Modeling of Economic and Financial Conditions for Nowcasting and Forecasting Recessions: A Unified Approach

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Abstract

In this paper, we propose a method for jointly estimating indexes of economic and financial conditions by exploiting the intertemporal link between their cyclical behavior. This method combines a dynamic factor model for the joint modeling of economic and financial variables with mixed frequencies together with a tailored Markov regime switching specification for capturing their cyclical behavior. It allows for imperfect synchronization between the cycles in economic and financial conditions/factors by explicitly estimating the phase shifts between their cyclical regimes. We examine the efficacy of the model for predicting cyclical activity in a key emerging economy, namely, Turkey, by making use of a mixed frequency ragged-edge data set. A comparison of our framework with more conventional cases imposing common cyclical dynamics as well as independent cyclical dynamics for the economic and financial indicators reveals that the proposed specification provides precise estimates of indexes of economic and financial activity together with accurate and timely recession probabilities. Recession probabilities estimated using the available data in the first week of November 2018 indicate that Turkey entered a recession that is still ongoing starting from August 2018. We further conduct a recursive real-time exercise of nowcasting and forecasting business cycle turning points. The results show evidence for the superior predictive power of our specification by signaling oncoming recessions (expansions) as early as 3.6 (3.3) months ahead of the actual realization.

Keywords: *Financial conditions index; Coincident economic index; Dynamic factor model; Markov switching; Imperfect synchronization; Bayesian inference*
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1 Introduction

Monitoring economic and financial activity and anticipating economic downturns in a timely manner is of key importance for economic agents. To this end, various econometric methods have been proposed to create measures of economic and financial conditions using large sets of variables. These typically involve modeling the co-movement in the behavior of a large number of economic and financial variables to generate indicators that are conformable with the notion of common cycles in economic and financial activity.

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. However, economic and financial indicators are often measured in isolation of each other. Typically, the link between the two measures are established by pre-selecting financial variables according to their predictive capability of macroeconomic aggregates, i.e. GDP or industrial production, see for example Hatzius *et al.* (2010). Such sequential procedures can cause inefficiencies for several reasons. On the one hand, the intertemporal link between single variables does not necessarily reflect the joint cyclical behavior of economic and financial conditions in a broader sense. On the other hand, independent estimation of economic and financial conditions does not fully exploit all available information in economic and financial variables for measuring and now/forecasting the business cycle turning points.

In this paper, we propose a method for joint estimation of economic and financial conditions by exploiting the intertemporal link between their cyclical behavior explicitly. This method combines a dynamic factor model for the joint modeling of economic and financial variables with mixed frequencies together with a tailored Markov regime switching dynamics in model parameters for capturing the cyclical behavior embedded in economic and financial conditions. The specification for regime dynamics that we employ allows for imperfect synchronization between the cycles embodied in economic and financial indicators/factors by explicitly estimating the phase shifts between the cyclical regimes. This implies that we allow for the financial cycle to lead/lag the business cycle in a systematic way when estimating the indicators. 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 estimation of economic and financial conditions, even more importantly, for nowcasting and forecasting economic downturns accurately in real time.

We examine the efficacy of this approach in a key emerging economy, Turkey. Using our framework, we construct indicators of economic and financial conditions together with probabilities of recessions for Turkey.[1] We use a mixed frequency dataset with different time spans (for the earliest case) starting from January 1999 (for the most timely case) until October 2018, i.e. the data that are available to us as of the first week of November 2018. Our results reveal the imperfect synchronization between the cycles embedded in the indicators of economic and financial conditions. Specifically, we show that financial indicator enter recessions (expansions), on average, 3.6 (3.3) months earlier than the recession (expansion) for the economic indicator. A recursive now/forecasting exercise in real time indicate 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 in financial conditions captured by the financial indicator are not necessarily labeled as recessions, thereby eliminating false signals of recessions. Finally, our results indicate that Turkey entered an economic recession in August 2018 that is still ongoing, a finding not picked up by the model with independent cycles.

The comovement in the behavior of a large number of economic series was noted by Burns and Mitchell (1946) in their quest to define a 'business cycle'. 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

[1]While there is a lack of widely accepted indicators of economic and financial conditions for Turkey, 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). Our model clearly differs from those as we provide a unified framework for joint estimation of coincident and financial indicators together with their potentially imperfectly synchronized cyclical regimes due to phase shifts of the business cycle.

(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 involving variables with mixed frequencies and potentially mixed time span based on the unobserved components modeling framework that can handle missing values in a statistically optimal way. Mariano and Murasawa (2003) and Aruoba *et al.* (2009), among others, for example develop monthly and weekly coincident indicators for the US using such datasets. A similar approach is followed by Banbura *et al.* (2013) for 'nowcasting' key macroeconomic aggregates using multiple factors; see Bok *et al.* (2018) for a recent review on this.

While papers focusing on modeling and now/forecasting economic conditions are abundant, the research on financial conditions remains relatively limited prior to the Great Recession of 2008.[2] However, the global financial crisis of 2008 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 (2014), 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 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]

A number of papers consider estimating the capability of leading indicators in predicting recessions mostly in the context of US. Using quarterly US GDP and the leading indicator provided by the Conference Board, Hamilton and Perez-Quiros (1996) provide a framework

[2]For an exception, see Kaminsky and Reinhart (1999).

[3]See also Hatzius *et al.* (2010), who provide an extensive review and a comparison of alternative indexes, typically published by financial industry and central banks, that are available for the US and the EU. In their study, they construct an FCI for US that includes a large array of risk measures and conventional financial variables such as interest rates and asset prices, and show that their measure of financial conditions is tightly related to future economic conditions. Other examples include Wacker *et al.* (2012) who construct several indexes of financial conditions for major non-Euro Area economies, including the US, the UK, Japan, China, Brazil, Russia, India, and Turkey.

in a Markov regime Switching Vector AutoRegression (MS-VAR) context to model the lead/lag relation between the regimes of the corresponding variables, where they allow the turning points of the leading indicator to lead the turning points for US GDP. Their findings suggest that the leading indicator systematically leads the business cycle peaks and troughs by one quarter. Paap *et al.* (2009) extend this model by allowing for distinct lead times for peaks and troughs using the monthly data and conclude that this lead time escalates to almost 12 months for business cycle peaks. Finally, Çakmaklı *et al.* (2013) provide a general framework allowing for distinct phase shifts in the timing of multiple regimes. They conclude that the 12-month lead time shrinks considerably to 6 months in predicting more severe recessions such as the recent global crisis of 2008-9. The common feature of all of these approaches is that they model the intertemporal link characterizing the cyclical behavior of 'observed' indicators computed in isolation of each other.

