of the series, the ABK filter's relative performance increases, culminating at one observation from the end, where its performance (in terms of correlation with the target signal) is almost twice as high as that extracted by the CF filter. The relative performance decreases at the end-point of the sample to about 40% gain. (That decrease in the relative gain can be explained by the different mechanisms of making the filters extract nothing from the trend frequency - while all the coefficients of the ABK filter are adjusted by the same amount, the adjustment of the CF filter affects only the end-points of the filter.) The 40% gain at the end-point is still huge. Moreover, the ABK filter's performance is smooth over the point of extraction, and the relative decrease of the performance at the end-point is due to the (rather huge) increase of the performance in the CF filter at the end-point. In practice, it is important that a method's performance is smooth over the point of extraction in order to avoid breaks in the extracted output; this is one more reason to prefer the ABK over the CF filter.

2.2 Multivariate filter for high-dimensional and noisy datasets

Nowadays, data are abundant. Therefore, methods are demanded that are capable of effectively using potentially high-dimensional datasets. This section develops a method for signal estimation and forecasting using high-dimensional and noisy datasets. It is shown that the regularized filter is able to process high-dimensional data sets by controlling for effective degrees of freedom and that it is computationally fast. The section illustrates the features of the filter by tracking the medium-to-long-run component in GDP growth for euro area, including the replication of an established indicator's behavior, as well as producing more timely indicators. The regularized direct filter approach is found to be a promising tool for both concurrent estimation and forecasting using high-dimensional datasets, and a decent alternative to dynamic factor methodology.

2.2.1 Filtration methodology

This section is concerned with estimating a signal - a trendcycle or a business cycle - in real time. Denote y_T as the output of a symmetric, possibly bi-infinite filter, $\sum_{j=-\infty}^{\infty} \gamma_j L^j$, applied on input series x_T:

$$\begin{aligned} y_T &= \sum_{j=-\infty}^{\infty} \gamma_j L^j x_T \\ &= \sum_{j=-\infty}^{\infty} \gamma_j x_{T-j}, \end{aligned} \tag{2.13}$$

where L is called the lag operator. The filter in (2.13) is called the ideal filter and the filter output, y_T, is called the ideal filter output. Time series are finite in practice, therefore, the ideal filter is infeasible. A real-time estimate of y_T, given a finite input $\{x_1, \ldots, x_T\}$, can be written as

$$\hat{y}_T = \sum_{j=0}^{T-1} b_j x_{T-j}. \tag{2.14}$$

Denote the generally complex transfer functions of filters in (2.13) and (2.14) by $\Gamma(\omega) = \sum_{j=-\infty}^{\infty} \gamma_j \exp(-ij\omega)$ and $\hat{\Gamma}(\omega) = \sum_{j=0}^{T-1} b_j \exp(-ij\omega)$, respectively. A generally complex number, $\Gamma(\omega)$, can be represented in polar coordinates as $\Gamma(\omega) = A(\omega)\exp(-i\Phi(\omega))$, where $A(\omega) = |\Gamma(\omega)|$ is called the amplitude, and $\Phi(\omega) = -\arg(\Gamma(\omega))$ is called the phase. For a stationary process x_T, the mean squared filter error (MSFE) can be expressed as the mean squared difference between the ideal output and the real-time estimate:

$$\int_{-\pi}^{\pi} |\Gamma(\omega) - \hat{\Gamma}(\omega)|^2 dH(\omega) = E[(y_T - \hat{y}_T)^2], \tag{2.15}$$

where $H(\omega)$ is the unknown spectral distribution of x_T. A finite sample approximation of the MSFE, (2.15), is

$$\frac{2\pi}{T} \sum_{k=-[T/2]}^{[T/2]} w_k |\Gamma(\omega_k) - \hat{\Gamma}(\omega_k)|^2 S(\omega_k), \tag{2.16}$$

where $\omega_k = k2\pi/T$, $[T/2]$ is the greatest integer smaller or equal to $T/2$, and the weight w_k is defined as

$$w_k = \begin{cases} 1 & \text{for } |k| \neq T/2 \\ 1/2 & \text{otherwise.} \end{cases} \tag{2.17}$$

This section uses a `sufficient statistic' - periodogram, $I_{Tx}(\omega_k)$ - as $S(\omega_k)$ in (2.16):

$$S(\omega_k) := I_{Tx}(\omega_k) = \frac{1}{2\pi T} \left| \sum_{t=1}^{T} x_t \exp(-it\omega_k) \right|^2. \tag{2.18}$$

Minimizing expression (2.16) yields the real-time filter output optimally approximated to the ideal output in mean squared error sense.

