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MEASURING FINANCIAL CONDITIONS IN MAJOR NON-EURO AREA ECONOMIES

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In 2014 all ECB publications feature a motif taken from the €20 banknote.

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Abstract

In this paper, we develop financial conditions indices (FCIs) for 3 industrialized (US, Japan, UK) and 5 emerging (China, Brazil, Russia, India, Turkey) economies. The FCIs are formed as the principal component of a range of financial series for each country and are constructed to account for fluctuations in the business cycle. We show that these FCIs can help predict growth developments and thereby provide a potential leading indicator for the external environment of the Euro area. While we draw upon established methodological considerations in the literature, our main contribution lies in providing FCIs which are available for a broad set of countries, including many emerging economies, and whose movements can intuitively be interpreted. This latter fact allows us to track developments in the 8 investigated financial markets over the last decade.

Keywords: Financial Conditions Index, FCI, Principal Component Analysis, Forecasting

JEL Classifications: C43, E37, E44, G1

Non-Technical Summary

Recent economic events and academic work have highlighted the role of financial conditions for the real economy. To quantify financial conditions in the external environment of the Euro area, this paper develops financial conditions indices for eight economies (US, Japan, UK, China, Brazil, Russia, India, and Turkey).

Assessing financial conditions is helpful in many aspects. From a monetary policy perspective, changes in financial markets conditions influence the transmission channel through which monetary policy affects the real economy and the final outcome of a change in the monetary policy stance can be affected by shocks that influence the linkage between the key monetary policy instrument and other aspects of financial markets, such as asset prices. From the perspective of forecasting, economic activity is affected by the financing costs and credit availability for firms and households, broadly reflected in financial indicators, which could thus serve as leading indicators helping to predict real economic activity. Indeed, previous literature has shown that financial indicators in the US can help forecasting economic activity.

After an extensive review of previous attempts to construct measures for financial conditions, this paper provides a methodology and estimates for Financial Conditions Indices (FCIs) for a wide set of economies. Furthermore, it assesses their forecasting performance for economic activity. The FCIs are formed as the principal component of a range of financial series for each country. They are constructed to account for fluctuations in the business cycle.

We show that these FCIs can help predict growth developments and thereby provide a potential leading indicator for the external environment of the Euro area, which is important for regular economic analysis. Furthermore, they can provide information about the transmission channel of monetary policy to the real economy and about the monetary policy stance in the investigated economies.

While our work ties in with previous contributions, our newly developed indices have certain advantages compared to other financial conditions indices in the literature. First and foremost, they use a consistent methodology for a number of globally relevant economies while most other indices are only available for a single country. Furthermore, our indices do not need any assumptions about the relationship between the real and financial sector for its construction, as many other FCIs do (to generate the weights of the included series). Instead, our FCIs are generated by the comovement of financial variables themselves, but can still be interpreted in a meaningful manner, which is essential to policy analysis. Based on this feature, this paper tracks the development of financial conditions in the analysed economies over the last decades.

1. Introduction

The recent economic crisis has once again highlighted the multidimensional interactions that exist between financial and business cycles on a global scale, and the need to understand these interactions more clearly (e.g. Claessens et al., 2011b). By introducing new estimates for financial conditions in major non-Euro area countries[1] we aim to advance knowledge in this regard.

Assessing financial conditions is helpful in many aspects. From a monetary policy perspective, changes in financial markets conditions influence the transmission channel through which monetary policy affects the real economy. The final outcome of a change in the monetary policy stance can be affected by shocks that influence the linkage of the key monetary policy instrument and aspects of financial markets, such as asset prices (cf. Blanchard et al., 2010: 5, Dudley, 2010: 62; Curdia and Woodford, 2010), financial integration, and financial innovation (see Chen et al., 2012).

From the perspective of forecasting, economic activity is affected by the financing costs and credit availability for firms and households, broadly reflected in financial indicators, which could then serve as leading indicators helping to predict real economic activity. Indeed, previous literature has shown that financial indicators in the US can help forecasting economic activity.[2]

The aim of this paper is to provide a methodology and estimates for such broad measures, called Financial Conditions Indices (FCIs), for a wide set of economies and to assess their forecasting performance for economic activity. While we draw upon established methodological considerations in the literature, in particular using principal components analysis (PCA) as in Hatzius et al. (2010), our main contribution lies in the provision of a broad set of such indicators across countries using a consistent methodology. As we provide FCIs for a wide set of countries, including many emerging economies (overall for US, Japan, UK, China, Brazil, Russia, India and Turkey), we thereby address the critique of Dudley (2010) that the work of Hatzius et al. (2010) is based on very well-known data and financial events from a single country. A further point of departure from the most conventional literature on FCIs is that the sign of loadings on the variables we consider in the FCI are not at odds with economic intuition: as we show in an applications for advanced economies (in section 4), this can allow us to communicate to policy makers in a credible way not only that FCIs have changed but also which indicators mostly contributed to their change.

The remainder of this paper is organized as follows. Section 2 reviews the relevant previous literature on financial conditions indices. Section 3 explains the methodology we use for constructing our non-Euro area FCIs. Section 4 presents the obtained results. In sections 5 and 6 we assess the robustness and forecasting performance of our FCIs, respectively. Section 7 concludes.

2. Literature Review: from monetary to financial condition indices

In this literature review, we discuss what we consider to be the cornerstones of the literature on FCIs and furthermore provide an overall picture of the work in the field. While we consider this overview

[1] For a financial conditions index for the Euro area, see ECB (2012). An FCI for the Euro area, Japan, the UK and the US is constructed, for example, by Guichard et al. (2009). See also the literature review in the next section.
[2] See, inter alia, English et al. (2005), Estrella and Trubin (2006), Hatzius et al. (2010), Croux and Reusens (2013) and section 6 of this paper. For emerging economies, Gloede and Rungruxsirivorn (2013) provide evidence about the effect of financial development on investment and consumption in Thailand. Furthermore, Holló et al. (2012) show that financial stress can depress real economic activity.

to being comprehensive, it is by no means complete since the field has become extensive, sometimes with the contribution of single studies being rather narrow.

In the 1990s, central banks such as the Bank of Canada started to take into account or to explicitly target Monetary Condition Indices (MCIs), which are basically weighted averages of changes in the interest rate and the exchange rate. The main rationale behind this choice is that monetary policy has to work its way through the economic system in order to produce outcomes such as stable prices or closed output gaps. This is often referred to as the "monetary policy transmission channel." In an open flexible exchange rate regime, monetary policy generates its impact, inter alia, through interest rates and the exchange rate (cf. Freedman, 1994; Stevens, 1998; Batini and Turnbull, 2000). In such an environment, lowering interest rates will make monetary conditions more supportive by lowering credit costs. The associated depreciation of the exchange rate will also make domestic assets cheaper for foreigners. There will hence be a positive impact on output but also increased inflationary pressures through both the interest rate and the associated exchange rate channel.

2.1 From Monetary to Financial Condition Indices

The monetary policy transmission channel is of course more complex in practice and involves many more interlinkages. A first generation of FCIs hence tried to improve upon the MCI methodology by broadening the view on these linkages.[3] For example, Goodhart and Hofmann (2002) derived a Taylor-type optimal interest rate for the UK following the approach of Rudebusch and Svensson (1998) by first estimating a (backward looking) Phillips and IS curve, where the latter takes into account movements in equity and housing prices. They show that if these variables would be omitted, the optimal monetary policy response to inflation and output gaps (as well as to oil prices) would be much stronger, which results from a lower interest rate elasticity in the IS curve. The intuition for this result is the fact that equities and housing serve as collateral and hence also influence the lending capacity of households while share prices further influence the financing options of firms. While one would expect a relation between the policy rate and asset prices, the impact of monetary policy hence also depends on the impact of idiosyncratic movements in asset prices. Not considering the latter thus gives rise to an omitted variable bias in the IS curve, which leads to an increase in the Central Bank's loss function of 60%, as Goodhart and Hofmann (2002) show in their simulations. From the estimated parameters, they construct an MCI as well as a more comprehensive FCI and show that the correlation between them is only 0.44. Among the two, the FCI shows more variation and performs better (with regard to t-statistics and R-squared) in a simple model forecasting inflation.

Gauthier et al. (2004) constructed three different FCIs for Canada using monthly data on housing prices, equity prices, and bond yield risk premiums, in addition to short- and long-term interest rates and the exchange rate for the period 1980-2000. They use an IS-curve-based model similar to Goodhart and Hofmann (2002), a generalized impulse-response function from a VAR model, and factor analysis to construct their indices which are generally significant predictors in explaining output. More specifically, they find that the FCIs outperform the Bank of Canada's MCI in many aspects and that the IS-curve based FCI dominates over a short forecasting horizon (up to one year) while the VAR-based FCI provides the best results over a time horizon of 1-2 years.

English et al. (2005) aimed to forecast output, inflation and investment for 4 and 8 quarters using a financial diffusion index similar to Stock and Watson (2002) for three countries (Germany, UK, US). The index is constructed by extracting a set of principal components from data on interest rates,

[3] For more details on the relationship between MCIs and FCIs and the usefulness of asset prices in predicting output and inflation, see Mayes and Virén (2001).

exchange rates, risk spreads, asset prices, financial strength, credit aggregates, and the health and performance of the banking sector, although they are not able to include all variables for all countries. The authors compare the performance to an alternative model based on the short-term rate, the slope of the yield curve and growth in real equity prices and generally find that the latent financial factors help predicting the macroeconomic variables to a considerable extent, especially for a two-year horizon, though the performance is less convincing for inflation. While they allow for inclusion of up to the first six principal components, the Bayesian information criterion BIC selects a fairly small number of the estimated financial factors to enter the forecasting equations.

A revival after the financial crisis

The financial crisis gave a boost to the development and distribution of FCIs as it raised the awareness about multidimensional interactions between financial and business cycles and therefore suggested that close monitoring of developments in financial markets should be an integral part of macroeconomic surveillance and policy design (cf. e.g. Claessens et al., 2011b, Osinski et al., 2013). Furthermore, hitting the zero lower bound for the policy rate highlighted once more that the policy interest rate is not sufficient to describe financial conditions in an economy.

For example, Guichard and Turner (2008) constructed an US FCI including real short-term interest rates, real long-term interest rates, the real effective exchange rate, bond spreads, stock market capitalisation and credit standards. The index was used to summarise financial conditions in the OECD World Economic Outlook 2008 and was then extended to US, Japan, Euro area and UK by Guichard et al. (2009) based on judgemental calibration.

Swiston (2008) constructed an FCI for the US which attempts to disentangle the endogenous response of financial variables to real economic activity from the exogenous financial shocks using VARs. This is important if the aim of the FCI is to capture shocks exogenous to the system. He thereby shows that credit availability is an important driver of the business cycle for which the FCI could serve as a leading indicator.

Hatzius et al. (2010) provide a comprehensive review of 7 FCIs for the United States that are constructed and used mainly by investment banks, policy makers, and advisers (Bloomberg, Citi, DB, Goldman Sachs, Kansas Fed, Macroeconomic Advisers, OECD). They also assess their predictive power for GDP, employment, industrial production and unemployment rate over a time horizon of 2 and 4 quarters ahead, together with 5 individual financial leading indicators (term spread, real M2, S&P 500, federal funds rate, short-term credit spread). Comparing the forecasting performance of these series with a simple AR model, they generally obtain rather disappointing results. The stock market variable and credit spread did relatively well and pooling of the series to FCIs may somewhat increase the predictive power, at least during periods of unusual financial stress. With these results in mind, Hatzius et al. aimed at developing a new, broader index of financial conditions that includes a wider range of financial variables while covering a relatively long time span and accounting for cyclical influences. A main innovation that made their index a seminal reference-point in the literature is their approach to purge the index from main macroeconomic developments (growth and inflation) which is motivated by the claim that any FCI should ideally measure financial *shocks*, i.e. influences that are exogenous to the economy. After doing so, they summarize the information of their individual series using principal components. A main finding is that the one-factor variant does not perform worse than augmented factor structures. However, their FCI does not necessarily perform better than other approaches with respect to forecasting and is especially weak in the late 1990s. Purging had a positive impact on the performance of the index in the early 1990s and over the last decade. They also allow for the possibility that their 45 data series are generated by multiple (i.e. 3) factors instead of a single one.

Brave and Butters (2011) construct another important FCI for the US that is used for financial conditions' assessment by the Chicago Federal Reserve Bank. In its current form, it covers over 100 financial series and uses principal component analysis (PCA) in a state-space-representation, allowing for latent factor's dynamics (over the last 15 weeks) and accommodates data of different time frequencies and lengths. While their "national FCI" is unconditional on the business cycle, they also create an "adjusted national FCI" that sweeps out endogenous responses to the business cycle by regressing the underlying series on the current and the lagged 3-months moving averages of the Chicago Fed National Activity Index and personal consumption expenditure inflation (over three months), with the lag-length determined by BIC.

Hatzius and Stehn (2012) construct an FCI that updates a previous Goldman Sachs FCI mainly by including some more variables and by accounting for stationarity. More precisely, their index consists of a weighted average of eight variables in the broad categories of interest rates, spreads and equity wealth, where the weights are derived from a modified version of the Federal Reserve's large-scale econometric model of the US economy which is extended to include an explicit role for credit frictions. The index is available on a daily basis back to the year 2000 and is scaled to 100 for the average since 2000 so that an increase from this level indicates a tightening of financial conditions relative to "normal". They find that the index increases the 4-quarters-ahead growth forecasting performance by as much as 40 percentage points, relative to an autoregressive benchmark over the horizon 2000-2012.

Regarding the Euro-area, the ECB (2012) provided an FCI that sums deviations of 36 mainly financial variables from their long-run trend and corrects for the business cycle by isolating manufacturing production, inflation and EURIBOR rates. More recently, Angelopoulou et al. (2013) constructed an FCI for the Euro-area and 5 member countries (Germany, Ireland, Greece, Portugal, Spain) for the period 2003 to 2011 using principal component analysis of 24 individual series.[4]

Matheson (2011) constructed an FCI for the US and the Euro area covering 30 and 17 daily, monthly and quarterly financial indicators, respectively, using a dynamic factor model. Including the FCI into a baseline quarterly closed economy VAR (including the output gap, headline inflation, and the real short-term interest rate) improves the forecasting performance over a time horizon of 2 and 4 quarters ahead. The model's mean squared error (MSE) amounts to 79 – 89 % of the MSE of a simple AR forecast, depending on the time horizon and the area (baseline VAR: 102 – 123 %) suggesting that it is well suited for the purpose of forecasting real effects. Like the FCI of Hatzius et al. (2010), the FCI can be estimated when values for some indicators are missing.

Erdem and Tsatsaronis (2013) constructed FCIs for the US, the UK, Germany and Canada using principal component analysis over about 90 variables per country. They then weight the extracted factors by their forecasting power for different macroeconomic variables, such as GDP. There is no assessment how such approaches perform out of sample and the estimated FCIs show surprising pictures, such as rather tight financial conditions in the US in the mid-2000s.

[4] More precisely, the FCI is formed by summing the first *x* principal components weighted by each component's explanatory power, where *x* is the number of principal components that is necessary to explain at least 70 % of the total variance.

FCIs for Emerging and Developing Economies

The FCIs discussed so far highlight that the literature has focused on individual industrialised economies, especially the US. This is manifest due to their leading role in global financial markets and the related issue of data availability. However, there are also recent attempts to construct such indices for emerging market economies (EMEs).

The index of Osorio et al. (2011), for example, covers 13 Asian economies (Australia, China, Hong Kong SAR, India, Indonesia, Japan, Korea, Malaysia, New Zealand, Philippines, Singapore, Thailand, and Taiwan Province of China). For each of them, it calculates two separate indices. The first uses a weighted-sum approach based on Guichard and Turner (2008) and the other one uses PCA based on the generalized dynamic factor model developed by Forni and Lippi (2005). The overall index then takes the simple average of these two indices. The index is available quarterly for each individual country and the authors provide a comprehensive data appendix as well as an interesting comparison between different countries and how the relative contribution of financial variables relates to their development model. The FCIs add to the GDP forecasting performance over a horizon of two quarters. The combination of two construction methods to one average index works well but does not necessarily outperform the individual FCIs.

