Essays on Nowcasting and Forecasting Business Cycles and Real Economy

by

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Essays on Nowcasting and Forecasting Business Cycles and Real Economy

Koç University

Graduate School of Social Sciences and Humanities

This is to certify that I have examined this copy of a doctoral dissertation by

Hamza Demircan

and have found that it is complete and satisfactory in all respects,

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To my wife

ABSTRACT

Essays on Nowcasting and Forecasting Business Cycles and Real Economy
Hamza Demircan
Doctor of Philosophy in Economics
April 21, 2020

This dissertation consists of two essays about nowcasting and forecasting business cycles and real economy. First essay is joint work with Asst. Prof. Cem Çakmaklı and Prof. Sumru Güler Altuğ and it proposes a unified framework for joint estimation of the indexes that can broadly capture economic and financial conditions together with their cyclical regimes of recession and expansion. We aim to estimate the time when the real economy enters a recession or a expansion in Turkish economy by the proposed framework. Second essay is joint work with Asst. Prof. Cem Çakmaklı and it formulates a nowcasting model by incorporating Survey of Professional Forecasters (SPF) for improving the density nowcasting of gross domestic product growth at monthly frequency using Bayesian methods for U.S. economy.

More specifically, first essay propose a method for real-time prediction of recessions using large sets of economic and financial variables with mixed frequencies. This method combines a dynamic factor model for the extraction of economic and financial conditions together with a tailored Markov regime switching specification for capturing their cyclical behavior. Departing from conventional methods estimating a single common cycle governing economic and financial conditions, or extracting economic and financial cycles in isolation of each other, the model allows for a common cycle which is reflected with potential phase shifts to the financial conditions estimated alongside with other parameters. This in turn provides timely recession predictions by making efficient modeling of the financial cycle systematically leading the business cycle. We examine the model using a mixed frequency ragged-edge dataset for Turkey in real-time. The results show evidence for the superior predictive power of our specification by signaling oncoming recessions (expansions) as early as 3.6 (3.0) months ahead of the actual realization.

In the second essay, we utilize a dynamic factor model with stochastic volatility specification for nowcasting U.S. gross domestic product by using the surveys conducted by the Federal Reserve Bank of Philadelphia. Specifically, our model produces now/forecasts of predictive densities that are aligned with survey expectations at different horizons, thereby integrating the predictive content of the survey expectations into the conventional dynamic factor model. We further incorporate a stochastic volatility structure into the baseline model to accommodate the changing volatility of the GDP growth, which also enables us to make use of the disagreement between individual forecasters as a proxy for uncertainty to provide more accurate density nowcasts. We provide results on the accuracy of nowcasts of U.S. GDP growth in a real-time exercise from 1977 through 2017. Comparison over different specifications through predictive likelihoods and probability integral transforms (PIT) reveals the improvements on predictive power of proposed specifications. This is due to the fact that the model adapts to the rapidly changing conditions much faster than the conventional specification thanks to the stochastic volatility structure and exploitation of data provided by SPF.

ÖZETÇE

Konjonktür Hareketleri ve Reel Ekonomi Anlık Tahmini ve Öngörüsü Üzerine Makaleler

Hamza Demircan
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21 April 2020

Bu doktora tezi, konjonktür hareketleri ve reel ekonomiyi anlık tahmin etme ve öngörüsünde bulunma üzerine iki makaleden oluşmaktadır. İlk makale, Yrd. Doç. Dr. Cem Çakmaklı ve Prof. Sumru Güler Altuğ ile ortak çalışma olup, ekonomik ve finansal koşulları, döngüsel daralma ve büyüme rejimleriyle birlikte yakalayabilen endekslerin ortak tahmini için birleşik bir çerçeve önermektedir. Önerilen çerçeve ile Türkiye ekonomisinde reel ekonominin bir daralma ya da genişlemeye girdiği zamanı tahmin etmeyi amaçlamaktayız. İkinci makale, Yrd. Doç. Dr. Cem Çakmaklı ile ortak çalışma olup, ABD ekonomisi için Bayesyen yöntemleri kullanarak gayri safi yurtiçi hasıla büyüme oranının yoğunluğunu aylık frekansta anlık tahminini geliştirmek için Profesyonel Tahminciler Anketini (PTA) dahil eden anlık tahmin modeli oluşturmaktadır.

Daha ayrıntılı olarak, birinci makale karma frekanslarda olan geniş bir ekonomik ve finansal değişkenler kümesini kullanarak daralmaların gerçek zamanlı tahmini için bir yöntem önermektedir. Bu yöntem, ekonomik ve finansal koşulların çıkarılması için dinamik faktör modelini, döngüsel davranışları yakalamak için özel bir Markov rejim değiştirme spesifikasyonu ile birleştirmektedir. Model, ekonomik ve finansal koşulları yöneten tek bir ortak döngüyü tahmin eden veya ekonomik ve finansal döngüleri birbirinden izole ederek çıkaran geleneksel yöntemlerden yola çıkarak, diğer parametrelerle birlikte tahmin edilen finansal koşulların potansiyel faz kaymaları ile birlikte yansıdığı ortak bir döngüye izin vermektedir. Bu da, sistematik olarak konjonktür dalgalanmalarına öncülük eden finansal döngülerin verimli bir şekilde modellenmesiyle zamanında daralma tahminleri sağlamaktadır. Modeli, Türkiye için gerçek zamanlı olarak (farklı) karma frekanslı düzensiz kenarlı veri seti kullanarak incelemekteyiz. Sonuçlar, yaklaşmakta olan daralmaları (büyümeleri)

gerçekleşmesinden 3.6 (3.0) ay kadar erken bir zamanda bildirerek spesifikasyonumuzun üstün öngörü gücüne ilişkin kanıtlar sunmaktadır.

İkinci makalede, ABD gayri safi yurtiçi hasılasının anlık tahmini için Philadelphia Merkez Bankası tarafından yürütülen anketler ile birlikte stokastik volatilite spesifikasyonuna sahip dinamik bir faktör modeli kullanmaktayız. Daha ayrıntılı olarak, modelimiz farklı ufuklardaki anket beklentileriyle uyumlu tahmini yoğunlukların anlık ve ileriye dönük tahminlerini üretmektedir ve böylece anket beklentilerinin tahmin içeriğini geleneksel dinamik faktör modeline entegre etmektedir. GSYİH büyümesinin değişen volatilitesine uyum sağlamak için temel modele stokastik volatilite yapısı da eklemekteyiz, bu da daha kesin yoğunluk tahmini sağlamak için bireysel tahminciler arasındaki anlaşmazlığı belirsizlik için temsil edici olarak kullanmamızı sağlamaktadır. 1977'den 2017'e kadar gerçek zamanlı uygulamada ABD GSYİH büyümesinin anlık tahminlerinin doğruluğu hakkında sonuçlar çıkarmaktayız. Öngörücü olabilirlik ve Olasılık İntegral Dönüşümleri (OİD) ile farklı spesifikasyonlara göre karşılaştırma, önerilen spesifikasyonların tahmin gücü üzerindeki gelişmelerini ortaya koymaktadır. Bu gelişmenin nedeni, modelin stokastik volatilite yapısı ve PTA tarafından sağlanan verilerin kullanılması sayesinde hızla değişen koşullara geleneksel spesifikasyona göre çok daha hızlı adapte olmasıdır.

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ABBREVIATIONS

ABD	Amerika Birleşik Devletleri
ADL	Auto-regressive Distributed Lag
AIC	Akaike Information Criterion
AR(p)	Autoregression of order p
ASA	American Statistical Association
BBQ	Bry-Boschan Quarterly
BC	Business Cycle
BCDC	Business Cycle Dating Committee
BIST	Borsa Istanbul
BMF	Bayesian Mixed Frequency
CBOE	Chicago Board Options Exchange
CBRT	Central Bank of the Republic of Turkey
CEI	Coincident Economic Index
DFM	Dynamic Factor Model
EU	European Union
FCI	Financial Conditions Index
FED	Federal Reserve System
GDP	Gross Dometic Product
GNP	Gross National Product
GSYİH	Gayri Safi Yurtiçi Hasıla
HAC-DM	Heteroscedasticity and Autocorrelation Consistent Diebold-Mariano Test
HLN	Harvey, Leybourne, and Newbold Test
HPDI	Highest Posterior Density Interval

IP	Industrial Production
IS	Imperfect Synchronization
JP Morgan	John Pierpont Morgan
LIBOR	London Inter-Bank Offered Rate
M	Monthly
MCMC	Markov chain Monte Carlo
MH	Metropolis Hastings
MSCI	Morgan Stanley Capital International
MS-DFM	Markov regime Switching Dynamic Factor Model
MSFE	Mean Squared Forecast Error
MS-VAR	Markov regime Switching Vector Autoregression
NBER	National Bureau of Economic Research
NSA	Not Seasonally Adjusted
OİD	Olasılık İntegral Dönüşümleri
PIT	Probability Integral Transform
PMI	Purchasing Manager Index
PS	Perfect Synchronization
PTA	Profesyonel Tahminciler Anketi
Q	Quarterly
RMSE	Root Mean Squared Error
RMSFE	Root Mean Squared Forecast Error
RTDSM	Real-time Data Set for Macroeconomists
SA	Seasonally Adjusted
SPF	Survey of Professional Forecasters
SPF-M	The model with only SPF Mean
SV	Stochastic Volatility
SV-SPF-M	The model with Stochastic Volatility and SPF Mean
SV-SPF-MV	The model with Stochastic Volatility and both SPF Mean and Variance

SV-SPF-V	The model with Stochastic Volatility and SPF Variance
TED	Treasury Bill and ED, the ticker symbol for the Eurodollar futures contract
TPFE	Turning Point Forecast Errors
US	United States
VAR	Vector-Autoregression

Chapter 1

INTRODUCTION

Monitoring business activity for anticipating economic downturns in a timely manner is of key importance for economic agents. To this end, various econometric methods have been proposed to generate indicators of business conditions using large datasets. These typically involve modeling the co-movement of a large number of variables using econometric models extracting joint behavior, in other words factor models, conformable with the notion of a common cycle with distinct dynamics in economic expansions and contractions.

The recent global recession together with its underlying financial roots have made understanding the impact of financial conditions on real activity a key requirement for timely predictions of business cycle turning points. Therefore, on top of the conventional economic variables several financial series, that are available in real-time, are key variables in factor models for measuring business conditions. Typically, there are two polar cases for the use of economic and financial variables in econometric models to extract the common behavior in these series. On the one hand, conventional practice typically merge economic variables, often released with a delay, with timely available financial variables to extract the single common cyclical behavior in real-time, see for example [Aruoba et al., 2009, Doz and Petronevich, 2016]. On the other hand, economic and financial indicators are measured in isolation of each other leading distinct cycles for economic and financial conditions, see for example [Chauvet and Piger, 2008, Camacho et al., 2018], among others, for timely measurement of economic conditions and [Hatzius et al., 2010, Koop and Korobilis, 2014, Galati et al., 2016], among others, for measuring financial conditions.

However, neither joint nor independent modeling of cyclical behavior in economic and financial variables might be appropriate for timely predictions of economic downturns. Financial conditions typically are closely tied to the economic conditions but they presage these conditions due to the forward looking behavior of many financial variables, essentially implying an intermediary case. In the first essay, we focus on this intermediary case. Specifically, we propose an econometric model for estimation of economic and financial conditions that are governed by a common cycle, or put differently the business cycle, that is reflected in the cycle of the financial conditions potentially with phase shifts. This implies that we allow for the financial cycle to lead/lag the business cycle in a systematic way when estimating economic and financial conditions and thereby predicting recessions in real-time. This specification combines a dynamic factor model to extract economic and financial factors/conditions together with a Markov regime switching dynamics allowing for phase shifts between cyclical regimes of these factors. This, in turn, facilitates the inference of economic and financial indicators with a more precise estimation of the turning points of these indicators. Therefore, our model enables us to efficiently exploit a rich dataset of economic and financial variables for predicting economic downturns accurately in real-time.

We examine the efficacy of this approach in a key emerging economy, Turkey, where, unlike the US, neither an official business cycle dating procedure, nor widely accepted indicators of economic and financial conditions are available as it is the case in many other emerging or developed markets. Using our framework, we construct probabilities of recessions together with indicators of economic and financial conditions for Turkey.[1] We use a mixed frequency dataset with different time spans (for the earliest case) starting from January 1999 until November 2019, i.e. the data that are available to us as of the first week of December 2019. The results indicate that the financial indicator enters recessions (expansions), on average, 3.6 (3.0) months earlier than the recession (expansion) for the economic indicator. A re-

[1] Earlier studies on developing leading and coincident indicators for Turkey include [Atabek et al., 2005] who construct a composite leading indicator for the Turkish economy and [Aruoba and Sarikaya, 2013] who develop a monthly indicator of real economic activity using multiple indicators at mixed frequencies by employing the dynamic factor model proposed in [Aruoba et al., 2009].

cursive forecasting exercise in real-time shows that the proposed model can predict cyclical downturns in a more timely manner compared to a model with independent cycles and to a model with a single common cycle. Moreover, by virtue of the joint modeling of economic and financial indicators, the (mostly short-lasting) downturns observed only in financial conditions are not necessarily labeled as recessions, thereby eliminating false signals of recessions. Finally, our results indicate that Turkey entered a recession in August 2018 that is still ongoing, a finding not picked up by the model with independent cycles.

Following the seminal paper of [Stock and Watson, 1989] who construct a monthly coincident indicator of (US) real activity summarizing the behavior of key macroeconomic series, dynamic factor models have been the major workhorse of the empirical research on business cycles. [Chauvet, 1998], [Kim and Nelson, 1998], among others, integrate the Markov mixture structure proposed by [Hamilton, 1989] into the dynamic factor structure to capture the distinct dynamics of the different phases of the business cycle, i.e. expansions and recessions. A recent generation of factor models exploits larger datasets focusing on real-time prediction of economic conditions using economic and financial variables with mixed frequencies, see [Aruoba et al., 2009] among others. A similar approach is followed by [Banbura et al., 2013] for 'nowcasting' GDP using multiple factors.

The empirical research on the link between economic and financial conditions has experienced a surge following the great recession of 2008.[2] This global crisis has demonstrated that developments in financial markets may have a significant impact on the overall functioning of the economic system by deepening the link between financial and economic conditions; see [Gourinchas and Obstfeld, 2012, Borio, 2012], among others. Moreover, financial prices bear timely information on future economic conditions as they incorporate market expectations of future price and output development. Consequently, understanding the behavior of key financial variables such as credit, asset prices, their volatilities, interest rate spreads, and risk indicators of various sorts and establishing their link with economic conditions

[2]See [Kaminsky and Reinhart, 1999] for an earlier analysis.

has gained importance; see [Claessens et al., 2012] for an extensive analysis on the cyclical behavior of these variables. Therefore, several financial conditions indexes (FCI) have been developed using such key financial variables to examine the role of financial factors in determining future real activity.[3]

The approach used in the first work is related to [Koopman et al., 2016] who consider a dynamic factor model for extracting economic and financial cycles governing several economic and financial variables. Since factor dynamics are modeled using trigonometric specifications in their framework, one still needs to identify the regimes for the estimated cycles in order to capture phase shifts in recessions and expansions. Our motivation for adopting discrete Markov regime switching dynamic factor model (MS-DFM) is that the conventional discrete turning point approach is intrinsically embedded in these models, which also enables us to estimate distinct phase shifts between the economic and financial cycles. [Billio and Petronevich, 2017] consider such interactions of economic and financial cycles using the MS-DFM framework. Extending the Markov dynamics of the business cycle, they allow for the cyclical regimes embedded in the economic factor to depend on the first lag of the cyclical component of the financial factor. In our specification, rather than using only the first lag, we explicitly estimate the amount of the phase shifts which is allowed to differ during recessions and expansions along with other model parameters. Finally, [Hamilton and Perez-Quiros, 1996, Paap et al., 2009] and [Çakmaklı et al., 2013] provide a similar approach using the MS-VAR model framework allowing for distinct phase shifts in the timing of multiple cyclical regimes using 'observed' indicators that are not available in real-time. In the first study, we integrate this approach into the DFM framework by making use of a large set of economic and financial variables at mixed frequencies to obtain real-time (i) predictions of recessions and (ii) estimates of economic and financial conditions.

Assessing the current economic condition in real-time is of central importance to economic agents, especially for policy-makers for conducting economic policy

[3] See also [Hatzius et al., 2010], who provide an extensive review and a comparison of alternative indexes that are available for the US and the EU and [Wacker et al., 2012] for an application to major non-Euro Area economies.

and can be done by following other strategies such as directly observing Gross domestic product (GDP) rather than the predictions of recessions and estimates of economic and financial conditions. However, GDP are released with a long delay and revised for several times and collected on a quarterly basis. As a consequence, business, finance, and policy communities want accurate estimates of such indicators for making decisions in real-time. Developing models for predicting the near future, current state and recent past of the economy, i.e. GDP nowcasting, has been drawing substantial interest in the literature.

Most of the literature on nowcasting has been focusing on developing models that produce point forecast of the conditional mean of GDP growth and improve the accuracy of the models in terms of mean squared errors, see [Evans, 2005] and [Kuzin et al., 2011] among others. However, such point forecast contains no information about the associated uncertainty and may give misleading picture of the state of the economy, especially in an environment characterized by high degree of macroeconomic volatility, such as in the recession periods or as the data-generating process changes. This naturally leads to question the reliability of the point forecasts. Furthermore, experiences with macroeconomic forecasting in an environment characterized by high level of uncertainty has underlined the deficiency of point forecasts for forward-looking policy implications and the importance of the information on the risks surrounding the economic outlook[4]. This has been demonstrated by the increasing number of Central Banks that have started publishing fan-charts and confidence bands around their forecasts of inflation and output for the sake of transparency (e.g. Bank of England[5], Norges Bank, South Africa Reserve, Bank of Canada, the Bank of Italy the US Fed and Central Bank of the Republic of Turkey among others).

To this end, density nowcast is an estimate of the probability distribution which

[4]See [Diebold et al., 1998], [Tay and Wallis, 2000], [Garratt et al., 2003] and [Granger and Pesaran, 2000] for an earlier discussion of the importance for providing measures of uncertainty around the point forecast.

[5]For the first time, it was the Bank of England that had started publication of fan charts in 1996.

can provide appropriate characterizations of uncertainty, thus informs the economic agents about the risks in using nowcast, see [Gneiting, 2011] for further elaboration about the difference between the point and density forecasting. Any types of measures of risk and uncertainty, e.g. volatility, as measured by the variance, can be extracted from the density nowcast. In the second essay, our aim is to produce full distribution of real GDP growth by utilizing SPF data. Specifically, we nowcast density of real GDP growth in a econometric model that combines the expectations on survey of professional forecasters and model based predictions over the period 1968-2018.

We evaulate the model in a recursive pseudo real-time exercise over the period 1977-2018. We update the density nowcasts for every new data release during a quarter at the end of the months. We provide results on the accuracy of the density nowcasts of real GDP growth of U.S. by showing logarithmic scores of the predictive densities and probability integral transforms (PIT) over different specifications with both five hard variables considered by (NBER's Business Cycle Dating Committee) BCDC and seventeen variables used in [Banbura et al., 2013]. It turns out that in terms of density forecasts our proposed specifications improves substantially on stochastic volatility specification and integration with SPF for both datasets.

Our choice of Survey of Professional Forecasters (SPF) among other surveys for real activity in the United States is motivated by several reasons. The SPF done by the Federal Reserve Bank of Philadelphia has the longest history providing releases nowcasts and forecasts of US economic activity indicators, such as GDP, for up to four quarters ahead in the middle of each quarter. On top of its availability, the SPF is regarded as challenging to outperform for its real-time predictive accuracy and has widely been used as benchmark to make comparisons in the literature, see [Giannone et al., 2008], [Banbura et al., 2013], [Carriero et al., 2015] and [McCracken et al., 2015] among others. Furthermore, [D'Agostino and Schnatz, 2012] provides a comparative analysis of the performance of surveys including SPF on real activity with a long history in a real-time out-of-sample comparison exercise over a long sample period of 1968-2011. They conclude that SPF conveys valuable information for assessing current economic conditions. [Ang et al., 2007] and [Faust and Wright, 2013] present evidence that survey of professional forecasters or forecasts based on the judgement of the central bankers usually gives useful information besides that contained in statistical models, whereas [Campbell, 2007] and [D'agostino et al., 2012] claims the SPF improves and complements the forecasts made by macro models.

Further exploitation of surveys beyond aggregate expectations is to measure uncertainty through micro data at individual level. The dispersion of cross-sectional forecasts in the surveys reflects the disagreement level amongst forecasters. A rise in dispersion reflects that economic agents disagree more, which leads an increase in uncertainty. [Conflitti, 2011] consider several measures of uncertainty and disagreement at both aggregate and individual level by using the European SPF and claims that disagreement is a component of the aggregate uncertainty, which can be defined as the sum of the average of forecasters' variances and the variance of forecasters' mean.[6] [Bachmann et al., 2013] utilizes micro data of business surveys of US and Germany to make comparison between the measure of uncertainty derived from disagreement among forecasters and the forecast standard errors of production expectations and provides supporting evidence that forecast disagreement is a good proxy for uncertainty level. [Bloom, 2014] examine the SPF data between 1968-2012 and uses disagreement amongst professional forecasters as a proxy of uncertainty. He shows that in recessionary periods, the variance across forecasts of industrial production growth was higher about 64 percent. [Baker et al., 2016] develops an economic policy uncertainty index based on the weighted average of text scans of the top ten American newspapers for dispersions of survey responses related to economic policies. All these studies justifies our choice of using disagreement among forecasters as a proxy for uncertainty in the stochastic volatility framework.

SPF are released at quarterly frequency as output, which is a crucial disadvantage. Although they provide timely information, giving expectations about the current quarter as opposed to hard data, they suffer from infrequent releases. [Ghy-

[6] See [Grishchenko et al., 2017] for further details.

sels and Wright, 2009] construct forecasts at daily frequency of upcoming survey releases using asset price data in order to measure the effects of events and news announcements on expectations from both the Consensus Forecasts and SPF. They use daily estimated surveys to forecast several macroeconomic variables. In our framework, we produces monthly factor by DFM using both macroeconomic variables and SPF, thus make it possible to combine the information of monthly releases of macroeconomic variables and quarterly releases of SPF and output.

To place our proposed methodology within the literature, we combine two approaches: i) nowcasting by matching the model-based forecasts with the distribution of the surveys, which is generally incorporated by entropic tilting in a VAR specification, ii) nowcasting using dynamic factor model with stochastic volatility. This is achievable in the state space representation via the Kalman filter, which generates projections for the GDP growth and its variance in a stochastic volatility structure and therefore allows us to integrate the first two moments of survey of professional forecasters and the model based expectations in a coherent manner. Similar approach for using Kalman Filter projections to match survey information have been used in [Altug and Çakmaklı, 2016], who construct a local linear trend model for providing inflation forecasting that incorporates survey based expectations within statistical predictive model in the state space framework for two emerging economies, Brazil and Turkey.

To incorporate the surveys distributions into the models, [Krüger et al., 2017] consider entropic tilting to improve macroeconomic density forecasts by using external nowcasts from the surveys. Specifically, they combine the medium-term forecasts from Bayesian VAR(BVAR) with short-term nowcasts from the surveys by tilting not only the means but also the variances. [Tallman and Zaman, 2019] extends this study in terms of horizons by tilting the medium to long horizon forecasts derived from VARs to match the long-horizon forecast of the SPF. They claim meaningful improvements in forecast accuracy for incorporating long-term survey expectations. [Altavilla et al., 2017] also use relative entropy to tilt forecasts of the yield curve from the term structure models to match survey expectations. Our model differs from these studies since we use DFM to extract common factor from macroeconomic variables and at the same time matching the forecasts with survey conditions.

Another related study is [Clark et al., 2018] who develops a multiple-horizon specification of stochastic volatility for forecast errors to model time-varying uncertainty from sources such as the SPF, the Blue Chip Consensus and the Fed's Greenbook. They compute the time-varying conditional variance of forecast errors at any horizon of interested variables including real GDP growth for the purpose of improving the accuracy of uncertainty estimates around the forecasts. The most similar methodology used in [Grishchenko et al., 2017], who constructs a dynamic factor model with stochastic volatility that produces survey-consistent distributions of inflation at multiple horizons, except their aim was not nowcasting, accordingly they did not use other macroeconomic variables containing informations about the variable to be forecasted, but they use DFM to show commonalities between inflation dynamics and interconnectedness amongst developed economies. Using inflation forecasts of SPF for various horizons, at varying frequencies and with different definitions, they drive the dynamics of inflation rates in both U.S. and euro-area economies.

In a broader point of view to the nowcasting models of classes, DFMs has been widely used to summarize the information contained large datasets for nowcasting by modelling both the high frequency and low frequency in the same framework, see [Giannone et al., 2008] and [Bok et al., 2018]. [Banbura et al., 2013] classify this as "full system models", including mixed frequency VARs[7], whereas the models are constructed according to low frequency variable as "partial models", including bridge equation and MIDAS models. Among these nowcasting methodologies, [Aastveit et al., 2014] uses there of these classes, namely bridge equation models, DFMs, and MF-VAR models to produce combined density nowcast by weighting through log scores for the predictive densities for each model. As an another partial model, Bayesian vector autoregressions(BVARs) with shrinkage has been become as an alternative to DFMs in capturing the relative information using large datasets for monitoring macroeconomic conditions in real-time (see e.g. [Koop, 2013], [Carriero

[7] see e.g. [Giannone et al., 2009] and [Mariano and Murasawa, 2010] among others.

et al., 2015] and [Bańbura et al., 2010]). In this work, we uses the DFM framework falling in the "full system models", because modelling at the high frequency and linking with low frequency variable jointly enables us to produce survey consistent density nowcast.

I continue with the details of the model and the results for the first essay in Chapter 2. In Chapter 3, I give the modeling approach for nowcasting GDP and corresponding findings. Finally, I conclude in Chapter 4. I give more details about the models and the findings in Appendix A to Q.

Chapter 2

MODELING OF ECONOMIC AND FINANCIAL CONDITIONS FOR REAL-TIME PREDICTION OF RECESSIONS

This chapter gives the details about the first essay, the real time prediction of recessions by constructing two indexes summarizing the financial and economic conditions in an unified framework. We employ this framework for Turkish economy, but one can implement the model for other emerging economies and\or developed economies by taking the characteristics of the data into account. The flow of this chapter is as follows. Section 2.1 presents the model. 2.2 presents the data and how we select the variables to be used in the model. Section 2.3 describes the estimation approach. Section 2.4 presents the empirical results and discusses forecasting in real-time. We leave the details of the data and variable selection results to Appendix A and B, details of the model including the state space representation of the model, likelihood function and prior distributions to Appendix C, the posterior inference including simulation scheme and conditional posterior distributions to Appendix D, the results of competing models to Appendix E and robustness checks of the model specifications to Appendix F, H, I and J.

2.1 *The Model*

In this section, we present the dynamic factor model for the extraction of the economic conditions, or in other words, coincident economic index (CEI) and financial conditions index (FCI) from a broad set of mixed frequency variables. The cyclical phases of these indicators, i.e. recessions and expansions, are captured by a single Markov process. However, we allow these phases of the business cycle for being transmitted to the financial conditions with certain phase shifts.

Let $y_{i,t}$ denote the growth rate of the i^{th} variable in period t for $i = 1, \ldots, N$ and $t = 1, \ldots, T$. We assume that these are driven by (the growth rates of) the economic and financial factors, denoted as $f_t = (f_{1,t}, f_{2,t})'$, that are common across all variables and idiosyncratic factors, denoted as $\varepsilon_{i,t}$. The resulting specification is as follows

$$y_{i,t} = \gamma_{i,1} + \lambda_i f_t + \varepsilon_{i,t}, \tag{2.1}$$

where $\lambda_i = (\lambda_{1,i}, \lambda_{2,i})'$ are the loadings of the i^{th} variable, $y_{i,t}$, on the common factors, f_t. We allow the idiosyncratic component to follow an autoregressive process as

$$\psi_i(L)\varepsilon_{it} = \epsilon_{i,t}. \tag{2.2}$$

For now, we do not specify the evolution of the common factors explicitly, but we return to this in detail below.

The fact that we use a broad dataset involving stock and flow variables with missing observations implies some care in the handling of the data. Here we follow the practice in [Banbura et al., 2013] to match the monthly factors together with lower frequency stock and flow data and we refer to [Banbura et al., 2013] for details. Departing from the similar specifications as in [Aruoba et al., 2009] and [Banbura et al., 2013] we add two modifications to the general framework to capture the characteristics specific to emerging markets. First, as is the case for many emerging economies during the 2000s, Turkey experienced a normalization in its macroeconomic environment following the major financial and banking crisis of 2000-1. To capture this normalization, we allow for a single structural break in the variances of the variables as

$$\sigma^2_{i,t} = \sigma^2_{i,1}\, \mathbb{I}\left[t \leq \tau\right] + \sigma^2_{i,2}\, \mathbb{I}\left[t > \tau\right], \tag{2.3}$$

where τ is the period of the structural break to be estimated and $\mathbb{I}[.]$ denotes the indicator function, which takes the value 1 if the condition in brackets is true and 0 otherwise.[1]

Second, data for emerging market economies often embrace more aberrant observations compared to those for developed economies with deeper financial markets. Considering this, we model the distribution of the variables, $\epsilon_{i,t}$ with a t-distribution with variance $\sigma^2_{i,t}$ and ν degrees freedom. We note that the t-distribution with ν degrees of freedom is essentially a scale mixture of the normal distribution as follows:

$$\epsilon_{i,t} = \xi_t^{-1/2}\sigma_{i,t}\zeta_t, \tag{2.4}$$

where ζ_t follows a standard normal distribution. When ξ_t follows a Gamma distribution with $\Gamma(\frac{\nu}{2}, \frac{\nu}{2})$, then $\epsilon_{i,t}$ follows a Student's t-distribution with ν degrees of freedom and accordingly $\epsilon_{i,t}|\xi_t \sim N(0, \sigma^2_{i,t}/\xi_t)$.[2]

Next, we proceed with the specification of the evolution of factors, f_t, which are comprised by (the growth rate of) the coincident economic and financial conditions indexes. We specify an autoregressive process for the factors with intercept parameter depending on the cyclical regime of the corresponding factor. Specifically, in case of first-order autoregressive dynamics for the factors, our assumptions imply the model specification

$$f_t = \alpha_{\mathbb{S}_t} + \delta + \Phi f_{t-1} + \eta_t \quad \eta_t \sim N(0, \Sigma), \tag{2.5}$$

where

$$f_t = \begin{pmatrix} f_{1,t} \\ f_{2,t} \end{pmatrix}, \mathbb{S}_t = \begin{pmatrix} S_{1,t} \\ S_{2,t} \end{pmatrix}, \alpha_{\mathbb{S}_t} = \begin{pmatrix} \alpha_{1,S_{1,t}} \\ \alpha_{2,S_{2,t}} \end{pmatrix}, \eta_t = \begin{pmatrix} \eta_{1,t} \\ \eta_{2,t} \end{pmatrix}, \Phi = \begin{pmatrix} \phi_{1,1} & \phi_{1,2} \\ \phi_{2,1} & \phi_{2,2} \end{pmatrix}, \Sigma = \begin{pmatrix} \sigma^2_{f_1} & \sigma_{1,2} \\ \sigma_{2,1} & \sigma^2_{f_2} \end{pmatrix}.$$

[1] We also estimate models, where we allow for a structural break only in the factor error variances and where we allow for structural breaks both in the variances of error terms of factors as well observables. The results indicate that the break is estimated most precisely for the variances in the error terms of the observables, while the distribution of the break point parameters for the factor error variances is quite flat.

[2] See [Geweke, 2005] for a textbook exposition.

Here $S_{l,t}$, $l = 1, 2$ are latent binomial variables taking the value 0 (1), if $f_{l,t}$ is in expansion (recession) at time t representing the cyclical regimes embedded in economic and financial factors. $\delta = (\delta_1, \delta_2)'$ is a function of the long-run growth rates of the factors which are constant over time while $\alpha_{\mathbb{S}_t}$ varies cyclically depending on whether the economy is in a recession or expansion. We assume that $S_{1,t}$ and $S_{2,t}$ are governed by the first-order Markov processes with transition probabilities as

$$\begin{aligned} Pr(S_{l,t} = 0 \mid S_{l,t-1} = 0) &= q_l \\ Pr(S_{l,t} = 1 \mid S_{l,t-1} = 1) &= p_l \quad \text{for } l = 1, 2. \end{aligned} \tag{2.6}$$

Define $\alpha_{\mathbf{i}} = \alpha_{\mathbb{S}_t = i}$ for $i = 0, 1$. In line with the regime specifications as expansion and recession, we restrict the vector of state-dependent means as $\alpha_{\mathbf{0}} > \alpha_{\mathbf{1}}$.

Next, to implement the joint estimation of the factors, we need to specify the intertemporal links between the cyclical dynamics of the growth rates of the CEI and the FCI. Without loss of generality, we assume that $f_{1,t}$, i.e. the (growth rate of the) CEI, is the 'reference series' and we define the properties of $S_{2,t}$, the regime indicator of $f_{2,t}$, i.e. the (growth rate of the) FCI, relative to $S_{1,t}$. Different specifications of the relation between the two Markov processes $S_{1,t}$ and $S_{2,t}$ imply different types of relations between the cycles of the two indicators. We start the analysis with two polar cases. First, we assume that the cycles embedded in economic and financial conditions are independent. In this case, the probability of both cycles to be in the same phase is simply the cross products of marginal probabilities. In the second polar case, we assume that the cycles in both indicators are identical, that is,

$$S_{2,t} = S_{1,t}, \tag{2.7}$$

essentially implying a single cycle. Following [Harding and Pagan, 2006], we refer to this case as 'perfect synchronization' (PS).

In practice, the relation between the cycles governing economic and financial conditions may not be perfect. In fact, as stated in [Hatzius et al., 2010], financial conditions often lead the business cycle. Following [Paap et al., 2009] and [Çakmaklı et al., 2011], we model the intermediary cases to allow for the cycle in the FCI to lead/lag the cycle in the CEI by $\kappa_{S_{1,t}}$ periods, i.e.

$$S_{2,t-\kappa_{S_{1,t}}} = S_{1,t}. \tag{2.8}$$

This implies that to specify the cycle in the FCI, we assume that the regime indicator $S_{1,t}$ itself is shifted but we allow the amount of the phase shift to differ across expansions and recessions of the CEI. The subscript $S_{1,t}$ to κ indicates that the regime indicator is shifted by a possibly different number of time periods for each regime. Hence, this specification involves a separate regime shift parameter κ_j for expansions and recessions for $j = 0, 1$. To put things differently, we assume that the lead/lag time is different per regime, such that each regime in the other series starts later or earlier by $\kappa_j, j = 0, 1$ periods. This specification is denoted as 'imperfect synchronization' of the cycles with regime dependent phase shifts (IS).

Nevertheless, the specification in (2.8) is not a complete description of the phase shifts, as it may lead to situations where for some time periods $S_{2,t}$ is assigned multiple values or it is not defined at all. In these cases, the regime with the larger amount of phase shift is assigned to such conflicting periods, ensuring that $S_{2,t}$ is assigned only a single regime and each regime starts with a phase shift of κ_j for $j = 0, 1$ periods relative to $S_{1,t}$. To elaborate further, consider a recession of CEI that starts in period t_0 and ends in period t_1. We further assume that $\kappa_1 > \kappa_0$. In this case, (2.8) implies that the recession (expansion) regime indicators for the FCI relative to that of the CEI should be shifted by κ_1 (κ_0) periods. Considering the initial switch of CEI from the expansion to the recession in period t_0, for the FCI the expansion ends in period $t_0 - 1 - \kappa_0$ while the recession starts in period $t_0 - \kappa_1$. As $\kappa_1 > \kappa_0$ this leads to the fact that for the periods $t_0 - \kappa_1, \ldots, t_0 - 1 - \kappa_0$ FCI is assigned multiple regimes. If the recession indicator is assigned for these conflicting periods, as its shift parameter is larger, the resulting specification implies that the recession in the FCI starts κ_1 periods earlier/later than that of the CEI. On the other hand, in case of the latter switch from recession to the expansion in period

$t_1 + 1$, the recession of the FCI ends in period $t_1 - \kappa_1$ while the expansion of the FCI starts in period $t_1 + 1 - \kappa_0$. In this case, FCI is not assigned any regime for the periods $t_1 + 1 - \kappa_1, \ldots, t_1 - \kappa_0$. Assigning the recession indicator for FCI in these periods ensures that the expansion of FCI starts or, put differently, the recession in the FCI ends κ_0 periods earlier/later than that of the CEI. This indicates that, using this specification indeed κ_0 and κ_1 serve as phase shift parameters of recession and expansion regimes, respectively. Consequently, recessions in the FCI are $\kappa_0 - \kappa_1$ periods shorter than recessions in the CEI. Notice that if the duration of the recession, $t_1 - t_0 + 1$, in CEI is shorter than $\kappa_0 - \kappa_1$ then the recession in FCI completely vanishes.

We conclude the specification of the factor model by describing the assumptions required for the identification of the factors, since both factors and their loadings are unobserved. First, to better identify the factors related to the economic and the financial conditions, the coefficients of the financial (coincident) variables that load on the first (second) factor are set as zero to identify the first factor as the CEI and the second as the FCI. We also estimate the model where we do not impose any restrictions on factor loadings. The results of this specification indicate that almost for all of the factor loadings related to financial (coincident) variables that load on the first (second) factor zero is inside the 95% Highest Posterior Density Interval (HPDI). Moreover, a model comparison based on Bayes factors evidently favors the model with the zero exclusion restrictions on these factor loadings.[3]

Second, as both the constant terms in the measurement equation, $\gamma_{i,1}$ for $i = 1, \ldots, N$, and δ are not uniquely identified, we standardize the dataset and we restrict the unconditional variance of the factors to be unity for identification of the scale and location of the factors following [Sargent and Sims, 1977], [Stock and Watson, 1989] and [Stock and Watson, 1993], for example.[4] We then recover the long-run

[3]The results related to this unrestricted model are provided in Appendix H.

[4]Alternatively, [Bernanke et al., 2005] and [Bańbura and Modugno, 2014], among others, set the upper $N \times k$ part of the matrix of factor loadings for identification, where N and k are the number of variables and factors, respectively, to align factors with the variables. Such a strategy is sensitive to the ordering of variables which might even be more sensitive in our application for emerging markets. See also [Del Negro and Otrok, 2008] and [Bai and Wang, 2015] for other types

growth rates of the factors, δ, that are required for constructing the levels of CEI and FCI by reverse engineering the long-run growth rate of the factors from the average growth rates of the observed variables, see [Stock and Watson, 1989] for example.

Combining (2.1),(2.2) and (2.5) together with (2.3)-(2.8) and imposing the identification specifications we can summarize the final model as

$$\begin{aligned} y_{i,t} &= \lambda_i f_t + \varepsilon_{i,t} \\ \psi(L)\varepsilon_{i,t} &= \epsilon_{i,t} \quad \epsilon_{i,t} \sim t(0, \nu, \sigma^2_{i,t}) \\ \sigma^2_{i,t} &= \sigma^2_{i,1}\, \mathbb{I}[t \leq \tau] + \sigma^2_{i,2}\, \mathbb{I}[t > \tau] \;\text{ for } i = 1, \ldots, N \\ f_t &= \alpha_{\mathbb{S}_t} + \Phi f_{t-1} + \eta_t \quad \eta_t \sim N(0, \Sigma) \\ S_{2,t-\kappa_{S_{1,t}}} &= S_{1,t}. \end{aligned} \tag{2.9}$$

2.2 Data

We use a comprehensive set of variables for the estimation of the CEI and FCI to estimate the model in (2.9). The dataset has a ragged-edge due to delays of releases mainly for economic variables. Given that the dataset mostly involves monthly and quarterly variables, we design the model to estimate 'monthly' indicators of coincident and financial conditions. Our dataset covers the periods (for the earliest case) starting from January 1999 (for the most timely case) until November 2019, i.e. the data that are available to us as of the first week of December 2019. A brief description of the economic and financial variables is provided in Appendix A.

For the construction of the CEI, we follow the common practice of choosing variables that broadly represent different aspects of the real economy; see [Stock and Watson, 1989] or [Kim and Nelson, 1998]. In the final set of coincident variables, we include the industrial production index (*ip*) and the purchasing manager index (*pmi*) representing the production side of the economy, total non-agricultural employment (*empna*) representing labor markets, the trade and services turnover index (*traserv*) and the retail sales volume index (*retails*) representing trade and sales, and finally,

of identifications.

the total export and import quantity indexes (*export* and *import*), which take into account the small open-economy characteristics of Turkey and are less prone to nominal fluctuations. The quarterly trade and services turnover index ($traserv^q$) is discontinued in January 2018 and replaced by a monthly measure of the index ($traserv^m$). We use both of the variables in the in-sample analysis. In the recursive out-of-sample analysis we include the monthly index only in March 2018 which is the first release date of the monthly index. Finally, we exclude the GDP series which was subject to substantial revision in 2016. This is due the fact that the GDP growth implied by the old and new series substantially diverge. Therefore, we exclude this series to preclude any potential bias in our analysis. However, we provide the results with the GDP series in Appendix F.

Turning to the construction of the financial indicators, the common practice involves choosing those series that represent the financial side of the economy together with the ability to predict future real activity; see, for example, [Hatzius et al., 2010].[5] In our analysis, first, we assess the predictive abilities of various financial variables to construct a subset of the whole dataset. Then we use the subset of variables with superior predictive power to construct the final dataset after conducting an analysis using several combinations of variables from this subset and evaluate the variables based on their ability to predict recessions using our unified framework, in which we take the advantage of our unified modeling approach of constructing both indexes jointly.