The above univariate customized filter has been generalized to a multivariate filter in Wildi (2011). However, the unregularized multivariate direct filter contains many parameters whose number increases with filter's dimension. Thus, the filter in Wildi (2011) cannot be too long or cannot contain tens of variables due to the limited sample size, otherwise the filter would be overparameterized and the filter output would be of poor quality in out of sample. Wildi (2012) introduces three shrinkage parameters in a multivariate direct filter appraoch (Wildi, 2011) and that control for cross-sectional shrinkage, shrinkage along time dimension, and that impose smoothness of filter coefficients.

Recalling that Tikhonov regularization problem (e.g. Tikhonov and Arsenin, 1977) can be cast in the form $(Y-Xb)'(Y-Xb)+\lambda b'b \to \min_b$, the regularized direct filter approach problem introduced in Wildi (2012) is of the familiar form:

$$(Y-Xb)'(Y-Xb)+\lambda_s b'Q_s b+\lambda_c b'Q_c b+\lambda_d b'Q_d b \to \min_b, \qquad (2.19)$$

where Y and X are complex-valued information about the target and the explanatory variables, respectively, and the three additional expressions of bilinear form represent three different regularization directions - coefficient smoothness (subscript `s'), cross-sectional shrinkage (subsript `c'), and shrinkage along time dimension (subscript `d').

2.2.2 High-dimensional filtering

This section studies how to apply the regularization features of the multivariate filter in order to use it for possibly high-dimensional data sets. (Wildi (2012) does not consider high-dimensional filtration, i.e., the application of the filter on tens of variables).

The findings in the thesis suggest that the longitudinal shrinkage might be the most useful of the three regularization features. Moreover, this section will use only the longitudinal and the cross-sectional shrinkages from the considered regularization `troika'.

Fig. 2.7 shows a flowchart for using the regularized filter with many variables. First, the user selects the target variable and its any additional explanatory variables (if they exist), Next, one should decide on the target amplitude and the targeted lag or lead of the signal. Also, the user decides on the training sample length. The explanatory and the target variable should be cointegrated, otherwise all data should be stationarized. Then follows the most important part of deciding on the metric to be used as a measure of goodness-of-fit. Since the output of the ideal filter is unobserved, one cannot use a metric that uses the output of the ideal filter (i.e., a metric such as the mean squared error or the mean absolute error). Rather, one can use the correlation between the target variable and the output of the one-sided filter at the pre-specified targeted lead or lag when the target amplitude is trendcycle. Thus, the algorithm follows by running the filter and incrementally increasing the longitudinal shrinkage parameter (`ld' in the diagram) until the maximum correlation between the target variable and the

