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DISSECTING THE FINANCIAL CYCLE WITH DYNAMIC FACTOR MODELS

August 18, 2017

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ABSTRACT

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Abstract

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Keywords: Financial cycle, dynamic factor model, Granger causality, recession forecasting, dynamic probit models, early warning systems.

JEL Classification System: C35, C38, C52, C53, E32, E47

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1 Introduction

A major lesson of the 2007-08 global financial crisis was the remainder that financial markets act not only as amplifiers of developments taking place on the real side of the economy, but that they are also influenced to a significant extent by self-reinforcing interactions between the subjective perceptions and attitudes towards risk and financial constraints by market participants (Drehmann et al., 2012; Borio, 2014). As a result, the study of the so-called financial cycle and its interaction with the macroeconomy has become a major topic for many academic researchers, central banks and other policy-oriented institutions.

However, despite of the large amount of studies that have emerged in recent times, there is no general consensus on the definition of the financial cycle yet Borio (2014). Early works which investigate the interactions between the macroeconomy and financial markets go back to Bernanke et al. (1999) and Kiyotaki and Moore (1997) that highlight the financial accelerator mechanisms of credit and asset prices on macroeconomic dynamics over the business cycle. Domanski and Ng (2011) proposed a rather abstract definition of the financial cycle that can be characterized by the underlying ebbing and flowing of general risk sentiment that is embodied in the positive correlation of many systemic risk indicators (Domanski and Ng, 2011). A similar definition by Ng (2011) refers to the financial cycle as *"[...] fluctuations in perceptions and attitudes about financial risk over time [...]"* (Ng, 2011, p.53), that is often characterized by swings in credit growth, asset prices, liquidity, financing constraints and other financial indicators. Borio (2014) denote the financial cycle as a self-reinforcing mechanism working through market participants' perceptions of risk and financing constraints leading to a recurrence of booms and busts. Rey (2013) argues that the global financial cycle comoves with the VIX index which resembles aggregate market risk perceptions and uncertainty. Given the abstract nature of these definitions various approaches to measuring and analyzing the properties of the financial cycle emerged under the ongoing debate.

So far, the great majority of studies has focused on the cyclical properties of a small number of aggregate financial indicators meant to summarize the dynamics of the financial cycle. Claessens et al. (2011, 2012) use a turning-point approach to analyze the cyclical properties of credit, house and equity prices and find that while cyclical upward trends are often long and slow, downturns often feature harsh declines. Further, their results suggest that an economic recession tends to be longer and deeper if it occurs simultaneously to a disruption in the financial cycle. Drehmann et al. (2012) use the band-pass filter by Christiano and Fitzgerald (2003) to isolate short- and medium-term cycles from a sample of six variables. They find that the financial cycle can be adequately described by credit and property prices with average cycle lengths of 16-20 years, which is considerably longer than the business cycle. Similarly, Borio (2014) use credit and property prices to show that financial crises occur at, or close to, peaks in the financial cycle. Strohsal et al. (2015) estimate ARMA-models to a set of indicators and analyze their theoretical spectra to show that the financial cycle has become longer and more pronounced over time. Schüler et al. (2015) apply a multivariate spectral measure of power cohesion and find that credit, housing and equity prices exhibit common cyclical frequencies of 7.2 years on average.

However, as the aforementioned works all use aggregate indicators chosen in an ad hoc manner it cannot be taken for granted that they may always be representative for the dynamics of the financial cycle. Thus, another strand of this recent literature seeks to condense information from large sets of variables in order to gain insights into the (not directly observable) financial cycle fluctuations. For instance, English et al. (2005) conduct a principal components analysis following the approach of Stock and Watson (2002) and try to extract information from a large data set for the US, Germany, and the UK. These authors test if the principal components of various financial indicators perform better at forecasting output, inflation, and investment than an alternative model that uses only interest rates and spreads. In almost all cases, the inclusion of financial components is significant at ordinary levels indicating that the components seem to provide substantial information. Hatzius et al. (2010) follow a similar approach and construct a financial conditions index that summarizes the information of a large set of financial variables about the future state of the US economy. Their results suggest that condensing the information contained in a large number of variables seems to improve the forecasting power of financial indicators especially in times of financial stress. Further, Breitung and Eickmeier (2014) construct a multi-level factor model and propose two simple estimation procedures for a two-factor model based on sequential least squares (LS) and canonical correlations. Extending the LS approach to a three-level factor model, with regional, global and variable specific factors they can show that regional factors became more important over time, whereas global factors became less important. Furthermore, their results suggest that financial variables exhibit a large degree of co-movement on an international level and both, financial and macroeconomic dynamics, share common factors highlighting the high degree of interdependence of the real and financial sector.

Along this line of research, this paper aims to develop a parsimonious measure of the financial cycle based on a broad set of macro-financial indicators using the dynamic factor model approach originally introduced by Geweke (1977). As it is well known, the main assumption of this econometric methodology is that many variables may be driven by a small number of common driving forces that are, however, not directly observable. Previous related works mainly rely on principal components analysis by constructing linear combinations of a set of variables which implies that the observed variables contribute to the components. Instead, in our work we favor the dynamic factor model that aims to model latent factors that cannot be measured directly with a single variable but cause the responses on observed data, thereby taking a fundamentally different approach than previous works. As the concept of the financial cycle implies the existence of general risk perceptions and attitudes that are behind the dynamics of many financial variables, this econometric methodology seems to be the most appropriate choice for its statistical characterization. Moreover, as the concept of the financial cycle embodies thus both macroeconomic fundamentals-driven fluctuations in perceptions and attitudes towards financial risk, as well as moods and fads resulting from the speculative and extrapolative nature of financial markets, we aim to characterize the financial cycle along these dimensions and analyze the predictive power of these isolated financial cycle components to other economic variables such as GDP growth, inflation and short-term interest rates. Further, using a probit approach we assess the ability of the financial cycle factors to forecast recessions. To the best of our knowledge, there is no existing empirical application of dynamic factor models to characterize the financial cycle and explicitly analyze its interactions with the real economy and its forecasting power in a linear (by means of VAR-based Granger causality tests) and nonlinear (by means of a probit approach) dimension. Thus this paper contributes to the growing empirical literature that strives for a deeper understanding of the financial cycle by estimating synthetic factors that are meant to represent the financial cycle in a parsimonious and economically interpretable manner.

The remainder of the paper is organized as follows: In section 2 we describe the dynamic factor model estimation procedure and parameter restrictions that we used in our empirical analysis. Section 3 presents our empirical results including the Granger causality tests stemming from factor-augmented VAR models and the estimation of recession probabilities. Finally, the last section concludes and gives an outlook for future research.

2 Econometric Methodology

In the following, we pursue a dynamic factor model (DFM) approach as originally introduced by Geweke (1977) for our characterization of the financial cycle.[1] In state space formulation, a dynamic factor model can be written as:

$$\underset{(N\times 1)}{y_t} = \underset{(N\times p)}{Z}\underset{(p\times 1)}{x_t} + \underset{(N\times 1)}{\nu_t}, \tag{1}$$

$$\underset{(p\times 1)}{x_t} = \underset{(p\times p)}{\Phi}\underset{(p\times 1)}{x_{t-1}} + \underset{(p\times 1)}{\epsilon_t}. \tag{2}$$

where y_t is an $N \times 1$ vector of observations for $t = 1, ..., T$, that depends on the $p \times 1$ dynamic factors x_t by a $N \times p$ observation matrix Z. The observable data is generally assumed to be stationary with $p \ll N$. The dynamic factors x_t themselves are assumed to depend on their past $p \times 1$ values x_{t-1} for $t = 1, ..., T$, where Φ denotes the $p \times p$ coefficient matrix as in equation (2). Both, ϵ_t and ν_t are assumed to be independent and identically distributed zero-mean normal vectors with variance-covariance matrix R and W. The start value x_0 is assumed to have mean μ_0 and a $p \times p$ variance-covariance matrix Σ_0, that is

[1]Surveys on dynamic factor models can be found in Stock and Watson (2005, 2010), Bai and Ng (2002) and Bai and Wang (2012).

$$\underset{(p\times 1)}{\epsilon_t} \overset{i.i.d.}{\sim} MVN(0, \underset{(p\times p)}{W}), \tag{3}$$

$$\underset{(N\times 1)}{\nu_t} \overset{i.i.d.}{\sim} MVN(0, \underset{(N\times N)}{R}), \tag{4}$$

$$\underset{(p\times 1)}{x_0} \sim MVN(\mu_0, \underset{(p\times p)}{\Sigma_0}). \tag{5}$$

For the estimation of the hyperparameters $\Theta = \{Z, \Phi, W, R, \mu, x_0, \Sigma_0\}$ we apply the Expectation-Maximization algorithm (EM) developed by Dempster et al. (1977), which provides an iterative procedure for identifying the maximum likelihood estimates of Θ by including the Kalman Filter and Kalman Smoother in the computation of the conditional expected value. Under the given model assumptions this estimation method provides optimal estimates of the factors. In contrast to frequency domain methods, this procedure entails a direct estimation of the factors that can be used for forecasting in the following analysis. Further, we prefer this method over nonparametric estimation as we specifically aim to interpret the factor loadings and derive economic relationships.

As already discussed by Harvey (1989), the dynamic factor model given by equations (1) and (2) is not identified since for any non-singular $p \times p$ matrix F, the factor loadings matrix Z could be transformed in a way such that $Z^* = ZF^{-1}$, $\Phi^* = \Phi F^{-1}$ and $x_t^* = Fx_t$. In this case, the model could be written as

$$y_t = Z^* x_t^* + \nu_t, \tag{6}$$

$$x_t^* = \Phi^* x_{t-1}^* + \epsilon_t^*, \tag{7}$$

$$\epsilon_t^* = F\epsilon_t, \tag{8}$$

$$\mathrm{Var}(\epsilon_t^*) = FWF^{-1}, \tag{9}$$

which is equivalent to the model given in equation (1) and (2). Thus restrictions regarding the hyperparameters Θ are necessary in order to ensure identifiability. According to Harvey (1989), we use the following parameter restrictions:

- Φ is set to be diagonal.
- In Z the first $p-1$ rows, for $i > j$ the z-value in the j-th column and i-th row is set to zero.
- W is set to be the identity matrix (I_p).

Further restrictions on R are optional. In line with standard literature we found setting R to be diagonal with different variances on the main diagonal to deliver the most promising results. Alternatively, R might be set to be (i) diagonal with equal variances on the main diagonal, (ii) equal variances on the main diagonal and equal covariances on the off-diagonal entries or (iii) be left completely unconstrained.[2] In order to determine the adequate number of factors to be considered, we use the modification of the Bai and Ng (2002) information criteria as proposed by Hallin and Liška (2007) and Alessi et al. (2008), i.e.

$$IC^{*}_{p1}(k) = \log(V(k)) + ck\left(\frac{N+T}{NT}\right)\log\left(\frac{NT}{N+T}\right), \tag{10}$$

$$IC^{*}_{p2}(k) = \log(V(k)) + ck\left(\frac{N+T}{NT}\right)\log(\min\{N,T\}), \tag{11}$$

$$IC^{*}_{p3}(k) = \log(V(k)) + ck\frac{\log(\min\{N,T\})}{\min\{N,T\}}, \tag{12}$$

where

$$V(k) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it} - z_i^{(k)'}x_t^{(k)}\right)^2, \tag{13}$$

for $k \in [0; p_{max}]$.

The optimal number of factors to include k^* satisfies

$$k^{T*}_{a,N} = \underset{0\leq k\leq p_{\max}}{\arg\min}\, IC^{T*}_{a,N}, \qquad a = 1, 2, 3. \tag{14}$$

Notice that for $c = 1$ the adjusted criteria by Alessi et al. (2008) are equivalent to the original criteria by Bai and Ng (2002). For $c = 0$ we always get $k^* = p_{max}$. Increasing c makes the penalty function stronger. Following the procedure by Alessi et al. (2008) we compute the information criteria from equation (10) to (12) for $k = 1, \cdots, 6$ by increasing c from zero to five in 0.1 steps and determine plateaus in which the optimal number of factors k^* is stable for a sequence of differing values of c.

3 Empirical Analysis

3.1 Data Description

We use a broad data set along the lines of Breitung and Eickmeier (2014) and Eickmeier et al. (2014) to construct our data-driven measure of the financial cycle.[3] In total, the data set comprises $N^F = 25$ financial data series and $N^M = 7$ macroeconomic data series from the US for a time span from 1991-Q1 until 2015-Q4 ($T = 100$). The data set is balanced and consists of quarterly data of various

[2]Notice that in the case of an unrestricted R matrices the number of estimated parameters increases sharply leading to possibly unstable results. The estimation results for these and the other aforementioned model specifications are available upon request.

[3]See Appendix B for an overview of the data set and summary statistics.

measures of interest rate spreads between (i) long and short term government bonds, (ii) interbank loans and treasury bills, (iii) corporate and government bonds, and (iv) spreads between private loans (such as car and personal loans) and government bonds. Furthermore, we include charge-off rates on business loans and single family mortgages, the spread between 30 year mortgages and government bonds, three measures of "Senior Loan Officer Surveys on Bank Lending Practices", the implied stock volatility as described by the VIX and an extract of three index values of the "Survey of Consumers" conducted by the Survey Research Center at the University of Michigan. Finally, various measures of credit aggregates such as the total amount of consumer credit outstanding or commercial mortgages as a percentage of GDP and a measure of money supply (M2) as a percentage of GDP are included. Financial leverage represents the amount of financial market credit outstanding in relation to business credit outstanding and the "S&P Case-Shiller National Home Price Index" serves as an indicator of house prices.

The estimation procedure of the dynamic factor model described above requires stationary data (Stock and Watson, 2005). Therefore, each time series has been tested for unit-roots using the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. According to the test results it is unclear in some cases whether the series is I(1) or I(2). However, we prefer to apply the same transformation to all series in order to keep interpretation simple. Thus except for interest rate spreads and indices that remain in levels, we take the first difference of all series so that the transformed series are approximately stationary. Since the raw data is already available in seasonally adjusted form we do not make any additional adjustments for seasonality. Following Stock and Watson (2005) outliers are defined as observations of the stationary series with absolute median deviation larger than three times the interquartile range. Identified outliers are removed and replaced by the median value of the preceding five observations. Finally, all series are standardized to have a zero mean and unit variance. The final data is collected in an N-dimensional vector of variables $\mathbf{y}_t = \{y_{1,t}, \cdots y_{N,t}\}'$ for $t = 1, \cdots, T$ that is plotted in figure 1.