The literature on leading indicators has followed the approach of selection of variables useful for predicting future real activity using a pseudo out-of-sample forecasting procedure; see, for example, [Stock and Watson, 2001], [Leigh and Rossi, 2002] and [Altug and Uluceviz, 2014]. We follow a similar approach for construction of subset of variables to be used in FCI. We use pseudo out-of-sample forecasting, which is based on a estimation of coefficients recursively instead of a full-sample (or in-sample) analysis, because the coefficients which are estimated by full-sample

[5]See [Estrella and Mishkin, 1998, Kauppi and Saikkonen, 2008, Liu and Moench, 2016], among others, for analysis of financial variables for predicting US recessions based on econometric methods suited for the binary nature of NBER recession dates.

regressions may not show the true nature of relationship between the variables and independent variable and may not perform well in out-of-sample forecasting exercises. This will be the scenario if the coefficients associated with the regression are prone to change over time. We measure real activity by the industrial production index (IP) or alternatively, by real GDP on a monthly frequency,[6], since we construct the indexes at monthly frequency and examine the predictive ability of each variable individually using an auto-regressive distributed lag (ADL) model. We include the lags of independent variables as a regressor to control the effect of past values of the indicator of real activity. The forecasting model is

$$Z^h_{t+h} = \beta_0 + \beta_1(L)X_t + \beta_2(L)Z_t + u^h_{t+h} \tag{2.10}$$

where $Z^h_{t+h} = (\frac{1200}{h})\log(\frac{Z_{t+h}}{Z_t})$ is the variable to be forecasted h months ahead, Z_t represents IP or alternatively, real GDP growth at time t, and X_t represents the financial variable we asses. The out-of-sample forecasting exercise begins in 2006:12. For each of the variables, we use the largest sample period possible according to availability of both the dependent and independent variables. Therefore, our sample period for each financial variable is possibly different.[7] In addition, we use expanding windows for the forecasts, that start date of period is fixed and sample period is expanding.[8] The orders of the lag polynomials, $\beta_1(L)$ and $\beta_2(L)$, are chosen by the Akaike Information Criterion(AIC) for each regression and restricted to be between (min) 1 to (max) 12 months. We compare the mean squared forecast error (MSFE) of the auto-regressive (AR) model which includes only own lags of the real indicator with the model that also includes the candidate financial variable and its lags.[9]

[6]We calculate monthly Real GDP by following the approach in [Fernandez, 1981], The method is a minimization based on a quadratic loss function of the differences between series to be created and the high frequency series' linear combination, giving the best linear unbiased estimator. We use the industrial Production Index for the high frequency series.

[7]For the sample periods for each variable, see Table A.2 and Table A.4.

[8]In a rolling window, the number of observation is fixed for each regression, since the start date also moves as the end date of sample.

[9]A MSFE relative the AR value that is smaller than one means that adding X variable enhances the forecasting performance. Hence, X is taken to have predictive power for real activity.

Using this procedure, the results are shown in Table B.1 and B.2, starting with one month ahead (h=1), up to 12 months ahead forecast. Table B.1 shows that the variables used to predict IP growth have relative MSFE's of substantially less that 1 at almost all horizons. As an example, both *rbist* and *VOL* have substantial forecasting power relative to the simple $AR(p)$ model. These variables typically proxy for the portfolio flows that constitute an important component of funding for emerging economies such as Turkey, and help to determine its real growth in the short term. The variable *Conf* which denotes the Real Confidence Index obtained from the surveys of the Central Bank of the Republic of Turkey (CBRT) also has small MSFE's relative to the simple autoregressive model at all horizons. Table B.2 shows that the variables *rbist* and *Conf* also have forecasting power for the growth rate of the monthly GDP series. Indicators such as *embitr* and *msciem* which denote the spread between the JP Morgan Emerging Bond Index and the 1-month interest rate on deposits and the MSCI Emerging Market Index, respectively, measure the risk appetite to emerging economies more generally and hence, have predictive power for IP growth in Turkey. Table B.2 shows that the MSCI Emerging Market Index has stronger predictive power at horizons 2 to 4 months for real GDP growth compared to real IP growth, indicating that the more broadly defined measure of real activity given by real GDP growth is even more sensitive to the attitudes of international investors as captured by this variable. The interest rate and term spreads denoted by *TETS* and *termspread* as well as the Treasury auction rate denoted by *TAuc* have predictive power for IP growth by measuring the short-term cost of credit, where *TETS* considers the risk premium on short-term Turkish debt relative to short-term borrowing on the London Interbank Money Market using LIBOR while *termspread* provides an indication of the term premium for the Turkish economy. Tables B.1 and B.2 show that the variable *TETS* is efficacious in predicting real GDP growth at horizons greater than 3 months, indicating that the divergence between the domestic short-term interest rate and LIBOR is an important driver of real activity for the Turkish economy. Finally, the variable *Cred* provides an indication of overall credit conditions by measuring the quantity of real sector credit loans while *rforexr* which measures the CBRT's real gross foreign exchange reserves provides an indication of the external fragility in the face of volatile capital flows.[10]

After we conduct analysis using several combinations of variables from the subset of variables with predictive power, we implement the various combinations of variables and evaluate them based on their ability to predict recessions to finalize our selection. The final set of financial variables used to create the FCI are indicated with $*$'s in Tables B.1 and B.2. These includes firstly, variables that represent stock and (sovereign) bond markets. The variables representing the stock market are the stock market index (BIST100) in real terms (*rbist*), price-earnings ratio (P/E) of the portfolio used for computing the BIST100, the MSCI emerging market index (*MSCIem*)[11], and realized volatility on the BIST100 (*VOL*) while the treasury auction rate (*TAuc*) is used to represent (sovereign) bond market. The second set of variables is intended to capture credit risk on financial markets given by various spreads including the term spread (*TermS*) computed as the spread between the interest rate on deposits - up to 1 year and more and the interest rate on deposits up to 1 month[12], the TET spread (*TETS*) computed as the difference between the 3-month interest rate on deposits and 3-month LIBOR, and the spread between the JP Morgan Emerging Markets Bond Index[13] and the 1-month interest rate on deposits (*EMBI-Tr*), which is intended to represent other sources of risk in emerging economies. We also include the Central Bank of the Republic of Turkey (CBRT)'s gross foreign exchange reserves in real terms (*FXRes*), the confidence index of CBRT (*Conf*), and banking sector credit loans (*Cred*).

[10]We did not include some indicators such as *efunr* which denotes the effective Federal Funds Rate in the US because it is likely to be correlated by variables such as *rbist* or *VOL*, as stock price movements in an emerging economy such as Turkey are highly sensitive to interest rate changes in the US.

[11]The MSCI emerging market index is a broad stock market index encompassing all emerging markets serving as a measure of the risk appetite to emerging economies.

[12]We use the interest rates on deposits rather than the sovereign bond (zero-coupon) yields for computing the term spread. This is mainly due to the fact that short-term sovereign bonds possess limited liquidity.

[13]JP Morgan Emerging Markets Bond Index is a broad bond market index encompassing all emerging markets serving as a measure of the cost of funding for emerging markets.

2.3 Estimation

The model specified in (2.9) is a special case of the unobserved components model together with (Markov) regime dependent parameters, as neither the factors, i.e. economic and financial indicators, nor the regimes and the phase shifts are observed. We adopt a Bayesian approach for estimation and inference on all these components and we make use of Markov Chain Monte Carlo (MCMC) techniques. Specifically, we use Metropolis within Gibbs sampling together with data augmentation for posterior inference. We discuss the details on inference including the likelihood function of the model, the specifications of the prior distributions and the resulting algorithm for simulating from the posterior distribution together with full details on the conditional posterior distributions in Appendix D.1 and D.2 for the sake of brevity. Here, we discuss briefly the prior specifications regarding to phase shift parameters as these are essential for our analysis. For these parameters, $\kappa = (\kappa_0, \kappa_1)$, we use a uniform prior assigning equal probability to each value of κ in a predefined set

$$f(\kappa) \propto \begin{cases} 1 & \text{for all } (\kappa_0, \kappa_1) \in \mathcal{C}, \\ 0 & \text{otherwise.} \end{cases} \tag{2.11}$$

The set $\mathcal{C} = \{(\kappa_0, \kappa_1) \in \mathbb{Z}^2 \mid -c \leq \kappa_j \leq c \text{ for } j = 0, 1, \; |\kappa_0 - \kappa_1| \leq d\}$ specifies the restrictions imposed on κ_0 and κ_1. Specifically, we set $c = 8$ and $d = 6$ implying that κ_0 and κ_1 are restricted to lie in the interval $[-8, 8]$ and their difference is restricted not to exceed 6.[14] Note that setting $d = 0$ and $c = 0$ leads to the model with single common cycle. See [Çakmaklı et al., 2011] for more details.

2.4 Empirical Findings

In this section, we report our empirical findings using our model specification. We first conduct an analysis on the cross-autoregressive parameters of the (growth rates

[14] We experiment with various setups. The results are quite similar and available upon request. Setting these values to sensibly small values without affecting the results facilitates the computation substantially.

of the) economic and financial conditions, or in other words, coincident economic index (CEI) and financial conditions index (FCI). Posterior odds ratios using mildly informative priors indicate that zero is inside the Highest Posterior Density Interval (HPDI) and therefore, we exclude these parameters. We further conduct an extensive analysis on the lag order of the idiosyncratic factors. Model comparisons suggest that a lag order of 3 (0) for the idiosyncratic factors of economic (financial) variables provides a better description of the data.

First, we display findings of the full-sample estimation. In the next section, we provide a detailed analysis on the performance of the competing models in real-time forecasting of business cycle turning points. The competing models involve (i) the model with independent cycles for the CEI and FCI, (ii) the model with Perfectly Synchronized cycles, i.e. a single cycle for the CEI and FCI (PS), (iii) the model with Imperfectly Synchronized cycles due to regime dependent phase shifts (IS) between the cyclical components of the CEI and the FCI.

For model comparison, we use the (logarithm of the) marginal likelihood metric to analyze the conformity of the models with the data. These are reported at the bottom panel of Table 2.1.

Table 2.1: Posterior means and standard deviations (in parentheses) of parameters in the transition equations of CEI and FCI for competing models

		Imperfect synchronization of cycles	Perfect synchronization of cycles	Independent cycles
Phase shifts	κ_0	3.002 (1.778)		
	κ_1	3.561 (2.245)		
Intercepts	$\alpha_{1,0}$	0.080 (0.055)	0.075 (0.052)	0.026 (0.070)
	$\alpha_{1,1}$	-0.558 (0.231)	-0.515 (0.196)	-0.779 (0.091)
	$\alpha_{2,0}$	0.141 (0.068)	0.137 (0.066)	0.154 (0.085)
	$\alpha_{2,1}$	-0.709 (0.154)	-0.704(0.160)	-0.625 (0.121)
Autoregressive coefficients	$\phi_{1,1}$	0.173 (0.116)	0.245 (0.132)	0.296 (0.134)
	$\phi_{2,2}$	0.410 (0.091)	0.406 (0.088)	0.416 (0.091)
Transition probabilities	p_1	0.971 (0.011)	0.971 (0.011)	0.972 (0.015)
	q_1	0.928 (0.025)	0.929 (0.025)	0.931 (0.025)
	p_2			0.965 (0.015)
	q_2			0.928 (0.025)
Conditional variances	$\sigma^2_{\eta_1}$	0.957 (0.052)	0.921 (0.025)	0.894 (0.084)
	$\sigma^2_{\eta_2}$	0.824 (0.073)	0.828 (0.132)	0.818 (0.075)
Log-marginal likelihood		-872.17	-898.18	-914.17

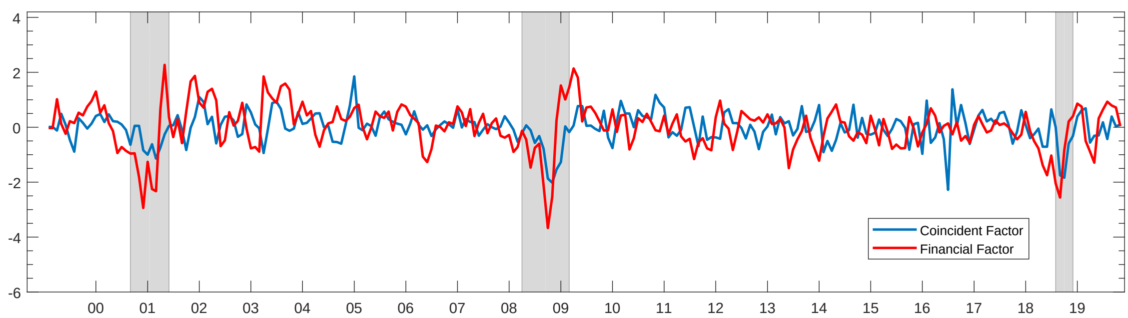
Note: The table shows posterior means and standard deviations (in parentheses) of the parameters in the transition equation defining the autoregressive process for CEI and FCI in (2.5) for competing models estimated using the data for the periods starting from January 1999 until November 2019. The competing models are constituted by the model with imperfect synchronization between the cyclical components of the CEI and the FCI, the model with perfect synchronization of cycles of the CEI and FCI and the model with independent cycles for the CEI and FCI. Posterior results are based on 60,000 draws from the posterior distribution where the first 10,000 draws are discarded as burn-in sample.

Marginal likelihood values indicate that both of the models with independent cycles and PS perform worse than the IS model. While the model with independent cycles has the lowest marginal likelihood value, we observe an increase in the marginal likelihood by 16 points for the PS model. It seems that modeling economic and financial variables jointly for extraction of the indicators with a single common cycle improves upon modeling the indicators with independent cycles. Notice that while the model with independent cycle constitutes the majority of studies that extract the business cycle using conventional economic variables, see [Kim and Nelson, 1998] among others. The model with single common cycle could be seen as an example of the models to extract higher frequency measures of business cycle that often use financial information as the source of higher frequency variation, see [Aruoba et al., 2009], among others. Allowing for phase shifts between cycles of the financial and economic activity improves the marginal likelihood value further by almost 26 points. This indicates that the cycles embedded in economic and financial conditions are indeed closely tied but not perfectly synchronized. Modeling these phase shifts between the cyclical patterns of economic and financial indicators explicitly pays off, as the highest marginal likelihood value is achieved by the model allowing for imperfectly synchronized cycles. In the next section, we discuss these findings in detail.

2.4.1 Full sample results

In this section, we discuss the estimation results using the full sample. We first describe the coincident economic and financial conditions factors and their corresponding indexes that are estimated using the model that allows for imperfectly synchronized cycles as in (2.9). As discussed in Section 2.1 this model is estimated using growth rates of variables. Figure 2.1 displays the growth rate of indexes, which we define as factors f_t as in (2.9), together with the dates of recessions indicated by the gray shaded area computed using the BBQ algorithm.[15]

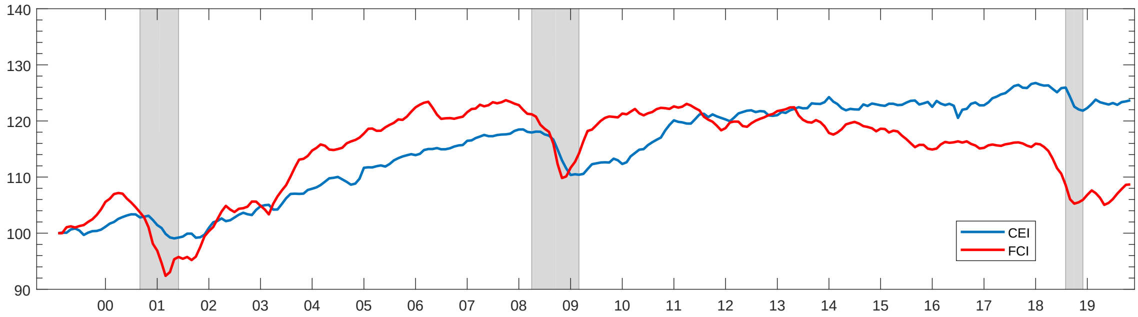
Figure 2.1: Estimate of Growth of Coincident Economic Index and Financial Conditions Index (Factors)



[15]The BBQ algorithm, proposed by [Bry and Boschan, 1971] and simplified by [Harding and Pagan, 2002], is a nonparamatric procedure used for dating business cycle turning points. This approach uses the quarterly real GDP series or the monthly industrial production growth rate. The resulting recession dates are identified as the periods from October 2000 until June 2001, from April 2008 until March 2009 and from August 2018 until December 2018 in our sample.

We, then, reverse engineer the levels of CEI and FCI as in [Stock and Watson, 1989].[16] Figure 2.2 displays these indexes together with the dates of recessions, the same as in Figure 2.1.

Figure 2.2: Estimate of Coincident Economic Index and Financial Conditions Index



These figures show that the CEI is successful in tracking the business cycle and predicting accurately the economic downturns that occurred in 2000-1, 2008-9 and 2018. Moreover, it captures the accelerated expansion of the Turkish economy between 2002-8 and right after the 2008-9 crisis, which is replaced by a slower growth path after 2012. The FCI displays similar behavior but with a clear lead of the cyclical regimes by several months. While both the CEI and the FCI capture the downturns during the recessions of 2000-1 and 2008-9, these are amplified further for the FCI, with frequent downturns in 2011, 2013 and 2015 reflecting the relatively volatile nature of the financial variables that are used to constitute it. The divergence between the CEI and FCI can be tracked in the second half of the sample after 2011. This period coincides with the start of the relatively unconventional monetary policy initiated by the Central Bank of the Republic of Turkey (CBRT), which involved various mixes of policy tools. Finally, we observe a sizable downturn in the FCI in early 2018 accompanied by a downward swing in the CEI which starts around August 2018 following an increase in July 2018. This recent recession is finalized around January 2019, as can be seen from the upward swing in the first quarter of

[16]We show how we calculate the indexes from the factors, by giving the summary of the steps of [Stock and Watson, 1989] in Appendix D.2.

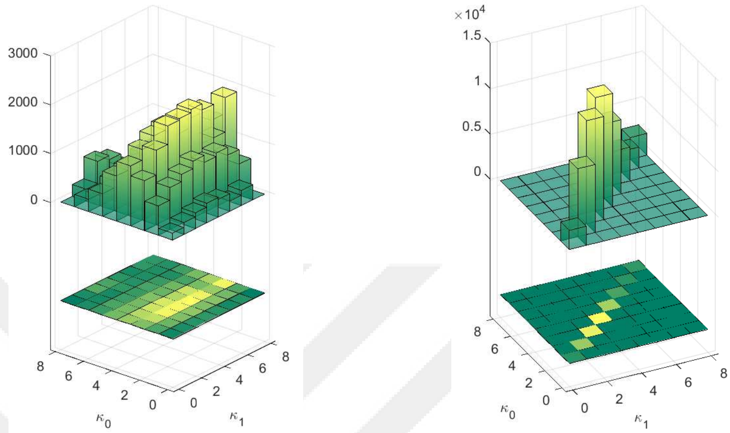
2019.

Table 2.1 reports the estimates of the parameters related to the growth rates of the CEI and FCI estimated using the three competing models, which differ according to the nature of the assumed synchronization between the cyclical components of the CEI and FCI. The first panel displays the estimates of the lead/lag parameters, i.e. the phase shift in the expansion phase of the FCI, κ_0, and the phase shift in the recession phase of the FCI, κ_1, for the model that allows for the imperfect synchronization between the cycles embedded in FCI and CEI. The posterior means of the phase shift parameters for expansions and recessions is estimated as 3.00 and 3.56 months, respectively. In line with the improved marginal likelihood value of the IS model compared to other polar cases, these findings suggest that the cycle embedded in the FCI systematically leads the cycle in the CEI by more than a quarter ahead. Therefore, the FCI constructed using the proposed methodology as in (2.9) may serve as a leading indicator of the CEI. Even more importantly, it provides an early warning indicator for the oncoming recessions 3.56 months ahead.[17]

The left panel of Figure 2.3 displays the posterior distribution for the phase shift parameters κ_0 and κ_1.

[17]For the case of the US, using the 'observed' indicators of the Conference Board's monthly composite coincident index and the leading indicator [Çakmaklı et al., 2013] find that the lead time for mild recessions is 12 months while for severe recessions this lead time reduces to 6 months. For expansions, the lead time further reduces to 4 months. While these findings show that the lead times are larger for the US, nevertheless, given the severity of recessions in emerging markets, the magnitude of the phase shifts seems to be comparable.

Figure 2.3: Histograms of the phase shift parameters, κ_0 and κ_1, for models with imperfect synchronization with regime dependent phase shifts (left) and with a unique phase shift (right)



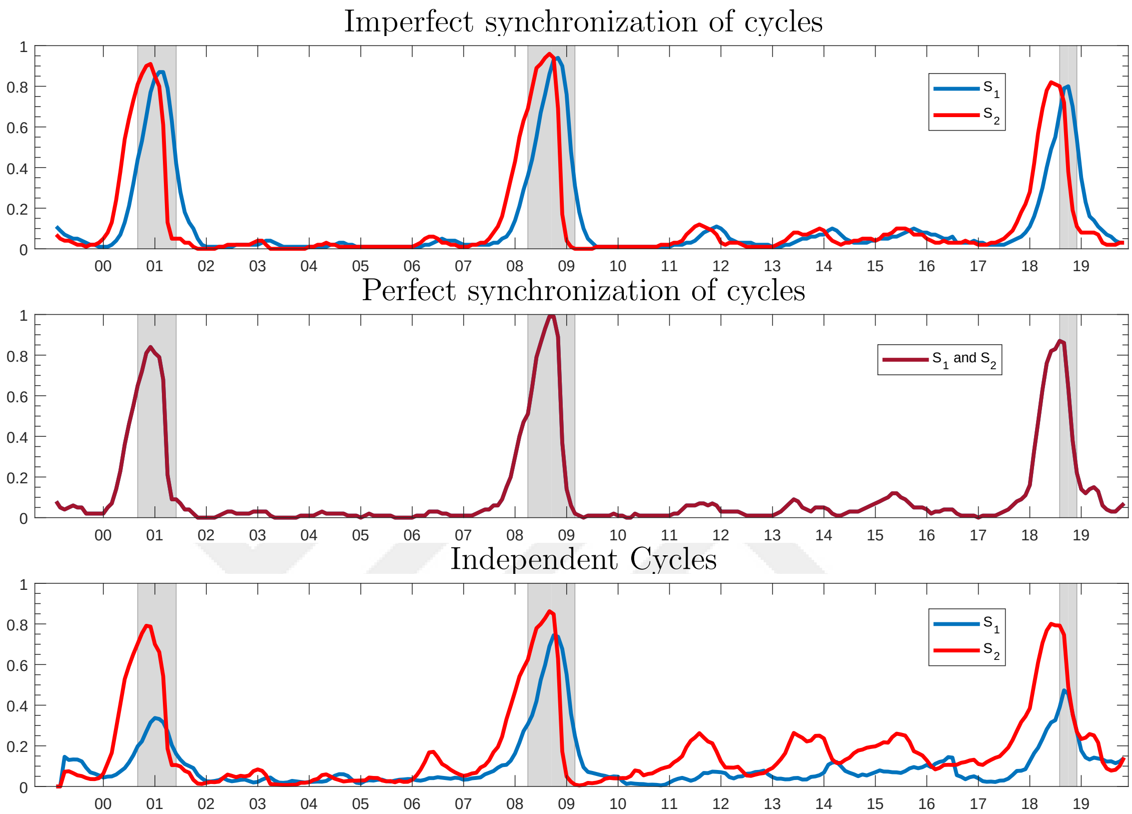
Note: The graph displays the posterior distribution of the phase shift parameters, κ_0 and κ_1, between the cyclical components of CEI and FCI estimated for the model with imperfect synchronization of cyclical components of CEI and FCI with regime dependent (unique) phase shifts in the left (right) panel using the data for the periods starting from January 1999 until December 2019. Posterior results are based on 60,000 draws from the posterior distribution where the first 10,000 draws are discarded as burn-in sample.

Figure 2.3 shows that the mode of the posterior joint distribution of κ_0 and κ_1 is 3 and 4 months with a large probability mass around this mode. Interestingly, there is also large probability mass around 8 months for the phase shift parameter of recessions, κ_1. This indicates that for some recessions the lead time may be as high as 8 months, similar to findings for US, but we need to have a larger dataset for enhancing the probability mass in this part of the distribution. Since the lead times of recessions and expansions are close to each other for the major part of the joint distribution of phase shift parameters, we estimate a model where the phase shift parameters are restricted to be identical. The right panel of Figure 2.3 displays the posterior distribution for this unique phase shift parameter. In this case, it is seen that the posterior distribution of the unique phase shift parameter is nicely gathered around the values of 3 and 4 months. A large probability mass around the lead time of 8 months, as in the case of regime dependent phase shifts, cannot be observed if the phase shift parameters are restricted to be identical. This is due to the fact that the large lead time of recessions, that is observed when the phase shift parameters are regime dependent, are not accompanied by the large lead time of expansions.

The second and third panel of Table 2.1 reports estimates of the parameters related to the growth rates of the CEI and FCI. As it can be seen in the second panel, regimes are identified quite precisely with negative growth rates for recessions and positive growth rates for expansions apart from each other. While models with perfectly or imperfectly synchronized cycles produce similar results, the model with independent cycles implies more severe downturns. Estimated transition probabilities, displayed in the fourth panel of Table 2.1 implies that the duration of expansions is predicted to be 35 months while the duration of recessions is given by 15 months for the models with perfect or imperfect synchronization reflecting the asymmetry in the business cycle. By contrast, the model with independent cycles yields a slightly lower probability of remaining in recessions, with an implied duration of recessions being equal to 14 months capturing more severe periods of the recessions.

We now examine the behavior of the different model specifications based on their ability to determine turning points and to identify recessionary episodes. Figure 2.4 shows recessionary episodes for the Turkish economy based on the BBQ algorithm together with the smoothed recession probabilities implied by the models.

Figure 2.4: Posterior recession probabilities estimated using competing models



Note: The graphs display the posterior recession probabilities computed for competing models estimated using the data for the periods starting from January 1999 until November 2019. The shaded areas show recessionary episodes for Turkish economy based on the nonparametric business cycle dating algorithm proposed by [Harding and Pagan, 2002]. Posterior results are based on 60,000 draws from the posterior distribution where the first 10,000 draws are discarded as burn-in sample.

The first panel of Figure 2.4 displays the recession probabilities estimated using the specification with imperfect synchronization of the cycles. Consistent with Figure 2.2 and the nonzero estimates of phase shifts between the cyclical components of CEI and FCI, the smoothed probabilities of being in recession for the FCI precede the smoothed probabilities of being in recession for the CEI for the 2000-1, 2008-9 and 2018 recessions. This occurs at the onset when entering recessions as well as at the end when leaving recessions. Moreover, the timing of the recessions for the CEI when smoothed probabilities of being in recession for CEI exceed 0.5 match with the periods of recessions computed by the BBQ algorithm. This implies that the constructed FCI not only measures the current financial conditions but also serves as an early warning indicator for the oncoming downturns of economic activity.

When we consider the model with perfect synchronization, displayed in the second panel of Figure 2.4, we observe that it has some success in capturing the cyclical turning points, specifically, at the onset of the 2008-9 recession. However, a comparison of the smoothed recession probabilities computed using the financial cycle of the IS model and those using the unique cycle of the PS model indicates that the PS model captures the financial cycle rather than the business cycle. It can clearly be seen that due to the leading capability of the financial variables, it produces false signals of recessions at the onset of the 2000-1 and 2018 recessions. For these recessions, the periods when smoothed probabilities exceed 0.5 precede the periods of the actual realizations. Even more pronounced, the model produces false signals of expansions towards the end of all recessions during the transition periods from recession to expansion in the sense that model implied probabilities decline to levels below 0.5 much earlier than the actual periods of expansionary phases following recessions.

Finally, considering the model with independent cycles for the CEI and the FCI, displayed in the third panel of Figure 2.4, we observe the poor performance of CEI in capturing the cyclical behavior of economic activity. First, it does not deliver decisive signals of the 2000-1 and 2018 recessions producing smoother probabilities below 0.5 over the course of these periods. Second, it enters the 2008-9 recession with a substantial lag, and similarly, it leaves the recession before the actual trough occurs. Still, the FCI for this specification appears capable of capturing the financial cycle, as the smoothed probabilities in this case are very similar to the smoothed probabilities for the model with imperfect synchronization. We observe frequent increases in recession probabilities that exceed 0.3 in 2011, 2013 and around 2015 which can be perceived as signals of an oncoming recession. However, the model with imperfect synchronization remains relatively silent in these periods where the recession probabilities fluctuate only around 0.1. This is due to the fact that, for the IS model, the cycles embedded in CEI and FCI are modeled jointly using a unique cycle which is reflected with the phase shifts to the FCI. Therefore, even though there is a short-lasting downturn in the FCI, it is not translated into recession probabilities when a similar downturn cannot be observed for the CEI. This substantially eliminates the false signals as it can be seen from Figure 2.4.[18]

Table 2.2 displays the parameter estimates related to the measurement equation in (2.9) with the exception of the autoregressive coefficients of the idiosyncratic components. Here we display the parameter estimates of the model with imperfectly synchronized cycles embedded in CEI and FCI for the sake of brevity. The parameter estimates of other competing models together with the autoregressive coefficients of the idiosyncratic components of all competing models are provided in Appendix E.

[18]We also observe a similar effect, albeit much milder, when we consider the model with imperfect synchronization of cycles but with cross-autocorrelations and cross-correlation estimated without any restriction. While these coefficients turn out to be relatively small, still for this model, the recession probabilities mistakenly signal a recession in 2013-4 with probabilities attained values close to 0.4 as a result of this additional link.

Table 2.2: Estimates of factor loadings, conditional variances of the variables for the model with imperfect synchronization of the cycles

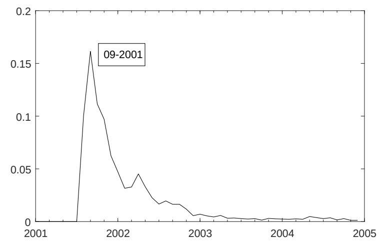
	Economic variables				Financial variables			
	Factor loadings		Variances		Factor loadings		Variances	
ip	$\lambda_{1,1}$	0.443 (0.087)	$\sigma^2_{1,1}$ / $\sigma^2_{1,2}$	1.095 (0.324) / 0.719 (0.103)	rbist $\lambda_{9,2}$	0.458 (0.078)	$\sigma^2_{9,1}$ / $\sigma^2_{9,2}$	1.814 (0.607) / 0.574 (0.136)
import	$\lambda_{2,1}$	0.272 (0.078)	$\sigma^2_{2,1}$ / $\sigma^2_{2,2}$	1.998 (0.638) / 0.631 (0.085)	FXRes $\lambda_{10,2}$	0.286 (0.070)	$\sigma^2_{10,1}$ / $\sigma^2_{10,2}$	3.407 (1.147) / 0.507 (0.070)
export	$\lambda_{3,1}$	0.111 (0.055)	$\sigma^2_{3,1}$ / $\sigma^2_{3,2}$	1.244 (0.377) / 0.585 (0.067)	Conf $\lambda_{11,2}$	0.587 (0.077)	$\sigma^2_{11,1}$ / $\sigma^2_{11,2}$	0.685 (0.244) / 0.644 (0.090)
retails	$\lambda_{4,1}$	0.462 (0.138)	$\sigma^2_{4,1}$ / $\sigma^2_{4,2}$	1.638 (2.329) / 0.775 (0.138)	TermS $\lambda_{12,2}$	0.333 (0.092)	$\sigma^2_{12,1}$ / $\sigma^2_{12,2}$	1.643 (2.188) / 0.810 (0.235)
pmi	$\lambda_{5,1}$	0.136 (0.142)	$\sigma^2_{5,1}$ / $\sigma^2_{5,2}$	1.626 (2.152) / 0.943 (0.152)	VOL $\lambda_{13,2}$	-0.203 (0.080)	$\sigma^2_{13,1}$ / $\sigma^2_{13,2}$	1.234 (0.318) / 0.930 (0.108)
empna	$\lambda_{6,1}$	0.116 (0.105)	$\sigma^2_{6,1}$ / $\sigma^2_{6,2}$	1.595 (2.198) / 0.871 (0.106)	P/E $\lambda_{14,2}$	0.131 (0.111)	$\sigma^2_{14,1}$ / $\sigma^2_{14,2}$	2.218 (1.309) / 0.686 (0.322)
traserv^q	$\lambda_{7,1}$	0.231 (0.150)	$\sigma^2_{7,1}$ / $\sigma^2_{7,2}$	1.582 (2.023) / 0.924 (0.235)	TAuc $\lambda_{15,2}$	-0.324 (0.075)	$\sigma^2_{15,1}$ / $\sigma^2_{15,2}$	1.655 (0.478) / 0.762 (0.113)
traserm^m	$\lambda_{8,1}$	0.484 (0.145)	$\sigma^2_{8,1}$ / $\sigma^2_{8,2}$	1.666 (2.706) / 0.738 (0.128)	TETS $\lambda_{16,2}$	-0.151 (0.056)	$\sigma^2_{16,1}$ / $\sigma^2_{16,2}$	10.791(6.072) / 0.081 (0.023)
					Cred $\lambda_{17,2}$	-0.181 (0.096)	$\sigma^2_{17,1}$ / $\sigma^2_{17,2}$	1.584 (1.823) / 0.892 (0.172)
					MSCIem $\lambda_{18,2}$	0.571 (0.103)	$\sigma^2_{18,1}$ / $\sigma^2_{18,2}$	1.624 (3.135) / 0.729 (0.119)
					EMBI-Tr $\lambda_{19,2}$	0.121 (0.036)	$\sigma^2_{19,1}$ / $\sigma^2_{19,2}$	6.798 (3.792) / 0.051 (0.021)
	Most likely break date			τ	2001:09			

Note: The table shows posterior means and standard deviations (in parentheses) of the factor loadings, the variances in the measurement equations in (2.9) for the model with imperfect synchronization between the cyclical components of the CEI and the FCI estimated using the data for the periods starting from January 1999 until November 2019. Posterior results are based on 60,000 draws from the posterior distribution where the first 10,000 draws are discarded as burn-in sample.

We display the parameters related to (the growth rates of) the CEI (FCI) on the left (right) panel of the Table 2.2. Considering the loadings on the CEI, we observe that all of the eight variables used to construct the CEI load positively on the common factor due to the procyclicality of the selected variables. For a majority of the variables zero is outside the 95% HPDI, though for the purchasing manager index (*pmi*), quarterly turnover index of trade and services (*traserv*^{q}) and total non-agricultural employment (*empna*) the 95% HPDIs contain zero. When we consider the *pmi*, the CEI and the *pmi* seem to have commonality mostly at the end of the sample period, when the economy experiences a boom after 2017 and the following bust after mid 2018. Therefore, while *pmi* does not seem to be perfectly related to the economic conditions, it is quite informative during the periods when the economy is overheated and when it experiences a downturn. A similar pattern is also the case for the $traserv^q$ though the probability mass on the positive domain exceeds 0.90, even though it has a limited number of observations due to the quarterly frequency of this series. For the *empna*, this might be due to the high persistence of this series documented in Table E.3 of the Appendix. This implies that the effect of the *empna* prevails over longer periods in addition to the contemporaneous effect. Turning to the factor loadings for the FCI, we observe that variables that are related to various risk sources such as the stock market volatility (*VOL*), the Treasury auction rate (*TAuc*) and the liquidity spread (*TETS*), have sizable negative loadings on the common factor. An important finding refers to the loading of the credit (*Cred*). Similar to the risk-related variables, this variable has a negative loading, attesting to its importance in signaling recessions. By contrast, an increase in the real stock market index (*rbist*) or the MSCI Emerging Markets Index (*MSCIem*) tend to signal favorable developments and hence, lead to an increase in the FCI.

Finally, when we consider the conditional variances of economic and financial variables and the timing of the structural break in these variances, we observe that the posterior mode for the breakpoint parameter τ is estimated as September 2001. Figure 2.5 shows the posterior density of the break parameter for the IS model.

Figure 2.5: Posterior density of the break point parameter, τ, for the structural break in conditional variances of variables



Note: The graph displays the posterior distribution of the break date, τ, in conditional variances of variables estimated for the model of imperfect synchronization of cycles with regime dependent phase shifts using the data for the periods starting from January 1999 until December 2019. Posterior results are based on 60,000 draws from the posterior distribution where the first 10,000 draws are discarded as burn-in sample.

We observe that the bulk of the posterior mass is located around the years 2001-2, which corresponds to the ending of the major banking and financial crisis of 2000-1, reflecting the financial turbulence and the large increases in sovereign risk that Turkey endured during this period and the normalization that occurred in its aftermath. Therefore, we can track a general reduction in the shock variances of almost all variables following the break date of September 2001. This finding is similar to the Great Moderation, that is, the reduction in the variation of many macroeconomic and financial series in the US and most industrialized countries, which is dated to around mid 1980's. Although the timing of the moderation is different in the Turkish case, this is also not surprising in the sense that Turkey could not be considered a liberal economy until the 1990's, see for example [Aricanli and Rodrik, 1990].[19]

2.4.2 *Predicting business cycle turning points in real-time*

Economic agents are often interested in predicting economic downturns before they are actually realized. In fact, the uncertainty about the state of the business cycle is often unresolved even after it is realized, as data on economic activity, i.e. GDP, are often released with substantial lags. Therefore, we also assess the efficacy of the model in signaling business cycle turning points in real-time. Specifically, we conduct a recursive prediction exercise for examining the ability of the models in

[19]There is an intense debate on the causes of the Great Moderation in developed countries, but three main causes present themselves as the most likely. These are referred to as 'good policy', 'good luck' and structural changes in the economy, see [Gambetti and Galí, 2009] among others. Viewed in this light, the reduction of the variances in the Turkish case bears some resemblance to the Great Moderation in terms of the underlying dynamics. In particular, Turkey has experienced substantial structural reforms at the beginning 2000's following the banking and financial crises of 2000-1. One of the major reforms was central bank independence as well as creation of other regulatory institutions, see [Yeldan and Ünüvar, 2016]. Therefore, one explanation for this moderation in variation could be good policy in the sense that independence of the central bank may have led to better conduct of monetary policy. On the other hand, good luck may also have played a significant role as the size of shocks, especially external shocks, hitting emerging markets were reduced substantially at the beginning of 2000's. Last but not least, the structure of the Turkish economy has also changed, with a major shift towards the service sector and much deeper financial markets facilitating the access of the private sector to funds. Still, a more structural investigation is required to uncover these aspects which is beyond the scope of this work. We acknowledge an anonymous referee for pointing out this similarity.

predicting business cycle turning points over the evaluation period starting from December 2006 until December 2019. To obtain the predictions in real-time, we first restructure the dataset leading to a ragged-edge in each period to account for the delays in releases. This implies that we simulate a forecaster who estimates the model in the first week of each month starting from January 2007 until December 2019 to construct the predictions.[20]

To compare the predictive ability of the models in predicting business cycle turning points, we make use of the metric of turning point forecast errors (TPFE) using predictive probabilities of being in a recession. To obtain these probabilities, we first compute the predictive distribution of the regime indicator of being in a recession in period $t_0 + h$, $f(S_{1,t_0+h} = 1|\theta, Y^{t_0})p(\theta|Y^{t_0})$, where $p(\theta|Y^{t_0})$ is the posterior distribution of model parameters given the observations until t_0. We use the posterior simulator to obtain a sample from this posterior distribution $\{\theta^{(m)}\}_{m=1}^{M}$ and then to obtain a sample of predictive distribution of regime indicators $\{S_{1,t_0+h}^{(m)}\}_{m=1}^{M}$, where M is a large number of draws from the posterior distribution. Finally, predictive recession probabilities for period $t_0 + h$ are computed using the sample average as

$$\bar{S}_{1,t_0+h} = M^{-1} \sum_{m=1}^{M} S_{1,t_0+h}^{(m)} \tag{2.12}$$

The TPFE is given by

$$\text{TPFE}(h) = \frac{1}{T_2 - h - T_1 + 2} \sum_{t=T_1}^{T_2+1-h} (BC_{t+h} - \bar{S}_{1,t+h})^2, \tag{2.13}$$

where BC_{t+h} is the indicator function that equals to 1 if the economy is in recession at time $t+h$ and 0 otherwise, according to the BBQ algorithm. T_1 and T_2 correspond to the first and terminal dates of the evaluation period, respectively. We examine the

[20]Given the timing of estimation as of the first week of each month, many of macroeconomic variables including *ip*, *import*, *export*, *traserv*^{m} and *retails* are released with a lag of 3 months, other variables including *empna* and *traserv*^{q} are released with lags of 4 and 5 months, respectively. *pmi* is the only variable with a timely release at the end of the corresponding month. Conversely, financial variables are released timely, except *FXRes*, *P-E*, *MSCIem*, *EMBI-Tr*, *TermS* and *TETS* are released with a lag of 2 months.

out-of-sample predictive accuracy of the models by conducting pairwise comparisons using the robust version of the Diebold–Mariano test (HAC-DM) of [Diebold and Mariano, 1995] together with the finite sample correction noted by [Harvey et al., 1997].

The IS model has two attractive features in terms of predicting the recessions. First, similar to nowcasting models of [Banbura et al., 2013] we use a mixed frequency ragged-edge dataset in a real-time setup for efficient backcasting and nowcasting. Second, we estimate the CEI and FCI jointly by exploiting the phase shifts between their cyclical components. Given the positive phase shift parameters of several months, the IS model has potentially superior forecast ability. Therefore, we examine the ability of the IS model in backcasting, nowcasting and forecasting the business cycle turning points. In our prediction exercise, we compute the TPFEs for horizons of $h = -3, -2, -1, 0, 1, \ldots, 8$ to evaluate the predictive ability of competing models for various horizons related to backcasting, nowcasting and forecasting. We evaluate these features in Table 2.3, which displays the TPFE differences of the competing models with respect to the IS model.

Table 2.3: Turning point forecast error differences to the model with imperfect synchronization of cycles

Horizon h	Perfect synchronization of cycles	Independent cycles
-3	1.741**	1.589**
-2	1.566**	1.757**
-1	1.417***	2.764***
0	1.345***	3.797**
1	0.722***	3.976**
2	0.377**	3.524***
3	0.334***	3.210**
4	0.074	2.316**
5	-0.235	1.553*
6	-0.102	0.960*
7	0.067	0.484
8	0.204	0.304

Note: The table shows the difference between the TPFE(h) (multiplied by 100) of the models with (i) perfect synchronization of cycles and (ii) independent cycles from the model with imperfect synchronization of cycles with regime dependent phase shifts (IS). Pairwise comparisons are carried out using HAC-DM test with HLN finite-sample correction. The comparisons involve the competing models against the model with imperfect synchronization of cycles with regime dependent phase shifts. '***' indicates significance at 1%, '**' indicates significance at 5%, '*' indicates significance at 10% against one sided alternative of the positive loss differential. A larger (smaller) RMSE with asterisk indicates statistical significance for inferior (superior) performance of the competing model.

The model specifications with independent cycles and with perfect synchronization of the cycles of the CEI and the FCI perform much worse than our general model specification, as can be seen in the second and third columns of Table 2.3. Essentially, the specification with independent cycles performs worst with sizable differences in TPFEs compared to our specification. The HAC-DM tests indicate that these sizable differences are significant at least at 10% significance level in terms of backcasting and they increase gradually as the predictive horizon approaches to 0. In terms of nowcasting, the outperformance of the IS model is significant even at 1% significance level with a difference of the TFPE as high as 3.6 at the prediction horizon $h = 0$. The superior performance of our specification in nowcasting is carried over to the forecasting horizons as well. The sizable differences are significant at 1% significance level up to a forecast horizon of 4 months. The statistical significance of the results at the 10% significance level prevails up to 7-month forecast horizon.