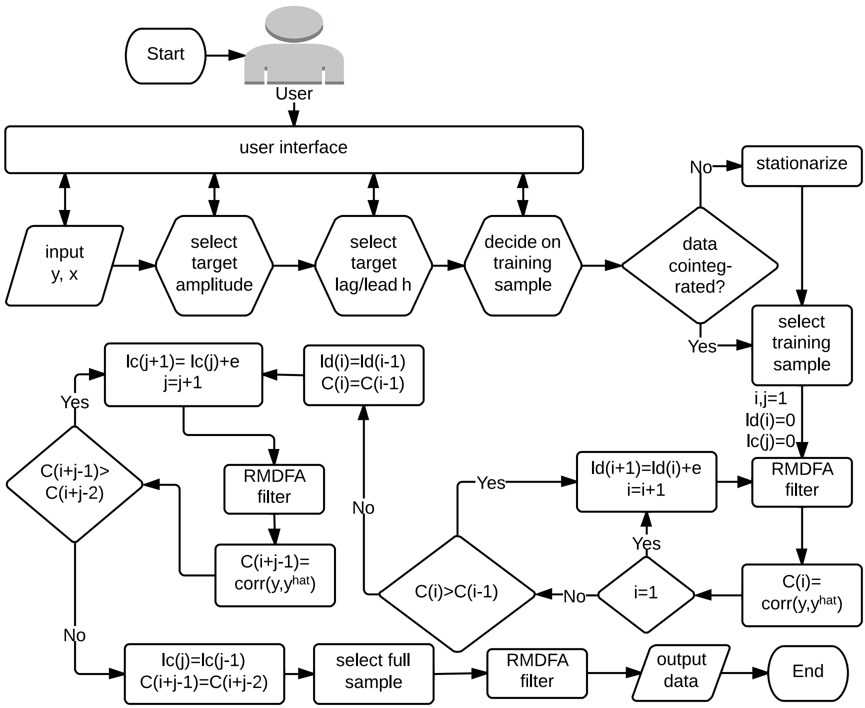


Fig. 2.7. A flowchart of the high-dimensional regularized filter algorithm

filter output at the prespecified lead or lag has been reached. Then, the algorithm selects the longitudinal shrinkage parameter that maximizes the correlation and then moves on to incrementally increasing the cross-sectional shrinkage parameter (`lc' in the diagram) to find the one that maximizes the chosen distance measure at the prespecified target lead or lag. Once the optimal shrinkage parameters have been found, the algorithm moves on by selecting the full sample and gives the output.

Such an algorithm is applied on all 72 variables to track trendcycle in quarterly growth of the GDP of the euro area. The resulting real-time filter output is plotted in Fig. 2.8 along with Eurocoin which is the output of the alternative (generalized principal components) methodology (Altissimo et al. 2010).

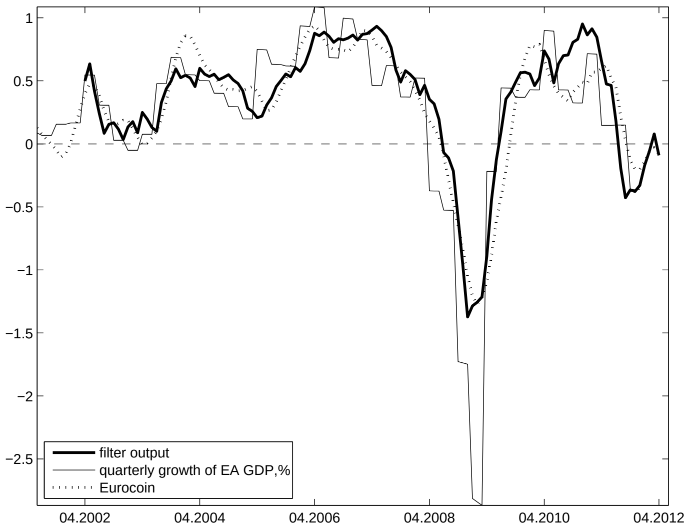


Fig. 2.8. Filter output versus Eurocoin

Fig. 2.8 shows that the filter output tracks the level of the target well. The peak correlation (0.882) of Eurocoin with GDP is located at a two months lag w.r.t. GDP, and the second highest correlation (0.879) being located at a one month lag w.r.t. GDP. For the filter output in Fig. 2.8, the peak correlation (0.883) is located at a one month lag w.r.t. GDP, with the second highest correlation (0.870) being at a zero month lag w.r.t. GDP. Thus, the proposed methodology yields an indicator that is on average about one month more timely than the best alternative.

2.2.3 True real-time out-of-sample performance

The indicator tracking the trendcycle of quarterly growth of the euro area GDP has been tested and used at Bank of Latvia by producing its outputs each month since it has been developed at around April, 2012. Since it is May, 2013 when this text is written, it means there is a 13-month long sample of true real-time out-of-sample performance of this indicator. Its output, together with the realized final GDP and the alternative indicator - Eurocoin (produced by Banca d'Italia) are plotted in Fig. 2.9.

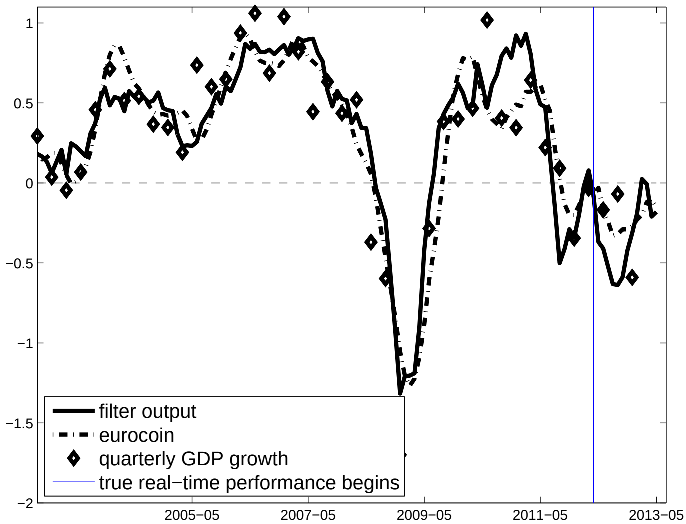


Fig. 2.9. True 13-month long real-time out-of-sample performance of the euro area GDP indicator versus Eurocoin from April, 2012 till May, 2013

Fig. 2.9 shows that the filter's true real-time performance does not seemingly deteriorate compared to the `training' period. Particularly, it does not get more volatile and captures the decline of the GDP growth well and in advance, and does not lose to Eurocoin with respect to timeliness.

