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European Investment Bank
The EU bank

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The simpler the better: measuring financial conditions for monetary policy and financial stability*

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Abstract

In this paper we assess the merits of financial condition indices constructed using simple averages versus a more sophisticated alternative that uses factor models with time varying parameters. Our analysis is based on data for 18 advanced and emerging economies at a monthly frequency covering about 70% of the world's GDP. We assess the performance of these indicators based on their ability to capture tail risk for economic activity and to predict banking and currency crises. We find that averaging across the indicators of interest, using judgmental but intuitive weights, produces financial condition indices that are not inferior to, and actually perform better than, those constructed with more sophisticated statistical methods. An indicator that gives more weight to measures of financial stress, which we term WA-FSI, emerges as the best indicator for anticipating banking crisis, and is therefore better suited for financial stability.

JEL codes: E32, E44, C11, C55.

Keywords: financial conditions, quantile regressions, banking crises, SVARs, spillovers.

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1 Introduction

The concept of financial conditions, a summary measure of how easily firms, households, and governments finance themselves, plays a central role both in financial stability as well as in monetary policy monitoring. Financial crises are typically heralded by long period of low volatility, characterized by cheap borrowing rates, high asset prices, low volatility and compressed spreads, during which imbalances build-up. Loose financial conditions bring debtors close to their borrowing constraints, setting the stage for non-linear effects when financial conditions tighten. In this context, financial condition indices (FCIs) can help monitoring the phase of imbalances build-up (Adrian et al., 2018) and can be used to appropriately calibrate macro-prudential policies. Yet, changes in financial conditions are also at the center of the transmission mechanism of monetary policy. Even small movements in short term rates can generate large movements in credit costs, mostly via a widening of both term premia and credit spreads (Gertler and Karadi, 2015; Borio and Zhu, 2012). Monetary policy makers therefore monitor the behavior of a number of indicators of financial conditions, not only to identify shocks to which to react, but also to gauge the effects of their own actions on the macro-economy.

Financial conditions are a function of various asset prices and of the quantity and price of credit in the economy.[1] Making this concept operational requires choosing the set of variables to be aggregated as well as the aggregation weights. Given that the financial sector can send conflicting signals, a large number of papers have developed FCIs by summarizing in a single indicator the information coming from different segments of the financial sector. A non-exhaustive list of papers on the topic includes Illing and Liu (2006), Hakkio et al. (2009), Hatzius et al. (2010), Matheson (2012), Brave et al. (2012), Hollo et al. (2012), and Koop and Korobilis (2014). Most of these papers borrow their methodological setup from the factor model literature (Stock and Watson, 2002; Forni et al., 2000; Doz et al., 2012; Stock and Watson, 2011) and build on the idea that the relevant information contained in a large dataset can be summarized by a small number of linear combinations of the available series (”factors”). The level of sophistication of

[1] In practice, indices of financial conditions are of two types. Some are more twisted versus spreads and volatilities, and are more effective measures of stress in the financial system. Some give more relevance to the level of credit costs, and are more closely related to measuring credit conditions in the economy.

these indices has increased over time. For instance, Koop and Korobilis (2014) have proposed to use factor model with time-varying loadings and time-varying volatilities to aggregate a large number of macroeconomic and financial variables into financial condition indices. This methodology should account for the fact that the relationship between the financial sector and the real economy is subject to structural changes over time. Model instability can indeed be a concern. Hatzius et al. (2010), for instance, find that the predictive ability of their FCIs for future GDP relative to a simple autoregressive benchmark changes over time.

In this paper we argue that indices based on sophisticated factor models may be prone to some flaws when used to construct measures of financial conditions. First, these techniques are designed to reduce information dimensionality in datasets that are characterized by high collinearity. The intuition is that when many series behave in a very similar way, their linear combination summarizes efficiently the information that they convey. Yet, the series that enter popular measures of financial conditions have very heterogeneous behavior. Table 1 shows the correlation structure of a representative sample of nine macro-financial indicators that are typically used to construct financial condition indices, including credit growth, interest rates, asset prices, volatilities and exchange rates.[2] Out of the 36 correlations that fill the off-diagonal elements of the table, only 3 are higher than 0.3 in absolute value. Given this heterogeneity and the lack of collinearity, it is very likely that the final composite index is largely going to reflect the behavior of a limited block of the time series that compose the information set. To illustrate this point in a "large data" context, Figure 1 shows the correlation between the National Financial Condition Index (NFCI) for the US economy computed by the Federal Reserve of Chicago and the individual series that compose the index.[3] The different colors illustrate the block to which the series belong (blue for *Spreads and volatilities*, violet for *Yields*, yellow for *Credit ratios*, orange for *Failure rates and delinquencies*, green for *Lending standards*, purple for *Issuance and open interests*). Visual inspection of Figure 1 shows that the NFCI loads very heavily on credit spreads, as shown by the large

[2]The table is constructed by computing this correlation matrix for each of the 18 countries that we analyze in this paper and then averaging across countries.

[3]The Chicago Fed NFCI provides a comprehensive weekly update on US financial conditions in money markets, debt and equity markets, and the traditional and "shadow" banking systems. The NFCI is constructed using a dynamic factor model. Appendix H reports the series that are included in the index.

dominance of blue bars at the high end of the correlation spectrum. Some yields are also represented, but most of them have a correlation lower than 0.4 with the final index. Finally, some categories display a negligible contribution to the common factor, like for instance *Lending standards*.

