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Full Length Article

Composing a High-Frequency Financial Conditions Index and The Implications for Economic Activity[☆]

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Abstract

In this study, we construct an index using high-frequency data related to financial markets and intermediation services in Turkey, called the High-Frequency Financial Conditions Index, employing alternative statistical techniques for the period from 2006 to 2020. We also analyze the informative nature of the indices constructed with respect to the course of economic activity. Additionally, we perform a detailed empirical analysis of the relationship between financial conditions and growth tendencies. The results of the time-series analysis show that the series constructed are quite informative for monitoring economic activity. In this context, probit model estimations indicate that the index constructed can be used as an early indicator to predict “loss of momentum” episodes in economic growth, taking the lead-lag relationship into consideration. When a similar methodology is applied to emerging market economies, indices exhibit a high level of comovements with growth indicators. Panel vector autoregression estimation shows that, after country-specific characteristics are controlled for, a shock to financial conditions facilitates a significant response in the growth rates of emerging market economies. In terms of policy making, the indices can contribute to a better understanding of the financial outlook and its interaction with economic activity.

JEL classification: E17; E44; E66; G10

Keywords: Economic growth; Factor analysis; Financial conditions; Panel VAR; Probit

1. Introduction and related literature

After the global financial crisis (GFC), concerns about financial stability emerged because of growing awareness of the more globalized, interconnected, and complicated financial markets. In addition to complexity, the rapid increase in available data makes model specification much harder for economists who are monitoring the linkages between financial and real economic variables. Therefore, composite indicators that summarize the financial outlook and give clues about the future course of the economy have become popular. These indicators provide convenience in terms of monitoring the economic conditions in a broad perspective, and they enable policy makers to take timely and appropriate proactive policy measures. The Financial Conditions Index (FCI) is the standard index of this kind, as it portrays tightening or loosening in financial conditions by summarizing multiple indicators. Considering the staggering nature of the monetary policy transmission mechanism, the FCI might also have important implications for output and price dynamics in the domestic economic outlook. The pioneering studies regarding the FCI concentrated on developed markets (mainly the US economy), but a recently growing body of literature focuses on emerging markets (EM).

Among the studies focused on advanced economies, Swiston (2008) attempts to construct the FCI for the US by

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employing a vector autoregressive (VAR) model and impulse-response function (IRF) analysis to determine the weight of the subcomponents of the index. Guichard and Turner (2008) follow a similar methodology (VAR and reduced-form equations) to construct the FCI for the US using variables such as the exchange rate, interest rates, bond spreads, and some asset prices. Hatzius et al. (2010) employ the principal component analysis (PCA) method to obtain the FCI and examine its ability to predict economic activity. Examining the euro area, Montagnoli and Napolitano (2005) use the Kalman filter to obtain the weight assigned to each variable, constructing the FCI for the euro area and the US. In addition, Angelopoulou (2014) prefers the PCA method in building the FCI for some European countries.

Among the studies of EMs, Gomez (2011) constructs the FCI for Colombia by adapting the PCA methodology with a broad range of variables, comprising interest rates, exchange rates, and asset prices. Cottani et al. (2012) build an indicator to summarize the state of financial conditions in Latin American countries. Moreover, Osorio et al. (2011) create a quarterly FCI for 13 Asian economies, including those in the region that are developing. They create FCIs based on two main statistical techniques: a VAR model and a dynamic factor model (DFM). Gumata et al. (2012) devise an FCI for South Africa based on both global and domestic financial indicators through a combination of PCA and DFM.

In the Turkish case, there are some previous studies focusing on FCI construction. Kara et al. (2012, 2015), in influential papers, build a quarterly FCI series for the Turkish economy employing VAR methodology with selected variables based on expert judgment and various methods. Then, they examine the predictive performance of the constructed FCI series for output growth.

Kara et al. (2015) identify a broader set of variables that embody information about the exchange rate market, the equity market, risk premiums, and bond markets. They also include series that represent capital flows, the banking sector outlook, housing prices, and the money supply. Having assembled this broad list, they embrace a subjective approach and form a smaller subgroup using expert judgment. However, to obtain more robust inferences, they also include variables with a longer historical time series and cover a wider range of financial markets. This approach is enhanced with econometric tests to analyze the informative nature of the variables excluded in the first step. In particular, they run linear regressions of growth in the gross domestic product (GDP) on the FCI constructed and excluded variables with four lags. Then, they conduct joint F-tests to identify whether the lags in excluded variables are jointly insignificant. In the following step, impulse responses generated from the VAR models, including growth patterns and financial variables are taken as inputs in determining the appropriate weight of each individual variable in the ultimate FCI indexation procedure.

Chadwick and Ozturk (2019) focus specifically on the concept of financial stress to build an indicator for Turkey. Their methodology entails the extraction of overall financial stress from five different financial markets with the help of PCA, basic portfolio theory, variance equal weights, and Bayesian DFM. A "horse race" among different model specifications is performed to analyze the predictive power of the indices constructed in order to explain the business conditions and economic cycles. A recent study by Çakmaklı et al. (2020) on FCI construction for Turkey introduces another perspective by combining a dynamic factor model with a Markov-switching framework. Their joint estimation model for economic and financial conditions enables phase shifts between economic and financial cycles. By incorporating a reported 3.6 months in the lead/lag structure, their model can predict economic downturns, so it works as an early-warning indicator.

As shown in earlier studies, the FCIs created differ in terms of the scope (variables included), frequency (quarterly, monthly, or weekly), and statistical methodology (PCA, DFM, or VAR). In this study, our goal is to construct a novel version of the FCI based on high-frequency data related to financial markets and intermediation services in Turkey.