This true real-time performance of the filter output reassures that the high-dimensional filtration methodology proposed in this section is well suited for practical application.

2.3 Robustness check of traditional forecasting methods and system overview

2.3.1 Bayesian Minnessota prior

Bayesian inference requires an analyst to set a prior. Setting the right prior is crucial for precise forecasts. This subsection analyzes how optimal Litterman prior changes when there is a sudden change in dynamics of the target variable. By an 'optimal Litterman prior' in this section we define Litterman hyperparameters that minimize the root mean squared error from one-period ahead forecasts. For this task, an autoregressive distributed lag model (ARDL) is chosen. The prior is set up like in Litterman (1979). The model is solved by `mixed estimation' set forth in Theil and Goldberger (1961). Latvia's gross domestic product (GDP) was found to be well suited for the analysis. The results show that a sharp economic slowdown changes the structure of the optimal weight prior by setting smaller weight on the lagged dependent variable compared to variables containing more recent information. Thus, Bayesian Minnessota prior is not robust against rapid change in the dynamics of the target variable.

Bayesian ARDL model

Consider an autoregressive distributed lag model (ARDL) of order (p, q):

$$y_t = \sum_{m=1}^{p} \beta_m y_{t-m} + \sum_{n=0}^{q} \gamma_n' x_{t-n} + \epsilon_t \tag{2.20}$$

where y_t is the dependent variable, x_t is a $d \times 1$ vector of key explanatory variables $x = [x_1\ x_2\ \ldots\ x_d]$, and $\epsilon_t \sim N(0, \sigma^2)$. The Bayesian prior is set to

$$\begin{aligned} \beta_m &\sim N(\mathbb{1}_{\{1\}}(m), \sigma_m^2) \\ \gamma_{in} &\sim N(0, \sigma_{in}^2) \end{aligned} \tag{2.21}$$

where $\mathbb{1}_{\{\}}()$ is an indicator function, $m = 1, 2, \ldots, p$, $i = 1, 2, \ldots, d$, and $n = 0, 1, \ldots, q$. The specification of the standard deviation of the prior is *à la* Doan, Litterman and Sims (1984):

$$\begin{aligned} \sigma_m &= \theta k m^{-\phi} \\ \sigma_{in} &= \theta l (1+n)^{-\phi} \left(\frac{\hat{\sigma}_{u,i}}{\hat{\sigma}_{u,y}} \right) \end{aligned} \tag{2.22}$$

where $\hat{\sigma}_{u,y}$ and $\hat{\sigma}_{u,i}$ are the standard errors from a univariate autoregression involving y and x_i, respectively, so that $\hat{\sigma}_{u,i}/\hat{\sigma}_{u,y}$ is a scaling factor that adjusts for varying magnitudes of the involved variables. The parameter θ is referred as the overall tightness. The terms $m^{-\phi}$ and $(1+n)^{-\phi}$ are referred as lag decay functions for y and x_i, respectively, with $\phi \geq 0$ reflecting a shrinkage of the standard deviation with increasing lag length. The parameters k and l specify the relative tightness of the prior for variables y and x_i, respectively. Note that, for simplicity, we set l the same for all x_i.

The model (2.20) to (2.22) is estimated using the `mixed estimation' method set forth in Theil and Goldberger (1961).

Results

The dependent variable of the model (2.20) is Latvia's quarterly GDP series from $1995Q1$ till $2009Q1$. The additional explanatory variable x is the sum of outputs in manufacturing industry and in electricity, gas and water supply industry.

Both the GDP and the explanatory variables are chain-priced as of year 2000 and twice regularly and once seasonally differenced. The second regular difference is performed for better forecasting performance during the latter part of the GDP series due to a sharp economic downturn (see Buss (2009) for a discussion). The sample is split in halves because the first half contains a smooth growth whereas the second half contains rapid economic downturn (see the GDP series in Fig. 2.10).