The specification with perfect synchronization of cycles produces better predictions than the model with independent cycles for the CEI and FCI indicating the importance of utilizing financial information for the extraction of the business cycle. Nevertheless, it delivers worse signals for recessions compared to our specification, as indicated by the positive differences displayed in the second column of the Table 2.3. These differences are significant over a horizon involving backcasting up to 3 months and forecasting up to 3 months. These results are in line with the in-sample findings displayed in the previous section. First, as shown also in Figure 2.4 the model with perfect synchronization of cycles produces early and false signals of recessions before the start of the actual recession. Since this model essentially captures the financial cycle rather than the business cycle, it also delivers early false signals of expansions. This explains the inferior performance of this model in terms of back- and nowcasting compared to our specification. Indeed, while for these horizons all differences are significant at least at the 10% significance level, in terms of nowcasting when $h = 0$, the large difference is significant at the 1% significance level as well. This difference is preserved also for the forecasting horizons up to 3 months where our findings suggest a significance at least at 5% significance level. Consistent with the estimates of the phase shift parameters indicating the lead time of financial cycle as around 3 and 4 months for expansions and recessions, the large differences between TPFEs decline for forecast horizons of 4 months and longer.

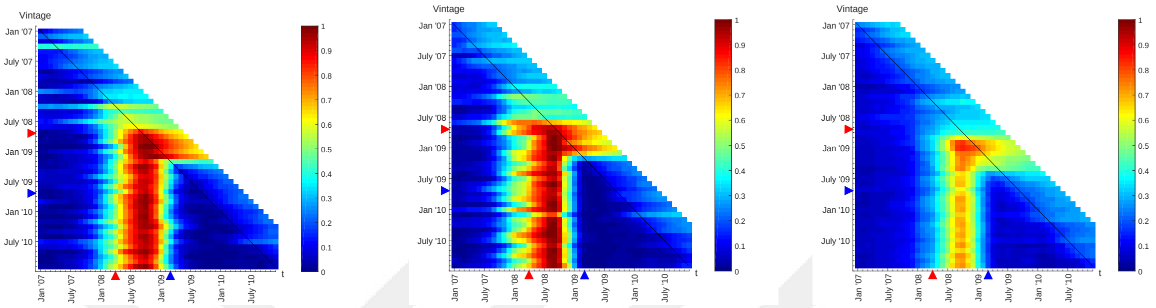
The upper panel of Figure 2.6 displays the performance of the models in predicting the economic downturns with a focus on the 2008-9 recession, whereas the lower panel displays the 2018 recession.[21]

[21] In Figure G.1, we display the same estimation with Figure 2.6 for providing with a different illustration, where the transition from one phase to other is more noticeable in Appendix G. Values of the recession probabilities which are bigger than 0.5 are represented by circles filled black and getting bigger as recession probabilities getting close to 1. Values of the recession probabilities which are lesser than 0.5 are represented by unfilled circles black and getting smaller as recession probabilities getting close to 0.

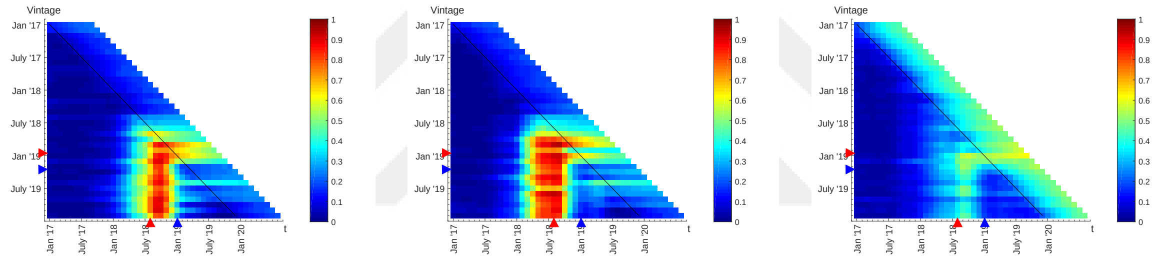
Figure 2.6: real-time nowcasting/forecasting exercise: In sample estimates and out-of-sample predictions of recession probabilities

Imperfect Synchronization Perfect Synchronization Independent Cycles

For the 2008-9 recession



For the periods covering 2017-2019



Note: The graphs display the recession probabilities in an expanding horizon, where at every point on the vertical axes, the latest data vintage (each starts at January 1999 and ends at the indicated date) is used to compute in-sample estimates and out-of-sample predictions for $h = 0, 1, 2, \ldots, 8$ months ahead. Values of the recession probabilities which are bigger than 0.5 are represented by the shades of red color getting darker as the probabilities are getting closer to 1 and values less than 0.5 are represented by the shades of the blue color getting darker as the probabilities are getting closer to 0 as shown in the bars next to the graphs. On the horizontal axes, the red and blue pointers mark the dates of the start and the end of the 2008-9 recession for the upper panel and for period after 2017 for the lower panel, respectively, computed using the BBQ algorithm. On the vertical axes for the upper panel, the pointers mark the announcement date of the II. quarter-2008 and II. quarter-2009 GDP, whereas for the lower panel the pointers mark the announcement date of the III. quarter-2018 and IV. quarter-2018 GDP when the BBQ algorithm signals the peak and through for 2008-9 and 2018 recessions for the first time given the available data in real-time.

Specifically, we display the posterior probabilities of being in a recession for a given vintage T, before and at the terminal date, i.e. in-sample probabilities together with back- and nowcasts of recessions, and after the terminal date of the vintage, i.e. predictive probabilities of being in recession up to eight months ahead. These probabilities are computed for data vintages spanning the periods from December 2006, T_1, until January 2011. This episode comprises the periods just before, during and after the 2008-9 recession. The vertical axis shows the specific vintage, T, used to compute the posterior probabilities while the horizontal axis shows time, t, starting from January 2007 to February 2011. Each row of the graphs represents the values of the posterior probabilities of a recession over time, $Pr(S_{1,t} = 1|\mathbf{y}^T)$ for $t = T_1, T_1 + 1, \ldots, T, T + 1, \ldots, T + 8$, based on the vintage as indicated on the vertical axis. Values of the recession probabilities greater than 0.5 are represented by the shades of red color getting darker as the probabilities are getting closer to 1. Probabilities smaller than 0.5 are represented by the shades of the blue color getting darker as the probabilities are getting closer to 0. If, for a particular vintage, the color changes from blue to red in a certain month and remains red thereafter, then this month is considered as a business cycle peak, i.e., the onset of a recession. A change from red to blue similarly represents a business cycle trough, the onset of an expansion. We indicate the periods of the 2008-9 recession identified according to the BBQ algorithm on the horizontal axis with the red marker as the peak and the blue marker as the trough of the cycle. Looking across the columns of these graphs shows how the assessment of the probability of a recession changes across the different data releases.[22]

The upper panel of Figure 2.6 provides insights on the dynamics of the competing models through the lens of the 2008-9 recession. First, we consider the onset of the recession, i.e. the business cycle peak, which is dated as April 2008 by the BBQ algorithm in September 2008. Focusing on the January 2008 vintage, the IS model specification starts to deliver signals with predictive probabilities approaching to 0.4 for around April 2008. Interestingly, the model with perfectly synchronized cycles produces signals of the oncoming recession starting almost from January 2008, with recession probabilities wandering around 0.4-0.5. However, in line with our in-sample findings, these 'false' early signals are due to the fact that this model captures the financial cycle rather than the business cycle. By contrast, the IS model captures

[22]We also add the red and blue markers on the vertical axis. In this case, they represent the release date of the GDP or industrial production series, when, in real-time, the BBQ algorithm computed using these vintages indicates the recession date. We include these markers on the vertical axis to compare our methodology with more conventional methods in terms of generating recession signals in a timely manner.

the business cycle peak of April 2008 in a timely and accurate manner. At first sight, these false signals produced by the PS model might be considered as 'positive' false signals, as it still signals recessions early though imprecisely. However, the model produces these signals in almost every downturn of the financial cycles in 2011, 2013 and 2015 which did not evolve into recessions in real sector. This also explains the poorer performance of the PS model relative to IS model in Table 2.3. Finally, the model with independent cycles displays the poorest performance for signaling recessions. The first signals using this specification emerge as late as April 2008 and these are interrupted later on until August 2008. Since the model with independent cycles resembles the conventional methodology of measuring business cycles, its failure to accurately capture the business cycle peak of April 2008 points the inadequacy of this approach.

Next, we consider the performance of the models in predicting the oncoming expansion, i.e. business cycle trough, which is (*ex post*) dated as March 2009 by the BBQ algorithm in September 2009. Focusing on the January 2009 vintage, the IS specification delivers recession probabilities for March and April 2009 that gradually decline to values around 0.6-0.7. These probabilities reduce well below 0.5 with the release of the March 2009 vintage. For the model specification with perfect synchronization of the cycles, signals of oncoming expansion are delivered much earlier than the actual date of the trough. Even for the vintages released after March 2009, in-sample estimates of recession probabilities indicate the end of the recession as early as December 2008, confirming the finding that this model essentially conveys information about the financial cycle rather than the business cycle. Finally, the model with independent cycles performs worst, providing false signals of the trough much earlier than the actual realization.

Recently, Turkey has experienced a turmoil period of economic fluctuations starting with the massive depreciation of the local currency in August 2018 which has lasted until the first quarter of 2019. Therefore, we repeat the analysis for the periods starting from January 2017 until the end of the sample. The bottom panel of Figure 2.6 displays the performance of the models in predicting the economic downturn with a focus on the periods in 2017-9. In this case, the IS model starts to deliver timely accurate signals of recession as early as in June 2018 and it provides the signals of the oncoming expansion as early as in November 2018. As in the case of 2008-9 recession, the model with perfect synchronization starts to produce signals of the peak and trough of the business cycle as early as the IS model but with the peak and trough dated earlier than the actual time of realization reflecting the effects of the financial cycle. The model with independent cycles also produces a recession signal for August 2018 by July 2018. However, this model almost uniformly produces recession signals in the forecasts using most of the vintages considered in this subsample, as can be seen in the last graph. Correspondingly, the model with independent cycles performs worst providing false signals repeatedly.

Chapter 3

IMPROVING DENSITY NOWCASTING OF GDP USING SURVEY OF PROFESSIONAL FORECASTERS

This chapter gives the details about the second essay, nowcasting and forecasting density of GDP using surveys. We use surveys as not for any other variables to be included in the data set, but we align the surveys with the model forecasts. We utilize this nowcasting model for U.S. real GDP growth rate using Survey of Professional Forecasters (SPF), but the model can be seen as a prototype for nowcasting not only U.S. GDP, but also the other indicators of interest at different frequencies such as employment and inflation as well as for the important indicators of other developed countries and\or emerging economies with surveys in hand.

The remainder of this chapter is organized as follows. Section 3.1 presents model specifications. Section 3.2 presents the data. Section 3.3 briefly describes the estimation methodology, whereas we give full details about conditional distributions and Gibbs Sampling in Appendix L. Section 3.4 presents the estimation of the conditional GDP distributions and evaluates the results of real-time nowcasting and forecasting for different specifications over RMSFE, (log score of) predictive likelihoods and PITs.

3.1 Model

For the methodology we will propose in this study, [Modugno, 2013] and [Banbura et al., 2013] model is quite useful to begin with as a baseline model as well as using for as a benchmark. We adopt their monthly model to build on, but it can be easily extended for higher frequency.[1]

[1]By the same methodology, [Modugno, 2013] produces nowcasts of inflation, [Angelini et al., 2010] nowcasts the GDP components and [Banbura et al., 2013] nowcasts GDP.

We first model the dynamics for monthly data. The transformations we adopt for the series to ensure the stationarity property are given in Table 3.1. The stationary series are standardized to mean 0 and unit variance. Let $y_t^m = [y_{1,t}^m, y_{2,t}^m, .., , y_{n_m,t}^m]'$, $t = 1, 2, .., T$ denote the n_m-dimensional vector of stationary standardized monthly series. The monthly series and parameters are denoted with a superscript of 'm'[2]. We assume that y_t^m admits the following factor model structure:

$$y_t^m = \lambda^m f_t^m + \varepsilon_t^m \ , \quad \varepsilon_t^m \sim N(0, diag(\sigma_1^2, \sigma_2^2, .., \sigma_{n_m}^2)) \tag{3.1}$$

where f_t^m is a latent common factor, λ^m is n_m-dimensional factor loadings and $\varepsilon_t^m = [\varepsilon_{1,t}^m, \varepsilon_{2,t}^m, .., \varepsilon_{n_m,t}^m]'$ is the idiosyncratic term uncorrelated with f_t^m for all leads and lags. Furthermore, we assume for the common factor to follow a stationary AR(1) process:

$$f_t^m = \phi f_{t-1}^m + u_t^m \ , \quad u_t^m \sim N(0, \sigma_u^2) \tag{3.2}$$

[Banbura et al., 2013] concludes that using more than one factor does not change the results qualitatively and continue with single factor for the same model. We follow them by choosing single factor with AR(1) process from the beginning in order to keep the model parsimonious and avoid the difficulty of the estimation of parameters as we will introduce non-linear extension to the existing model.

We construct temporal aggregator variable f_t^q to aggregate f_t^m recursively at every month to keep the size of state vector moderate. At the end of the each quarter, we have:

$$f_t^q = \sum_{s=0}^{4} w_s f_{t-s}^q \ , \quad t = 3k, \ k = 1, 2, .., K \tag{3.3}$$

where w_k represent the elements of $w = [1, 2, 3, 2, 1]'$ with sample-size of K-quarters.

We have one quarterly series, real GDP, which is a flow variable and sixteen monthly variables. We construct the model at monthly frequency, therefore there is

[2]For quarterly series and parameters we use a superscript of 'q'.

no need to distinguish between stock and flow variables for monthly variables, as all monthly variables are always observed, i.e. they are not regularly missing. Let g_t^q be GDP level at the time t. In a monthly model where t increases as monthly intervals, g_t is observed at time $t = 3k,\ k = 1, 2, .., K$ with the sample size of L quarters and missing otherwise. Let g_t be unobserved monthly counterparts of g_t^q, where g_t^q is sum of the values of the three months for the current quarter: $g_t^q = \sum_{k=0}^{2} g_{t-k}$, see [Harvey, 1990]. Let denote logarithm of GDP as z_t^q and logarithm of monthly unobserved counterpart as z_t. Following [Mariano and Murasawa, 2003] and [Bańbura and Modugno, 2014] among others, we take logarithm of g_t^q and approximate this with logarithm of the monthly counterparts yields $z_t^q \approx \sum_{k=0}^{2} z_{t-k}$. Finally, let y_t^q and y_t be the log-differenced series as quarterly and unobserved monthly counterpart, respectively. This yield as follows:

$$\begin{aligned} y_t^q = (\sum_{k=0}^{2} z_{t-k}) - (\sum_{k=3}^{5} z_{t-k}) &= \Delta z_t + 2\Delta z_{t-1} + 3\Delta z_{t-2} + 2\Delta z_{t-3} + \Delta z_{t-4} \\ &= y_t + 2y_{t-1} + 3y_{t-2} + 2y_{t-3} + y_{t-4} \end{aligned} \tag{3.4}$$

As monthly series y_t is not observed, we estimate y_t and its lags using the common factor f_t^m as follows:

$$y_t^q = \sum_{k=0}^{4} w_k y_{t-k} = \sum_{k=0}^{4} w_k(\lambda f_{t-k}^m + \varepsilon_{t-k}) = \lambda^q f_t^q + \varepsilon_t^q \tag{3.5}$$

We assume ε_t^q is white noise at quarterly intervals by following [Banbura et al., 2013] as opposed to [Mariano and Murasawa, 2003] and [Camacho and Perez-Quiros, 2010], where they treat the quarterly error terms as aggregation of monthly error terms as in (3.4). Inclusion of the GDP growth yields the state-space representation of the baseline model as in [Banbura et al., 2013], the measurement and transition equations respectively as:

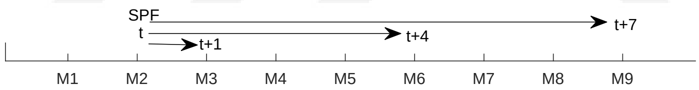
$$\begin{bmatrix} y_t^q \\ y_t^m \end{bmatrix} = \begin{bmatrix} \tilde{\lambda}^q & 0 \\ 0 & \lambda^m \end{bmatrix} \begin{bmatrix} \tilde{f}_t^q \\ f_t^m \end{bmatrix} + \begin{bmatrix} \varepsilon_t^q \\ \varepsilon_t^m \end{bmatrix} \text{ and } \begin{bmatrix} I_{2r} & W_t \\ 0 & I_r \end{bmatrix} \begin{bmatrix} \tilde{f}_t^q \\ f_t^m \end{bmatrix} = \begin{bmatrix} I_{2,t} & 0 \\ 0 & \phi \end{bmatrix} \begin{bmatrix} \tilde{f}_{t-1}^q \\ f_{t-1}^m \end{bmatrix} + \begin{bmatrix} 0 \\ u_t \end{bmatrix} \tag{3.6}$$

where W_t includes aggregation weights, $I_{2,t}$ contains zeros and ones. Both W_t and $I_{2,t}$ are time-varying. $\tilde{f}_t^q = [f_t^q \ \bar{f}_t^q]'$ has an auxiliary aggregator variable, $\bar{f}_t^q$ and $\tilde{\lambda}^q = [\lambda^q \ 0]$.[3]

3.1.1 Mean of SPF

To introduce the expectations of SPF into the model, let $E_t^S[y_{t+3l+1}^q]$ be the expectation of l quarters ahead value of GDP growth for $l = 0, 1, 2, 3, 4,$ where the superscript S stands for 'SPF-based expectations'. $E_t^S[y_{t+3l+1}^q]$ is observed for $t = 3k - 1, \ k = 1, 2, .., K$ since SPF is released at the middle month of the current quarter. We represent the nowcast of SPF as $E_t^S[y_{t+1}^q]$ $(l = 0)$ and forecasts for up to 4 quarters ahead as $E_t^S[y_{t+3l+1}^q]$ for $l = 1, 2, 3, 4$ as illustrated for the release of the SPF at the second month in Figure 3.1.

Figure 3.1: Expectations of SPF



We now produce "model-based expectations", $E_t^M[y_{t+3l+1}^q]$, at time t for $l = 0, 1, 2, 3, 4$. Given the information set containing observations for all variables for times up to and including period t, the nowcast of the GDP growth(at the end of the quarter, month $t + 1$) would be

$$E_t^M[y_{t+1}^q] = \lambda^q(f_{t+1}^m + 2f_t^m + 3f_{t-1}^m + 2f_{t-3}^m + 1f_{t-4}^m) = \lambda^q(\phi f_t^m + f_t^q) \qquad (3.7)$$

representing the 'nowcast' produced by the model where we replace f_{t+1}^m with ϕf_t^m, using the projection f_t^m in the transition equation, and the remaining part accumulated in the f_t^q at time t. For the forecasts up to 4 quarters ahead, it turns out

[3] See Appendix K for further details.

$$E_t^M[y_{t+3l+1}^q] = \lambda^q(\sum_{s=0}^{4} \phi^{3l+1-s} w_s) f_t^m \text{ [4]} \qquad l = 1,2,3,4. \tag{3.8}$$

We assume that the survey expectations should match the prediction from the DFM with some error. By matching these, we seek to accommodate the model-based expectations with the projections obtained from professional forecasters in a statistically coherent way. The relationship can be written as:

$$E_t^S[y_{t+3l+1}^q] = E_t^M[y_{t+3l+1}^q] + v_{l,t} \qquad l = 0,1,2,3,4. \tag{3.9}$$

Let denote the inside of the parenthesis in (3.8) as $\mathbb{A}_l$, $y_{t,n}^q$ for survey nowcast ($l = 0$) and y_{t,f_l}^q for l-ahead survey forecast for representing (3.9) as new measurement equations. While the transition equation remains unchanged, the measurement equations augmented with surveys can be represented as follows:

$$\begin{bmatrix} y_t^q \\ y_{t,n}^q \\ y_{t,f_{1:p}}^q \\ y_t^m \end{bmatrix} = \begin{bmatrix} \tilde{\lambda}^q & 0 \\ \tilde{\lambda}^q & \phi \\ 0 & \mathbb{A}_{1:p} \\ 0 & \lambda^m \end{bmatrix} \begin{bmatrix} \tilde{f}_t^q \\ f_t^m \end{bmatrix} + \begin{bmatrix} \varepsilon_t^q \\ \varepsilon_{t,n}^q \\ \varepsilon_{t,f_{1:p}}^q \\ \varepsilon_t^m \end{bmatrix} \tag{3.10}$$

where $y_{t,f_{1:p}}^q = [y_{t,f_1}^q, .., y_{t,f_p}^q]'$ and $\mathbb{A}_{1:p} = [\mathbb{A}_1, .., \mathbb{A}_p]'$ for $p = 1,2,3,4$. In order to evaluate the inclusion of further horizons of survey-based-expectations, we consider five specifications: one for only nowcasts excluding $y_{t,f_{1:p}}^q$ along with corresponding rows in factor loading matrix and error term vector, four for including $y_{t,f_{1:p}}^q$ for

[4]We could iterate the quarterly factor f_t^q rather than iterating the monthly factor f_t^m as follows:

$$E_t^M[y_{t+3l+1}^q] = \lambda^q \Phi^l f_t^q \qquad l = 1,2,3,4.$$

where we estimate Φ given f_t^q, the coefficient of AR(1) process. This method yields similar results. However, estimation of Φ means an extra parameter to be estimated and we have already estimated ϕ in the transition equation, thus we stick with the monthly factor at these steps. The results of iterating f_t^q are available upon request.

$p = 1, 2, 3, 4$ in addition to the nowcast.

3.1.2 Stochastic volatility and variance of SPF

We only insert stochastic volatility structure into the measurement equation of GDP y_t^q rather than evolution of factor f_t^m for several reasons, as opposed to [Marcellino et al., 2016], that uses stochastic volatility structure in both the idiosyncratic term and the common component in mixed frequency DFM. First, we would need to drive the stochastic volatility of f_t^q taking into account the mixed frequency nature of the model and also deal with the identification issues coming from disentangling the summation of two time-varying variances. Second, inclusion of stochastic volatility into the error term of factor u_t in (3.2) for the baseline model does not improve the accuracy of prediction (in log score of predictive likelihoods) in unreported results[5], but modeling stochastic volatility in idiosyncratic term of GDP decreases predictive likelihoods, which we give the results of these in Section 3.4.2. Therefore, we only focus on the remaining error term of GDP apart from common factor component for the sake of simplicity. We follow [Justiniano and Primiceri, 2008] as it is common in the literature for the stochastic volatility for the measurement equation of GDP in (3.5) as the following equations:

$$
\begin{aligned}
\varepsilon_t^q &= \exp(\tfrac{h_t}{2})\epsilon_t\ , \quad \epsilon_t \sim N(0,1) \\
h_t &= h_{t-3} + \sigma\eta_t\ , \quad \eta_t \sim N(0,1)
\end{aligned}
\tag{3.11}
$$

where $t = 3k,\ k = 1, 2, .., K$, defined at quarterly intervals at a monthly model. We model the auto-regressive equation of h_t as random walk, since this type of specification is found to be quite useful in forecasting literature.[6]

[5] The results are available upon request.

[6] [Clark, 2011] and [D'Agostino et al., 2013] claim that random walk specification enhances the accuracy in terms of point and density forecasts in VAR context. [Carriero et al., 2015] considers stationary specifications in a Bayesian Mixed Frequency (BMF) model and finds that the random walk specification preforms better than an stationary AR(1) model with different coefficients. In addition, [Diebold et al., 2017] concludes that PITs derived from stochastic-volatility specification with random walk process appear to be much more uniform compared to the other model specifications.

We first square, then take the logarithm of the first equation in (3.11) and obtain the following equation:

$$log((\varepsilon_t^q)^2) \quad = \quad h_t + log(\epsilon_t^2)\ , \quad \epsilon_t \sim N(0,1) \tag{3.12}$$

We approximate to the distribution of $log(\epsilon_t^2)$ by using ten mixture of normal distributions as [Omori et al., 2007].[7]

We now turn to the the second moment of the survey for the other measurement equations for h_t. We use the disagreement among individual forecasters as uncertainty proxy for variance.[8]. We represent the variance of SPF as $Var(SPF)_{t+3l}$ for $l = 0, 1, .., 4$, starting from the variance of the current quarters nowcast up to 4 quarters ahead forecasts. By taking the logarithm of the variances of SPF, we can align these with the projection of h_t with a scaling coefficient and some error as follows:

$$log(Var(SPF)_{t+3l}) = \sigma_w E[h_{t+3l}] + v_{l,t} \tag{3.13}$$

The random walk property of h_t allows us to iterate h_t for future values easily without any complicated non-linear functions of coefficient as in the case for incorporating the mean in the previous section, since $E[h_t] = E[h_{t+3l}]$ for $l = 1, 2, 3, 4$.

Then for the state-space representation, we align the variance of SPF with the variance of the error term of GDP measurement equation as follows:

$$\begin{bmatrix} log((\varepsilon_t^q)^2) \\ log(Var(SPF)_{(t:t+3l)}) \end{bmatrix} = \begin{bmatrix} 1 \\ \sigma_w \end{bmatrix} h_t + \begin{bmatrix} log(\epsilon_t^2) \\ v_{t,(0:l)} \end{bmatrix} \tag{3.14}$$

where $v_{t,0:l} = [v_{t,0}, .., v_{t,l}]'$ for $l = 0, 1, 2, 3, 4$ with 0 indicates nowcast. Similarly we consider five specifications, starting from using only nowcast(l=0), gradually increase the number of equations as adding up to 4 quarters ahead variances.

[7]We give the details about the distributions in Appendix L.2.

[8]We explicitly show how we calculate the variance of SPF in Appendix L.2

3.2 The Data

We consider quarter-on-quarter real GDP growth rate for nowcasting application. The output is measured as Gross National Product (GNP) until 1991 and Gross Domestic Product(GDP) after that period. We refer output series in general as GDP for simplicity. At quarterly frequency, we have real GDP along with SPF expectations of current quarter up to 4 quarters ahead, whereas at monthly frequency our dataset includes 16 series which are broadly informative about real activity. Table 3.1 provides the list of series, including the start date, publication delay, observation frequency and the transformation we have applied. This is the dataset that [Banbura et al., 2013] uses excluding daily and weekly variables except SPF.[9] We have selected their dataset of monthly model since it performs well in the same framework and comparable to SPF, even outperforms starting at the end of the third month of a quarter. By this way it would be worth considering to incorporate the surveys if the proposed model outperforms the baseline model without SPF.

[9] [Banbura et al., 2013] concludes that daily and weekly information such as financial variables do not improve the accuracy of nowcasting GDP. Our model can easily be adopted at higher frequency such as daily in terms of modeling approach, but the computation is intensive for the specifications with the non-linear parts with the same parameters appear in different equations-computed by Metropolis Hastings, thus it is not feasible for out-of-sample exercise. For a weekly model, we would have to construct the framework at daily frequency with missing observations as in [Aruoba et al., 2009] since number of weeks in a month changes and does not reflect the working days in a coherent way.

Table 3.1: Set of variables: The frequencies, transformations, periods and publication delays

No	Series	F	T	Start	Delay
1	Real Gross Domestic Product	Q	1	1968:IV	1M
2	Industrial Production Index	M	1	1968:12	1M
3	Purchasing Manager Index: Manufacturing	M	2	1968:12	1M
4	Real Disposable Personal Income	M	1	1968:12	1M
5	Unemployment Rate	M	2	1970:1	1M
6	All Employees: Total Nonfarm Payrolls	M	1	1968:12	1M
7	Personal Consumption Expenditures	M	1	1968:12	1M
8	Housing Starts: Total: New Privately Owned Housing	M	1	1968:12	1M
9	New One Family Houses Sold	M	1	1968:12	1M
10	Manufacturers' New Orders: Durable Goods	M	1	1992:2	1M
11	Producer Price Index: Finished Goods	M	1	1968:12	1M
12	Consumer Price Index for All Urban Consumers	M	1	1968:12	1M
13	Imports of Goods and Services	M	1	1992:1	2M
14	Exports of Goods and Services	M	1	1992:1	2M
15	Philadelphia Fed Survey: General Business Conditions	M	2	1968:12	-
16	Retail Sales: Retail and Food Services	M	1	1992:1	1M
17	Conference Board Consumer Confidence	M	2	1968:12	-
	Survey of Professional Forecasters				
	Real Gross Domestic Product	Q	1	1968:IV	-1M

Note: T indicates the type of transformation of variables to ensure stationarity (1=first difference of logarithm, 2=first difference) and F indicates frequency. Series at higher frequencies are converted to monthly by using corresponding frequency averages. The brighter grey shaded ones are the variables we use in our small model and also these are the five hard variables considered by the NBER's Business Cycle Dating Committee (BCDC). Our reference point for delays is the end of the months in which we produce the nowcasts. The darker grey shows the data on SPF for real GDP. "-1M" indicates that nowcast for the reference quarter and forecasts for the subsequent four quarters are available at the second month of the current quarter.

In order to incorporate into the model, we consider the expectations for real GDP growth from the Survey of Professional Forecasters at forecaster level. The Figure 3.2 shows the mean of SPF. The black line shows the observed real GDP growth rate which is released with one month lag, whereas the red line represents the nowcast. The other lines with different colours depict the SPF expectations of indicated date's GDP on the horizontal axis, available already before the current quarter, according to their horizon of forecast.

The Figure 3.2 suggests that the mean of SPF generally performs well, justifying the common usage as a benchmark in the literature, except for the periods in the middle of 1980s and in the late 1990s, where the SPF persistently underestimates the GDP growth as discussed in [D'Agostino and Schnatz, 2012]. In addition, one can see that predictive content gradually decreases towards the further quarters ahead forecasts as expected, also discussed in [Stark et al., 2010].[10]

[10]This case is the same for the model based estimation via Kalman Filter, since the forecasts

For the second moment of the SPF, Figure 3.3 shows the standard deviation derived as the square root of the cross-sectional dispersion. We align the series according to the times for which forecasts are made, as in Figure 3.2. The overall trend of deviation are in line with the literature about the estimation of the volatility of GDP, see [Carriero et al., 2015] and [Marcellino et al., 2016] among others. It seems that the high volatility period before the mid-1980s are reflected and then decreased substantially, followed with low volatility period, called as "Great Moderation" in the literature.[11]

Figure 3.2: The mean of SPF

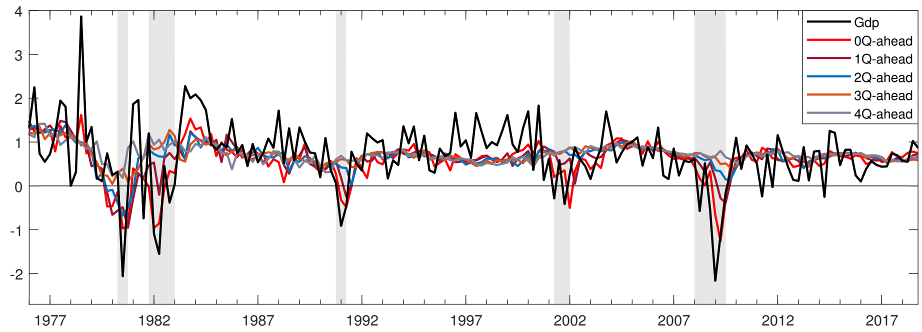
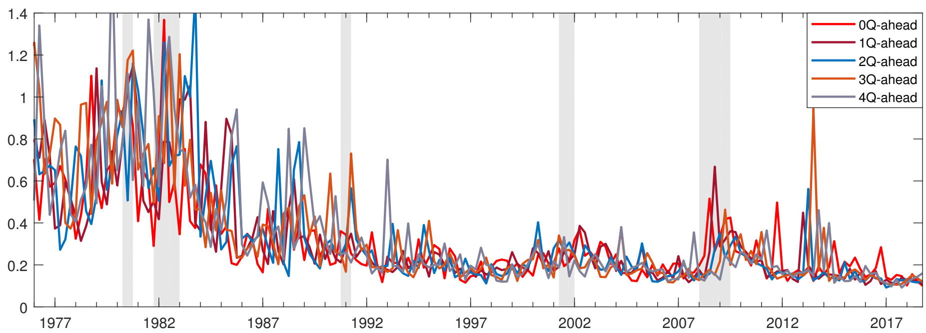


Figure 3.3: The Standard Deviation of SPF



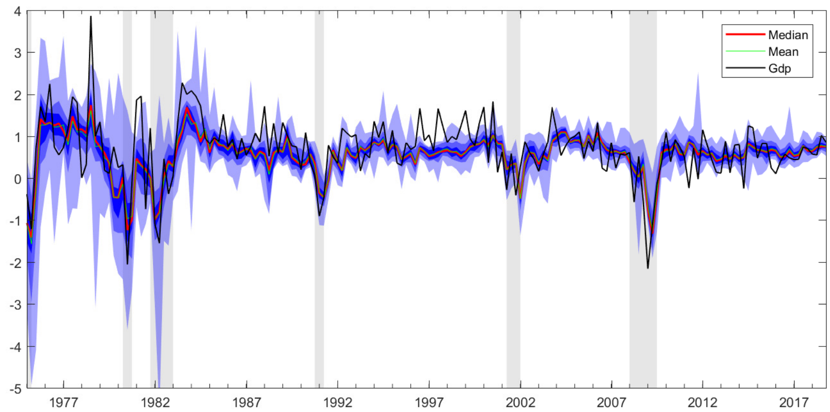
To give a broader picture about the distribution of the nowcast of SPF over time, we provide the 1th, 10th, 25th, 75th, 90th, 99th percentiles with the median and the

of factors for further quarters will fade away because of the nature of AR(1) process, given in Section 3.1.1. Therefore, aligning the model forecasts with survey based expectations have effect on the estimation of the auto-regressive coefficient of the model.

[11] See [Stock and Watson, 2002] and [Clark et al., 2009] among others.

mean of the individual data for the current quarter nowcast of real GDP growth in Figure 3.4. It also appears from the the percentiles of SPF that the recessions are associated with high volatility such as late 1970s and early 1980s and 2008 financial crisis.

Figure 3.4: The percentiles of SPF for nowcast



The SPF data that we use in the models contains forecasts made during every quarter from 1968:Q4 to 2017:Q4 of both current quarter-nowcasts (h = 0) and future horizons up to four quarters ahead-forecasts (h = 4). Although prior to 1974:Q4, the SPF forecasts were not always available up to the fourth quarter horizon, our framework can handle the missing observations. Therefore, to use the all available survey information we select the same starting point for our sample as the beginning of the SPF expectations. For each quarter ahead, we take the forecasts of real output levels and transform into quarter-on-quarter growth rate.[12]

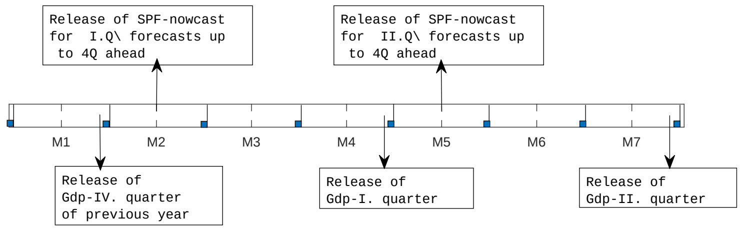
Figure 3.5 gives the time-line for variables of interest and the time when nowcasting are done. Real GDP is generally released at the end of the first month of the following quarter, whereas SPF is released at the second week of the middle month in the current quarter.[13] The blue rectangles indicates the time that we do nowcast

[12]We use the difference between the natural logarithms of forecasts of the output levels to use the same transformation as real GDP growth rate indicated in Table 3.1, as opposed to Federal Reserve Bank of Philadelphia using growth formula including taking fourth power of fraction of levels and releasing the growth rates of median and mean forecasts accordingly. See SPF Documentation.

[13]This release date is valid for the time after 2005:Q1.

for the current quarter and forecasts for further quarters.

Figure 3.5: The timeline



We consider now-forecasts at the end of the months for several reasons: First, in the first month of every quarter, our estimate of unavailable output data is now-cast rather than back-cast, since we estimate after the release of output for the previous quarter. This would allow us to evaluate the predictive likelihoods more conveniently. Second, the goal of the study is not to detect the impact of the updates of the nowcast from different data releases throughout the quarter as discussed in [Aastveit et al., 2014], [Bok et al., 2018] and [Banbura et al., 2013], but rather evaluate the integration of the SPF. Third, true deadline and news release dates for surveys are not known before 1990:Q2. After that period, although the release times are known, they have been changed over time. For example, during 1990s, surveys are released towards the end of the months, whereas during 2000s, they are released in the middle of the months.[14]

We produce the out-of-sample nowcasts and forecasts on the basis of psuedo real-time data vintages using two datasets besides SPF: The five hard variables which are considered by the NBER's Business Cycle Dating Committee (BCDC), shown as gray-shaded in Table 3.1 and the seventeen variables considered by [Banbura et al., 2013].

The out-of-sample evaluation period begins from 1977:M3 through 2017:M3,

[14]For the periods between 1968:Q4 and 1990:Q1, the SPF were conducted by the American Statistical Association (ASA) and the National Bureau of Economic Research (NBER). The Philadelphia Fed had taken over the surveys in 1990:Q2. For the release dates after 1990:Q2, see Dates of Previous Surveys.

whereas the model estimation sample starts always at 1968:M12, the soonest possible given SPF data availability. We make nowcasting at the end of the months using pseudo real-time data vintages, which we construct according to the data publication delays given in Table 3.1. This non-synchronous data releases lead to missing observations at the end of the sample referred to as 'ragged' or 'jagged'-edge, which we can handle in the Kalman Filter.

Given the difficulties of preparing the fully real-time vintages of the variables we consider for the period between 1977-2017, we disregard the possible effects of data revisions. We have only replicated the evaluations for real-time output series, by using the second release of GDP by following [Romer and Romer, 2000], [Faust and Wright, 2009] and [Carriero et al., 2015]. We have used the quarterly vintage of GDP/GNP releases from Philadelphia Fed's real-time data set for macroeconomists, (RTDSM) and obtained qualitatively similar results[15], as [Robertson and Tallman, 1998] and [Schumacher and Breitung, 2008] discusses using only the latest available vintage of data does not affect the model's ranking. [Stark et al., 2010] also makes a comparison between the univariate time-series models and the surveys in a real-time exercise for GDP growth and found that data revisions change the accuracy only in terms of the values and does not have any effect on the comparative performance of surveys to the benchmark models.

3.3 Estimation Procedure

We adopt a Bayesian approach for nowcasting and inference on all parameters and we utilize Markov Chain Monte Carlo (MCMC) techniques. More specifically, we use Metropolis–Hastings algorithm within Gibbs sampling[16] for the specifications with non-linear parts for posterior inference. We further give the details on specifi-

[15]The in sample fit is improved substantially by looking at the marginal likelihoods, if we use real-time data for output series. This is probably due to the fact that the survey of professional forecasters is real-time by default. This is also testified with the finding of [Stark et al., 2010], evaluated SPF in real-time and concluded that SPF predictive performance for GDP growth deteriorates when the actuals are used. The results from the replication with the second releases of GDP growth are available upon request.

[16]See [Geweke and Tanizaki, 2001].

cations of the prior distributions and inference including the likelihood function of the model, and the algorithm scheme for simulating from the posterior distributions together with full details on the conditional posterior distributions in Appendix L. We compute the marginal likelihood values and predictive likelihoods to compare models with different specifications.

3.4 Empirical Findings

In this section, we report our empirical findings using different models as well as different datasets. We give in-sample results for the period between the first quarter of 1968 and 2017, and out-of-sample results for the first quarter of 1977 and 2017, as noted in Section (3.2). We estimate the models at the end of the months. Specifically, for the first month of a given quarter, we make estimation after the release of previous quarter's GDP, thus we discard back-casts.

We report the results for the models for two datasets: five hard variables considered by BCDC, given as grey-shaded in Table (3.1)-"small" scale version and seventeen variables considered by [Banbura et al., 2013]-"large" scale version, besides SPF. The comparison between small and large factor model gives the opportunity to understand whether SPF reflect the information contained in other variables beyond five-hard variables, such as PMI, business conditions and confidence surveys.

In the following section, we provide broad analysis on the performance of the competing models in real-time nowcasting and forecasting of GDP in detail. The competing models include (i) **"Baseline Model"** - the baseline model in (3.6), (ii) **"SPF-M"** - only the mean of SPF is incorporated as in (3.10) (iii) **"SV"** - the baseline model with stochastic volatility given in (3.11), (iv) **"SV-SPF-M"** - the mean of SPF is incorporated along with stochastic volatility, (v) **"SV-SPF-V"** - stochastic volatility augmented with the variance of SPF as in (3.14), (vi) **"SV-SPF-MV"** - both the variance and the mean of SPF are incorporated with stochastic volatility, combination of (3.10) and (3.14). For the model specifications with SPF, (ii)-(iv)-(v)-(vi), we gradually increase the survey information for up to further horizons to analyze whether future expectations of professional forecasters give further information beyond nowcast. More specifically, first we estimate these models with using only survey nowcasts, and then increase the size of the survey data in which we use up to 4 quarters ahead forecasts.

First, we give the findings of the full-sample estimation. Figure 3.6 shows in-sample estimation only derived from the **Baseline Model** and **SV-SPF-MV-4Q** for the entire sample period for the sake of brevity.[17] The grey areas are the recession periods at a quarterly basis determined by NBER. It seems both the **Baseline Model** of [Banbura et al., 2013] and the proposed model tracks GDP well for in-sample estimation with slight differences for some periods.

Figure 3.6: The estimated mean of GDP growth

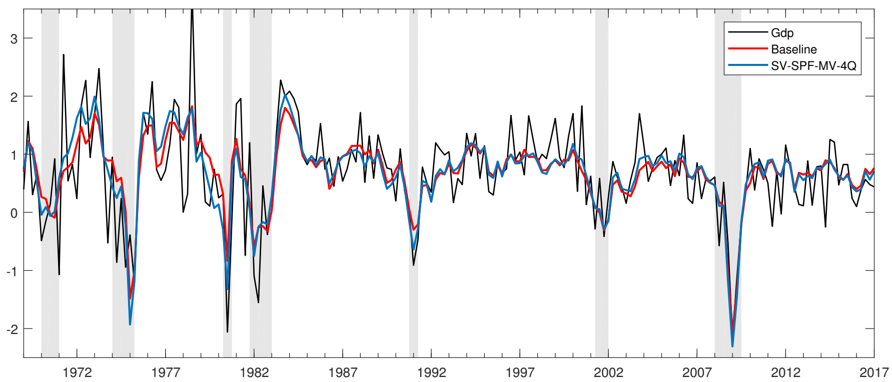
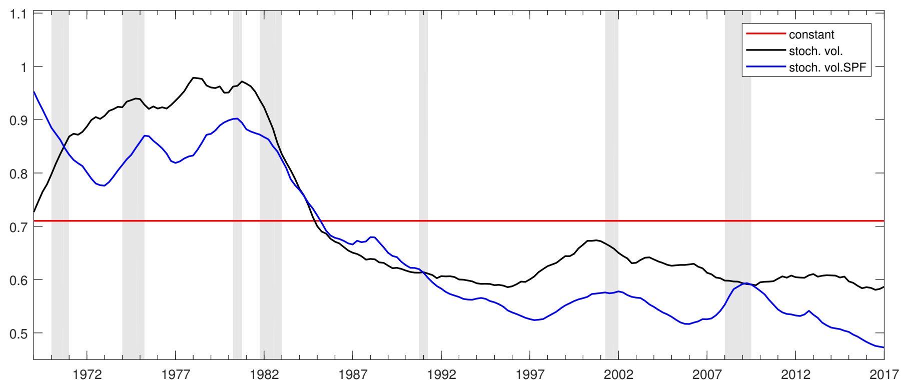


Figure 3.7 shows in-sample estimation of the standard deviation of the measurement equation of GDP for three different models; **Baseline Model** in which the variance of error term is constant, **SV**- only the stochastic volatility specification is included to baseline model and **SV-SPF-V-4Q** model, stochastic volatility aligned with the variance of SPF, all horizons included. The estimated variance of GDP from different specifications show the importance of modeling changing volatility, especially for the Great Moderation period. The movements of the standard deviations derived from the **SV** and **SV-SPF-V-4Q** are similar for most of the times, except the 2008 financial crises, reflecting that **Baseline Model** performs well in

[17]The results for the models with 5 variables as well as for other specifications are available upon request.

the financial crisis and does not have high errors.