3.2 Estimation Results

In the following, we discuss our estimation results using the data set just described. We estimated the dynamic factor model as in equation (1) - (2) with one to six factors using the same initial conditions for all model specifications under consideration. As can be shown by a Monte Carlo initial conditions search and update algorithm, our estimation results are not sensitive to changes in the initial conditions.[4]

[4]The following start values were used in the estimation:

$$\begin{bmatrix} x_{1,0} \\ \vdots \\ x_{p,0} \end{bmatrix} \sim MVN \left(\begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}, \begin{bmatrix} 5 & 0 & 0 \\ & \ddots & \\ 0 & & 0 \\ 0 & 0 & 5 \end{bmatrix} \right).$$

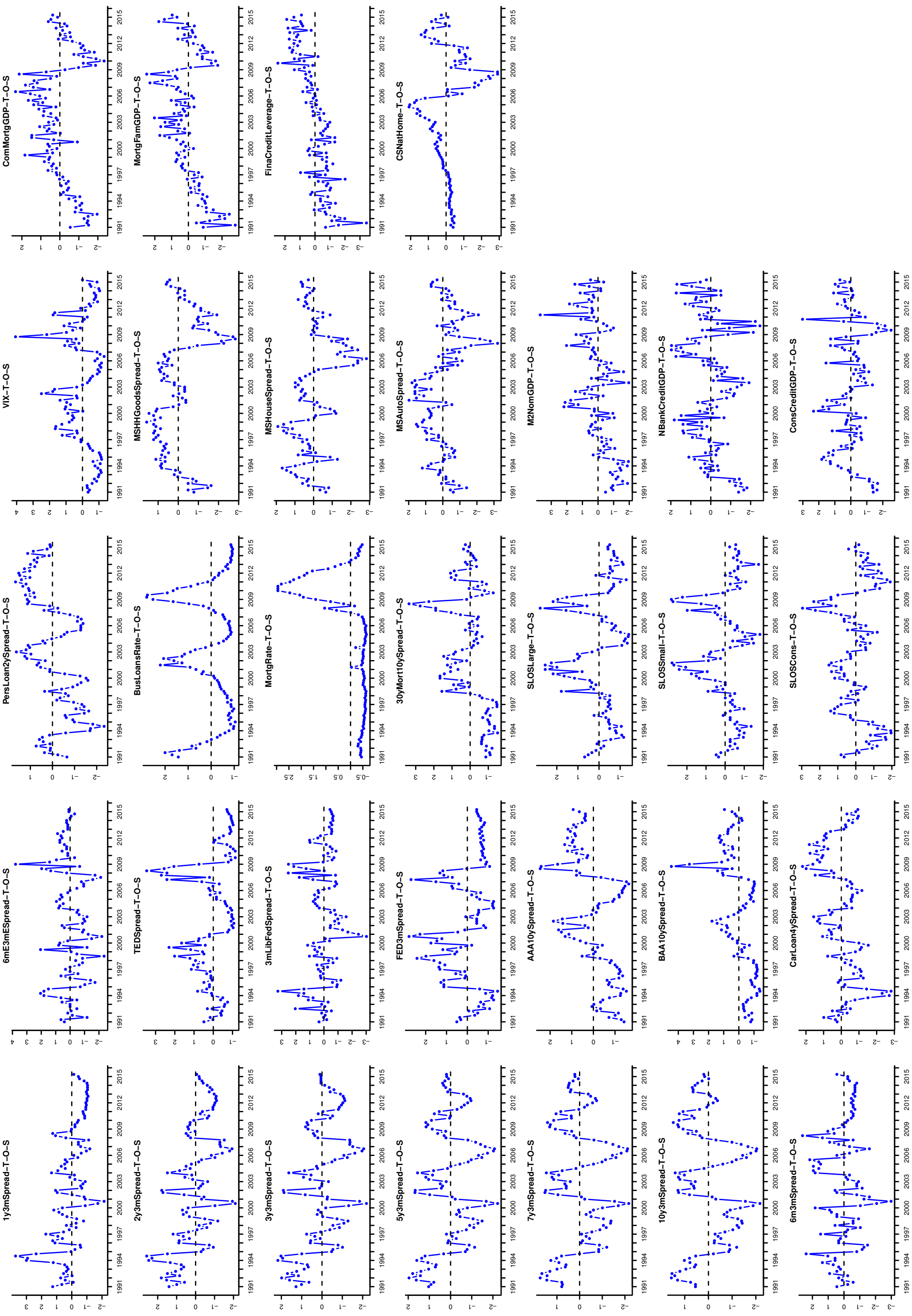


Figure 1: Plot of the transformed and standardized data.

Note: The index “T-O-S” stands for **T**ransformed, **O**utliers removed, **S**tandardized.

The results are summarized in figure 2 where the suggested optimal number of factors is plotted for every possible value of c according to the three adjusted information criteria as in equations (10) to (12). As mentioned earlier, we observe that for low values of c the criteria suggest the boundary solution $k^* = p_{max}$. However, the case in which the inclusion of more parameters is not penalized is an unfavorable situation. Thus the boundary solution will not be considered in the following. Similarly, for high values of c we observe a very strong penalization leading to the other boundary solution of including only one factor. This will not be considered either, because one factor only explains around 19% of the total variation (see table 1), whereas two and more factors account for more than 32% which is more consistent with previous findings in dynamic factor analysis that suggest a range between 30 and 60% as a reasonable fit (Breitung and Eickmeier, 2005). For intermediate values of c the criteria exhibit plateaus or regions in which the optimal number of factors k^* is stable for a sequence of differing values of c. In figure 2 we observe stable plateaus suggesting to include either three or four factors. Notice that the plateau for three factors is considerably longer than for four factors, i.e. there is more support for the inclusion of three factors. Although there is some minor support for the inclusion four factors, the gain in explained variance is negligible. Accordingly, we choose to analyze three dynamic factors that account for approximately 45% of the total variation in the remainder of this paper.

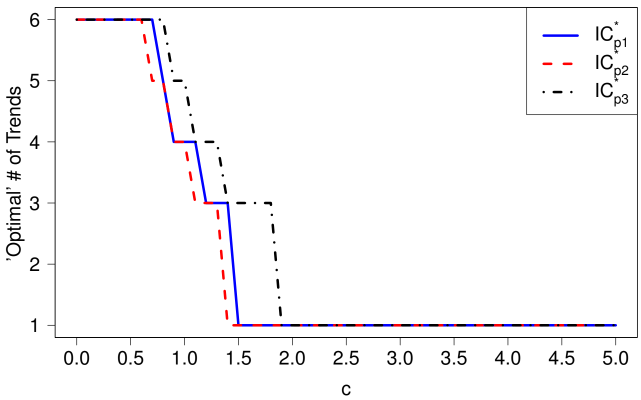


Figure 2: Optimal number of factors depending on the penalty parameter c.

Table 1: Explained Variance Share.

No. of Factors	Explained Variance Share
1	0.19
2	0.32
3	0.45
4	0.53
5	0.58
6	0.62

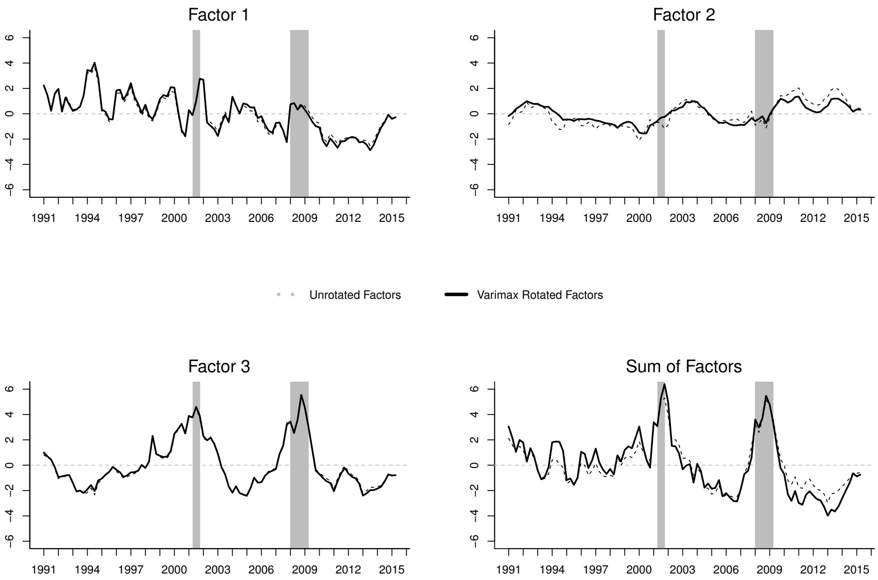


Figure 3: Estimated factors before and after Varimax rotation. The shaded areas denote recessions as determined by the National Bureau of Economic Research (NBER).

A first visual inspection of the three factors that are plotted in figure 3 shows that the first factor `DF1` seems to fluctuate with more or less regular occurring up- and downswings every two to five years around a constant mean of zero. The second factor `DF2` shows longer lasting swings around the mean while the third factor `DF3` features mainly two large spikes and only minor fluctuations otherwise. The first impression is that the first factor resembles the swings in the financial markets induced mainly by business cycle fluctuations, the second factor might be associated with amplification effects intrinsic in the financial markets during normal times, while the third factor seems to be related in a leading manner with the occurrence of economic recessions.

In order to evaluate this working hypothesis we rotate the factors via the Varimax method developed by Kaiser (1958). In particular, we can see in table 2 that after Varimax rotation the loadings of “5y3mSpread”, “7y3mSpread” and “10y3mSpread” have shifted from `DF1` and `DF2` so that after rotation these variables primarily load on `DF2` only. Thus `DF1` mainly features positive loadings on short-term government bond yield spreads (“1y3mSpread”, “2y3mSpread” and “3y3mSpread”) and negative loadings on corporate bond spreads (“AAA10ySpread” and “BAA10y-Spread”), private loan and mortgage rate spreads (“CarLoan4ySpread”, “PersLoan2ySpread”, “MortgRate” and “30yMort10ySpread”). The interpretation of `DF1` is motivated by well-established results from a large branch of literature that is concerned with the term structure of interest rates and yield spreads. Among others, Campbell (1987) and Fama and French (1989) showed that the term structure of in-

Table 2: Factor loadings before and after Varimax rotation. Bold factor loadings are larger than 0.5 in absolute terms, whereas those in italics are marginally below.

	Unrotated factor loadings			Varimax rotated factor loadings		
Variable	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
1y3mSpread	**0.63**	0.00	0.00	**0.60**	0.18	0.04
2y3mSpread	**0.88**	**0.60**	0.00	**0.66**	**0.83**	0.04
3y3mSpread	**0.93**	**0.95**	0.10	**0.61**	**1.18**	0.13
5y3mSpread	**0.89**	**1.28**	0.19	*0.47*	**1.49**	0.20
7y3mSpread	**0.84**	**1.40**	0.23	*0.37*	**1.59**	0.23
10y3mSpread	**0.76**	**1.46**	0.24	0.28	**1.62**	0.23
6m3mSpread	*0.44*	0.05	-0.11	*0.41*	0.17	-0.08
6mE3mESpread	*0.43*	*0.40*	-0.04	*0.30*	**0.51**	-0.03
TEDSpread	-0.15	**-0.74**	0.07	0.07	**-0.75**	0.08
3mLibFedSpread	0.29	-0.07	-0.07	*0.30*	0.01	-0.05
FED3mSpread	*-0.46*	**-0.95**	0.03	-0.16	**-1.04**	0.03
AAA10ySpread	-0.04	**0.70**	*0.42*	-0.28	**0.67**	*0.39*
BAA10ySpread	0.00	**0.68**	*0.46*	-0.23	**0.65**	*0.43*
CarLoan4ySpread	-0.15	**0.61**	*0.41*	*-0.35*	**0.55**	*0.37*
PersLoan2ySpread	0.07	**1.09**	*0.32*	-0.27	**1.07**	0.28
BusLoansRate	*0.39*	**0.90**	*0.49*	0.08	**0.98**	*0.48*
MortgRate	-0.05	**0.66**	0.17	-0.25	**0.62**	0.14
30yMort10ySpread	-0.26	-0.06	*0.36*	-0.25	-0.13	*0.34*
SLOSLarge	0.06	0.03	**0.50**	0.02	0.05	**0.50**
SLOSSmall	0.05	0.09	**0.51**	-0.01	0.11	**0.51**
SLOSSCons	-0.08	*-0.30*	*0.33*	-0.01	*-0.30*	*0.33*
VIX	-0.01	0.15	**0.41**	-0.09	0.15	**0.41**
MSHHGoodsSpread	-0.17	**-0.91**	*-0.37*	0.13	**-0.92**	*-0.35*
MSHouseSpread	*0.35*	**0.52**	0.00	0.18	**0.59**	0.00
MSAutoSpread	0.16	-0.06	-0.04	0.17	-0.01	-0.03
M2NomGDP	*-0.44*	-0.11	0.23	*-0.41*	-0.23	0.21
NBankCreditGDP	*-0.45*	**-0.76**	-0.12	-0.20	**-0.85**	-0.13
ConsCreditGDP	-0.26	**-0.50**	-0.05	-0.10	**-0.55**	-0.05
ComMortgGDP	*-0.34*	**-0.76**	0.00	-0.10	**-0.83**	0.01
MortgFamGDP	*-0.31*	*-0.37*	0.15	-0.20	*-0.44*	0.15
FinaCreditLeverage	-0.24	0.17	-0.01	-0.28	0.09	-0.03
CSNatHome	-0.04	-0.14	-0.22	0.02	-0.15	-0.22

terest rates at short horizons is negatively related to economic activity. Thus we associate the first factor `DF1` with the effect of the business cycle on the term structure of interest rates.

The second factor `DF2` displays large positive loadings on all government bond yield spreads, especially for medium- and long-term maturities, and large negative loadings on various measures of credit aggregates. The interpretation of these factor loadings builds on the fact that an increase in the long-term/short-term bond yield spread is generally associated with an economic downturn that comes about through postponed investments (Stock and Watson, 1989). Hence, the positive loadings of “5y3mSpread”, “7y3mSpread”, “10y3mSpread” suggest that an increase (decrease) of the second factor is associated with a widening (contraction) of these long-term/short-term government bond yield spreads. This in turn leads to postponed (induced) investments and a decline (increase) in the amount of credit outstanding that is incorporated in the negative loadings of “NBankCreditGDP”, “ConsCreditGDP”, “ComMortgGDP” and “MortgFamGDP”. According to Gertler et al. (1990), this countercyclical behavior can be attributed to a financial element in the business cycle propagation mechanism that came to be known as the “financial accelerator” and has become the focus of numerous research contributions, see e.g., Bernanke et al. (1996) and Kiyotaki and Moore (1997).