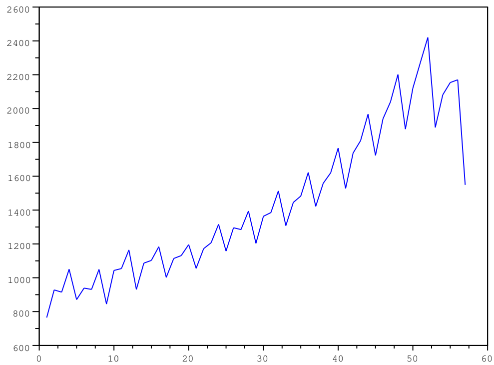
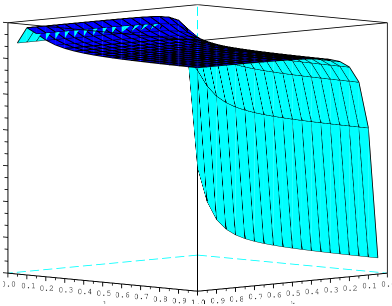


Fig. 2.10. Latvia's seasonally unadjusted GDP series

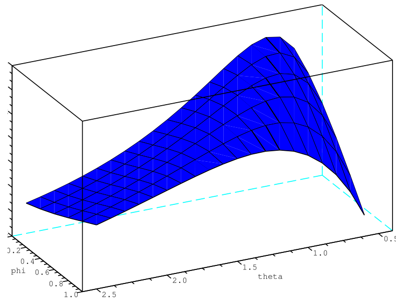
Note: Series spans from 1995Q1 till 2009Q1. Horizontal axis represents time.

In the thesis, it has been found that Bayesian ARDL (BARDL) models compare well with frequentist ARDL (FARDL). It has also been found that the BARDL models give precise one-period ahead forecasts for the whole sample, but they are outperformed by FARDL for the second half of the series. This observation suggests that the optimal Bayesian prior might be different for the first half of the model (smooth positive growth) compared to the second half of the sample when there is a rapid economic downturn. We check this hypothesis further by employing grid search for the optimal prior.

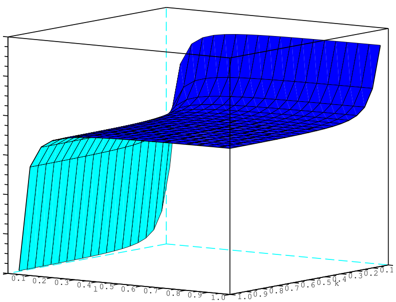
Consider the grid search performed for BARDL(2,1). The weight vector $[k\ l]$ is 2-dimensional, one element, k, for the dependent variable and one,



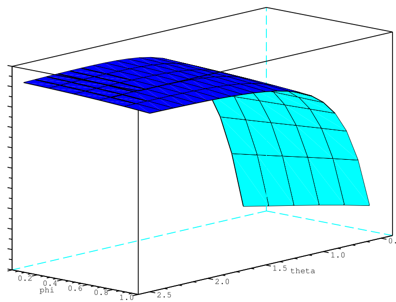
(a) Full sample. Optimal $k = .95$ and optimal $l = .1$.



(b) Full sample. Optimal $\theta = .9$ and optimal $\phi = 0$.



(c) Second half of the sample. Optimal $k = .05$ and optimal $l = 1$.



(d) Second half of the sample. Optimal $\theta = 2$ and optimal $\phi = 0$.

Fig. 2.11. Results from grid search for optimal prior for BARDL(2,1)

l, for a single explanatory variable x, both ranging from .05 to 1 with step size .05. The overall tightness, θ, is set to range from .6 to 2.5 with step .1, and the lag decay, ϕ, from 0 to 1 with step .2. So, the grid size is $20 \times 20 \times 20 \times 6$ containing overall 48000 prior combinations for each one-period ahead forecast with sample size ranging from 17 to 51.

Fig. 2.11(a) and 2.11(b) show the inverse of the RMSE as a function of the prior for the whole sample, whereas Fig. 2.11(c) and 2.11(d) - for the second half of the sample. For each figure, the horizontal plane is formed by two hyperparameter vectors, keeping the rest of the hyperparameter values at the RMSE-minimizing values.

It can be seen that the optimal prior weight is very different compared to the full sample - the two lower graphs look almost like inverses of the respective upper graphs. Thus the Bayesian Minnessota prior is not robust against a rapid change in the dynamics of the target variable.

2.3.2 Factor methods

Factor methods are popular data dimension-reduction techniques. There are several types of factor methods, mainly, statically and dynamically computed factors. Although there are many papers studying the factor methodology, none studies their robustness against rapid change in the dynamics of the target variable. This subsection tries to fill the gap by studying the robustness of the static versus dynamic factor models under a rapid change in the dynamics of the target variable. The results show that static factors are more robust than their dynamic counterparts.