Table 1: Correlation across macro-financial indicators

	Credit growth	Real 10Y yields	Sovereign spread	Inter-bank spread	Term spread	Equity volatility	Stock returns	Real house prices	Exchange rates
Credit growth	1.00	-0.10	0.19	0.02	-0.09	0.14	0.20	0.27	0.02
Real 10Y yields	-0.10	1.00	-0.13	-0.02	0.21	0.06	-0.12	-0.06	-0.02
Sovereign spread	0.19	-0.13	1.00	0.33	-0.12	0.55	0.25	0.12	-0.08
Inter-bank spread	0.02	-0.02	0.33	1.00	0.09	0.20	0.14	0.08	0.00
Term spread	-0.09	0.21	-0.12	0.09	1.00	0.00	-0.16	0.06	-0.02
Equity volatility	0.14	0.06	0.55	0.20	0.00	1.00	0.44	0.13	-0.22
Stock returns	0.20	-0.12	0.25	0.14	-0.16	0.44	1.00	0.07	-0.08
Real house prices	0.27	-0.06	0.12	0.08	0.06	0.13	0.07	1.00	0.14
Exchange rates	0.02	-0.02	-0.08	0.00	-0.02	-0.22	-0.08	0.14	1.00

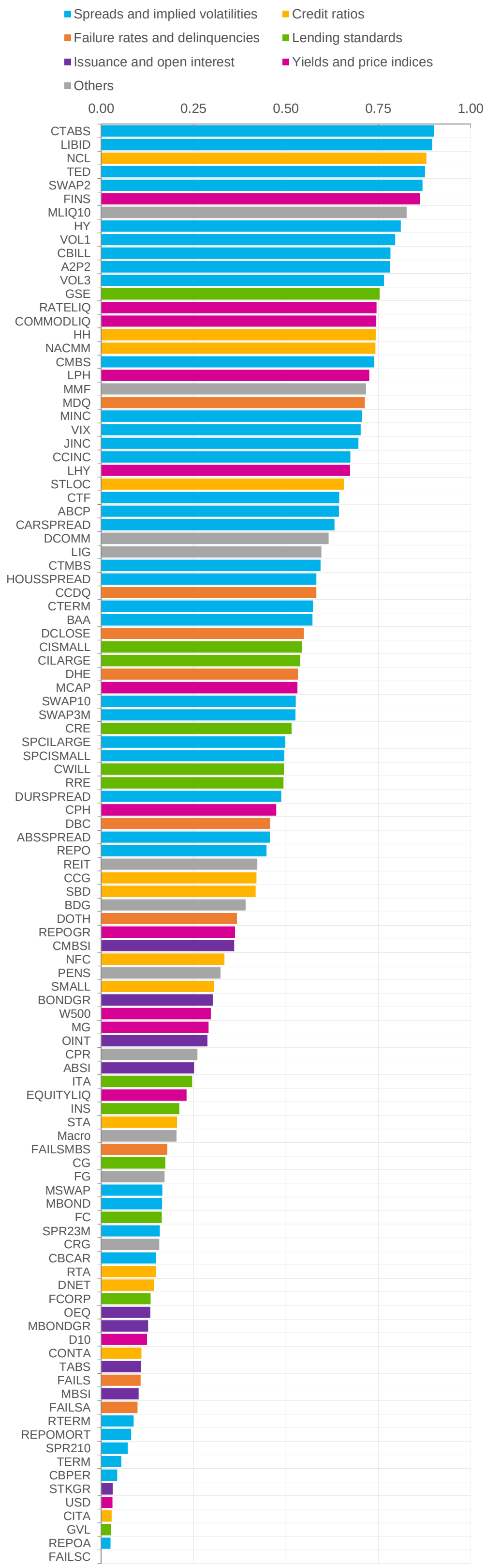
Notes. Correlations are unweighted averages across countries. Country specific correlations are computed over the period January 1995-February 2020 for a sample of 18 countries including China, United States, India, Japan, Germany, Russia, Brazil, United Kingdom, France, Mexico, Italy, Turkey, South Korea, Canada, Australia, Sweden, Norway, New Zealand.

The second problem is that some of these statistical techniques do not give much control over the sign with which the individual components end up contributing to the final indicator. Yet, there is outside information that one might want to use to discipline the direction in which the individual series affect the final index. For instance, exchange rates will move financial conditions in different directions depending on the role that foreign currencies have in the domestic economy. For countries that borrow in foreign currency, a depreciation implies an increase of the cost of debt in domestic currency, i.e. a tightening of borrowing conditions. For countries that lend in domestic currency, on the other hand, an appreciation of the exchange rate generates a positive wealth effect.

The third issue is that the weight that the single indicators receive reflects the nature of past shocks and past crises. It can therefore be the case that some variables that in the past did not cause any crises, yet that ex-ante would be interesting to monitor, end up receiving zero weight in a composite index, therefore exiting the radar of policymakers.

We argue that simply averaging across the indicators of interest, using judgmental but reasonable weights, produces financial condition indices that are not inferior to, and actually perform better than those constructed with more sophisticated statistical methods. First, by making sure that no series receives zero weight, the heterogeneity of the underlying components is by definition reflected in the final index. Second, one can

Figure 1: Correlation of NFCI subcomponents with the final index



Notes. For variables definitions and details on allocation to categories see Figure A2 in Appendix H. Due to data availability, correlations are computed over the period 3 June 2005 - 29 May 2020 (weekly).

judgmentally decide the sign of some variables, like for instance the exchange rate, based on information on the financial structure of the economy. Finally, one can make sure that all the indicators that one wants to keep in sight actually enter the final indicators. Of course, these advantages need to be traded off against the costs of not using any statistical objective function to aggregate information. This cost, however, can be assessed by checking the performance of different financial condition indices based on given criteria.