The third factor is different from the other two factors not only from a superficial point of view (see again figure 3), but also from the interpretation of the factor loadings. Factor three features high loadings on the values of the Senior Loan Officer Surveys (“SLOSLarge”, “SLOSSmall” and “SLOSCons”) and implied stock market volatility (“VIX”). This means that while the first two factors resemble risk perceptions for the near and distant future that are *realized* in interest rate spreads and credit aggregates, factor three is more related to expectations and uncertainty concerning aggregate and financial market risk. Indeed, as an increase in the SLOS indices reflects a tightening of the expected credit conditions and a higher VIX reflects an increased risk aversion and market uncertainty, positive loadings of the third factor on these variables indicate that a rise in `DF3` may signal the expected occurrence of a significant downturn in economic activity. Further, given its significant association with the VIX, the third factor `DF3` could be interpreted as being related to Rey’s (2013) global financial cycle.

As we have shown, the estimation of the factors and their interpretation enables us to dissect the financial cycle into three distinct components giving us a deeper understanding of the mechanics of the financial cycle. Furthermore, these components can now be tested for their predictive power to forecast other economic variables and thus allow for an analysis of the interrelations between the financial cycle and the real economy.

3.3 Granger Causality Analysis

We start our analysis of the forecasting power of our financial cycle components concerning key macroeconomic variables by setting up a linear VAR model. More specifically, we set up Factor-Augmented VARs consisting of real quarter-to-quarter GDP growth, short-term interest rates and inflation and various combinations of the three dynamic factors (`DF1`, `DF2`, `DF3`).[5] The federal funds rate (`FEDFUNDS`) serves as a proxy for interest rates, inflation is computed as $\pi_t = 400 \ln(P_t/P_{t-1})$, where P_t is the GDP deflator (`GDPDEF`). The usual lag length selection criteria (AIC, SC, HQ) suggest including only one lag and a constant c. Thus we estimate the following FAVAR(1)

$$y_t = c + \mathbf{A}_1 y_{t-1} + u_t, \tag{15}$$

where y_t is a set of endogenous variables. As the Quandt-Andrews Breakpoint Test suggests a break point at 2008Q4 (approximately the date where interest rates started moving very closely along the zero lower bound), we restrict the following analysis to the subsample from 1991Q1 - 2008Q4. We start with a benchmark model along the lines of Stock and Watson (2001) consisting only of GDP growth, inflation and interest rates and then stepwise add the financial cycle measures independently and as various combinations. The different model specifications are presented in table 3.

[5] We focus on GDP growth and not on the output gap due to the well known measurement problems, uncertainty and end-point bias problems linked with the latter measure.

Table 3: Summary of VAR Model Specifications. × denotes the inclusion of the respective variable.

	VAR_BM	VAR01	VAR02	VAR03	VAR04	VAR05	VAR06	VAR07	VAR08	VAR09	VAR10	VAR11
GDP Growth	×	×	×	×	×	×	×	×	×	×	×	×
Inflation	×	×	×	×	×	×	×	×	×	×	×	×
Interest Rates	×	×	×	×	×	×	×	×	×	×	×	×
DF1		×			×		×	×				
DF2			×		×	×		×				
DF3				×		×	×	×				
DF1 + DF2									×			
DF2 + DF3										×		
DF1 + DF3											×	
DF1 + DF2 + DF3												×

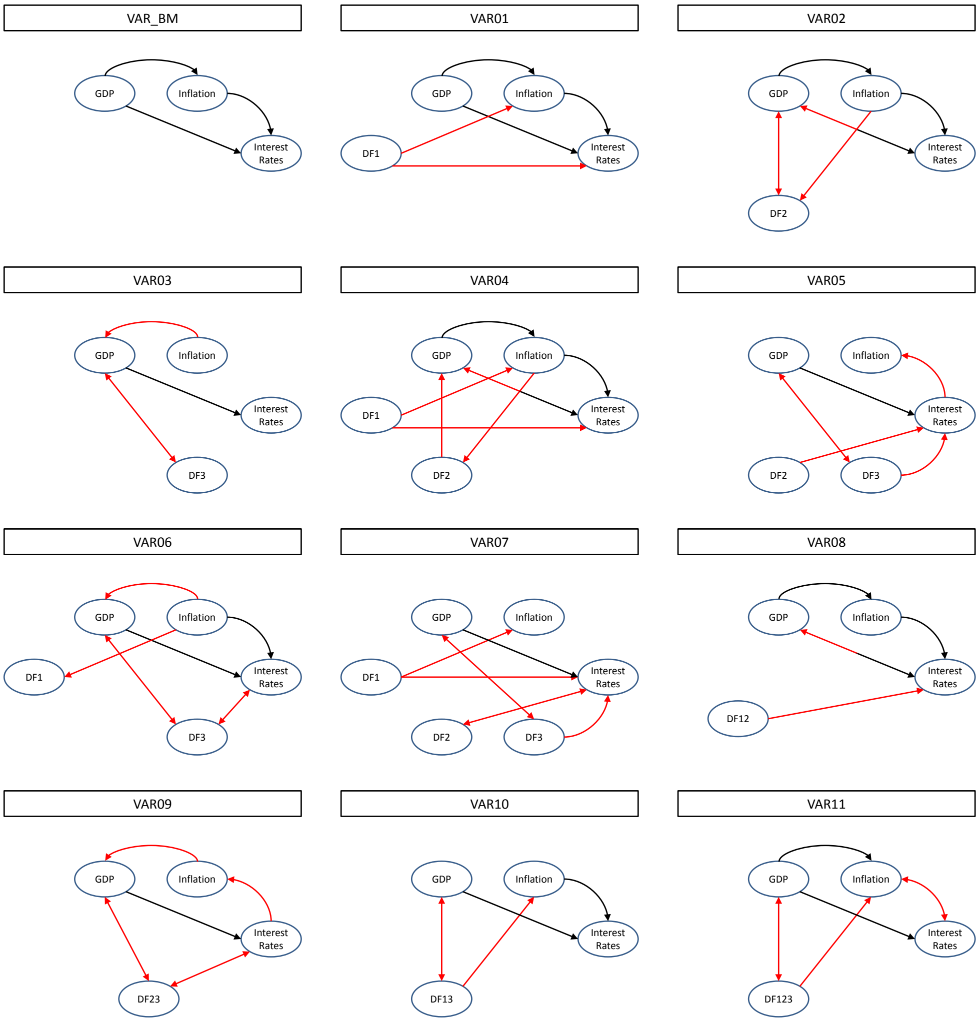


Figure 4: Summary of Granger-Causality Tests. Black arrows denote the causal relations from the benchmark model and red arrows changes due to the inclusion of factors.

Figure 4 illustrates our Granger causality test results for all model specifications, with simple arrows denoting unidirectional and two-pointed arrows denoting bidirectional Granger causality (note that according to the parameter restriction of setting Φ to be diagonal in the factor estimation there cannot be any causality between the factors).[6] In the benchmark model without any factors (VAR_BM) GDP growth unidirectional Granger-causes interest rates and inflation. Further, inflation itself Granger causes interest rates, illustrating the interaction between price inflation developments and the conduct of monetary policy (see e.g., Stock and Watson, 2001). By adding the first factor to the VAR set-up (`VAR1`) we obtain a unidirectional Granger causality from `DF1` to inflation and short term interest rates. As `DF1` is associated with the term structure of interest rates, which can be related with the *expectations* of future economic activity, we interpret this finding as a reflection of the effect of expected future output on inflation and monetary policy. This effect on the causal relations of including the first factor is the same in almost all cases even if we include additional factors.

Adding the second factor to the benchmark VAR results in bidirectional (unidirectional) causality from `DF2` to GDP growth as in `VAR2` (`VAR4`) and unidirectional causality from inflation to `DF2`. Especially the former result supports the association of `DF2` to financial accelerator effects, as previously discussed.

The inclusion of factor `DF3` changes the causal relations considerably across all model specifications. The Granger causal effect of inflation on interest rates vanishes and the one between GDP growth on inflation is reversed. In return, we observe bidirectional causality from factor three to GDP growth in all cases, which suggests that `DF3` may have a significant predicting power of financial and macroeconomic risk. It may however be the case that this relationship is nonlinear, being stronger around turning points of the business cycle. We investigate this conjecture below.

Our results indicate that the Granger causal relations between the components of the financial cycle and GDP growth, inflation and interest rates are statistically significant and economically meaningful. However, although we can provide statistical evidence for a bi-directional causal relation between `DF3` and GDP growth, our results seem to indicate that linear VAR-based Granger causality tests may not be able to capture the nonlinearities introduced by the inclusion of factor three. Thus in order to shed some more light on the aforementioned early warning indicator properties we apply a (nonlinear) probit-based recession estimation in the following section.

3.4 Recession Prediction

As it is standard in the literature (see e.g., Estrella and Hardouvelis (1991)), we use the NBER Business Cycle Dating to construct our binary recession indicator series R_t that is defined such that[7]

[6] Detailed estimation results are presented in table 8 - 19 in Appendix A.

[7] For a detailed description of the series see https://fred.stlouisfed.org/series/USREC.

$$R_t = \begin{cases} 1, & \text{if the economy is in a recessionary period in time } t, \quad \text{and} \\ 0, & \text{if the economy is in a expansionary period in time } t. \end{cases} \tag{16}$$

Along the lines of Dueker (1997) and Estrella and Mishkin (1998) we use a dynamic probit model with the linear model equation

$$\psi_t = c + \beta_1 R_{t-h-r} + \sum_{j=h}^{q} \beta_2 X_{t-j} + \varepsilon_t, \tag{17}$$

where X denotes a set of explanatory variables, ε_t is an iid mean-zero normal disturbance term, q a pre-specified number of maximal lags to include (in our case $q = 4$), h is the forecast horizon, and r denotes the number of lags that are necessary for identification of a recession by the underlying turning points algorithm. According to Dueker (1997) we use $r = 2$ in the case of the NBER recession indicator. The probability of a recession in time t is given by

$$\text{Prob}(R_t = 1) = \Phi(\psi_t), \tag{18}$$

where Φ is the cumulative standard normal density function. In the following analysis we examine the estimation results for eight model specifications summarized in table 4.[8,9]

Table 4: Summary of Dynamic Probit Model Specifications. $\times$ denotes the inclusion of the first lag of the respective variable.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
YC	×	×	×	×	×	×	×	×
DF1		×						
DF2			×					
DF3				×				
DF1 + DF2					×			
DF2 + DF3						×		
DF1 + DF3							×	
DF1 + DF2 + DF3								×

Note: In line with Dueker (1997) the yield curve (YC) is determined as the spread between the yields on 30-year Treasury bonds and 3-month T-bills.

We examine whether our financial cycle components improve the forecasts of recessions in comparison to a benchmark model (X_1) using only the yield curve and lagged values of R_t as proposed by Dueker (1997). The first step in our analysis is the adequate specification of the number of lags for each variable. In order to avoid including statistically insignificant variables, we use a general-to-specific

[8]Given the inclusion of various lags of the explanatory variables we face the problem of complete multicollinearity when we include all factors (with their corresponding lags) in the regression equation. Therefore, here we restrict our analysis to model specifications including only one factor (or the sum of two or three factors).

[9]Notice that, in contrast to the previous section, here we consider the complete sample from 1991Q1-2015Q4.

Table 5: Summary of Dynamic Probit Model Specifications, One- to Three-Period Ahead Forecast. The asterisks indicate the smallest value according to the respective information criterion and the largest value of the Pseudo R^2.

1-Period Ahead Forecast Horizon								
	YC	YC_DF1	YC_DF2	YC_DF3	YC_DF12	YC_DF13	YC_DF23	YC_DF123
USRec	3	3	-	-	3	3	-	3
YC	1,3	2,3	1,3	2,3	2,3	1,3	3	1,3
DF1	-	1	-	-	-	-	-	-
DF2	-	-	1	-	-	-	-	-
DF3	-	-	-	1	-	-	-	-
DF1+DF2	-	-	-	-	1,2	-	-	-
DF1+DF3	-	-	-	-	-	-	-	-
DF2+DF3	-	-	-	-	-	-	1	-
DF1+DF2+DF3	-	-	-	-	-	-	-	-
Pseudo R^2	0.49972	0.57190	0.53584	0.65574	0.69487*	0.49972	0.64095	0.49972
AIC	0.41075	0.38615	0.38745	0.31007	0.32878	0.41075	0.29764*	0.41075
BIC	0.52112	0.52411	0.49781	0.42044	0.49433	0.52112	0.38041*	0.52112
HQC	0.45528	0.44181	0.43197	0.35460	0.39557	0.45528	0.33103*	0.45528
2-Period Ahead Forecast Horizon								
	YC	YC_DF1	YC_DF2	YC_DF3	YC_DF12	YC_DF13	YC_DF23	YC_DF123
USRec	4	4	-	4	4	-	-	-
YC	4	2,4	2,4	4	2,4	2,4	4	2,4
DF1	-	2	-	-	-	-	-	-
DF2	-	-	3	-	-	-	-	-
DF3	-	-	-	2	-	-	-	-
DF1+DF2	-	-	-	-	2	-	-	-
DF1+DF3	-	-	-	-	-	4	-	-
DF2+DF3	-	-	-	-	-	-	2	-
DF1+DF2+DF3	-	-	-	-	-	-	-	4
Pseudo R^2	0.42765	0.53405	0.51749	0.56430	0.59598*	0.45803	0.54669	0.45302
AIC	0.43879	0.41406	0.40260	0.37217	0.37379	0.44126	0.36139*	0.44452
BIC	0.52212	0.55293	0.51371	0.48327	0.51267	0.55236	0.44472*	0.55562
HQC	0.47239	0.47006	0.44741	0.41697	0.42979	0.48606	0.39499*	0.48932
3-Period Ahead Forecast Horizon								
	YC	YC_DF1	YC_DF2	YC_DF3	YC_DF12	YC_DF13	YC_DF23	YC_DF123
USRec	-	-	-	5	5	-	-	-
YC	6	6	3,6	5	6	3,4	5	3,4
DF1	-	-	-	-	-	-	-	-
DF2	-	-	4,6	-	-	-	-	-
DF3	-	-	-	4,6	-	-	-	-
DF1+DF2	-	-	-	-	3	-	-	-
DF1+DF3	-	-	-	-	-	4,6	-	-
DF2+DF3	-	-	-	-	-	-	4,6	-
DF1+DF2+DF3	-	-	-	-	-	-	-	4,6
Pseudo R^2	0.37530	0.37530	0.55033	0.63492*	0.49651	0.51476	0.55958	0.51854
AIC	0.45782	0.45782	0.41046	0.35462*	0.42326	0.43394	0.38163	0.43145
BIC	0.51412	0.51412	0.55122	0.49538	0.53587	0.57470	0.49424*	0.57221
HQC	0.48050	0.48050	0.46717	0.41133*	0.46863	0.49065	0.42700	0.48816

procedure to determine the optimal number of lags as done e.g., in Proaño and Theobald (2014). In particular, the general-to-specific approach comprises to start with a maximal number of lags q and test each respective lag using a redundant variables Likelihood Ratio (LR) test, thus stepwise removing insignificant lags until all remaining lags are significant. The final model specifications for the one to three-period ahead forecasts are presented in table 5.