Static and dynamic factor models

Consider an $(n+1)$-dimensional vector autoregressive model of order r, VAR(r). If n is large, VAR(r) incurs in a curse-of-dimensionality problem. A cure for this problem is to use a relatively small number of factors that are weighted averages of the predictors. We will consider two types of factor extractions - static and exact dynamic. Static factors are obtained *à la* Stock and Watson (1998) as follows. It is assumed that x_t can be represented as

$$x_t = \Lambda F_t + e_t, \tag{2.23}$$

where F_t is a $k \times 1$ vector of common factors at time t, Λ is an $n \times k$ matrix of factor loadings, and e_t is an $n \times 1$ vector of white noise processes at time t. It is assumed that

$$E(y_{t+1}|F_t, x_t, y_t, F_{t-1}, x_{t-1}, y_{t-1}, \ldots) = E(y_{t+1}|F_t, y_t, F_{t-1}, y_{t-1}, \ldots). \tag{2.24}$$

The assumption in (2.24) permits the dimension reduction of the matrix of explanatory variables from n to k. F_t is obtained by principal components analysis, i.e., by selecting k eigenvectors ν_j, $j = 1, 2, \ldots, k$ (that are of unit length) of $x'x$, where $x = (x_1, \ldots, x_T)'$, associated with the largest k eigenvalues of $x'x$ and projecting x on the eigenvectors, $F_j = x\nu_j$, $j = 1, 2, \ldots, k$; F_t then is the tth column of $(F_1, \ldots, F_k)'$.

The dynamic factor model is estimated as in Doz and Lenglart (1999). It is estimated by the maximum likelihood (ML) method under a Gaussian hypothesis. A dynamic factor model with the common factors following an ARMA(p, q) process and the idiosyncratic components following an AR(l) process can be written as

$$\begin{aligned} x_{it} &= m_i + \lambda_{i1} F_{1t} + \ldots + \lambda_{ik} F_{kt} + u_{it} \\ (1 - \phi_{j1} L - \ldots - \phi_{jp} L^p) F_{jt} &= (1 - \theta_{j1} L - \ldots - \theta_{jq} L^q) \epsilon_{jt} \\ (1 - \rho_{i1} L - \ldots - \rho_{il} L^l) u_{it} &= \xi_{it} \end{aligned} \tag{2.25}$$

for $i = 1, \ldots, n$, $j = 1, \ldots, k$ and for all t, where ϵ_{jt} and ξ_{it} are the innovations of F_t and u_{it} at time t, l is the order of the AR process governing u_{it}, and the processes (ϵ_{jt}) and (ξ_{it}) are mutually independent. Model (2.25) is estimated by the ML using the Kalman filter (Kalman, 1960).

Results

The dependent variable in the model (2.23) is Latvia's quarterly GDP series from $1995Q1$ till $2009Q3$. The explanatory variables considered are i) an aggregate output in mining and quarrying, manufacturing, electricity, gas and water supply, and construction industries (cp), ii) imports, iii) exports, iv) a ratio of exports over imports (nx), and v) money supply M1 (m). All series are quarterly, expressed in logs, and once regularly and once seasonally differenced, except m, that is not seasonally differenced.

We produce one-period ahead forecasts for GDP, given that all explanatory variables are known for the forecasting horizon (we call this exercise `nowcasting').

The GDP series is divided in halves, the first half contains smooth growth, whereas the second half contains a pronounced switch of business cycle phases from growth to a deep recession.

Table 2.2 shows a summary of mean and minimum RMSFE of static and dynamic factors for the between-phases sample. Clearly, static factors have been found to be on average by 20 per cent more precise, in terms of RMSFE, than dynamic factors. Also, the table shows the mean RMSFE for the best performing static and dynamic factor over five different data sets; again, the static factor shows more robustness in terms of forecasting precision than a particular best-performing dynamic factor specification.

Table 2.2.
A summary of factor model comparisons between phases

Factor	Mean RMSFE	Min RMSFE
static	100	84
dynamic	120	82
best static	86	-
best dynamic	109	-

Note: Numbers are normalized such that mean RMSFE of static factor is 100.

Plotting stationary GDP, static first common factor, and dynamic first common factor formed from the variable set $\{cp,nx,m\}$, where dynamic factors are generated by various ARMA specifications, starting from ARMA(0,1) and ending at ARMA(2,2) (to save space, Fig. 2.12 shows only the results for the ARMA(1,1) case), it has been found that the dynamic common factor, regardless of dynamics specification, hardly detects the recession period and never its depth. On the the other hand, the static first common factor is able to detect the recession and its depth and, thus, static factor methodology is considered to be more robust against rapid change in the dynamics of the target variable.