The approach used in this paper combines various modeling approaches in a unified framework. First, following Aruoba *et al.* (2009) and Banbura *et al.* (2013), we employ a dynamic factor model framework using a real-time ragged-edge dataset comprised of variables with mixed frequencies. Second, departing from these studies, we incorporate Markov regime dynamics into the dynamic factor model structure. Barnett *et al.* (2016) propose a related approach that allows for structural breaks of selected model parameters using a restricted Markov dynamics in the spirit of change point models. In our framework, we employ an unrestricted Markov dynamics to capture distinct phases of the business cycle rather than structural breaks. Furthermore, we model structural breaks in selected parameters using a different modeling approach. Third, we allow for potential phase shifts of the business cycle for modeling the financial cycle by explicitly estimating the temporal link between the cyclical dynamics of the coincident and financial indicators/factors using the approach of Çakmaklı *et al.* (2013). We use simulation-based Bayesian inference for joint estimation of all of these features in a unified framework.

The remainder of this paper is as follows. Section 2 presents the model and data. Section 3 describes the estimation approach. Section 4 presents the empirical results and discusses real-time estimation and forecasting. Finally, Section 5 concludes.

2 The Model

In this section, we present the dynamic factor model for the extraction of the coincident economic index (CEI) and financial conditions index (FCI) from a broad set of variables with mixed frequencies. The cyclical phases of the indicators, i.e. recessions and expansions, are captured by a single Markov process. One of the key features of our analysis is that we exploit the intertemporal link between the cyclical regimes of the CEI and FCI by estimating the phase shifts in the single common cycle for the economic and financial indexes.

Let $y_{i,t}$ denote the first difference or the growth rate of the i^{th} variable in period t for $i = 1, \ldots, N$ and $t = 1, \ldots, T$. We assume that the growth rate of variables 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

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

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

$$\psi_i(L)\varepsilon_{it} = \epsilon_{i,t}. \tag{2}$$

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), which we discuss briefly only for the case of quarterly data being used for the estimation of monthly factors, and refer to Banbura *et al.* (2013) for further details. Consider the transformation of variables measured at the quarterly frequency, denoted by $X^Q_{i,t}$ and by $y^Q_{i,t}$ as its first difference, to the monthly frequency.

For stock variables, this would imply missing observations for all periods excluding the corresponding period of the observation. For flow variables, however, temporal aggregation should be taken into account. Specifically, for the differenced variables, the transformation to the higher frequency is implemented as follows

$$
\begin{aligned}
y^Q_{i,t} &= X^Q_{i,t} - X^Q_{i,t-3} = \sum_{k=0}^{2} X_{i,t-k} - \sum_{k=0}^{2} X_{i,t-k-3} \\
&= y_{i,t} + 2y_{i,t-1} + 3y_{i,t-2} + 2y_{i,t-3} + y_{i,t-4}.
\end{aligned}
\tag{3}
$$

For the log-differenced variables, we use the approximation in (Mariano and Murasawa, 2003) in line with Banbura *et al.* (2013), which allows us to use (3) also for those variables.

So far, the model is similar to the methodologies employed for the developed countries as in Aruoba *et al.* (2009) and Banbura *et al.* (2013). Departing from these studies we add two modifications to the general framework to capture the characteristics that are 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 severe 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

$$
\sigma^2_{i,t} = \sigma^2_{i,1}\, \mathbb{I}\left[t \leq \tau\right] + \sigma^2_{i,2}\, \mathbb{I}\left[t > \tau\right], \tag{4}
$$

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.

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:

$$
\epsilon_{i,t} = \xi_t^{-1/2} \sigma_{i,t} \zeta_t, \tag{5}
$$

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 $\epsilon_{i,t}|\xi_t \sim N(0, \sigma^2_{i,t}/\xi_t)$.[4]

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

[4] See Geweke (1993), Geweke (2005) for textbook expositions and Curdia *et al.* (2014) for an application in the context of a structural macroeconomic model.

cyclical regime of the corresponding factor. Specifically, in case of first-order autoregressive dynamics for the factors, our assumptions imply the model specification

$$f_t = \alpha_{\mathbb{S}_t} + \delta + \Phi f_{t-1} + \eta_t \quad \eta_t \sim N(0, \Sigma), \tag{6}$$

where

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

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

$$\begin{aligned} Pr(S_{l,t} = 0 \mid S_{l,t-1} = 0) \quad &= q_l \\ Pr(S_{l,t} = 1 \mid S_{l,t-1} = 1) \quad &= p_l \quad \text{for } l = 1, 2. \end{aligned} \tag{7}$$

In line with the regime specifications as expansion and recession, we restrict $\alpha_0 > \alpha_1$, an assumption which we discuss further when we specify the prior distributions. 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. Note that (6) already indicates a linear association between the factors by means of cross-autoregressive coefficients. In addition, we seek to uncover the nonlinear association between these factors by specifying the link between their cyclical regimes.

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. Note that this specification does not rule out the synchronization of the cycles completely, as the two cycles are in the same regime with probability

$$\Pr(S_{2,t} = S_{1,t}) = p_1 p_2 + q_1 q_2 > 0. \tag{8}$$

Second, we assume that the cycles in both indicators are identical, that is,

$$S_{2,t} = S_{1,t}, \tag{9}$$

or, put differently, there is a single cycle governing both indexes. 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.

$$S_{2,t-\kappa_{S_{1,t}}} = S_{1,t}. \tag{10}$$

To specify the cycle in the FCI, we assume that the regime indicator $S_{1,t}$ itself is shifted but allow the amount of phase shift to be different 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 (10) 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, (10) 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 the loadings are unobserved as in (1). First, to better identify the factors of the economic and the financial conditions, the coefficientss 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. Second, as neither the constant terms in the measurement equation for the idiosyncratic factors, $\gamma_{i,1}$ for $i = 1, \ldots, N$, nor δ are not uniquely identified, we standardize the dataset and we restrict the unconditional variance of the factors to be one 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[5]. We then recover the long-run growth rate factors, δ, that is required for constructing the levels of CEI and FCI using the methodology proposed by

[5]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 to identity, where N (k) is the number of variables (factors), to set the factor orientation according to the order of the variables. Such a strategy is prone 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 alternative identification schemes.

Stock and Watson (1989) and also used in Kim and Nelson (1998) by reverse engineering the long-run growth rate of the factors from the average growth rates of the observed variables.