Akarli et al. (2012) from Goldman Sachs constructed an FCI for seven Central Eastern European, Middle Eastern and African economies (Czech Republic, Hungary, Poland, Russia, Turkey, Israel, South Africa), based on a previous 2010 version of the index. The index covers three domestic (real 3-month interbank rate, 10-year rate less 3-month rate as a proxy for the yield curve, spread between private borrowing cost and risk-free domestic rates) and two external factors (CDS spreads and real effective exchange rate). These stationary components are expressed in real terms and standardised and normalised. They enter the FCI by weights derived from a VAR exercise calculating the cumulative impact on GDP growth after 3-4 quarters. Similarly, Goldman Sachs constructed FCIs for China and India, based on work by Kim et al. (2004, 2007) which uses a vector error correction model to generate the weights for three and four variables, respectively.

Gumata et al. (2012) provided an FCI for South Africa that is based on both global and South Africa-specific financial indicators. Their contribution is also interesting from a methodological point of view because they construct two indices using not only PCA (similar to Hatzius et al., 2010) but also a Kalman filter that should overcome the lack of dynamic (autocorrelation) pattern in the former method. The results, based on the period 1991Q1 to 2011Q4, show that the two indices follow a similar pattern. It seems that the FCI based on the Kalman filter is smoother and responds more sluggishly and captures turning points in financial conditions later. While Granger causality tests for both indices show unidirectional causality from the FCIs to GDP, the PCA-based FCI outperforms the one based on the Kalman filter over a forecasting horizon equal to 1, 2 and 4 quarters ahead in almost all aspects considered. The indices also outperform the South African Reserve Bank's leading indicators as well as all individual financial variables (in case of the PCA-based FCI) with respect to forecasting performance.

Cottani et al. (2012) built a simple indicator using PCA to summarize the state of financial conditions in Brazil, Chile, Colombia and Mexico based on data from 9 different categories. The latter do not only include pure financial shocks but also real factors such as consumer and business expectations and to a large extend credit demand factors. This is in line with their claim to measure other conditions than monetary policy that affect financial conditions and it is instructive to see that their FCIs differ from respective MCIs (calculated as the average of policy rate and exchange rate) since this provides evidence that other international factors can dominate the financial environment. Since their FCI construction involves a large degree of in-sample model selection with respect to the explanatory power for GDP growth, their forecasting performance should not be taken too serious.

Kara, Özlü and Ünalmış (2012) built an FCI for Turkey that weights a number of domestic and foreign variables[5] based on a 4-quarter ahead cumulative response of GDP growth to a one-unit shock to each variable. The weighted sum over the Pearson-standardised series gives their FCI.[6] Their work also emphasises that it makes a considerable difference for the series' weights whether or not one controls for external factors in the case of Turkey.

The Bank of Russia (2013) also uses an FCI to assess financial conditions. It is based on 6 financial series weighted by impulse responses from a VAR model.

Ho and Lu (2013) constructed a VAR-based FCI as well as one relying on factor analysis for Poland and test its forecasting performance for real economic activity. They find that their newly constructed FCI can outperform the OECD composite leading indicator.

Financial Conditions and Financial Stress

So far, we have disregarded work on financial stress and stability indicators. This literature (covering, inter alia, contributions such as ECB, 2009; Gadanecz and Jayaram, 2009; Blix Grimaldi, 2010; Kamada and Nasu, 2011; Ishikawa et al., 2012; Schularick and Taylor, 2012) is clearly related to ours but we consider it to be different in scope. First, financial conditions are not necessarily the same as financial stress. And second, we think that a financial stress index should be concerned about rare but extreme events using an appropriate statistical foundation (such as extreme value theory and Bayesian methods), while financial conditions in general could be seen as measuring a more common, "normal" process. We still mention this strand of the literature because we think that further work is needed on the relationship between financial conditions and financial stress and because of non-negligible methodological contributions in the field of financial stress indicators. Specifically, we want to emphasise the contribution by Holló et al. (2012) because their methodological approach highlights an important aspect. They create a Composite Indicator of Systemic Stress (CISS) for five market-specific subindices from a total of 15 individual financial variables. Besides from using order statistics that are more robust in the context of extreme values, they take into account the time-varying cross-correlation between sub-indices. This emphasises that financial *stress* is more than the aggregate of *conditions* in financial markets. Suppose the financial system provides financial services to different segments of the real sector, e.g. capital to firms and credit to households. Demand for finance will be restricted to the supply in its respective market. For example, households cannot finance their homes by raising capital on equity markets. The relevant financial conditions for the real economy will hence be some aggregation of conditions in these financial markets. The financial sector, however, can adjust supply between different sectors according to the situation in these sectors. If "stress" is high in one sector (i.e. supply is already very high), it will move to another sector. If stress is high in all sectors (i.e. 'systemic'), however, these substitutions are not easily possible anymore. This highlights that stress across markets can exacerbate each other. While Holló et al. (2012) empirically account for this aspect, Korinek et al. (2010) provide a theoretical motivation showing that, when financial stress is relatively low, adverse situations in one market will lead to favourable conditions in another due to

[5] These series are the ratio of annual change in total credit stock to annual GDP, quarterly data for credit standards, the real effective exchange rate, the real ex ante benchmark rate, quarterly capital inflows, the spread between credit and deposit rates, the annual percentage change in the real equity return index, the export weighted global production index (as a proxy of external demand) and the volatility index (VIX).
[6] The Pearson transformation makes the mean of a series equal to 0 and its standard deviation equal to 1.

substitution ('decoupling'), while this is no longer true when financial stress is overall high ('recoupling').[7]

3. Methodology

Based on the considerations above, a financial conditions index should generally reflect the supply of finance that is available to market participants in the real sector for financing their operations. Moreover, it should account for the fact that these conditions are partially endogenous to the business cycle. In the next pages, we explain how we try to meet these challenges. In essence, we first regress each of the included financial series on past GDP growth and inflation, and then take the first principal component from these residual series, similar to the approach of Hatzius et al. (2010). We construct series for eight major non-euro area economies: US, UK, Japan, Brazil, Russia, India, China and Turkey.

<u>Data</u>

We first collect a wide range of financial variables per country. Most of these series are sourced from Haver Analytics. A detailed list of the included variables can be found in Appendix B. They can generally be summarized under the following categories:

- *risk measures*, mainly spreads and often including the relative performance of the financial sector (relative to the overall market or the manufacturing sector)
- *wealth and related collateral*, e.g. returns on stock indices, price-to-earnings ratios, developments of housing prices
- *quantity developments* such as capital issuance, credit developments etc., usually in first differences or percent changes
- *survey data* on credit and lending standards
- *external financial conditions*, mainly proxied by exchange rate developments and the country's bond yield developments and
- *other measures.*

The rationale for including *risk measures* such as spreads or indicators of stock market volatility is relatively straightforward: Spreads, i.e. the interest rate of an asset class relative to another, usually less profitable (and less risky) asset class, measure the relative price at which finance is available to certain market participants. The inclusion of *wealth and other collateral* developments is also standard in the literature and motivated by the fact that households holding higher collateral values will find it easier to borrow against these assets. In fact, the early literature we build on (e.g. Goodhart and Hofmann, 2002), was mainly concerned about the effect of taking into account these wealth effects on optimal monetary policy. The inclusion of *survey data* on credit and lending standards is again straightforward since these surveys are a good indicator how easy it is to get bank credit, which is especially relevant for access to finance in bank-based financial systems. The inclusion of *quantity developments* is somewhat more problematic since they reflect to some degree demand-side conditions. In essence, it could be seen as the ultimate aim of an FCI to explain these quantity

[7] The latter has been the case, for example, after the default of Lehman Brothers in 2008. Consistently, Holló et al. (2012) find that high correlation between the subindices are historically the exception, rather than the rule, "with the period in the aftermath of the collapse of Lehman Brothers clearly standing out in this regard." Similarly, Contessi et al. (2013) find that pairwise correlations between 11 US fixed income spreads were systematically higher during the 2007-2009 crisis period.

developments, for example the credit gap. Nevertheless, in line with the literature[8] we include a few quantity developments, especially those which respond quite rapidly such as corporations' new bond and equity issues, because we find them helpful in assessing how easily agents can finally access finance and even price developments (such as spreads) are not fully free of demand influences.

The relevance and specific role of the *exchange rate* and other external measures depends on the economy, its financial openness and level of development. Generally, an appreciation of a country's currency will make its assets more expensive to foreigners. It might hence be more difficult for domestic firms to issue equity, for example. While the literature on MCIs thus established a negative link between the exchange rate appreciation and financial conditions, a positive relationship is especially manifest for emerging economies where an appreciation can be the result of large capital inflows leading to loose financial conditions and often reflects positive growth prospects of the country with the corresponding appreciation pressures (due to anticipated Balassa-Samuelson effects). Furthermore, a depreciation reduces the value of collateral in foreign currency, so for countries that suffer from the 'original sin' of having to borrow in foreign currency (especially developing and emerging countries), a real exchange rate depreciation should be contractionary (see also Bianchi, 2010; Kara et al., 2012; Gumata et al., 2012).[9]

In choosing the final variables that enter the countries' FCIs, we relied on feedback from the country desks at the ECB and tried to ensure that the variables' loadings on the first factor after PCA, which finally constitutes our FCI (see below), generally correspond to economic rationale.[10] This is especially relevant for policy purposes. Furthermore, we generally sought data that is available as long back in time as possible. To deal with still differing (or partially missing) data coverage, we use iterative methods, more precisely the Expectation Maximization algorithm (EMA) for PCA, as proposed by Stock and Watson (2002b) and described in more detail in Appendix A.

To ensure the stationarity of the variables that is required for PCA, we generally take spreads in levels (Curdia and Woodford, 2010), while stock prices and the exchange rate are in log differences, so that we consider stock returns and exchange rate appreciation/depreciation, also consistent with standard macro-financial modelling. More precise information on the performed variable transformations is given in Appendix B.

Methodology

After gathering and transforming the data, we end up with N financial variables f_i, $i = 1,\dots,N$ for a given country.[11] As discussed above, we would like to purge these variables from those movements that are endogenous to the business cycle. That is, we want to calculate the deviation of these variables from the value one would expect for these variables, given the current state of overall economic conditions. More formally, we want to calculate

$$u_{it} := f_{it} - \mathbf{E}(f_{it} | \Phi_t) \qquad (1),$$

[8] For example, Braves and Butters (2011) include nonfinancial business debt outstanding (relative to GDP) and new US corporate debt issuance in their FCI for the Federal Reserve Bank of Chicago. Hatzius et al. (2010) also include private nonfinancial debt and total bank credit.

[9] This issue also highlights that including the same data across different countries does not ensure a consistent interpretation of financial conditions.

[10] We made an exception for variables for which the loading on the first factor was counter-intuitive but small, while the loading on the second and/or third factor was larger and of the expected direction. Keeping these variables can help improve the interpolation of data gaps which relies on three factors (see Appendix A).

[11] We refrain from introducing country-specific subscripts to keep notation simple and because it will not provide any helpful information.

where Φ_t is the state of the (real) economy at time t (supposing no contemporaneous effect of f_{it} has influenced Φ_t). To make this approach estimable, we model the estimated value of our financial variable as a linear function of past inflation and growth[12]:

$$\mathbf{E}(f_{it} | \Phi_t) = a_i + b_{i1}x_{t-3} + b_{i2}\pi_{t-1} + b_{i3}\pi_{t-2} \qquad (2),$$

where x is the quarter-on-quarter GDP percentage growth rate, π is year-on-year inflation, [13] and t indexes a month. Taking (1) and (2) together, our financial series can be expressed as the sum of its expected value and the financial "shock" u_{it} we actually want to measure:

$$f_{it} = \mathbf{E}(f_{it} | \Phi_t) + u_{it} = a_i + b_{i1}x_{t-3} + b_{i2}\pi_{t-1} + b_{i3}\pi_{t-2} + u_{it} \qquad (3),$$

To calculate u_{it}, we then run a simple OLS regression on (3). From there, we can easily construct the estimated residuals by plugging into (1):

$$\hat{u}_{it} = f_{it} - \left(\hat{a}_i + \hat{b}_{i1}x_{t-3} + \hat{b}_{i2}\pi_{t-1} + \hat{b}_{i3}\pi_{t-2}\right) \qquad (4),$$

which we take as the raw series for our 'conditional' financial conditions index (FCI).[14] Intuitively, these 'conditional' series attempt to measure movements in financial markets that are not endogenous to real or nominal developments but instead isolate exogenous changes in financial conditions. Of course, quantifying the impact of real and nominal developments on financial series is inherently difficult due to the choice of control variables, issues of simultaneity/endogeneity and the simplifying assumption of linearity, particularly given extreme movements of many variables during financial distress. While these difficulties provide scope for future research, our approach should filter out the most relevant cyclical influences and is consistent with methods previously used in the literature.[15]

There is no clear indication in the surveyed literature, which method is best-suited to aggregate the financial variables into a single indicator. Generally, the question is how to weight the individual series to construct an aggregate index. Two broad approaches have been used in this respect.

The first approach weights the financial series by their *contribution to some real outcome* variable, most notably GDP growth. This can be done, for example, intuitively (similar to Guichard et al., 2009), via VAR (e.g. Matheson, 2011), or based on a larger-scale economic model (e.g. Hatzius and Stehn, 2012). The other approach (e.g. Hatzius et al., 2010; Braves and Butters, 2011) extracts the *common movement* among the financial variables themselves, based on some factor model or principal component analysis. Thereby, the weights are attributed according to the contribution that each variable has for explaining all the other variables.

In our view, the first approach has the possible advantage that the interpretation of FCIs would be economically intuitive, which is especially helpful in a policy context, and fairly consistent across countries. For example, a certain change in the FCI by the same magnitude in two different countries

[12] For the US, Giannone et al. (2005) show that two orthogonal shocks that can be identified as inflation and output explain the fundamental business-cycle behaviour of all key variables.
[13] We take q-o-q growth for GDP to incorporate the most recent developments in activity. For inflation, we take y-o-y price changes to ensure there is no seasonality in the data. The lag structure in equation 3 ensures that we regress the financial variable on last quarter's GDP. We want to avoid controlling for real developments which are potentially *caused* by developments in the financial variable. We have to rely on quarterly data because monthly GDP estimates are not available.
[14] We also construct an 'unconditional' FCI that does not do the purging regression from equation (3). For this 'unconditional' version we simply take the f_{it} as the raw series in the following steps, instead of the $\hat{u}_{it}$.
[15] We tested a large variety of lag lengths and reviewed many of the purging regressions in more detail. Some FCIs determine the "optimal lag length" based on some likelihood function, such as the BIC. Our overall impression is that there seem to be some series that are more influenced by the "cycle," while others are less influenced by the cycle. Within this linear framework, the issue therefore is less about the "optimal lag length," but – if anything – about which series to purge and which not. Nonetheless, we found that choices of lag did not make much difference to our overall FCI.

could indicate an expected future change in GDP growth of equal magnitudes for both countries. While such an approach is tempting, it suffers from serious shortcomings. First, it needs a considerable modelling effort for each individual economy which might be advisable when focusing on only one economy but conflicts with our aim to construct FCIs for a wide range of non-Euro area countries. Second, and more importantly, this approach has to assume that the contribution of each financial variable to real output is stable over time. We find this assumption very strict even for advanced economies. The financial crisis has not only emphasised once more the overall relationship between financial markets and the real economy, but that this relationship is manifold and often subject to change. For emerging economies which often experience considerable developments in their financial system, changes in the monetary policy framework and swift financial shocks and regime-changes depending on boom-and-bust cycles in external capital flows, this assumption is even more heroic.