We observe that in all model specifications the lagged values of the yield curve are statistically significant at standard levels providing further support for the yield curve serving as a predictor of US recessions along the lines of Dueker (1997). Most of the dynamic factors enter with only one lagged value for the one- and two-period ahead forecast and with two lagged values in the three-period ahead forecast. However, in some cases the factors are not significant at standard levels and thus drop out in the model specification process (e.g., YC_DF13 and YC_DF123). Interestingly, we observe that the recession indicator R_t becomes insignificant in many cases when financial cycle components are included. Especially at the three-period ahead forecast horizon past values of R_t are insignificant in the majority of all model specifications. Further, the information criteria consistently suggest that the model including the yield curve and the sum of the second and third factor *excluding* the recession indicator R_t should be preferred over all other model specifications. At the three-period ahead forecast horizon the model including only the third factor is preferred by the information criteria. Thus in contrast to the Granger-causality tests from the previous section, the dynamic probit approach provides some statistical evidence for the importance of factor `DF3` as a predictor of economic recessions. Figure 5 presents exemplary graphical illustrations of the estimation results comparing the model specifications YC, YC_DF3, YC_DF12, YC_DF23 at the one-period ahead forecast horizon.[10] We can see in the first panel that the probit model including only the yield curve (YC) has the tendency to generate weak "false signals" around 1996 and 1999 and is not able to predict the recession in 2001Q1 in advance. Panel (b) and (d), however, show that including the third factor significantly improves the prediction of recessions ahead of time around the 2001 recession. Furthermore, the inclusion of financial cycle components seems to provide a clearer indication about the duration of recessions as the benchmark model. Although less formal our graphical analysis gives further support for the predictive power of our financial cycle components in predicting recessions.

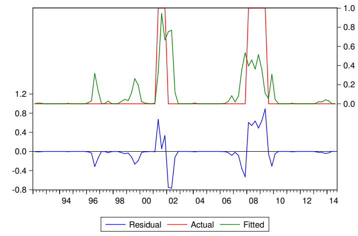
As next, we analyze the quality of the probit specifications to correctly predict recessions in the form of binary point forecasts that equal one if the estimated recession probability exceeds a success cut-off of λ. Following the methodological approach of Sarlin (2013) we can illustrate the estimation results in a confusion matrix as in table 6 and compute corresponding performance measures.

Table 6: Confusion Matrix. Adapted from Sarlin (2013).

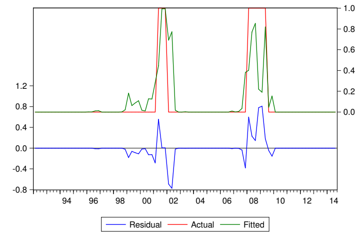
		Observed Class	
		Crisis ($R_t = 1$)	No Crisis ($R_t = 0$)
Predicted Class	Signal	**A** *True Positive*	**B** *False Positive*
	No Signal	**C** *False Negative*	**D** *True Negative*

The threshold λ, above which a signal is issued, depends on the forecaster's risk perceptions of missing a crisis and issuing false signals. Taking the perspective of a policymaker that has relative preference

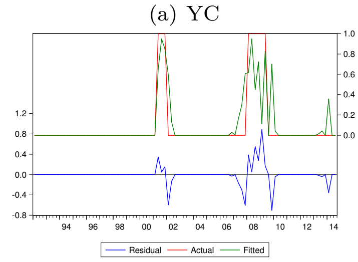
[10]More detailed graphs including the two- and three-period ahead forecast horizon can be found in figure 8 - 10 in the appendix.



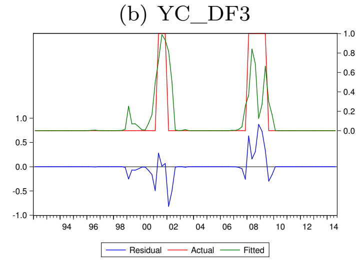
(a) YC



(b) YC_DF3



(c) YC_DF12



(d) YC_DF23

Figure 5: Estimated Recession Probabilities, One-Period Ahead Forecast.

between missing a crisis ($\mu \in [0, 1]$) and issuing a false alarm $(1 - \mu)$ he/she should choose λ such that her loss function

$$L(\mu) = \mu T_1 P_1 + (1 - \mu) T_2 P_2 \tag{19}$$

is minimized, where T_1 and T_2 are the type 1 and 2 errors as well as P_1 and P_2 denote the unconditional probabilities of crises and no crises respectively. Given a value for λ and μ we can use the entries in the confusion matrix to calculate the parameters above and determine the absolute and relative Usefulness (U_a and U_r) introduced by Sarlin (2013) as[11]

$$U_a(\mu) = \min(\mu P_1, (1 - \mu) P_2) - L(\mu), \tag{20}$$

$$U_r(\mu) = \frac{U_a(\mu)}{\min(\mu P_1, (1 - \mu) P_2)}. \tag{21}$$

The absolute Usefulness of a model denotes the degree to which a chosen model yields better results in comparison to not using any model at all, whereas the relative Usefulness puts the absolute Usefulness in relation to the gain obtained from a perfectly performing model. For the one-period ahead forecast the results are presented in table 7 and figure 6-7 while the results for the two- and three-period ahead forecast are illustrated in and in table 20-21 and figure 11-14 in the appendix.[12]

[11]Further information regarding the computation of P_1, P_2, T_1, T_2 can be found in Sarlin (2013), Holopainen and Sarlin (2016) and Alessi and Detken (2009).

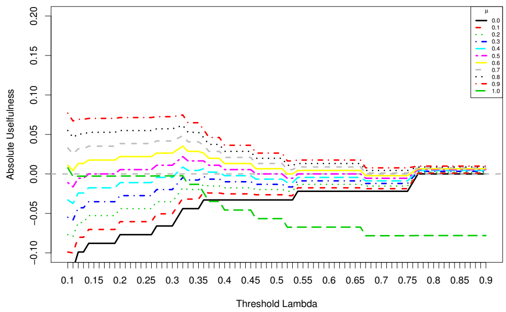
[12]More detailed estimation results are left out for the sake of clarity and are available upon request.

Table 7: In-sample Performance at the One-Period Ahead Forecast Horizon for $\mu = 0.0, 0.1, ..., 1.0$.

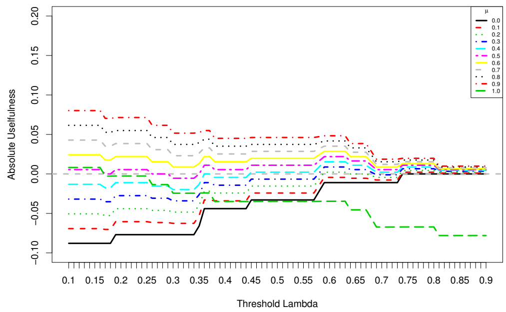
	μ	λ	Accuracy (%)	$U_a(\mu)$	$U_r(\mu)$		μ	λ	Accuracy (%)	$U_a(\mu)$	$U_r(\mu)$
YC	0.0	0.77	0.912	0.000	0.111	YC_DF3	0.0	0.78	0.945	0.000	0.444
	0.1	0.77	0.912	0.001	0.111		0.1	0.78	0.945	0.004	0.444
	0.2	0.77	0.912	0.002	0.111		0.2	0.78	0.945	0.009	0.444
	0.3	0.77	0.912	0.003	0.111		0.3	0.78	0.945	0.013	0.444
	0.4	0.32	0.945	0.009	0.222		0.4	0.39	0.956	0.018	0.444
	0.5	0.32	0.945	0.022	0.444		0.5	0.39	0.956	0.027	0.556
	0.6	0.32	0.945	0.035	0.593		0.6	0.19	0.956	0.042	0.704
	0.7	0.32	0.945	0.048	0.698		0.7	0.19	0.956	0.056	0.810
	0.8	0.32	0.945	0.062	0.778		0.8	0.19	0.956	0.070	0.889
	0.9	*0.10*	*0.879*	*0.077*	*0.864*		*0.9*	*0.19*	*0.956*	*0.085*	*0.951*
	1.0	0.10	0.879	0.008	0.866		1.0	0.19	0.956	0.009	0.951
YC_DF1	0.0	0.74	0.923	0.000	0.222	YC_DF12	0.0	0.71	0.956	0.000	0.556
	0.1	0.74	0.923	0.002	0.222		0.1	0.71	0.956	0.005	0.556
	0.2	0.74	0.923	0.004	0.222		0.2	0.71	0.956	0.011	0.556
	0.3	0.59	0.945	0.009	0.296		0.3	0.71	0.956	0.016	0.556
	0.4	0.59	0.945	0.015	0.389		0.4	0.61	0.967	0.024	0.611
	0.5	0.59	0.945	0.022	0.444		0.5	0.61	0.967	0.033	0.667
	0.6	0.59	0.945	0.029	0.481		0.6	0.61	0.967	0.042	0.704
	0.7	0.10	0.912	0.043	0.619		0.7	0.36	0.956	0.052	0.746
	0.8	0.10	0.912	0.062	0.778		0.8	0.10	0.923	0.064	0.806
	0.9	*0.10*	*0.912*	*0.080*	*0.901*		*0.9*	*0.10*	*0.923*	*0.081*	*0.914*
	1.0	0.10	0.912	0.008	0.902		1.0	0.10	0.923	0.008	0.915
YC_DF2	0.0	0.82	0.923	0.000	0.222	YC_DF23	0.0	0.82	0.934	0.000	0.333
	0.1	0.82	0.923	0.002	0.222		0.1	0.82	0.934	0.003	0.333
	0.2	0.82	0.923	0.004	0.222		0.2	0.82	0.934	0.007	0.333
	0.3	0.82	0.923	0.007	0.222		0.3	0.51	0.956	0.012	0.407
	0.4	0.82	0.923	0.009	0.222		0.4	0.51	0.956	0.020	0.500
	0.5	0.23	0.934	0.016	0.333		0.5	0.51	0.956	0.027	0.556
	0.6	0.23	0.934	0.033	0.556		0.6	0.51	0.956	0.035	0.593
	0.7	0.23	0.934	0.049	0.714		0.7	0.26	0.945	0.048	0.698
	0.8	0.23	0.934	0.066	0.833		0.8	0.10	0.912	0.062	0.778
	0.9	*0.23*	*0.934*	*0.082*	*0.926*		*0.9*	*0.10*	*0.912*	*0.080*	*0.901*
	1.0	0.23	0.934	0.008	0.927		1.0	0.10	0.912	0.008	0.902

Note: The results for DF_13 and DF_123 are not included since all lags of the factors were insignificant and thus equal to the benchmark model (YC). λ is computed as the optimal value yielding the highest U_a. Numbers in italics indicate the values for the highest U_a of each model specification.

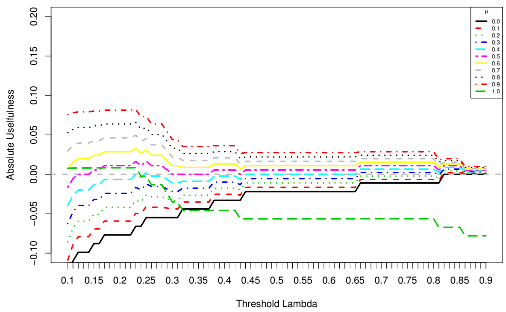
Overall we observe that for low levels of μ, that is a policymaker being primarily concerned about not issuing false signals (type two errors), the optimal threshold above which a signal is issued tends to be high. For a risk-averse policymaker (high μ) whose primary goal is not to miss a crisis (type one error) the threshold tends to be relatively small. For low values of μ the Usefulness barely reaches levels larger than zero, while the absolute Usefulness for all models is largest for $\mu = 0.9$ with values for $U(\mu) = [0.077, 0.085]$. At the two- and three-period ahead forecast horizon we see the same picture with slightly better results. Interestingly, factor three seems to be the dominating factor yielding the best results at each forecast horizon. In fact, at the three-period ahead forecast horizon the model including the third factor delivers the best results of *all* model specification even for *all* forecast horizons with $\mu = 0.9$, $\lambda = 0.27$, $U_a(\mu) = 0.085$ and $U_r(\mu) = 0.949$. These results give further support for the predictive power of factor three in predicting recessions at all forecast horizons.



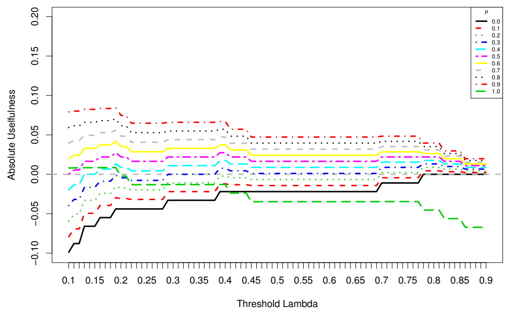
(a) YC



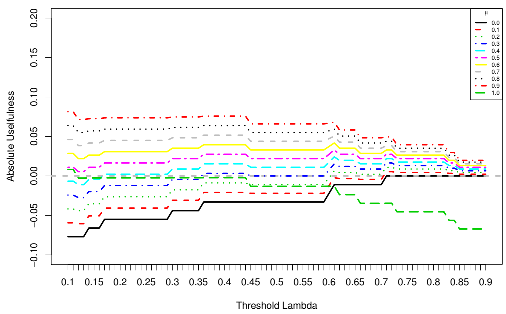
(b) YC_DF1



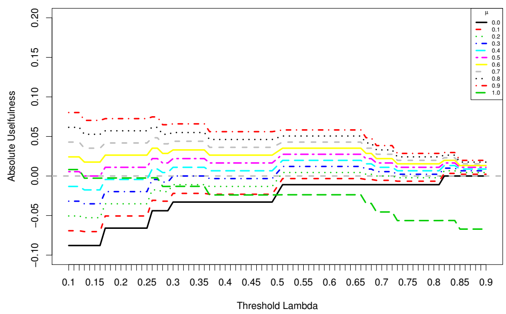
(c) YC_DF2



(d) YC_DF3



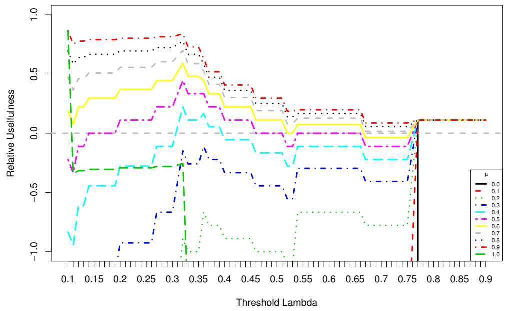
(e) YC_DF12



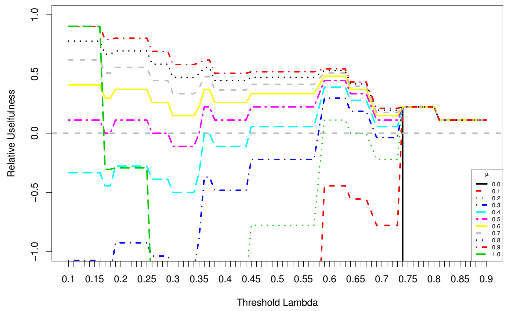
(f) YC_DF23

Figure 6: Absolute Usefulness. One-Period-Ahead Forecast.