Combining (1),(2) and (6) together with (4)-(10) and imposing the identification specifications we can summarize the final model as

$$\begin{aligned} y_{i,t} &= \lambda_i f_t + \varepsilon_{i,t} \\ \psi(L)\varepsilon_{i,t} &= \epsilon_{i,t} \quad \epsilon_{i,t} \sim t(0, \nu, \sigma^2_{i,t}) \\ \sigma^2_{i,t} &= \sigma^2_{i,1}\, \mathbb{I}\left[t \leq \tau\right] + \sigma^2_{i,2}\, \mathbb{I}\left[t > \tau\right] \text{ for } i = 1, \ldots, N \\ f_t &= \alpha_{\mathbb{S}_t} + \Phi f_{t-1} + \eta_t \quad \eta_t \sim N(0, \Sigma) \\ S_{2,t-\kappa_{S_{1,t}}} &= S_{1,t}. \end{aligned} \tag{11}$$

2.1 Data

We use a comprehensive set of variables for the estimation of the CEI and FCI to estimate the model in (11). However, as we describe in detail below, our dataset suffers from the problem of missing observations. This stems from the use of data (1) with mixed frequency, leading to periodically missing observations; (2) with mixed time span, leading to successive periods with missing observations; and (3), exhibiting lags in their releases, leading to missing observations at the end of the dataset referred to as ragged-edge. 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 October 2018, i.e. the data that are available to us as of the first week of November 2018.

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 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. Still, our robustness checks suggest that the model estimates with the GDP series are very similar to those without the GDP, which will be discussed in the next section. 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, 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 measures 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.

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). Predictive ability is often measured in terms of the success of predictive regressions with a quadratic loss function, i.e. the mean squared forecast error criterion.[6] In our analysis, first, we construct a dataset comprised of a large number of financial variables. A brief description of the economic and financial variables is provided in Section A of the supplementary material. We take the advantage of our unified modeling approach of constructing both indexes jointly, and conduct an analysis using several combinations of variables from each group. We, then, evaluate the variables based on their ability to predict recessions using our framework.

The final set of financial variables includes firstly, variables that represent stock market and (sovereign) bond market behavior. The stock market variables are given by the stock market index (BIST100) in real terms (*rbist*), price-earnings ratio of the portfolio (P/E) used for computing the BIST100, the MSCI emerging market index (*MSCIem*)[7], and realized volatility on the BIST100 (*VOL*) while the treasury auction rate (*TAuc*) is used to represent (sovereign) bond market behavior. The second set of variables is intended to

[6]An early application involves Estrella and Mishkin (1998), who examine the ability of individual series such as interest rate spreads for predicting US recessions based on econometric methods suited for the binary nature of NBER recession dates; see also Kauppi and Saikkonen (2008). Liu and Moench (2016) conduct a similar analysis using various financial variables.

[7]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.

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[8], 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[9] 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*). This last variable has been the focus of much discussion following the failure of traditional approaches to predict the recent global crisis; see, for example, Gadea and Perez-Quiros (2015), for example. We discuss its contribution to our analysis in subsequent sections.

3 Estimation

The model specified in (11) 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. Since we conduct a joint estimation strategy taking into account the uncertainty related to all of these components, classical inference is not feasible due to the discrete nature of the phase shift. Therefore, we adopt a Bayesian approach for estimation and inference 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. In Section 3.1 we derive the likelihood function of the model, while we discuss the specifications of the prior distributions in Section 3.2. In Section 3.3 we outline the resulting algorithm for simulating from the posterior distribution. Full details on the model specification and conditional posterior distributions are given in Sections B and C of the supplementary material for the sake of brevity.

[8] 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.

[9] 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.

3.1 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 (11) into state-space form as

$$\begin{aligned} \mathbf{y}_t &= \mathbf{H}\boldsymbol{\beta}_t + \boldsymbol{\varepsilon}_t & \boldsymbol{\varepsilon}_t|\xi_t \sim N(\mathbf{0}, \mathbf{R}_t) \\ \boldsymbol{\beta}_t &= \boldsymbol{\alpha}_{\mathbb{S}_t} + \mathbf{F}\boldsymbol{\beta}_{t-1} + \boldsymbol{\eta}_t & \boldsymbol{\eta}_t|\xi_t \sim N(\mathbf{0}, \boldsymbol{\Omega}_t), \end{aligned} \tag{12}$$

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 $\boldsymbol{\Omega}_t$ includes the variances (and covariances) of these factors. The time variation in $\mathbf{R}_t$ as well as $\boldsymbol{\Omega}_t$ 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

$$\begin{aligned} \boldsymbol{\beta}_{t|t-1} &= \boldsymbol{\alpha}_{\mathbb{S}_t} + \mathbf{F}\boldsymbol{\beta}_{t-1|t-1} \\ \mathbf{P}_{t|t-1} &= \mathbf{F}\mathbf{P}_{t-1|t-1}\mathbf{F}' + \boldsymbol{\Sigma} \\ \mathbf{v}_{t|t-1} &= \mathbf{y}_t - \mathbf{H}^*\boldsymbol{\beta}_{t|t-1} \\ \mathbf{V}_{t|t-1} &= \mathbf{H}^*\mathbf{P}_{t|t-1}\mathbf{H}^{*'}, \end{aligned} \tag{13}$$

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

$$f(\mathbf{y}^T, \mathbb{S}^T|\boldsymbol{\theta}) = \left(\prod_{i=1}^{2}\prod_{j=1}^{2} p_{ij}^{T_{ij}}\right)\prod_{t=1}^{T}\left(\frac{1}{\sqrt{2\pi}}\right)|\mathbf{V}_{t|t-1}|^{-\frac{1}{2}}\exp\left(-\frac{1}{2}\sum_{t=1}^{T}\mathbf{v}'_{t|t-1}\mathbf{V}^{-1}_{t|t-1}\mathbf{v}_{t|t-1}\right), \tag{14}$$

where T_{ij} is the number of transitions from regime i to regime j and $P = \{p_{ij}\}^2_{i,j=0,1}$ 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 (14) over all the possible states

$$f(\mathbf{y}^T|\boldsymbol{\theta}) = \sum_{S_{1,1}=0}^{1}\sum_{S_{2,1}=0}^{1}\cdots\sum_{S_{T,1}=0}^{1} f(\mathbf{y}^T, \mathbb{S}^T|\boldsymbol{\theta}). \tag{15}$$

3.2 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

$$f(\kappa) \propto \begin{cases} 1 & \text{for all } (\kappa_0, \kappa_1) \in \mathcal{C}, \\ 0 & \text{otherwise.} \end{cases} \tag{16}$$

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.[10] Note that setting $d = 0$ and $c = 0$ leads to the model with single common cycle.

[10] 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.