Principal component analysis (PCA) on the other hand has the advantage that it lets the data speak "as it is," by extracting the common movement (the so-called 'factor' F_t) from the observed financial variables. More formally, it is assumed that the 'conditional financial variables' u_{it} can be expressed as a common component consisting of a factor loading λ_i and the factor F_t, together with an idiosyncratic error term e_{it}:[16]

$$u_{it} = \lambda_i{}' F_t + e_{it}. \qquad (5)$$

The conventional approach to decompose the common component into the factor loading λ_i and the factor F_t, is to minimise the quadratic differences between the observed data u_{it} and the common component $\lambda_i{}'F_t$ for all N financial series over the complete sampling period T:

$$\min \sum_{i=1}^{N} \sum_{t=1}^{T} (u_{it} - \lambda_i{}' F_t)^2. \; (6)$$

This estimation via ordinary least squares (OLS) is straightforward, widely implemented, and the required assumptions and statistical properties are well-studied (see e.g. Stock and Watson, 2002a; Bai and Ng, 2008). While in principle up to N factors are estimated, we only focus on the first factor which we take as our FCI. Intuitively, the FCI is hence a weighted average over the N financial variables u, where the factor loadings λ_i constitute the weights and these weights are derived so that the 1-dimensional FCI explains the maximum of variation in all the observed financial variables u.

At this stage, hence, no assumption has to be made about the relationship between the financial system and the real economy. As discussed above, we consider this a major advantage. In fact, summarising the financial variables "as they are" principally allows monitoring the evolving and fluctuating relationship between financial conditions and the real economy over time. As Hatzius et al. (2010) find, there is instability in FCIs' forecasting performance with respect to GDP. While an approach weighting financial variables on structural models or VARs assumes away such instabilities, detecting a "decoupling" of financial markets from real activity can be very informative from a monetary policy perspective. For example, if loose financial conditions do not translate into real activity, this could suggest that the monetary policy transmission channel is disturbed.

That said, there are critiques to the PCA approach as well. One might argue that instead the correlation structure between the financial variables u might change over time (for a motivation see

[16] In principle, λ_i and F_t are k-dimensional objects with $k \leq N$ being the number of factors. For our FCI, we only focus on the first factor, so $k = 1$ and for simplicity one can indeed interpret λ_i and F_t as scalars. Of course, optimisation in equation (6) is done over all factors but we finally focus on the one factor that explains the largest part of the variance in all the data. To iteratively estimate the unavailable observations in our unbalanced panel via the EM algorithm (discussed below and in Appendix A), we take 3 factors.

Korinek et al., 2010) and conflict with our approach of computing a weighted average via PCA. While there is indeed evidence that relations among financial variables change over time (e.g. Holló, 2012, Contessi et al., 2013), a slow-moving change would not impede consistent principal component estimation of the factor F_t and hence of our FCI (see Stock and Watson, 2002a).

A second potential line of critique concerns the selection bias of variables (cf. Dudley, 2010) and the possibility that comovements in financial variables can have directly opposed effects on real activity. For example, Hatzius and Stehn (2012) mention the observation that long-term interest rates typically rise when the equity market rallies. With PCA, these two observations could be interpreted as *one* comovement but would have contrary effects on real financing opportunities. While other methods do not necessarily solve this problem either,[17] our approach is to only include variables with intuitive and interpretable factor loadings.[18] This is especially important in a policy context where economic meaning has to be given to movements in the estimated FCI.

In summary, our method of extracting the common movement across a set of financial variables which are purged from the most important influences of the business cycle allows us to summarise a relevant set of financial indicators into a single index for a wide range of countries. While the method is far from perfect, it has the advantage of tying in with well-known contributions to US financial conditions and extends it to a wider set of countries. Furthermore, we see it as an advantage that the construction method is "data driven" and does not require any assumptions concerning the impact of financial variables on real activity, because these linkages are often subject to change and therefore can themselves be a relevant object of investigation.

To deal with the unbalanced nature of our financial data panel, we use iterative methods. This was necessary because some financial data were not yet recorded at the beginning of the intended sampling period, while other data at the end of the sampling period only become available with a certain lag. Furthermore, there might be some data gaps in the middle of the sampling period. To generate estimated data points for these missing values, the EM algorithm for PCA as suggested by Stock and Watson (2002b) is applied. The algorithm is briefly explained in Appendix A.

Finally, our index is transformed so that the mean over the sampling period is 0, while the standard deviation is 1 ("Pearson transformation").

How should the FCIs be interpreted?

Movements in the conditional FCI could be interpreted as changes in financial conditions that are exogenous to the business cycle. In the standard macroeconomic framework these exogenous financial conditions should capture mainly changes in liquidity preferences of investors, i.e. they translate to shifts of the LM curve that are not directly induced by the central bank's change in money supply nor endogenous to income (which would entail a movement al*ong* the LM curve). If the liquidity preference of investors increases due to an exogenous shock, it will be harder for many firms and households to acquire finance, financial conditions should accordingly tighten and the FCI decline, the LM curve would then shift to the left.

The final Pearson transformation entails that movement in the FCI can be interpreted as changes in these financial conditions relative to the past. For example, a value of 0 means average, or normal,

[17] For example, most VAR studies find a positive initial response of prices on contractionary monetary policy, at odds with economic intuition ("price puzzle").

[18] We made an exception when the loading on the first factor was counter-intuitive but small, see footnote 10. In selecting the relevant financial variables, we relied on the ECB country desk experts. Furthermore, we had no prior on the effects of the exchange rate which exercises different impacts in different countries, as discussed above.

financial conditions (with respect to the sampling period), while a positive value indicates looser-than-average financial conditions, and a negative value indicates tighter-than-average financial conditions. The absolute value of the FCI can only be interpreted with respect to the sample variance of the FCI itself. For example, if one is willing to assume that the FCI is normally distributed, a value greater than 1 would indicate that the FCI is looser than in 84.1% of times.[19]

4. Results

In the following sections, we present our FCIs covering eight major non-euro area economies: US, UK, Japan, Brazil, Russia, India, China and Turkey. We begin with an overview of recent financial conditions and then discuss each country in detail.

The Crisis and its Aftermath: A Global Overview

We start with an assessment of financial conditions during and after the financial crisis of 2007/2008. Our estimated FCIs are depicted in figures 1 and 2 for industrialised and emerging countries, respectively.[20] The FCIs are 'conditional' in that they correct for the state of the business cycle. It can be seen from figure 1 that all three industrialised countries depicted (US, Japan, UK) experienced deteriorating financial conditions from historically loose levels following the bursting of the US housing market bubble in 2007. While there was some recovery towards normal levels in early 2008, conditions worsened considerably after the "Lehman" bankruptcy in September 2008. After a relatively swift (conditional) response in late 2008/early 2009, financial conditions remained relatively suppressed for quite some time, especially in Japan. After some pickup in the aftermath of the second round of quantitative easing by the US Federal Reserve from late 2010, a new contraction was experienced in early fall 2011 amid growing concerns about sovereign debt in some Euro economies. From there, (conditional) financial conditions improved in the US and UK, although in fits and starts. Financial conditions also improved in Japan with a particularly rapid pick-up from November 2012, coinciding with the announcement of elections which heralded a significant change in policy with the new government led by Shinzō Abe.

In emerging economies (figure 2), the deterioration in financial conditions started somewhat later, at the turn from 2007 to 2008, and a significant tightening in financial conditions at the climax of the financial crisis in autumn 2008 is clearly visible, although the magnitudes of the effects varied across economies. In each of the depicted cases, a swift recovery to (conditionally) looser-than-post-2000-average financial conditions is observable, with conditions being relatively favourable in 2009, especially in China. This was reflected in strong credit growth in those economies during that period. For example, year-on-year real credit growth averaged around 24% in China in 2009-10, while it was close to 14 % in Brazil. In the years thereafter, however, (conditional) financial conditions generally moderated as policy tightened and experienced some decline in 2011 (with the exception of India). A modest improvement in financial conditions in most EMEs through 2012 was followed by a swift

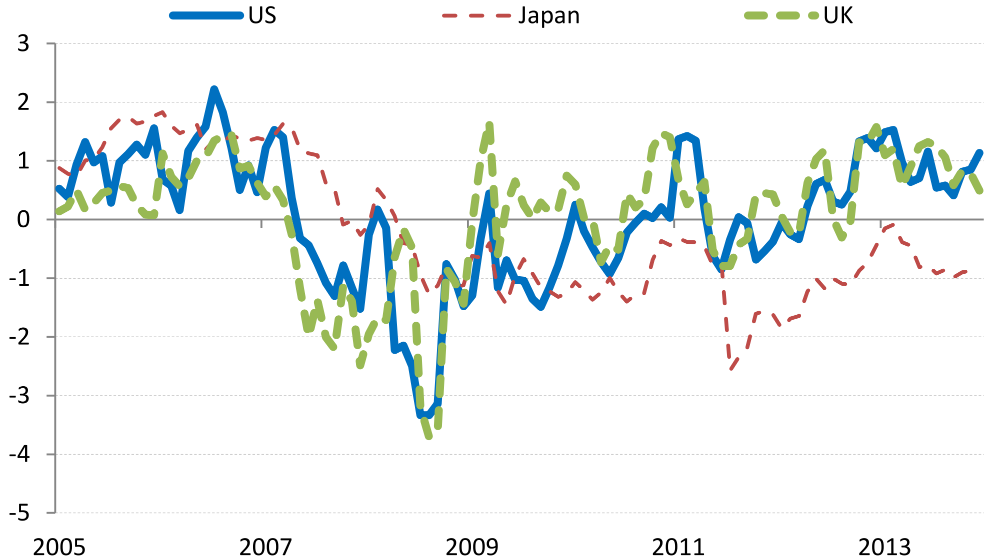
[19] 68.2% of the normal distribution are within one standard error relative to the mean. Disregarding the negative part of the distribution adds another (100-68.2)/2 = 31.8/2 = 15.9 percent.

[20] For the cross-country results presented in this section, we estimate the FCI for the period after 2000. This allows a methodologically consistent comparison across countries, taking into account a large part of the available information, since financial data is not widely available for many countries in our sample in the 1990s. The cut-off in 2000 is of course somewhat arbitrary, but we find it relatively easy to communicate our FCI as measuring financial conditions relative to the "post-2000" average. We depict developments since 2006 to focus on the developments around the 2007/2008 financial crisis in our aggregate view. For the specific country discussions below, we estimate our FCIs over longer time horizons, depending on data coverage.

deterioration from May 2013 amid increased concern about the impact on emerging economies from the possible tapering of Federal Reserve asset purchases.

Figure 1: Financial conditions indices for advanced non-euro area economies

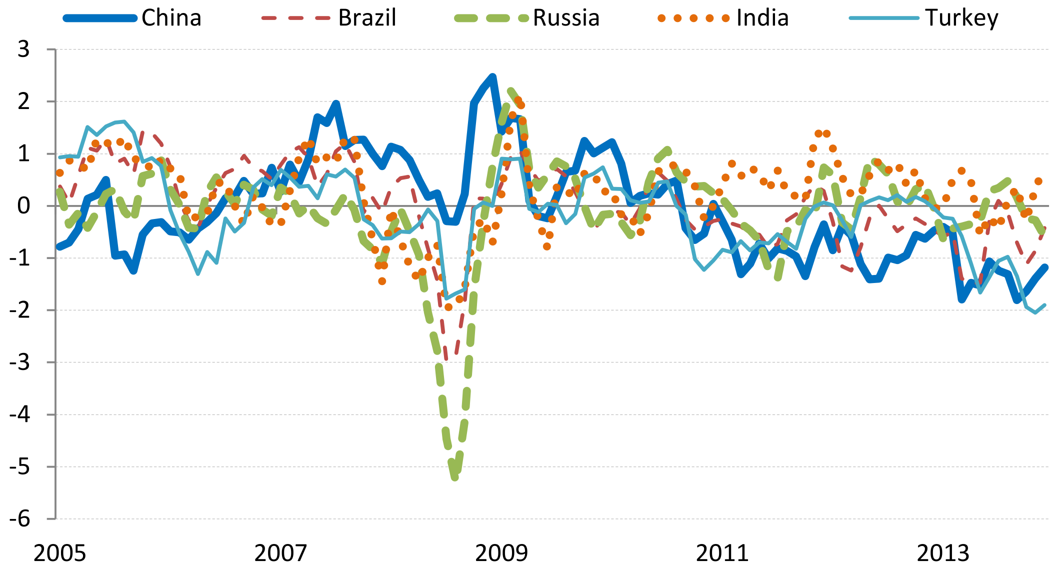
(normalised data)



Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country. The FCIs are 'conditional' and correct for the state of the business cycle.

Figure 2: Financial conditions indices for emerging economies

(normalised data)



Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country. The FCIs are 'conditional' and correct for the state of the business cycle.

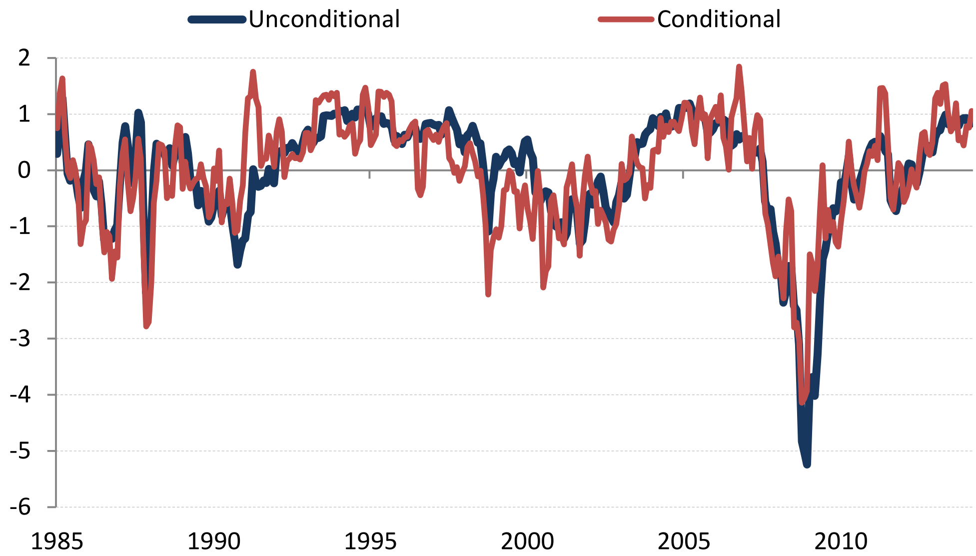
<u>United States</u>

Turning to each country in more detail, in the US, the 2007/2008 financial crisis was clearly the most severe downturn in financial conditions over our sampling period after 1985. The decline is even more severe when looking at the unconditional FCI, which does not purge the impact of the business cycle: it is over 5 standard deviations lower than the long-run historical average in late 2008.

Nevertheless, the US also experienced other periods of rather tight financial conditions with the conditional FCI being more than 2 standard errors below its long-term average. After generally weak financial conditions in the mid-1980s, the "Black Monday" stock market crash on October 19, 1987 led to a decline of the conditional US FCI in November. However, financial conditions recovered quickly and after some more years of financial conditions being rather depressed, they considerably improved over the first years of the 1990s. After some moderation during the mid-1990s, another downward shock was experienced at the collapse of the hedge fund firm "Long-Term Capital Management" by October 1998. After the peak of the NASDAQ index in March 2000, severely tight financial conditions can be observed around July 2000 in the context of the bursting dot-com bubble, while another adverse shock is clearly visible in September 2001. Despite some fluctuations, an overall upward trend can be seen from there, in accordance with the relatively loose monetary policy under Federal Reserve Chairman Greenspan at that time and with the conditional US FCI reaching a 15-year high in October 2006. A significant downward period started when the US subprime mortgage industry collapsed in March 2007. Despite brief upturns in the FCI such as in June 2007 and May 2008, the FCI declined to a trough in October 2008 after the default of the investment bank Lehman Brothers. As indicated above, financial conditions remained suppressed after a relatively swift (conditional) response but picked up somewhat after quantitative easing measures in late 2010 and early 2011. After a new contraction in early autumn 2011, financial conditions improved, rising particularly strongly from the middle of 2012 onwards.