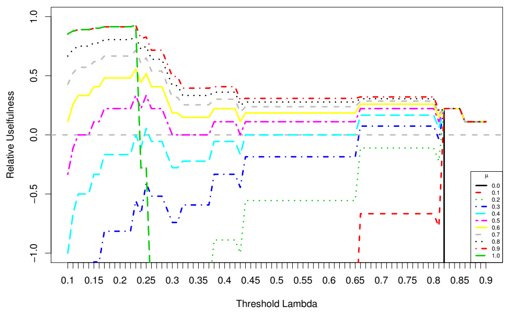
Note: The results for DF_13 and DF_123 are not included since all lags of the factors were insignificant and thus equal to the benchmark model (YC).



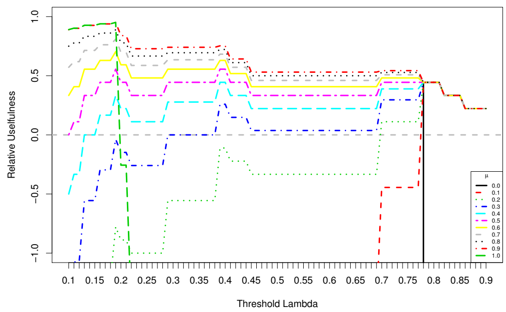
(a) YC



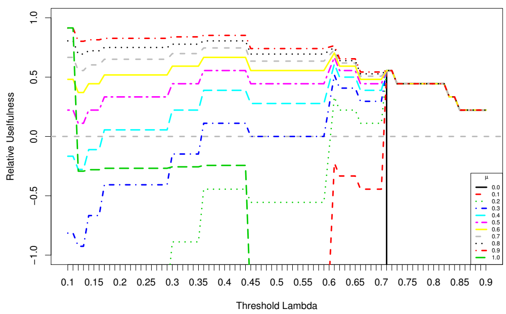
(b) YC_DF1



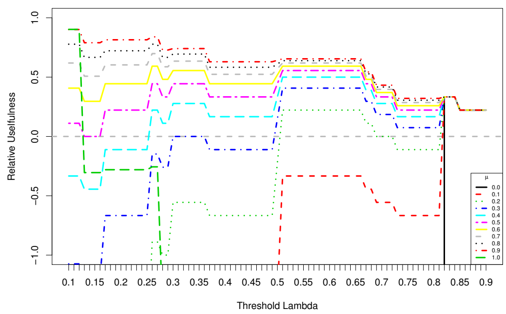
(c) YC_DF2



(d) YC_DF3



(e) YC_DF12



(f) YC_DF23

Figure 7: Relative Usefulness. One-Period-Ahead Forecast.

Note: The results for DF_13 and DF_123 are not included since all lags of the factors were insignificant and thus equal to the benchmark model (YC).

4 Concluding Remarks

While there is a wide consensus in the macroeconomics literature about the definition and statistical properties of the business cycle, this is much less true for its financial counterpart, the financial cycle. One reason for this little consensus is that no single variable seems to fully resemble the concept of the financial cycle, as pointed out e.g. by Borio (2014).

Against this background, this paper's contribution to the growing literature that strives for a deeper understanding of the empirical properties of the financial cycle was to pursue a dynamic factor model approach to estimate synthetic factors meant to represent the financial cycle in a parsimonious manner. The three synthetic factors we focused on do not only explain a significant amount of the variability of our data set, but are also highly economically interpretable. After a Varimax rotation the factor loadings indicated that the first factor represents the effect of the business cycle on the term structure of interest rates. By contrast, factor two seems to be associated with the financial accelerator dynamics, while the third factor appears to be related to Rey's (2013) global financial cycle that is characterized by a strong comovement with the VIX.

Further, using Granger causality tests in a FAVAR set-up we were able to show that the Granger causal relations between the estimated financial cycle components and GDP growth, inflation, as well as short-term interest rates are both statistically significant and economically meaningful.

Finally, we applied a probit based recession estimation comparing various model specifications including our financial cycle components to a benchmark model consisting only of the yield curve and lagged values of the recession indicator as proposed by Dueker (1997). Using well established Usefulness measures along the lines of Sarlin (2013), our results indicate that the inclusion of our financial cycle components significantly improves the forecast accuracy of recessions at the one- to three-period ahead forecast horizon. In particular, the third financial cycle component seems to be the dominating factor of recessions prediction at a forecast horizon of nine months.

However, a noteworthy limitation of our estimation procedure lies in the parametric form where the number of estimated parameters increases proportional to the number of included variables. Thus due to the small sample size we faced limitations in terms of the maximal number of parameters we could estimate. Therefore, it might be worth using nonparametric or Bayesian estimation procedures for higher dimensional models.

A straightforward extension of our approach would be to look for further nonlinearities between the financial cycle components and the macroeconomy by estimation of threshold vector autoregressions, for instance. Finally, since our analysis was based exclusively on data from the United States, it would be interesting to extend our analysis to other countries and strive for insights into the synchronization of international financial and business cycles and their interdependencies along the lines of Rey (2013) and Strohsal et al. (2017).

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A Detailed Estimation Results

Table 8: Summary p-values of Granger causality tests. VARBM. Bold figures denote significance at the 10% level or below.

Excluded Variable	**Dependent Variable**					
	DF1	**DF2**	**DF3**	**GDP Growth**	**Inflation**	**Interest Rates**
DF1	-	-	-	-	-	-
DF2	-	-	-	-	-	-
DF3	-	-	-	-	-	-
GDP Growth	-	-	-	-	**0.0536**	**0.0000**
Inflation	-	-	-	0.5870	-	**0.0007**
Interest Rates	-	-	-	0.6319	0.1407	-

Table 9: Summary p-values of Granger causality tests. VAR01.

Excluded Variable	**Dependent Variable**					
	DF1	**DF2**	**DF3**	**GDP Growth**	**Inflation**	**Interest Rates**
DF1	-	-	-	0.9234	**0.0967**	**0.0005**
DF2	-	-	-	-	-	-
DF3	-	-	-	-	-	-
GDP Growth	0.9941	-	-	-	**0.0156**	**0.0000**
Inflation	0.6541	-	-	0.5893	-	**0.0002**
Interest Rates	0.3550	-	-	0.6301	0.1755	-

Table 10: Summary p-values of Granger causality tests. VAR02.

Excluded Variable	**Dependent Variable**					
	DF1	**DF2**	**DF3**	**GDP Growth**	**Inflation**	**Interest Rates**
DF1	-	-	-	-	-	-
DF2	-	-	-	**0.0057**	0.9425	0.9585
DF3	-	-	-	-	-	-
GDP Growth	-	**0.0402**	-	-	**0.0619**	**0.0000**
Inflation	-	**0.0038**	-	0.3892	-	**0.0009**
Interest Rates	-	0.2808	-	**0.0166**	0.3039	-

Table 11: Summary p-values of Granger causality tests. VAR03.

Excluded Variable	**Dependent Variable**					
	DF1	**DF2**	**DF3**	**GDP Growth**	**Inflation**	**Interest Rates**
DF1	-	-	-	-	-	-
DF2	-	-	-	-	-	-
DF3	-	-	-	**0.0025**	0.1783	**0.0000**
GDP Growth	-	-	**0.0293**	-	0.2758	**0.0002**
Inflation	-	-	0.4575	**0.0602**	-	0.1402
Interest Rates	-	-	**0.0001**	0.6995	0.1247	-

Table 12: Summary p-values of Granger causality tests. VAR04.

Excluded Variable	Dependent Variable					
	DF1	DF2	DF3	GDP Growth	Inflation	Interest Rates
DF1	-	-	-	0.4969	**0.0950**	**0.0004**
DF2	-	-	-	**0.0046**	0.7868	0.5013
DF3	-	-	-	-	-	-
GDP Growth	0.7792	0.1659	-	-	**0.0208**	**0.0000**
Inflation	0.5317	**0.0025**	-	0.3798	-	**0.0002**
Interest Rates	0.5591	0.5066	-	**0.0134**	0.4995	-

Table 13: Summary p-values of Granger causality tests. VAR05.

Excluded Variable	Dependent Variable					
	DF1	DF2	DF3	GDP Growth	Inflation	Interest Rates
DF1	-	-	-	-	-	-
DF2	-	-	-	0.2365	0.2499	**0.0004**
DF3	-	-	-	**0.0981**	0.0764	**0.0000**
GDP Growth	-	0.7245	**0.0202**	-	0.3072	**0.0001**
Inflation	-	0.4659	0.7436	0.1170	-	0.4466
Interest Rates	-	0.2028	0.3976	0.2323	**0.0686**	-

Table 14: Summary p-values of Granger causality tests. VAR06.

Excluded Variable	Dependent Variable					
	DF1	DF2	DF3	GDP Growth	Inflation	Interest Rates
DF1	-	-	-	0.6142	**0.0601**	**0.0009**
DF2	-	-	-	-	-	-
DF3	-	-	-	**0.0023**	0.1076	**0.0000**
GDP Growth	0.7958	-	**0.0405**	-	0.1158	**0.0031**
Inflation	0.4889	-	0.4677	**0.0576**	-	**0.0702**
Interest Rates	0.3475	-	**0.0001**	0.6740	0.1559	-

Table 15: Summary p-values of Granger causality tests. VAR07.

Excluded Variable	Dependent Variable					
	DF1	DF2	DF3	GDP Growth	Inflation	Interest Rates
DF1	-	-	-	0.4829	**0.0866**	**0.0000**
DF2	-	-	-	0.2023	0.3773	**0.0000**
DF3	-	-	-	**0.0984**	**0.0700**	**0.0000**
GDP Growth	0.9122	0.7776	**0.0242**	-	0.1408	**0.0034**
Inflation	0.7207	0.4106	0.7422	0.1136	-	0.3116
Interest Rates	0.4882	**0.0915**	0.4228	0.1960	0.1273	-

Table 16: Summary p-values of Granger causality tests. VAR08.

Excluded Variable	**Dependent Variable**			
	DF12	**GDP Growth**	**Inflation**	**Interest Rates**
DF12	-	0.4568	0.1365	**0.0022**
GDP Growth	0.7092	-	**0.0176**	**0.0000**
Inflation	0.3596	0.5751	-	**0.0004**
Interest Rates	**0.0398**	0.5081	**0.0664**	-

Table 17: Summary p-values of Granger causality tests. VAR09.

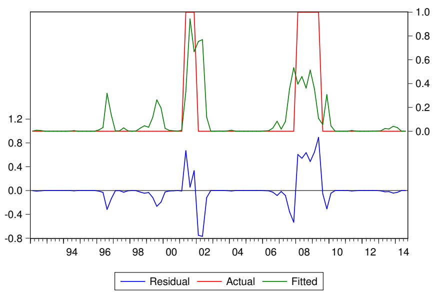
Excluded Variable	**Dependent Variable**			
	DF23	**GDP Growth**	**Inflation**	**Interest Rates**
DF23	-	**0.0107**	0.1070	**0.0000**
GDP Growth	**0.0074**	-	0.3284	**0.0004**
Inflation	0.7898	**0.0822**	-	0.3369
Interest Rates	**0.0001**	0.5909	**0.0452**	-

Table 18: Summary p-values of Granger causality tests. VAR10.

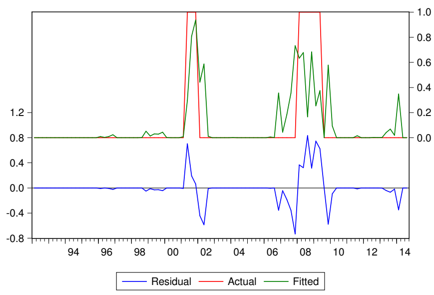
Excluded Variable	**Dependent Variable**			
	DF13	**GDP Growth**	**Inflation**	**Interest Rates**
DF13	-	**0.0110**	**0.0220**	0.3326
GDP Growth	**0.0136**	-	0.1227	**0.0000**
Inflation	0.5041	0.1280	-	**0.0064**
Interest Rates	0.2535	0.5818	0.1407	-

Table 19: Summary p-values of Granger causality tests. VAR11.