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

$$f(\alpha_l) = \begin{cases} 1 & \text{if } \alpha_l \in \{\alpha_l \in \mathbb{R}^2 \mid \alpha_{l,0} > \alpha_{l,1}\} \\ 0 & \text{elsewhere.} \end{cases} \tag{17}$$

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

$$f(\Phi) \propto 1 \quad \text{and} \quad f(\psi_i) \propto 1 \quad \text{for } i = 1, \ldots, N \tag{18}$$

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

For the factor loading parameters we also use flat priors

$$f(\lambda_i) \propto 1 \quad \text{for } i = 1, \ldots, N. \tag{19}$$

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

$$\begin{aligned} f(\sigma^2_{k,i}) &\propto \sigma^{-2}_{k,i} \quad \text{for } k = 1, 2 \text{ and } i = 1, \ldots, N \\ f(\Sigma) &\propto |\Sigma|^{-1}. \end{aligned} \tag{20}$$

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.

3.3 Posterior simulation scheme

The posterior distribution is proportional to the product of the likelihood in (15) together with the prior specifications described in (16)-(20). 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.

4 Empirical Findings

In this section, we report our empirical findings for the competing models for the construction of the coincident economic index (CEI) and the financial conditions index (FCI). We first conduct an analysis on the cross-autoregressive parameters of the (growth rates of the) CEI and 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 the best fit of the model to 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 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.

First, we compare the fit of the competing models with the data using the (logarithm of the) marginal likelihood metric computed for each of the models. These are reported at the bottom panel of Table 1.

[Insert Table 1 about here]

Marginal likelihood values indicate that both of the models with independent cycles and PS model 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 20 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. Allowing for phase shifts between cycles of the financial and economic activity improves the marginal likelihood value further by almost 20 points. This indicates that modeling the intertemporal link 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 the findings of this model.

4.1 The coincident economic index and the financial conditions index

This section describes the coincident economic and financial conditions indexes that are estimated using the model that allows for imperfectly synchronized cycles as in (11). As discussed in Section 2 this model is estimated using growth rates of variables. We, then, reverse engineer the levels of CEI and FCI as in Stock and Watson (1989).

Figure 1 displays these indexes together with the dates of recessions indicated by the gray shaded area computed using the BBQ algorithm[11].

[Insert Figure 1 about here]

This figure shows that the CEI is successful in tracking the business cycle and predicting accurately the economic downturns that occurred in 2000-1 and 2008-9. 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 mixing various policy tools. Finally, we observe a sizable downturn in the FCI in early 2018 accompanied by a downward swing in the CEI which seems to start in August 2018 following an increase in July 2018.

Table 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 3.27 and 3.55 months, respectively. In line with the improved marginal likelihood value of the IS model compared to other polar cases, these findings

[11] As Turkey lacks a business cycle dating committee as opposed to US (NBER dating committee) we use the dates estimated by the BBQ algorithm as reference recession dates. The BBQ algorithm is a nonparamatric procedure used for dating business cycle turning points based on the definition of a recession as two consecutive quarters decline in economic activity. The algorithm is proposed by Bry and Boschan (1971) and simplified by Harding and Pagan (2002). This approach uses the aggregate real GDP series or the monthly industrial production growth rate according to the choice of frequency. The resulting recession dates are identified as the period from October 2000 until June 2001 and from April 2008 until March 2009 in our sample.

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 (11) may serve as a leading indicator of the CEI. Even more importantly, it provides an early warning indicator for the oncoming recessions 3.55 months ahead. 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. Notice that the relatively more volatile markets in countries like Turkey may limit the ability of financial markets to forecast future events accurately relative to the developed countries.

The left panel of Figure 2 displays the posterior distribution for the phase shift parameters κ_0 and κ_1.

[Insert Figure 2 about here]

Figure 2 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 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 1 reports estimates of the parameters related to the growth rates of the CEI and FCI estimated using the three competing models. As it can be seen in the second panel, the estimates of intercepts in recessions differ substantially from those in expansions, indicating that the regimes are identified quite precisely. For the models with imperfect and perfect synchronization, the estimates of the intercepts in recessions vary between -0.531% (-0.686%) and -0.503% (-0.715%) and those in expansions between 0.079% (0.153%) and 0.075% (0.146%) for the CEI (FCI), respectively. However, for the model with independent dynamics for the cyclical components, estimates of the intercepts during recessions and expansions are somewhat different, with values of -0.780% (-0.632%) during recessions and of 0.027% (0.175) during expansions for the CEI (FCI), respectively. Taking together with the estimates of the autoregressive coefficients, which are displayed in the third panel, these estimates imply more severe downturns for the model with independent cycles than those for the other two models.

The fourth panel of Table 1 displays the estimates of the transition probabilities. The probability of remaining in recessions is less than the probability of remaining in expansions for all three models, reflecting the fact that expansions last longer than recessions. Based on the posterior estimates of the transition probabilities, 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. 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. This indicates the concordance of cyclical behavior of financial and economic conditions in that the length of the cycles are quite similar across the different specifications.

We now examine the behavior of the different model specifications based on their ability to determine turning points and to identify recessionary episodes. Figure 3 shows recessionary episodes for the Turkish economy based on the BBQ algorithm together with the smoothed recession probabilities implied by the models.

[Insert Figure 3 about here]

The first panel of Figure 3 displays the recession probabilities estimated using the specification with imperfect synchronization of the cycles. Consistent with Figure 1 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 both the 2000-1 and 2008-9 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 where smoothed probabilities of being in a recession for CEI exceed 0.5 match with the periods of recessions computed by the BBQ algorithm. This implies that the FCI not only measures the current financial conditions but also serves as an early warning indicator for the oncoming downturns of economic activity. An interesting pattern can be observed in the final periods of the sample in 2018. Our results indicate that the smoothed probabilities of being in recession exceed 0.5 in August 2018, indicating quite a recent and still-ongoing recession as of the first week of November 2018, i.e. based on using the dataset until October 2018, when these results are generated. The FCI, on the other hand, enters the recession in May 2018 reflecting the phase shift when entering recessions. Notice that, the BBQ algorithm still does not signal any recession for these periods.

When we consider the model with perfect synchronization, displayed in the second panel of Figure 3, 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 recession. For this recession, the periods when smoothed probabilities exceed 0.5 precede the periods of the actual realization. Even more pronounced, the model produces false signals of expansions towards the end of both 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 phase following recessions. This indicates that blending economic variables together with financial variables for estimation of indicators of economic activity and its cyclical turning points often yields false signals of this cyclical behavior. This implies that economic and financial variables have distinct characteristics in terms of their relation to the underlying business cycle. This is the focal point of our model for construction of the indicators of economic and financial conditions.

Finally, considering the model with independent cycles for the CEI and the FCI, displayed in the third panel of Figure 3, 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 recession 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. Finally, the recession signals in 2018 are much weaker than those for the PS and IS models. While there is an increase in recession probabilities at the onset of 2018, these probabilities remain below 0.5. 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 3.

A final remark is on the effect of exclusion of the GDP series in our model as discussed in earlier sections. To examine this further, we estimate the IS model together with the new GDP series. Figure 4 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.