Figure 3: US Financial conditions in Historical Perspective

(normalised data)

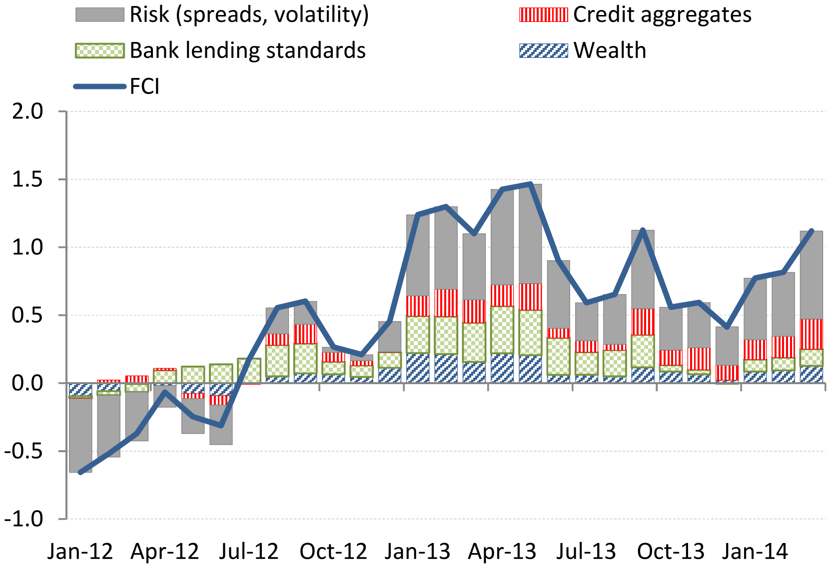


Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

For the US, we also decompose the movements in recent FCI observations into the four sub-categories risk, credit aggregates, bank lending standards, and wealth (see figure 4). This allows us to give more intuition to the driving forces causing movements in the FCI and thereby see whether these movements are due to some single categories or more broadly based. From figure 4, it can be seen that the marked loosening in financial conditions in the US came from improvements across most financial markets since early 2012. Easier lending standards had a positive impact on financial conditions from April 2012 onwards. However, lower spreads and volatility measures made a strong contribution to the overall improvement in financial conditions from early 2013 onwards.

Figure 4: Contribution to developments in the US financial conditions index

(normalised data)



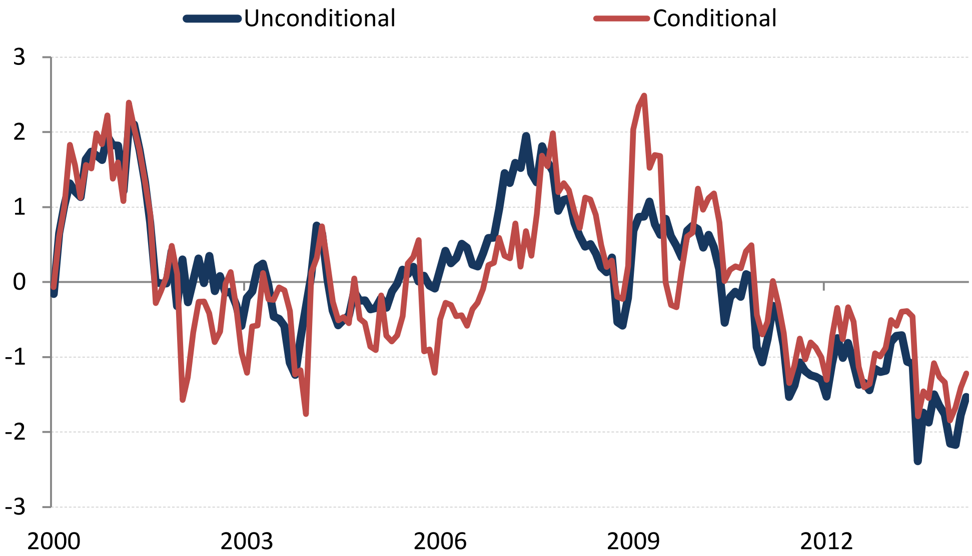
Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

China

After relatively loose financial conditions in the early 2000s, China saw a period of FCI declines after mid-2001 and experienced rather tight conditions thereafter. This reflects especially movements in the real exchange rate which drive these early observations, and a downward trend in the Shanghai Stock Exchange’s PE ratio at that period. Financial conditions improved after 2005, reflecting especially developments in market capitalisation, real estate equities, and the traded value of equities at the Shanghai stock exchange. The conditional FCI for China peaked in the months of August – October 2007, when the PE ratio reached a value of 70 (October) and the index of financial equities in Shenzhen outperformed the composite equity market by 25 % (August). From there, especially equities and mortgages saw a swift decline but stress in the interbank market was also very high at the turn from 2007 to 2008 with the spread between the 120-day to the overnight rate reaching 400 basis points. Most equity categories caught up quickly, however, so that a swift recovery in the conditional FCI is seen in late 2008 / early 2009. High bond yields in early 2009 added to that picture. While above-average financial conditions from December 2008 to November 2010 and the accompanying bold policy action helped to engineer astonishing growth in credit around 24 % (y-o-y) over the 2009-2010 period, a deterioration in financial conditions from 2010 is also clearly visible. This inter alia reflects underperformance of financial equities, and continuously rising spreads. During 2011 and 2012 financial conditions remained relatively tight, compared to the past. More restrictive monetary and macro-prudential conditions may have influenced financial conditions. But the picture also contrasts somewhat with the very strong growth of Chinese total social financing, a broad measure of financing published by the government. One explanation is that, given limitations on data availability, our summary measure of financial conditions in China focuses on traditional financial segments. Our FCI suggests that financial conditions – on traditional forms of credit at least – have been tight by historical standards in the past couple of years. In turn, that may have been one factor behind the rapid growth of so-called shadow-banking products witnessed in China in recent years.

Figure 5: China Financial conditions in Historical Perspective

(normalised data)



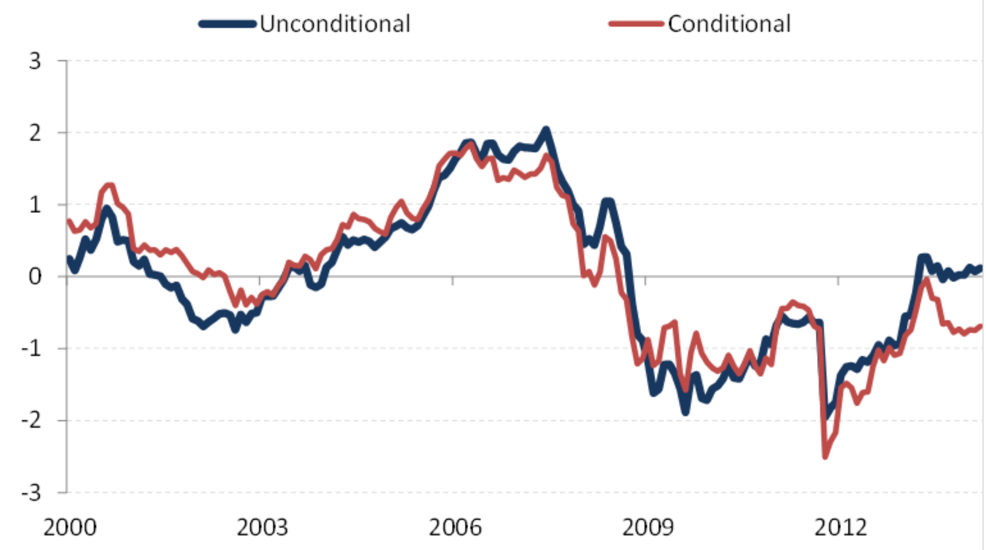
Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

<u>Japan</u>

Assessing financial conditions in Japan over the recent history is inherently difficult due to the specific nature of the “Lost Decade(s)” following the bursting of the Japanese asset price bubble in the early 1990s. Our estimated FCIs, however, pick up the relative recovery that has taken place after 2003. This recovery is relatively widely based on different underlying series. The improvement in financial conditions halted in early 2006 and reversed in July 2007 until late 2008 reflecting global financial trends. Despite some moderation in early 2009, Japan saw rather subdued financing conditions in the three years thereafter, with a very severe downturn in mid-2011 when market capitalisation at the Tokyo stock exchange slumped and bond yields between AA and BBB rated bonds skyrocketed. Following a gradual recovery during 2011 and early 2012, financial conditions have improved markedly from mid-2012. The election of a new prime minister and announcements of “Abenomics” combining short-term fiscal stimulus, large monetary easing and structural reform have seen widespread improvements in financial conditions, which have been reflected in the FCI which surged in the first months of 2013. As shown in chart 6b, wealth measures improved rapidly, as the stock market rose strongly, while credit availability became somewhat easier.

Figure 6a: Japan Financial conditions in Historical Perspective

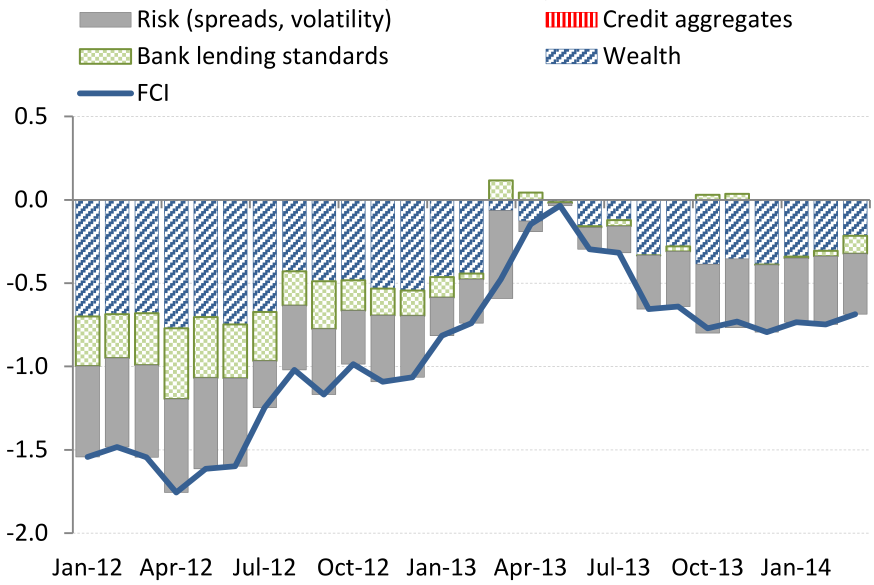
(normalised data)



Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

Figure 6b: Contribution to developments in the Japan financial conditions index

(normalised data)



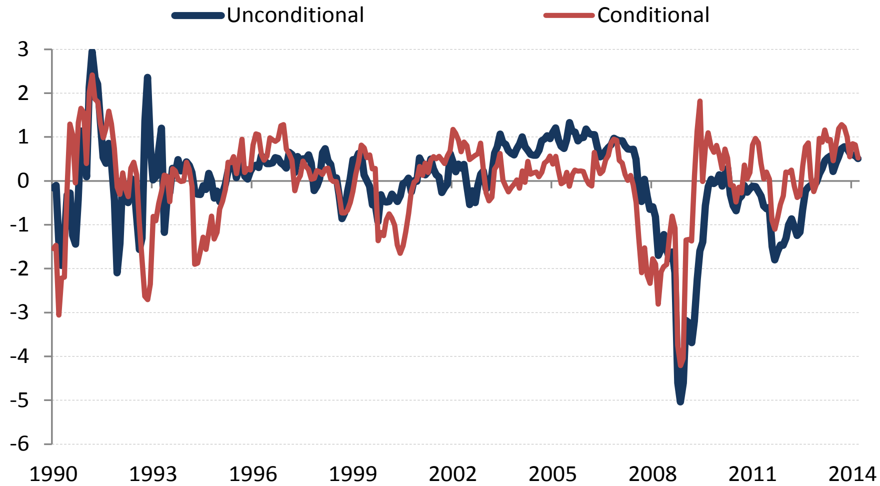
Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

<u>United Kingdom</u>

Looking at UK financial conditions after 1990, the "Black Wednesday" - when the government had to withdraw the Pound Sterling from the European Exchange Rate Mechanism - in September 1992 stands out. Figure 7a also shows some remarkable deviations of the conditional from the unconditional FCI over that period (1992, 1994). This is especially due to the high inflation rates in the early 1990s which rapidly declined by about 500 basis points in early 1992 and q-o-q GDP growth picking up in early 1994, resulting in a conditional FCI that suggests rather tight conditions when taking the business cycle into account. From 1994 to late 1996, UK financial conditions somewhat eased before declining again but generally did not significantly deviate from the long-run average. A favourable exchange rate, wealth effects via housing prices, and low volatility of the FTSE100 equity index contributed to a fairly loose level of financial conditions at the turn from 1996 to 1997. The (conditional) trough from late 1999 to mid-2000 was mainly caused by a relative decline in housing prices and by a historically high 150 basis point spread between the 1-year and the overnight SONIA. By and large, financial conditions were broadly in line with past averages until late 2006, when a financial tightening period started at a relatively early stage, similar to the US and probably reflecting the tight financial and economic relationship between the two countries. The tightening is visible in many of the underlying series, but can especially be seen in spreads between different categories of 3-year corporate bonds (see Appendix B) and in housing price developments. The recovery after 2008 was also rather broad-based. More recently, as shown in Chart 7b, falling spreads and volatility measures have helped to lift financial conditions significantly. At the same time, the rapid improvement in the housing market as well as equity markets contributed to the rise of the FCI in the UK.