Another contribution of the paper is to examine the informative nature of the FCI constructed for economic activity in Turkey. From this perspective, our study conducts an empirical analysis of the relationship between financial conditions and growth tendencies with higher-frequency data. Moreover, using similar dimensions of financial conditions, we then construct HFFCIs for a sample of EM economies. To the best of our knowledge, this is the first study that presents a weekly FCI that has high predictive power over economic activity in multiple EM economies. Moreover, looking at the course of the High-Frequency Financial Conditions Index (HFFCI) across different EMs, we can pinpoint a significant common global factor that drives financial conditions and influences economic activity in the sample countries.

The rest of the paper is structured as follows. Section 2 introduces the framework for estimating and composing the HFFCI by providing detailed information about the PCA and DFM methodologies. Section 3 presents empirical results on the predictive power of the HFFCI for economic growth in Turkey through time-series analysis and estimation of the binary outcome model. Section 4 applies the same methodology of index construction to selected EM economies and presents the results of panel VAR estimations regarding the association between local financial conditions and economic growth by also taking country-specific fixed effects into consideration. Section 5 concludes the paper.

2. Methodology

2.1. Composition and formation of the HFFCI

As stated earlier, in the literature HFFCI-type indices are obtained with PCA, DFM, and VAR models. Each method enables the researcher to take advantage of different aspects in each approach, but one important issue that remains to be clarified is the data selection. In this study, we provide an HFFCI with a clear economic intuition. In other words, instead of choosing the components that performing best statistically through variable selection procedures, we choose specific

Table 1
Market indicators used in the construction of the HFFCI.

No	Subdimensions	Description of data	Conversion method
1	Equity Market	BIST Banking Index BIST Tourism Index BIST Industry Index BIST Services Index BIST Trade Index	Year-on-year logarithmic change is taken.
2	Exchange Rate Market	USDTRY 1M Implied Volatility USDTRY 1Y Implied Volatility Real Effective Exchange Rate	Year-on-year logarithmic change is taken. (Real effective exchange rate basket is calculated through linear interpolation of price indices of US, Europe, and Turkey)
3	Credit Conditions	Consumer Loans Interest Rate Commercial Loans Interest Rate Consumer Loans – Deposit Rates Spread Commercial Loans – Deposit Rates Spread	12 months and 24 months ahead inflation expectations are used to convert nominal rates into real interest rates.
4	Yield Curve	Turkey Cross-Currency Swap (CCS) Yield Curve	Turkey CCS yield curve is estimated through the NS method. First and second factors from PCA are taken as level and slope of the yield curve.
5	Risk Premium	CDS Premium EMBIG Spread 3M TRLIBOR – 3M Treasury Yield (TED Spread)	Year-on-year basis point difference is taken.
6	Portfolio Flows	Nonresidents' Equity Holdings Nonresidents' Government Bond Holdings Nonresidents' Private Sector Bond Holdings	Year-on-year percentage change is taken.

variables that are conceptually relevant and easy to monitor in the monetary transmission mechanism: equity, bond, exchange rate, and credit markets, portfolio flows, together with market inflation expectations and the associated credit risk. In this sense, the traditional interest rate channel, the exchange rate channel, and the asset price channel in the monetary transmission mechanism, among others, are represented by our variable set. Table 1 provides descriptive information on each indicator used in the construction of the HFFCI.

The HFFCI is formed from June 2006 until the end of August 2020 on a weekly frequency with PCA and DFM. HFFCIs constructed with PCA and DFM summarize common movement in the variables chosen, thus the resulting index serves as a composite indicator of the financial conditions. Unlike common factor models, VAR analysis requires a priori model specification in which the variables chosen are initially regressed on a growth variable, and then the cumulative coefficients are obtained from an IRF to specify the weight of individual data in the index's mechanism. However, because VAR analysis requires judicious choices in variable selection and model specification processes, in addition to the observation loss caused by the lower frequency of GDP growth or Industrial Production Index (IPI) series in extracting weights, we use factor models to obtain the HFFCI on a weekly basis. Nonetheless, as a robustness check, we also aggregate similar data with the VAR model. The graphical illustration shows that indices generated with the basic static factor model and VAR are not very different (Fig. S6, available online).

Most of the variables in Table 1 are retrieved from publicly available data sources. The only exception is variables for yield curves, which are derived from a prior yield curve–fitting procedure. The yield curve for Turkey is estimated with the Nelson and Siegel (NS; 1987) methodology for one-month to ten-year maturity cross-currency swap rates. The NS model is one of the most common parametric yield-curve estimation methods because of its reliable interpretation of the coefficients as the level, slope, and curve. The spot rate function $r(\tau)$ in the NS specification is generalized as follows:

$$r(\tau)=\begin{bmatrix}\beta_0\\ \beta_1\\ \beta_2\end{bmatrix}'\begin{bmatrix}1\\ \lambda\left(1-e^{-\tau/\lambda}\right)/\tau\\ \dfrac{\lambda\left(1-e^{-\frac{\tau}{\lambda}}\right)}{\tau}-e^{-\frac{\tau}{\lambda}}\end{bmatrix} \quad (1)$$

where β_0, β_1, and β_2 denote the level, slope, and curve coefficients. τ indicates the time to maturity. The flexibility of the yield obtained is dominant, as τ goes to infinity, or the zero spot rate converges to β_0 and $(\beta_0+\beta_1)$, respectively. β_2 depicts the rate at which the curve flattens, such that the slope and curve tend toward zero along the yield curve. Lastly, λ establishes the location of hump/trough behavior, together with the shape of the curve.

Given its flexible structure, numerous studies present alternative estimation techniques based on the NS methodology, but considering the scope of this paper, we apply the NS (1987) model to construct yield curves.[1] The NS approach enables us to optimize not only the level and slope coefficients that minimize mean squared errors (MSE) but also λ every day. This enables a varying λ in the yield curve construction, which allows the short end of the curve to be more reactive. An

[1] Kucuksarac et al. (2018) provide a detailed discussion on swap curve estimation using the Nelson-Siegel methodology.