We use two empirical criteria to evaluate the performance of our indicators. First, we examine across different methods the strength of the correlation between tightening in financial conditions and recessions using quantile regressions. It is well known that recessions that originate in the financial sector are deeper than standard ones. A desirable property of a financial condition index is, therefore, to bear stronger information for the left tail of GDP distribution (Adrian et al., 2019). We perform this exercise both in-sample as well as out-of-sample. The latter exercise is particularly challenging, although recent studies have documented a lack of predictability of tail GDP movements (Hasenzagl et al., 2020). Second, and related to the first, we examine how the various alternatives are correlated with future banking and currency crises (broadly speaking financial crises). Financial crises are somewhat related to deep recessions, so we see this exercise as complementary to the previous one. The results of our empirical analysis show that, for both exercises, FCIs constructed as weighted averages outperform indices constructed with more sophisticated methods, and in particular those constructed using the TVP-factor model by Koop and Korobilis (2014) that we take as our benchmark.[4]

One key contribution of our paper is to develop comparable indicators for a large set of countries. This forces to limit the number of variables underlying each index but also raises the question of whether "large data" alternatives, available for large advanced economies like the US or the euro area (EA), outperform our simple indices. In the paper we show that our FCIs outperform comfortably two popular alternatives, namely the Chicago Fed's National Financial Conditions Index (NFCI) for the US and the Composite Index of Systemic Stress (CISS) by Hollo et al. (2012) for the euro area.[5]

[4]We take as a benchmark a "sophisticated" type of financial condition index, constructed as in Koop and Korobilis (2014), because it is at the highest level of the sophistication spectrum, and it has been used in policy analysis, for instance by the IMF in the 2017 Global Financial Stability Report in the context of "growth at risk" analysis.

[5]Results available upon request show that for the US also other popular alternative like the VIX are

The paper is organized as follows. Section 2 provides some motivation from an empirical and theoretical point of view for the analysis. Section 3 provides a description of the data and details on the construction of the indices. Section 4 describes the criteria that we employ to assess the performance of our financial condition indices and discusses the empirical results. Section 5 concludes.

2 Motivating evidence and theoretical background

Before delving into the core of the paper, we present some evidence on the causal and predictive relationship between financial conditions and the business cycle. We then discuss the channels through which asset prices affect the business cycle in theoretical models.

We start with a simple but instructive analysis of the effects of a US financial conditions shock on two neighbouring countries, namely an emerging economy (Mexico) and an advanced economy (Canada). We proxy US financial conditions via the Excess Bond Premium, a widely used measure of risk aversion and financial market sentiment for the US economy (Gilchrist and Zakrajsek, 2012; Lopez-Salido et al., 2017) and study the effect of a US financial shock on the financial system (in particular on long term interest rates, stock prices, sovereign spreads, stock market volatility and the exchange rate) and on the macroeconomy (CPI, GDP and monetary policy rates) of Mexico and Canada.[6] In order to conserve space we discuss the identification of the shock, which follows closely Gilchrist and Zakrajšek (2012), as well as the technical details on the model estimation in Appendix A.

Following the shock, in both countries stock prices fall, sovereign spreads rise, implied stock market volatility increases, the domestic currency depreciates against the US dollar and GDP falls (Figure 2). Importantly, asset prices respond very quickly to the shock, while GDP falls with a significant delay. Besides these similarities, there are important differences. In Mexico, like in most EMEs where inflation expectations are poorly anchored and monetary policy is not perceived as credible, an exchange rate depreciation raises inflation and long term yields (i.e. leads to a further tightening of

outperformed by our indicators.

[6]GDP is interpolated at the monthly frequency using a cubic spline.

financial conditions). The central bank raises policy rates to stabilize the exchange rate, resulting in a deeper and longer contraction of economic activity. In Canada, similar to other AEs that have a credible monetary policy framework in place, no trade off between stabilizing inflation and GDP emerges (as they both fall) and the central bank can afford cutting rates to alleviate financial conditions and to support the economy. At the same time, GDP falls less and recovers sooner than in Mexico.

Figure 2: Effects of a tightening of global financial conditions in AEs and EMEs

Notes. Impulse responses to a shock to the global financial conditions. The IRFs comprise confidence bands. The methodology used to obtain these responses is explained in Appendix A.

We take two important points away from this exercise. First, there is a wide array of shocks that induce a sharp tightening of financial conditions *that leads by several months a fall in GDP*. This dynamics, which resembles closely the lead-lag relation between asset prices and economic activity that emerges in financial accelerator models of the business cycle (Bernanke et al., 1999), calls for a close monitoring of financial conditions, and has indeed constituted the main motivation behind the literature on FCIs discussed in the Introduction.[7] Second, the use of judgment in constructing FCIs allows us to complement

[7] Alessandri and Mumtaz (2014) show that this predictive power is particularly strong for recessions. This does not mean that *all recessions* are preceded by a tightening of financial conditions. The Covid-19

statistical analyses with economic intuition when assigning weights to different asset prices. This means, for instance, giving the exchange rate a different role in FCIs for AEs and EMEs.