[Insert Figure 4 about here]

As can be seen in Figure 4, 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.

Table 2 displays the parameter estimates related to the measurement equation in (11). These are the factor loadings, the variances and the autoregressive coefficients of the idiosyncratic factors. 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 are provided in Section D of the supplementary material.

[Insert Table 2 about here]

Loadings of the variables on the CEI and FCI are displayed in the left panel of the Table 2. 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% Highest Posterior Density Interval (HPDI), though for the purchasing manager index (*pmi*) and total non-agricultural employment (*empna*) the 95% HPDIs contain zero. While for the *pmi* this might be due to the lack of data as it starts only after 2011, for the *empna* this might be due to the persistently high levels of unemployment observed throughout the sample for Turkey.

Turning to the factor loadings for the FCI, we observe that variables that are related to various risk sources such as the volatility of the return on the stock market index BIST100 (*VOL*), the Treasury auction rate (*TAuc*) and the spread between the 3-month rate and the 3-month LIBOR Rate (*TETS*), have sizable negative loadings on the common factor. Moreover, the distributions related to these loadings have relatively small standard deviations, leading to quite precise estimates. These results seem intuitive in that greater volatility on local stock markets described by (*VOL*) or an increase in the spread variable, *TETS*, is likely to signal adverse developments in financial markets and the related distress in the real economy. An important finding refers to the loading of the credit-related variable banking sector credit loans (*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 value of the 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.

The middle panel of the Table 2 provides estimates of the conditional variances of economic and financial variables together with the timing of the structural break in these variances in the bottom line of the Table. The posterior mode for the breakpoint parameter τ

is estimated as September 2001. Figure 5 shows the posterior density of the break parameter for the IS model.

[Insert Figure 5 about here]

We observe that the bulk of the posterior mass is located around the years 2001-2 reflecting the precision in the break parameter estimate. For the variance parameters, we can track a general reduction in the shock variances of almost all variables following the break date of September 2001. This date corresponds to the ending of the severe financial crisis of 2000-1 in Turkey. Financial variables exhibit even larger declines in the estimated shock variances compared to economic variables, reflecting the financial turbulence and the large increases in the sovereign risk that Turkey endured during this period and the normalization that occurred in its aftermath.

Finally, we display the estimates of the autoregressive coefficients related to idiosyncratic factors in the right panel of the Table 2. In many of the cases, zero is outside 95% HPDI. These results show the importance of modeling the dynamics of the idiosyncratic factors for identification of the common factors.

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 a timely manner in real-time. To do this, we conduct a recursive prediction exercise for examining the ability of the models in predicting business cycle turning points over the evaluation period starting from December 2006 until October 2018. 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.[12] This implies that we simulate a forecaster who estimates the model in the first week of each month starting from

[12] Specifically, while many of macroeconomic variables including *ip*, *import*, *export*, $traserv^m$ and *retails* are released with a lag of 2 months, other variables including *empna* and $traserv^q$ are released with lags of 3 and 4 months, respectively. *pmi* is the only variable with a timely release at the end of the corresponding month. On the other hand, financial variables are released in a timely manner, except *FXRes*, *P-E*, *MSCIem*, *EMBI-Tr*, *TermS* and *TETS* are released with a lag of 2 months.

January 2007 until November 2018 to construct the predictions.

To compare the real-time 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. To do this, we use the posterior simulator to obtain a sample from the distribution of the model parameters $\{\theta^{(m)}\}_{m=1}^{M}$ 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 $\bar{S}_{1,t_0+h} = M^{-1} \sum_{m=1}^{M} S_{1,t_0+h}^{(m)}$. The TPFE is given by

$$\text{TPFE}(h) = \frac{1}{T_2 - h - T_1 + 2} \sum_{t=T_1}^{T_2+1-h} (BC_{t+h} - \bar{S}_{1,t+h})^2, \tag{21}$$

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 out-of-sample predictive accuracy of the models by using the robust version of the Diebold–Mariano test (HAC-DM) of Diebold and Mariano (1995). We employ pairwise comparisons of the competing models using TFPEs as loss functions to compute the DM test statistics which follows a standard normal distribution asymptotically.[13] Nevertheless, the finite sample approximations may be poor, as was noted by Harvey *et al.* (1997) (HLN), and we therefore use a HLN-corrected version of the HAC-DM test in our pairwise forecast comparison.

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.

[13] This test relies on the differential of the loss functions from the forecast errors of two competing models, and tests its significance. Note that the DM test can also be formulated as a regression of the loss differentials on a constant, and heteroskedasticity and autocorrelation robust (HAC) standard errors can be used. Under certain conditions involving the covariance stationarity of the loss differential, the test statistic follows a standard normal distribution asymptotically.

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 $h = -3, -2, -1, 0, 1, \dots, 8$ to evaluate the predictive ability of competing models for various horizons related to backcasting, nowcasting and forecasting. We evaluate these features in Table 3, which displays the TPFE differences of the competing models with respect to the IS model.

[Insert Table 3 about here]

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 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 horizon 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. This shows 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 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 3 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.

Figure 6 displays the performance of the models in predicting the economic downturns with a focus on the 2008-9 recession.

[Insert Figure 6 about here]

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.[14]

Figure 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 (*ex post*) dated as April 2008 by the BBQ algorithm. 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. A striking finding occurs for the signals delivered by the specification with perfect synchronization of cycles. For the January 2008 vintage, this model 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 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 3 where we display the differences in TPFEs. 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. 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

[14] 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, while, 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.

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.

Beginning with 2017 and 2018, there has been an increasing pressure on emerging economies as the monetary policy practiced by the FED has been shifted towards a more hawkish stance relative to the earlier post-Great Recession periods. Therefore, we repeat the analysis in the most recent periods starting from January 2017 until the end of the sample, i.e. October 2018. Figure 7 displays the performance of the models in predicting the economic downturns with a focus on the periods in 2017-8.

[Insert Figure 7 about here]

As can be seen from the left panel of Figure 7, in June 2018 the IS model starts to deliver signals of a potentially oncoming recession. Specifically, the recession probabilities generated in June 2018 exceed the probability level of 0.3 for August 2018. In subsequent periods, the recession probabilities seem to settle to values over 0.5 in August 2018. Note that the in-sample results displayed in the last row of the graph as well as in the first panel of Figure 3 also date the start of the recession as August 2018. Considering the signals produced by the model with perfect synchronization of cycles, the first signals of a recession appear in June 2018, as in the case of the IS model. In this case, these indicate the start of the recession by May 2018. In the subsequent periods, this model signals the business cycle peak as early as March 2018. Given the positive GDP growth of 0.6% in the second quarter of 2018 and negative growth rate of -1.1% in the third quarter of 2018, a recession seems quite likely to start in the third quarter of 2018. 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 right panel of Figure 7.