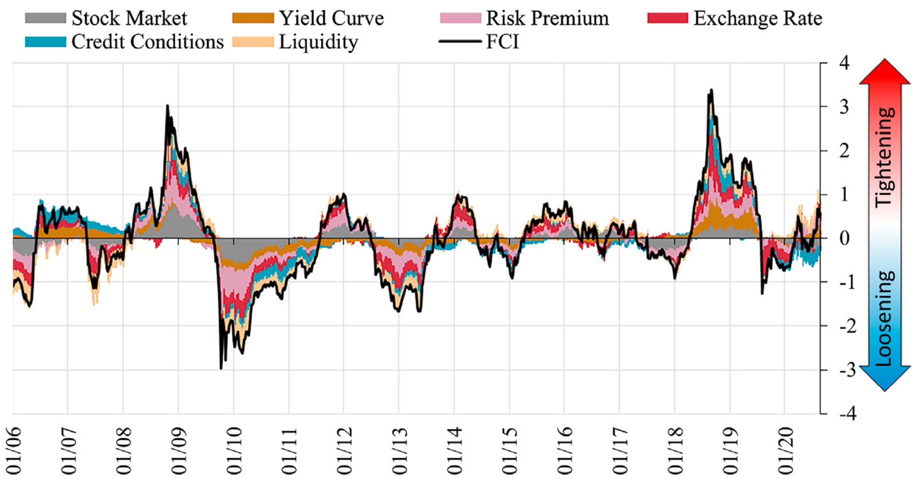

Fig. 1. HFFCI constructed with PCA and contributions to the index.

alternative approach proposed by Diebold and Li (2006) regards λ as a fixed variable and, as a result, produces smoother first and second factors and a smooth yield curve. To capture the significant level and slope changes caused by volatile price movements that are observed in the dataset for Turkey, we employ the NS approach.

After obtaining the yield curve, we extract the level and slope coefficients with PCA analysis, in which the first and second components denote the level and the slope of the curve, respectively.[2] The estimation of a yield curve for market interest rates is important in capturing instantaneous changes in the current and expected market conditions. In this sense, the interpretation of the level component is straightforward: a nominal increase in overall interest rates interacts with financial conditions by inflating financing costs. Additionally, the slope of the yield curve is also informative because it depicts long-term rates as a combination of short-term and forward interest rates. Hence, the slope of the yield curve provides information regarding market expectations of future market conditions. If long-term rates are notably higher than short-term rates, then we can conclude that market participants expect short-term rates to increase in the near future. This reflects a deterioration in the inflation outlook and risk sentiment or an expected hike in central bank policy rates. In this context, the abovementioned components of the yield curve are jointly considered indicators in the estimation procedure of the HFFCI.

2.2. Principal components analysis

In the first step, the baseline version of the index is constructed with PCA, performed in multiple steps. To this end, one market indicator is obtained through the first principal components of the six data groups in Table 1, representing different dimensions of financial conditions (see Fig. S4, available online).[3] Using the standardized indicators obtained for equity, exchange rates, credit conditions, risk premiums, portfolio flows, and yield curves, we estimate another PCA on a weekly frequency in which the first component is treated as the HFFCI.[4] In this estimation procedure, the HFFCI turns out to be a composite indicator that reflects common movement in explanatory variables and thus is also thought to summarize the outlook of the financial conditions. With these characteristics, the HFFCI by PCA also enables us to observe the total effect of a shock on a specific subsector of financial conditions, holding other factors constant.

Fig. 1 presents the HFFCI that results from PCA, in which the construction of a two-step analysis enables us to observe the varying effects of subdimensions over time. The decomposition of the HFFCI presents the drivers of the overall financial conditions in which the movements in the sub-indices can be associated with the monetary or fiscal shocks observed. To analyze the overall effect of the HFFCI, we need to see the contributing factors and a standardized version of the HFCCI, as shown in Fig. 1. Looking at the eigenvector signs for the first principal component enables us to comment on the economic interpretation of the contributing sub-indices and the resulting HFFCI, and this interpretation defines whether the FCI level is considered tightened or loosened. By PCA construction, the resulting FCI is calculated as the sum of the sub-indices and their first factor loadings, in which an increase in the HFFCI should be assessed as a worsening in overall financial conditions. Here, the sign for equity and liquidity factors is negative

[2] The data on Turkish lira swap rates is available for numerous maturities, so we prefer to use the swap curve in HFFCI estimation for Turkey. For emerging market analysis, however, we construct the yield curves on Treasury rates because data on swap rates place more constraints on the dataset. But, because the Treasury rates have a limited maturity spectrum, we use a constant λ, which minimizes the overall MSE for each country to ensure the stability of coefficients. This difference explains the implementation of the yield curve in HFFCI estimation, in which the coefficients of swap curve are volatile whereas the coefficients of the Treasury curve are stable. Hence, we use PCA to extract level and slope coefficients for the swap curve, instead of β_0 and β_1, which are used in EM analysis.

[3] Two factors are used for the level and slope coefficients in the yield curve.

[4] This factor explains almost 60 percent of the total variation in the data.

whereas yield curve, risk premium, exchange rate, and credit conditions produce a positive sign. On the other hand, when credit growth is included a negative sign is attributed to the credit conditions sub-index. Although at first glance this finding seems puzzling, it could be related to desynchronization of the credit cycle with the business cycle in Turkey. In recent years, when financial indicators show high volatility because of domestic and global factors, subsidized credit mechanisms are implemented to limit the negative shocks to the real sector. Because of this countercyclical use of credit, PCA yields a negative sign for credit conditions. Although this effect is plausible for explaining recent conditions, we prefer not to include credit growth in the credit conditions sub-index in our interpretation of the contributions of the HFFCI for the full sample period.