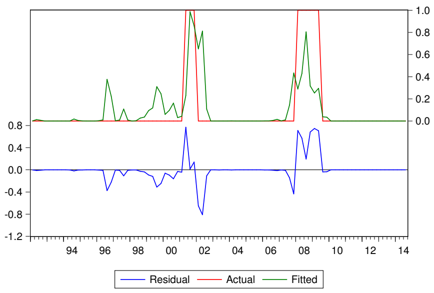
Excluded Variable	**Dependent Variable**			
	DF123	**GDP Growth**	**Inflation**	**Interest Rates**
DF123	-	**0.0482**	**0.0131**	0.3067
GDP Growth	**0.0043**	-	**0.0939**	**0.0000**
Inflation	0.2659	0.1965	-	**0.0068**
Interest Rates	0.6990	0.9740	**0.0344**	-



(a) YC



(b) YC_DF1



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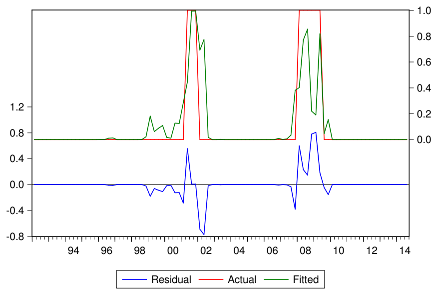

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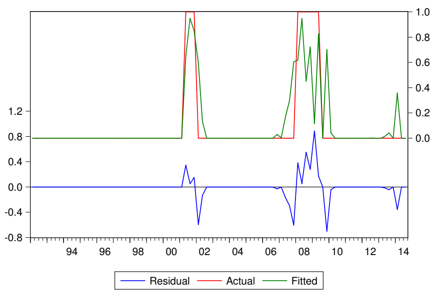
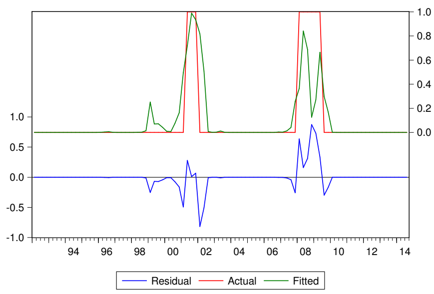


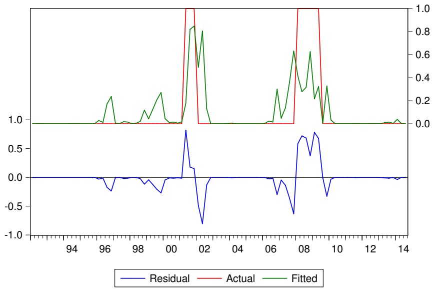
(e) YC_DF12



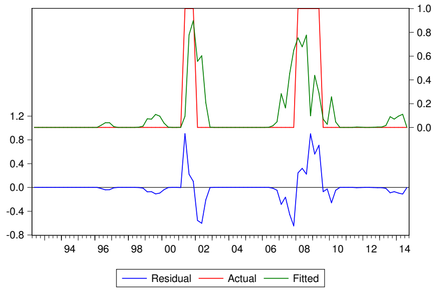
(f) YC_DF23

Figure 8: Estimated Recession Probabilities. One-Period Ahead Forecast.

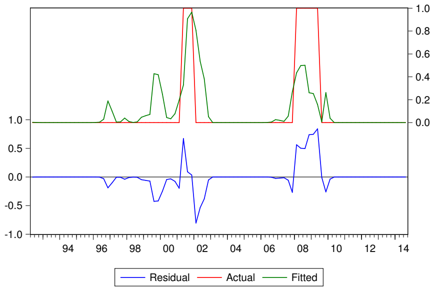
Note: The results for DF_13 and DF_123 are not included since all lags of the factors were insignificant and thus equal to the benchmark model (YC).



(a) YC



(b) YC_DF1



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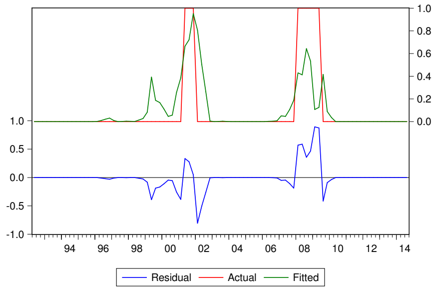
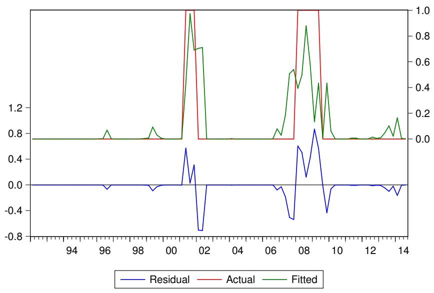
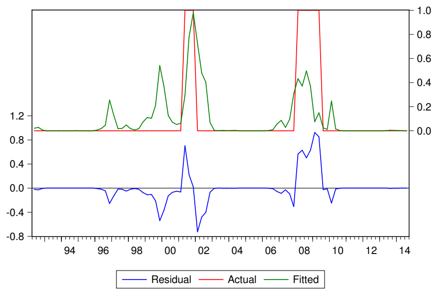


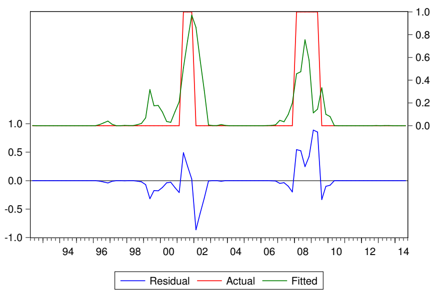
(d) YC_DF3



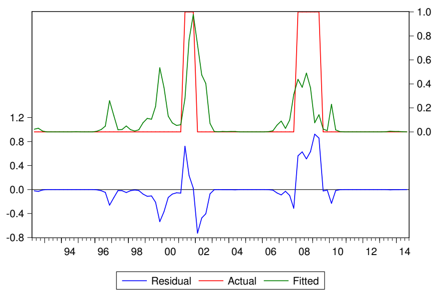
(e) YC_DF12



(f) YC_DF13

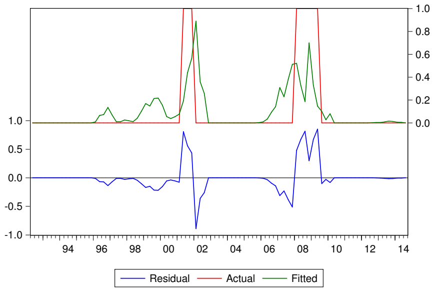


(g) YC_DF23

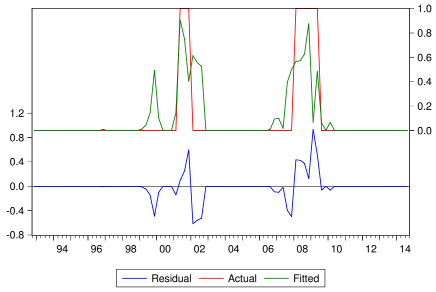


(h) YC_DF123

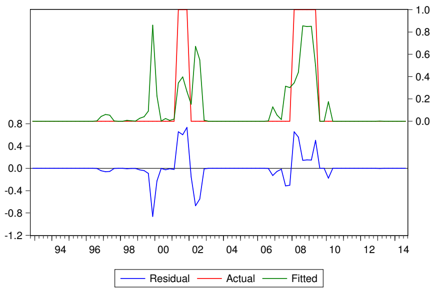
Figure 9: Estimated Recession Probabilities. Two-Period Ahead Forecast.



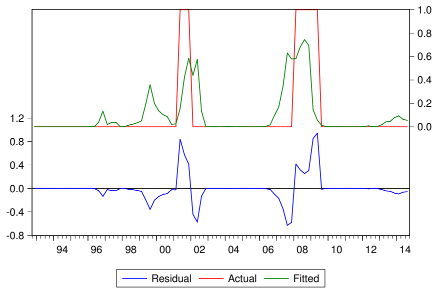
(a) YC



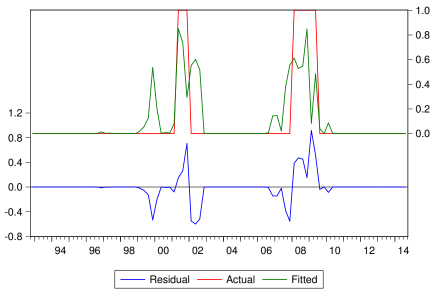
(b) YC_DF2



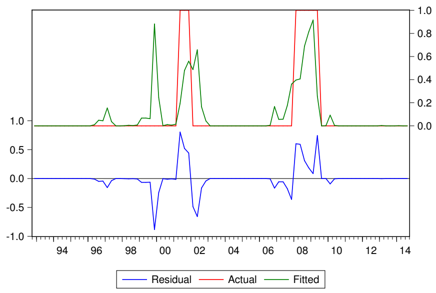
(c) YC_DF3



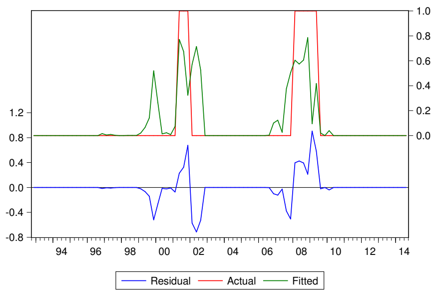
(d) YC_DF12



(e) YC_DF13



(f) YC_DF23



(g) YC_DF123

Figure 10: Estimated Recession Probabilities. Three-Period Ahead Forecast.

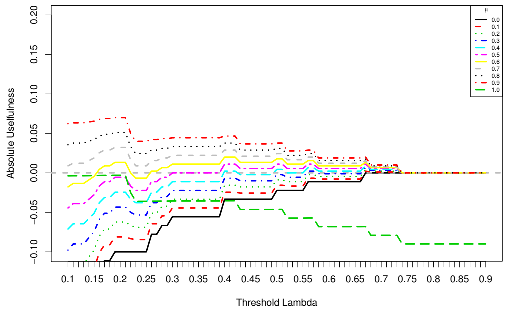
Note: The results for DF_1 is not included since all lags of the factors were insignificant and thus equal to the benchmark model (YC).

Table 20: In-sample Performance at the Two-Period Ahead Forecast Horizon.

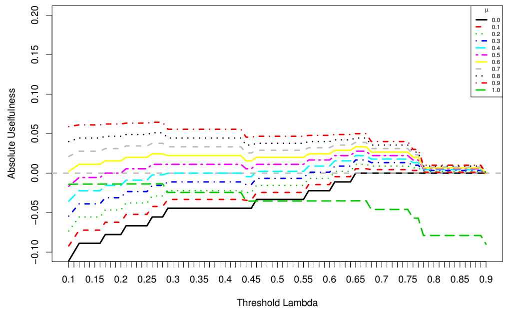
	μ	λ	Accuracy	$U_a(\mu)$	$U_r(\mu)$		μ	λ	Accuracy	$U_a(\mu)$	$U_r(\mu)$
YC	0.0	0.67	0.922	0.000	0.222	YC_DF12	0.0	0.63	0.956	0.000	0.556
	0.1	0.67	0.922	0.002	0.222		0.1	0.63	0.956	0.006	0.556
	0.2	0.67	0.922	0.004	0.222		0.2	0.63	0.956	0.011	0.556
	0.3	0.67	0.922	0.007	0.222		0.3	0.63	0.956	0.017	0.556
	0.4	0.67	0.922	0.009	0.222		0.4	0.63	0.956	0.022	0.556
	0.5	0.40	0.922	0.011	0.222		0.5	0.63	0.956	0.028	0.556
	0.6	0.40	0.922	0.020	0.333		0.6	0.63	0.956	0.033	0.556
	0.7	0.19	0.889	0.032	0.460		0.7	0.14	0.922	0.042	0.603
	0.8	0.19	0.889	0.051	0.639		0.8	0.14	0.922	0.058	0.722
	0.9	0.19	0.889	0.070	0.778		0.9	0.14	0.922	0.073	0.815
	1.0	0.19	0.889	-0.003	-0.333		1.0	0.14	0.922	-0.003	-0.296
YC_DF1	0.0	0.65	0.956	0.000	0.556	YC_DF13	0.0	0.73	0.922	0.000	0.222
	0.1	0.65	0.956	0.006	0.556		0.1	0.73	0.922	0.002	0.222
	0.2	0.65	0.956	0.011	0.556		0.2	0.73	0.922	0.004	0.222
	0.3	0.65	0.956	0.017	0.556		0.3	0.73	0.922	0.007	0.222
	0.4	0.65	0.956	0.022	0.556		0.4	0.73	0.922	0.009	0.222
	0.5	0.65	0.956	0.028	0.556		0.5	0.73	0.922	0.011	0.222
	0.6	0.65	0.956	0.033	0.556		0.6	0.26	0.911	0.020	0.333
	0.7	0.65	0.956	0.039	0.556		0.7	0.26	0.911	0.034	0.492
	0.8	0.26	0.922	0.051	0.639		0.8	0.13	0.889	0.051	0.639
	0.9	0.26	0.922	0.064	0.716		0.9	0.13	0.889	0.070	0.778
	1.0	0.26	0.922	-0.014	-1.506		1.0	0.13	0.889	-0.003	-0.333
YC_DF2	0.0	0.81	0.922	0.000	0.222	YC_DF23	0.0	0.87	0.911	0.000	0.111
	0.1	0.81	0.922	0.002	0.222		0.1	0.87	0.911	0.001	0.111
	0.2	0.81	0.922	0.004	0.222		0.2	0.87	0.911	0.002	0.111
	0.3	0.81	0.922	0.007	0.222		0.3	0.34	0.956	0.008	0.259
	0.4	0.43	0.933	0.009	0.222		0.4	0.34	0.956	0.018	0.444
	0.5	0.43	0.933	0.017	0.333		0.5	0.34	0.956	0.028	0.556
	0.6	0.43	0.933	0.024	0.407		0.6	0.34	0.956	0.038	0.630
	0.7	0.25	0.911	0.039	0.556		0.7	0.34	0.956	0.048	0.683
	0.8	0.10	0.889	0.058	0.722		0.8	0.34	0.956	0.058	0.722
	0.9	0.10	0.889	0.079	0.877		0.9	0.11	0.878	0.078	0.864
	1.0	0.10	0.889	0.008	0.877		1.0	0.11	0.878	0.008	0.864
YC_DF3	0.0	0.77	0.922	0.000	0.222	YC_DF123	0.0	0.73	0.922	0.000	0.222
	0.1	0.77	0.922	0.002	0.222		0.1	0.73	0.922	0.002	0.222
	0.2	0.77	0.922	0.004	0.222		0.2	0.73	0.922	0.004	0.222
	0.3	0.77	0.922	0.007	0.222		0.3	0.73	0.922	0.007	0.222
	0.4	0.43	0.944	0.013	0.333		0.4	0.73	0.922	0.009	0.222
	0.5	0.43	0.944	0.022	0.444		0.5	0.73	0.922	0.011	0.222
	0.6	0.43	0.944	0.031	0.519		0.6	0.27	0.911	0.020	0.333
	0.7	0.19	0.922	0.042	0.603		0.7	0.27	0.911	0.034	0.492
	0.8	0.15	0.900	0.060	0.750		0.8	0.14	0.889	0.051	0.639
	0.9	0.15	0.900	0.080	0.889		0.9	0.14	0.889	0.070	0.778
	1.0	0.15	0.900	0.008	0.889		1.0	0.14	0.889	-0.003	-0.333

Table 21: In-sample Performance at the Three-Period Ahead Forecast Horizon.