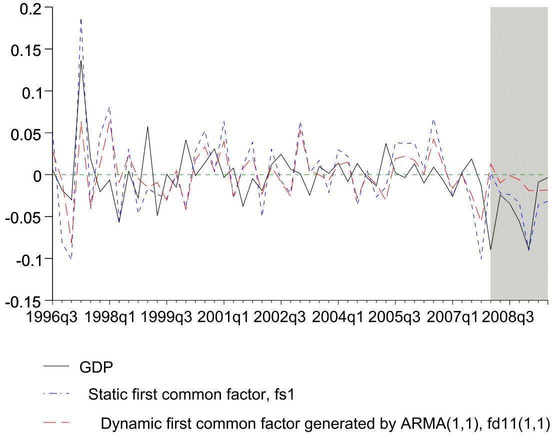


Fig. 2.12. Static versus dynamic factor following ARMA(1,1)

2.3.3 Overview of the forecasting system

As a summary, Fig. 2.13 shows a chart of the main forecasting methods considered in this thesis. The signal-targeting methods in blue are developed, while the all-pass forecasting methods in green are studied for their robustness.

For one-dimensional data, if all frequencies are forecasted then ARIMA is a good benchmark. If business cycle frequencies are estimated then this thesis suggests the ABK filter. If, in addition to the dependent variable, there are some $n < 10$ additional explanatory variables, and if all frequencies are forecasted, then Bayesian methods perform decently, although, they are not robust against rapid changes in economic environment.

In practice, however, there are often many potential explanatory variables available. For example, Bank of Latvia collects more than 200 variables just for short-term forecasting of GDP alone. Therefore, methods capable of using high-dimensional data are demanded. One of the most successful methods dealing with high-dimensional datasets is factor methodology. This thesis suggests that using static factors from principal component analysis yields more robust performance than using exact dynamic factors estimated by Kalman filter.

If, however, business/trend-cycle frequencies are of interest, this thesis proposes using high-dimensional RMDFA which is shown to compete well with the generalized principal components method and have some clear advantages over the latter in forecasting, effect decomposition, and potential performance in presence of many redundant variables.

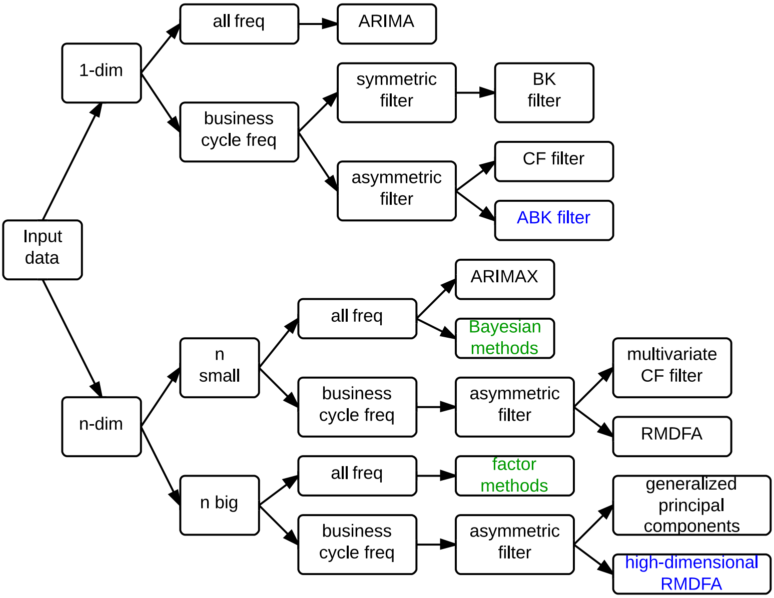


Fig. 2.13. A summary chart of the considered data and their forecasting methods in the thesis

Fig. 2.14 shows a short-term economic forecasting system developed at Bank of Latvia that uses the methods developed in this thesis.

The system involves technical stuff (system maintainer, model developer and filter developer), economists with their domain expert, and decision makers. The system maintainer is responsible for maintaining the forecasting system's technical part, which involves data collection from various in-house and world wide web sources, and storing that information in an orderly manner in the local database. The system maintainer is also responsible to run the software of allpass models (developed by a model developer) and business cycle or trendcycle filters (developed by filter developer), collect their results and produce local reports to economists on a regular basis (particularly, twice a month).