Figure 7a: UK Financial conditions in Historical Perspective

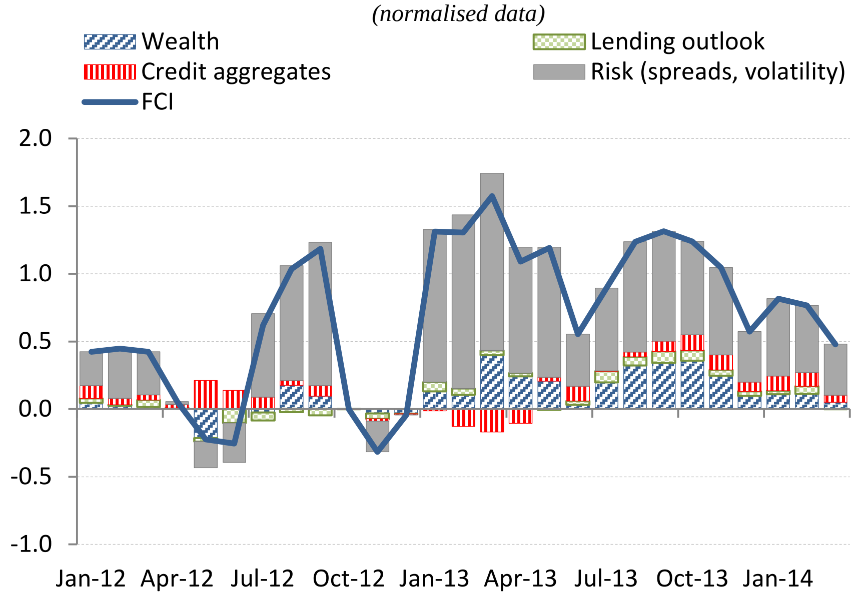
(normalised data)



Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

Figure 7b: Contribution to developments in the UK financial conditions index

(normalised data)



Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

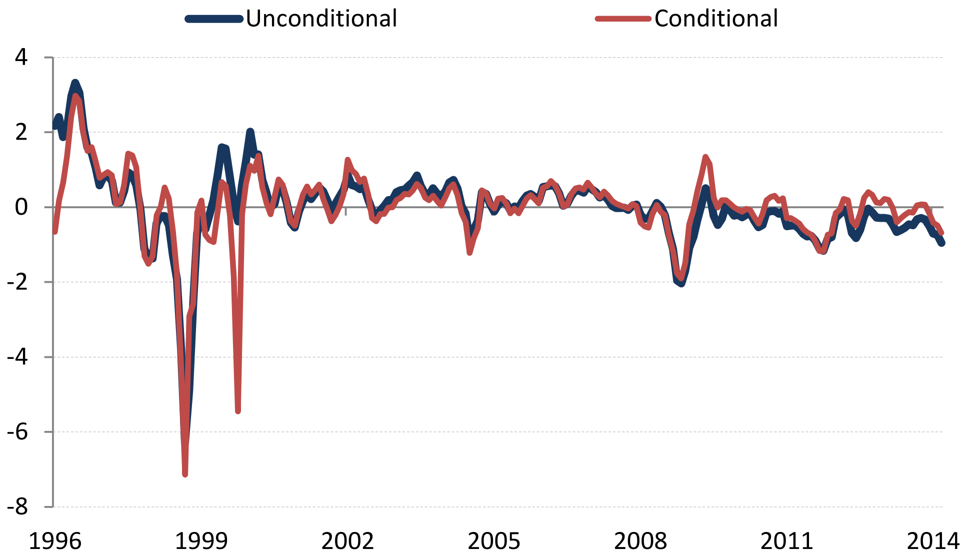
Russia

Perhaps not surprisingly, Russia experienced a more severe deterioration in financial conditions previous to the 2007/2008 financial crisis: the financial crisis from August 1998 which resulted in the devaluation of the Rouble and a default on government debt is clearly visible as the most severe downturn in the FCI, with the conditional FCI hitting lows in August and September, respectively. After the recovery, another setback occurred in fall 1999 when stock and bond markets suffered corrections and associated market capitalisation declined. While these movements were generally much smaller in size, they amplified in the conditional FCI version against the background of high inflation rates.[21]

In the 2000s, Russia's financial conditions were generally moderate, with a fall occurring in mid-2004 when stocks and associated market values declined and especially financials were affected. Furthermore, smaller wealth effects occurred via decreasing bond returns. Compared to other countries, the slump of the 2007/2008 financial crisis started to weigh on Russian financial conditions relatively lately and the recovery path was also somewhat more protracted but generally followed those of other emerging economies (cf. figure 2).

Figure 8: Russia Financial conditions in Historical Perspective

(normalised data)



Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

Brazil

For Brazil, most relevant financial data start in 1994.[22] The sample period started turbulent, with swift changes in the stock and government bond markets. Against this volatile background, the stabilisation programme "Plano Real" was introduced. Generally, the country has seen less volatility in financial conditions since 1994/1995, despite short episodes of considerable turmoil. The turn of the year

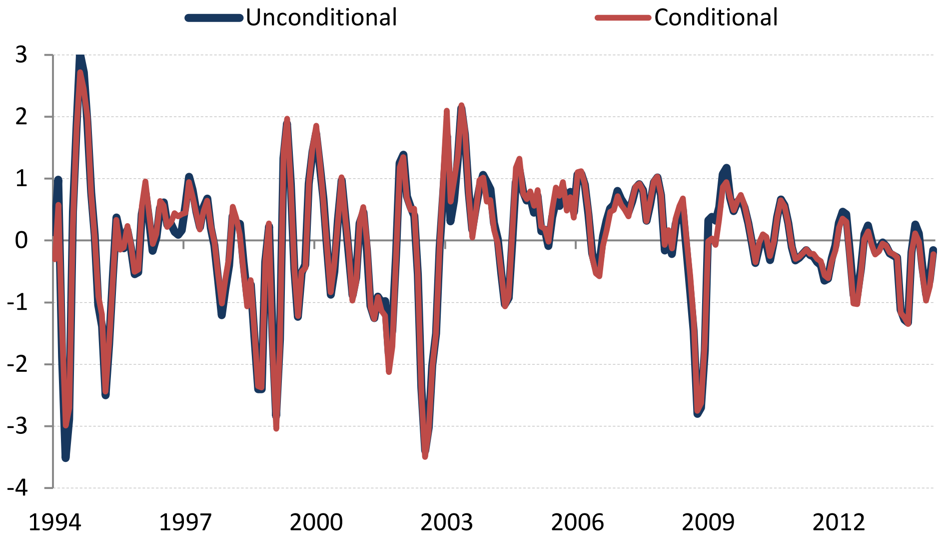
[21] Both regression coefficients are positive in Russia when regressing the unconditional FCI on lagged growth and inflation (cf. equations 3 and 4).

[22] For Brazil, up to 8 financial series are included in the construction of the FCI. Regardless of the sampling period, market capitalisation, stock and bond returns are important drivers of the FCI, but the exchange rate also exercises a considerable influence.

1994/95 itself was shadowed by contagion from the Mexican crisis: from late 1994 to March 1995, the Brazilian stock index, the Bovespa, lost about 40 % of its value (cf. Garcia, 1997). As many emerging economies, Brazil also suffered from spill-overs of the Asian Crisis after mid-1997. The Russian bond default in August 1998 heralded a new wave of investors' risk aversion towards emerging economies which is clearly visible from our index and operated via bond and stock returns, and a corresponding drop in market capitalisation. The country thus suffered from years of reserve-depleting external stress when a mainly home-made financial crisis hit in early 1999 that forced to let the Real float, with a sharp depreciation following suit. This downturn considerably below the long-run average is clearly visible in our FCI as well. From there, financial conditions were mainly neutral until a low was seen in September 2001, driven by stock markets and relatively high swap spreads. This responsiveness of Brazilian financial markets to the global business cycle is not too surprising, considering the country's relatively shallow financial market, the fact that the Bovespa is mainly based on basic materials and energy and that most investors in equities are foreign (Park, 2012).

Figure 9: Brazil Financial conditions in Historical Perspective

(normalised data)



Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

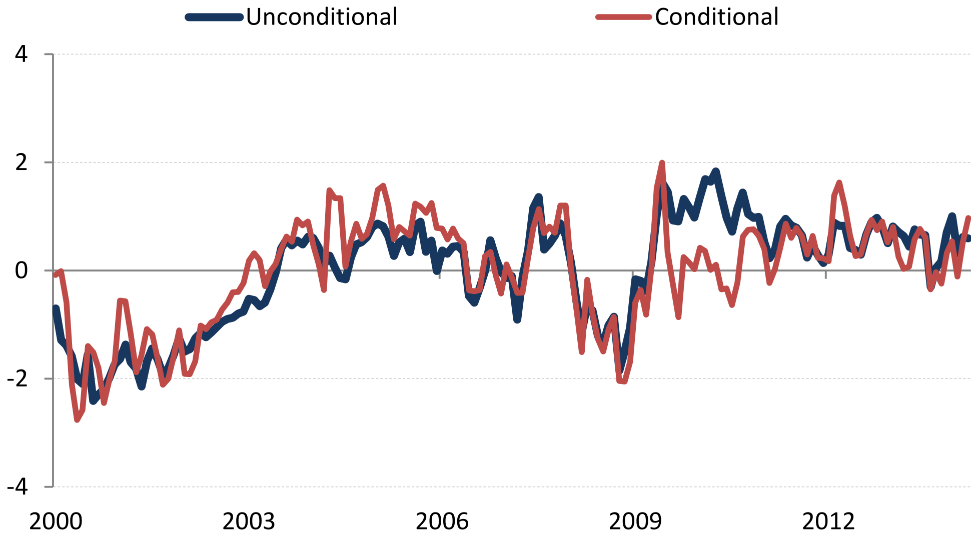
The intensification of the Argentinian crisis in December 2001 did not directly leave a noticeable mark on financial conditions in Brazil, but a depreciating Real in spring 2002 put pressures on bond spreads, possibly fuelled by uncertainties over the upcoming presidential election, which led up to a crash in sovereign bond returns in summer. Swap spreads hiked and banks' financing via money market instruments decreased considerably. Another severe crash of the FCI far below the average occurred. The rebound, however, was relatively quick and by December 2002 the financial system was at average conditions, according to our indicator. From there, conditions were generally moderate, although a similar fall as in Russian financial conditions is visible in mid-2004 (and similarly induced by movements in stocks, market capitalisation and bonds). In the current crisis, Brazil's FCI entered negative territory below -1.0 in October 2008, with a trough in November 2008. In the mid of 2009, financial conditions were already back to supportive conditions and Brazil saw an average year-on-year growth of real credit close to 14 % in 2009 and 2010. While (conditional) financial conditions were close to historical average over most parts of 2012, a sharp deterioration was experienced in mid-2013 when market worries over the Brazilian growth model intensified and large-scale public demonstrations in many Brazilian cities took place.

India

India experienced FCI levels of 2 standard deviations below normal in the early 2000s (mid-2000 and September, 2001) due to weak stock performance, especially of lower-tier equities, and possibly reflecting the breakup to the US dot-com bubble. From there, financial conditions saw an improvement until 2006. The divergence between the conditional and unconditional FCI in this period is due to relatively modest inflation rates.[23] While our FCI does not indicate adverse effects from the bursting of the US housing market bubble (the Indian stock market rose very strongly between March and December 2007), the following deterioration in financial conditions was quite quick. Stock prices declined from early 2008 and the relative fall in house prices intensified from May to November 2008, when the conditional FCI hit a local minimum of -1.8. Similar to Russia, the rebound was somewhat protracted and financial conditions recovered only gradually from 2009 onwards. From 2012 conditions were relatively loose, dipping only temporarily in mid-2013, during the period of turmoil in emerging economy financial market, and recovering strongly since the end of 2013 as confidence in the Indian economy rebounded.[24]

Figure 10: India Financial conditions in Historical Perspective

(normalised data)



Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

Turkey

Not surprisingly, the estimated Turkish FCI shows great volatility in the early 2000s, reflecting a shallow financial system with a politically unstable high yield / high inflation history and macroeconomic imbalances unwinding into a financial crisis. Despite some improvements due to an IMF-supported, exchange rate based disinflation programme launched in late 1999 and the setup of a 'Banking Regulation and Supervision Agency' in early 2000, 5 banks were insolvent in 1999 and three more in 2000 (Özatay and Sak, 2003: table 11). A new IMF credit facility relaxed increasing tensions towards the end of 2000 but the crisis fully hit in February 2001; the interbank market dried

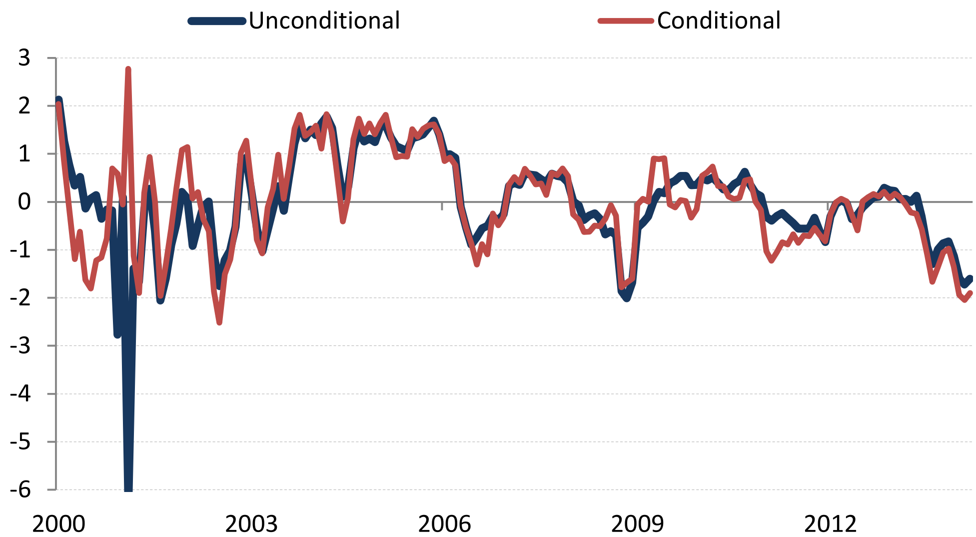
[23] Both regression coefficients are positive in India when regressing the unconditional FCI on lagged growth and inflation (cf. equations 3 and 4). The extremely strong divergence between conditional and unconditional FCI in the second quarter of 2004 is due to the fact that India entered a severe economic downturn in the quarter before (after a quarter of extremely high growth). Considering these weaknesses in the real economy, the conditional FCI therefore indicates very loose financial conditions.

[24] Growth rebounded very strongly in the second quarter of 2009, explaining the subsequent underachievement of the conditional FCI relative to the unconditional one.

up completely and the crawling peg exchange rate regime collapsed. During that period, our unconditional version of the FCI seems to reflect the market tensions better, indicating the trough in February 2001 and still indicating severely tightened financial conditions in March and April, while the conditional FCI even spikes in February but also indicates financial tightness in March and April. The former increase possibly reflects the overall unstable movement in the business cycle during that period.

Figure 11: Turkey Financial conditions in Historical Perspective

(normalised data)



Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

Prudent macroeconomic stabilisation policies since 2003 have generally improved and stabilised financial conditions; market capitalisation and other financial series improved, reflected in rather loose FCI values. A setback occurred during 2006, when concerns rose over widening current account imbalances, increased exchange rate volatility, and rising external private debt (cf. OECD, 2006: ch. 2). As a result, the Istanbul stock market suffered a downward correction, bank lending standards tightened, gloomier expectations were reflected in rising expected interest rates and spreads (consumer loans, commercial loans, Trilibor), and the exchange rate depreciated which generally has a contractionary impact on financial conditions in Turkey (cf. Kara et al., 2012).

After a return to normal financial conditions, the global financial crisis hit soon, where Turkey generally followed the path of other emerging economies (cf. table 2). After remaining at average financial conditions in 2009 and 2010, the new policy strategy that the Central Bank of the Republic of Turkey (CBRT) has introduced in late 2010[25] seemed to have resulted in overall tighter financial conditions. While this might be surprising when having in mind that policy rates were rather low during this period, it possibly reflects the fact that the CBRT uses a variety of policy instruments to achieve its goals (cf. IMF, 2012). From May 2013 onwards, financial conditions deteriorated sharply. Following speculation that the US Federal Reserve intended to begin tapering of asset prices, external financing conditions tightened for several emerging markets and Turkey was particularly affected.

[25] The new framework puts relatively more emphasis on other objectives than price stability, especially on financial stability. See IMF (2012) for a summary.

5. Robustness

In this section, we report the results of two different robustness checks on the stability of our FCIs.[26] First, we show that changing the sampling window does not alter the results, although there might be theoretical reasons for believing so. Then, we show that taking the role of monetary policy on board (either as a supplementary explanatory financial variable or as a purging variable to condition on) also leaves results broadly unchanged.

5.1 Different Samples

Changing the sampling window might theoretically impact the estimated FCIs in (at least) three ways:

1. The correlation structure between the explanatory financial variables might change over time. For example, an included measure for housing prices might be relevant to overall financial conditions after 2002, but not before. Estimating the FCI in the pre-2002 period will thus attribute another weight to this housing price measure than in the post-2002 period. This might potentially have an impact on the FCI.

2. The endogenous response of financial variables to the business cycle might vary over time. This will hence impact the parameter estimates in the purging regression (see equation 4). Assuming that financial conditions did not endogenously respond to the business cycle after 2002 but did so before, taking into account the situation before 2002 would hence incorrectly purge the cycle (at least partially) after 2002.