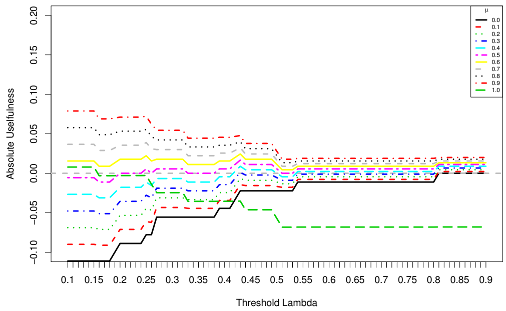
	μ	λ	Accuracy	$U_a(\mu)$	$U_r(\mu)$		μ	λ	Accuracy	$U_a(\mu)$	$U_r(\mu)$
YC	0.0	0.68	0.898	0.000	0.000	YC_DF12	0.0	0.68	0.932	0.000	0.333
	0.1	0.68	0.898	0.000	0.000		0.1	0.68	0.932	0.003	0.333
	0.2	0.68	0.898	0.000	0.000		0.2	0.68	0.932	0.007	0.333
	0.3	0.68	0.898	0.000	0.000		0.3	0.68	0.932	0.010	0.333
	0.4	0.43	0.920	0.005	0.111		0.4	0.68	0.932	0.014	0.333
	0.5	0.43	0.920	0.011	0.222		0.5	0.47	0.932	0.017	0.333
	0.6	0.43	0.920	0.018	0.296		0.6	0.47	0.932	0.027	0.444
	0.7	0.43	0.920	0.025	0.349		0.7	0.47	0.932	0.038	0.524
	0.8	0.10	0.795	0.041	0.500		0.8	0.12	0.886	0.052	0.639
	0.9	0.10	0.795	0.069	0.772		0.9	0.12	0.886	0.069	0.772
	1.0	0.10	0.795	0.007	0.772		1.0	0.12	0.886	-0.003	-0.367
YC_DF1	0.0	0.68	0.898	0.000	0.000	YC_DF13	0.0	0.70	0.909	0.000	0.111
	0.1	0.68	0.898	0.000	0.000		0.1	0.70	0.909	0.001	0.111
	0.2	0.68	0.898	0.000	0.000		0.2	0.70	0.909	0.002	0.111
	0.3	0.68	0.898	0.000	0.000		0.3	0.70	0.909	0.003	0.111
	0.4	0.43	0.920	0.005	0.111		0.4	0.33	0.943	0.011	0.278
	0.5	0.43	0.920	0.011	0.222		0.5	0.33	0.943	0.023	0.444
	0.6	0.43	0.920	0.018	0.296		0.6	0.33	0.943	0.034	0.556
	0.7	0.43	0.920	0.025	0.349		0.7	0.28	0.932	0.047	0.651
	0.8	0.10	0.795	0.041	0.500		0.8	0.28	0.932	0.061	0.750
	0.9	0.10	0.795	0.069	0.772		0.9	0.28	0.932	0.074	0.823
	1.0	0.10	0.795	0.007	0.772		1.0	0.28	0.932	-0.003	-0.316
YC_DF2	0.0	0.66	0.943	0.000	0.444	YC_DF23	0.0	0.89	0.909	0.000	0.111
	0.1	0.66	0.943	0.005	0.444		0.1	0.89	0.909	0.001	0.111
	0.2	0.66	0.943	0.009	0.444		0.2	0.89	0.909	0.002	0.111
	0.3	0.66	0.943	0.014	0.444		0.3	0.89	0.909	0.003	0.111
	0.4	0.48	0.955	0.018	0.444		0.4	0.37	0.943	0.011	0.278
	0.5	0.48	0.955	0.028	0.556		0.5	0.37	0.943	0.023	0.444
	0.6	0.48	0.955	0.039	0.630		0.6	0.18	0.943	0.039	0.630
	0.7	0.48	0.955	0.049	0.683		0.7	0.18	0.943	0.055	0.762
	0.8	0.25	0.932	0.061	0.750		0.8	0.18	0.943	0.070	0.861
	0.9	0.25	0.932	0.074	0.823		0.9	0.18	0.943	0.084	0.937
	1.0	0.25	0.932	-0.003	-0.316		1.0	0.18	0.943	0.008	0.937
YC_DF3	0.0	0.51	0.977	-0.011	NA	YC_DF123	0.0	0.67	0.92	0.000	0.222
	0.1	0.51	0.977	-0.001	-0.111		0.1	0.67	0.920	0.002	0.222
	0.2	0.51	0.977	0.009	0.444		0.2	0.67	0.920	0.005	0.222
	0.3	0.51	0.977	0.019	0.630		0.3	0.67	0.920	0.007	0.222
	0.4	0.51	0.977	0.030	0.722		0.4	0.46	0.943	0.011	0.278
	0.5	0.51	0.977	0.040	0.778		0.5	0.46	0.943	0.023	0.444
	0.6	0.51	0.977	0.050	0.815		0.6	0.46	0.943	0.034	0.556
	0.7	0.51	0.977	0.060	0.841		0.7	0.46	0.943	0.045	0.635
	0.8	0.27	0.955	0.073	0.889		0.8	0.21	0.920	0.059	0.722
	0.9	0.27	0.955	0.085	0.949		0.9	0.21	0.920	0.073	0.810
	1.0	0.27	0.955	0.009	0.949		1.0	0.21	0.920	-0.003	-0.329



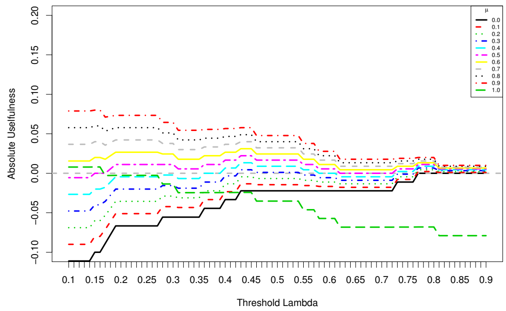
(a) YC



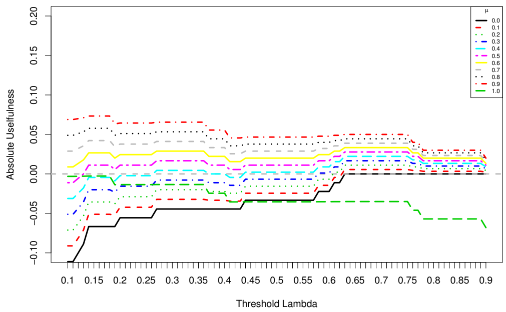
(b) YC_DF1



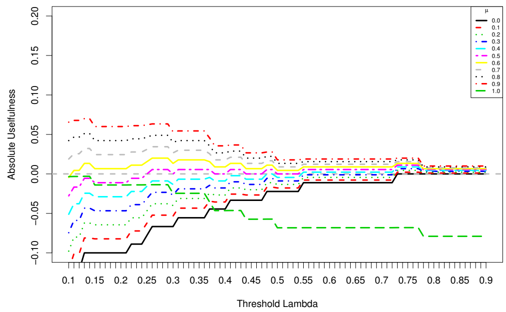
(c) YC_DF2



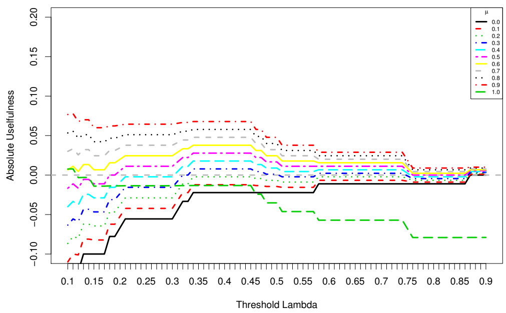
(d) YC_DF3



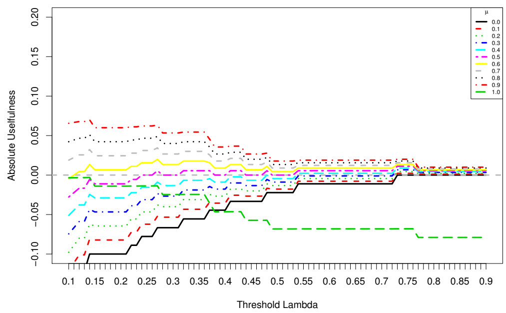
(e) YC_DF12



(f) YC_DF13

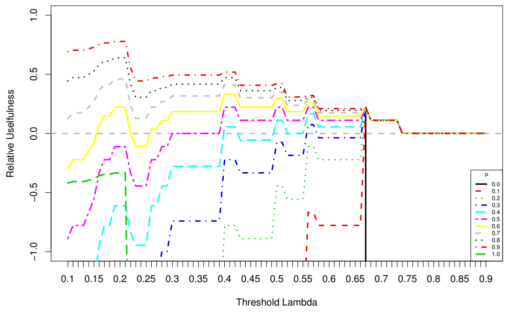


(g) YC_DF23

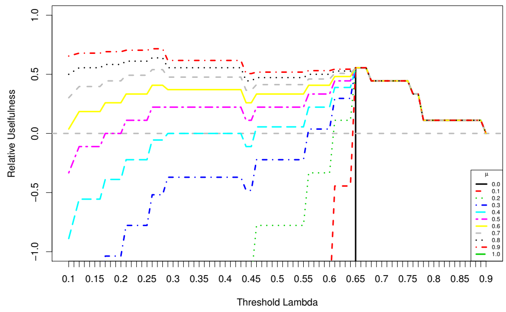


(h) YC_DF123

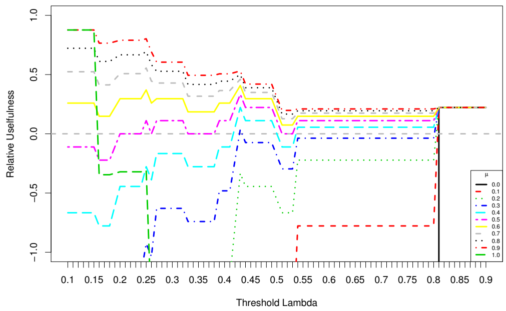
Figure 11: Absolute Usefulness. Two-Period-Ahead Forecast.



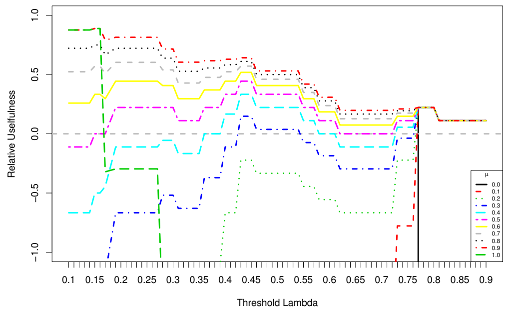
(a) YC



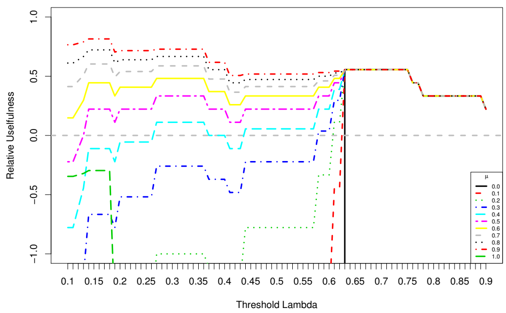
(b) YC_DF1



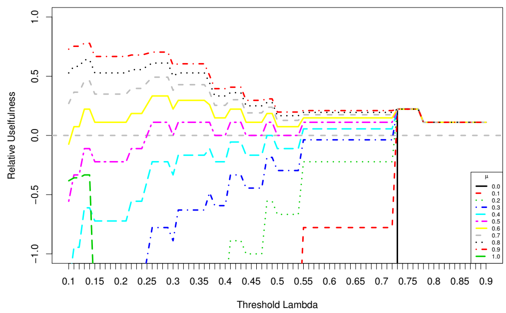
(c) YC_DF2



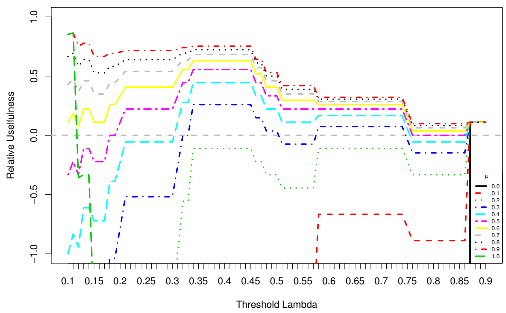
(d) YC_DF3



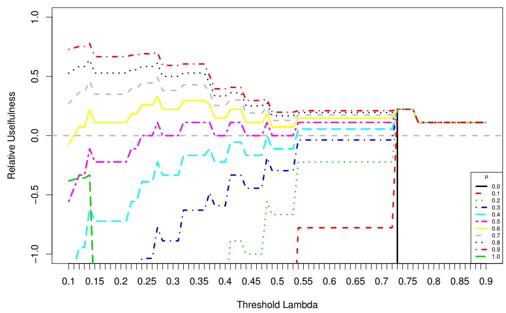
(e) YC_DF12



(f) YC_DF13

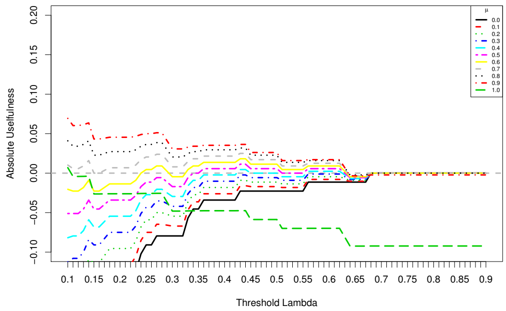


(g) YC_DF23

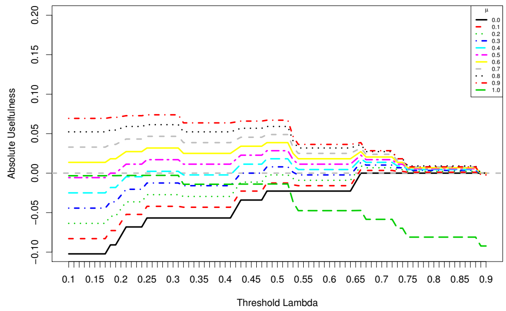


(h) YC_DF123

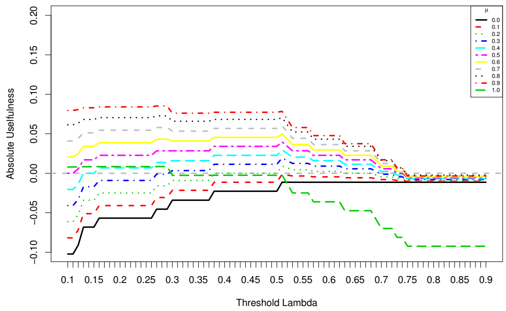
Figure 12: Relative Usefulness. Two-Period-Ahead Forecast.