A broad overview of the index shows two periods of major contraction as well as one period of prominent expansion. The common characteristic of these periods is that all the subcomponents of the index move in a similar direction, exacerbating the magnitude of the HFFCI. It is practical to observe cyclical behavior in the index, given the data conversion that is expected to capture overall financial conditions over time. Another important advantage of the HFFCI is its ability to observe movements in each contributing factor within high-frequency intervals, which is likely to fade when the observations are at lower frequencies. Variables with high sensitivity to economic and political news tend to present quick surges, which usually have a subtle pattern. Thus, quarterly variables, whether used as averages or end-of-period changes, are likely to underestimate the total effect of sudden movements in the exchange rate, stock market, or risk premium. This characteristic shows its merit during periods of high volatility because it is very hard to capture sudden movements and turning points in financial variables in low-frequency models.

The recent course of the HFFCI reveals two distinct periods. First, after August 2018, the stress in the HFFCI of financial markets reaches unprecedented levels, in which all the sub-indices contribute to overall tightening. After the monetary and fiscal policy measures taken in that period, the HFFCI exhibits a sharp improvement in late 2019, dominated by the exchange rate, risk premiums, and credit conditions. During the second prominent period in February 2020 a rather unique behavior is observed in the HFFCI, after the outbreak of Covid-19 and volatility related to it. Because financial markets are highly integrated in Turkey, the sign of the majority of sub-indices tends to be the same, which is widely visible over estimated contributions, except in the period before the 2008 financial crisis. However, in the Covid-19 period, we observe surprising divergence among the factors, in which capital flows (liquidity) and risk premium factors are significantly tightening, unlike credit conditions. Once again, high-frequency observations show the reactions of different factors to numerous global and domestic policy measures.

2.3. Dynamic factor model

As an alternative method, the HFFCI is re-estimated with DFM. PCA is purely a static estimation tool and does not incorporate information along the time dimension into the composition of the HFFCI, but this procedure allows us to add the dynamics of some finite order to the latent factors (Brave & Butters, 2011). In this way, we construct another version of the HFFCI that can take into account both cross correlations (of selected financial indicators) and the historical course of the index to further assist the tracking of financial innovations.

This method is widely used in practice to summarize the informational content in a list of financial variables. Brave and Butters (2012) state that the National Financial Conditions Index (NFCI) of the Federal Reserve Bank of Chicago, for instance, incorporates the use of statistical techniques, one of which is a dynamic factor framework estimated with the Kalman filter (Doz et al., 2006). To represent the common movements of a broad set of financial variables in the US, Hatzius et al. (2010) employ an approximate dynamic factor model. Similarly, Matheson (2012) retrieves information from a broad set of high-frequency financial indicators, specifically about the US and euro-area economies. To provide a quantitative assessment of overall financial developments in Asian

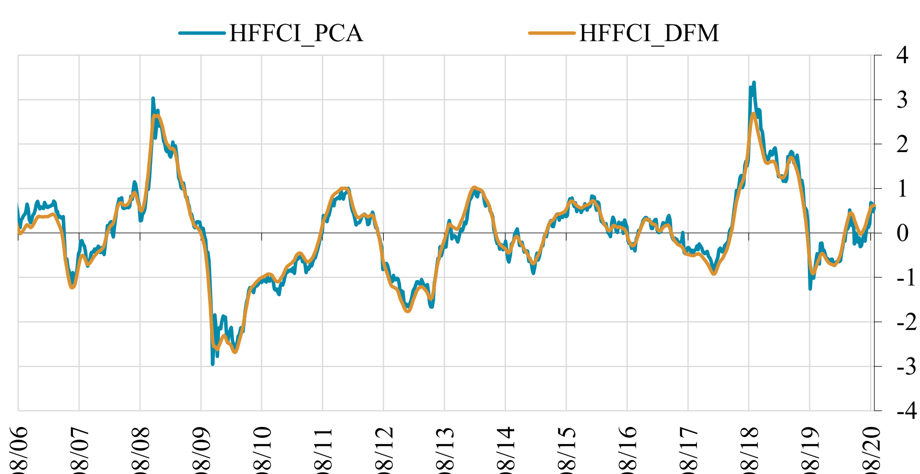

Fig. 2. The HFFCI constructed with alternative methods.

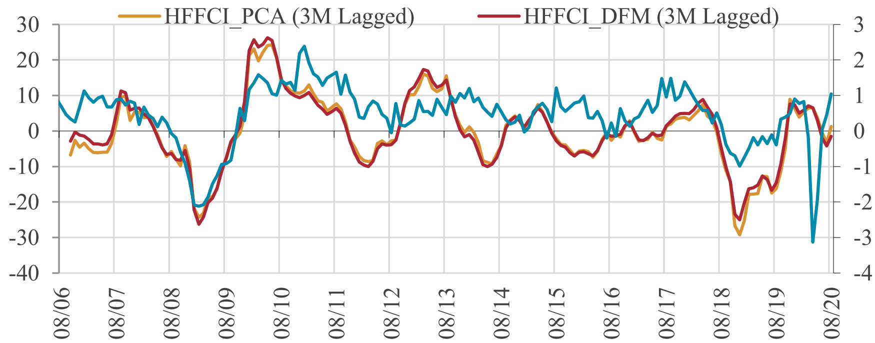

Fig. 3. The HFFCI and economic activity indicators.

countries, Osorio et al. (2011) calculate their index by applying a generalized dynamic factor model developed by Forni and Lippi (2001).