On the economists' side, there is a domain expert who produces his expert judgment on what happens and what will happen in the economy. There is a mutual information flow between the expert judgment and the results produced by the technical stuff - 1) expert judgment is influenced by the local reports produced by the technical stuff, and 2) the expert judgment enters as one of the `models' in the allpass models block in order to improve i) communication, and possibly also ii) forecasting performance.

The domain expert, together with his fellow economists, partly based on the local reports produced by the technical stuff, then produce a global report to the decision makers.

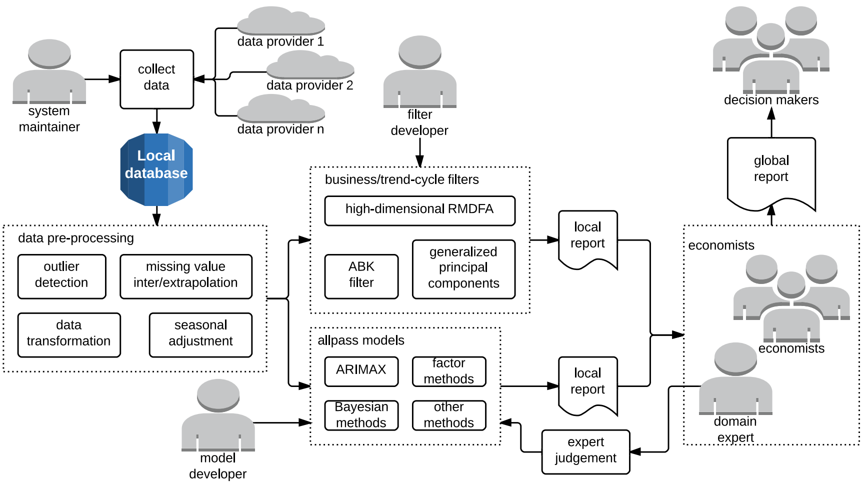


Fig. 2.14. A flowchart of the short-term economic forecasting system at Bank of Latvia using the methods considered in the thesis

3 RESULTS AND CONCLUSIONS

The main objective of the thesis is to develop robust forecasting methods that are able to work with high-dimensional and noisy data, with application to macroeconomics. In order to fulfil the objective of the thesis, the following tasks have been proposed: 1) develop a univariate asymmetric bandpass filter for end-point estimation problems, 2) compare the performance of the developed asymmetric filter to the currently most popular alternative in macroeconomics, 3) develop a method suitable for forecasting and signal extraction using high-dimensional and noisy data, 4) assess the properties of the above method and compare with the currently best alternative in macroeconomics and 5) investigate the robustness issues for Bayesian and factor forecasting models.

The main objective of the thesis has been achieved; the proposed tasks have been accomplished:

1. An asymmetric filter has been developed for frequency band extraction at the end-points of univariate series.
2. The developed filter's performance has been compared to the currently most popular alternative in macroeconomics - the Christiano-Fitzgerald filter - in monte carlo simulations.
3. A method has been developed for signal extraction and forecasting using high-dimensional and noisy datasets.
4. The properties of the developed high-dimensional filter have been assessed and compared to the factor methodology.
5. Robustness issues of Bayesian and factor methods have been studied when the dynamics of the target variable is subject to a rapid change.
6. The forecasting system module of Bank of Latvia has been developed.

Main conclusions:

1. The developed asymmetric band pass filter outperforms the Christiano-Fitzgerald filter within two years from the end-point.
2. The developed high-dimensional filter is better suited for signal forecasting, effect decomposition and for dealing with irrelevant explanatory variables than the factor methodology.
3. The Bayesian Minnessota prior is not robust against rapid change in the dynamics of the target variable, thus making the forecasts imprecise if the prior is unchanged.
4. Static factor models are more robust than the dynamic factor models against unexpected change in dynamics of the data, and thus are to be preferred.

Main theses of defense:

1. The developed high-dimensional filtration algorithm allows for signal extraction and forecasting using high-dimensional and noisy datasets.
2. The developed univariate asymmetric filter is more precise than the Christiano-Fitzgerald filter for business-cycle frequency extraction at the end-points of univariate macroeconomic series.
3. The traditional methods for forecasting with many time series - Bayesian Minnessota prior and exact dynamic factors - are subject to robustness issues when the dynamics of the target are subject to rapid change.

The approbation of the thesis has been achieved by presenting the results at 11 international scientific conferences and seminars, by publishing 11 articles in international scientific journals or conference proceedings, by implementing the methods at the Central statistical bureau of Latvia for producing the flash release of Latvia's GDP since year 2009. The developed methods are used for forecasting purposes at Bank of Latvia since 2011.

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