Figure 3.7: Estimated standard deviation of the measurement equation of GDP



For in-sample model comparison, we use metric of the (logarithm of) marginal likelihood for the goodness of fit between data and the models. For out-of-sample comparison, we use RMSFE for point-forecast and the (log score) of predictive likelihoods and probability integral transforms (PITs) for selected models to evaluate the accuracy of density forecasts. We evaluate the results from following perspectives: i)including more timely variables in addition to 5 main variables given in Table 3.1, ii) the different model specifications added to baseline model iii) different months (**M1-M2-M3**) in a given quarter at various horizons (**Q0-Q1-Q2**). In the next sections, we asses the findings in detail.

3.4.1 Point forecasts: RMSFE

Although in this essay we aim to improve the density nowcasts, we also check the results in terms of point forecasts. The results on point evaluation are based on Root Mean Squared Forecast Error (RMSFE) of all models predictions on each months of current quarters up to 2 quarters ahead. We calculate RMSFE starting from the first quarter of 1977 up until the first quarter of 2017 with respect to realized GDP, available in April 2018. The results of RMSFE on 5 variables and 17 variables are given in Table 3.2 and Table 3.3. We calculate RMSFE at the end of the each month in a given quarter, **M1**, **M2** and **M3**, and for up to 2 quarters ahead starting from

Table 3.2: The RMSFE: 5-variables model over different specifications

	RMSFE								
	Q0			Q1			Q2		
	M0	**M1**	**M2**	**M0**	**M1**	**M2**	**M0**	**M1**	**M2**
Baseline Model	0.642	0.558	0.569	0.736	0.727	0.684	0.748	0.748	0.745
SPF		1.021			0.972			1.038	
SPF-M-0Q	1.008	1.014	1.007	1.000	0.988	1.000	1.009	0.997	0.992
SPF-M-1Q	1.002	0.989	0.981	0.995	0.972	1.003	1.004	0.987	0.993
SPF-M-2Q	0.998	0.995	0.968	0.993	0.957	0.991	1.013	0.980	0.992
SPF-M-3Q	0.991	1.013	0.970	0.995	0.960	0.991	1.004	0.980	0.989
SPF-M-4Q	0.986	1.013	0.968	0.988	0.964	0.994	1.000	0.984	0.992
SV	1.005	0.998	0.998	0.990	0.989	1.003	1.004	0.996	1.004
SV-SPF-M-0Q	1.008	1.007	1.005	0.997	0.992	1.013	1.005	0.995	1.000
SV-SPF-M-1Q	1.000	0.991	0.970	0.996	0.959	0.994	1.009	0.975	0.996
SV-SPF-M-2Q	1.000	0.991	0.972	0.986	0.963	0.991	1.000	0.980	0.996
SV-SPF-M-3Q	1.000	0.998	0.972	0.992	0.952	0.990	0.999	0.983	0.996
SV-SPF-M-4Q	0.998	1.013	0.963	0.990	0.959	0.991	0.993	0.981	0.983
SV-SPF-V-0Q	1.005	0.987	0.995	0.997	0.982	1.007	1.005	0.992	1.008
SV-SPF-V-1Q	1.000	1.000	0.989	0.999	0.988	0.997	1.000	0.995	1.007
SV-SPF-V-2Q	1.011	1.002	0.998	0.989	0.990	1.006	1.013	0.995	0.997
SV-SPF-V-3Q	1.002	1.002	0.996	0.996	0.992	1.010	1.008	0.999	0.999
SV-SPF-V-4Q	1.002	1.000	1.002	0.996	0.992	1.006	1.005	0.993	1.005
SV-SPF-MV-0Q	1.017	1.009	1.002	0.996	0.992	1.004	1.011	0.991	0.995
SV-SPF-MV-1Q	1.003	0.989	0.979	0.996	0.967	0.996	1.007	0.984	0.995
SV-SPF-MV-2Q	0.994	0.998	0.968	0.999	0.959	0.997	1.001	0.973	0.992
SV-SPF-MV-3Q	1.002	1.009	0.974	0.986	0.960	0.987	1.000	0.977	0.992
SV-SPF-MV-4Q	0.994	1.005	0.967	0.992	0.959	0.994	1.007	0.976	0.989

Note: The Root Mean Square Forecast Errors are calculated three times per quarter for three consecutive quarters (from the first month of the current quarter, Q0-M1; to the third month of the two quarters ahead, Q2-M3) over the periods starting from the first quarter of 1977 until the first quarter of 2017 over a recursive window where the sample starts from last quarter of 1968. SPF-M represents that we use only the first moment of the individual forecasts in SPF; SPF-V represents we use only the second moment and SPF-MV represents we use both the first and the second moments, the mean and variance of individual forecasts. SV shows we incorporate the stochastic volatility structure in the measurement equation of real Gdp growth. The last part of the labels represents how many quarters ahead used from SPF; 0Q shows only the current quarter nowcast is used from SPF as it increases up to 4 quarters ahead.

Table 3.3: The RMSFE: 17-variables model over different specifications

	RMSFE								
	Q0			Q1			Q2		
	M0	**M1**	**M2**	**M0**	**M1**	**M2**	**M0**	**M1**	**M2**
Baseline Model	0.610	0.566	0.557	0.727	0.723	0.673	0.752	0.765	0.745
SPF		1.007			0.977			1.015	
SPF-M-0Q	1.015	0.989	1.007	0.997	0.990	1.019	0.999	0.983	0.980
SPF-M-1Q	0.993	0.973	0.984	1.001	1.000	1.004	1.000	0.982	0.989
SPF-M-2Q	1.002	1.005	1.025	0.979	0.985	0.991	1.011	0.990	0.962
SPF-M-3Q	0.987	1.002	0.977	0.967	0.974	0.981	1.027	0.976	0.992
SPF-M-4Q	0.993	1.014	0.995	0.982	0.945	0.975	1.007	0.979	0.979
SV	1.028	0.963	0.973	0.992	0.990	1.010	0.999	0.980	1.001
SV-SPF-M-0Q	1.041	0.998	1.020	0.990	0.990	0.994	0.997	0.983	1.000
SV-SPF-M-1Q	1.005	0.970	0.986	0.989	0.985	0.999	1.015	0.963	0.984
SV-SPF-M-2Q	1.010	0.982	0.978	0.988	0.976	1.016	1.012	0.979	0.991
SV-SPF-M-3Q	0.979	0.988	0.966	0.952	0.965	0.976	0.975	0.966	0.993
SV-SPF-M-4Q	1.007	0.996	1.005	1.008	0.968	0.981	1.020	0.969	0.987
SV-SPF-V-0Q	1.013	0.958	0.995	0.989	0.994	1.031	1.020	0.959	1.008
SV-SPF-V-1Q	1.033	0.959	0.996	0.999	1.000	1.012	0.996	0.983	0.992
SV-SPF-V-2Q	1.028	0.958	0.991	1.007	0.990	0.999	0.999	0.965	1.007
SV-SPF-V-3Q	1.007	0.966	0.995	1.011	0.997	1.025	1.013	0.990	0.993
SV-SPF-V-4Q	0.993	0.954	1.004	0.975	0.986	1.022	1.011	0.979	1.001
SV-SPF-MV-0Q	0.997	0.993	1.004	1.010	1.014	1.016	1.011	0.970	1.003
SV-SPF-MV-1Q	1.016	0.970	0.968	0.985	0.971	1.024	1.007	0.963	0.983
SV-SPF-MV-2Q	0.984	0.986	0.975	0.983	0.972	1.000	1.005	0.967	0.988
SV-SPF-MV-3Q	0.982	1.007	0.998	0.993	0.964	0.969	1.007	0.966	0.984
SV-SPF-MV-4Q	0.975	1.000	0.978	0.963	0.970	0.976	1.021	0.971	0.968

Note: The Root Mean Square Forecast Errors are calculated three times per quarter for three consecutive quarters (from the first month of the current quarter, Q0-M1; to the third month of the two quarters ahead, Q2-M3) over the periods starting from the first quarter of 1977 until the first quarter of 2017 over a recursive window where the sample starts from last quarter of 1968. SPF-M represents that we use only the first moment of the individual forecasts in SPF; SPF-V represents we use only the second moment and SPF-MV represents we use both the first and the second moments, the mean and variance of individual forecasts. SV shows we incorporate the stochastic volatility structure in the measurement equation of real Gdp growth. The last part of the labels represents how many quarters ahead used from SPF; 0Q shows only the current quarter nowcast is used from SPF as it increases up to 4 quarters ahead.

the current quarter, **Q0**, as nowcast. Note that at the end of the second month, the previous quarter GDP and the surveys about the current quarter nowcast and up to 4 quarters ahead forecast are available.

We do not calculate the RMSFE several times in a given month which would enable us to understand the effect of both the GDP and SPF release separately. However, we can determine these effects by assessing different specifications, i.e. baseline model and the models with SPF.[18] The first row (**SPF**) corresponds to RMSFE of the mean of expectations of professional forecasters for GDP growth rate relative to baseline model, available in the second months of a given quarter. **SPF** performs comparable to the baseline model with 5 and 17 variables, performs better for one quarter ahead forecast and worse for nowcast and two quarter ahead forecast.

As time passes in a given quarter and more information becomes available, the RMSFE decreases generally as documented in [Banbura et al., 2013] and [Aastveit et al., 2014] among others, except for some cases of the estimation in second months in which GDP and SPF are released. Across the small and large scale baseline model, adding more timely 12 variables serve for the point predictions in the first month of current quarter, leading the RMSFE to decline 5% by the help of the information including soft variables. After the release of previous quarters GDP at the second month, the difference starts to decrease.

Integrating stochastic volatility specification (**SV**) into the baseline model makes no difference in terms of RMSFE for the small scale model. For the large model, the RMSFE increases at the first month, but it decreases almost 7% at the second month with the GDP release compared to the first month, 4% compared to the same month nowcast of baseline model.

Incorporating the mean of SPF expectations into the small baseline model, the RMSFE decreases up to 3.2% for M3 nowcast and 4.3% for **M2** one quarter ahead forecast (**SPF-M-2Q**), whereas for the full model it decrease about 3% for nowcast

[18] SPF release dates are different throughout for the sample period. Release dates are the at the end of the second month in a quarter at the start of our sample, at late of the months up to 2004 and generally at the middle of months after that period. The estimation of the models at the end of the months guarantees the avaliability of SPF.

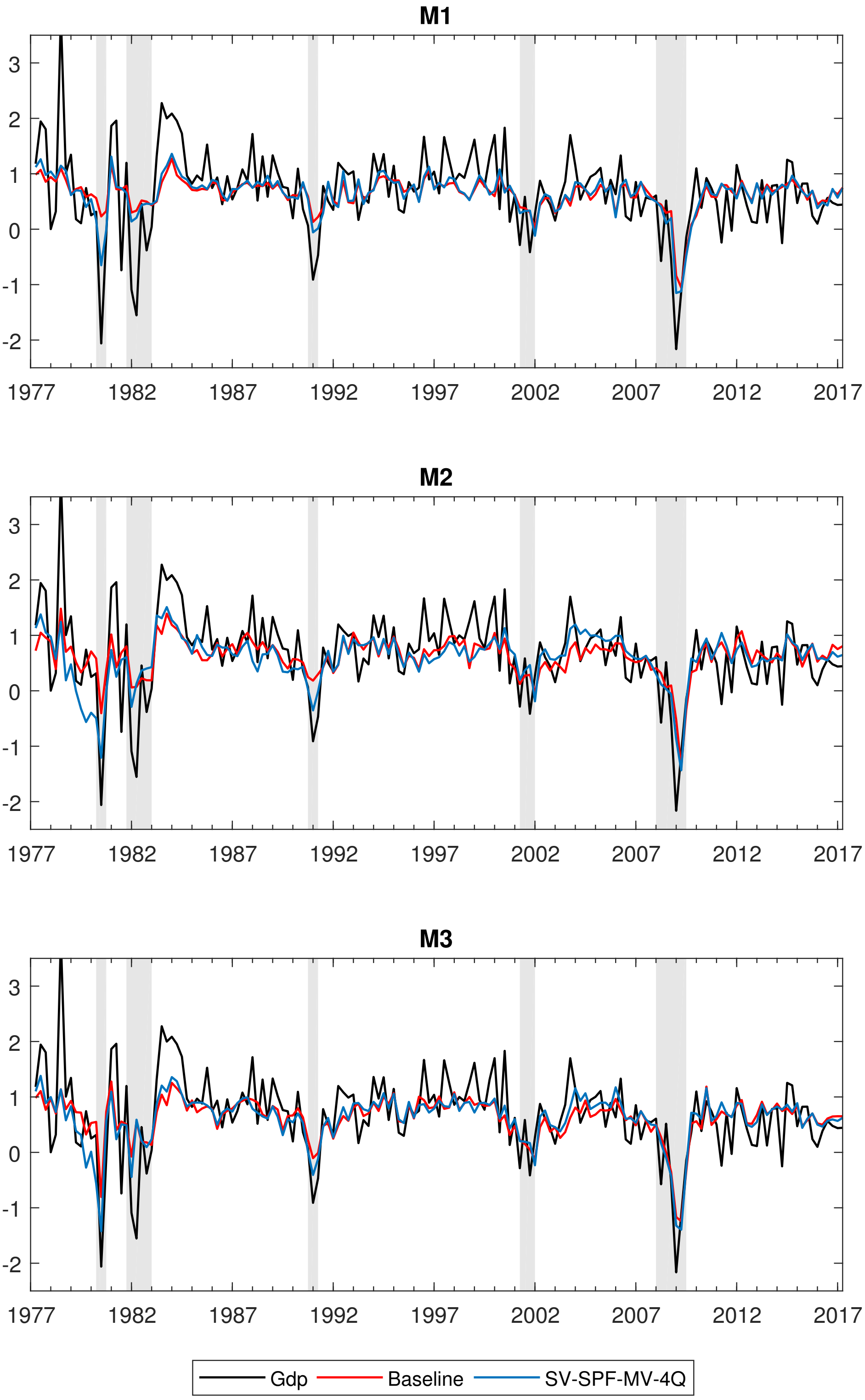
(**SPF-M-1Q**), up to 5.5% for one quarter ahead forecast (**SPF-M-4Q**). It seems that the mean of SPF carries further information than the additional 12 variables do.

We observe that the RMSFE remains the same with the addition of the second moment of SPF for the small scale model, whereas it decreases up to 4.5 for nowcast (**SV-SPF-V-4Q**) and 4.1% for 2 quarters ahead forecast (**SV-SPF-V-0Q**) for the large scale model. This implies that the second moment of SPF may be useful for the uncertainty coming from additional variables.

Finally, inclusion of both the first two moments of SPF (**SV-SPF-MV**) into the small and large model does not lead further improvements in terms of point forecast. Figure 3.8 depicts the mean of out-of-sample density nowcasts that we use for calculation of the RMSFE, for the **Baseline Model** and **SV-SPF-MV-4Q** with 17 variables for the sake of brevity.[19] It seems even in the real-time exercise both the **Baseline Model** of [Banbura et al., 2013] and the proposed model tracks GDP well. For some periods such as late 1970s, SPF information distorts the nowcasts, but in some periods such as early 1990s, the proposed model reacts more timely where SPF information comes in the second month. However, it can be seen from the figure as well as from the RMSFE that there is not a substantial difference over the specifications for the pointwise comparisons.

[19]We give the graphs of the models with 5 variables in Figure N.1 in the Appendix N. We exclude the graphs of other specifications, but they are available if requested.

Figure 3.8: The mean of the Nowcast of GDP growth with **17 variables** for each month between 1977:Q1-2017:Q1



3.4.2 Density forecasts: Predictive Likelihoods

We evaluate the density nowcast and forecasts of the models through their predictive likelihoods following [Geweke and Amisano, 2010] and [Ando and Tsay, 2010], among others. We calculate the predictive likelihoods starting from the first quarter of 1977 up until the first quarter of 2017, at the end of the each month in a given quarter, **M1**, **M2** and **M3**, and for up to 2 quarters ahead starting from the current quarter, **Q0**, as nowcast.[20] Additionally, we calculate the (logarithm of) marginal likelihoods for the goodness of fit between data and the models for in-sample evaluations.[21] We follow the harmonic mean method of [Gelfand and Dey, 1994] and [Geweke, 1999] to compute the marginal likelihoods.

We present both the marginal likelihoods and predictive likelihoods for nowcast and forecast together for all model specifications in Table 3.4 and 3.5, for the small and large scale models, respectively. In the first three columns show the marginal likelihoods, whereas the other columns display the predictive likelihoods starting from the nowcast (**Q0**) and up to 2 quarters ahead forecasts, calculated for each month, **M1**, **M2** and **M3**. Although SPF includes the individual information and rough density forecast information, it is not in a form that can be calculated directly as predictive likelihood for the nowcast and forecasts of GDP growth, as mentioned in [Carriero et al., 2015]. Therefore, we can not compare SPF with the models in terms of density. To make comparison between models, we give the actual values of marginal and predictive likelihoods of baseline model in the first row. The difference between these values in the first row and the values estimated for the indicated model specifications are represented at the lower rows. Note that for comparison we use the monthly DFM model of [Banbura et al., 2013] as a benchmark model, which is comparable with SPF in terms of point prediction, and outperforms the other

[20]We calculate all RMSFE and predictive likelihoods for up to 5 quarters ahead, but give the results only up to 2 quarters ahead for the sake of brevity. The differences between the results over various models fade away for further quarters. The results for further quarters ahead will be available upon request.

[21]Decomposition of marginal likelihood can be represented by predictive likelihoods. For the relationship between marginal and predictive likelihoods, see [Geweke and Amisano, 2010], and [Geweke, 2005] for further details.

Table 3.4: The marginal and predictive likelihoods: 5-variables model over different specifications

	Marginal Likelihoods			Predictive Likelihoods								
	Q0			Q0			Q1			Q2		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Baseline Model	-219.59	-220.09	-219.55	-171.46	-156.83	-150.20	-188.15	-185.59	-179.10	-192.15	-190.85	-189.65
SPF-M-0Q	-1.160	-0.070	-0.320	3.720	3.450	1.390	5.040	4.930	4.220	5.150	5.260	5.030
SPF-M-1Q	7.050	7.000	6.530	4.780	7.250	4.190	5.260	7.420	5.270	5.160	5.820	5.160
SPF-M-2Q	8.220	9.660	9.740	4.680	7.280	5.130	4.820	7.880	5.290	4.500	5.520	4.380
SPF-M-3Q	10.180	10.250	8.910	4.390	6.950	5.460	4.370	7.630	5.170	3.920	5.490	4.500
SPF-M-4Q	10.120	10.540	10.070	4.340	6.710	5.250	4.050	7.770	5.120	3.750	5.120	4.350
SV	-6.530	-9.170	-7.780	10.000	12.140	13.880	9.230	8.810	9.990	8.280	8.430	8.750
SV-SPF-M-0Q	-4.610	-3.450	-3.550	14.350	15.930	15.950	14.900	14.720	15.020	14.230	14.350	14.320
SV-SPF-M-1Q	-1.020	1.520	-0.270	14.450	20.140	18.650	14.660	16.980	16.010	13.730	14.640	14.170
SV-SPF-M-2Q	-1.000	2.290	0.380	14.060	19.840	19.760	13.880	17.100	15.830	12.690	14.070	13.610
SV-SPF-M-3Q	4.480	8.690	9.490	14.070	19.520	19.820	13.780	17.150	15.460	12.290	13.910	13.100
SV-SPF-M-4Q	7.950	6.460	10.200	13.910	19.090	19.870	13.230	16.930	15.490	12.330	13.820	13.170
SV-SPF-V-0Q	5.060	5.160	6.610	14.050	17.830	19.250	12.080	12.480	13.990	11.010	11.750	12.250
SV-SPF-V-1Q	8.420	7.430	8.380	14.450	17.800	19.670	12.560	13.030	14.480	11.640	12.320	12.810
SV-SPF-V-2Q	6.520	6.040	4.290	14.870	18.440	20.010	13.050	13.530	14.810	11.940	12.860	13.000
SV-SPF-V-3Q	9.140	8.050	4.030	15.480	18.850	20.590	13.600	14.120	15.440	12.550	13.540	13.760
SV-SPF-V-4Q	9.730	9.610	8.950	15.820	19.210	20.860	14.070	14.510	15.760	12.950	13.650	13.980
SV-SPF-MV-0Q	6.660	4.860	4.020	17.220	20.930	20.520	16.430	16.730	17.450	15.770	16.590	16.800
SV-SPF-MV-1Q	14.740	16.460	16.260	18.100	24.750	23.380	17.160	19.890	18.830	15.560	17.100	16.730
SV-SPF-MV-2Q	17.490	14.570	15.910	18.080	24.470	24.270	16.620	20.430	19.090	15.060	17.390	16.760
SV-SPF-MV-3Q	17.380	13.370	17.650	18.230	24.080	24.780	17.130	20.890	19.420	15.390	17.330	16.880
SV-SPF-MV-4Q	20.470	20.060	17.330	18.530	24.330	25.210	17.060	21.000	19.490	15.410	17.600	16.820

Note: The marginal likelihoods are calculated for the first, second and third months of the current quarter for the period starting from the last quarter of 1968 until the first quarter of 2017. The predictive likelihoods are calculated three times per quarter for three consecutive quarters (from the first month of the current quarter, Q0-M1; to the third month of the two quarters ahead, Q2-M3) over the periods starting from the first quarter of 1977 until the first quarter of 2017 over a recursive window. SPF-M represents that we use only the first moment of the individual forecasts in SPF; SPF-V represents we use only the second moment and SPF-MV represents we use both, the mean and variance of individual forecasts. SV shows we incorporate the stochastic volatility structure in the measurement equation of real gdp growth. The last part of the labels represents how many quarters ahead used from SPF; 0Q shows only the current quarter nowcast is used from SPF as it increases up to 4 quarters ahead.

Table 3.5: The marginal and predictive likelihoods: 17-variables model over different specifications

	Marginal Likelihoods			Predictive Likelihoods								
	Q0			Q0			Q1			Q2		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Baseline Model	-218.54	-215.53	-214.62	-168.67	-154.45	-147.76	-186.78	-186.01	-178.34	-192.03	-191.27	-189.35
SPF-M-0Q	4.120	-0.290	-1.770	3.660	2.550	0.610	4.000	4.390	3.200	3.910	4.470	4.280
SPF-M-1Q	8.640	7.510	5.960	4.800	5.150	2.710	4.400	6.480	4.190	3.980	4.600	4.400
SPF-M-2Q	11.120	8.100	8.780	5.080	5.290	2.800	3.710	6.700	4.130	3.130	4.370	3.390
SPF-M-3Q	11.570	8.990	7.400	5.260	4.040	2.350	3.510	6.230	4.250	1.480	3.570	3.320
SPF-M-4Q	11.180	8.500	7.860	5.090	2.540	1.760	3.630	6.800	5.030	1.650	3.750	2.730
SV	-0.010	-11.550	-3.050	11.990	13.850	16.530	10.050	10.720	10.780	9.240	9.220	9.450
SV-SPF-M-0Q	2.800	-6.940	-5.210	15.290	15.650	16.900	14.250	14.140	14.860	14.050	13.810	14.560
SV-SPF-M-1Q	8.760	6.790	7.250	13.930	16.370	15.750	12.350	14.010	12.560	11.420	11.570	11.680
SV-SPF-M-2Q	16.070	9.140	7.050	13.890	15.660	14.780	12.070	13.940	12.280	10.600	11.410	10.260
SV-SPF-M-3Q	14.360	10.840	8.230	13.530	14.650	14.490	11.320	14.770	12.300	9.300	10.460	9.980
SV-SPF-M-4Q	13.900	12.110	10.980	16.500	16.940	18.680	12.930	17.130	15.770	10.600	12.500	12.430
SV-SPF-V-0Q	12.040	10.700	11.000	15.350	18.850	20.270	12.200	12.720	13.560	11.320	11.080	11.460
SV-SPF-V-1Q	11.110	11.990	10.230	15.410	18.600	20.400	12.420	12.680	13.990	11.140	11.710	12.510
SV-SPF-V-2Q	11.160	10.290	10.460	16.080	19.320	20.940	12.730	13.700	14.610	11.600	12.600	12.630
SV-SPF-V-3Q	11.170	8.650	8.430	16.440	19.140	21.070	13.090	14.120	15.000	12.360	12.820	13.120
SV-SPF-V-4Q	13.870	13.210	5.790	16.560	19.860	21.580	13.440	14.660	15.290	12.580	13.300	13.970
SV-SPF-MV-0Q	11.650	9.480	11.190	18.210	20.490	20.500	16.300	16.610	16.480	14.930	15.770	15.560
SV-SPF-MV-1Q	19.530	16.320	15.430	18.760	22.900	22.890	16.280	18.410	17.430	14.540	15.740	15.140
SV-SPF-MV-2Q	17.940	18.240	17.800	18.880	22.280	22.650	15.710	18.440	17.660	13.130	15.350	15.220
SV-SPF-MV-3Q	20.850	19.340	16.910	19.600	21.370	22.190	16.100	19.050	18.280	12.290	14.840	15.510
SV-SPF-MV-4Q	23.160	17.770	15.900	19.620	21.260	22.660	17.000	18.730	18.470	13.130	15.510	16.330

Note: The marginal likelihoods are calculated for the first, second and third months of the current quarter for the period starting from the last quarter of 1968 until the first quarter of 2017. The predictive likelihoods are calculated three times per quarter for three consecutive quarters (from the first month of the current quarter, Q0-M1; to the third month of the two quarters ahead, Q2-M3) over the periods starting from the first quarter of 1977 until the first quarter of 2017 over a recursive window. SPF-M represents that we use only the first moment of the individual forecasts in SPF; SPF-V represents we use only the second moment and SPF-MV represents we use both, the mean and variance of individual forecasts. SV shows we incorporate the stochastic volatility structure in the measurement equation of real gdp growth. The last part of the labels represents how many quarters ahead used from SPF; 0Q shows only the current quarter nowcast is used from SPF as it increases up to 4 quarters ahead.

models used for nowcasting such as bridge equation in [Banbura et al., 2013].

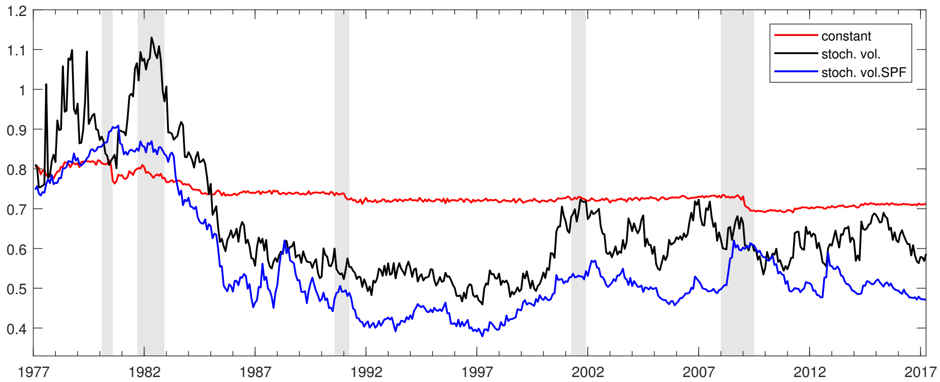
Firstly, for the baseline model, adding 12 variables decrease the marginal likelihoods as 5 points for **M2** and **M3**, whereas decrease 3 points in the predictive likelihoods for nowcast for every months. For the further quarters, more variables makes no difference in the predictive likelihoods. The small scale baseline model do not show any improvement across additional information within the quarter according to the marginal likelihoods, whereas the predictive likelihood decrease 15 points from **M1** to **M2** with the release of the previous quarter of GDP (and possibly IP among other variables) and 6 points from **M2** to **M3** for nowcast as the differences diminish for the forecasts of further quarters. For the large scale model the marginal likelihoods slightly decrease with additional information within the quarter, with the similar effects on the predictive likelihoods as the small scale model.

Inclusion of the mean of SPF into the models improves the marginal likelihoods considerably up to 10 and 11 points gradually for the small and large scale models, but with additional information within the quarter limits the decrease to 8 points for the large model, reflecting that although some of information carried by the forecasters overlap with the information of additional variables, there is still room for the first moment of SPF. The decrease in the predictive likelihoods of the current quarter for **SPF-M** models reflects the same point, the improvement decreases at the third month for large-scale model, but the gains for the forecasts of further quarters are sizeable for both of them.

Introduction of stochastic volatility to the baseline model deteriorates the marginal likelihoods, possibly due to the uncertainty carried by the new parameters, but the gains in the predictive likelihoods of all horizons are substantial for both small and large scale models. Interestingly, more information within quarter as well as with 12 additional variables decrease predictive likelihoods more, showing that the models may predict with more precision with the stochastic volatility structure as more information becomes available. Aligning with the mean of SPF in addition to stochastic volatility structure (**SV-SPF-M**) eliminate the deterioration of the marginal likelihoods for both models, even increased up to 14 points compared to the baseline, with the finding that the improvement is more pronounced for the large scale model. Moreover, the first moment of SPF deepens the improvements of the predictive likelihoods, which are already increased with the stochastic volatility framework.

Aligning the second moments of SPF with the variance of GDP in the stochastic volatility model (**SV-SPF-V**) enhances considerably both the marginal and predictive likelihoods. The enhancement in the marginal likelihoods is more pronounced for the large scale model. For both datasets, the predictive likelihoods for nowcast rise 6-7 points onto the **SV** model, whereas the effects gradually decline for further quarters, but still considerable. To show the difference of introducing of stochastic volatility and aligning with the second moment of SPF, we present the estimated standard deviation of the measurement equation of GDP growth for the **Baseline**, **SV** and **SV-SPF-V-4Q** models in Figure 3.9. The high volatility periods before the middle 1980s are well captured except for the baseline model with the constant volatility. The variance of SPF lowered the standard deviation in general, especially in 1990s, however in the financial crisis of 2008 the variance of **SV-SPF-V-4Q** model is increased as opposed to the baseline, resembling the in-sample estimation, given in Figure 3.7. The high variance of **SV-SPF-V-4Q** model for this period reflects that the disagreement of the second moment of SPF rises and dominates the variance of errors in the measurement equation of GDP.

Figure 3.9: Estimated standard deviations of the measurement equation of GDP



Note: The graph displays the estimated standard deviations of the measurement equation of GDP using the **Baseline**, **SV** and **SV-SPF-V-4Q** models, (represented by constant, stoch. vol., stoc. vol. SPF, respectively) with **17 variables** through the periods starting from the first quarter of 1977 until the first quarter of 2017 over a recursive window. All data vintages used for nowcasting start from the last quarter of 1968. The graph is at a monthly basis, including nowcasts for each month, **M1, M2** and **M3**. For each month in a given year, we use the available data at the indicated date, based on the publication delays given in Table 3.1.

Finally incorporating both the first and second moments of SPF (**SV-SPF-MV**) increases the marginal likelihoods averagely 20 points and the predictive likelihoods up to 25 (23) points for small (large) scale model for the current quarter nowcast. This is a large increase and corresponds to 16.8% (15.4%).[22] The improvements are still substantial for the further quarter ahead forecasts, showing that the way of our modeling is not only useful for nowcast, but for the further quarters as well. Moreover, both the marginal and predictive likelihoods for nowcast and forecasts in **M2** outperforms other months, where the GDP and SPF are released for the model using SPF dissimilar to the baseline model in which the scores of M3 is better than M2. These results imply that SPF information and our way of modeling contribute to make better predictions.

For the assessment of the models in terms of density, we present the 70% interval forecast for the current quarter GDP for only the **Baseline** and **SV-SPF-MV-**

[22]The percentage change can be better understood by looking at the average scores. Therefore, we give the average scores of marginal and predictive likelihoods compared to baseline model in Table M.1 and M.2 in Appendix M.

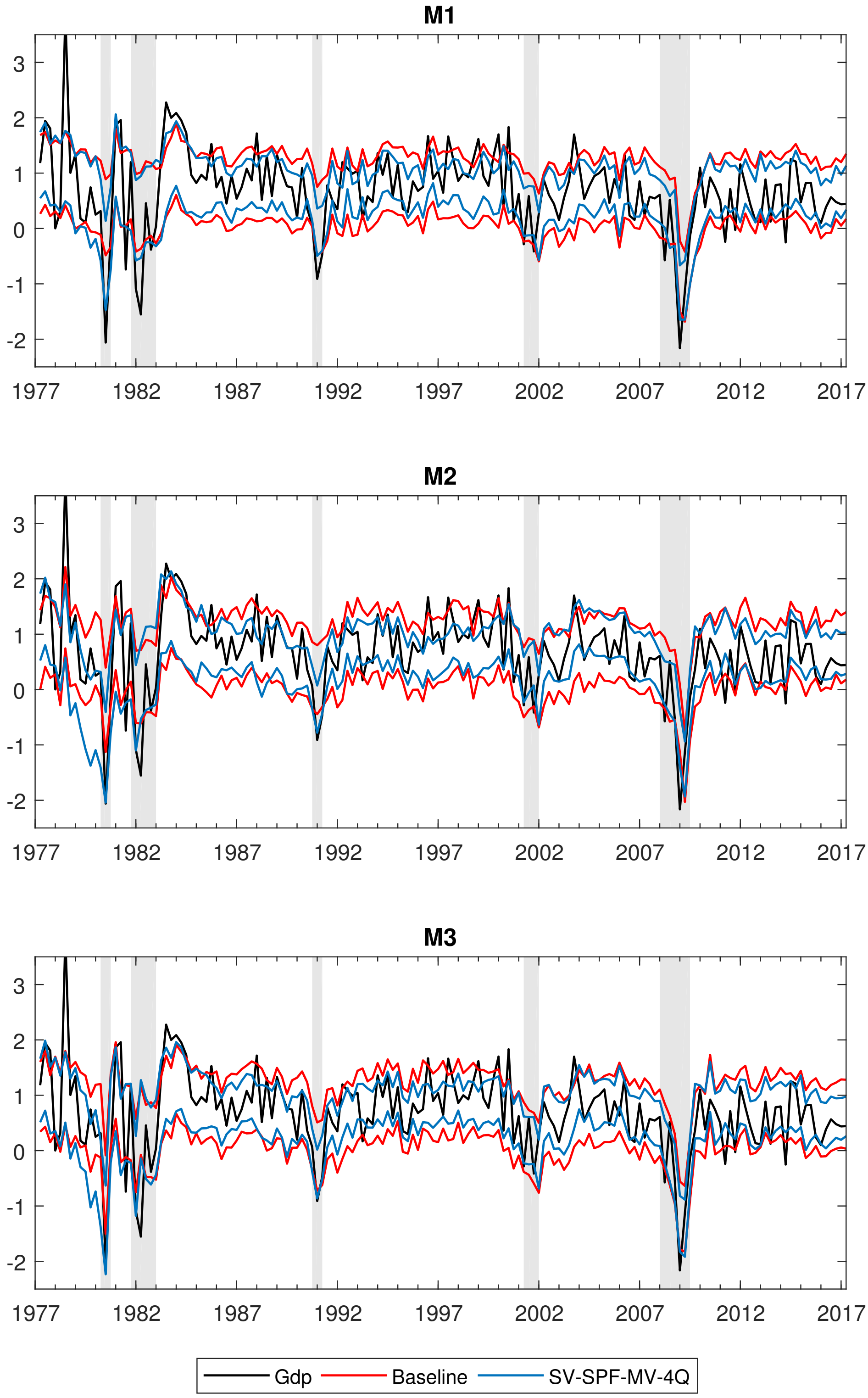
4Q large scale models for simplicity. After the high volatility period of middle 1980s, **SV-SPF-MV-4Q** model does nowcasts with more precision compared the **Baseline**, in which the precision over time is not changing due to the constant variance.[23] Despite of the poor performance of late 1970s, the proposed model does a good job over the periods such as early 1990s and 2000s.[24] The divergence in terms of density between the models is more pronounced for some periods such as middle 2000s at the second month nowcast. Note that although the proposed model often make predictions with more precision compared to the baseline, the nowcasts in the recessionary periods such as the early 1990s, 2001 and 2008 generally fall in the 70% interval forecasts.[25]

[23]**SV** structure accounts for the biggest part of the improvement in precision. However, the second moment of SPF information leads for further enhancement. The results are available upon request.

[24]We depict the Bayes factors with respect to Baseline Model for small and large scale models over time for different specifications in Figure P.1 and P.2 for each month in Appendix P. The evolution of the predictive likelihoods can be seen from these graphs. The Bayes factors of the further quarters are similar to those represented, only with a lower magnitude, available and can be presented upon request.

[25]In Appendix N we gave the results for small scale model. In addition, we present 5th, 15th, 25th, 35th, 65th, 75th, 85th, 95th quantiles for these models in grayscale coloured graphs with GDP growth and the median of the nowcasts in Figure O.1 and Figure O.2 in the Appendix O. Moreover, we approximate the densities of the nowcasts by using Matlab Kernel Smoothing Function, which gives probability density estimates based on a normal kernel function. The corresponding graphs for the **Baseline** and **SV-SPF-MV-4Q** large scale models are given in Figure O.3 and O.4. The effects and significance of the precision on the approximated densities can be seen by looking at the two graphs.

Figure 3.10: 70% Interval Forecast of the current quarter GDP with **17 variables** for each month between 1977:Q1-2017:Q1



3.4.3 Probability integral transforms (PITs)

The predictive likelihoods evaluate the models with respect to density nowcast and forecasts according to the calculated likelihoods over the observed realization of GDP growth rate. They can only be used for model comparison, since they are part of Bayes factors, as discussed in [Geweke and Amisano, 2010]. PIT, on the other hand, is a non-local evaluation of density forecasts, shows how well the predictive distribution is calibrated. If the predictive distribution is well calibrated, the forecast models were properly specified, PIT deciles would be uniformly distributed (0,1) as independent random variables, resulting a perfectly flat histogram. Following [Diebold et al., 1998], we calculate the PITs and use PITs to test how well the density forecasts made by the proposed specifications fit the true but unknown data generating process.

We show the PITs for both small and large scale models in Figure 3.11 and Figure 3.12. Specifically, we depict the PITs for the baseline model as **"Baseline"**, stochastic volatility **"SV"**, and for other specifications, we present only the models with all horizons SPF data used, from nowcast to forecasts up to 4 quarters ahead, **"SPF-M-4Q"**, **"SV-SPF-M-4Q"**, **"SV-SPF-V-4Q"** and **"SV-SPF-MV-4Q"**, for the sake of brevity.

The PITs derived from models without the stochastic volatility specification have a distinct tent-type shape as discussed in [Carriero et al., 2015] and [Diebold et al., 2017], which are consistent with dispersed forecast distributions for both the small and large scale models. However, incorporating the mean of SPF somewhat stabilize the PITs, but still falls outside the confidence interval for some deciles. The stochastic volatility framework fixes the tent-shape and generally performs well compared to the constant-volatility models. For the small scale models, **SV-SPF-MV-4Q** outperforms all other specifications, whereas the other models with SPF moments still manage to fall between the confidence intervals. Aligning with SPF volatility with stochastic volatility of GDP considerably flattens the PITs for large-scale model. The stochastic volatility model performs poor for the large scale models, but the addition of SPF smoothes PITs, as it is the case for their predictive likelihoods.

Figure 3.11: PITs with **5 variables** for nowcast of GDP 1977:M3-2017:M3

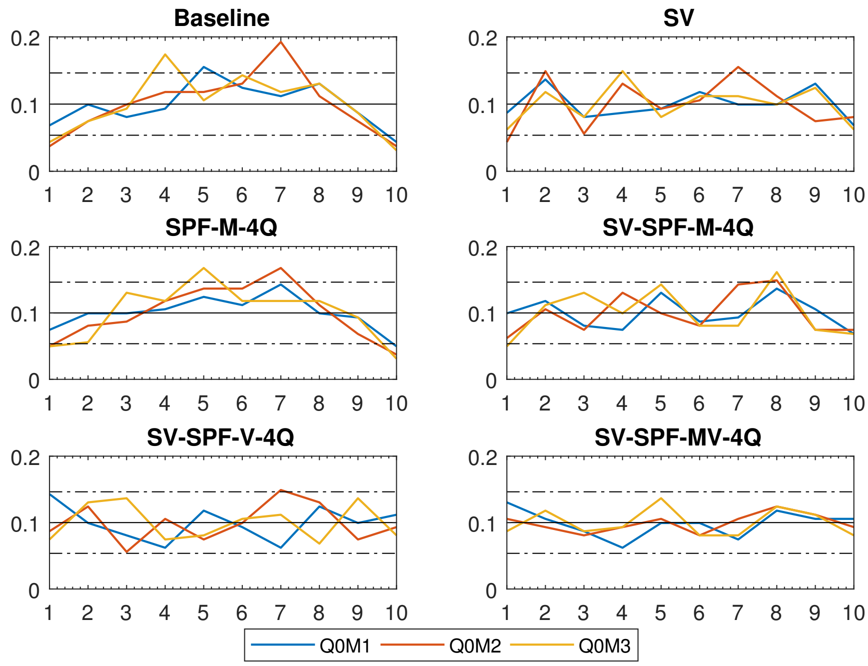
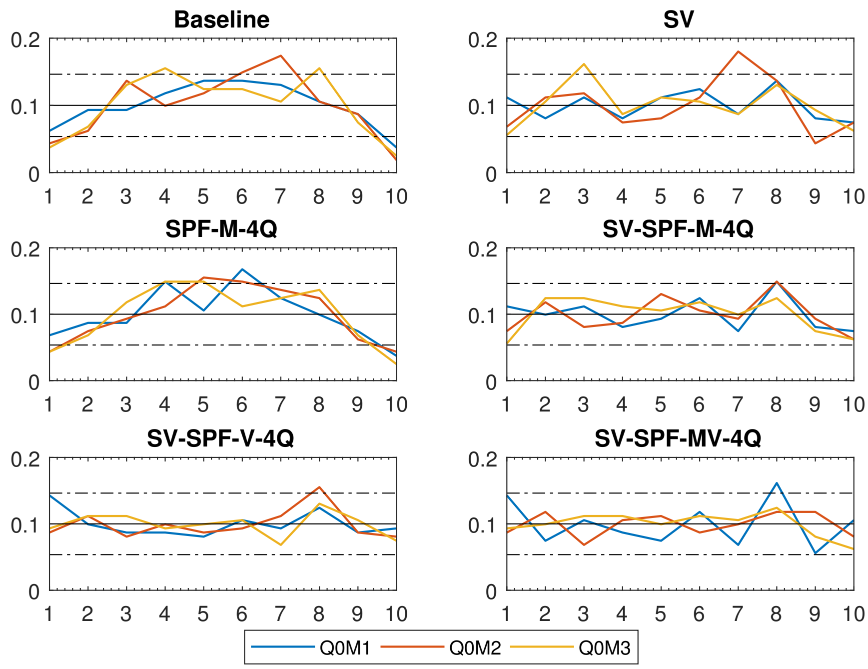


Figure 3.12: PITs with **17 variables** for nowcast of GDP 1977:M3-2017:M3



Chapter 4

CONCLUSION

Tracking economic and financial conditions in a timely and systematic manner is central for accurate predictions of economic downturns and for resolving economic and financial uncertainty. Conventional methods for this aim typically merge large datasets of economic and financial variables to construct indicators of recessions or they estimate economic and financial cycles in isolation of each other. The first essay fills this gap by proposing a unified framework for estimation of the economic and financial conditions with a single common cycle, namely the business cycle, which is transmitted to the financial conditions with potential phase shifts. This, in turn, allows the financial conditions to lead the economic conditions extracted from large sets of economic and financial variables systematically producing timely and accurate signals of recessions.