On top of the evaluation of the predictive performance of the parametric methods, we further conduct a real-time dating exercise of recessions using the nonparametric BBQ algorithm estimated based on GDP and IP series. The timing of the BBQ algorithm relies on the release dates of these variables. Indeed, the algorithm sets the starting (final) date of the recession as April 2008 (March 2009) only in September 2008 (September 2009) for the 2008-9 recession, considerably 'lagging' the business cycle. On the contrary, our IS model is able to signal the oncoming recession (expansion) as early as January 2008 (January 2009), essentially 'leading' the business cycle. For the recent period of 2018, the BBQ algorithm still fails to signal any recession. Given the negative growth rate of -1.1% in the third quarter of 2018 we expect the algorithm to produce this signal with the release of first quarter of 2019 GDP data in March 2019.

5 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. Not surprisingly, many central banks and policy makers construct such indexes of economic and financial conditions to anticipate developments regarding the future state of the economy. Interestingly, economic and financial conditions are often constructed independently of each other, thereby missing the important link between the cyclical components of these measures. This is a key deficiency of this approach, as it is widely accepted that many financial variables serve as important leading indicators of business cycle phases, i.e. of recessions and expansions.

This paper fills this gap by proposing a unified framework for joint estimation of the Coincident Economic Index (CEI) and Financial Conditions Index (FCI) by modeling the cyclical behavior of these indexes allowing for imperfect synchronization together with regime dependent phase shifts between the cyclical regimes. We estimate our model using a dataset with mixed frequencies to construct the CEI and FCI for Turkey and for dating cyclical regimes of the Turkish business cycle over the period starting from January 1999 until October 2018. The results from the full-sample estimation show that these indexes as well as the model-implied recession probabilities are able to capture stylized facts of the Turkish economy quite precisely and match with the dates of recessions computed using the nonparametric BBQ algorithm. We document the capacity of the FCI in leading the business cycle phases by showing 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 3.3 months for entering expansions. We further conduct a real-time recursive forecasting exercise for predicting the recessions over the periods starting from January 2006 until the end of the sample, and provide convincing evidence for the superior backcasting, nowcasting and forecasting ability of our specification. In this context, we show that it outperforms competing parametric models with perfect synchronization of cycles as well as independent cycles and the nonparametric BBQ algorithm. 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. Indeed, our in-sample results estimated as of the first week of November 2018 indicate a recession starting by August 2018.

Our model provides a prototype for joint estimation of the CEI and the FCI together with their cyclical components in a data-rich environment of variables with mixed frequencies. 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 with similar characteristics, and it may serve as a useful tool for the joint construction of the CEI and the FCI in high frequencies such as at the weekly or even at the daily frequency for advanced economies such as the US.

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Table 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	3.269 (1.984)		
	κ_1	3.552 (2.300)		
Intercepts	$\alpha_{1,0}$	0.079 (0.054)	0.075 (0.051)	0.027 (0.071)
	$\alpha_{1,1}$	-0.531 (0.221)	-0.503 (0.188)	-0.780 (0.094)
	$\alpha_{2,0}$	0.153 (0.074)	0.146 (0.070)	0.175 (0.092)
	$\alpha_{2,1}$	-0.686 (0.144)	-0.715 (0.160)	-0.632 (0.124)
Autoregressive coefficients	$\phi_{1,1}$	0.206 (0.135)	0.288 (0.152)	0.329 (0.151)
	$\phi_{2,2}$	0.354 (0.088)	0.347 (0.087)	0.349 (0.090)
Transition probabilities	p_1	0.970 (0.012)	0.970 (0.012)	0.972 (0.011)
	q_1	0.933 (0.024)	0.931 (0.025)	0.930 (0.026)
	p_2			0.962 (0.016)
	q_2			0.930 (0.024)
Variances	$\sigma^2_{f_1}$	0.939 (0.070)	0.894 (0.095)	0.869 (0.105)
	$\sigma^2_{f_2}$	0.867 (0.063)	0.872 (0.061)	0.870 (0.063)
Log-marginal likelihood		-855.16	-873.35	-893.59

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 (6) for competing models estimated using the data for the periods starting from January 1999 until October 2018. Log-marginal likelihood values are computed for the full model as given in (11). 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.

Table 2: Estimates of factor loadings, conditional variances and autoregressive coefficients of the idiosyncratic factors of the variables for the model with imperfect synchronization of the cycles