In the literature on dynamic factor models, the estimation of latent factors is handled with three different generations of methods. The first generation relies on low-dimensional parametric frameworks estimated over the time domain through the implementation of the MLE technique and the Kalman filter. Because this technique requires a nonlinear optimization procedure, the number of parameters to be estimated is inevitably restricted, and the number of series to be excluded in factor analysis is limited. In response to this weakness, a second generation of models was developed that involve nonparametric estimation with large cross-sectional dimensions via averaging methods, including PCA analysis. The principal components–based estimator of the factors is consistent, and the factors can be estimated precisely to be further used in separate regressions if the number of observations is rather large. Finally, the third generation of models prefers nonparametric estimations within a state-space framework to overcome the dimensionality problem encountered by first-generation models with the help of Bayesian methods. In our case, the factor estimation relies on the work of Giannone et al. (2008). That study discusses third-generation models and benefits the superiorities of the combination of state-space framework and PCA analysis. Moreover, the use of the Kalman filter makes it convenient for real-time analysis and smoother processes the data both in time and series dimensions. The method is based on a two-step procedure. Initially, the factors are estimated by principal components or generalized principal components. In the following step, the factors retrieved are used to estimate the unknown parameters of the state-space representation. Apart from the mechanical differences between PCA and DFM, two methods also exhibit heterogeneity in how they partition the variance structure of the dataset. DFM accepts overall variation as consisting of different parts, which are common and unique variance, whereas PCA makes the strict assumption that total variance is fully governed by common variance, which is the portion shared by the set of items examined. It is also known that DFM assumes a normal distribution of the errors embedded in the data generation process. However, PCA is distribution agnostic and does not have this requirement.

As mentioned above, our analysis employs the dynamic model framework of Giannone et al. (2008). As a typical feature of these models, individual data series consist of the components that are common to all elements of financial variables (i.e., unobserved latent factors) as well as an orthogonal idiosyncratic component. More formally, this model can be expressed as a system with two equations, a measurement equation (Equation (2)) linking the observed financial variables to the common factor and a transition equation (Equation (3)) governing the dynamics of the common factor and the residuals of the measurement equation. After these equations are written in a state-space form, the Kalman filter and smoother are applied to estimate the model parameters.

The DFM framework can be defined as follows:

$$Y_t = \Lambda F_t + \varepsilon_t,\ \varepsilon_t \sim N(0,\ \Sigma_e) \tag{2}$$

$$F_t = \sum_{i=1}^{p} \beta_i F_{t-i} + v_t,\ v_t \sim N(0, Q) \tag{3}$$

where Y_t is a vector of observable financial variables at week t, whereas F_t is an r × 1 vector of common factors with zero mean and variance of one. Furthermore, Λ is an N × 1 factor-loading matrix, and ε_t is an idiosyncratic disturbance term (which is uncorrelated with F_t at all leads and lags) with a diagonal covariance matrix Σ_e. As described in Equation (2), unobservable common factors can be represented as a VAR(p) process governed by a q × 1 vector of shocks v_t, which is distributed with a mean of 0 and a covariance matrix of Q as well as β_i, indicating r × r matrices of autoregressive coefficients.[5] Moreover, the common shocks v_t and idiosyncratic component ε_t are orthogonal to each other.

As in the PCA approach, a bottom-up empirical strategy is chosen. In the first step, individual series relevant to the different subsectors of financial markets are combined with sectoral DFM estimations. In particular, indices are constructed to keep track of the movements in equity markets, risk premiums, foreign exchange market, credit conditions, liquidity, and yield curves. In the following step, those dimension-wise sub-indices are aggregated through the application of the

[5] The lag length p is selected using Schwarz-Bayesian information criteria.

Table 2
Probit model results.

Dependent variable: *Momentum*$_t$	Coefficient	Marginal effect (*dy*/*dx*)	Sensitivity	Hosmer–Lemeshow goodness-of-fit test statistic (*p*-value)
Model with HFFCI_PCA	0.129*	0.051*	71%	167.00 (0.463)
Model with HFFCI_DFM	0.164**	0.064**	71%	166.98 (0.464)

Notes: **, * denotes the statistical significance at 5% and 10% levels, respectively.

Table 3
Market indicators used in the construction of an emerging market HFFCI.

Variable	Description of data used	Conversion method
Equity market	Stock exchange indices	Year-on-year logarithmic change is taken.
Exchange rate market	Nominal exchange rate against USD	Year-on-year logarithmic change is taken. (Real effective exchange rate is calculated through linear interpolation of price indices of US and each EM country)
Yield curve	Treasury yield curve	Each Treasury yield curve is estimated through the NS method. First and second coefficients are taken as the level and slope of the yield curve.
Risk premium	CDS premium EMBIG spread	Difference in year-on-year basis points is taken.
Portfolio flows	Debt and equity flows	1-year cumulative weekly debt and equity flows. Source: Institute of International Finance.

ultimate factor analysis (Fig. S5, available online). As seen in Fig. 2, the HFFCI constructed with DFM moves closely with the HFFCI obtained by static factor estimation. To quantify the level of comovement, we calculate a correlation matrix (Table S1, available online). The Pearson correlation coefficients show a high level of association between indicators for financial conditions and the proxy for growth, yet they retain statistical significance.

3. Empirical results for Turkey

In this section, we initially provide descriptive analysis about the degree of comovement between the monthly economic activity indicator and the HFFCI. In the following step, we assess the role of the HFFCI in predicting the probability of economic slowdown.

3.1. Relationship with economic activity

To compare the movements in the HFFCI with economic activity, we use the year-on-year growth rate in the IPI as an indicator.[6] Fig. 3 illustrates the monthly FCIs, which are constructed as the simple averages of weekly HFFCIs, together with IPI growth.[7] Both versions of the HFFCI seem to have a leading nature for the cyclical behavior of economic growth, given the fact that episodes of financial tightening are mostly followed by contractions or weakening in growth.

To understand the joint movements of financial conditions and economic growth, we conduct further descriptive time-series analyses. More specifically, the existence of a long-run relationship is evaluated with the bounds testing procedure similar to Pesaran et al. (2001). The results for all specifications show that a statistically significant long-run relationship exists between the activity indicator and proxies for financial conditions from a time-series perspective (Table S2, available online).