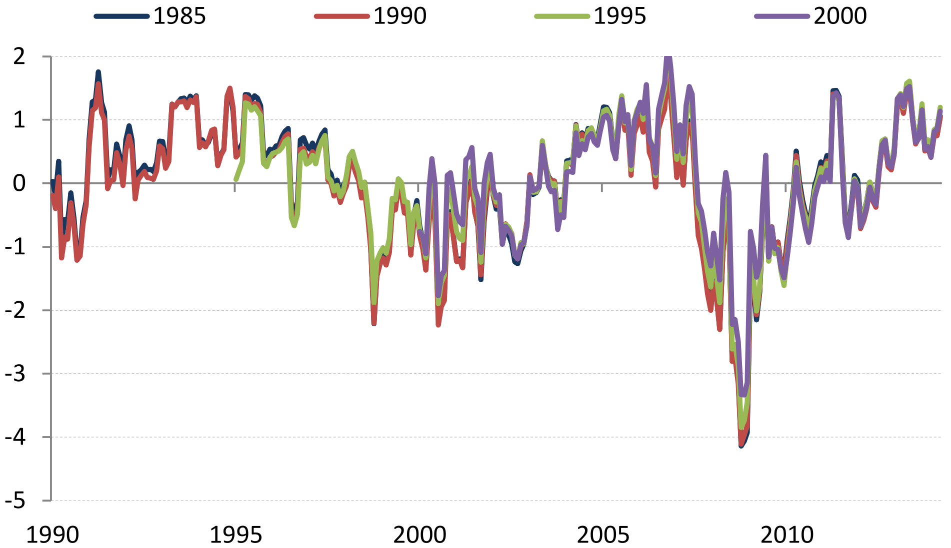
3. Differing data availability across periods might introduce instabilities. For example, an essential financial variable might not be available before 2002 and is hence estimated from the post-2002 sample via the EM algorithm.

Despite these concerns, the results of our estimated FCI barely depend on the sampling window. Figure 12, for example, depicts the conditional US FCI estimated over 4 different sampling periods up to the end of 2012 and starting in 1985, 1990, 1995 and 2000 respectively.[27] While there are small differences in the magnitude of financial developments, the overall story of financial conditions over time remains unchanged.

[26] We furthermore performed other stability checks. For example, we excluded certain series from the set of financial variables. Overall, results were robust, although some instabilities for certain periods may arise for specific variables in single emerging economies.
[27] To keep results comparable, the Pearson-standardisation is based on the period 2002-2012 for all four FCIs.

Figure 12: Robustness of US FCI concerning sample period

(normalised data)

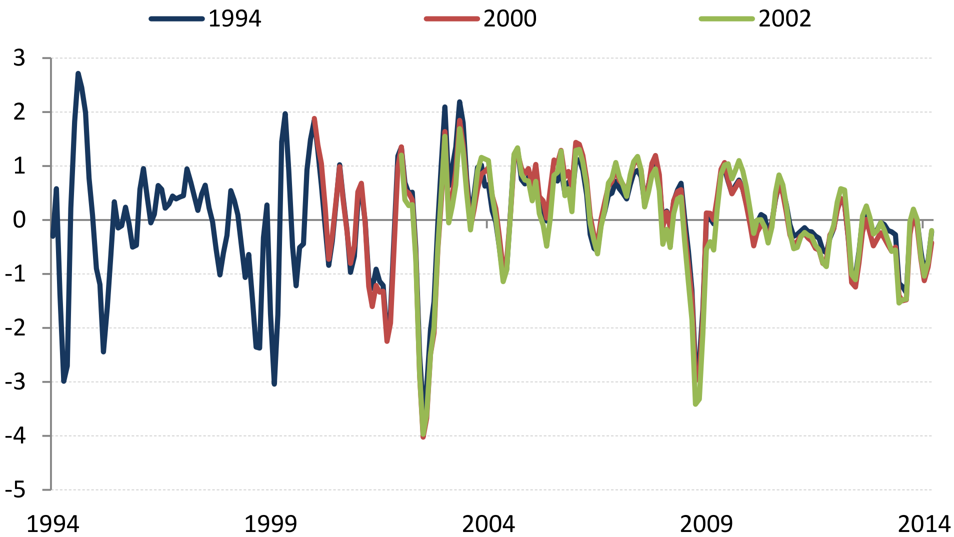


Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

This stability does not only hold for the US but also for other countries, which have seen more significant developments in financial markets over the last decades. In Brazil, FCIs compiled after the year 1994, 2000, and 2002, respectively, similarly lead to very minor differences in the overall FCI estimated (see figure 13). Even China, where major developments have occurred over the last decade, results are remarkably stable (not depicted).[28]

Figure 12: Robustness of Brazil FCI concerning sampling period

(normalised data)



Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

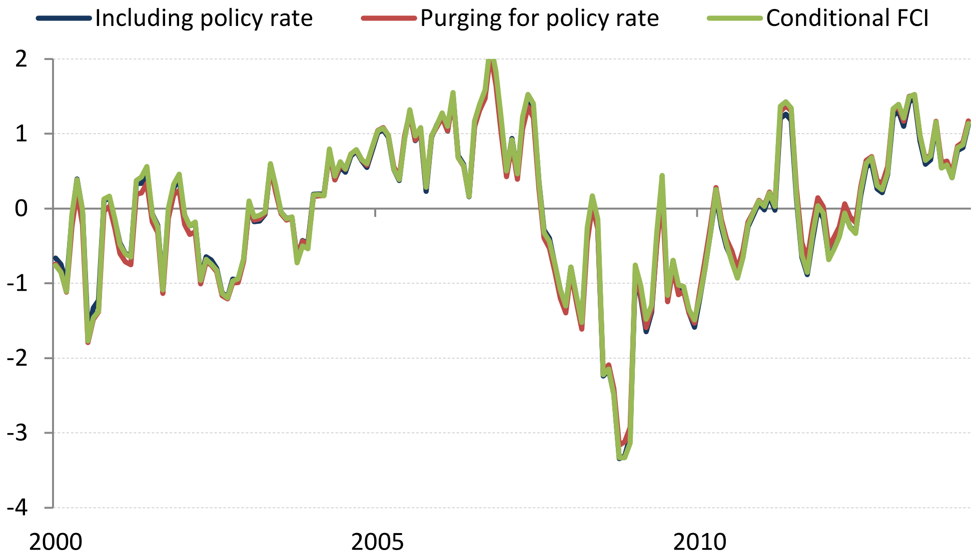
[28] This could only be investigated for subsamples starting in 1999 or afterwards since before 1999 only two financial series are available.

5.2 The Role of Monetary Policy

So far, we have not explicitly considered the role of monetary policy for our FCIs. One may argue that standard instruments of monetary policy might impact those financial conditions we try to capture in our FCIs. There are two possible – contradictory – directions to explore. First, one could be tempted to argue that monetary policy directly impacts financial conditions, i.e. an ease in the policy stance is tantamount to an ease in financial conditions. Accordingly, one would then include the policy rate among the set of financial variables that are used to capture financial conditions. A second approach might be instead to 'purge' our FCIs of any influence on monetary policy. In that approach, one might argue that our FCI should measure those innovations in financial conditions that are not managed by the Central Bank. In that case, we should purge the FCI of effects stemming endogenously from monetary policy – in short including the policy rate alongside inflation and growth in equation 4.

Figure 14: Robustness of US FCI to monetary policy treatment

(normalised data)



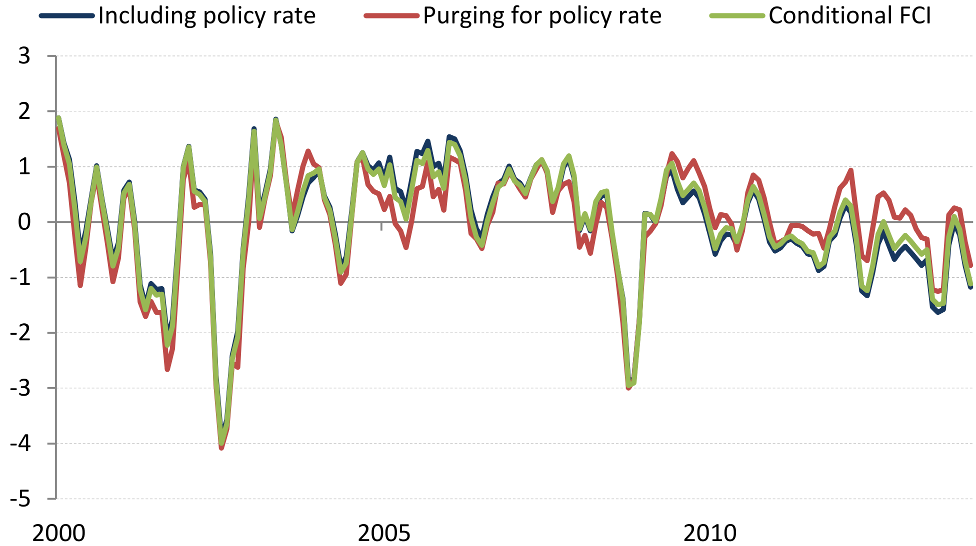
Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

It turns out, though, that adjusting our calculations for these two views of the interaction of monetary policy and financial conditions does not materially alter our results. Again, we depict the results for the US (figure 14) and for Brazil (figure 15). In one case, we include the monetary policy rate amongst our set of financial series (labelled "including policy rate"). In a second case, we instead use the policy rate in our purging equation (labelled "including policy rate"). There is virtually no difference between the three series in case of the US. After some consideration, however, this should not be too surprising. In the first case, where the policy rate is seen as an integral part of financial conditions, it will be sufficiently reflected in the other financial variables, so adding the policy rate itself will not provide much more information. More interesting is the second case of purging the policy rate. One would intuitively expect a change in estimated financial conditions once one takes into account the current (or lagged) monetary policy stance. However, if the Central Bank follows a simple backward looking Taylor rule, controlling for inflation and growth as in equation 4 is sufficient to take the Central Bank's policy stance into account. Accordingly, there is virtually no difference in case of the US, where the Central Bank's mandate focuses on these two variables and where the monetary policy reaction function is hence sufficiently described by them.[29]

For other emerging economies including the depicted case of Brazil, the difference between the different FCI measures is fairly small as well. While the overall development of the indices tells the same story about financial conditions, there are some periods where the levels of the FCIs somewhat differ. In the Brazilian case, this especially concerns the period around 2005 and from 2009 to 2011, but similar differences can occur in other emerging economies over different periods as well. Again, this should not come as too much a surprise: the key determinant of the Central Bank's reaction function will still be highly correlated with inflation and growth. However, especially in emerging economies there might be periods when other concerns (such as the exchange rate or financial stability considerations) come into focus which could behave orthogonal to inflation and growth – e.g. movements in the exchange rate that are induced by capital inflows which respond to push factors in their source country and therefore might have few correlation with the host country's business cycle.

Figure 15: Robustness of Brazil FCI to monetary policy treatment

(normalised data)



Note: FCI is the first principal component of a series of financial indicators. A level of 0 indicates average financial conditions in that country.

In such environments, however, purging on the policy rate can give a very misleading picture of the monetary policy stance because Central Banks also address these concerns via "non-standard" instruments (such as foreign exchange interventions or reserve requirement ratios, see e.g. Ostry et al., 2012, or Glocker and Towbin, 2012). This is reflected in current work by Magud and Tsounta (2012) who point out that the use of macroprudential policies in Brazil and Peru affects the estimated neutral real interest rate, possibly through their effect on credit conditions.

Overall, we therefore conclude that not purging monetary policy is less susceptible to potential problems arising from shifts in instruments used by the Central Bank to influence financial conditions. Correcting for inflation and growth should absorb most movements in the Central Bank's policy stance and hence implicitly controls for monetary policy, no matter what instrument is used. In essence, this approach induces an omitted variable bias which implies that the exact parameters (for

[29] This line of reasoning also holds if the Central Bank responds to more macroeconomic variables which could themselves be expressed (or approximated) as a linear function of inflation and growth (cf Giannone et al., 2005).

inflation's and growth's impact on financial conditions) in equation 4 cannot be correctly identified but that they also implicitly take on board the monetary policy stance. Controlling for individual policy instruments, such as the policy rate, on the other hand will only partially account for the monetary policy stance if there is a shift to other policy instruments, which is especially the case in the environment of the lower-bound interest rate or in many emerging economies.

6. Forecasting Performance

In this section, we assess the forecasting performance of our newly constructed FCIs. Therefore, we estimate the following functional form of a growth forecasting model:

$$g_{t+h} = a + \sum_{i=1}^{P} \theta_i g_{t+1-i} + \sum_{i=1}^{Q} \beta_i X_{t+1-i} + \varepsilon_t, \qquad (7)$$

on a quarterly basis, similar in fashion to, inter alia, Bernanke (1990), Hatzius et al. (2010), and Osorio et al. (2011), and where g is the growth rate of GDP over the relevant quarter. More specifically, we compare the following models:

1. a "simple-mean" model, i.e. the parameters for all θ and β are restricted to be 0. Since this is the most restricted model we consider, it is also our "benchmark" against which we compare the forecasting performance of all our other models.
2. a "random walk" model, i.e. $P = 1$ and the parameter restrictions are $\theta_1 = 1$ and $\beta = 0$ for all β.
3. an AR(1) model, i.e. the parameters for all β are restricted to be 0 and P=1.[30]
4. the FCI model, i.e. X stands for some form of our newly constructed FCI, and the other parameter restrictions are $\theta = 0$ for all θ and Q=1.
5. the AR(1) augmented with our unconditional FCI.[31]

For the FCI model, we consider 4 different versions of the FCI:

4a. the conditional FCI from the last month of the respective quarter
4b. the unconditional FCI from the last month of the respective quarter
4c. the conditional FCI averaged over the respective quarter
4d. the unconditional FCI averaged over the respective quarter

6.1 Out-Of-Sample, Rolling Window and In-Sample Significance

Our assessment of the forecasting performance should respect the fact that only information up to period t could be used when forecasting $t+h$ in period t. Optimally, this means that we estimate the FCI up to period t, then estimate the coefficients of model (7) up to period t and forecast g_{t+h} based on this model.[32]

However, data limitations – principally the availability of many of the financial series in the past – limit the extent to which we can conduct 'true' out of sample forecast evaluation. For the US, the UK and Russia where we can create a forecasting window of reasonable size, we conduct an out-of-

[30] We also tried deeper lags of AR models but overall results were most encouraging for the AR(1) model. This does not mean, however, that deeper lags do not perform particularly well for single economies. To keep the discussion clearly represented, we limit it to the AR(1) model.
[31] This model is only applied to in-sample regressions to check the statistical significance of the FCI variable.
[32] This does not consider the fact that GDP data might be revised after time t.

sample evaluation.[33] For the remaining countries, we do a *rolling window* forecast. That is, we first estimate the FCI for the whole period 1997 until the end of 2012, although this would not have been feasible before the end of 2012. However, our robustness check in section 5.1 suggests that the estimated FCI is relatively stable for many periods, with respect to the sampling horizon, so we consider this a reasonable approach. From there, we estimate model (7) over the last 4 years at each time period *t* (starting with 2001) and compute the forecasts from there. This approach also allows us to compare the performance of our newly constructed US FCI to the one computed by the Chicago FED (cf. Braves and Butters, 2011).

In conducting an assessment of forecasting power, it is important to remember that in real time there might be missing values or publication lags that do not exist in our backward-looking exercise. However, this does not appear to be a severe problem for our forecasting exercise as financial series are typically available in a timely manner. Only a few of the series included in our FCIs are published with a significant lag[34] and as discussed in section 5, our FCIs are mostly robust to the exclusion of single variables (see footnote 26). Furthermore, one should note that GDP data mostly come in with a much higher publication lag and are often subject to major revisions. By treating these data as given and comparing our FCI to the mean, AR and random walk models, we potentially even favour the non-FCI models. Finally, one should note that we are conducting quarterly forecasting exercises, i.e. even if financial variables would come with several weeks of delay, our FCI would still incorporate some information about this variable in real time.

6.2 Assessment Metric

For the out-of-sample and the rolling window forecast, we use a relative root mean squared error (RRMSE) to assess the forecasting performance. Therefore, we first compute the root mean squared error between the growth values g^* predicted by model 7 and the actually observed ones (g):

$$RMSE = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(g_t^* - g_t)^2}. \qquad (8)$$

For each of the forecasting models outlined above, these RMSEs are then expressed relative to the benchmark mean model 1 (or relative to the Chicago Fed, where this is the relevant benchmark) and denoted RRMSE.