Economic variables	Factor loadings		Variances		Autoregressive coefficients	
ip	$\lambda_{1,1}$	0.434 (0.079)	$\sigma^2_{1,1}$	1.095 (0.315)	$\psi_{1,1}$	-0.230 (0.085)
			$\sigma^2_{1,2}$	0.731 (0.106)	$\psi_{1,2}$	-0.070 (0.083)
					$\psi_{1,3}$	0.003 (0.079)
import	$\lambda_{2,1}$	0.259 (0.068)	$\sigma^2_{2,1}$	1.987 (0.633)	$\psi_{2,1}$	-0.394 (0.078)
			$\sigma^2_{2,2}$	0.631 (0.097)	$\psi_{2,2}$	-0.059 (0.084)
					$\psi_{2,3}$	0.054 (0.076)
export	$\lambda_{3,1}$	0.115 (0.055)	$\sigma^2_{3,1}$	1.263 (0.389)	$\psi_{3,1}$	-0.582 (0.069)
			$\sigma^2_{3,2}$	0.592 (0.071)	$\psi_{3,2}$	-0.314 (0.076)
					$\psi_{3,3}$	-0.073 (0.067)
retails	$\lambda_{4,1}$	0.405 (0.112)	$\sigma^2_{4,1}$	1.622 (2.034)	$\psi_{4,1}$	-0.358 (0.131)
			$\sigma^2_{4,2}$	0.775 (0.149)	$\psi_{4,2}$	-0.117 (0.136)
					$\psi_{4,3}$	-0.082 (0.125)
pmi	$\lambda_{5,1}$	0.169 (0.151)	$\sigma^2_{5,1}$	1.648 (2.103)	$\psi_{5,1}$	-0.030 (0.116)
			$\sigma^2_{5,2}$	0.933 (0.160)	$\psi_{5,2}$	-0.167 (0.111)
					$\psi_{5,3}$	0.037 (0.114)
empna	$\lambda_{6,1}$	0.113 (0.117)	$\sigma^2_{6,1}$	1.615 (2.074)	$\psi_{6,1}$	0.128 (0.085)
			$\sigma^2_{6,2}$	0.889 (0.114)	$\psi_{6,2}$	0.275 (0.079)
					$\psi_{6,3}$	-0.183 (0.080)
traserv^q	$\lambda_{7,1}$	0.236 (0.154)	$\sigma^2_{7,1}$	1.620 (2.042)	$\psi_{7,1}$	0.011 (0.168)
			$\sigma^2_{7,2}$	0.921 (0.229)	$\psi_{7,2}$	0.135 (0.159)
					$\psi_{7,3}$	0.149 (0.160)
traserm^m	$\lambda_{8,1}$	0.419 (0.112)	$\sigma^2_{8,1}$	1.600 (2.040)	$\psi_{8,1}$	-0.307 (0.119)
			$\sigma^2_{8,2}$	0.736 (0.132)	$\psi_{8,2}$	-0.078 (0.119)
					$\psi_{8,3}$	0.113 (0.116)
Financial Variables						
rbist	$\lambda_{9,2}$	0.576 (0.066)	$\sigma^2_{9,1}$	1.877 (0.618)		
			$\sigma^2_{9,2}$	0.352 (0.069)		
FXRes	$\lambda_{10,2}$	0.260 (0.070)	$\sigma^2_{10,1}$	3.325 (1.138)		
			$\sigma^2_{10,2}$	0.510 (0.072)		
Conf	$\lambda_{11,2}$	0.607 (0.072)	$\sigma^2_{11,1}$	0.635 (0.217)		
			$\sigma^2_{11,2}$	0.627 (0.091)		
TermS	$\lambda_{12,2}$	0.290 (0.084)	$\sigma^2_{12,1}$	1.735 (2.976)		
			$\sigma^2_{12,2}$	0.721 (0.129)		
VOL	$\lambda_{13,2}$	-0.238 (0.078)	$\sigma^2_{13,1}$	1.266 (0.333)		
			$\sigma^2_{13,2}$	0.899 (0.122)		
P/E	$\lambda_{14,2}$	0.184 (0.104)	$\sigma^2_{14,1}$	2.190 (1.252)		
			$\sigma^2_{14,2}$	0.681 (0.318)		
TAuc	$\lambda_{15,2}$	-0.311 (0.075)	$\sigma^2_{15,1}$	1.622 (0.472)		
			$\sigma^2_{15,2}$	0.776 (0.111)		
TETS	$\lambda_{16,2}$	-0.117 (0.059)	$\sigma^2_{16,1}$	10.441 (5.965)		
			$\sigma^2_{16,2}$	0.083 (0.027)		
Cred	$\lambda_{17,2}$	-0.180 (0.095)	$\sigma^2_{17,1}$	1.589 (2.135)		
			$\sigma^2_{17,2}$	0.893 (0.206)		
MSCIem	$\lambda_{18,2}$	0.643 (0.095)	$\sigma^2_{18,1}$	1.587 (2.014)		
			$\sigma^2_{18,2}$	0.651 (0.108)		
EMBI-Tr	$\lambda_{19,2}$	0.104 (0.038)	$\sigma^2_{19,1}$	6.624 (3.782)		
			$\sigma^2_{19,2}$	0.055 (0.024)		
Most likely break date	τ	2001:09				

Note: The table shows posterior means and standard deviations (in parentheses) of the factor loadings, the variances and the autoregressive coefficients of the idiosyncratic factors in the measurement equations in (11) 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 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.

Table 3: Turning point forecast error differences to the model with imperfect synchronization of cycles

Horizon h	Perfect synchronization of cycles	Independent cycles
-3	1.742*	1.787**
-2	1.526*	2.017*
-1	1.432**	2.668**
0	1.369***	3.627**
1	0.791***	3.800**
2	0.597**	3.534***
3	0.501**	3.504***
4	0.311	3.153***
5	-0.057	2.456**
6	0.041	1.871*
7	0.087	1.323*
8	0.310	1.133

Note: The table shows the difference between the TPFE(h) (multiplied by 100) described in (21) 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.

Figure 1: Estimate of Coincident Economic Index and Financial Conditions Index

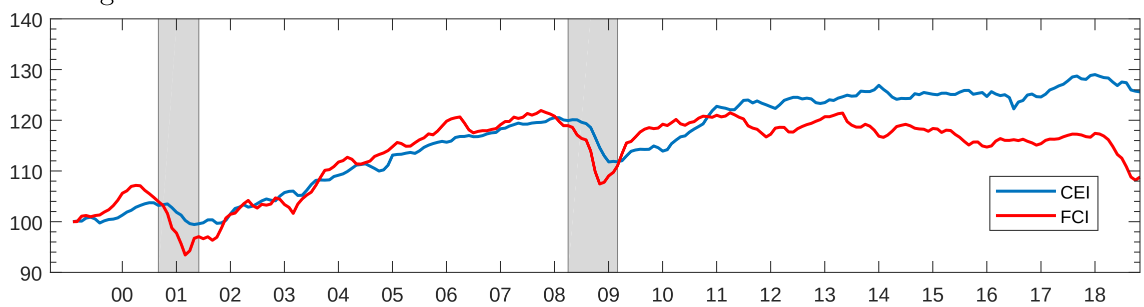
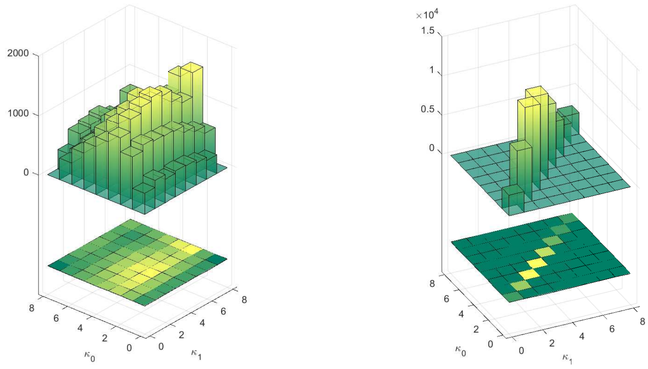
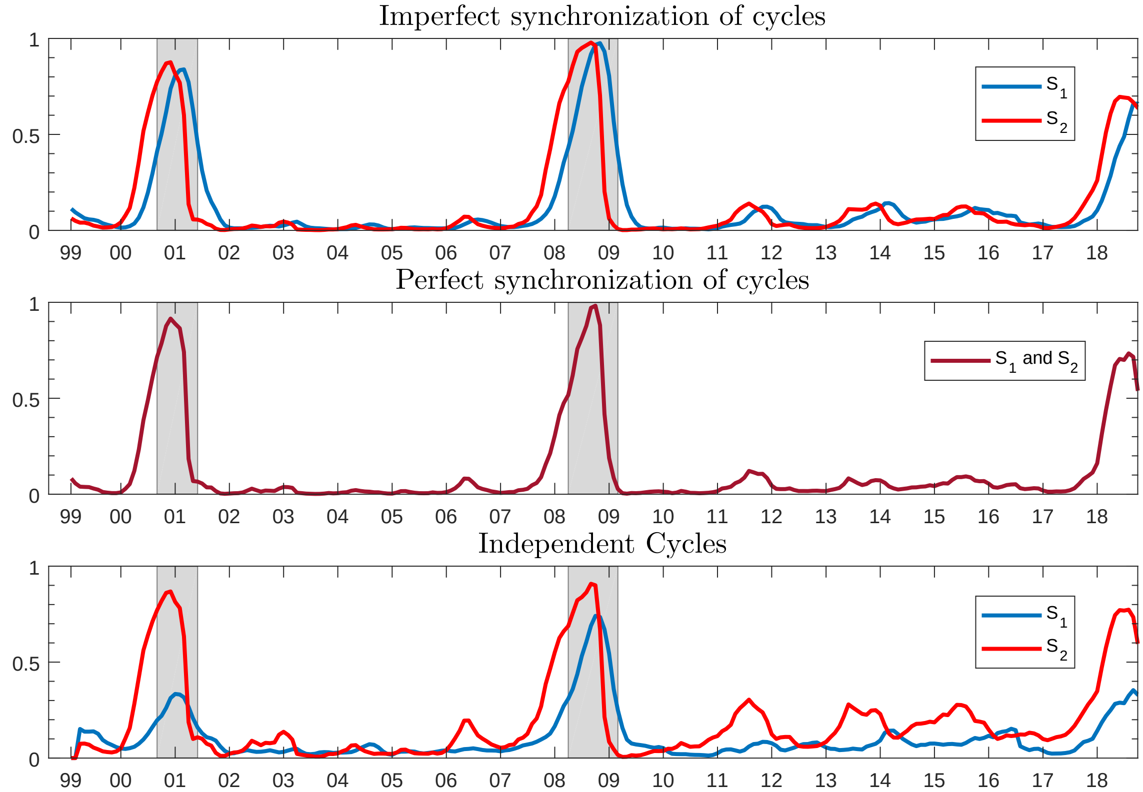