This preliminary analysis also raises questions over what is the economic mechanism that drives this relationship between asset prices and the real economy. A broad review of this literature is beyond the scope of this paper but at least two different strands are of interest for our purpose. The first is the set of papers that focus on economies with occasionally binding constraints (Deaton, 1991; Guerrieri and Lorenzoni, 2017). In these economies credit constraints embody a pecuniary externality that induces private agents to borrow excessively. Individual agents fail to internalize the aggregate consequences of their individual over-borrowing and carry too much debt when they face a tightening of financial conditions (Bianchi, 2011). When asset prices fall and their borrowing constraint becomes binding they need to scale back consumption significantly. This intuition can be generalized to non-financial firms, see for instance Jermann and Quadrini (2012) and Liu et al. (2013). Interestingly, in line with the empirical evidence presented in Figure 2, these models predict that the loss of net worth due to a large drop in asset prices can lead to long-lasting effects.[8] In the second set of papers, financial intermediaries take center stage. Financially leveraged institutions face a sudden spike in their leverage (debt to asset ratio) when the price of the assets that they hold suddenly falls and their net worth plummets. As they try to return to their leverage target, they generate fire sales, exacerbating the initial price spiral and causing a financial crisis (Brunnermeier and Oehmke, 2013). Similar amplification effects emerge in models that include frictions in the financial intermediation process, see for instance Gertler and Karadi (2011), Gertler and Kiyotaki (2010), He and Krishnamurthy (2019), and Brunnermeier and Sannikov (2015).

Summarizing, incomplete markets and financial frictions make the real economy vulnerable to sudden shifts in financial conditions. This gives financial conditions indices predictive power for economic activity and makes them a useful element in the toolbox

recession, for instance, occurred in an environment of favourable financial conditions.

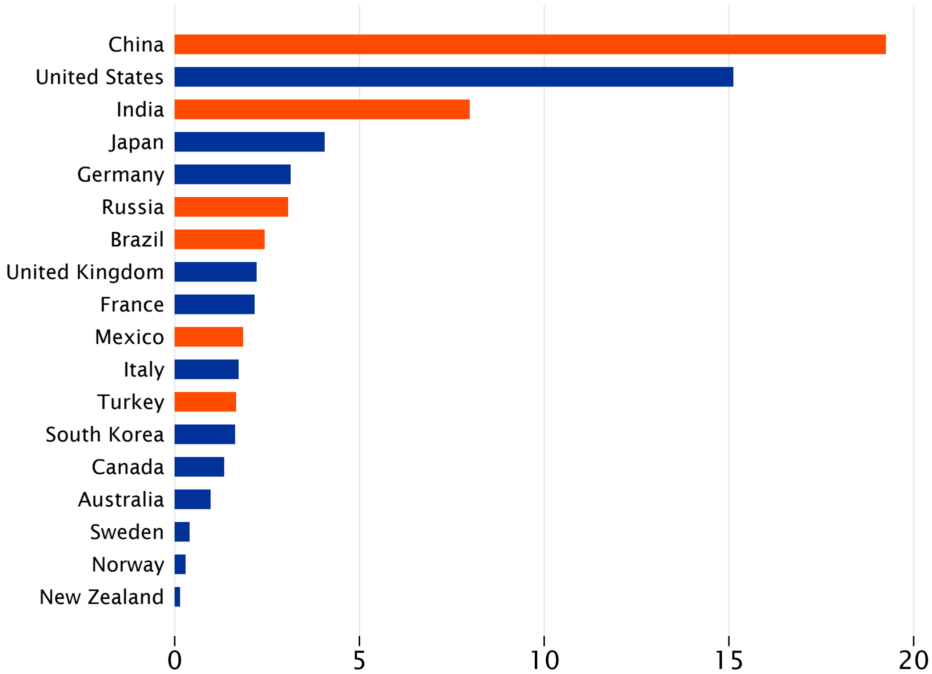
[8] In Bernanke and Gertler (1989), for instance, once a shock lowers the net worth of leveraged entrepreneurs, economic activity and profits falls. This implies that it takes entrepreneurs a long time before they accumulate sufficient retain earnings to rebuild their net worth.

of economists interested in having a synthetic (and comparable across countries) view of the state of financial markets.

3 Data

Our analysis is based on data for 18 advanced and emerging economies at a monthly frequency from January 1995 to May 2020. As Figure 3 shows, these countries represent about 70% of the world's GDP at Purchasing Power Parity.

Figure 3: Shares of GDP at Purchasing Power Parity



Notes. Blue bars represent advanced economies, red bars represent emerging market economies. Data in percentages of the world's total. Source: IMF World Economic Outlook, 2019 data.

Our dataset includes a set of financial as well as macroeconomic variables, which are used in different combinations to construct three sets of financial conditions and stress indicators. For details on data sources see Table A1 in Appendix B.

TVP-FCI (Time Varying Parameters - FCI). We start by constructing FCIs in the spirit of Koop and Korobilis (2014) and Arregui et al. (2018). The information set includes (i) real long term government bond yields; (ii) a set of various spreads, namely sovereign (for emerging economies only), corporate (for advanced economies only), inter-bank and term spreads (for all countries); (iii) the percentage change of equity and real residential house prices; (iv) the growth rate of credit to households and non-profit institutions serving households; (v) realized equity volatility; (vi) the bilateral exchange rate with the US Dollar. Common dynamics across these indicators are summarized through a (single) factor model with time-varying parameters that, according to Koop and Korobilis (2014), provides a flexible weighting scheme for the input variables. For more details on the methodology see Appendix C. The estimated common factor is our TVP-FCI. The resulting indices are strongly correlated with those constructed by the IMF for the 2017 Global Financial Stability Report. Visual inspection, and a simple correlation analysis, reveal that these indices load heavily on some specific indicators, either inter-bank spreads or realized equity volatility.