For our forecasts based on FCIs, we then also investigate whether their forecasting performance is statistically different from the AR(1) model in the Diebold-Mariano (1995) sense by regressing the difference (between the FCI and AR model) of squared and absolute forecasting errors, respectively, against a constant (using Newey-West standard errors to correct for autocorrelation). If this constant is statistically significant, we can reject the null hypothesis of equal predictive accuracy (thus, the model with the lower forecasting error is significantly better).

[33] The out of sample forecast in case of unbalanced panel data requires that at least as many observations as purging regressors are available for all series. In many cases, some financial series do not start long enough before the recent financial crisis, so the out-of-sample forecasting window would be arguably small and fall mostly into a period (i.e. post 2007) which can be considered a singularity. In case of the US, the LIBOR-OIS spread starts in December 2001, so FCIs can be computed where 2002Q1 is the endpoint. This means that a one-quarter and a four-quarter ahead forecast can be derived for 2002Q2 and 2003Q1, respectively. We let the FCI estimation start in 1985 to roughly cover the Great Moderation. For the UK and Russia, latest series available start in September 2004 and January 2003, respectively. Accordingly, forecasting windows start later than in case of the US.

[34] These are mainly some credit variables and surveys of credit conditions (e.g. the Federal Reserve Senior loan officer Survey).

6.3 Results

Table 1 summarises the RRMSEs of our out of sample forecast for the US, the UK, and Russia for the horizons h=1, 4 quarters ahead. As table 1 shows, all variants of our FCI perform very well when forecasting GDP growth for the next quarter. Focusing on the average conditional FCI, it outperforms the mean-model in all three countries by reducing the RRMSE by as much as 32 percent (in case of the UK), and falls slightly short of the AR model only in case of Russia. However, it is also true that any improvement over the AR model is not statistically significant in the Diebold-Mariano sense. Also, over a longer forecasting performance of h=4 quarters the good forecasting performance of our newly constructed FCIs diminishes. Generally, the forecasts taking into account the FCIs perform similar to the mean or the AR model. For the time period in between (not shown in the table), especially the conditional US FCI performs well, outperforming the AR model over h=2 and h=3. For different time horizons up to h = 8 quarters ahead and time windows starting later than 2002, the forecasting performance of our US FCIs is generally solid and rarely falls more than 10 % short of the AR model.

Table 1: RRMSEs for Out of Sample Forecast

		US		**UK**		**Russia**	
		h=1	**h=4**	**h=1**	**h=4**	**h=1**	**h=4**
1	**mean**	1.00	1.00	1.00	1.00	1.00	1.00
2	**random walk**	0.92	1.26	0.67	1.27	0.56	1.44
3	**AR**	0.85	1.01	0.68	1.02	0.65	1.01
4a	**last month FCI conditional**	0.84 [0.60/0.25]	1.01 [0.67/0.57]	0.70 [0.22/0.64]	1.06 [0.02/0.02]	0.66 [0.58/0.80]	1.02 [0.63/0.80]
4b	**last month FCI unconditional**	0.75 [0.31/0.39]	1.03 [0.61/0.73]	0.67 [0.40/0.29]	1.01 [0.80/0.43]	0.66 [0.74/0.55]	1.03 [0.59/0.72]
4c	**average FCI conditional**	0.81 [0.36/0.85]	1.00 [0.68/0.55]	0.68 [0.86/0.88]	1.07 [0.05/0.02]	0.70 [0.22/0.42]	1.02 [0.45/0.51]
4d	**average FCI unconditional**	0.76 [0.33/0.61]	1.06 [0.80/0.54]	0.65 [0.29/0.28]	1.02 [0.85/0.36]	0.69 [0.31/0.84]	1.03 [0.45/0.93]

Note: FCIs estimated from 1985 onwards for the US, 1990 onwards for the UK and Russia. The first forecast is for 2002Q2 (US)/2005Q2 (UK)/2004Q2 (Russia);[35] the latest for 2013Q4. Numbers in parentheses below the FCI RRMSEs are p-values of the Diebold-Mariano test for equal forecasting accuracy as the AR model using squared and absolute forecasting errors, respectively.

Overall, these results suggest that our FCIs perform especially well over a short forecasting horizon. Whether the unconditional or the conditional version of our FCI better helps to forecast GDP developments depends on the country and the forecasting horizon. Although our FCI does not necessarily outperform all the other forecasting models in this setting, it has the potential advantages that it adds an economic intuition by explaining forecasts based on current developments in financial conditions and that it might perform better in real time because GDP data come in with some delay and are often subject to substantial revision (which will impact especially the random walk and AR but to some degree also the mean model) while financial data is usually available very timely.

[35] This refers to the h=1 forecast. For the h=4 forecast, 3 quarters have to be added.

As historical data availability is constrained in many countries, table 2 shows rolling window forecasts for those countries where we were not able to compile an out of sample FCI estimate for early-enough time periods. The results for the US, UK and Russia allow a comparison with the out-of-sample forecast. They show similarly encouraging results for forecasting over h=1 quarter ahead, but less so for h=4 quarters ahead. Possibly, the fact that estimation is only based on sixteen observations introduces an especially large instability for the h=4 quarter ahead forecast.

Generally, the results of this exercise show again that the forecast including the FCI for h=1 quarter ahead works particularly well for the US, UK, and Russia and also reasonably well for most other countries, where the FCI models perform similar to the AR model. Again, the forecasting performance for h=4 quarters ahead is less appealing.

Table 2: Rolling Window Forecasting Performance (RMSEs relative to mean model)

	US		China		Japan		UK	
	h=1	h=4	h=1	h=4	h=1	h=4	h=1	h=4
mean	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
random walk	0.87	1.28	1.25	1.27	1.16	1.56	0.80	1.40
AR	0.95	1.09	1.07	1.04	1.10	0.98	0.79	1.09
last month FCI conditional	0.92	1.12	1.13	1.09	1.14	1.13	0.76	0.96
last month FCI unconditional	0.91	1.24	1.08	1.11	1.15	1.13	0.86	1.12
average FCI conditional	0.94	1.16	1.14	1.03	1.14	1.16	0.78	1.03
average FCI unconditional	0.95	1.31	1.08	1.07	1.16	1.10	0.94	1.29
	Russia		Brazil		India		Turkey	
	h=1	h=4	h=1	h=4	h=1	h=4	h=1	h=4
mean	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
random walk	0.79	1.43	1.16	1.59	1.36	1.50	1.14	1.53
AR	0.85	1.10	1.12	1.00	1.09	1.05	1.10	1.00
last month FCI conditional	0.69	1.28	1.28	1.04	1.10	1.07	1.05	1.01
last month FCI unconditional	0.73	1.27	1.25	1.07	1.07	1.08	1.01	1.01
average FCI conditional	0.87	1.36	1.18	1.11	1.07	1.08	1.08	1.03
average FCI unconditional	0.89	1.35	1.17	1.11	1.04	1.10	1.00	1.04

Note: Sampling period: 1997Q1 to 2012Q4. Parameters of the forecasting model are estimated over four years back in time, the first forecast is thus generated for 2001Q1.

When comparing the rolling window forecasting performance of our US FCI with the US FCI compiled by the Chicago Fed FCI, our newly constructed FCI performs reasonably well, especially for h=1 quarter ahead and if the averages over a quarter are taken (see table 3). With respect to the forecasting RMSE, our FCI outperforms the one of the Fed over this time horizon but performs worse for h=4 quarters ahead, especially if the last month's conditional FCI is considered.[36]

Finally, we also checked for the marginal significance of our conditional FCI in an augmented AR(1) model, as described as model 5 above, using in-sample estimation. Our newly constructed FCI adds explanatory power supplementary to an AR(1) term in the sense that its marginal impact is different from 0 for the US, the UK, and India, on the 10 percent, 5 percent, and 1 percent level of statistical significance, respectively. It is not statistically significant for the other countries. This can mainly be due two reasons: either, financial conditions do not significantly influence real economic fluctuations

[36] Due to better data availability in case of the US, our first window of estimating the relationship between FCI and growth ranges from 1987Q1 to 1992Q4 and the according forecast is created for 1993Q1 and 1993Q4 for h=1 and h=4, respectively. The window then moves forward quarter by quarter until the forecast of 2012Q4 is reached.

additionally to real developments themselves in those countries (e.g. because financial systems are relatively underdeveloped), or there is mismeasurement present. The latter can take the form of inadequately constructed FCIs, or be due to GDP data itself being noisy. Without excluding the former possibility, the latter seems to be a problem, as in those countries where our FCI is not statistically significant, the overall model (hence also the AR part) performs poorly. In case of Japan and Turkey, the augmented AR model only obtains an R-squared of 0.08 and 0.01, respectively. In case of China, Brazil, and Turkey, the AR term itself is not statistically significant at the 10 percent level. This suggests noisiness of GDP data over short time horizons in those countries.

Table 3: Rolling-Window Forecasting comparison to Chicago Fed FCI (RMSE relative to the latter)

	h=1	**h=4**
last month FCI conditional	1.01	1.17
last month FCI unconditional	0.97	1.08
average FCI conditional	0.91	1.02
average FCI unconditional	0.88	1.03

Note: Sampling period: 1997Q1 to 2012Q4. Parameters of the forecasting model are estimated over four years back in time, the first forecast is thus generated for 2001Q1.

6.4 Summary of forecasting results

Overall, the forecasting performance of our newly developed FCI is particularly good for the US for short forecasting horizons. Results for the UK are similar, while the findings for other countries are more mixed. Less encouraging results for specific countries do not necessarily imply a badly designed FCI but could also be due to other facts:

1. Maybe, the relationship between the financial and the real sector is weaker (or more volatile) in these countries.

2. Maybe, the sampling period is too short. For the rolling window forecasts, we had to rely on parameter estimates based on quarterly data for 4-year periods which necessarily leads to imprecise estimates of the forecasting model. Furthermore, financial data availability for some countries included is relatively poor before the mid-2000s.

3. The regressions underlying the forecasting exercise could be subject to potential misspecification. For instance, the obtained results do not clearly favour one variant of our FCI, suggesting that different aspects and lag structures of our FCIs could be relevant for different countries. Similarly, it has to be investigated on the country level what optimal combination of AR terms and FCI lags performs best.

By and large, the obtained results suggest that our newly constructed FCIs can help forecast short-term real developments but that the relationship between financial conditions and these real developments is not that straightforward and more modelling efforts seem to be appropriate for certain economies.

7. Conclusion

In this paper we constructed and presented financial conditions indices (FCIs) for 8 major non-Euro area economies (US, China, Japan, UK, Russia, Brazil, India, Turkey) by means of principal component analysis (PCA). These FCIs summarise a set of underlying financial variables and are furthermore conditional on the business cycle, i.e. they aim to capture developments in financial conditions that are exogenous to most important real developments.

Contrary to most other indicators based on PCA, which suffer from the "black-box" properties of this method, we can give an intuitive economic interpretation to movements in our FCIs which also allowed us to trace back developments in financial conditions in the mentioned economies over the last decades and interpret major shifts in the estimated FCIs. On the other hand, basing our FCIs on PCA prevents the potential problems of other methods which generate weights for variables based on their contribution to GDP which might be unstable over time. In fact, we see such potentially changing relationships between the financial and real sector as one of the most important issues to address in future work on the assessment of financial conditions (see also Hatzius et al., 2010, Hubrich and Tetlow, 2012). In this context, it could also be of interest to compare differences in real effects between supply-driven shocks in financial conditions and demand-induced changes (see also Chen et al., 2012).

We also showed that different approaches of considering the role of monetary policy for our FCIs do not considerably change the results and provided an economic rationale for this finding. We argued that controlling for the monetary policy rate can be problematic in the lower-bound interest rate environment and in many emerging economies because the policy rate only captures a fraction of the policy stance in these cases.

Furthermore, we showed that our FCIs can help predict short-term real developments in major non-Euro area economies, thereby providing an important policy tool for near-term assessment of the external environment of the Euro area.

For what concerns future work, a broader view of prevailing financial conditions can be particularly important when the monetary policy stance is not straightforward to assess. For example, the monetary policy rate can no longer serve as the sole indicator of the monetary policy stance when the zero-interest-rate bound becomes binding, as it has been the case in many advanced economies over the last years. A similar rationale applies for many emerging market economies, where central banks often use a variety of policy measures besides from the policy rate, switch from one instrument to another (as the recent focus on the repo rate in China) or where the overall policy strategy of the central bank shifts (as for Turkey in 2006 or more recently Russia). We leave considerations on the interaction between such non-standard monetary policy measures and financial condition indices to future work.

APPENDICES

Appendix A: The Expectation Maximisation Algorithm (EMA)

The EMA is a classical algorithm to deal with missing (or censored) information in statistical computing. While the applicability of the algorithm to a wide class of problems is known since the late 1970s, it was first applied to PCA in econometrics by Stock and Watson (2002b).

The main idea is to repeat two steps until convergence (i.e. until the steps do not lead to a 'significant' improvement):

1. In a first, 'expectation' step, the missing observations are filled with those values one would expect from the model, given the available information.
2. In the second, 'maximisation' step, these estimated values are used to re-estimate the model's parameters so that the likelihood of the data under the model is maximised.

This algorithm is designed to minimise the distance between the data X and the estimates from the factor model:

$$\min_{F,\Lambda} V^{+}(F,\Lambda) = \sum_{i=1}^{N}\sum_{t=1}^{T} I_{it}(X_{it} - \lambda_i' F_t)^2, \qquad \text{(A.1)}$$

where I is the indicator function with $I=1$ if X is available and 0 otherwise.

More precisely, in the very first step, all missing observations are filled with a 0, which is the unconditional expectation (due to the Pearson-standardisation). From there, the factors and loadings of the model are estimated. The first three factors are used to update those initially missing observations (which were filled with 0 in the very first step) by multiplying the factors with the respective loadings. This updating is carried on until convergence is reached.