We estimate our model using a dataset with mixed frequencies for Turkey over the period starting from January 1999 until November 2019. We document that the financial cycle enters recessions on average 3.6 months earlier than that of the business cycle, while this lead time becomes on average 3.0 months for entering expansions. A real-time recursive exercise for predicting the recessions over the periods starting from January 2006 until the end of the sample provide convincing evidence for the superior backcasting, nowcasting and forecasting ability of our specification. An interesting finding is that starting from the vintage as early as June 2018, our model specification produces signals of a recession that appears to have started in August 2018 and finalized in January 2019.

Our model provides a prototype for joint estimation of the economic and financial conditions together with their cyclical components in a data-rich environment. It also serves as an effective early-warning indicator of oncoming recessions by exploiting the joint behavior of the forward-looking financial variables efficiently. Therefore, the framework would also be useful for other emerging markets as well as for EU and US for construction of early warning indicators at higher frequencies.

In the second work, we construct a dynamic factor model with stochastic volatility for nowcasting density of the United States real GDP growth by incorporating individual survey data. Our model produces survey-consistent measures of output expectations and of time-varying uncertainty. We use the output projections for different horizons from surveys of professional forecasters to match the first and second moments of the distributions for future output growth. We provide results on the accuracy of nowcasts of U.S. GDP growth in a real-time exercise from 1977 through 2018. Comparison over different specifications through the predictive likelihoods and PITs reveals that stochastic volatility structure improves density forecast accuracy substantially, whereas the matching the surveys implies further improvements over log-scores and PITs. The results are robust to the choice of GDP series vintages. While in-sample and out-of-sample exercises implies better performance for the second release of GDP real-time vintages over psuedo real-time vintages, the comparisons over the specifications we have applied does not change.

The proposed framework can be applied to nowcast of the variables included in the model, such as inflation, unemployment, industrial production along with their surveys.[1] The recursive methodology that produces different aggregation levels generating factors at any frequency allows us to incorporate the surveys regardless of the frequency of the surveys and variables to be forecasted in a straightforward manner.

Looking ahead, we consider a potentially useful extension to our specifications. [Adrian et al., 2019] reveals that the conditional distribution of GDP growth is left-skewed in recessionary periods while it is closer to being symmetric in expansions. To this end, one could extend the model by taking into account the third moment of the GDP growth by using skewed-t distribution and match the third moment of SPF accordingly. This extension would allow us to differentiate the periods in terms

[1] SPF includes all of the variables mentioned.

of asymmetry and consider the downside risk in the model. Nevertheless, the third moment has been beyond the scope of this study.

Further interesting extension would be nowcasting at daily frequency with proposed model by using financial variables, modelling with stochastic volatility and big shocks, see [Marcellino et al., 2016] and [Cúrdia et al., 2014]. Surveys can also be easily incorporated into the daily model at the release days by the help of the aggregation of factors throughout the quarter and taking the projections of daily factors for the day up to end of the forecasted quarters in the survey. We have omitted the daily extension because of the computational limitations.

Appendix A

THE DATA SET FOR CHAPTER 2

Table A.1: Set of Economic Variables: Series labels and their descriptions

Series Label	Description
ip	Industrial production index
import	Import quantity index
export	Export quantity index
retails	Retail sales volume index
pmi	Purchasing manager index
empna	Total employment less agricultural employment
traserv^q	Trade and services turnover index - quarterly
traserv^m	Trade and services turnover index - monthly

Table A.2: Set of Economic Variables: The transformations, adjustments, periods, frequencies and sources of coincident series

Series Label	T	Start	End	SA&NSA	Freqency	Source
ip	3	1986:7	2019:10	SA	M	TURKSTAT[1]
import	3	1997:1	2019:10	SA	M	TURKSTAT
export	3	1997:1	2019:10	SA	M	TURKSTAT
retails	3	2010:1	2019: 9	SA	M	TURKSTAT
pmi	3	2011:1	2019:11	SA	M	ICI[2]
empna	3	2005:1	2019: 8	SA	M	TURKSTAT
traserv^q	3	2005:I	2019:II	SA	Q	TURKSTAT
traserv^m	3	2009:1	2019: 9	SA	M	TURKSTAT

Note: T indicates the transformation of variable to ensure stationarity (1=level, 2=first difference, 3=first difference of logarithm). SA and NSA denote the adjustment to remove potential seasonality from series, where SA stands for Seasonally Adjusted or NSA for Not Seasonally Adjusted. M and Q denote frequency of the series, where M stands for Monthly and Q for Quarterly.

[1] TURKSTAT : Turkish Statistical Institute

[2] ICI : Istanbul Chamber of Industry

Table A.3: Set of financial variables: Series labels and their descriptions

Series Label	**Description**
FXRes	Real Central Bank's Gross Foreign Exchange Reserves
goldres	Central Bank's Gross Gold Reserves
m1	Money Stock : M1
m2	Money Stock : M2
m3	Money Stock : M3
rm1	Real Money Stock : M1
rm2	Real Money Stock : M2
rm3	Real Money Stock : M3
bist100tra	Stock Exchange Trading Volume on the Istanbul Stock Exchange
rbist	Real Stock Price Index on the Istanbul Stock Exchange
VOL	Volatility on the Istanbul Stock Exchange 100
P/E	Price-Earning Ratio on the Istanbul Stock Exchange 100
liv	Cost of Living Index for Wage Earners
ppi	Producer Price Index
Conf	Real Confidence Index
embi	JP Morgan Emerging Markets Bond Index-Turkey
EMBI-Tr	Spread between JP Morgan Emerging Markets Bond Index-Turkey and 1-month Interest Rate on deposits
MSCIem	MSCI-Emerging Market Index
TETS	Spread between the 3-month Interest Rate on deposits and 3-month London Interbank Offered Rate
TermS	Spread between the 1-year and 1-month Interest Rate on Deposits
intbnk	Interbank Overnight Interest Rate
int1m	Interest Rate on Deposits - up to 1 month
int3m	Interest Rate on Deposits - up to 3 months
int6m	Interest Rate on Deposits - up to 6 months
int1y	Interest Rate on Deposits - up to 1 year
int1y_m	Interest Rate on Deposits - up to 1 year and more
discount	Discount Rate
TAuc	Treasury Auction Rate
cds	Credit Default Swap for Turkey 5-year Bond
dbeta	Downside Beta-Bist100 and MSCI World Index
exrate	Average USD-TRY Nominal Exchange Rate
exratecpi	CPI-based Effective Real Exchange Rate (base year=2003)
curac	Current Account Balance/ Nominal GDP (in $)
finac	Balance Of Payments-Financial Account/Nominal GDP (in $)
intdebt	Real Internal Debt Stock
Cred	Banking Sector Credit Loans
bnksec	Banking Sector-Securities at fair value through profit/loss, Securities available for sale, and securities to be held till maturity-real value
elpro	Gross Electricity Production
bullp	Gold Price Growth Rate (in $)
euribor3m	Euro Interbank Offered Rate-3 month
libor3m	London Interbank Offered Rate-3 month
efunr	Effective Federal Funds Rate
tedsprd	TED Spread: Spread between 3-month US Treasury bill and 3-month LIBOR
vix	CBOE Volatility Index: VIX growth rate

Table A.4: Set of financial variables: The transformations, adjustments, periods, frequencies and sources of coincident series

Series Label	T	Start	End	SA&NSA	Source
FXRes	3	1990:2	2019:10	NSA	CBRT[3]
goldres	3	1990:2	2019:11	NSA	CBRT
m1	3	1990:1	2019:11	SA	CBRT
m2	3	1986:2	2019:11	SA	CBRT
m3	3	1986:2	2019:11	SA	CBRT
rm1	3	1990:1	2019:11	SA	CBRT
rm2	3	1986:2	2019:11	SA	CBRT
rm3	3	1986:2	2019:11	SA	CBRT
bist100tra	3	1998:2	2019:11	NSA	Bloomberg
rbist	3	1986:3	2019:11	NSA	Bloomberg
VOL	3	1988:2	2019:11	NSA	ISE[4]
P-E	2	1988:2	2019:10	NSA	ISE
liv	3	1996:2	2019:11	SA	CBRT
ppi	3	1994:2	2019:10	SA	CBRT
Conf	3	1988:1	2019:11	NSA	CBRT
embi	3	1999:8	2019:11	NSA	World Bank
EMBI-Tr	2	1996:6	2019:10	NSA	World Bank
MSCIem	2	1996:6	2019:10	NSA	World Bank
TETS	2	1996:6	2019:10	NSA	World Bank
TermS	2	1996:6	2019:10	NSA	World Bank
intbnk	2	1990:1	2019:11	NSA	OECD Statistics
int1m	2	2002:8	2019:10	NSA	TDM[5]
int3m	2	2002:8	2019:10	NSA	TDM
int6m	2	2002:8	2019:10	NSA	TDM
int1y	2	2002:8	2019:10	NSA	TDM
int1y_m	2	2002:8	2019:10	NSA	TDM
discount	2	1964:1	2019:10	NSA	IFS[6]
TAuc	3	1994:6	2019:11	NSA	TREASURY
cds	3	2000:11	2019:11	NSA	Bloomberg
dbeta	2	1987:1	2019:11	NSA	Thomson One
exrate	3	1990:1	2019:11	NSA	CBRT
exratecpi	3	1994:1	2019:10	NSA	BIS[7]
curac	1	1992:1	2019:10	SA	CBRT
finac	1	1992:1	2019:10	SA	TREASURY
intdebt	3	1998:1	2019:10	NSA	TREASURY
Cred	3	1998:1	2019:11	NSA	CBRT
bnksec	3	1986:1	2019:10	NSA	CBRT
elpro	3	1999:1	2019:11	SA	TETC[8]
bullp	3	1998:1	2019:11	NSA	CBRT
euribor3m	2	1999:1	2019:11	NSA	FRED[9]
libor3m	2	1986:2	2019:11	NSA	FRED
efunr	2	1954:8	2019:11	NSA	FRED
tedsprd	3	1986:1	2019:11	NSA	FRED
vix	3	2004:2	2019:11	NSA	FRED

Note: T indicates the type of transformation of variables to ensure stationarity (1=level, 2=first difference, 3=first difference of logarithm). SA stands for Seasonally Adjusted or NSA for Not Seasonally Adjusted. All series are at monthly frequency. Series at higher frequencies are converted to monthly frequency by using daily averages. The volatility of the market index BIST100, *VOL*, is the realized volatility computed using the daily returns of the index for in the corresponding month. The downside beta for Turkey, *dbeta*, is computed using the market index BIST100 and MSCI World Index. For further details, see [Bawa and Lindenberg, 1977].

[3] Central Bank of Republic of Turkey
[4] Istanbul Stock Exchange (Borsa Istanbul)
[5] Turkey Data Monitor
[6] International Financial Statistics
[7] Bank for International Settlements
[8] Turkish Electricity Transmission Company
[9] Federal Reserve Bank of St. Louis Economic Database

Appendix B

PRELIMINARY ANALYSIS FOR CHAPTER 2

This chapter presents Root Mean Squared Forecast Errors (RMSFE) of Out-Of-Sample exercise using the financial variables (as independent variable) individually in explaining IP and real GDP growth rate on a monthly basis relative to autoregressive models for the data selection in Section 2.2. "T" stands for the transformations adopted for the indicated series; "1" represents no transformation, "2" represents the first difference and finally "3" is the difference of the logarithm of the series. The transformations are made according to the characteristic of a variable and the common practice in the literature. The series with (*) are selected as financial variables to be used in the model throughout the Chapter 2. The sample period starts from 1998 up to 2014 and horizons are up to 12 months. The bold numbers represents better predictive performance relative to the baseline AR model, since they are less than 1. Table B.1 represents Out-Of-Sample Forecasting Results on IP growth rate, whereas Table B.2 represents Out-Of-Sample Forecasting Results on Real GDP growth rate.

Note that this exercise is only for the consideration and preselection of variables. We have done more thorough examination of variables by the help of our unified model.

Table B.1: IP Growth Out-Of-Sample Forecasting Results for 1998-2014 Sample

Horizon		h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Univariate AR		Root Mean Squared Forecast Error											
		44.00	23.70	20.31	16.84	15.47	14.07	13.00	11.73	11.16	10.73	10.19	9.61
Bivariate Forecasts	T	Mean Squared Forecast Error Relative to AR Model											
(*) FXRes	3	1.03	1.04	1.00	1.00	1.01	**0.98**	**0.99**	**0.99**	**0.99**	**0.98**	1.01	**0.98**
goldres	3	1.16	1.07	1.10	1.04	1.02	1.02	**0.98**	**0.99**	1.01	1.00	**0.98**	1.01
m1	3	1.10	1.01	1.05	1.05	1.05	1.10	1.07	1.04	1.08	1.12	1.15	1.16
m2	3	1.06	1.03	1.03	1.01	1.02	1.04	**0.99**	1.02	1.01	1.01	1.00	1.00
m3	3	1.06	1.02	1.01	1.00	1.02	1.04	**0.99**	1.02	1.01	1.00	1.01	1.01
rm1	3	1.07	1.14	1.06	1.01	1.01	1.02	**0.99**	**0.99**	1.00	**0.99**	1.01	**0.99**
rm2	3	**0.99**	**0.99**	1.00	1.00	1.00	**0.99**	**0.99**	1.00	1.00	1.00	1.01	1.00
rm3	3	**0.99**	**0.99**	1.00	1.01	1.01	**0.99**	**0.98**	1.01	1.00	1.02	1.00	1.00
bist100tra	3	1.02	1.03	**0.97**	**0.88**	1.00	**0.99**	1.00	**0.99**	1.00	**0.99**	**0.99**	**0.99**
(*) rbist	3	**0.92**	**0.89**	**0.90**	**0.91**	**0.94**	**0.93**	**0.93**	**0.94**	**0.91**	**0.92**	**0.94**	**0.95**
(*) VOL	3	**0.99**	**0.95**	**0.94**	**0.91**	**0.92**	**0.88**	**0.92**	**0.93**	**0.92**	**0.90**	**0.87**	**0.89**
(*) P/E	3	**0.99**	1.04	**0.90**	**0.98**	1.02	**0.97**	1.01	**0.98**	**0.99**	**0.97**	**0.99**	**0.98**
liv	3	1.05	1.01	1.03	1.04	1.06	1.09	1.12	1.10	1.14	1.11	1.16	1.13
ppi	3	1.09	1.00	1.04	**0.97**	1.01	1.00	1.02	1.01	1.02	1.03	1.04	1.05
(*) Conf	3	**0.82**	**0.76**	**0.72**	**0.79**	**0.86**	**0.82**	**0.87**	**0.86**	**0.85**	**0.82**	**0.90**	**0.85**
embi	3	1.12	**0.96**	**0.98**	**0.84**	**0.88**	**0.89**	**0.84**	**0.90**	**0.91**	**0.97**	**0.94**	**0.99**
(*) EMBI-Tr	2	**0.98**	1.00	1.02	**0.95**	**0.94**	**0.97**	**0.95**	**0.91**	**0.95**	**0.93**	**0.93**	**0.98**
(*) MSCIem	2	1.23	**0.96**	**0.85**	1.04	1.28	1.08	1.09	1.13	1.17	1.12	1.08	1.08
(*) TETS	2	1.01	1.02	**0.95**	**0.90**	**0.88**	**0.95**	**0.91**	**0.89**	**0.90**	**0.93**	**0.92**	**0.96**
(*) TermS	2	**0.89**	1.06	1.05	**0.95**	1.02	**0.99**	1.00	**0.99**	**0.98**	**0.98**	**0.98**	**0.99**
intbnk	2	1.12	1.06	1.05	1.01	**0.97**	1.02	**0.94**	1.00	**0.97**	**0.98**	**0.96**	**0.97**
int1m	2	1.02	**0.98**	**0.98**	**0.91**	**0.92**	**0.94**	**0.91**	**0.93**	**0.94**	**0.96**	**0.96**	**0.95**
int3m	2	**0.99**	**0.94**	**0.98**	**0.97**	**0.92**	**0.93**	**0.91**	**0.91**	**0.91**	**0.97**	**0.96**	**0.95**
int6m	2	1.02	**0.96**	1.00	**0.94**	**0.96**	**0.94**	**0.95**	**0.92**	**0.94**	**0.99**	**0.98**	**0.98**
int1y	2	**0.96**	**0.99**	**0.97**	**0.99**	**0.93**	**0.96**	**0.95**	**0.95**	**0.93**	**0.96**	1.00	**0.99**
int1y_m	2	1.04	**0.97**	1.02	**0.96**	**0.93**	**0.95**	**0.93**	**0.93**	**0.90**	**0.99**	**0.98**	**0.97**
discount	2	1.03	1.04	1.01	1.01	**0.99**	**0.99**	1.02	1.03	1.00	1.03	**0.97**	1.01
(*) TAuc	3	1.00	1.10	**0.93**	1.02	**0.98**	**0.98**	**0.94**	**0.97**	**0.92**	**0.95**	**0.97**	**0.98**
cds	3	**0.99**	**0.97**	**0.96**	1.01	**0.97**	**0.98**	1.04	**0.98**	**0.94**	**0.97**	**0.95**	1.00
dbeta	2	1.00	1.00	1.00	1.00	1.00	0.99	1.01	0.98	0.99	1.00	1.00	0.99
exrate	3	1.09	1.02	**0.99**	1.00	1.01	1.02	**0.97**	**0.99**	1.02	1.04	1.00	1.03
exratecpi	3	1.05	1.02	1.03	1.10	1.02	1.00	1.03	1.02	1.01	1.01	1.00	1.01
curac	1	1.03	1.03	1.02	1.04	1.02	1.00	**0.98**	**0.96**	**0.94**	**0.86**	**0.90**	**0.88**
finac	1	1.03	1.01	1.05	1.01	1.08	1.03	1.01	1.01	**0.97**	**0.97**	**0.96**	**0.94**
intdebt	3	1.00	1.00	1.00	1.00	1.00	**0.99**	1.00	1.00	**0.99**	**0.99**	1.00	**0.98**
(*) Cred	3	1.01	1.02	**1.00**	**1.00**	1.02	**0.99**	**1.00**	**1.00**	**0.99**	**0.99**	1.01	**0.98**
bnksec	3	**0.99**	**0.99**	1.00	**0.99**	1.00	1.00	1.00	1.00	1.00	1.01	**0.99**	1.00
elpro	3	1.08	1.23	1.18	1.09	1.16	1.17	1.09	1.07	1.08	1.14	1.01	1.02
bullp	3	**0.99**	1.01	**0.98**	1.02	1.09	1.04	1.03	1.00	1.01	1.05	1.07	1.08
euribor3m	2	1.01	**0.94**	**0.95**	**0.99**	1.08	1.09	**0.97**	**0.98**	1.02	1.04	**0.99**	1.00
libor3m	2	1.00	1.01	1.07	1.02	1.06	1.12	1.05	1.05	1.10	1.00	**0.99**	**0.97**
efunr	2	**0.97**	**0.93**	**0.94**	**0.93**	**0.95**	**0.91**	**0.93**	**0.90**	**0.94**	**0.90**	**0.88**	**0.88**
tedspread	3	**0.99**	1.01	1.00	**0.97**	1.00	1.01	1.02	**0.97**	**0.97**	**0.99**	**0.97**	**0.95**
vix	3	1.03	**0.98**	**0.98**	1.01	1.03	**0.96**	1.06	1.06	1.05	1.02	1.04	1.04

Table B.2: Real GDP Growth Out-Of-Sample Forecasting Results for 1998-2014 Sample

Horizon		h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Univariate AR		Root Mean Squared Forecast Error											
		16.58	12.35	10.38	9.76	8.78	8.35	7.83	7.26	6.91	6.69	6.56	6.43
Bivariate Forecasts	T	Mean Squared Forecast Error Relative to AR Model											
(*) FXRes	3	1.04	1.04	1.02	**1.00**	1.03	**1.00**	**0.99**	**0.99**	1.00	1.01	1.05	1.02
goldres	3	1.10	1.01	1.01	1.01	1.02	**0.97**	1.02	1.04	**0.99**	**0.99**	1.00	**0.99**
m1	3	1.12	1.00	1.00	1.05	1.09	1.10	1.13	1.17	1.21	1.18	1.18	1.21
m2	3	1.09	1.04	1.08	1.00	1.02	**0.96**	1.01	1.04	1.01	1.01	1.01	1.01
m3	3	1.01	1.00	1.00	1.01	1.02	1.02	1.00	1.02	1.01	1.01	1.00	1.01
rm1	3	1.12	**0.99**	1.00	1.00	1.00	**0.96**	1.00	**0.99**	1.00	1.00	1.00	1.00
rm2	3	1.01	**0.94**	**0.95**	**0.95**	**0.98**	**0.98**	1.01	1.02	1.02	1.00	1.00	1.00
rm3	3	**0.99**	1.02	**0.99**	1.00	**0.97**	**0.97**	1.01	1.02	1.05	1.02	1.00	1.00
bist100tra	3	1.00	**0.98**	**0.97**	**0.98**	**0.99**	**0.95**	1.00	1.00	1.01	**0.99**	**0.99**	**0.99**
(*) rbist	3	**0.98**	**0.95**	**0.86**	**0.88**	**0.90**	**0.89**	**0.83**	**0.83**	**0.83**	**0.84**	**0.85**	**0.87**
(*) VOL	3	1.07	1.00	**0.99**	1.00	1.08	1.03	1.02	1.04	1.10	1.11	1.09	1.04
(*) P/E	3	1.00	1.01	**0.98**	**0.98**	**0.98**	1.01	**1.00**	1.01	**0.96**	**0.99**	**0.98**	**0.95**
liv	3	1.05	1.06	1.06	1.09	1.17	1.09	1.11	1.18	1.19	1.16	1.18	1.18
ppi	3	1.07	1.05	1.06	1.12	1.17	1.10	1.11	1.19	1.18	1.15	1.12	1.13
(*) Conf	3	**0.88**	**0.85**	**0.79**	**0.82**	**0.92**	**0.93**	**0.98**	1.01	**0.95**	**0.94**	**0.94**	**0.91**
embi	3	1.13	1.06	**0.95**	**0.93**	**0.91**	**0.87**	**0.90**	**0.84**	**0.93**	**0.92**	**0.94**	**0.94**
(*) EMBI-Tr	2	1.03	1.04	1.04	**0.97**	**0.93**	**0.93**	**0.91**	**0.89**	**0.94**	**0.97**	**0.93**	**0.89**
(*) MSCIem	2	1.18	**0.81**	**0.74**	**0.77**	1.12	1.24	1.39	1.80	2.02	1.80	1.88	1.75
(*) TETS	2	1.05	1.10	1.10	**0.95**	**0.88**	**0.87**	**0.89**	**0.88**	**0.89**	**0.88**	**0.84**	**0.89**
(*) TermS	2	1.14	1.12	1.05	1.03	1.01	**0.98**	1.03	**0.96**	**0.99**	**0.99**	**0.99**	**0.99**
intbnk	2	1.04	1.09	1.05	1.04	1.04	**0.98**	**0.98**	1.00	1.00	1.00	1.00	**0.97**
int1m	2	1.07	**0.99**	**0.98**	**0.93**	**0.90**	**0.94**	**0.88**	**0.86**	**0.85**	**0.85**	**0.79**	**0.87**
int3m	2	1.16	1.11	**0.97**	**0.93**	**0.92**	**0.91**	**0.85**	**0.91**	**0.83**	**0.84**	**0.80**	**0.98**
int6m	2	1.19	1.10	1.08	**0.98**	**0.88**	**0.96**	**0.91**	**0.93**	**0.88**	**0.92**	1.09	1.06
int1y	2	1.15	1.17	1.05	1.03	**0.95**	1.04	**0.96**	**0.91**	**0.96**	**0.96**	1.04	1.03
int1y_m	2	1.15	1.00	1.06	**0.91**	**0.88**	**0.91**	**0.87**	**0.85**	**0.88**	**0.94**	**0.90**	1.08
discount	2	1.00	**0.97**	**0.97**	**0.98**	1.00	**0.94**	**0.97**	**0.98**	**0.97**	1.02	**0.99**	1.00
(*) TAuc	3	1.06	1.02	1.01	**0.99**	1.04	**0.94**	**0.87**	**0.89**	**0.90**	**0.95**	**0.97**	**0.97**
cds	3	1.04	1.09	1.06	**0.97**	**0.93**	**0.91**	**0.89**	**0.89**	1.00	1.01	1.03	1.04
dbeta	2	1.00	1.01	**0.99**	**0.99**	**0.98**	**0.91**	**0.94**	**0.97**	0.98	1.02	0.99	1.01
exrate	3	1.06	1.01	**0.96**	1.00	1.06	1.04	1.11	1.20	1.15	1.14	1.16	1.16
exratecpi	3	1.03	1.01	1.00	1.00	1.00	**0.96**	1.02	1.05	1.00	1.02	1.03	1.00
curac	1	1.02	1.03	1.02	1.02	1.02	**0.97**	**0.97**	**0.94**	**0.94**	**0.92**	**0.93**	**0.87**
finac	1	**0.99**	1.01	1.02	1.01	1.02	1.02	1.01	1.01	**0.96**	**0.99**	1.01	**0.98**
intdebt	3	1.05	1.08	1.04	1.02	1.07	1.02	1.01	1.05	1.02	1.02	1.05	1.01
(*) Cred	3	**1.00**	1.01	1.01	1.00	1.01	**0.98**	1.00	1.01	**0.96**	**0.98**	**0.98**	**0.98**
bnksec	3	1.04	1.09	1.05	1.04	1.07	1.01	**0.95**	**0.95**	**0.90**	**0.96**	**0.96**	**0.97**
elpro	3	**0.96**	1.21	1.15	1.14	1.15	1.12	1.16	1.13	1.10	1.02	1.00	1.01
bullp	3	1.05	1.27	1.03	**0.97**	1.03	1.04	1.00	**0.98**	**0.99**	1.03	1.04	1.03
euribor3m	2	1.08	1.15	1.13	**0.92**	**0.94**	**0.90**	**0.96**	**0.95**	1.04	1.18	1.05	1.00
libor3m	2	1.24	1.50	1.31	1.33	1.51	1.49	1.44	1.45	1.53	1.44	1.41	1.37
efunr	2	**0.99**	**0.82**	**0.84**	**0.81**	**0.84**	**0.87**	**0.92**	**0.94**	1.01	**0.97**	1.07	1.03
tedspread	3	1.01	1.10	1.21	1.12	1.16	1.10	1.05	1.06	1.11	1.11	1.12	1.10
vix	3	1.30	1.38	1.22	1.14	1.06	1.02	**0.97**	1.02	**0.99**	1.07	1.15	1.09

Appendix C

ECONOMETRIC MODEL FOR CHAPTER 2

In this section we provide details about the econometric model. In the next section we discuss Bayesian inference of the model parameters in detail. The econometric model is as follows

$$\begin{aligned}
y_{i,t} &= \lambda_i f_t + \varepsilon_{i,t} \\
\psi(L)\varepsilon_{i,t} &= \epsilon_{i,t} \quad \epsilon_{it} \sim t(0, \nu, \sigma^2_{i,t}) \\
\sigma^2_{i,t} &= \sigma^2_{i,1}\, \mathbb{I}\left[t \leq \tau\right] + \sigma^2_{i,2}\, \mathbb{I}\left[t > \tau\right] \text{ for } i = 1, \ldots, N \\
f_t &= \alpha_{\mathbb{S}_t} + \Phi f_{t-1} + \eta_t \quad \eta_t \sim N(0, \Sigma) \\
S_{2,t-\kappa_{S_{1,t}}} &= S_{1,t}.
\end{aligned} \tag{C.1}$$

For the autoregressive dynamics of the idiosyncratic factors, we use an AR(3) specification for the coincident variables. For the financial variables, we assume that the idiosyncratic factors are temporally independent. The resulting model can be cast into a state-space form as

$$\begin{aligned}
\mathbf{y}_t &= \mathbf{H}\boldsymbol{\beta}_t + \boldsymbol{\varepsilon}_t & \boldsymbol{\varepsilon}_t|\xi_t \sim N(\mathbf{0}, \mathbf{R}_t) \\
\boldsymbol{\beta}_t &= \boldsymbol{\alpha}_{\mathbb{S}_t} + \mathbf{F}\boldsymbol{\beta}_{t-1} + \boldsymbol{\eta}_t & \boldsymbol{\eta}_t|\xi_t \sim N(\mathbf{0}, \mathbf{\Omega_t}),
\end{aligned} \tag{C.2}$$

where

$$\mathbf{H} = \begin{bmatrix} \mathbf{H}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{H}_2 \end{bmatrix}, \boldsymbol{\beta}_t = \begin{bmatrix} \boldsymbol{\beta}_{1,t} \\ f_{2,t} \end{bmatrix}, \mathbf{R}_t = \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{R}_{2,t} \end{bmatrix}, \boldsymbol{\alpha}_{\mathbb{S}_t} = \begin{bmatrix} \boldsymbol{\alpha}_{1,S_{1,t}} \\ \alpha_{2,S_{2,t}} \end{bmatrix},$$

$$\mathbf{F} = \begin{bmatrix} \mathbf{F}_1 & \mathbf{F}_{1,2} \\ \mathbf{F}_{2,1} & \phi_{2,2} \end{bmatrix} \quad \mathbf{\Omega_t} = \begin{bmatrix} \mathbf{\Omega}_{1,t} & \mathbf{\Omega}_{1,2} \\ \mathbf{\Omega}_{2,1} & \sigma^2_{f_2} \end{bmatrix}.$$

More specifically,

$$
\mathbf{H}_1 = \begin{bmatrix} \lambda_{1,1} & 1 & 0 & 0 & 0 & \dots & 0 & 0 & 0 \\ \lambda_{2,1} & 0 & 0 & 0 & 1 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & & \ddots & \vdots & \vdots & \vdots \\ \lambda_{8,1} & 0 & 0 & 0 & 0 & \dots & 1 & 0 & 0 \end{bmatrix}
\mathbf{H}_2 = \begin{bmatrix} \lambda_{9,2} \\ \lambda_{10,2} \\ \vdots \\ \lambda_{19,2} \end{bmatrix}
\boldsymbol{\beta}_{1,t} = \begin{bmatrix} f_{1,t} \\ \varepsilon_{1,t} \\ \varepsilon_{1,t-1} \\ \varepsilon_{1,t-2} \\ \varepsilon_{2,t} \\ \varepsilon_{2,t-1} \\ \varepsilon_{2,t-2} \\ \vdots \\ \varepsilon_{8,t} \\ \varepsilon_{8,t-1} \\ \varepsilon_{8,t-2} \end{bmatrix}
$$

$$
\mathbf{R}_{2,t} = \begin{bmatrix} \sigma^2_{9,t}/\xi_t & 0 & \dots & 0 \\ 0 & \sigma^2_{10,t}/\xi_t & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma^2_{19,t}/\xi_t \end{bmatrix}
$$

$$
\boldsymbol{\alpha}_{1,S_{1,t}} = \begin{bmatrix} \alpha_{1,S_{1,t}} \\ 0 \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \\ 0 \end{bmatrix}
\mathbf{F}_1 = \begin{bmatrix} \phi_{1,1} & 0 & 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & \psi_{1,1} & \psi_{1,2} & \psi_{1,3} & \dots & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & \psi_{8,1} & \psi_{8,2} & \psi_{8,3} \\ 0 & 0 & 0 & 0 & \dots & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 1 & 0 \end{bmatrix}
$$

$$
\mathbf{Q}_{1,t} = \begin{bmatrix} \sigma^2_{f_1} & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 \\ 0 & \sigma^2_{1,t}/\xi_t & 0 & 0 & \dots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & 0 & \sigma^2_{8,t}/\xi_t & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 \end{bmatrix}
$$

The contemporaneous and temporal link between CEI and FCI in **linear** form is through the specifications of the $\mathbf{\Omega}_{1,2}$ and $\mathbf{F}_{1,2}, \mathbf{F}_{2,1}$ respectively. As we model the **nonlinear** link between CEI and FCI through their relation between the cyclical components, we set these matrices to zero to improve identification. Bayes factors computed using mildly informative priors favors these restrictions as well.

C.1 Likelihood Function

Given the fact that the dynamic factor model involves regime dependent parameters governed by a Markov process, we need to derive the complete data likelihood function. To do this, first, we cast the model in (C.1) into state-space form as

$$\begin{aligned} \mathbf{y}_t &= \mathbf{H}\boldsymbol{\beta}_t + \boldsymbol{\varepsilon}_t \qquad & \boldsymbol{\varepsilon}_t|\xi_t \sim N(\mathbf{0}, \mathbf{R}_t) \\ \boldsymbol{\beta}_t &= \boldsymbol{\alpha}_{\mathbb{S}_t} + \mathbf{F}\boldsymbol{\beta}_{t-1} + \boldsymbol{\eta}_t \qquad & \boldsymbol{\eta}_t|\xi_t \sim N(\mathbf{0}, \mathbf{\Omega}_t), \end{aligned} \tag{C.3}$$

where $\mathbf{y}_t = (y_{1,t}, \ldots, y_{i,t}, \ldots, y_{N,t})'$, $\mathbf{H}$ is comprised by the factor loadings with the specific location and form depending on the frequency and on the type as flow and stock of the corresponding variable. $\mathbf{R}_t$ is the diagonal matrix with conditional variances of the variables on the diagonal. The state vector $\boldsymbol{\beta}_t$ includes $f_t = (f_{1,t}, f_{2,t})'$, i.e. factors representing the coincident and financial indicators, as well as error components $\varepsilon_{i,t}$ as idiosyncratic factors and their lags. $\mathbf{F}$ is comprised of the autoregressive coefficients of the coincident and financial factors as well as idiosyncratic factors and accordingly $\mathbf{\Omega}_t$ includes the variances (and covariances) of these factors. The time variation in $\mathbf{R}_t$ as well as $\mathbf{\Omega}_t$ stems from the fact that we allow for a single structural change for the variances of the variables. Notice that these variances are scaled by the Gamma-distributed elements of $\xi_t = (\xi_{1,t}, \ldots, \xi_{i,t}, \ldots, \xi_{N,t})'$ leading to a $t-$distribution as discussed earlier. Finally, the regime dependent parameters, $\boldsymbol{\alpha}_{\mathbb{S}_t}$, include $\alpha_{1,S_{1,t}}$ and $\alpha_{2,S_{2,t}}$. Conditional on the model parameters and regimes, we can proceed with standard inference of the linear Gaussian state-space models by running the Kalman filter. However, before running the Kalman filter a slight modification to the system is required for handling missing observations. This is simply achieved by creating a selection matrix, $\mathbf{W}_t$, that is a diagonal matrix with the ith diagonal element taking the value 1 if $y_{i,t}$ is observed and 0 otherwise. The Kalman filter is then run by replacing $\mathbf{y}_t$, $\mathbf{H}$ and $\mathbf{R}$ with $\mathbf{y}_t^* = \mathbf{W}_t\mathbf{y}_t$, $\mathbf{H}^* = \mathbf{W}_t\mathbf{H}$ and $\mathbf{R}_t^* = \mathbf{W}_t\mathbf{R}_t\mathbf{W}_t'$, respectively as

$$\begin{aligned}
\boldsymbol{\beta}_{t|t-1} &= \boldsymbol{\alpha}_{\mathbb{S}_t} + \mathbf{F}\boldsymbol{\beta}_{t-1|t-1} \\
\mathbf{P}_{t|t-1} &= \mathbf{F}\mathbf{P}_{t-1|t-1}\mathbf{F}' + \boldsymbol{\Sigma} \\
\mathbf{v}_{t|t-1} &= \mathbf{y}_t - \mathbf{H}^*\boldsymbol{\beta}_{t|t-1} \\
\mathbf{V}_{t|t-1} &= \mathbf{H}^*\mathbf{P}_{t|t-1}\mathbf{H}^{*'},
\end{aligned} \tag{C.4}$$

to compute the prediction error, $\mathbf{v}_{t|t-1}$, and its variance, $\mathbf{V}_{t|t-1}$. Let $\mathbf{y}^T = \{\mathbf{y}_1, \ldots, \mathbf{y}_i, \ldots, \mathbf{y}_T\}$ and $\mathbb{S}^T = \{\mathbb{S}_1, \ldots, \mathbb{S}_i, \ldots, \mathbb{S}_T\}$, then, the complete data likelihood can be written as

$$f(\mathbf{y}^T, \mathbb{S}^T|\boldsymbol{\theta}) = \left(\prod_{i=1}^{2}\prod_{j=1}^{2} p_{ij}^{T_{ij}}\right)\prod_{t=1}^{T}\left(\frac{1}{\sqrt{2\pi}}\right)|\mathbf{V}_{t|t-1}|^{-\frac{1}{2}}\exp\left(-\frac{1}{2}\sum_{t=1}^{T}\mathbf{v}_{t|t-1}'\mathbf{V}_{t|t-1}^{-1}\mathbf{v}_{t|t-1}\right), \tag{C.5}$$

where T_{ij} is the number of transitions from regime i to regime j and $P = \{p_{ij}\}_{i,j=0,1}^2$ is the matrix with transition probabilities. $\theta = (\text{vec}(\Phi)', \alpha', \lambda', \sigma^{2\prime}, \psi', \text{vec}(P)', \kappa, \text{vec}(\Sigma)')'$ represent all model parameters with $\alpha = (\alpha_{1,0}, \alpha_{1,1}, \alpha_{2,0}, \alpha_{2,1})'$, $\lambda = (\lambda_1', \ldots, \lambda_i', \ldots, \lambda_N')'$ where $\lambda_i = (\lambda_{i,1}, \lambda_{i,2})'$, $\sigma^2 = (\sigma_1^{2\prime}, \ldots, \sigma_i^{2\prime}, \ldots, \sigma_N^{2\prime})'$ where $\sigma_i^2 = (\sigma_{i,1}^2, \sigma_{i,2}^2)'$ and $\psi = (\psi_1', \ldots, \psi_i', \ldots, \psi_N')'$ where $\psi_i = (\psi_{i,1}, \ldots, \psi_{i,p})'$ where p is the lag order of the autoregressive process for the idiosyncratic factors, and $\kappa = (\kappa_0, \kappa_1)'$. The likelihood function conditional only on the model parameters can be obtained by summing (C.5) over all the possible states

$$f(\mathbf{y}^T|\boldsymbol{\theta}) = \sum_{S_{1,1}=0}^{1}\sum_{S_{2,1}=0}^{1}\cdots\sum_{S_{T,1}=0}^{1} f(\mathbf{y}^T, \mathbb{S}^T|\boldsymbol{\theta}). \tag{C.6}$$

C.2 Prior Distributions

We use diffuse priors for most of the parameters in order to let the data be decisive for estimation results. For the discrete parameters this can be achieved using proper priors but this strategy leads to use of improper priors for the continuous parameters.

For the phase shifts parameters, $\kappa = (\kappa_0, \kappa_1)$, we use a uniform prior assigning equal probability to each value of κ in a predefined set

$$f(\kappa) \propto \begin{cases} 1 & \text{for all } (\kappa_0, \kappa_1) \in \mathcal{C}, \\ 0 & \text{otherwise.} \end{cases} \tag{C.7}$$

The set $\mathcal{C} = \{(\kappa_0, \kappa_1) \in \mathbb{Z}^2 \mid -c \leq \kappa_j \leq c \text{ for } j = 0, 1,\ |\kappa_0 - \kappa_1| \leq d\}$ specifies the restrictions imposed on κ_0 and κ_1. Specifically, we set $c = 8$ and $d = 6$ implying that κ_0 and κ_1 are restricted to lie in the interval $[-8, 8]$ and their difference is restricted not to exceed 6.[1] Note that setting $d = 0$ and $c = 0$ leads to the model with single common cycle. See [Çakmaklı et al., 2011] for more details.

For the transition probabilities, we use an informative Beta prior such that 95% highest posterior density interval covers the domain of 0.9 to 1 to match the duration of the recession and expansions with stylized facts.

The prior for the regime-dependent intercept parameters α is specified using improper distributions with sign restrictions as

$$f(\alpha_l) = \begin{cases} 1 & \text{if } \alpha_l \in \{\alpha_l \in \mathbb{R}^2 \mid \alpha_{l,0} > \alpha_{l,1}\} \\ 0 & \text{elsewhere.} \end{cases} \tag{C.8}$$

for $l = 1, 2$ to identify expansions and recessions as discussed in Section 2. For the matrix of autoregressive coefficients of common factors, Φ, and for the vector of autoregressive coefficients of idiosyncratic factors, ψ, we use flat priors

$$f(\Phi) \propto 1 \quad \text{and} \quad f(\psi_i) \propto 1 \quad \text{for } i = 1, \ldots, N \tag{C.9}$$

if the condition that characteristic roots of Φ and ψ lie outside the unit circle holds and 0 otherwise.

[1] We experimented with various setups. The results are quite similar and available upon request. Setting these values to sensibly small values without affecting the results facilitates the computation substantially.