Figure 2: Histograms of the phase shift parameters, κ_0 and κ_1, for models with imperfect synchronization with regime dependent phase shifts (left) and with a unique phase shift (right)



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 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.

Figure 3: 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 October 2018. 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.

Figure 4: Estimate of Coincident Economic Index with and without the real GDP series

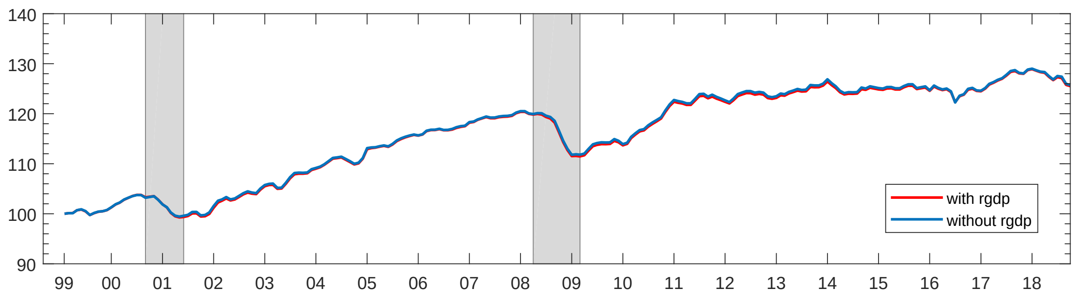
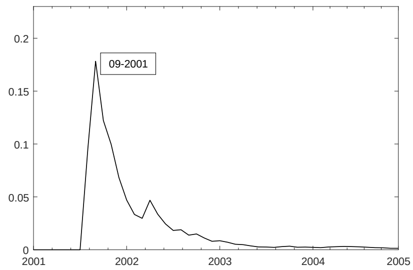


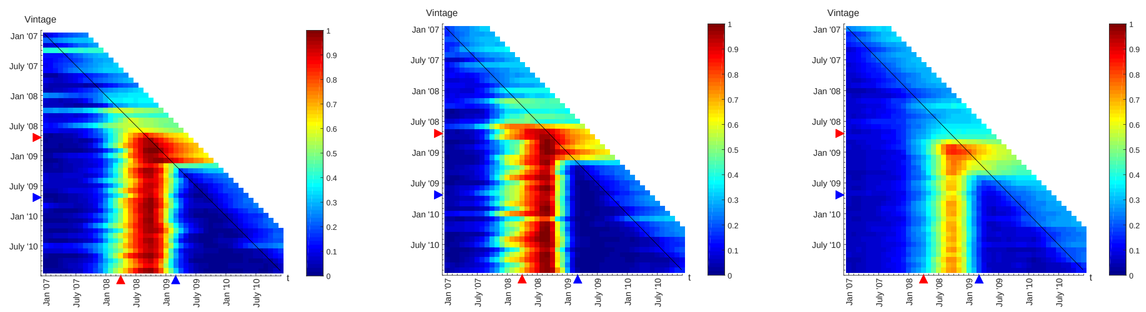
Figure 5: Posterior density of the break point parameter, τ, for the structural break in conditional variances of variables



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 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.

Figure 6: Real time nowcasting/forecasting exercise: In sample estimates and out-of-sample predictions of recession probabilities for the 2008-9 recession

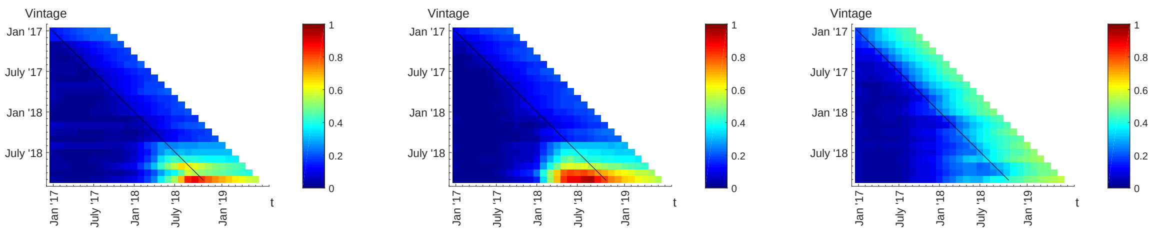
Imperfect Synchronization | Perfect Synchronization | Independent Cycles



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, respectively, computed using the BBQ algorithm. On the vertical axes, the pointers mark the announcement date of the II. quarter-2008 and II. quarter-2009 GDP, when the BBQ algorithm signals the peak and through for 2008-9 recession for the first time given the available data in real-time.

Figure 7: Real time nowcasting/forecasting exercise: In sample estimates and out-of-sample predictions of recession probabilities after 2017

Imperfect Synchronization | Perfect Synchronization | Independent Cycles



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 2017 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. See Figure 6 for details.