3.2. The predictive ability of the HFFCI: probit model to detect "loss of momentum" episodes

Because of their ability to explain cyclical movements in the economy, information extracted from financial variables is also commonly used to predict the probability of economic slowdowns. To this end, the financial information contained in interest rate differentials, the term structure of interest rates, corporate bond spreads, and stock returns is commonly considered in a probit model framework.[8] Because our focus is more recent periods, and our HFFCIs cover a shorter time span, we employ a flexible alternative definition of economic slowdown, called a "loss of momentum" in growth. In our probit model estimations, the value of an observable binary indicator depends on the state of the economy as follows:

[6] All the estimations in Section 3 are repeated by taking "year-on-year growth rate of monthly GDP" as a proxy for economic activity. Similar results are obtained, regardless of the choice of economic growth indicator.
[7] HFFCI proxies are inverted for illustrative purposes.

[8] For similar approaches aimed at associating FCI-type indices with recession episodes, see, e.g., Fornari and Lemke (2010), Chen et al. (2011), Liu and Moench (2016), Fornaro (2016), and Hsu (2016).

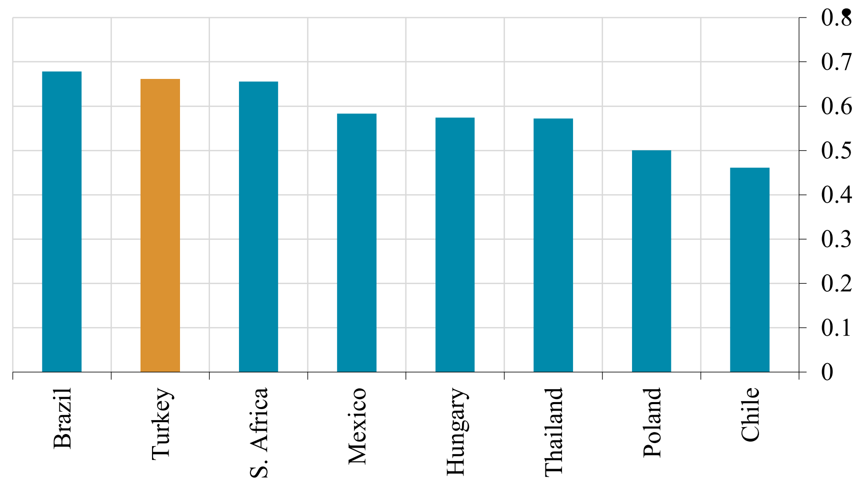

Fig. 4. Correlation between the HFFCI and economic growth (percentage).

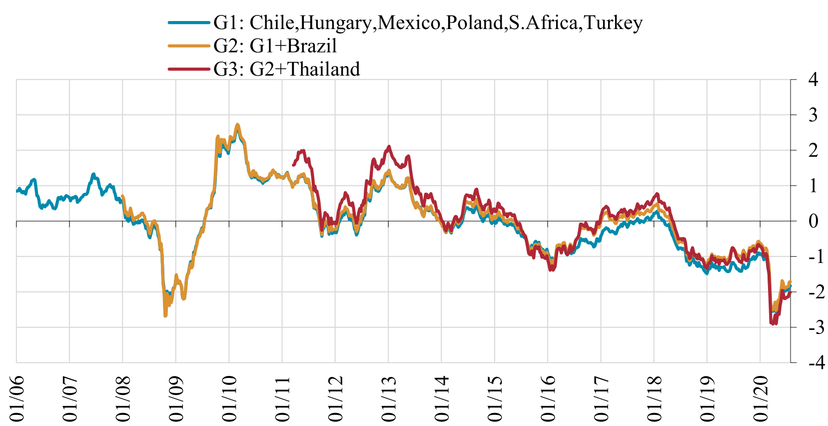

Fig. 5. HFFCI_EM common component (first principal component).

$$Momentum_t = \begin{cases} 1 \; if \;\; YoY \;\; growth\, rate \;\; of \;\; IPI \;\; declines \;\; consecutively \;\; for \;\; 3 \;\; months; \\ 0 \; otherwise \end{cases} \quad (4)$$

This dependent variable is estimated with the three-month lagged HFFCI indices in Section 2.[9] In other words, we consider two different probit models, with different HFFCI definitions, depending on whether the index is produced with a static or dynamic factor model.

$$\Pr(Momentum_t = 1 | HFFCI_{t-3}) = \Phi(\alpha_0 + \alpha_1 HFFCI_{t-3}) \quad (5)$$

where $\Phi(.)$ denotes the cumulative distribution function of a normal distribution, and $HFFCI_{t-3}$ is the variable for the HFFCI indices produced with static and dynamic factor extraction procedures.

Table 2 shows that coefficients on HFFCI are positive and statistically significant in two separate models. We obtain similar findings for marginal effects. It can be inferred that, regardless of the choice of method for the construction of the HFFCI, the movements that represent tightening in financial conditions increase the likelihood of a loss of momentum in economic activity. Furthermore, the sensitivity of probit models appears to be 71 percent, indicating that 17 of the 24

[9] We evaluated several probit models in terms of criteria such as statistical significance, log-likelihood, and McFadden Pseudo R-square before deciding on this particular specification.