Appendix B: Series and their Factor Loadings by Country

Note: Factor loadings are based on estimation from 2000 - 2013

US FCI

Abbreviation	Series Explanation	Loading	Haver code & Transformation
HOUSEPRICE	CoreLogic national HPI development	0.12	log(uslphpis) -log(uslphpis(-3))
NASDAQ	Nasdaq Index development	0.10	log(spny) - log(spny(-3)
NYSE	NYSE index development	0.18	log(spna) - log(spna(-3))
WILSHIRE PRCIDX	Wilshire 5000 Price Index development	0.16	log(spwi) - log(spwi(-3))
USD EXRAT	real broad trade-weighted exchange value of USD, qoq log differences	-0.10	log(fxtwbc) - log(fxtwbc(-3))
BANKS TIGHT	Residental Mortages: net share, banks tightening (FRB Sr. Loan Svy)	-0.19	ftcnmh
CONSLEND WILL	Bank willingness to lend to consumers (FRB Sr. Officers Survey)	0.20	fwill
CREDIT TIGHT	percent reporting that credit was harder to get last time, net (SA %)	-0.10	nfib20
TIGHT COMREALEST	Tightening standards for com. Real estate (FRB Sr. Loan Svy)	-0.21	ftcre
TIGHT LARGE	Banks tightening C & I loans to large firms (FRB Sr. Officers Svy)	-0.22	ftcil
TIGHT SMALL	Banks tightening C & I loans to small firms (FRB Sr. Officers Svy)	-0.23	ftcis
MONEY STOCK	Money Stock Zero Maturity, HP-detrended	-0.12	fmzm - fmzm hp
SP PERATIO	Robert Shiller's cycl. Adj. S&P Price to Earnings Ratio	0.02	specape
CREDMKT LIABS	domestic nonfin. Sector liabilities: Credit Mkt instruments (Bil. USD), HP-detrended	0.11	fl38tcr5-fl38tcr5 hp
MKT CAP	S&P500 + combined NSYE&WFE + Nasdaq comp. market cap, HP-detrended	0.11	(spsp5cap+spnycaph+spnacap) - (spsp5cap+spnycaph+spnacap) hp
MMFUND ASSETS	money market mutual funds assets / all long term funds (excl. MM) assets	-0.20	icmma/icia
NEW CORPDEBT	new US corporate security issues: Bonds (Mio. USD), HP-detrended	0.20	fnsipb/month gdp
NEW CORPEQ	new US corporate security issues: Stocks (Mio. USD), HP-detrended	-0.02	fnsips/month gdp
REPO VOLUME	primary dealers: repo total (Mio USD) / (total repo + reverse repo)	0.12	log(fdfr/(fdfr+fdfv)) - log (fdfr(-12) / (fdfr(-12)+fdfv(-12)))
BAA GOV10 SPR	BAA corp bond yield - 10 yr Treasury Note yield at const. maturity	-0.24	fbaa-fcm10
BBPLUS AAA SPR	Industrials BB+ Bond Yields - Industrials AAA Bond Yields	-0.20	fsbbp10-fsaaa10
CAR48 GOV10 SPR	48 months new car loan com. Bank interest rate - 10 yr Treasury Note yield at const. maturity	-0.13	fk48nc - fcm10
CREDCARD QUAL	Credit Card 90+ day delinquency rate	-0.15	ccqid3
FED T3 SPREAD	Fed Funds effective rate - 3 months treasury bills (secondary market)	-0.09	ffed - ftbs3
FIN MANU SPR	Credit Corp. Bond Yield: Finance - Manufacturing	-0.22	sycf - sycim
GOV10 T3 SPREAD	10 yr Treasury Note yield at const. maturity - 3 months treasury bills (secondary market)	-0.09	fcm10 - ftbs3
GOV2 T3 SPREAD	2 yr Treasury Note yield at const. maturity - 3 months treasury bills (secondary market)	-0.05	fcm2 - ftbs3

HIGHY BAA SPR	High Yield Corp Master II effect. Yield - BAA corp bond yield	-0.25	fmlhy - fbaa
LIBOR3 OIS SPR	3 months LIBOR OIS spread	-0.23	
M48CARL 2YRT SPR	48 months new car loan com. Bank interest rate - 2 yr Treasury Note yield at const. maturity	-0.15	fk48nc - fcm2
MBS REPO FAIL	MBS fails to deliver ($) / (MBS fails to deliver + MBS outright transactions ($))	0.04	fddm/(fddm+fdtm)
MCOM1 FED SPREAD	1 month non-fin com. Paper - Fed Funds effective rate	-0.04	fcp1 - ffed
MORT30 GOV10 SPR	30 year mortgage rate - 10 yr Treasury Note yield at const. maturity	-0.21	fcm - fcm10
SWAP10 T SPREAD	USD 10 yr interest rate swap - 10 yr Treasury Note yield at const. maturity	-0.05	t111wa - r111ga
SWAP2 T SPREAD	USD 2 yr interest rate swap - 2 yr Treasury Note yield at const. maturity	-0.21	t111w2 - r111g2
TED SPREAD	3 month LIBOR USD - 3 months treasury bills (secondary market)	-0.18	flod3 - ftbs3
VIX	market volatility index	-0.24	spvix
FIN3B 3A SPR	yield spread financial corporate bonds: BBB to AAA	-0.10	fmlf3b/fmlf3a
FINANCEBDS	bond performance: finance / corporate credit bonds	0.11	bcf/bct

China FCI

Abbreviation	**Series Explanation**	**Loading**	**Haver code & Transformation**
BONDRETURN	EMBI 3 months bond return	0.09	G924T3M
HOUSEMORTLOAN	Housing mortgage loans / GDP	0.32	log((n924fchm /gdp_nombil_sa) / (n924fchm (-12)/gdp_nombil_sa(-12)))
HY STOCKS	relative performance of high yield stocks	0.25	s924shy/s924s50
INTBK 120SPREAD _	120 day interbank rate - overnight interbank rate	-0.27	n924ri4 - n924rio
INTBK7D PRIM SPR	7 day interbank rate - prime lending rate	-0.20	n924ri1w - n924rle
LOAN DEMAND IDX	index of loan demand	0.36	N924VFML
MKT CAP	Shanghai and Shenzhen stock mkt cap / GDP	0.13	log(((N924FKCS+N924FKCZ)/gdp_nombil_sa)) - log((N924FKCS(-3)+N924FKCZ(-3))/ gdp_nombil_sa(-3)))
RE STOCKS	relative performance of real estate stocks	0.24	s924sre/s924s50
REAL EXRAT	JPM Broad Real Effective Exchange Rate Development	0.15	log(N924XJRB) - log(N924XJRB(-3))
REPO3M PR SPR	3 months repo rate - prime lending rate	-0.27	N924RR3M - N924RL
SHIBOR SPR	spread 6m SHIBOR - 6m lending rate	-0.41	r924i6m - r924l6m
SSE EXTRADVAL	Shanghai Stock Exchange Trading Value / GDP	0.28	N924FKSV /gdp_nombil_sa
SSE PE RATIO	PE Ratio Shanghai Stock Exchange	0.25	N924APE
SZH FIN2MKT	Shenzhen Stock Price Index: Finance & Insurance relative to Composite	0.20	N924FVFI/N924FV
TOT SOC FIN	Total Amount of Social Financing / GDP	0.25	(H924FCTM)/gdp_nombil_sa

Japan FCI

Abbreviation	Series Explanation	Loading	Haver code & Transformation
AASPR10T3YR	AA-rated 10 yr straight bond yield - 3 yr	0.13	QR10AA - QR3AA
BANKSTOCK	Tokyo Banks Stock Price Index / Tokyo General Stock Price Index	0.35	S158KBK/S158KT
BDSPR BBB2AA	Straight Bond Yield 5 Yr. rated BBB - Straight Bond Yield 5 Yr. rated AA	-0.29	QR5BBB - QR5AA
GOVSPR15T5YR	15 yr. benchmark govt bond yield - 5 yr	-0.27	R158GF - R158G5
HOUSPRC	qoq house price index changes	0.02	log(MCMPS) - log(MCMPS(-3))
MKTCAP	TSE market capitalization / GDP	0.35	SMMV / N9DP
OTHFINANCESTOCKS	Tokyo Stock Price Index of other financial institutions / Tokyo General Stock Price Index	0.30	SMPIOF1 / SMPI1
RE STOCKS	TSE real estate / general index performance	0.00	S158KRE/S158KT
REEXRAT	Trade weighted real effective exchange rate index	-0.19	log(EERBR) - log(EERBR(-3))
SPR BBBTAA 3Y	BBB-rated 3 yr staight bond yield vs. AA-rated	-0.33	QR3BBB - QR3AA
SPR LIBINTSWP 1Y	Japan: 1 Yr. Libor based on JPY - Jap. Yen 1 Yr. interest rate swap (%)	-0.33	T158I1 - T158W1
STOCKMKT	qoq stock price index changes	0.17	log(S158NK3) - log(S158NK3(-3))
TKN COMPAP IS	TANKAN: All Industries/Enterprises: act. conditions for com. paper issuance (easy - severe)	0.21	SAJCPA
TKN ENTRLOANINTR	TANKAN: All Industries/Enterprises: act. chg. in loan interest rate (rise-fall)	0.26	SAJIRA
TKN FINLENDING	TANKAN: All Industries/Enterprises: Lending attitude of Fin. Inst. (accom. vs. severe)	0.30	SAJLAA

UK FCI

Abbreviation	Series Explanation	Loading	Haver code & Transformation
BDFINAASPR	spread between 3 yr corporate bonds: financial AA to AA total	-0.31	Bloomberg
BDQUALSPR	spread between 3 yr corporate bonds: BBB to AA	-0.33	Bloomberg
BDSPR 3Y	spread between 3 yr corporate bonds A+ to 3 yr government gilt	-0.42	Bloomberg
COMPAP SPR	3-months commercial paper (Sterling) - 3-month gilt repo rate	-0.41	R112N3P - R112R3M
EFFEXRAT	Effective Exchange Rate Development	0.16	log(X112EB) - log(X112EB(-3))
FIN DERIV	development of gross assets of financial derivatives	-0.15	(UNTADIQ.x12*100/gdp_deflator_sa) - (UNTADIQ.x12(-3)*100/gdp_deflator_sa(-3))
FTSEVOLAT	Option-Implied PDFs on FTSE 100: 3-Mo Const Maturity: Implied Volatility (%)	-0.33	UKVF3IV
HOUSEINFL	development of aggregate of nationwide building society and Halifax house price index	0.23	log((UHPNBS + UHPAAS)/2) - log((UHPNBS + UHPAAS)/2 (-3))
LOAN WRITEOFF	development of NFCs' sterling loan write-offs/revaluations of loans	-0.06	(UNTFHBQ.x12*100/gdp_deflator_sa) - (UNTFHBQ.x12(-3)*100/gdp_deflator_sa(-3))
MKTCAP	development of market capitalization	0.08	(UNEQA.x12*100/gdp_deflator_sa) - (UNEQA.x12(-3)*100/gdp_deflator_sa(-3))
NFC LOANSPR	private NFC average interest rate on new bank loans - BoE repo rate	0.00	UNBJ82 - R112RD
PE ALLSHARE	FTSE All Share PE Ratio	0.24	S112AAP
SLIB REPO SPR	3-months sterling interbank lending rate - BoE repo rate	-0.33	R112I3M - R112RD
SONIA SPR 1YON	sonia_1y - sonia_on	-0.20	UNVYRA - UNSOIA
STOCKMKT	FT All Share Stock Index Development	0.18	log(S112FTA) - log(S112FTA(-3))
UNSEC MORT LSPR	unsecured lending rate for personal loan > 10,000 pounds - fixed mortgage rate (3-Year 75% LTV)	-0.07	UNHPTL - UNBV37

Russia FCI

Abbreviation	Series Explanation	Loading	Haver code & Transformation
BONDRETURN	EMBI Bond Total Return Index Development	0.51	log(G922I) - log(G922I(-3))
FINANCEMKTCAP	Finances Market Capitalization / RTS Maket Capitalization	0.27	N922FKCF/ N922FKC
HOUSEPRC	Houseprice Developments	0.03	log(N922HG1) - log(N922HG1(-12))
MIBOR REFIN SPR	MIBOR 7 day - Refinancing Rate	-0.38	R922I1W - R922RD
MKTCAP	RTS Market Capitalization Development	0.48	log(N922FKC) - log(N922FKC(-3))
REALEXRAT	JPM Broad Real Effective Exchange Rate Development	-0.09	log(N922XJRB) - log(N922XJRB(-12))
STOCKINDEX	Stock Index Development	0.53	log(S922RTS) - log(S922RTS(-3))

Brazil FCI

Abbreviation	Series Explanation	Loading	Haver code & Transformation
BK MMINSTRSH	Money Market Instruments / Bank Total Liabilities	0.34	(N223FMMK / N223FML)
BONDRETURN	EMBI 3 months bond return	0.41	log(G223I) - log(G223I(-3))
EXRAT	jpm nomexratidx	0.41	log(N223XJRB) - log(N223XJRB(-3))
IBOR SPR	overnight interbank (CDI) - overnight Selic	-0.05	(R223RCD-R223RO)
MKT CAP	development of market capitalization	0.34	log(N223FQA / nom_gdp) - log(N223FQA (-3) / nom_gdp(-3))
STOCKRETURN	Stock Index Development	0.40	log(S223BOV) - log(S223BOV(-3))
SWAP SPR	swap1y - swap1m	-0.38	R223W1 - R223W1M

India FCI

Abbreviation	Series Explanation	Loading	Haver code & Transformation
BANKPERF	BSE Banking Stocks / BSE 30	0.31	S534KBK/S534NF
EXRAT	RBI Broad Real Effective Exchange Rate Development	0.02	log(N534XRE) - log(N534XRE(-3))
EXTERNALBORROW	Development of External Commercial Borrowings (yoy, relative to GDP)	0.30	log(N534FYFB/nom_gdp) - log(N534FYFB(-12)/nom_gdp(-12))
FIN ASSESSMENT	Industrial Assessment: Overall Financial Situation	0.29	N534VMF
GOV 5Y1Y SPR	Spread in govt. bond yields: 5 year - 1 year	0.21	N534RG5 - N534RG
HOUSEPRC SA	Housing CPI / overall CPI	0.36	(N534PCHF/N534PC).x12
MIBOR 3M SPR	MIBOR 3 months - mibor overnight	-0.07	R534I3M - R534ION
MIBOR PR SPR	MIBOR overnight - prime rate	-0.24	R534ION - R534SBP
REPO PR SPR	repo rate - prime rate	-0.30	R534RP - R534SBP
STK5TO1	BSE 500 Stock Index / BSE 100 Stock Index	0.41	S534B5 /S534B1
STOCKMKTCAP	Development of NSE Market Capitalization (qoq, relative to GDP)	0.30	(N534FQAA /nom_gdp) - (N534FQAA (-3)/nom_gdp(-3))
STOCKRETURN	NSE Nifty Stock Exchange Index Development (qoq)	0.30	log(S534NF) - log(S534NF(-3))

Turkey FCI

Abbreviation	Series Explanation	Loading	Haver code & Transformation
AVGBUSLOAN MARG	Bank Surv: Bus Loan:Chg in Terms: Margin on Average Credit (Net % Easing)	0.31	N186VNTV
AVGHHLOAN MARG	Bank Surv: Housing Loan Chg in Cr Stds: Margin on Average Credit (Net%Easing)	0.34	N186VNUV
BONDRETURN	EMBI Plus: Turkey Index qoq log changes	0.20	log(P186I) - log(P186I(-3))
BUSCOLLATRISK	Bank Survey: Bus Loan Chg in Cred Stds Due to: Risk on Collateral (Net % Easing)	0.21	N186VNWT
BUSCRED STD EXPCH	Bank Survey: Bus Loan: Chg in Cr Stds: Next 3 Mo: Overall (Net % Easing)	0.18	N186VXW
COM LOAN SPR	commercial loan avg interest rate - policy rate	-0.20	R186RLM - monpol
CONS LOAN SPR	consumer loan avg interest rate - policy rate	-0.21	R186RLN - monpol
CONSCRED STD EXPCH	Bank Surv: Housing Loan Chg in Cr Stds: Next 3 Months (Net % Easing)	0.32	N186VXJ
EXRATE	JPM Broad Real Effective Exchange Rate Development	0.20	log(N186XJRB) - log(N186XJRB(-3))
EXRATEXP	expected USD Exchange Rate at End of Year / actual rate	0.22	N186VUAP - N186XUSE
FINANCIALS	ISE Financial / Composite Stock Price Index	0.04	S186RNF/S186RMK
GOV2Y SPR	2 Year Government Bond Yield - policy rate	-0.28	T186G2 - monpol
INTRATEXP	expected reverse repo on rate - policy rate	-0.25	N186VRIP - monpol
L2VRATIO	Bank Surv: Housing Loan Chg in Cr Stds: Ln-to-Value Ratio (Net % Easing)	0.25	N186VNUS
MKTCAP	ISE Market Capitalization, relative to GDP	-0.06	N186FQA/currgdp
NEW FIRM	newly established firms, qoq change	0.11	log(N186FE) - log(N186FE(-12))
NFINLOAN	loans to non-financial sector, yoy log changes	0.01	log(D186TLS) - log(D186TLS(-12))
ON POL SPR	avg. overnight interest rate - policy rate	0.03	N186RC - monpol
SOVSPREAD	EMBI Plus: Turkey: Sovereign Spread (bp)	-0.08	P186S
STOCKMKT	ISE National 100 Stock Price Index, qoq log change	0.24	log(S186IMK) - log(S186IMK(-3))
TRADEVAL	ISE Total Value Traded, qoq log change	0.18	log(S186TV) - log(S186TV(-3))
TRILIBOR POL SPR	Trilibor Reference Rate, 3 months ask - policy rate	-0.28	R186I3M - monpol

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