WA-FSI (Weighted Averages - FSI). As a first alternative, we construct another indicator using the same set of variables used for the TVP-FCI but aggregated through simple weighted averages. Table 2 summarizes the weights and the signs of the input variables. We choose the weights so as to give relative more importance to measures of stress, like equity volatility and spreads, which account for half of the final weights. The remaining weights are, by and large, evenly distributed across the remaining indicators. The exchange rate plays less of a role as it is heavily correlated with interest rates differentials with respect to the dollar, and therefore somewhat reflected in other variables. Given that an increase in the index is interpreted as a tightening, we assign a positive sign to interest rates, spreads and volatilities and a negative sign to equity prices, house prices and credit volumes. We let the exchange rate have a different role for indices constructed for advanced and emerging economies. Since emerging economies own a non-negligible part of their debt in US dollars (Bénétrix et al., 2019), when the local currency weakens against the dollar, the cost of debt expressed in national currency rises and financial conditions tighten. For advanced economies we let the exchange rate work through a traditional trade channel, so that for these countries a weakening of the domestic currency results in an easing of the FCI.

WA-FCI (Weighted Averages - FCI). The second alternative index is constructed as the weighted average of a smaller set of financial variables, which are potentially available at daily frequency. This FCI could be used, for instance, for the high frequency

Table 2: WA-FSI, summary of weights

	AEs		EMEs	
	Weight	Sign	Weight	Sign
Credit to HHs and NPIs, m-o-m growth rate †*	10%	-	10%	-
Real 10 years government bond yields	15%	+	15%	+
Sovereign spread			10%	+
Corporate spread †	10%	+		
Inter-bank spread †	15%	+	15%	+
Equity volatility †	25%	+	25%	+
Equity prices, m-o-m growth rate †	15%	-	15%	-
Real residential house prices, m-o-m growth rate †	15%	-	15%	-
Bilateral exchange rate with the US Dollar	5%	-	5%	+

Notes. A positive sign indicates a tightening in the index, while a negative sign an easing. An increase in the bilateral exchange rate (being it expressed as national currency per USD) denotes a depreciation of the national currency, while a decrease an appreciation. In line with how we want the exchange rate to contribute to the FCI, this explains the positive sign for emerging economies and the negative sign for advanced economies. * HHs = households, NPIs = Non-profit Institutions serving households. † A 3 months centered moving average is applied to the variables defined by this symbol.

monitoring of financial markets routinely conducted in central banks between monetary policy decision meetings. For the sake of comparison with the other two sets of indices, we aggregate these daily variables at the monthly frequency. The input variables are (i) short (3/6 month or 1 year according to best availability) and long term (10 years) interest rates; (ii) price to earnings ratios; (iii) exchange rates (bilateral with the US Dollar for emerging markets and the nominal effective exchange rate, NEER, for advanced economies[9]); and (iv) a measure of spread, namely corporate spreads for advanced economies and the JP Morgan EMBI stripped[10] spreads for emerging markets.

Both the choice of variables as well as the weights are inspired by the widely used financial condition indices developed by Goldman Sachs (Hatzius et al., 2016) and readily available to financial market observers. These indices are designed to capture the

[9] An increase in the NEER denotes an appreciation of the currency, while a decrease a depreciation.

[10] The stripped spread is a better measure of spread for emerging markets, in which calculation the value of collateralized flows are stripped from the bond. In the case of a bond with principal collateral, the present value of the collateral is discounted using US Treasury Strip rates and subtracted from the price of the bond. The zero curve is then parallel shifted upward and used to discount the remaining unsecured flows until the present value of the cash flows equals the ex-collateral price of the bond. The number of basis points the curve must be shifted upward is called the Stripped Spread, i.e. the value of Z such that market value of portfolio equals $\sum[CashFlow/(1+R(t)+Z)^t]$, where R(t) is the zero-coupon rate at the t-year point of the Treasury curve. This calculation is also valid for uncollateralized bonds. Stripped spread is calculated using offer side prices. (Source: Haver Analytics)

evolution of financial conditions in normal times, rather than in crisis times. This implies giving relatively more weight to long term interest rates, which are used as a benchmark for a variety of interest rates for loans to households and non-financial corporations, as well as to equity valuations. As a result, long term rates and price earning ratios represent around half of our WA-FCIs. The rest of the weights are chosen so as to broadly match the indices produced by Goldman Sachs on standardized series. Tables 3 and 4 summarize the weights and respective signs of the input variables.

Table 3: WA-FCI, summary of weights for Emerging Economies

	Weight	Sign
Short term yields	5%	+
Long term yields	35%	+
Price/Earning ratio	20%	-
Bilateral exchange rate with the US Dollar	20%	+
JPM EMBI sovereign spread	20%	+

Notes. A positive sign indicates a tightening in the index, while a negative sign an easing. An increase in the bilateral exchange rate (being it expressed as national currency per USD) denotes a depreciation of the national currency, while a decrease an appreciation. This explains the positive sign. When variables have missing values, FCIs are computed on re-scaled weights on the total weight of the available variables.