For the factor loading parameters we also use flat priors

$$f(\lambda_i) \propto 1 \quad \text{for } i = 1, \ldots, N. \tag{C.10}$$

For the variance parameters of the variables as well as factors, we use noninformative Jeffrey's priors of the form

$$\begin{aligned} f(\sigma^2_{k,i}) &\propto \sigma^{-2}_{k,i} \quad \text{for } k = 1, 2 \text{ and } i = 1, \ldots, N \\ f(\Sigma) &\propto |\Sigma|^{-1}. \end{aligned} \tag{C.11}$$

For the distribution of the structural break parameter, τ, we use a discrete uniform distribution assigning equal probability for all time periods but the first and the last 12 observations, that is, we trim the first and last year of the sample period.

Appendix D

POSTERIOR INFERENCE FOR CHAPTER 2

The posterior distribution is proportional to the product of the likelihood in (C.6) together with the prior specifications described in (C.7)-(C.11).

D.1 Posterior simulation scheme

For inference of the posterior distribution, we use Metropolis within Gibbs algorithm that leads to the following sampling scheme. Starting with initializing the parameters, at step (m) of the iteration

1. Sample f^T from $p(f^T|y^T, \alpha^{(m-1)}, \Phi^{(m-1)}, \Sigma^{(m-1)}, \mathbb{S}^{T(m-1)})$
2. Sample $\mathbb{S}^T$ from $p(\mathbb{S}^T|f^{T(m)}, \alpha^{(m-1)}, \Phi^{(m-1)}, \Sigma^{(m-1)}, \kappa^{(m-1)})$
3. Sample α from $f(\alpha|y^T, \mathbb{S}^{T(m)}, \Phi^{(m-1)}, \Sigma^{(m-1)}, \sigma^{2(m-1)}, \lambda^{(m-1)}, \psi^{(m-1)}, \tau^{(m-1)})$
4. Sample Φ from $f(\Phi|y^T, \mathbb{S}^{T(m)}, \alpha^{(m)}, \Sigma^{(m-1)}, \sigma^{2(m-1)}, \lambda^{(m-1)}, \psi^{(m-1)}, \tau^{(m-1)})$
5. Sample Σ from $f(\Sigma|y^T, \mathbb{S}^{T(m)}, \alpha^{(m)}, \Phi^{(m)}, \sigma^{2(m-1)}, \lambda^{(m-1)}, \psi^{(m-1)}, \tau^{(m-1)})$
6. Sample κ from $f(\kappa|y^T, S_1^{(m)}, \alpha^{(m)}, \Phi^{(m)}, \Sigma^{(m)}, \sigma^{2(m-1)}, \lambda^{(m-1)}, \psi^{(m-1)}, \tau^{(m-1)})$
7. Sample λ from $f(\lambda|y^T, f^{T(m)}, \sigma^{2(m-1)}, \psi^{(m-1)}, \tau^{(m-1)})$
8. Sample σ^2 from $f(\sigma^2|y^T, f^{T(m)}, \lambda^{(m)}, \psi^{(m-1)}, \tau^{(m-1)})$
9. Sample ψ from $f(\psi|y^T, f^{T(m)}, \lambda^{(m)}, \sigma^{2(m)}, \tau^{(m-1)})$
10. Sample τ from $f(\tau|y^T, f^{T(m)}, \lambda^{(m)}, \sigma^{2(m)}, \psi^{(m)})$
11. Sample P from $f(P|S_1^{(m)})$
12. Repeat (1)-(11) M times.

Our model specification implies that the unobserved regimes are linked to the variables through the common factors of economic and financial indicators. Therefore, direct sampling of $\mathbb{S}^T$ conditional on observed data requires the factor to be integrated out, which is not feasible in our case. The fact that our model specification involves potential phase shifts precludes efficient simulation techniques such as [Gerlach et al., 2000]. Accordingly, we sample the regimes conditional on factors in step (2). However, in steps (3)-(6) any factor-related parameters are sampled conditional on data rather than factors using Metropolis steps to alleviate autocorrelation in the draws that could decelerate the convergence.

D.2 Conditional Posterior Distributions

In this appendix, we derive the posterior distributions used in the sampling scheme described in the previous section.

D.2.1 Sampling of f_t Conditional on the discrete regimes and model parameters, the system (C.2) is a linear Gaussian state-space model and therefore, standard inference of the model can be carried out. This involves first running the Kalman filter forwards and running the simulation smoother backwards. The Kalman filter prediction steps are given in (13) in the main text. The remaining part of the Kalman filter is the updating steps, given as:

$$\begin{aligned} \boldsymbol{\beta}_{t|t} &= \boldsymbol{\beta}_{t|t-1} + \mathbf{K}_t \mathbf{v}_{t|t-1} \\ \mathbf{P}_{t|t} &= \mathbf{P}_{t|t-1} - \mathbf{K}_t \mathbf{H}^* \mathbf{P}_{t|t-1} \end{aligned} \tag{D.1}$$

where $\mathbf{K}_t = \mathbf{P}_{t|t-1}\mathbf{H}^{*'}\mathbf{V}_{t|t-1}^{-1}$ is the Kalman Gain. Once the Kalman filter is run forward, we can run a simulation smoother using the filtered values for drawing smoothed states as in [Carter et al., 1994] and [Frühwirth-Schnatter, 1994]. As this has become a standard practice in many applications, here we do not provide a detailed analysis but refer to standard textbooks such as [Durbin and Koopman, 2012].

D.2.2 Sampling of S_1^T To sample the discrete regime we employ a single-move sampler using the posterior density of $S_{1,t}$ as

$$f(S_{1,t}|S_1^{-t}, f^T, \theta) \propto f(S_{1,t}|S_{1,t-1}, \theta) f(S_{1,t+1}|S_{1,t}, \theta) \prod_{s=t-\kappa_{\min}}^{t+1+\kappa_{\max}} f(f_s|f^{s-1}, \mathbb{S}^s, \theta) \quad \text{(D.2)}$$

due to the Markov structure where $\kappa_{\max} = \max\{\kappa_0, \kappa_1\}$, $\kappa_{\min} = \min\{\kappa_0, \kappa_1\}$ and $X^t = \{X^1, \ldots, X^t\}$, $X^{-t} = \{X^1, \ldots, X^{t-1}, X^{t+1}, \ldots, X^T\}$.

Conditional on the factors, $f(f_s|f^{s-1}, \mathbb{S}^s, \theta)$ follows a Gaussian distribution derived from the standard regression framework with Gaussian error terms. The term $f(S_{1,t+1}|S_{1,t}, \boldsymbol{\theta})$ drops out at $t = T$. For $t = 1$, the term $S_{1,1}$ can be sampled from

$$f(S_{1,1}|S_1^{-1}, f^T, \theta) \propto f(S_{1,1}|\theta) f(S_{1,2}|S_{1,1}, \theta) \prod_{s=\max(0,1-\kappa_{\min})}^{2+\kappa_{\max}} f(f_s|f^{s-1}, \mathbb{S}^s, \theta) \quad \text{(D.3)}$$

where the unconditional density $f(S_{1,1}|\boldsymbol{\theta})$ follows a binomial density with probability $(1-p_1)/(2-p_1-q_1)$ derived from the ergodic probabilities of the Markov chain. Sampling of the state variables can be implemented by starting from the most recent value of S_1^T and sampling the states backward in time, one after another. After each step, the t^{th} element of S_1^T is replaced by its most recent draw.

We proceed with the estimation of the parameters that are related to the evolution of the common factors. For these parameters, we set up Metropolis Hastings samplers with candidates derived using the transition equations. The autoregressive process for the factors can be written as

$$f_{l,t} = (1 - S_{l,t})\alpha_{l,0} + S_{l,t}\alpha_{l,1} + \phi_{l,l} f_{l,t-1} + \eta_{l,t} \qquad \eta_{l,t} \sim N(0, \sigma^2_{f_l}) \text{ for } l = 1, 2 \quad \text{(D.4)}$$

D.2.3 Sampling of $\boldsymbol{\alpha}_l$ for $l = 1, 2$ We use a Metropolis Hastings (MH) step to sample $\boldsymbol{\alpha}_l = (\alpha_{l,0}, \alpha_{l,1})'$ conditional on the data. For obtaining an efficient candidate density, we first restructure (D.4) as

$$\sigma_{f_l}^{-1}(f_{l,t} - \phi_{l,l} f_{l,t-1}) = \sigma_{f_l}^{-1}\left((1 - S_{l,t})\alpha_{l,0} + S_{l,t}\alpha_{l,1}\right) + \sigma_{f_l}^{-1}\eta_{l,t} \quad \text{for } l = 1, 2 \tag{D.5}$$

to form a regression as

$$Y_t = X_t \boldsymbol{\alpha}_l + v_{l,t} \qquad v_{l,t} \sim N(0, 1)$$

To sample $\boldsymbol{\alpha}_l = (\alpha_{l,0}, \alpha_{l,1})'$ from the candidate density, we use a multivariate normal distribution with mean $(X'X)^{-1}X'Y$ and variance $(X'X)^{-1}$, where $Y = (Y_2, \ldots, Y_T)'$ and $X = (X_2', \ldots, X_T')'$. As discussed in Section 3.2. in the main text, we impose restrictions on the elements of α_1 by sampling the parameters from the corresponding truncated distribution as the candidate density for identification of regimes. We then evaluate the probabilities conditional on the data, required to compute acceptance probability, using the Kalman filter given the draw from the candidate density.

D.2.4 Sampling of $\phi_{l,l}$ and $\sigma_{f_l}^2$ for $l = 1, 2$ In order to impose unit unconditional variance for the identification of the factors, we sample $\phi_{l,l}$ and σ_l^2 jointly using the fact that $\sigma_{f_l}^2 = (1 - \phi_{l,l}^2)$ in case of unit unconditional variance. We use a MH step to sample $\phi_{l,l}$ and σ_l^2 jointly. As in the previous case, for obtaining an efficient candidate density, we first restructure (D.4) as

$$\sigma_{f_l}^{-1}(f_{l,t} - \alpha_{l,S_{l,t}}) = \sigma_{f_l}^{-1} f_{l,t-1}\phi_{l,l} + \sigma_{f_l}^{-1}\eta_{l,t} \tag{D.6}$$

to form a regression as

$$Y_t = X_t \phi_{l,l} + v_{l,t} \qquad v_{l,t} \sim N(0, 1)$$

To sample $\phi_{l,l}$ and σ_l^2 from the candidate density, we use an multivariate normal distribution with mean $(X'X)^{-1}X'Y$ and variance $(X'X)^{-1}$, where $Y = (Y_2, \ldots, Y_T)'$ and $X = (X_2', \ldots, X_T')'$. Stationarity is imposed by sampling the $\phi_{l,l}$ from the truncated distribution ensuring that $\phi_{l,l} < 1$. We optimize the density w.r.t. to this parameter using the restriction that $\sigma^2_{f_l} = (1 - \phi^2_{l,l})$ conditional on the factors to obtain a candidate draw for $\phi_{l,l}$ and therefore for $\sigma^2_{f_l}$. We then evaluate the probabilities conditional on the data, required to compute acceptance probability, using the Kalman filter given the draw from the candidate density.

D.2.5 Sampling of lead parameters $\boldsymbol{\kappa}$ As κ_0 and κ_1 parameters can only take discrete values we can compute the posterior probabilities for all $\boldsymbol{\kappa} \in \mathcal{C}$, where $\mathcal{C}$ defines restrictions and types of synchronization. We sample $\boldsymbol{\kappa}$ from the multinomial distribution, with the sampling occurring for both (κ_0, κ_1) parameters conditional on data rather than factors using a MH step. We can minimize the computational cost by using only the part that is related to the financial cycle S_2, as the shifts in S_1 and thus distinct values of $\boldsymbol{\kappa}$ are reflected as distinct values of S_2 while S_1 remains unaltered. Therefore, we decompose the Kalman filter recursion and the simulation smoother into parts for obtaining the kernel distribution $\boldsymbol{\kappa}$ which reduces the computational cost substantially.

Next, we proceed with parameters that are related to the measurement equation, which is rewritten below,

$$\begin{aligned} y_{i,t} &= \lambda_i f_t + \varepsilon_{i,t} \\ \psi(L)\varepsilon_{i,t} &= \epsilon_{i,t} \quad \epsilon_{it}|\xi_{i,t} \sim N(0, \sigma^2_{i,t}/\xi_{i,t}) \quad \xi_{i,t} \sim \Gamma(\tfrac{\nu}{2}, \tfrac{\nu}{2}) \\ \sigma^2_{i,t} &= \sigma^2_{i,1}\, \mathbb{I}\,[t \le \tau] + \sigma^2_{i,2}\, \mathbb{I}\,[t > \tau] \;\text{ for } i = 1, \ldots, N. \end{aligned} \tag{D.7}$$

We first sample ξ_t using Gamma distribution update as

$$f(\xi_{i,t}|y_{i,t}, f_t, \sigma^2_{i,1}, \sigma^2_{i,2}, \psi_i(L), \lambda_i) \sim \begin{cases} \Gamma(\frac{v+1}{2}, \frac{v+\sigma^{-2}_{i,1}\psi_i(L)(y_{i,t}-\lambda_i f_t)^2}{2}) & \text{for} \quad t < \tau \\ \Gamma(\frac{v+1}{2}, \frac{v+\sigma^{-2}_{i,2}\psi_i(L)(y_{i,t}-\lambda_i f_t)^2}{2}) & \text{for} \quad t \ge \tau \end{cases} \tag{D.8}$$

see for example [Albert and Chib, 1993], to transform the system to follow a Gaussian distribution. Let $a_{i,t} \equiv \xi^{1/2}_{i,t}\epsilon_{i,t}$ and $e_{i,t} \equiv \xi^{1/2}_{i,t}\varepsilon_{i,t}$ denote the scaled error terms that follow Gaussian distributions.

D.2.6 Sampling of λ_i To sample λ_i we first transform the measurement equation by pre-multiplying with $\psi_i(L)$, $\xi_{i,t}$ and $\sigma_{i,t}^{-1}$ as

$$\sigma_{i,t}^{-1}\xi_{i,t}^{1/2}\Big(\psi_i(L)y_{i,t}\Big) = \sigma_{i,t}^{-1}\xi_{i,t}^{1/2}\Big(\psi_i(L)f_t\Big)\lambda_i + \sigma_{i,t}^{-1}\Big(\psi_i(L)e_{i,t}\Big) \tag{D.9}$$

for forming the following regression

$$Y_t = X_t\lambda_i + v_{i,t} \qquad v_{i,t} \sim N(0,1)$$

To sample λ_i, we use a normal distribution with mean $(X'X)^{-1}X'Y$ and variance $(X'X)^{-1}$, where $Y = (Y_{k_i+1}, \dots, Y_T)'$ and $X = (X'_{k_i+1}, \dots, X'_T)'$. The lag structure of $\psi(L)$, k_i, is set as 3 for the economic variables whereas it is set to zero for the financial variables.

D.2.7 Sampling of $\sigma_{i,1}^2$ and $\sigma_{i,2}^2$ Following the transformation in the previous step we can sample $\sigma_{i,1}^2$ and $\sigma_{i,2}^2$ from an inverse-Gamma distributions with scale parameters $\left(\sum_{t=4}^{\tau-1} a_{i,t}^2\right)$ and $\left(\sum_{t=\tau}^{T} a_{i,t}^2\right)$ and degrees of freedom $(\tau - (k_i+1))$ and $(T - \tau + 1)$, respectively.

D.2.8 Sampling of $\psi_i(L)$ To sample $\psi_i(L)$ we first transform the measurement equations by pre-multiplying it with $\sigma_{i,t}^{-1}$. For the regression equations regarding to economic variables with 3 lags of idiosyncratic factors, we can write

$$\sigma_{i,t}^{-1}e_{i,t} = \sigma_{i,t}^{-1}e_{i,t-1}\psi_{i,1} + \sigma_{i,t}^{-1}e_{i,t-2}\psi_{i,2} + e_{i,t-3}\psi_{i,3} + \sigma_{i,t}^{-1}a_{i,t} \tag{D.10}$$

to form a regression as

$$Y_t = X_t\Psi_i + v_{i,t} \qquad v_{i,t} \sim N(0,1)$$

where $\Psi_i = (\psi_{i,1}, \psi_{i,2}, \psi_{i,3})'$. To sample Ψ_i, we use a normal distribution with mean $(X'X)^{-1}X'Y$ and variance $(X'X)^{-1}$, where $Y = (Y_{k_i+1}, \dots, Y_T)'$ and $X = (X'_{k_i+1}, \dots, X'_T)'$.

D.2.9 Sampling of τ The conditional posterior density of τ is as follows:

$$\begin{aligned} f(\tau|y^T, f^T, \theta) \propto \mathbb{I}[b+4 \leq \tau \leq T-b] \times \prod_{i=1}^{N} \Big((\sigma_{i,1}^{-1})^{(\tau-3)} (\sigma_{i,2}^{-1})^{(T-\tau+2)} \Big) \times \\ \exp\Big(-\frac{1}{2} \sum_{i=1}^{\hat{n}_1} \Big(\sigma_{i,1}^{-2} \sum_{t=4}^{\tau-1} a_{i,t}^2 + \sigma_{i,2}^{-2} \sum_{t=\tau}^{T} a_{i,t}^2 \Big) \Big) \end{aligned} \tag{D.11}$$

where N is the number of variables. We can sample τ as discrete values from the range $[b+4 \leq \tau \leq T-b]$ where $b = 12$ denoting the first and last 12 observations.

D.2.10 Sampling of p_i and q_i The conditional posterior densities of the transition parameters are given by

$$\begin{aligned} f(p_i \mid S_i) &\propto p_i^{T_{00}+N_{00}-1} (1-p_i)^{T_{01}+N_{01}-1} \\ f(q_i \mid S_i) &\propto q_i^{T_{10}+N_{10}-1} (1-q_i)^{T_{11}+N_{11}-1} \end{aligned} \tag{D.12}$$

where T_{ij} denotes the number of transitions from state i to state j and N_{ij} denotes the corresponding parameters regarding to prior distribution. This corresponds to the kernel of a Beta distribution. Therefore, the transition probabilities can be sampled from a Beta distribution with parameters $T_{ij} + N_{ij}$.

D.2.11 Generating the CEI and FCI, $\mathcal{F}_t = (\mathcal{F}_{1,t}, \mathcal{F}_{2,t})'$ Given $f_{1,t}$ for $t = 1, ..., T$, we need an estimate of $\delta = (\delta_1, \delta_2)'$, growth rate of the indexes, in order to construct the index $\mathcal{F}_t$. We have

$$\begin{aligned} \mathcal{F}_{1,t|t} &= \mathcal{F}_{1,t|t-1} + f_{1,t} + \delta_1 \\ \mathcal{F}_{2,t|t} &= \mathcal{F}_{2,t|t-1} + f_{2,t} + \delta_2 \end{aligned} \tag{C.14}$$

To estimate δ, we need to find the relationship between $\Delta\mathcal{F}_{t|t}$ and $\mathbf{y}_t$. Let this relationship be defined as

$$\Delta\mathcal{F}_{t|t} = \mathcal{W}(L)\mathbf{y}_t$$

Taking the expectation of both sides, we get

$$\hat{\delta} = \mathcal{W}\mathbb{E}[\mathbf{y}_t] = \mathcal{W}\bar{\mathbf{y}} \tag{C.15}$$

We know that $f_{t|t} = \mathcal{W}(L)\mathbf{y}_t$, so we can identify $\mathcal{W}$.[1] After solving steady state for a stationary transition equation, the Kalman Filter gives

$$\boldsymbol{\beta}_{t|t} = (\mathbf{I} - (\mathbf{I} - \mathbf{KH})\mathbf{F}L)^{-1}\mathbf{K}\mathbf{y}_t \tag{C.16}$$

where L is the lag operator. Because the first and the last elements of $\boldsymbol{\beta}_{t|t}$ is f_t, $\mathcal{W}$ is given by the first and the last elements of $(\mathbf{I} - (\mathbf{I} - \mathbf{KH})\mathbf{F}L)^{-1}\mathbf{K}$. After getting $\hat{\delta}$, we can estimate $\mathcal{F}_t$ from the equations (C.14) recursively.

[1]See [Stock and Watson, 1993].

Appendix E

ESTIMATION RESULTS OF THE COMPETING MODELS

Table E.1: Estimates of factor loadings

		Imperfect synchronization of cycles	Perfect synchronization of cycles	Independent cycles
Economic variables				
ip	$\lambda_{1,1}$	0.443(0.087)	0.418 (0.079)	0.401 (0.092)
import	$\lambda_{2,1}$	0.272(0.078)	0.253 (0.067)	0.246 (0.081)
export	$\lambda_{3,1}$	0.111(0.055)	0.109 (0.053)	0.097 (0.054)
retails	$\lambda_{4,1}$	0.462(0.138)	0.383 (0.114)	0.361 (0.137)
pmi	$\lambda_{5,1}$	0.136(0.142)	0.177 (0.153)	0.187 (0.158)
empna	$\lambda_{6,1}$	0.116(0.105)	0.136 (0.119)	0.141 (0.126)
traserv^q	$\lambda_{7,1}$	0.231(0.150)	0.252 (0.157)	0.241 (0.155)
traserv^m	$\lambda_{8,1}$	0.484(0.145)	0.397 (0.115)	0.364 (0.134)
Financial variables				
rbist	$\lambda_{9,2}$	0.458(0.078)	0.577 (0.066)	0.575 (0.067)
FXRes	$\lambda_{10,2}$	0.286(0.070)	0.262 (0.071)	0.261 (0.071)
Conf	$\lambda_{11,2}$	0.587(0.077)	0.612 (0.071)	0.606 (0.072)
TermS	$\lambda_{12,2}$	0.333(0.092)	0.293 (0.084)	0.292 (0.085)
VOL	$\lambda_{13,2}$	-0.203(0.080)	-0.239 (0.078)	-0.238 (0.078)
P/E	$\lambda_{14,2}$	0.131(0.111)	0.184 (0.103)	0.186 (0.104)
TAuc	$\lambda_{15,2}$	-0.324(0.075)	-0.311 (0.076)	-0.311 (0.075)
TETS	$\lambda_{16,2}$	-0.151(0.056)	-0.118 (0.065)	-0.117 (0.063)
Cred	$\lambda_{17,2}$	-0.181(0.096)	-0.180 (0.096)	-0.184 (0.096)
MSCIem	$\lambda_{18,2}$	0.571(0.103)	0.645 (0.095)	0.640 (0.096)
EMBI-Tr	$\lambda_{19,2}$	0.121(0.036)	0.105 (0.042)	0.105 (0.041)

Note: The table shows posterior means and standard deviations (in parentheses) of the factor loading parameters in the measurement equations in (11) in the main text for the competing models estimated using the data for the periods starting from January 1999 until November 2019. The competing models are constituted by the model with Imperfectly Synchronized phase synchronized with regime dependent phase shifts between the cyclical components of the CEI and the FCI, the model with Perfectly Synchronized cycles (PS) for the CEI and FCI and the model with independent cycles for the CEI and FCI. Posterior results are based on 60,000 draws from the posterior distribution where the first 10,000 draws are discarded as burn-in sample.

Table E.2: Estimates of conditional variances of the variables

		Imperfect synchronization of cycles	Perfect synchronization of cycles	Independent cycles
Most likely break date	τ	2001 : 09	2001 : 09	2001 : 09
Economic variables				
ip	$\sigma^2_{1,1}$	1.095 (0.324)	1.106 (0.320)	1.107 (0.317)
	$\sigma^2_{1,2}$	0.719 (0.103)	0.728 (0.105)	0.728 (0.110)
import	$\sigma^2_{2,1}$	1.998 (0.638)	2.025 (0.637)	2.017 (0.638)
	$\sigma^2_{2,2}$	0.631 (0.085)	0.635 (0.082)	0.630 (0.085)
export	$\sigma^2_{3,1}$	1.244 (0.377)	1.261 (0.392)	1.252 (0.395)
	$\sigma^2_{3,2}$	0.585 (0.067)	0.584 (0.067)	0.590 (0.065)
retails	$\sigma^2_{4,1}$	1.638 (2.229)	1.612 (1.964)	1.611 (1.810)
	$\sigma^2_{4,2}$	0.775 (0.138)	0.788 (0.139)	0.793 (0.143)
pmi	$\sigma^2_{5,1}$	1.626 (2.152)	1.653 (1.925)	1.646 (1.803)
	$\sigma^2_{5,2}$	0.943 (0.152)	0.940 (0.151)	0.933 (0.147)
empna	$\sigma^2_{6,1}$	1.585 (2.198)	1.667 (2.261)	1.619 (2.087)
	$\sigma^2_{6,2}$	0.871 (0.106)	0.863 (0.103)	0.863 (0.105)
traserv^q	$\sigma^2_{7,1}$	1.582 (2.023)	1.638 (1.896)	1.585 (1.640)
	$\sigma^2_{7,2}$	0.924 (0.235)	0.916 (0.226)	0.920 (0.230)
traserm^m	$\sigma^2_{8,1}$	1.666 (2.706)	1.579 (2.146)	1.628 (2.930)
	$\sigma^2_{8,2}$	0.738 (0.128)	0.749 (0.135)	0.766 (0.131)
Financial Variables				
rbist	$\sigma^2_{9,1}$	1.877(0.618)	1.877(0.619)	1.871(0.622)
	$\sigma^2_{9,2}$	0.352(0.069)	0.352(0.069)	0.351(0.071)
FXRes	$\sigma^2_{10,1}$	3.325(1.138)	3.320(1.148)	3.318(1.147)
	$\sigma^2_{10,2}$	0.510(0.072)	0.510(0.074)	0.509(0.072)
Conf	$\sigma^2_{11,1}$	0.635(0.217)	0.621(0.213)	0.639(0.218)
	$\sigma^2_{11,2}$	0.627(0.091)	0.626(0.091)	0.628(0.091)
TermS	$\sigma^2_{12,1}$	1.735(2.976)	1.712(2.083)	1.709(1.868)
	$\sigma^2_{12,2}$	0.721(0.129)	0.722(0.132)	0.719(0.132)
VOL	$\sigma^2_{13,1}$	1.266(0.333)	1.264(0.330)	1.263(0.330)
	$\sigma^2_{13,2}$	0.899(0.122)	0.898(0.123)	0.897(0.123)
P-E	$\sigma^2_{14,1}$	2.190(1.252)	2.188(1.260)	2.202(1.266)
	$\sigma^2_{14,2}$	0.681(0.318)	0.682(0.318)	0.676(0.321)
TAuc	$\sigma^2_{15,1}$	1.622(0.472)	1.614(0.472)	1.622(0.475)
	$\sigma^2_{15,2}$	0.776(0.111)	0.776(0.111)	0.773(0.111)
TETS	$\sigma^2_{16,1}$	10.441(5.965)	10.411(5.949)	10.332(5.903)
	$\sigma^2_{16,2}$	0.083(0.027)	0.083(0.028)	0.083(0.028)
Cred	$\sigma^2_{17,1}$	1.589(2.135)	1.594(2.016)	1.596(2.323)
	$\sigma^2_{17,2}$	0.893(0.206)	0.896(0.219)	0.895(0.212)
MSCIem	$\sigma^2_{18,1}$	1.587(2.014)	1.598(2.072)	1.570(2.063)
	$\sigma^2_{18,2}$	0.651(0.108)	0.650(0.108)	0.653(0.110)
EMBI-Tr	$\sigma^2_{19,1}$	6.624(3.782)	6.606(3.776)	6.581(3.793)
	$\sigma^2_{19,2}$	0.055(0.024)	0.055(0.024)	0.055(0.024)

Note: The table shows posterior means and standard deviations (in parentheses) of the variances of the idiosyncratic components in the measurement equations in (11) in the main text for the competing models estimated using the data for the periods starting from January 1999 until November 2019. Posterior results are based on 60,000 draws from the posterior distribution where the first 10,000 draws are discarded as burn-in sample. See Table 2 in the main text for further details.

Table E.3: Autoregressive coefficients of the idiosyncratic factors of economic variables

		Imperfect synchronization of cycles	Perfect synchronization of cycles	Independent cycles
	$\psi_{1,1}$	-0.243 (0.083)	-0.254 (0.084)	-0.264 (0.082)
ip	$\psi_{1,2}$	-0.049 (0.081)	-0.054 (0.082)	-0.059 (0.081)
	$\psi_{1,3}$	-0.016 (0.077)	-0.017 (0.077)	-0.019 (0.077)
	$\psi_{2,1}$	-0.381 (0.077)	-0.383 (0.076)	-0.392 (0.076)
import	$\psi_{2,2}$	-0.048 (0.082)	-0.048 (0.081)	-0.056 (0.081)
	$\psi_{2,3}$	0.056 (0.074)	0.055 (0.073)	0.051 (0.074)
	$\psi_{3,1}$	-0.617 (0.066)	-0.618 (0.065)	-0.616 (0.067)
export	$\psi_{3,2}$	-0.316 (0.074)	-0.318 (0.074)	-0.316 (0.074)
	$\psi_{3,3}$	-0.090 (0.065)	-0.092 (0.065)	-0.092 (0.064)
	$\psi_{4,1}$	-0.239 (0.121)	-0.249 (0.121)	-0.255 (0.114)
retails	$\psi_{4,2}$	-0.062 (0.120)	-0.070 (0.121)	-0.070 (0.121)
	$\psi_{4,3}$	-0.058 (0.116)	-0.060 (0.115)	-0.060 (0.115)
	$\psi_{5,1}$	-0.063 (0.117)	-0.063 (0.108)	-0.067 (0.109)
pmi	$\psi_{5,2}$	-0.156 (0.103)	-0.155 (0.101)	-0.160 (0.103)
	$\psi_{5,3}$	0.049 (0.103)	0.053 (0.104)	0.052 (0.104)
	$\psi_{6,1}$	0.167 (0.080)	0.159 (0.081)	0.160 (0.083)
empna	$\psi_{6,2}$	0.299 (0.075)	0.299 (0.076)	0.296 (0.077)
	$\psi_{6,3}$	-0.165 (0.077)	-0.165 (0.077)	-0.166 (0.079)
	$\psi_{7,1}$	0.020 (0.169)	0.010 (0.177)	0.004 (0.180)
traserv^q	$\psi_{7,2}$	0.133 (0.162)	0.127 (0.163)	0.132 (0.167)
	$\psi_{7,3}$	0.151 (0.162)	0.150 (0.163)	0.149 (0.165)
	$\psi_{8,1}$	-0.196 (0.118)	-0.222 (0.116)	-0.222 (0.114)
traserv^m	$\psi_{8,2}$	-0.034 (0.113)	-0.045 (0.113)	-0.041 (0.112)
	$\psi_{8,3}$	0.046 (0.113)	0.046 (0.111)	0.048 (0.109)

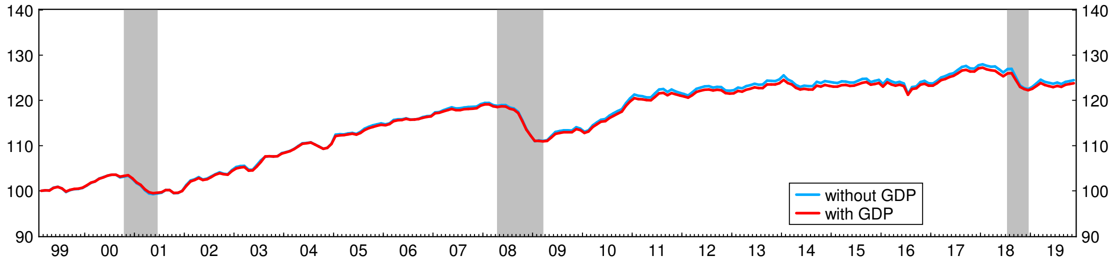
Note: The table shows posterior means and standard deviations (in parentheses) of the autoregressive coefficients of the idiosyncratic factors of economic variables in the measurement equations in (11) in the main text for the competing models estimated using the data for the periods starting from January 1999 until October 2018. Posterior results are based on 60,000 draws from the posterior distribution where the first 10,000 draws are discarded as burn-in sample. See Table E.1 for further details.

Appendix F

RESULTS WHEN GDP IS INCLUDED IN THE DATASET

In most applications, GDP is typically taken as a measure of economic conditions. However, the national accounts in Turkey have undergone a substantial revision in 2016 and the discussion of the accuracy of this revision has not reached a consensus. This is due the fact that not only the levels but also the growth rates of old and new series substantially diverge; see the discussion in [Yilmaz et al., 2017]. Therefore, we exclude this series in our analysis to preclude any potential bias in our analysis. To examine this further, we estimate the IS model together with the new GDP series. Figure F.1 displays the estimate of the CEI using the GDP series in addition to the other economic variables together with the CEI estimated without the GDP series.

Figure F.1: Estimate of Coincident Economic Index with and without the real GDP series



As can be seen in Figure F.1, the two series almost perfectly overlap with each other and we do not observe any noticeable difference. This implies that the estimated CEI already captures the effect of the GDP and the GDP series does not provide any additional information on top of the economic variables used in our dataset.

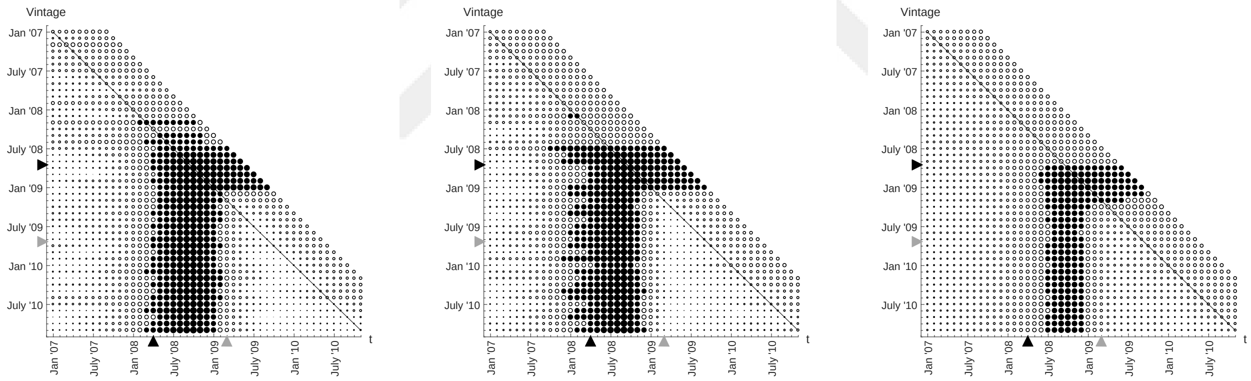
Appendix G

REAL-TIME PREDICTION EXERCISE WITH A DIFFERENT ILLUSTRATION

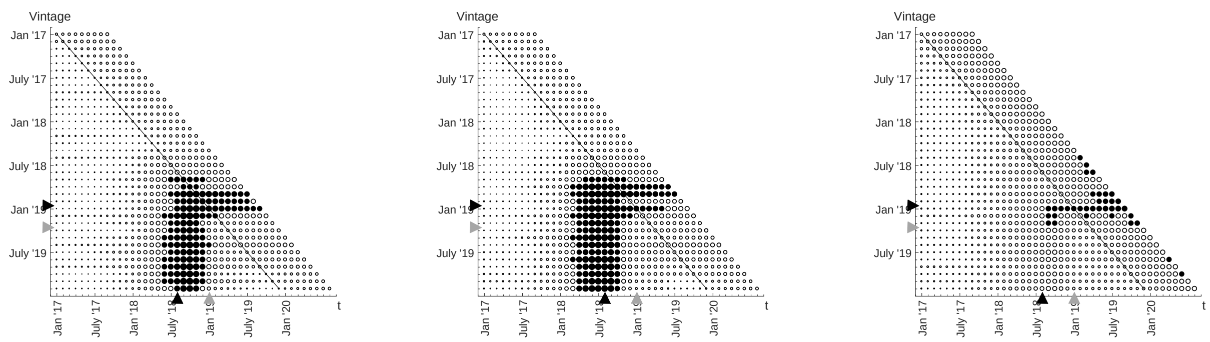
Figure G.1: real-time nowcasting/forecasting exercise: In sample estimates and out-of-sample predictions of recession probabilities

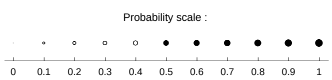
Imperfect Synchronization | Perfect Synchronization | Independent Cycles

For the 2008-9 recession



For the periods covering 2017-2019





Note: The sizes of circles with recession probabilities are given as "Probability scale". The probabilities bigger than 0.5 are shown as filled circles.

Appendix H

ESTIMATION RESULTS OF THE MODEL WITHOUT ANY RESTRICTION OF FACTOR LOADINGS

We display the estimation result related to the loadings in Table H.1 and the remaining model parameters in Table 2.1.

Table H.1: Estimates of factor loadings

	Loadings of economic factor		Loadings of financial factor	
Panel A:				
ip	$\lambda_{1,1}$	0.398 (0.074)	$\lambda_{1,2}$	0.091 (0.059)
import	$\lambda_{2,1}$	0.201 (0.060)	$\lambda_{2,2}$	0.220 (0.052)
export	$\lambda_{3,1}$	0.108 (0.058)	$\lambda_{3,2}$	-0.020 (0.041)
retails	$\lambda_{4,1}$	0.432 (0.100)	$\lambda_{4,2}$	0.149 (0.112)
pmi	$\lambda_{5,1}$	0.094 (0.139)	$\lambda_{5,2}$	0.197 (0.123)
empna	$\lambda_{6,1}$	0.099 (0.107)	$\lambda_{6,2}$	0.013 (0.100)
traserv^q	$\lambda_{7,1}$	-0.201 (0.401)	$\lambda_{7,2}$	-0.017 (0.185)
traserm^m	$\lambda_{8,1}$	0.473 (0.098)	$\lambda_{8,2}$	-0.094 (0.111)
Panel B:				
rbist	$\lambda_{9,1}$	0.026 (0.071)	$\lambda_{9,2}$	0.453 (0.080)
FXRes	$\lambda_{10,1}$	0.037 (0.069)	$\lambda_{10,2}$	0.268 (0.067)
Conf	$\lambda_{11,1}$	0.027 (0.069)	$\lambda_{11,2}$	0.583 (0.072)
TermS	$\lambda_{12,1}$	-0.066 (0.081)	$\lambda_{12,2}$	0.348 (0.091)
VOL	$\lambda_{13,1}$	0.021 (0.080)	$\lambda_{13,2}$	-0.206 (0.077)
P/E	$\lambda_{14,1}$	-0.035 (0.077)	$\lambda_{14,2}$	0.119 (0.108)
TAuc	$\lambda_{15,1}$	0.030 (0.078)	$\lambda_{15,2}$	-0.325 (0.076)
TETS	$\lambda_{16,1}$	-0.013 (0.027)	$\lambda_{16,2}$	-0.147 (0.042)
Cred	$\lambda_{17,1}$	0.212 (0.095)	$\lambda_{17,2}$	-0.223 (0.101)
MSCIem	$\lambda_{18,1}$	0.063 (0.083)	$\lambda_{18,2}$	0.554 (0.107)
EMBI-Tr	$\lambda_{19,1}$	0.004 (0.020)	$\lambda_{19,2}$	0.117 (0.028)
Log-marginal likelihood:			-893.01	

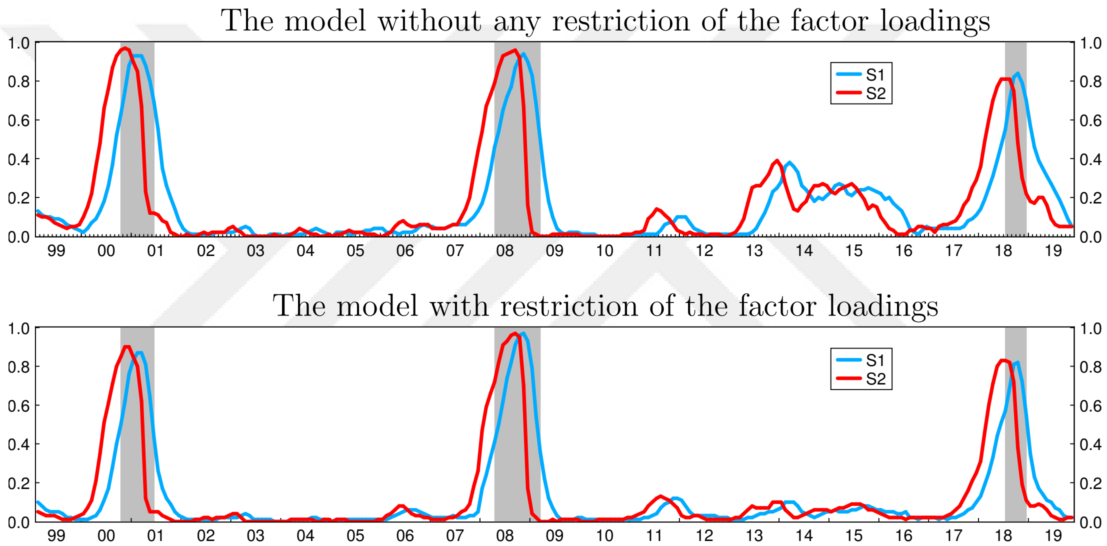
Note: The table shows posterior means and standard deviations (in parentheses) of the factor loadings for the general model explained in the main text in equations (1)-(10). Posterior results are based on 2,000 draws from the posterior distribution where the first 1,000 draws are discarded as burn-in sample.

The loadings related to the economic and financial variables are displayed in Panel A and Panel B of Table H.1. First and foremost, the loadings of economic variables on the financial factor and the loadings of financial variables on the economic factor are very close to 0. For almost all of these loadings, 0 is inside the 95% Highest Posterior Density Interval (HPDI) with the only exceptions of the loadings of *import* on the financial factor and credit, *Cred*, on the economic factor. Considering the import variable loading on the financial factor significantly, one reason for this might be related to the openness of Turkish economy. In fact, the Turkish economy is heavily dependent on external funds and growth in the economy relies almost exclusively on imported capital and intermediate goods, see for example [Yeldan and Ünüvar, 2016]. As the times of excess financial inflows typically coincide with the positive performance of financial markets, at least in the short term, this positive loading of the *import* variable on the financial factor might partly be explained by this link. However, a thorough analysis would require a structural model which is beyond the scope of our work. Considering the significant loading of the credit variable, denoted as *Cred*, on the economic factor, interestingly, the loading is positive, reflecting a contemporaneous positive relation between the credit cycle and the business cycle. On the other hand, the loading of *Cred* on the financial factor is negative and quite significant. This reflects the countercyclical dimension of the credit cycle with the business cycle, which we capture through this loading on the financial factor together with the phase shifts capturing the leading capability of the financial factor on the business cycle. As the leading capability of credit on leading the oncoming recessions is the central focus of many discussions surrounding the Great Recession and its aftermath, see, for example, [Jordà et al., 2011, Gadea and Perez-Quiros, 2015], we find it quite important that our model is able to capture the apt response of the credit variable to the real versus the financial factor.