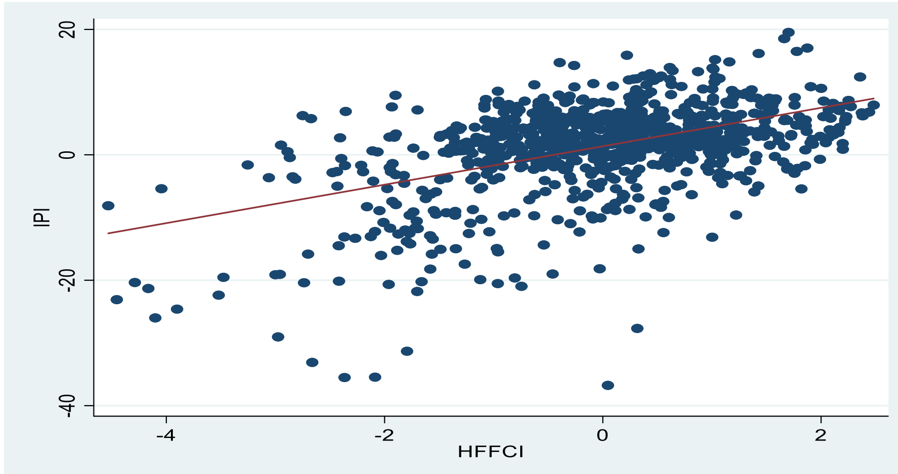

Fig. 6. The degree of association between the HFFCI and economic growth in EM countries.

identified "loss of momentum" episodes can be predicted by our simple model (Fig. S1 and S2, available online). To obtain more information about the validity of the models, we also perform the Hosmer–Lemeshow goodness-of-fit test. As shown in Table 2, failure to reject the null hypothesis in both models indicates that the models fit the data reasonably well.

4. Empirical results for emerging markets

Because of the deep relationship between economic activity and important predictive power in Turkey, we apply a similar methodology to EM economies. Determining these indices can reflect how these countries differ from one another in their financial conditions. To this end, we select a broad set of EM countries with consistent and adequately backdated data series (e.g., Treasury rates, stock exchange, country risk premiums, and exchange rates). Then, in the following step, we limit the sample to countries with available portfolio flows data: Brazil, Chile, Hungary, Mexico, Poland, South Africa, Thailand, and Turkey. Because weekly credit data availability is a restrictive constraint in several EM economies, we leave aside the credit conditions dimension of the HFFCI. A summary of the data used in EM analysis is given in Table 3.

The dataset obtained is processed with PCA to produce straightforward calculations of the HFFCI indicators. This time, in order to preserve consistency in calculation among EM countries, in which some have more than one indicator whereas others have only one for a specific variable, such as the equity market; we applied a one-step PCA for the calculation indices. Thus, for each country, all six variables are processed directly with PCA, without applying further second-step indexation. The resulting indices for each EM country display visible cycles, which are expected to be associated with the domestic macroeconomic outlook and a possible global driver. To express the relation between the indices and economic activity, we use the annual growth rate on industrial production as a proxy, and, for the possible effect of a global driving force, inspect the individual indices and extract their common component.

The level of correlation between the indices constructed and economic growth in these countries is shown in Fig. 4. Although the comparison is made for different values depending on the data availability, as is inferred in this figure, the correlation level is rather high for the EM countries. When a similar method is used for Turkey to construct a comparable index with other peer countries, not surprisingly, Turkey is one of the countries with the highest association between financial conditions and economic growth.[10] Brazil and South Africa are also economies with sizable interactions between financial conditions and output.

A graphical illustration of historical relations shows some financially volatile episodes during which EM economies experienced common tightening in their financial conditions and coincidental weakening in economic growth (Fig. S3, available online). The global financial crisis, eurozone crisis, and taper tantrum are characterized as episodes with financial repercussions.

Fig. 5 illustrates the extracted common factor that explains more than 60 percent of the variation among individual indices. In this analysis, we construct PCA differently, as the starting date is later for data on Brazil and Thailand than the rest of the sample, because of data limitations. Hence, we perform a base PCA for countries in group 1 (G1), whose HFFCI starts in 2006, and then another PCA with the next starting country (e.g., the HFFCI for Brazil starts in 2008). Because of the lower number of observations included, each consecutive common factor starts with a later date. Applying this methodology, we show that a common factor exists and is robust to the addition of new countries. Moreover, because the country sample includes EM economies with different characteristics, this common component can be attributed to global drivers and called

[10] HFFCI for Turkey in this section is calculated with the EM methodology in order to preserve equivalence among EM countries in common factor analysis. As a robustness control, both indices are checked, and we observe that the two methodologies produce similar results, in which both HFFCI exhibit very similar movements and have a similar correlation to the IPI.

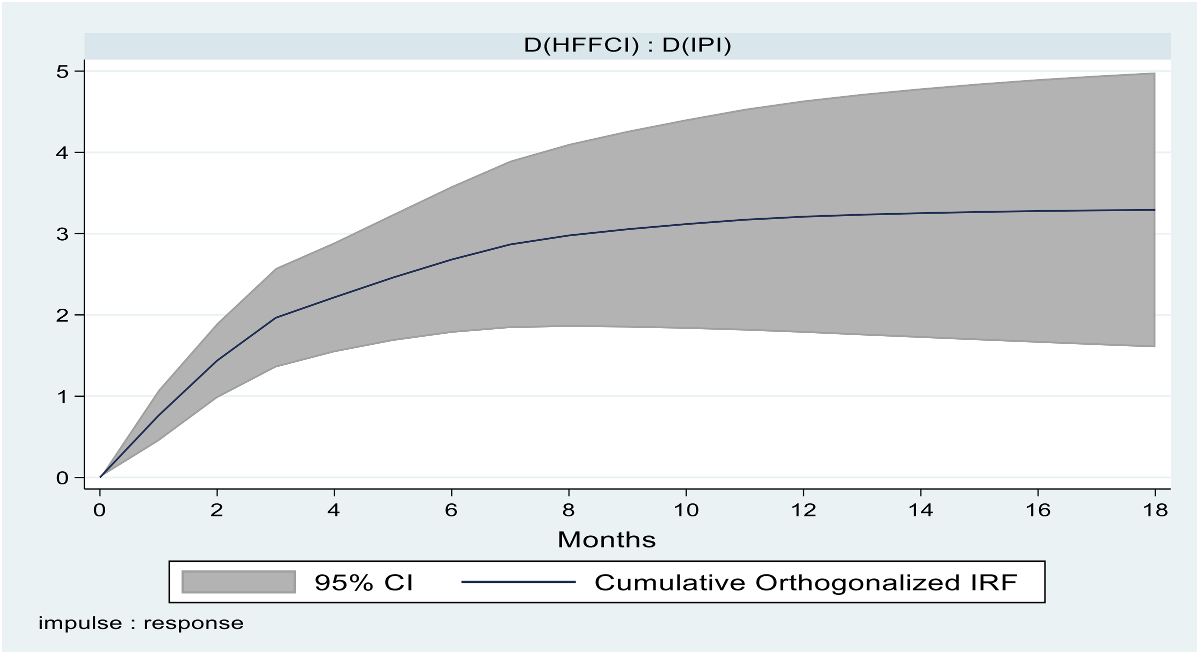

Fig. 7. Impulse-response function.