Table 4: WA-FCI, summary of weights for Advanced Economies

	Weight	Sign
Short term yields	8.5%	+
Long term yields	38.5%	+
Price/Earning ratio	23.5%	-
Nominal effective exchange rate (NEER)	23.5%	+
Corporate spread	6%	+

Notes. A positive sign indicates a tightening in the index, while a negative sign an easing. An increase in the NEER denotes an appreciation of the currency, while a decrease a depreciation. This explains why the positive sign. For United States we apply a different set of weights (i.e. 5%, 25%, 25%, 10%, 35%). The rationale of giving more weights to corporate spreads subtracting from long term yields follows a matching with the FCI by Goldman Sachs and the fact that US corporations tend to borrow a larger share from the bond and commercial paper markets than corporations in the other G10 economies.

Comments and comparisons. Figures 4 and 5 compare the three sets of indicators.

For some of the countries the factor model (blue lines) produces indices that are hard to interpret. Two main anomalies emerge. First, looking at Germany and Japan, the TVP-FCI presents a visible upward trend, hard to reconcile with falling rates in both countries. Second, looking at Italy, the factor model suggest that the financial crisis did not result in any major tightening of financial conditions, while only the European debt crisis led the index to spike. Both of these problem disappear implementing weighted averages on the same raw series (WA-FSI). Looking at the WA-FCI, it is clear that the prevalence of interest rates and equity valuations results in indices that are more cyclical and spike less during the GFC.

4 Empirical analysis

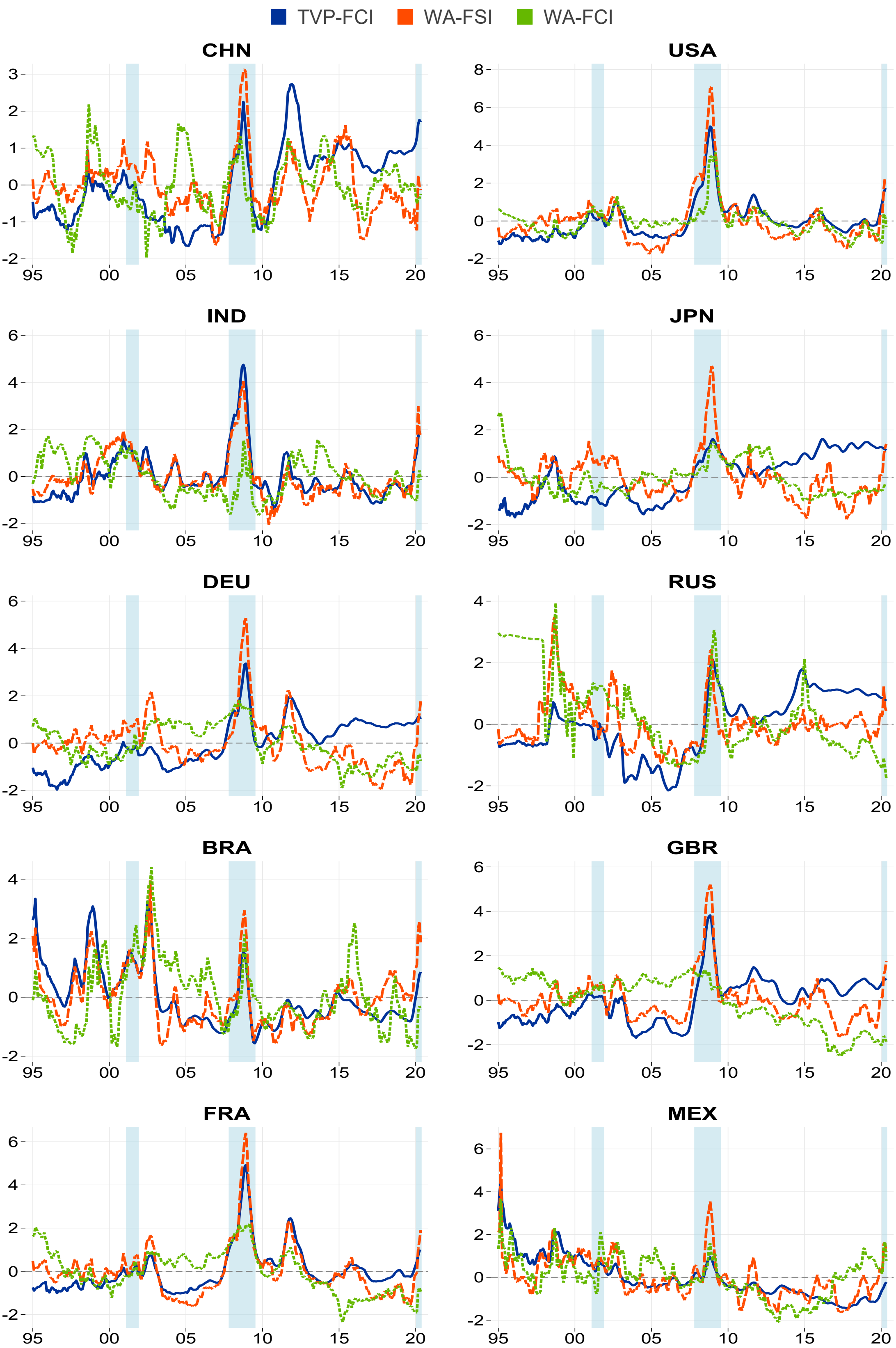
In this section we provide a more detailed description of the two criteria that we use to assess quantitatively and qualitatively the performance of the three indices of financial conditions.