Second, it is seen that allowing for economic variables to load on the financial factors leads to some minor erosion in the loadings of the economic variables on the economic factor when Table H.1 is compared to the Table 2.2. Interestingly and counter-intuitively, the sign of the loading of quarterly trade and services turnover index is negative, albeit insignificant.

We display the posterior recession probabilities estimated using the model without any restriction of the factor loadings in Figure H.1. While the graph at the upper panel displays the recession probabilities estimated using the model without any restriction on the factor loadings as reported in Table H.1, the graph at the bottom panel displays those with the restriction on the factor loadings. Note that this is identical to the graph at the top of the Figure 2.4. Here we display it again for the ease of comparison of recession probabilities.

Figure H.1: Effect of the restriction on the factor loadings on the recession probabilities



The comparison of the recession probabilities indicate the effect of the relaxing the restrictions on the factor loadings. While there is not any noticeable difference for the recessions in 2000-01 and 2008-09, we observe quite an increase in the recession probabilities approaching to values around 0.4 around 2013-15 for the model without any restriction on the factor loadings. These periods correspond to the taper tantrum referred as the panic and financial turmoil due to the FED's signaling the slow down of the quantitative easing. This downturn in financial cycle in 2013-15 is reflected as the increasing recession probabilities for the model without any restriction on the factor loading. Notice that, Turkey did not experience any economic recession or downturn over these periods. Therefore, our model allowing only the effect of the financial cycle on the business cycle through the phase shifts in the (common) cyclical phases does not produce any signal of recession over these periods with recession probabilities barely approaching to 0.1.

The remaining model parameters are displayed in Table H.2.

Table H.2: Posterior means and standard deviations (in parentheses) of parameters in the transition equations of CEI and FCI for competing models

Phase shifts	κ_0	3.898 (1.963)	Autoregressive	$\phi_{1,1}$	0.176 (0.106)
	κ_1	3.902 (2.133)	coefficients	$\phi_{2,2}$	0.391 (0.072)
Intercepts	$\alpha_{1,0}$	0.087 (0.057)	Transition	p_1	0.965 (0.014)
	$\alpha_{1,1}$	-0.473 (0.160)	probabilities	q_1	0.927 (0.025)
	$\alpha_{2,0}$	0.161 (0.077)		p_2	
	$\alpha_{2,1}$	-0.608 (0.082)		q_2	
Variances	$\sigma^2_{f_1}$	0.958 (0.044)			
	$\sigma^2_{f_2}$	0.842 (0.053)			
Log-marginal likelihood:			-893.01		

Note: The table shows posterior means and standard deviations (in parentheses) of the parameters in the transition equation defining the auto-regressive process for CEI and FCI. Posterior results are based on 2,000 draws from the posterior distribution where the first 1,000 draws are discarded as burn-in sample.

The parameter estimates related to the evolution of factors are very close to those reported in Table 2.1. Therefore, we conclude that both models with and without exclusion restrictions on the factor loadings of economic (financial) variables on the financial (economic) factor provide quite similar results.

Finally, the log-marginal likelihood value of the model without the restriction is -893.01 as shown in the bottom part of Table H.1, while for the restricted model the log-marginal likelihood value attains a higher value of -872.17 as can be seen in the bottom part of Table 2.1. This comparison of the marginal likelihoods provides a Bayesian testing device in the sense that the marginal likelihood metric penalizes the parameter uncertainty by integrating out the parameter (and thus loadings') space. Therefore, it penalizes all of these insignificant factor loadings, causing the large reduction in the log-marginal likelihood value and hence, validating the restriction we impose in the main text.

Appendix I

ESTIMATION RESULTS OF THE MODEL WITHOUT ANY RESTRICTION OF CROSS-AUTO-CORRELATION AND THE CORRELATION COEFFICIENTS

We impose restrictions, first, on the autoregressive coefficient matrix imposing zeros on cross-autocorrelations and, second, on the covariance matrix restricting the correlation coefficient to be zero in the model in the main text. As discussed also in the previous chapter, we do this to reinformance the identification of the factors, and in turn, identification of the cyclical phase shifts, i.e. the κ_i terms. Notice that the phase shift parameters already capture the cross-associations between the two factors in a broader sense through a nonlinear functional form which is likely to encompass linear relations. In that case, inclusion of the cross-autocorrelation might lead to some sort of identification problem which can reduce the predictability of the recessions through the estimated κ_i parameters. However, such a restriction might still be overly restrictive especially if the nonlinear functional form cannot approximate linear relations properly. Therefore, we first extend the model by allowing a full autoregressive coefficient matrix. We display the results regarding to the evolution of the factors in Table I.1.

Table I.1: Posterior means and standard deviations (in parentheses) of parameters in the transition equations of CEI and FCI

Phase shifts	κ_0	4.205 (2.176)	Autoregressive	$\phi_{1,1}$	0.130 (0.090)
	κ_1	3.695 (2.341)	coefficients	$\phi_{1,2}$	0.141 (0.080)
				$\phi_{2,1}$	0.045 (0.036)
				$\phi_{2,2}$	0.378 (0.071)
Intercepts	$\alpha_{1,0}$	0.069 (0.047)	Transition	p_1	0.968 (0.011)
	$\alpha_{1,1}$	-0.392 (0.081)	probabilities	q_1	0.929 (0.024)
	$\alpha_{2,0}$	0.149 (0.061)			
	$\alpha_{2,1}$	-0.658 (0.141)			
Conditional	$\sigma^2_{\eta_1}$	0.949 (0.037)			
variances	$\sigma^2_{\eta_2}$	0.849 (0.050)			
Log-marginal likelihood:			-886.74		

Note: The table shows posterior means and standard deviations (in parentheses) of the parameters in the transition equation defining the autoregressive process for CEI and FCI in (5) in the main text. Posterior results are based on 2,000 draws from the posterior distribution where the first 1,000 draws are discarded as burn-in sample.

Table I.1 displays the estimation results for the parameters related to factor dynamics including the autoregressive parameters related to the (growth of the) coincident economic factor, i.e. $\phi_{1,1}$ and $\phi_{1,2}$ on the top-right panel. Compared to the findings of the initial model where $\phi_{1,2}$ is restricted to be zero, adding the first lag of the (growth of the) financial factor on top of the first lag of economic factor seems to blur the autoregressive dynamics of the economic factor. Table I.1 indicates that zero is inside the 95% HPDI for both coefficients with posterior means of 0.14 and 0.13. When we consider the autoregressive dynamics of the (growth of the) financial factor, we see that the results are quite similar to the original findings where $\phi_{2,1}$ is restricted to be zero, i.e. the coefficient of the first lag of the economic factor. In this case while the posterior mean of $\phi_{2,2}$ is 0.38 compared to 0.41 in the restricted model with the zero outside the 95% HPDI for both cases, the posterior mean of $\phi_{2,1}$ is 0.05 with a large standard deviation of 0.04 implying that zero is inside the 95% HPDI.

Finally, in line with these findings, the log-marginal likelihood value of the model without the restriction is -886.74 as shown in the bottom part of Table I.1, while for the restricted model the log-marginal likelihood value attains a higher value of

-872.17 as reported in Chapter 2 at the bottom panel of Table 2.1. Therefore, we conclude that the restrictions imposing zero for the cross-autocorrelation coefficients are supported by the data.

We display the posterior recession probabilities estimated using the model with full autoregressive coefficient matrix in Figure I.1.

Figure I.1: Effects of allowing for full autoregressive dynamics on the recession probabilities

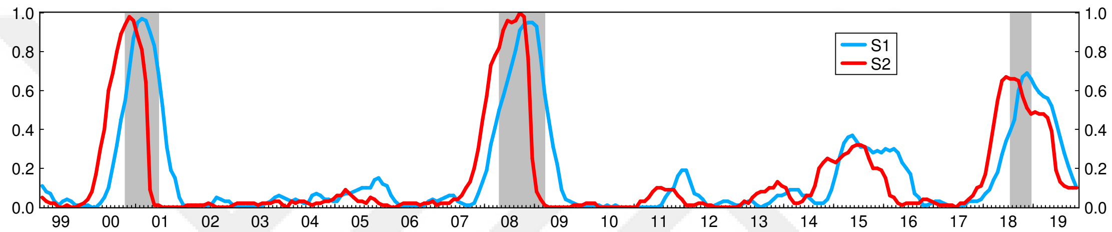


Figure I.1 indicates that, as in our model with restricted cross-autocorrelations, the recessions of 2000-1 and 2008-9 are captured sufficiently well. On the other hand, recession probabilities increase to levels of as high as 0.40 around 2013-2016. As discussed in the previous bullet point, this period corresponds to the financial turmoil due to the the taper tantrum and thereafter. While the real sector did not experience a major downturn that can be translated into increasing recession probabilities, the financial sector partially does. It seems that the additional link between the financial factor and the economic factor causes the recession probabilities to increase also for the real sector. We have a similar discussion related to this point when we compare the proposed model with the model where we impose independent cycles in Chapter 2. There, we also observe a similar, albeit much severe, effect in the sense that financial cycle signals a downturn with increasing probabilities in 2011-2, 2013-4 and 2015-6. In our case, this effect is reflected to the economic factor as well through the link provided by the first lag of the financial factor. The insignificance of the autoregressive coefficients together with the wrong signals of recession during the periods of 2014-15 deteriorates the log-marginal likelihood value compared to our proposed model with a decrease in the log-marginal likelihood value to -886.7 from -872.2.

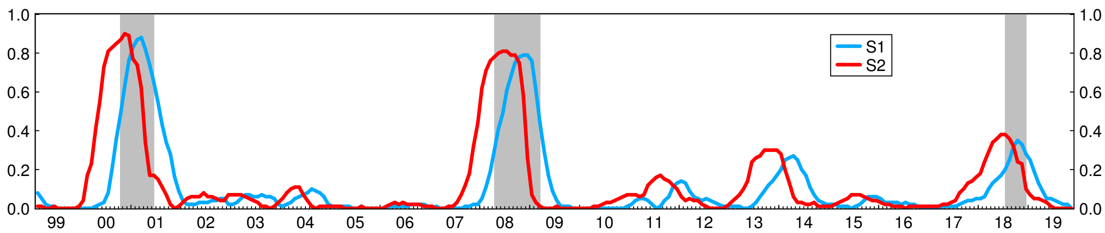
Next, we extend the model by also allowing a cross-correlation between the error terms, denoted as ρ. We display the result in Table I.2.

Table I.2: Posterior means and standard deviations (in parentheses) of parameters in the transition equations of CEI and FCI

Phase shifts	κ_0	4.190 (2.046)	Autoregressive coefficients	$\phi_{1,1}$	0.096 (0.077)
	κ_1	5.278 (2.205)		$\phi_{1,2}$	0.340 (0.085)
				$\phi_{2,1}$	0.044 (0.041)
				$\phi_{2,2}$	0.137 (0.073)
Intercepts	$\alpha_{1,0}$	0.083 (0.053)	Transition probabilities	p_1	0.973 (0.011)
	$\alpha_{1,1}$	-0.480 (0.139)		q_1	0.932 (0.023)
	$\alpha_{2,0}$	0.119 (0.067)			
	$\alpha_{2,1}$	-0.601 (0.090)			
Conditional variances	$\sigma^2_{\eta_1}$	0.862 (0.058)			
	$\sigma^2_{\eta_2}$	0.972 (0.024)			
Correlation	ρ	-0.125 (0.087)			
Log-marginal likelihood:			-886.03		

Table I.2 indicates two important results. First, for the correlation coefficient zero is inside the 95% HPDI with a relatively small posterior mean of -0.13. Still, inclusion of the correlation coefficient decreases the coefficient of the first lag of the economic factor on the economic factor and increases the coefficient of the first lag of the financial factor on the economic factor, thus, in this case the signals for oncoming recession are also affected by the first lag of the financial factor. In Figure I.2 we display the evolution of the posterior recession probabilities using this model.

Figure I.2: Effects of allowing for full autoregressive dynamics and cross-correlation on the recession probabilities



As can be seen in Figure I.2 posterior recession probabilities are very similar over the course of the period starting from 1999 until 2011 including the recessions of 2000-1 and 2008-9. However, we observe very similar hikes in recession probabilities during the financial turmoils around 2011 and 2013 as in the previous cases. Allowing for a linear relation between the financial and the economic factors through cross-autocorrelation coefficients leads to some periods of financial turbulence picked up as economic recessions. Finally, in line with these findings, the log-marginal likelihood value of this extended model increases to -886.0 (as it can be seen in the bottom panel of Table I.2) from -872.2 (for the restricted model proposed in Chapter 2) due to these additional parameters. Therefore, we conclude that the restrictions imposing zero for the cross-autocorrelation coefficients and the correlation coefficients are supported by the data.

Appendix J

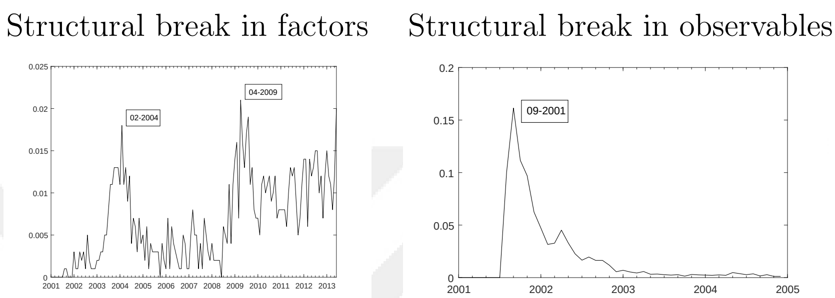
ESTIMATION RESULTS OF THE MODEL WITH A STRUCTURAL BREAK IN THE FACTORS

We have two main motivations behind the choice of this specification of the break in the idiosyncratic factors as in Chapter 2. First, when extracting the factors as the common cyclical components of the macroeconomic and financial time series, we would like to have these cyclical components as smooth as possible by modeling all structural changes in the irregular components as much as possible. That would enable us to measure the common driver of economic and financial activity throughout the sample period smoothly. The Markov dynamics is then solely devoted to capturing the turning points of these measures of economic and financial activity and the relation between these turning points as captured by the parameters, κ_i.

The second and more pragmatic motivation behind this choice is the computational complexity of the model. When we model this structural break in the second moment using the variance of the unobserved common factors in the state equation rather than in the measurement equation, it is quite likely that the inference will be harder compared to the current modeling approach when the break is in the variance of observables. Moreover, since we already have Markov dynamics in the intercept that may plague the inference both the identification of the Markovian switches and the structural break if they interact each other. In Chapter 2, we deal with this by imposing the structural break in the variances to the idiosyncratic factors while we have the Markovian dynamics in the intercept of the common factors.

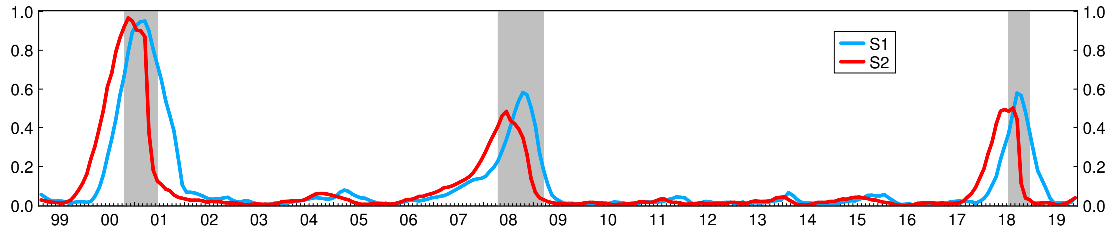
For elaborating the effects of the choice of the location of the structural break in the modeling framework further, we estimate a model where we shift the location of the structural break to the factor dynamics rather than the measurement equation. We display the distribution of the structural break parameter, τ, in the left panel of the Figure J.1 with the distribution of the structural break parameter when it is modeled using the observables on the right panel (which is the Figure 2.5 in Chapter 2) for the ease of comparison.

Figure J.1: Posterior density of the break point parameter, τ



When we focus on the distribution of the structural break in the factor error variances on the left panel, it is seen that there are two peak points of the distribution with the dates of February 2004 and March 2009. Moreover, the probability mass after 2009 is relatively higher than the previous period. Note that the March 2009 corresponds to the end of the 2008-9 recession, hence it is quite likely that this break interacts with this recession. To elaborate this further we display the recession probabilities estimated using this model where the structural break is captured in the factor error variances in Figure J.2.

Figure J.2: Effects of modeling structural break in factors on the recession probabilities

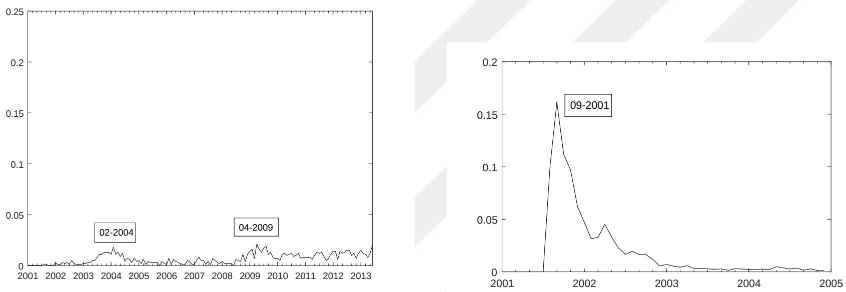


As can be seen in Figure J.2, indeed the recession probabilities for the 2008-09 recession reduces considerably to values below 0.5. In fact these exceed 0.5 only towards the end of 2008 at the brunt of the recession (as well as global recession).

This shows that modeling the structural break in the factor error variances blur the inference on recessions. Notice that although there are two peak points of this distribution the probabilities of these dates are only around 0.02. To illustrate this further we provide the same figure as in Figure J.1 this time fixing the $y-$axis at similar scales in Figure J.3.

Figure J.3: Posterior density of the break point parameter, τ

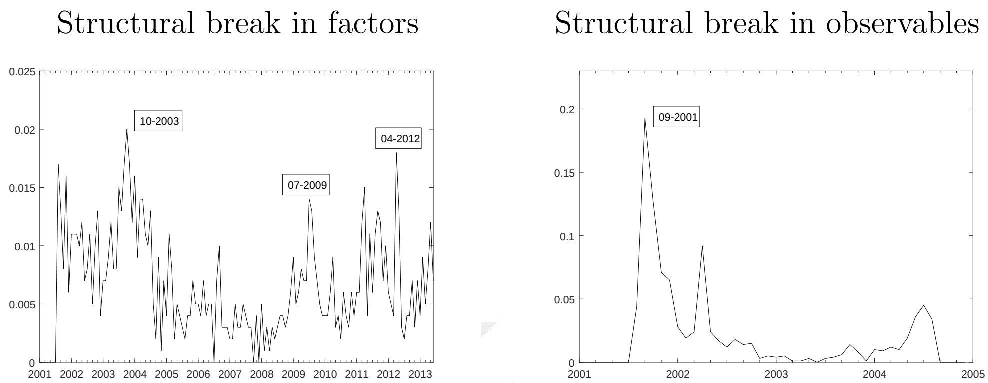
Structural break in factors Structural break in observables



As can be seen from Figure J.3 when the structural break is modeled in the measurement equation there is a large probability mass exceeding 0.15 at the date of September 2001. However, when the break is modeled in the factor evolution we do not see any clear probability mass gathered around some specific value.

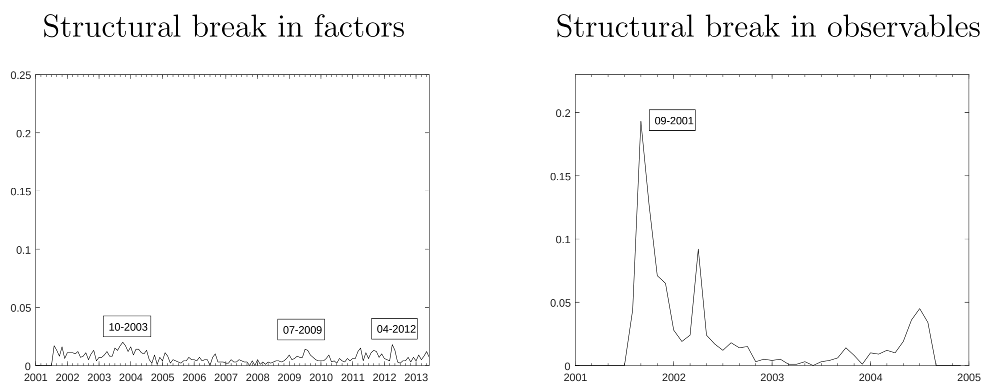
Next we estimate a model where we allow for a structural break both in the measurement equation and the factor evolution. We display the distribution of these structural breaks in Figure J.4.

Figure J.4: Posterior density of the break point parameter, τ, for the structural break in conditional variances of observables and factors



As can be seen in Figure J.4 we observe that there is a structural break in the conditional variance of the observables in September 2001 with a probability mass approaching to 0.2. On the other hand, we observe multiple peaks in the distribution of the break parameter in the conditional variance of the factors in 2003, 2009 and 2012. However, the probably around these dates is barely approaching to 0.02. To emphasize the differences in the distributions of break parameters, we provide the same figures with a similar scales on the $y-$axis in Figure J.5

Figure J.5: Posterior density of the break point parameter, τ, for the structural break in conditional variances of observables and factors



As can be seen from both graphs, while the structural break in the variances of observables can be estimated precisely, it cannot be estimated with a similar precision for the factor error variances. Therefore, we conclude that the structural break only in the variances of observables is supported by the dataset.

Appendix K

ECONOMETRIC MODEL FOR CHAPTER 3

In this section, we give the details about the model with all specifications, i.e. stochastic volatility structure and utilizing both the mean and variance of the SPF up to four quarters ahead starting from the nowcasts. The other specifications can be derived from the most encompassing form in a straightforward manner. We can represent all equations as:

$$
\begin{aligned}
y_t^q &= \lambda^q f_t^q + \varepsilon_t^q \\
y_{i,t}^m &= \lambda_i^m f_t^m + \varepsilon_{i,t}^m \quad \varepsilon_{i,t}^m \sim N(0, \sigma_i^2) \\
f_t^m &= \phi f_{t-1}^m + u_t^m \quad u_t^m \sim N(0, \sigma_u^2) \\
f_t^q &= \sum_{s=0}^{4} w_s f_{t-s}^q \text{ for } t = 3k,\ k = 1, 2, .., K \\
\varepsilon_t^q &= \exp(\tfrac{h_t}{2})\epsilon_t \quad \epsilon_t \sim N(0, 1) \\
h_t &= h_{t-3} + \sigma\eta_t \quad \eta_t \sim N(0, 1) \\
E_t^S[y_{t+1}^q] &= \lambda^q(\phi f_t^m + f_t^q) \\
E_t^S[y_{t+3l+1}^q] &= \lambda^q(\sum_{s=0}^{4} \phi^{3l+1-s} w_s) f_t^m \quad l = 1, 2, 3, 4 \\
log(V^S[y_{t+3l+1}^q]) &= E[h_{t+3l+1}] + v_{l,t}
\end{aligned}
\tag{K.1}
$$

The first part of the model, excluding stochastic volatility and the variance of SPF, can be cast into a state-space form as

$$
\begin{aligned}
\mathbf{y}_t &= \mathbf{H_1}\boldsymbol{\beta}_t + \boldsymbol{\varepsilon}_t \qquad \boldsymbol{\varepsilon}_t | h_t \sim N(\mathbf{0}, \mathbf{R}_{\mathbf{1},t}) \\
\boldsymbol{\beta}_t &= \mathbf{F}_t\boldsymbol{\beta}_{t-1} + \boldsymbol{\zeta}_t \qquad \boldsymbol{\zeta}_t \sim N(\mathbf{0}, \boldsymbol{\Omega}_\mathbf{t}),
\end{aligned}
\tag{K.2}
$$

$$\mathbf{y}_t = \begin{bmatrix} y_t^q \\ y_{t,n}^q \\ y_{t,f_1}^q \\ y_{t,f_2}^q \\ y_{t,f_3}^q \\ y_{t,f_4}^q \\ y_{1,t}^m \\ y_{2,t}^m \\ \vdots \\ y_{16,t}^m \end{bmatrix}, \mathbf{H_1} = \begin{bmatrix} \lambda^q & 0 & 0 \\ \lambda^q & 0 & \phi \\ 0 & 0 & \lambda^q \mathbb{A}_1 \\ 0 & 0 & \lambda^q \mathbb{A}_2 \\ 0 & 0 & \lambda^q \mathbb{A}_3 \\ 0 & 0 & \lambda^q \mathbb{A}_4 \\ 0 & 0 & \lambda_1^m \\ 0 & 0 & \lambda_2^m \\ \vdots & \vdots & \vdots \\ 0 & 0 & \lambda_{16}^m \end{bmatrix}, \boldsymbol{\beta}_t = \begin{bmatrix} f_t^q \\ \bar{f}_t^q \\ f_t^m \end{bmatrix},$$

$$\mathbf{R_1}_{,t} = \begin{bmatrix} \exp(\frac{h_t}{2}) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & \sigma_n^2 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & \sigma_{f_1}^2 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \sigma_{f_2}^2 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \sigma_{f_3}^2 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{f_4}^2 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_1^2 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_2^2 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & \sigma_{16}^2 \end{bmatrix}$$

$$\mathbf{F_1}_{,t} = \begin{cases} \begin{bmatrix} 0 & I_r & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \phi \end{bmatrix}, & t = 3k+1, \\ \begin{bmatrix} I_r & 0 & 0 \\ 0 & I_r & 0 \\ 0 & 0 & \phi \end{bmatrix}, & \text{otherwise}, \end{cases}, \mathbf{F_2}_{,t} = \begin{cases} \begin{bmatrix} I_r & 0 & -w_{R(3-t,3)} \\ 0 & I_r & 0 \\ 0 & 0 & I_r \end{bmatrix}, & t = 3k+1, \\ \begin{bmatrix} I_r & 0 & -w_{R(3-t,3)} \\ 0 & I_r & -w_{R(3-t,3)+3} \\ 0 & 0 & I_r \end{bmatrix}, & \text{otherwise}, \end{cases}$$

where $R(.,3)$ is the positive remainder of the division by 3 (e.g. $R(-1,3) =$

$(3-1))$ and $w = [1, 2, 3, 2, 1]'$.

$$\mathbf{Q} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \sigma_u^2 \end{bmatrix}$$

where $\mathbf{F}_t = \mathbf{F}_{\mathbf{1},t}^{-1}\mathbf{F}_{\mathbf{2},t}$ and $\mathbf{\Omega_t} = \mathbf{F}_{\mathbf{1},t}^{-1}\mathbf{Q}(\mathbf{F}_{\mathbf{1},t}^{-1})'$.

The stochastic volatility can be modelled for the error of the measurement equation of GDP growth as follows:

$$\begin{aligned} \varepsilon_t^q &= \exp(\tfrac{h_t}{2})\epsilon_t \ , \quad \epsilon_t \sim N(0,1) \\ h_t &= h_{t-3} + \sigma\eta_t \ , \quad \eta_t \sim N(0,1) \end{aligned} \tag{K.3}$$

where $t = 3k,\ k = 1, 2, .., K$, defined at quarterly intervals. Squaring and taking the logarithm of the first equation in (K.3), we obtain the following:

$$log((\varepsilon_t^q)^2) \ = \ h_t + log(\epsilon_t^2) \ , \quad \epsilon_t \sim N(0,1) \tag{K.4}$$

We represent the variance of SPF as $Var(SPF)_{t+3l}$ or $V^S[y_{t+3l}^q]$ for $l = 0, 1, .., 4$, starting from the variance of the current quarters nowcast up to 4 quarters ahead forecasts. By taking the logarithm of the variances of SPF, we can align these with the projection of h_t with a scaling coefficient and some error as follows:

$$log(Var(SPF)_{t+3l}) = \sigma_w E[h_{t+3l}] + v_{l,t} \tag{K.5}$$

Then in the state-space, we incorporate variance of SPF as

$$\begin{aligned} \mathbf{\Upsilon}_t &= \boldsymbol{\mu}_t + \mathbf{H_2}h_t + \boldsymbol{\xi}_t \qquad \boldsymbol{\xi}_t | w_t \sim N(\mathbf{0}, \mathbf{R}_{\mathbf{2},t}) \\ h_t &= h_{t-3} + \sigma\eta_t \qquad \eta_t \sim N(0,1), \end{aligned} \tag{K.6}$$

$$\boldsymbol{\Upsilon}_t = \begin{bmatrix} log((\varepsilon_t^q)^2) \\ log(V^S[y_t^q]) \\ log(V^S[y_{t+3}^q]) \\ log(V^S[y_{t+6}^q]) \\ log(V^S[y_{t+9}^q]) \\ log(V^S[y_{t+12}^q]) \end{bmatrix}, \mathbf{H_2} = \begin{bmatrix} 1 \\ \sigma_w \\ \sigma_w \\ \sigma_w \\ \sigma_w \\ \sigma_w \end{bmatrix}, \boldsymbol{\mu}_t = \begin{bmatrix} \mu_{w_t} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix},$$

$$\mathbf{R}_{\mathbf{2},t} = \begin{bmatrix} s_{w_t}^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{v_0}^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{v_1}^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{v_2}^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{v_3}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{v_4}^2 \end{bmatrix}$$

K.1 Likelihood Function

First, we cast the first part of the model in (K.1) into state-space form as

$$\begin{aligned} \mathbf{y}_t &= \mathbf{H_1}\boldsymbol{\beta}_t + \boldsymbol{\varepsilon}_t \qquad \boldsymbol{\varepsilon}_t|h_t \sim N(\mathbf{0}, \mathbf{R}_{\mathbf{1},t}) \\ \boldsymbol{\beta}_t &= \mathbf{F}_t\boldsymbol{\beta}_{t-1} + \boldsymbol{\zeta}_t \qquad \boldsymbol{\zeta}_t \sim N(\mathbf{0}, \mathbf{\Omega_t}), \end{aligned} \tag{K.7}$$

$\mathbf{H_1}$ is comprised of the factor loadings according to type (stock/flow) and frequency of corresponding variable as well as function of parameters for aligning the moments of the survey expectations. $\mathbf{R}_{\mathbf{1},t}$ includes the stochastic volatility for the error term of GDP and conditional variances for the other variables on the diagonal. The state vector $\boldsymbol{\beta}_t$ includes monthly and quarterly factors with auxiliary variable. $\mathbf{F}_t$ consists of the autoregressive coefficient of the monthly factor as well as weights for aggregation in a recursive way and accordingly $\mathbf{\Omega}_t$ includes the variance of the factor. The time variation in $\mathbf{R}_t$ and $\mathbf{\Omega}_t$ comes from the stochastic volatility for the variances of the error term of GDP and aggregate factor recursively. Conditional on the variance of error term of GDP over time, we can proceed with standard inference of the linear Gaussian state-space models by running the Kalman filter. We now modify the system for handling missing observations due to ragged edge and unbalanced data and mixed frequency. Let $\mathbf{W}_t$ be a selection matrix, which is diagonal and ith diagonal element takes 1 if $y_{i,t}$ is observed and 0 otherwise. Then we run the Kalman filter by replacing $\mathbf{y}_t$, $\mathbf{H_1}$ and $\mathbf{R}_{\mathbf{1},t}$ with $\mathbf{y}_t^* = \mathbf{W}_t\mathbf{y}_t$, $\mathbf{H_1}^* = \mathbf{W}_t\mathbf{H_1}$ and $\mathbf{R}_{\mathbf{1},t}^* = \mathbf{W}_t\mathbf{R}_{\mathbf{1},t}\mathbf{W}_t'$, respectively as

$$\begin{aligned} \boldsymbol{\beta}_{t|t-1} &= \mathbf{F}_t\boldsymbol{\beta}_{t-1|t-1} \\ \mathbf{P}_{t|t-1} &= \mathbf{F}_t\mathbf{P}_{t-1|t-1}\mathbf{F}_t' + \mathbf{\Omega}_t \\ \mathbf{v}_{t|t-1} &= \mathbf{y}_t - \mathbf{H_1}^*\boldsymbol{\beta}_{t|t-1} \\ \mathbf{V}_{t|t-1} &= \mathbf{H_1}^*\mathbf{P}_{t|t-1}\mathbf{H_1}^{*'} + \mathbf{R}_{\mathbf{1},t}^* \end{aligned} \tag{K.8}$$

$\mathbf{v}_{t|t-1}$ and $\mathbf{V}_{t|t-1}$ are the prediction error and its variance, respectively. Let $\mathbf{y}^T = \{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_T\}$, $\mathbf{h}^T = \{h_1, h_2, \ldots, h_T\}$, $\boldsymbol{\theta} = (\phi, \lambda^q, \boldsymbol{\lambda}^{m\prime}, \boldsymbol{\sigma}_m^{2\prime}, \boldsymbol{\sigma}_v^{2\prime}, \boldsymbol{\sigma}_{nf}^2, \sigma_u^2, \sigma_w, \sigma)'$ with $\boldsymbol{\sigma}_{nf}^2 = (\sigma_n^2, \sigma_{f_1}^2, .., \sigma_{f_4}^2)'$, $\boldsymbol{\sigma}_v^2 = (\sigma_{v_0}^2, \sigma_{v_1}^2, .., \sigma_{v_4}^2)'$, $\boldsymbol{\sigma}_m^2 = (\sigma_0^2, \sigma_1^2, .., \sigma_{n_{16}}^2)'$, representing all model parameters, then, the complete data likelihood can be written as

$$f(\mathbf{y}^T|\mathbf{h}^T,\boldsymbol{\theta}) = \prod_{t=1}^{T}\left(\frac{1}{\sqrt{2\pi}}\right)|\mathbf{V}_{t|t-1}|^{-\frac{1}{2}}\exp\left(-\frac{1}{2}\sum_{t=1}^{T}\mathbf{v}'_{t|t-1}\mathbf{V}^{-1}_{t|t-1}\mathbf{v}_{t|t-1}\right) \tag{K.9}$$

For the second part of the model, the stochastic volatility of the GDP error term and the survey variances equations can be cast into a state space representation as (K.6) and calculate the likelihood as $f(\mathbf{h}^T|\boldsymbol{\Upsilon}^T,\boldsymbol{\theta})$ following the same procedure in (K.8). By the approximation with mixture normal distributions, we can proceed with standard inference of the linear Gaussian state-space models by running the Kalman filter as for the first part.

K.2 Prior Distributions

We use diffuse priors for most of the parameters in order to let the data be decisive for estimation results. For the autoregressive coefficients of common (monthly) factor, ϕ we use flat prior

$$f(\phi) \propto 1 \tag{K.10}$$

on the condition that characteristic roots of ϕ lie outside the unit circle holds and 0 otherwise.

For the monthly factor loading parameters we also use flat priors

$$f(\lambda_i^m) \propto 1 \quad \text{for } i = 1,\ldots,n_m. \tag{K.11}$$

For the variance parameters of the variables as well as factors, we use noninformative Jeffrey's priors of the form

$$f(\sigma^2_{k,i}) \;\; \propto \;\; \sigma^{-2}_{k,i} \quad \text{for } k=1,2 \;\; \text{and} \;\; i=1,\ldots,N \tag{K.12}$$

Appendix L

POSTERIOR INFERENCE FOR CHAPTER 3

The posterior distribution is proportional to the product of the likelihoods in Section K.1 together with the prior specifications described in K.2.

L.1 Posterior simulation scheme

For inference of the posterior distribution, we use Metropolis within Gibbs algorithm that leads to the following sampling scheme. Starting with initializing the parameters, at step (s) of the iteration

1. Sample f^T from $p(f^T|y^T, \phi^{(s-1)}, \sigma_u^{2(s-1)})$
2. Sample ϕ from $f(\phi|y^T, f^{T(s)}, \sigma_u^{2(s-1)}, \sigma_{nf}^{2(s-1)}, \lambda^{q(s-1)})$
3. Sample σ_u^2 from $f(\sigma_u^2|y^T, f^{T(s)}, \phi^{(s)})$
4. Sample λ^m from $f(\lambda^m|y^T, f^{T(s)}, \sigma_m^{2(s-1)})$
5. Sample σ_m^2 from $f(\sigma_m^2|y^T, f^{T(s)}, \lambda^{m(s)})$
6. Sample λ^q from $f(\lambda^q|y^T, f^{T(s)}, h^{T(s-1)}, \phi^{(s)}, \sigma_{nf}^{2(s-1)})$
7. Sample σ_{nf}^2 from $f(\sigma_{nf}^2|y^T, f^{T(s)}, \phi^{(s)}, \lambda^{q(s)})$
8. Sample h^T from $p(h^T|y^T, f^{T(s)}, \lambda^{q(s)}, \sigma_v^{2(s-1)})$
9. Sample σ_v^2 from $f(\sigma_v^2|y^T, f^{T(s)}, h^{T(s)}, \lambda^{q(s)})$
10. Repeat (1)-(9) S times.

Our model specifications imply that the measurement equations of SPF have nonlinear form in parameter, ϕ and appears more than one equation along with λ^q. Therefore, we use Metropolis-Hastings (MH) Algorithm to sample these variables in steps (2) and (6). Conditional on these parameters, we can sample remaining parameters in a straightforward manner.

L.2 *Conditional Posterior Distributions*

In this section, we derive the conditional distributions used in the posterior sampling scheme in the previous section.

L.2.1 Sampling of f_t The framework (C.2) is a linear Gaussian state-space model conditional on the time varying variance and model parameters.

We first run the Kalman filter forwards and then run the simulation smoother backwards. The Kalman filter prediction steps are given in (K.8). The remaining part of the Kalman filter is the updating steps, given as:

$$\begin{aligned} \boldsymbol{\beta}_{t|t} &= \boldsymbol{\beta}_{t|t-1} + \mathbf{K}_t \mathbf{v}_{t|t-1} \\ \mathbf{P}_{t|t} &= \mathbf{P}_{t|t-1} - \mathbf{K}_t \mathbf{H}^*_{\mathbf{1}} \mathbf{P}_{t|t-1} \end{aligned} \tag{L.1}$$

where $\mathbf{K}_t = \mathbf{P}_{t|t-1}\mathbf{H}^{*\prime}_{\mathbf{1}}\mathbf{V}^{-1}_{t|t-1}$ is the Kalman Gain. Once the Kalman filter is run forward, we can run a simulation smoother using the filtered values for drawing smoothed states as in [Carter et al., 1994] and [Frühwirth-Schnatter, 1994].[1]

L.2.2 Sampling of ϕ and σ_u^2 We use a Metropolis-Hastings step to sample ϕ. To obtain an efficient candidate density, we consider the transition equation of the factor

$$f_t^m = \phi f_{t-1}^m + u_t^m \quad u_t^m \sim N(0, \sigma_u^2) \tag{L.2}$$

as a natural choice. To sample ϕ from the candidate density, we use a normal distribution with mean $(\sigma_u^2 \sum_{t=2}^T (f_{t-1}^m)^2)^{-1} \sum_{t=2}^T (f_t^m f_{t-1}^m)$ and variance $(\sigma_u^2 \sum_{t=2}^T (f_{t-1}^m)^2)^{-1}$.

We impose stationarity by sampling the ϕ from the truncated normal distribution ensuring that $\phi < 1$. We evaluate the probabilities conditional on the data to compute acceptance probability, using the Kalman filter, calculating the likelihoods (K.9) given the candidate draw and the previous draw. We refer to [Chib and

[1] We refer to textbooks such as [Kim et al., 1999] and [Durbin and Koopman, 2012] for further details.

Greenberg, 1995] for the details about acceptance probability and MH-algorithm. We calculate the average rate of acceptance probability with its standard deviation to check whether candidate draws are not always accepted or rejected, making sure that draws wander the entire posterior distribution, see the diagnostics discussed in [Koop, 2003]. Furthermore, as a robustness check against the candidate density function, we adopt random walk chain MH Algorithm by choosing proper mean and variance for "increment random variable", estimate the model and have similar results for ϕ.[2]

After sampling ϕ, we can sample σ_u^2 from an inverse-Gamma distribution with scale parameters $\left(\sum_{t=2}^{T}(f_t^m - \phi f_{t-1}^m)^2\right)$ and degrees of freedom $(T-1)$.

L.2.3 Sampling of λ_i^m and σ_i^2 To sample λ_i^m we consider the monthly measurement equation in (K.1) as a form of the following:

$$Y_t = X_t \lambda_i^m + \varepsilon_{i,t}^m \qquad \varepsilon_{i,t}^m \sim N(0, \sigma_i^2) \tag{L.3}$$

We sample λ_i^m using a normal distribution with mean $(X'X)^{-1}X'Y$ and variance $(\sigma_i^2 X'X)^{-1}$, where $Y = (Y_1, \ldots, Y_T)'$ and $X = (X_1', \ldots, X_T')'$.

After sampling λ_i^m, we calculate $\varepsilon_{i,t}^m$ conditional on λ_i^m, then we can sample σ_i^2 from an inverse-Gamma distribution with scale parameters $\left(\sum_{t=1}^{T}(\varepsilon_{i,t}^m)^2\right)$ and degrees of freedom T.

L.2.4 Sampling of λ^q and $\sigma_{\rho_i}^2$ To sample λ^q, we use MH-Algorithm in a similar way for sampling ϕ. In order to obtain a candidate generating density, we consider the equation

$$y_{i,t}^q \quad = \quad \lambda^q f_t^q + \varepsilon_t^q \tag{L.4}$$

by assuming that error term ε_t^q has constant variance σ^2. Let $Y_t = y_t^q$ and $X_t = f_t^q$ as the previous section for simplicity, then our candidate generating density is normal

[2] The results are available upon request.

distribution with mean $(X'X)^{-1}X'Y$ and variance $(\sigma^2 X'X)^{-1}$, which can be shown as $N((X'X)^{-1}X'Y, (\sigma_i^2 X'X)^{-1})$.

Conditional on λ^q and ϕ, we sample $\sigma^2_{\rho_i}$ from an inverse-Gamma distribution with scale parameters $\left(\sum_{k=1}^{K}(\varepsilon^q_{\rho_i,3k-1})^2\right)$ and degrees of freedom $K(= T/3)$.