the EM factor. Not surprisingly, some countries show high sensitivity to the common factor, whereas others are affected to a smaller degree (Fig. S7, available online).

The correlation of the HFFCIs among structurally different EM countries shows that global effects are more important than EM financial conditions. Moreover, an inspection of individual indices further reflects the country-specific variations. In this part of the study, we undertake an empirical analysis in a longitudinal setting, on top of descriptive analysis about the comovement between local financial conditions (calculated with our methodology) and the course of economic activity. This reaction seems to be a common trend in EM countries, which could be the result of the synchronization of financial conditions at a global scale (Fig. 6). To this end, we perform panel VAR estimations with a simplified setup, which considers only individual EM HFFCIs and economic growth patterns.

Our panel VAR specification embodies the endogenous variables of IPI_{it} and $HFFCI_{it}$, which stand for the year-on-year growth rate of the IPI and the level values of the HFFCI indicators. In this section, we include monthly data on six countries whose financial conditions and growth series date back to earlier periods: Brazil, Hungary, Mexico, Poland, South Africa, and Turkey. The sample covers the period January 2008–August 2020. Before conducting the estimation, we checked two different panel unit-root tests to determine the form of the variables in this longitudinal analysis (Table S3, available online), finding that differenced versions of the variables used are panel stationary. Lastly, we determine the optimal lag order in our model by reviewing the information criteria specified by Abrigo and Love (2016) and select four months as the optimal lag length.

We perform the estimation of the very basic panel VAR model using the generalized method of moments (GMM) approach described by Abrigo and Love (2016). The estimated system of equations for the panel VAR model of order p with country-specific fixed effects can be specified as follows:

$$Y_{it} = A_1 Y_{it-1} + A_2 Y_{it-2} + \ldots + A_p Y_{it-p} + u_i + e_{it} \tag{6}$$

$$Y_{it} = \begin{bmatrix} D(HFFCI_{it}) \\ D(IPI_{it}) \end{bmatrix} \tag{7}$$

$$\begin{aligned} &E[e_{it}] = 0;\ E\left[e'_{it} e_{it}\right] = \Sigma \\ &E\left[e'_{it} e_{is}\right] = 0,\ for\ t > s \end{aligned} \tag{8}$$

where Y_{it} stands for the vector of endogenous variables, and u_i and e_{it} represent dependent variable-specific panel fixed effects and idiosyncratic errors, respectively.[11] Using this method, we can control for unobserved heterogeneity across countries. First, we examine the Wald test of Granger causality constructed from the panel VAR model. The results show that financial conditions Granger cause economic growth in EM countries at conventional statistical levels (Table S4, available online). This hints that the HFFCI might have some predictive power over IPI growth in the cross-country setup. To shed more light on the association between financial conditions and growth as a common trend in EM countries, possibly shaped by the global financial conditions component and synchronization among EM peers, we produce the IRF from this basic panel VAR estimation. Fig. 7 shows that shocks to HFFCI are cumulatively transmitted to IPI.[12] The shifts in the HFFCI indices that correspond to

[11] The panel VAR model is found to be stable, given the fact that the roots of the companion matrix are within the unit circle.

[12] As in previous exercises in this study, we use the versions of country HFFCIs multiplied by −1. In this way, increases in the HFFCI correspond to financial loosening, while decreases are related to financial tightening.

loosening in the financial conditions reinforce the acceleration in economic growth.

5. Conclusion

This study creates an FCI with high-frequency data for Turkey using alternative statistical techniques (PCA and DFM). Observation of an FCI constructed on weekly financial variables enables economic activity to be observed at the highest frequency possible. Moreover, because low-frequency indices might capture noisy movements in each observation, it is difficult to capture financial market reaction to the policies applied whereas the HFFCI allows monetary and fiscal policy changes to be pinpointed. The explanatory power of HFFCI series is fairly high in considering changes in economic activity. Moreover, the HFFCI series, which takes into account the lag structure with respect to economic activity, should be treated as an early-warning indicator. Looking at the recent period, the HFFCI shows how financial variables reacted during the recession in Turkey in 2018, when the index reached its level with the highest tightening and thus how the normalization period reflected these factors. After 2020, Covid-19 had an effect on the HFFCI in which the contributing sub-indices move in a mixed way, similar to the pre-2008 period. During the pandemic, the yield curve, risk premiums, and liquidity factors behave in a contractionary way, whereas domestic measures have an impact on credit conditions and the stock market, in turn, producing a limited but tightening level of the HFFCI.

After examining the construction and possible use of the HFFCI in Turkey, we extend our empirical design to apply this methodology to other EMs. Using similar financial market variables, we obtain the HFFCI for each country. Not surprisingly, these indices are highly correlated with economic activity. Moreover, similar movements observed in EM indices enable us to obtain a common global factor that explains 70 percent of the total variation in the sample countries. This finding suggests that economic activity in EMs is highly vulnerable to global financial conditions, and observation of this common factor at a weekly frequency offers significant benefits to related parties.

Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bir.2022.01.002.

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