4.1 Quantile regressions

The quantile regression approach provides a framework for estimating the impact of a given variable X on the entire conditional distribution of a dependent variable y. This is achieved through separate coefficients for the various quantiles (see Appendix D for more details). Based on this approach, Adrian et al. (2018) find a close link between current financial conditions and the conditional distribution of future GDP growth. In particular, the lower quantiles of future GDP growth are much more sensitive than the higher ones to current financial conditions developments. Moreover, the entire distribution of future GDP growth evolves over time. Recessions are associated with left-skewed tails, while during expansions the conditional distribution is broadly symmetric. This asymmetry in the evolution of the conditional tails of the distribution of future GDP growth indicates that downside risks to economic activity vary more strongly over time and react more to developments in financial conditions compared to upside risks.

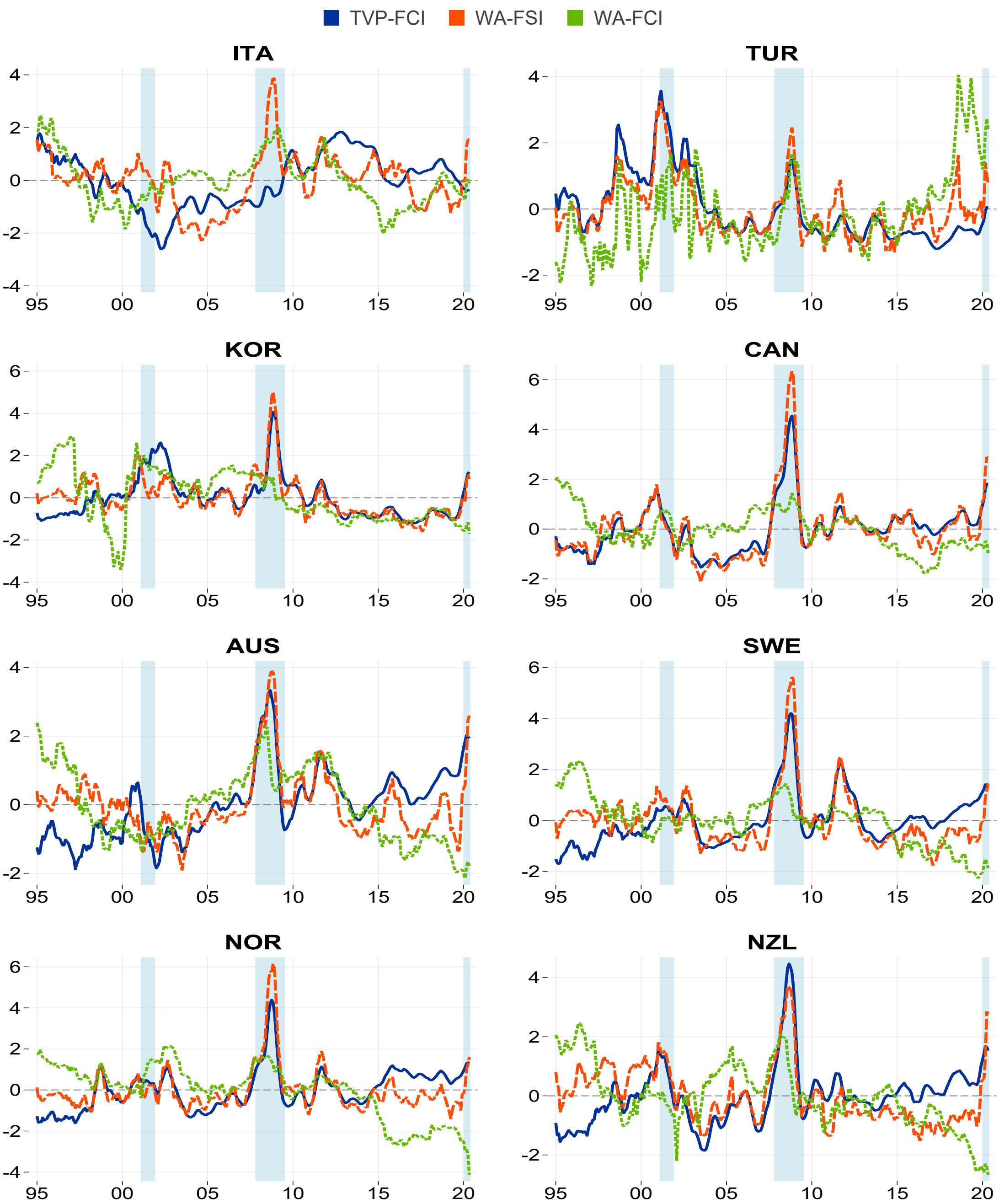
We use quantile regressions to test for the non-linear impact on the different quantiles of industrial production of the three measures of financial conditions described in Section

Figure 4: Comparison of the FCIs, 10 largest countries



Notes. Shaded areas represent NBER recessions. All indicators are standardized.

Figure 5: Comparison of the FCIs, continued



Notes. Shaded areas represent NBER recessions. All indicators are standardized.

3 (for data availability see Appendix E). Two main messages emerge from our analysis. Two main messages emerge. First, irrespective of the index used (TVP-FSI, WA-FSI, or WA-FCI) and for almost all the countries (but Norway), the impact of financial conditions on the lower quantiles of industrial production[11] is significantly more negative than either on the central tendency or on the upper tails. This implies that financial conditions convey powerful signals on downside risks to the real economy, but are less informative about median growth and economic booms. Second, for some countries the asymmetry is striking (e.g. United States, United Kingdom).[12] Figure 6 compares the impact on the lower (5th) quantile of the distribution among the three FCIs.[13]

Comparing the results across countries and financial indicators we find that for a number of countries (e.g. United Kingdom, China, South Korea, Sweden, Russia, New Zealand and Mexico) the WA-FSI has the biggest impact on the lower quantiles of the industrial production distribution. Downside risks for economic activity in the United States, Italy, Australia, Germany, India, Brazil, Turkey, France, Canada and Japan are better captured by developments in the WA-FCI.[14] Importantly for *all* the countries considered, the TVP-FCI is materially outperformed by the weighted average indicators, in terms of the impact on the 5th percentile of industrial production. Simpler, weighted average indicators convey more precise (in sample) information on downside risks for future economic activity.