L.2.5 Sampling of h_t and $\sigma^2_{v_l}$ We can obtain the error term of GDP ε^q_t, after sampling f^T and λ^q. We assume that this error term has stochastic volatility as in (K.1). After transforming this into additive form we have the following

$$log((\varepsilon^q_t)^2) \quad = \quad h_t + log(\epsilon^2_t)\ , \quad \epsilon_t \sim N(0,1) \tag{L.5}$$

We follow [Omori et al., 2007] to approximate to the distribution of $log(\epsilon^2_t)$ by using ten mixture of normal distributions[3], i.e. $log(\epsilon^2_t)|w_t \sim N(\mu_{w_t}, s^2_{w_t})$ where $w_t \in \{1, 2, .., 10\}$ for time t. We refer to [Omori et al., 2007] for the details of ten normal distributions. This approximation allows us to rewrite (L.5) in a linear and Gaussian form as

$$log((\varepsilon^q_t)^2) \quad = \quad \mu_{w_t} + h_t + \gamma_t\ , \quad \gamma_t \sim N(0, s^2_{w_t}) \tag{L.6}$$

For the other measurement equations, we now derive the dataset for the variances of SPF. We calculate the disagreement of individual forecasters to use as uncertainty proxy for variance (which is commonly used in the literature) as

$$Var(SPF_{t+3l+1}) = \frac{1}{N_t}\sum_{i=1}^{N_t}(S_{i,t,l} - S_{t,l})^2\ , \quad l = 0, 1, 2, 3, 4. \tag{L.7}$$

where $S_{i,t,l}$ is the forecast of the forecaster i at time t for l quarter ahead, $S_{t,l}$ is the mean of the forecasts of N_t forecasters. These are observed for $t = 3k - 1,\ k = 1, 2, .., K$. Number of forecasters N_t changes over time.[4]

[3] We preclude the direct method such as particle filter to estimate in non-linear form for computatinal purposes.

[4] The minimum number of N_t is 9, whereas the maximum is 52.

We can finally construct $\mathbf{\Upsilon}^T$ by taking the logarithm of variances of SPF, along with ε_t^q. Conditional on the mixture component w_t, (K.6) is linear Gaussian state space which can be estimated by Kalman Filter with the similar steps as (K.8) and (L.1). Conditional on h^T, we can sample $\sigma^2_{v_l}$ from an inverse-Gamma distribution with scale parameters $\left(\sum_{k=1}^{K}(v_{i,3k-1})^2\right)$ and degrees of freedom $K(= {}^{T}\!/_{3})$.

Appendix M

AVERAGE SCORES OF LIKELIHOODS

Table M.1: The marginal and predictive likelihoods: 5-variables model over different specifications

	Marginal Likelihoods			**Predictive Likelihoods**								
	Q0			**Q0**			**Q1**			**Q2**		
	M1	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
Baseline Model	-1.347	-1.350	-1.346	-1.051	-0.962	-0.921	-1.154	-1.138	-1.098	-1.178	-1.170	-1.163
SPF-M-0Q	-0.007	0.000	-0.002	0.023	0.021	0.009	0.031	0.030	0.026	0.032	0.032	0.031
SPF-M-1Q	0.043	0.043	0.040	0.029	0.044	0.026	0.032	0.046	0.032	0.032	0.036	0.032
SPF-M-2Q	0.050	0.059	0.060	0.029	0.045	0.031	0.030	0.048	0.032	0.028	0.034	0.027
SPF-M-3Q	0.062	0.063	0.055	0.027	0.043	0.033	0.027	0.047	0.032	0.024	0.034	0.028
SPF-M-4Q	0.062	0.065	0.062	0.027	0.041	0.032	0.025	0.048	0.031	0.023	0.031	0.027
SV	-0.040	-0.056	-0.048	0.061	0.074	0.085	0.057	0.054	0.061	0.051	0.052	0.054
SV-SPF-M-0Q	-0.028	-0.021	-0.022	0.088	0.098	0.098	0.091	0.090	0.092	0.087	0.088	0.088
SV-SPF-M-1Q	-0.006	0.009	-0.002	0.089	0.124	0.114	0.090	0.104	0.098	0.084	0.090	0.087
SV-SPF-M-2Q	-0.006	0.014	0.002	0.086	0.122	0.121	0.085	0.105	0.097	0.078	0.086	0.083
SV-SPF-M-3Q	0.027	0.053	0.058	0.086	0.120	0.122	0.085	0.105	0.095	0.075	0.085	0.080
SV-SPF-M-4Q	0.049	0.040	0.063	0.085	0.117	0.122	0.081	0.104	0.095	0.076	0.085	0.081
SV-SPF-V-0Q	0.031	0.032	0.041	0.086	0.109	0.118	0.074	0.077	0.086	0.068	0.072	0.075
SV-SPF-V-1Q	0.052	0.046	0.051	0.089	0.109	0.121	0.077	0.080	0.089	0.071	0.076	0.079
SV-SPF-V-2Q	0.040	0.037	0.026	0.091	0.113	0.123	0.080	0.083	0.091	0.073	0.079	0.080
SV-SPF-V-3Q	0.056	0.049	0.025	0.095	0.116	0.126	0.083	0.087	0.095	0.077	0.083	0.084
SV-SPF-V-4Q	0.060	0.059	0.055	0.097	0.118	0.128	0.086	0.089	0.097	0.079	0.084	0.086
SV-SPF-MV-0Q	0.041	0.030	0.025	0.106	0.128	0.126	0.101	0.103	0.107	0.097	0.102	0.103
SV-SPF-MV-1Q	0.090	0.101	0.100	0.111	0.152	0.143	0.105	0.122	0.116	0.095	0.105	0.103
SV-SPF-MV-2Q	0.107	0.089	0.098	0.111	0.150	0.149	0.102	0.125	0.117	0.092	0.107	0.103
SV-SPF-MV-3Q	0.107	0.082	0.108	0.112	0.148	0.152	0.105	0.128	0.119	0.094	0.106	0.104
SV-SPF-MV-4Q	0.126	0.123	0.106	0.114	0.149	0.155	0.105	0.129	0.120	0.095	0.108	0.103

Note: The marginal likelihoods are calculated for the first, second and third months of the current quarter for the period starting from the last quarter of 1968 until the first quarter of 2017. The predictive likelihoods are calculated three times per quarter for three consecutive quarters (from the first month of the current quarter, Q0-M1; to the third month of the two quarters ahead, Q2-M3) over the periods starting from the first quarter of 1977 until the first quarter of 2017 over a recursive window. SPF-M represents that we use only the first moment of the individual forecasts in SPF; SPF-V represents we use only the second moment and SPF-MV represents we use both, the mean and variance of individual forecasts. SV shows we incorporate the stochastic volatility structure in the measurement equation of real gdp growth. The last part of the labels represents how many quarters ahead used from SPF; 0Q shows only the current quarter nowcast is used from SPF as it increases up to 4 quarters ahead.

Table M.2: The marginal and predictive likelihoods: 17-variables model over different specifications

	Marginal Likelihoods			**Predictive Likelihoods**								
	Q0			**Q0**			**Q1**			**Q2**		
	M1	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
Baseline Model	-1.340	-1.322	-1.316	-1.034	-0.947	-0.906	-1.145	-1.141	-1.094	-1.178	-1.173	-1.161
SPF-M-0Q	0.025	-0.002	-0.011	0.022	0.016	0.004	0.025	0.027	0.020	0.024	0.027	0.026
SPF-M-1Q	0.053	0.046	0.037	0.029	0.032	0.017	0.027	0.040	0.026	0.024	0.028	0.027
SPF-M-2Q	0.068	0.050	0.054	0.031	0.032	0.017	0.023	0.041	0.025	0.019	0.027	0.021
SPF-M-3Q	0.071	0.055	0.045	0.032	0.025	0.014	0.022	0.038	0.026	0.009	0.022	0.020
SPF-M-4Q	0.069	0.052	0.048	0.031	0.016	0.011	0.022	0.042	0.031	0.010	0.023	0.017
SV	0.000	-0.071	-0.019	0.074	0.085	0.101	0.062	0.066	0.066	0.057	0.057	0.058
SV-SPF-M-0Q	0.017	-0.043	-0.032	0.094	0.096	0.104	0.087	0.087	0.091	0.086	0.085	0.089
SV-SPF-M-1Q	0.054	0.042	0.044	0.085	0.100	0.097	0.076	0.086	0.077	0.070	0.071	0.072
SV-SPF-M-2Q	0.099	0.056	0.043	0.085	0.096	0.091	0.074	0.086	0.075	0.065	0.070	0.063
SV-SPF-M-3Q	0.088	0.067	0.050	0.083	0.090	0.089	0.069	0.091	0.075	0.057	0.064	0.061
SV-SPF-M-4Q	0.085	0.074	0.067	0.101	0.104	0.115	0.079	0.105	0.097	0.065	0.077	0.076
SV-SPF-V-0Q	0.074	0.066	0.067	0.094	0.116	0.124	0.075	0.078	0.083	0.069	0.068	0.070
SV-SPF-V-1Q	0.068	0.074	0.064	0.095	0.114	0.125	0.076	0.078	0.086	0.068	0.072	0.077
SV-SPF-V-2Q	0.068	0.063	0.064	0.099	0.119	0.128	0.078	0.084	0.090	0.071	0.077	0.077
SV-SPF-V-3Q	0.069	0.053	0.052	0.101	0.117	0.129	0.080	0.087	0.092	0.076	0.079	0.080
SV-SPF-V-4Q	0.085	0.081	0.036	0.102	0.122	0.132	0.082	0.090	0.094	0.077	0.082	0.086
SV-SPF-MV-0Q	0.071	0.058	0.069	0.112	0.126	0.126	0.100	0.102	0.101	0.092	0.097	0.095
SV-SPF-MV-1Q	0.120	0.100	0.095	0.115	0.140	0.140	0.100	0.113	0.107	0.089	0.097	0.093
SV-SPF-MV-2Q	0.110	0.112	0.109	0.116	0.137	0.139	0.096	0.113	0.108	0.081	0.094	0.093
SV-SPF-MV-3Q	0.128	0.119	0.104	0.120	0.131	0.136	0.099	0.117	0.112	0.075	0.091	0.095
SV-SPF-MV-4Q	0.142	0.109	0.098	0.120	0.130	0.139	0.104	0.115	0.113	0.081	0.095	0.100

Note: The marginal likelihoods are calculated for the first, second and third months of the current quarter for the period starting from the last quarter of 1968 until the first quarter of 2017. The predictive likelihoods are calculated three times per quarter for three consecutive quarters (from the first month of the current quarter, Q0-M1; to the third month of the two quarters ahead, Q2-M3) over the periods starting from the first quarter of 1977 until the first quarter of 2017 over a recursive window. SPF-M represents that we use only the first moment of the individual forecasts in SPF; SPF-V represents we use only the second moment and SPF-MV represents we use both, the mean and variance of individual forecasts. SV shows we incorporate the stochastic volatility structure in the measurement equation of real gdp growth. The last part of the labels represents how many quarters ahead used from SPF; 0Q shows only the current quarter nowcast is used from SPF as it increases up to 4 quarters ahead.

Appendix N

NOWCAST RESULTS FOR SMALL-SCALE MODEL

Figure N.1: The mean of nowcast of GDP growth with **5 variables** for each month between 1977:Q1-2017:Q1

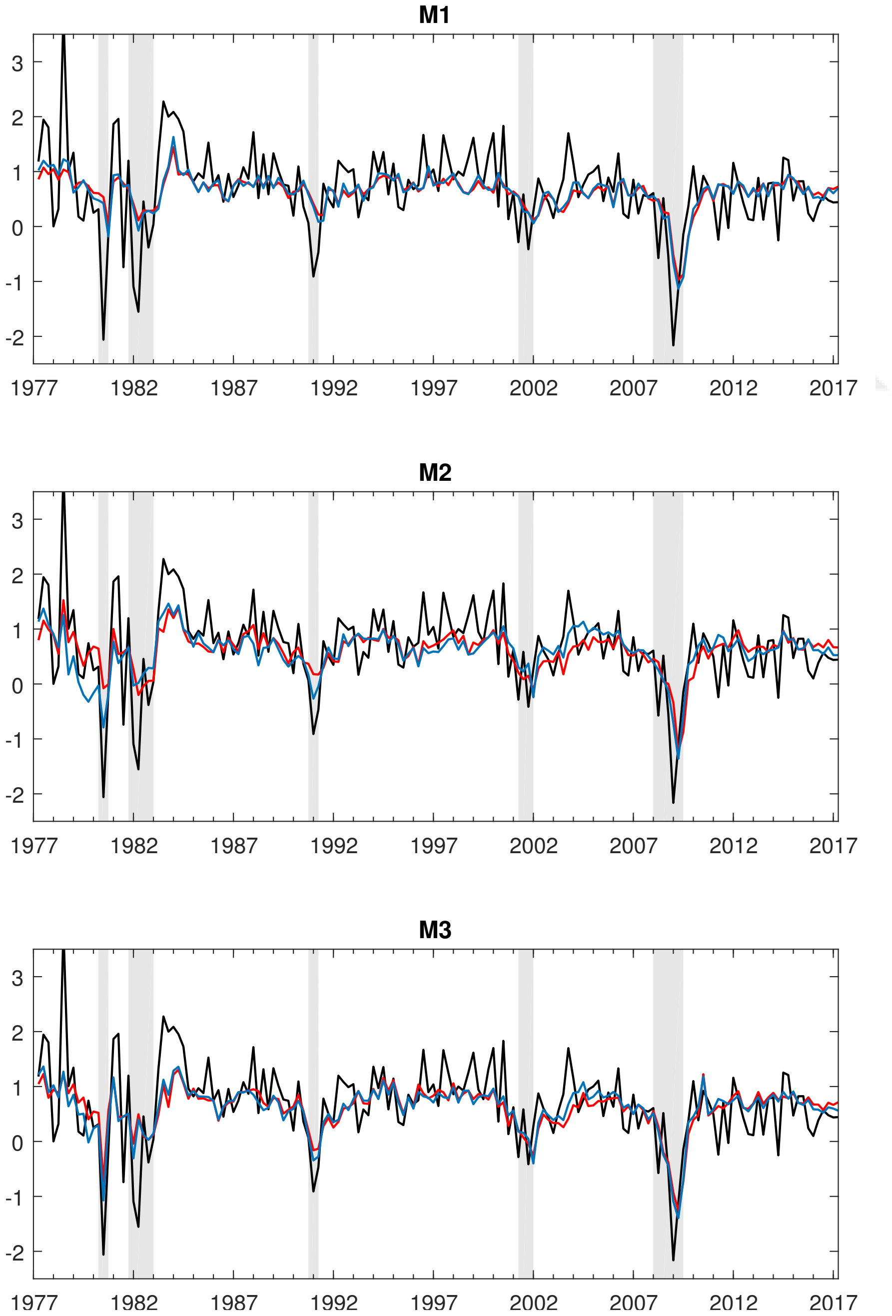
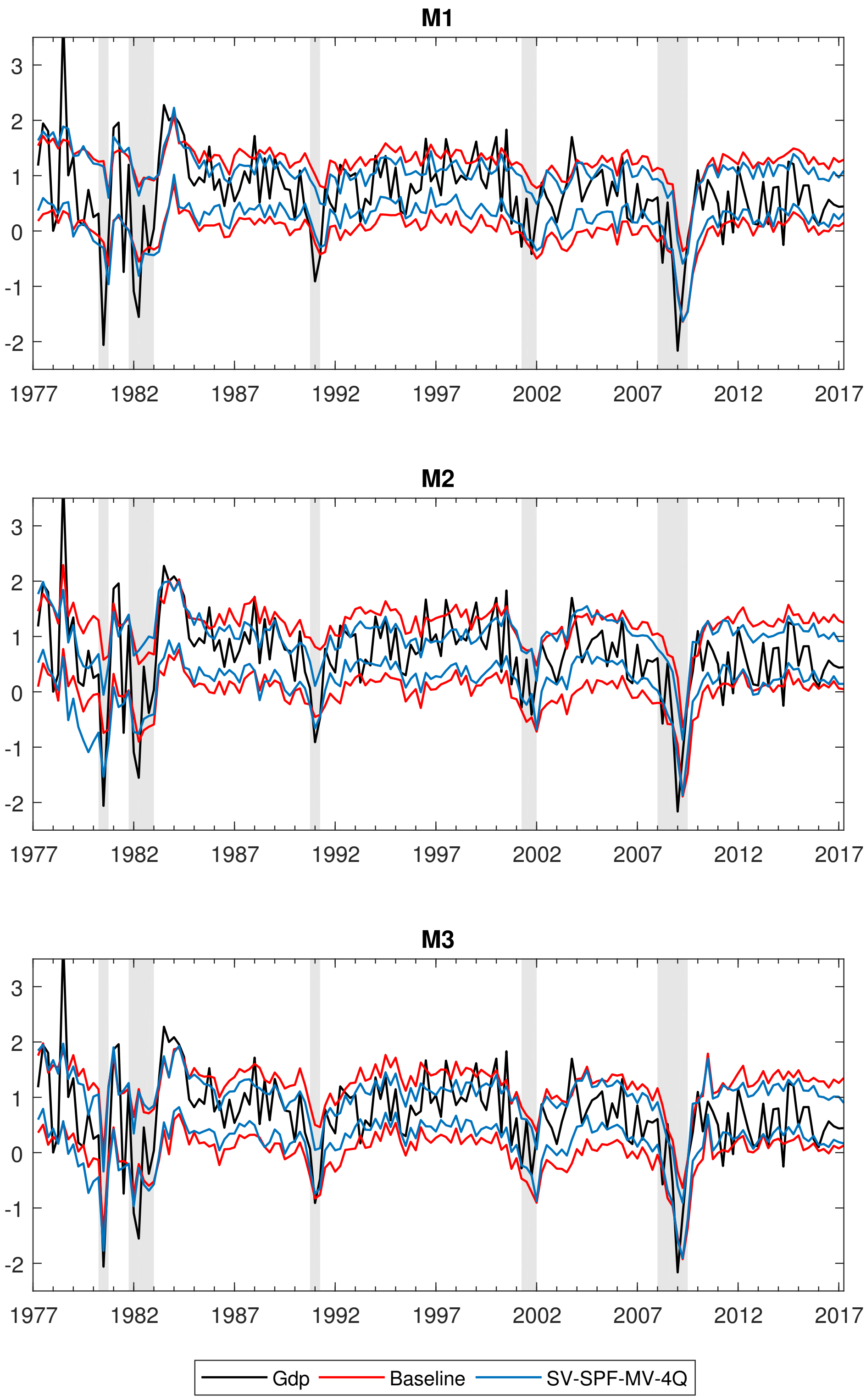


Figure N.2: 70% Interval Forecast of GDP growth with **5 variables** for each month between 1977:Q1-2017:Q1



Appendix O

QUANTILES OF DENSITY NOWCAST

Figure O.1: Large scale **Baseline Model**-30%, 50%, 70%, and 90% probability bands for nowcast of GDP growth between 1977:M3-2017:M3

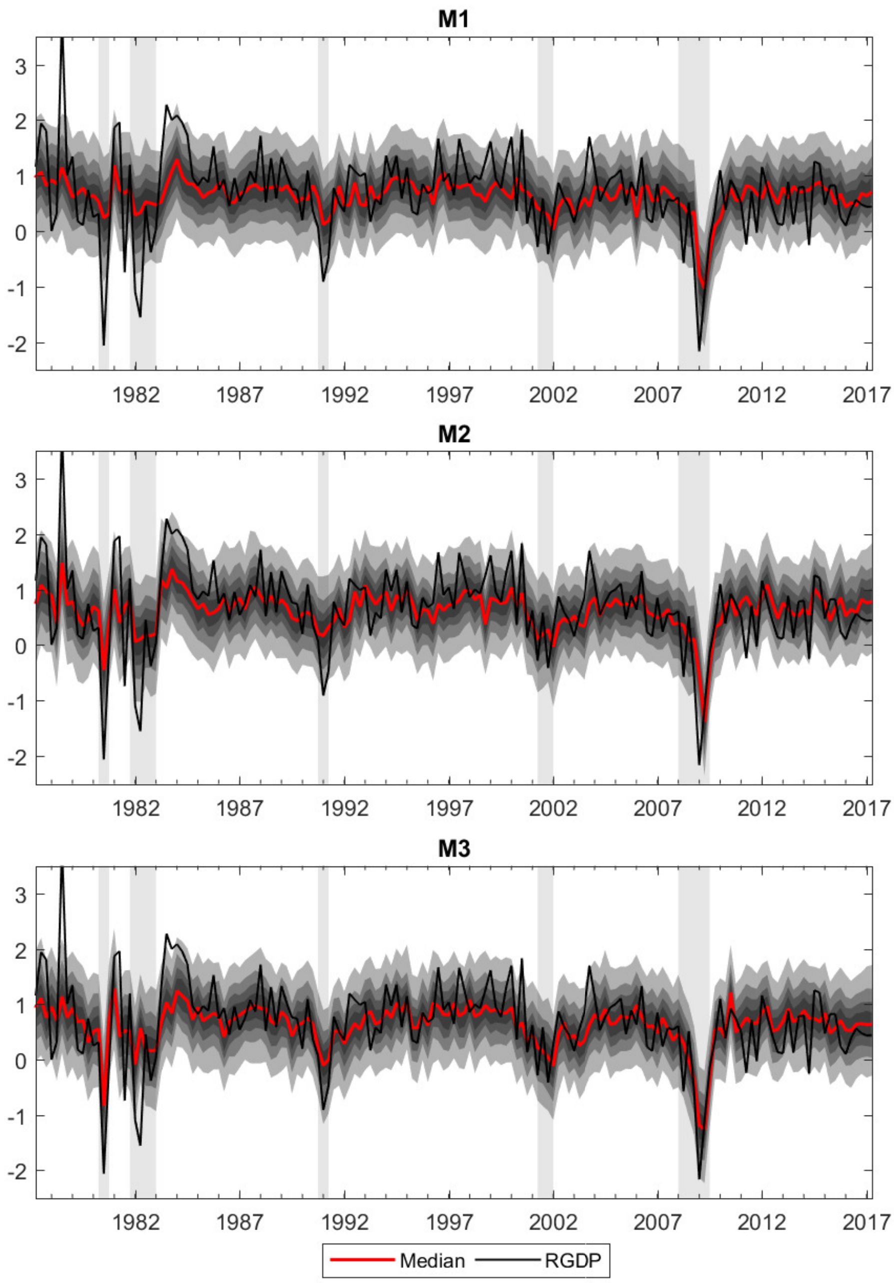


Figure O.2: Large scale **SV-SPF-MV-4Q Model**-30%, 50%, 70%, and 90% probability bands for nowcast of GDP growth between 1977:M3-2017:M3

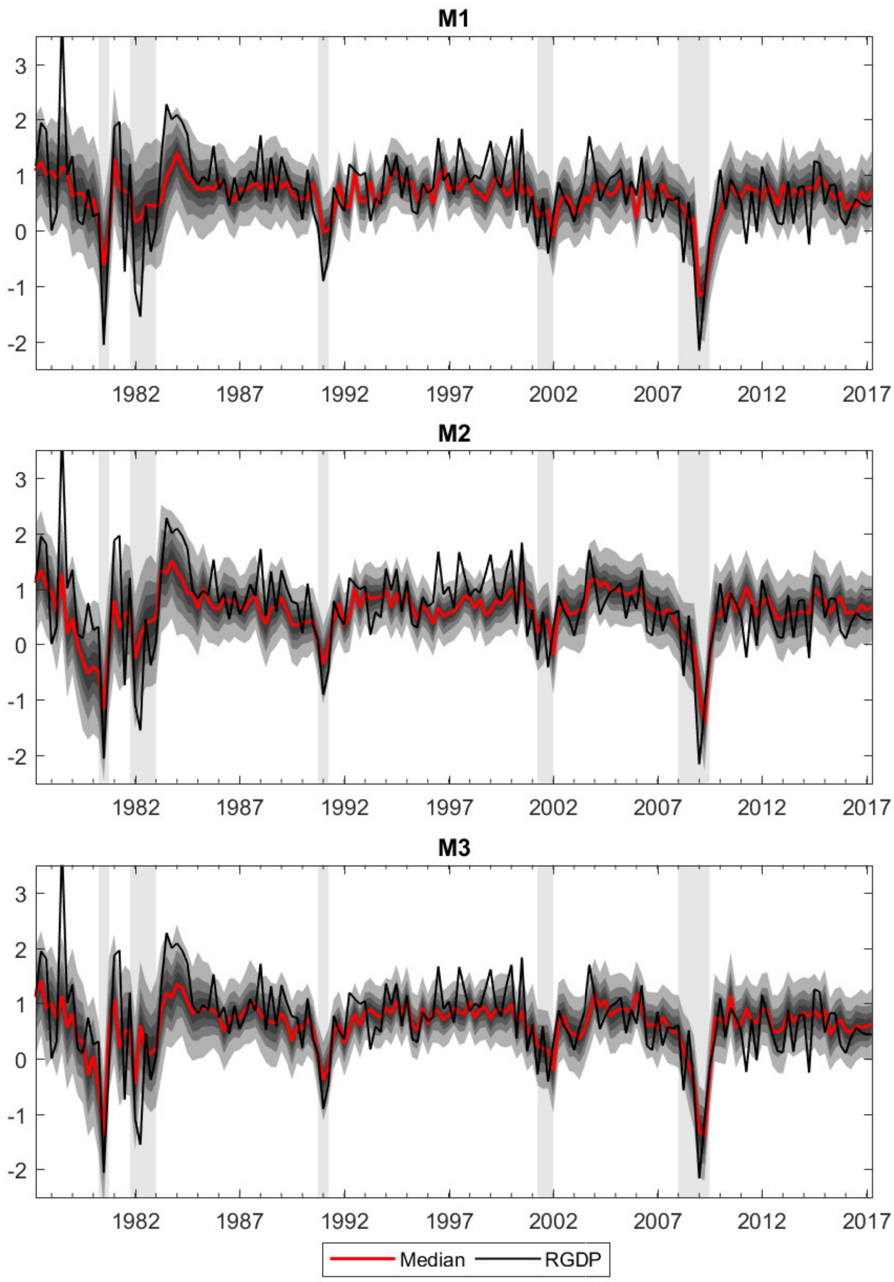
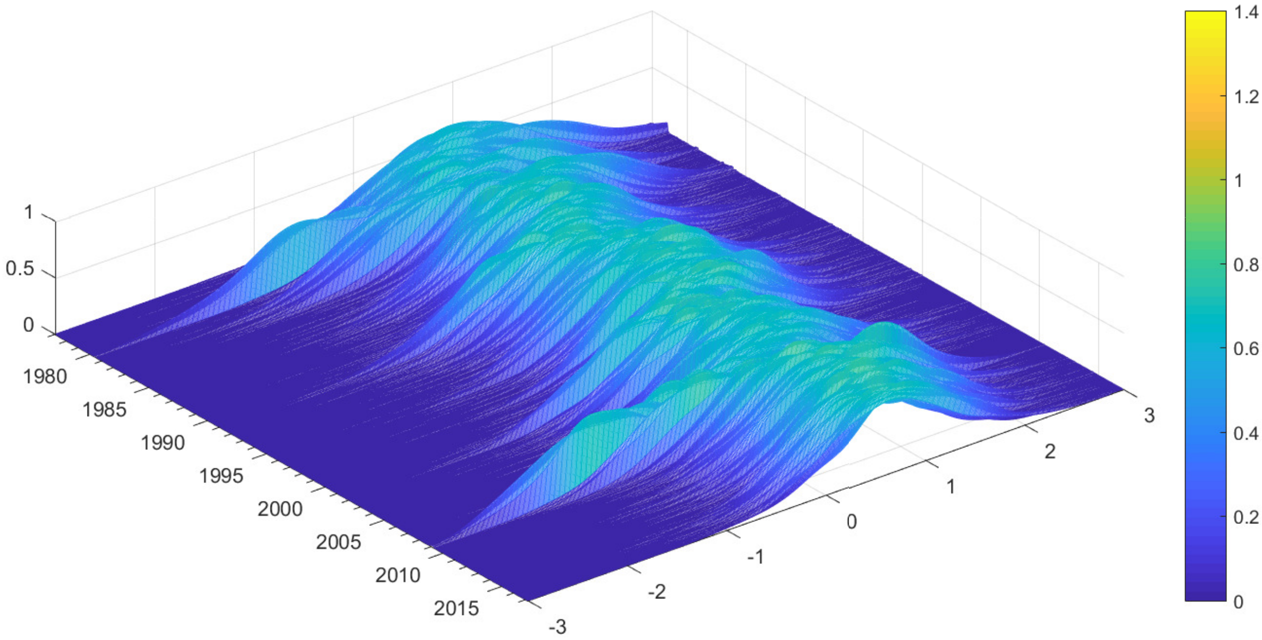
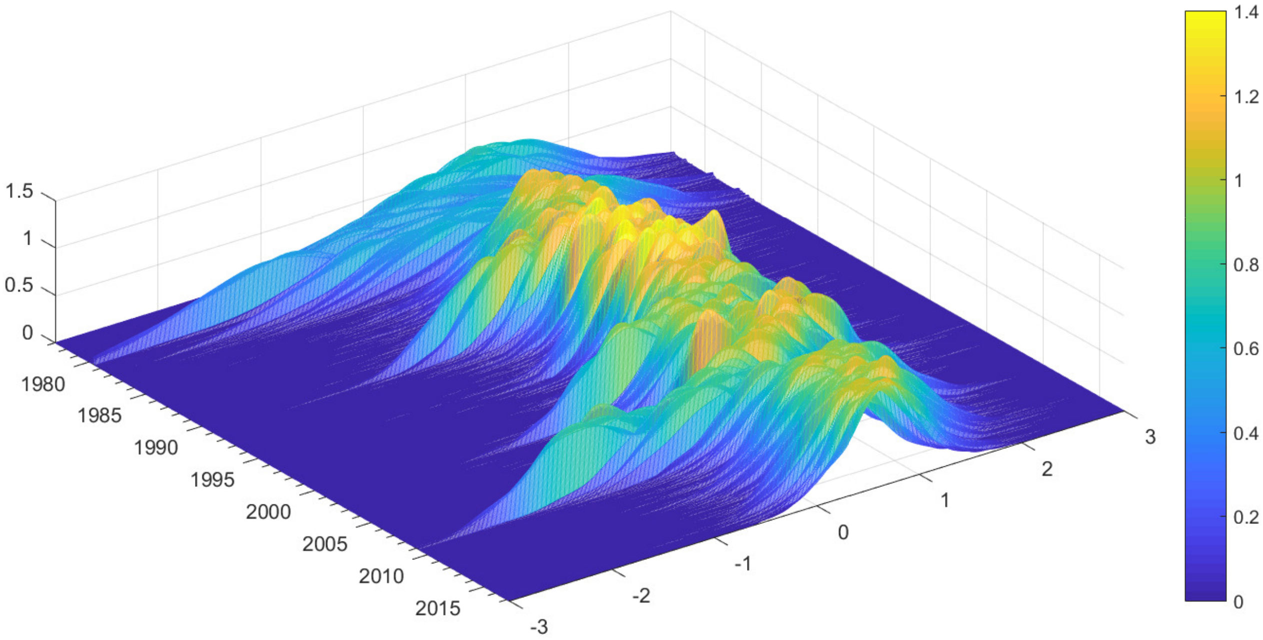


Figure O.3: Large Scale **Baseline Model**-Density Nowcast of GDP growth between 1977:M3-2017:M3



Note: The graph displays the distribution approximation for the nowcast of GDP growth rate using **Baseline Model** with **17 variables** through the periods starting from the first quarter of 1977 until the first quarter of 2017 over a recursive window. All data vintages used for nowcasting start from the last quarter of 1968. The graph includes nowcasts for each month, **M1, M2** and **M3**. For each month in a given year, we use the available data at the indicated date, based on the publication delays given in Table 3.1. The colour bar shows the density of the indicated values.

Figure O.4: Large scale **SV-SPF-MV-4Q Model**-Density Nowcast of GDP growth between 1977:M3-2017:M3



Note: The graph displays the distribution approximation for the nowcast of GDP growth rate using **SV-SPF-MV-4Q Model** with **17 variables** through the periods starting from the first quarter of 1977 until the first quarter of 2017 over a recursive window. All data vintages used for nowcasting start from the last quarter of 1968. The graph includes nowcasts for each month, **M1, M2** and **M3**. For each month in a given year, we use the available data at the indicated date, based on the publication delays given in Table 3.1. The colour bar shows the density of the indicated values.

Appendix P

BAYES FACTORS

Figure P.1: Bayes factors with respect to Baseline Model **5 variables** over time for different specifications

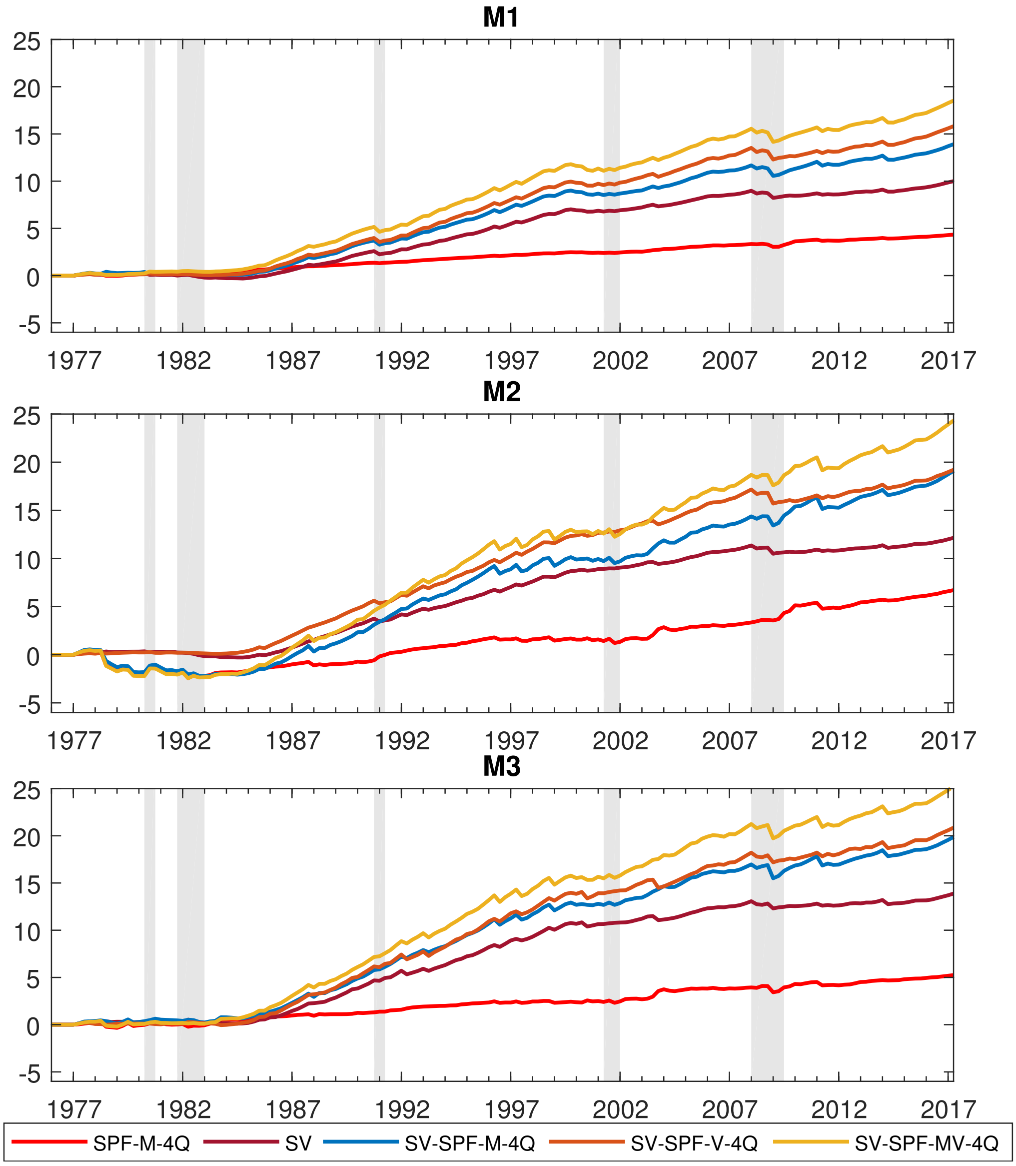
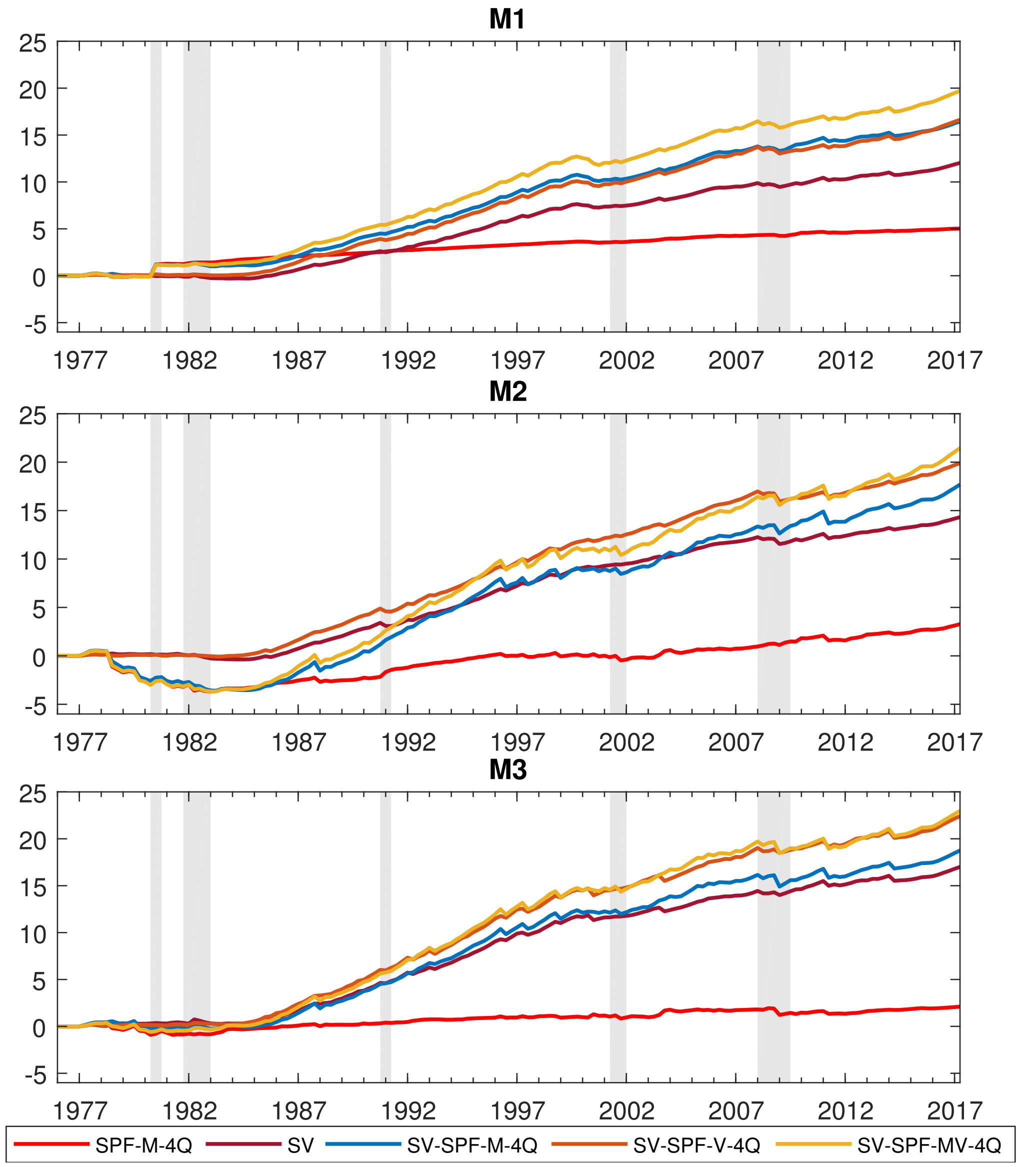


Figure P.2: Bayes factors with respect to Baseline Model **17 variables** over time for different specifications



Appendix Q

PIT FOR NOWCAST (DIFFERENT ILLUSTRATION)

Figure Q.1: PITs with **5 variables** for nowcast of GDP

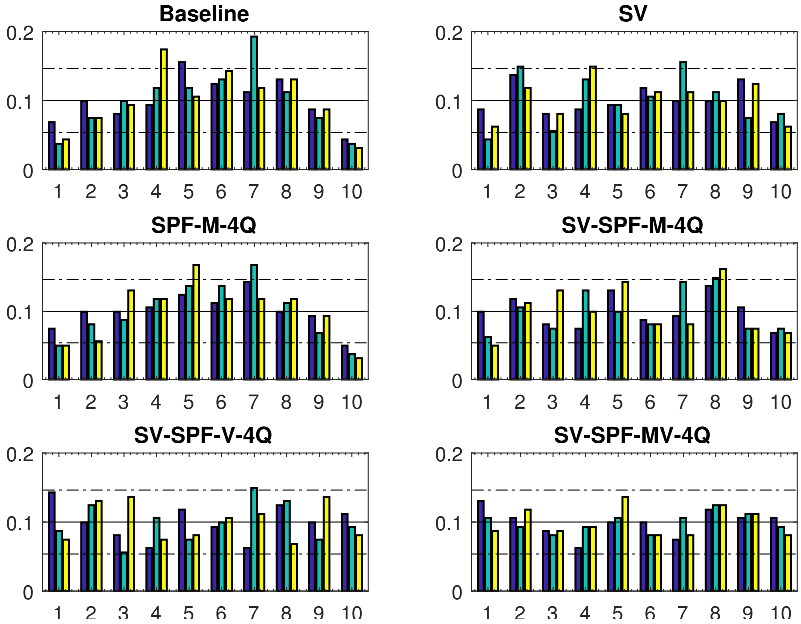
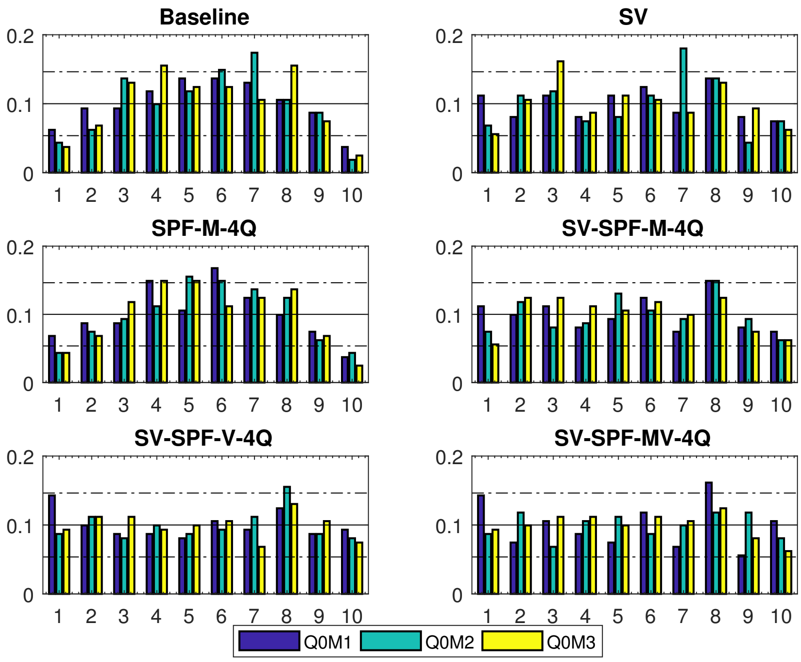


Figure Q.2: PITs with **17 variables** for nowcast of GDP



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