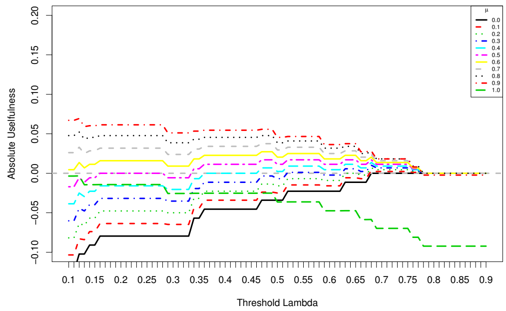
(a) YC



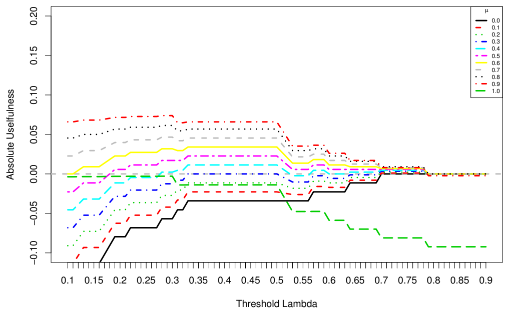
(b) YC_DF2



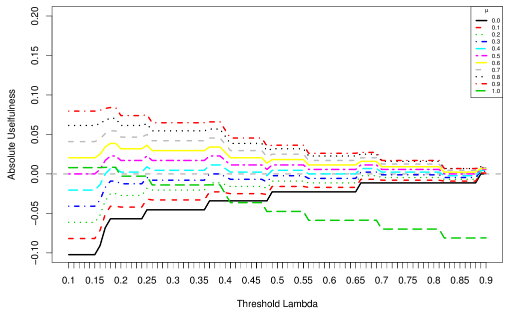
(c) YC_DF3



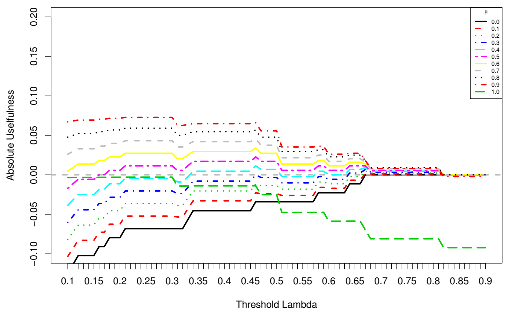
(d) YC_DF12



(e) YC_DF13



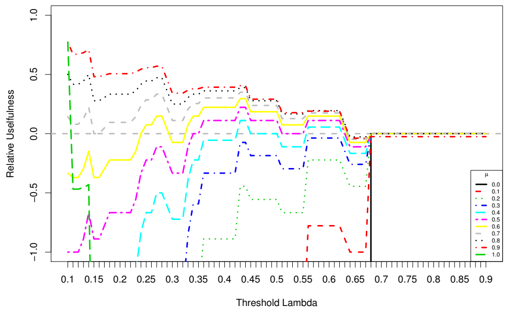
(f) YC_DF23



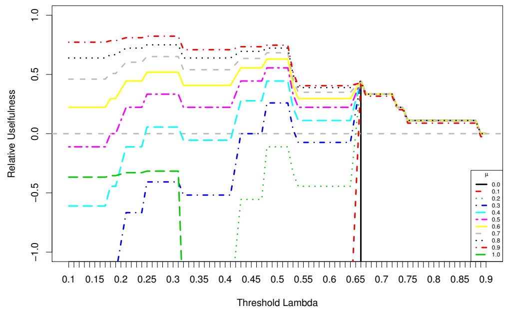
(g) YC_DF123

Figure 13: Absolute Usefulness. Three-Period-Ahead Forecast.

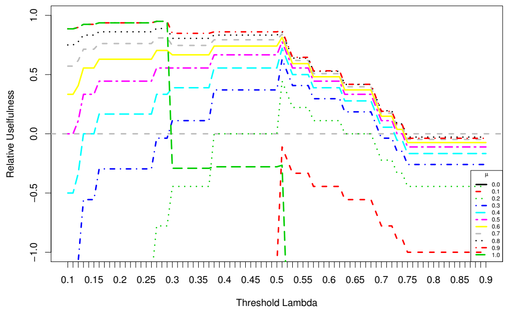
Note: The results for DF_1 are not included since all lags of the factors were insignificant and thus equal to the benchmark model (YC).



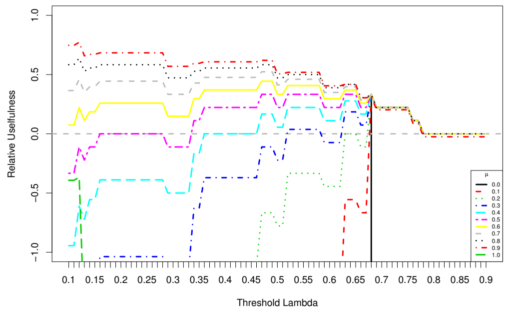
(a) YC



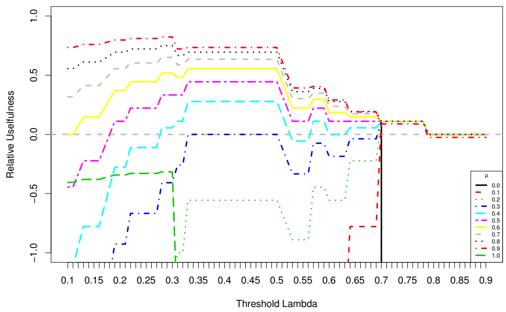
(b) YC_DF2



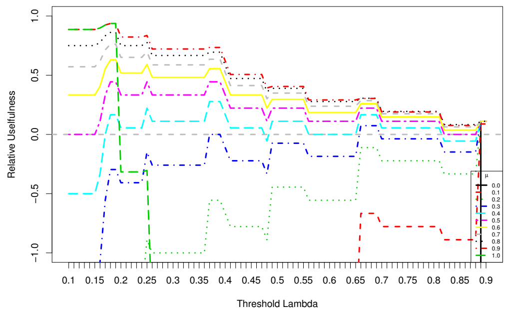
(c) YC_DF3



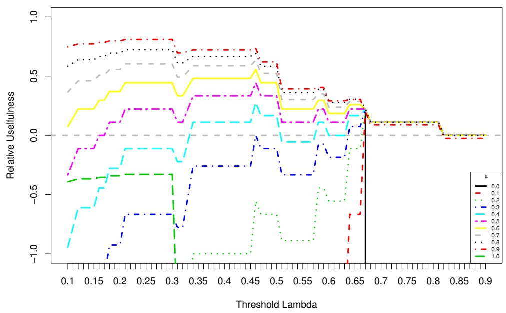
(d) YC_DF12



(e) YC_DF13



(f) YC_DF23



(g) YC_DF123

Figure 14: Relative Usefulness. Three-Period-Ahead Forecast.

Note: The results for DF_1 is not included since all lags of the factors were insignificant and thus equal to the benchmark model (YC).

B Data

Table 22: Interest rate data. The column "Trans." states which transformation was used on the particular time series: 0 = Levels, 1 = First Differences. The column "SA" indicates if the series was seasonally adjusted: 0 = Not seasonally adjusted; 1 = Seasonally adjusted.

#	Abbreviation	Variable Name	Unit	Source	Ticker	Calculation	Trans.	SA
		Interest Rates						
1	1y3mSpread	1y Treasury bond yield US / 3m Treasury bill yield Spread	%	FRED	DGS1	minus DTB3	0	0
2	2y3mSpread	2y Treasury bond yield US / 3m Treasury bill yield Spread	%	FRED	DGS2	minus DTB3	0	0
3	3y3mSpread	3y Treasury bond yield US / 3m Treasury bill yield Spread	%	FRED	DGS3	minus DTB3	0	0
4	5y3mSpread	5y Treasury bond yield US / 3m Treasury bill yield Spread	%	FRED	DGS5	minus DTB3	0	0
5	7y3mSpread	7y Treasury bond yield US / 3m Treasury bill yield Spread	%	FRED	DGS7	minus DTB3	0	0
6	10y3mSpread	10y Treasury bond yield US / 3m Treasury bill yield Spread	%	FRED	DGS10	minus DTB3	0	0
7	6m3mSpread	6m Treasury bill yield US / 3m Treasury bill yield US Spread	%	FRED	DTB6	minus DTB3	0	0
8	6mE3mESpread	6m Eurodollar deposit rate US / 3m Eurodollar deposit rate US Spread	%	FRED	DED6	minus DED3	0	0
9	TEDSpread	TED spread US	%	FRED	TEDRATE		0	0
10	3mLibFedSpread	3m Libor / Fed Funds spread US	%	FRED	USD3MTD156N	minus FEDFUNDS	0	0
11	FED3mSpread	FedFunds / 3monthTBill Spread	%	FRED	FEDFUNDS	minus DTB3	0	0
12	AAA10ySpread	AAA / 10y Treasury spread US	%	FRED	AAA10Y		0	0
13	BAA10ySpread	BAA / 10y Treasury spread US	%	FRED	BAA10Y		0	0
14	CarLoan2ySpread	Bank car loan rate 4y / 4y Treasury spread US	%	FRED	TERMCBAUTO48NS	minus (DGS3 + DGS5)/2	0	0
15	PersLoan2ySpread	Bank personal loan rate 2y / 2y Treasury spread US	%	FRED	TERMCBPER24NS	minus DGS2	0	0
16	BusLoansRate	Charge-Off Rate On Business Loans	%	FRED	CORBLACBS		0	1
17	MortgRate	Charge-Off Rate On Single Family Residential Mortgages	%	FRED	CORSFRMACBS		0	1
18	30yMort10ySpread	30y conv. mortgage rate / 10y Treasury bond spread US	%	FRED	MORTG	minus DGS10	0	0
19	SLOSLarge	FRB Senior loan officer survey: Net tightening of C&I loans to large firms	%	FRED	DRTSCILM		0	0
20	SLOSSmall	FRB Senior loan officer survey: Net tightening of C&I loans to small firms	%	FRED	DRTSCIS		0	0
21	SLOSSCons	FRB Senior loan officer survey: Net increased willingness to make consumer loans	%	FRED	DRIWCIL	times (-1)	0	0

Table 23: Indices and real variables. The column "Trans." states which transformation was used on the particular time series: 0 = Levels, 1 = First Differences. The column "SA" indicates if the series was seasonally adjusted: 0 = Not seasonally adjusted; 1 = Seasonally adjusted. * indicates that the series was transformed by taking their natural logarithms.

#	Abbreviation	Variable Name	Unit	Source	Ticker	Calculation	Trans.	SA
		Indices						
22	VIX	Implied volatility	Index Value	FRED	VIXCLS		0	0
23	MSHHGoodsSpread	Michigan Survey: Good/bad conditions for buying large HH goods spread US	Index Value	Uni. Michigan	N/A		0	0
24	MSHouseSpread	Michigan Survey: Good/bad conditions for buying houses spread US	Index Value	Uni. Michigan	N/A		0	0
25	MSAutoSpread	Michigan Survey: Good/bad conditions for buying autos spread US	Index Value	Uni. Michigan	N/A		0	0
		Real Variables						
26	M2NomGDP*	M2 / Nominal GDP	%	FRED	M2	over Nominal GDP	1	1
27	NBankCreditGDP	Total non-bank credit US / Nominal GDP	%	FRED	BCNSDODNS	over Nominal GDP	1	1
28	ConsCreditGDP	Consumer credit outstanding / Nominal GDP	%	FRED	TOTALSL	over Nominal GDP	1	1
29	ComMortgGDP	Commercial mortgages outstanding / Nominal GDP	%	FRED	ASCMA	over Nominal GDP	1	1
30	MortgFamGDP	Mortgages 1-4 family structures outstanding / Nominal GDP	%	FRED	ASMRMA	over Nominal GDP	1	1
31	FinaCreditLeverage	Total non-bank credit outstanding / Financial Business Credit outstanding	%	FRED	BCNSDODNS	over DODFS	1	1
32	CSNatHome	US S&P / Case-Shiller National Home Price Index SADJ	Index Value	Datastream	USCSHP.ME		1	1

Table 24: Summary Statistics of Original Data.

	Mean	SD	Median	Min	Max
1y3mSpread	0.346	0.264	0.295	-0.220	1.330
2y3mSpread	0.677	0.467	0.620	-0.300	1.880
3y3mSpread	0.919	0.594	0.950	-0.380	2.210
5y3mSpread	1.362	0.820	1.455	-0.460	2.970
7y3mSpread	1.697	0.957	1.795	-0.380	3.360
10y3mSpread	1.962	1.110	2.155	-0.450	3.700
6m3mSpread	0.091	0.087	0.070	-0.170	0.320
6mE3mESpread	0.119	0.127	0.130	-0.180	0.600
TEDSpread	0.465	0.276	0.420	0.150	1.420
3mLibFedSpread	0.245	0.165	0.224	-0.254	0.785
FED3mSpread	0.194	0.209	0.100	-0.110	0.780
AAA10ySpread	1.431	0.459	1.435	0.680	2.560
BAA10ySpread	2.350	0.704	2.230	1.370	5.490
CarLoan4ySpread	3.579	0.833	3.453	1.235	5.405
PersLoan2ySpread	8.984	1.094	9.115	6.430	10.810
BusLoansRate	0.776	0.627	0.540	0.120	2.530
MortgRate	0.475	0.643	0.170	0.060	2.370
30yMort10ySpread	1.653	0.293	1.615	1.210	2.640
SLOSLarge	2.580	18.950	-4.500	-24.100	55.400
SLOSSmall	1.985	14.332	-1.800	-24.100	42.300
SLOSCons	-8.625	10.568	-9.200	-29.300	22.600
VIX	19.317	6.317	17.470	11.030	45.000
MSHHGoodsSpread	147.571	17.512	151.000	98.000	175.000
MSHouseSpread	153.408	12.840	156.000	117.000	178.000
MSAutoSpread	136.122	11.555	136.000	99.000	159.000
M2NomGDP	0.001	0.009	0.001	-0.017	0.036
NBankCreditGDP	0.000	0.005	0.001	-0.011	0.010
ConsCreditGDP	0.001	0.002	0.001	-0.004	0.006
ComMortgGDP	0.001	2.349	0.321	-5.468	5.478
MortgFamGDP	0.113	0.679	0.182	-1.782	1.801
FinaCreditLeverage	-0.004	0.009	-0.004	-0.035	0.018
CSNatHome	0.987	2.379	0.730	-5.930	5.960

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