A possibility is that the particular method that we have picked as an alternative to our simple indices (i.e. a factor model with time-varying parameters) is a poor choice. Other methods among those proposed in the literature might work better. Two obvious alternatives are the Chicago Fed NFCI for the US and the CISS by Hollo et al. (2012) for the euro area. While the former is estimated via a large factor model, the latter is obtained by aggregating 13 indicators of financial stress through a time varying correlation model.

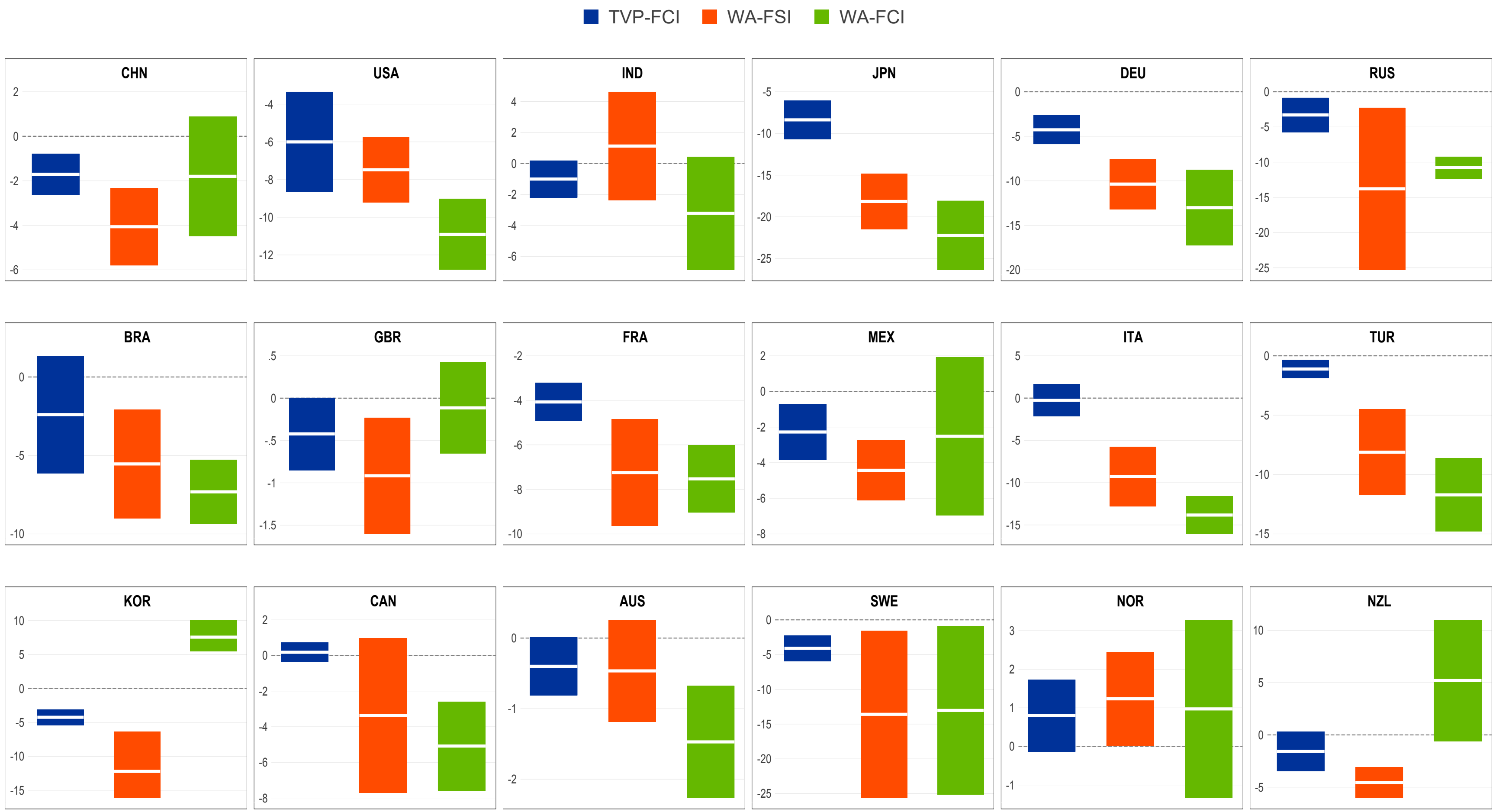
[11] We use industrial production rather than GDP as data are available at monthly frequency and for a longer period of time, especially for emerging markets.

[12] For Italy the asymmetry in terms of the impact of the three financial indicators on industrial production distribution is only valid for WA-FSI and WA-FCI. For India and Norway the asymmetry is not so evident for any of the measures considered.

[13] For reasons of space we only report here the impact on the 5th percentile (left tail) of the distribution of industrial production. The results obtained for the other percentiles of the distribution are available upon request.

[14] Norway is the only country for which none of the three financial indices yields significant and plausible effects on the lower quantiles of industrial production.

Figure 6: Impact of FCIs on the 5th percentile of the Industrial Production distribution



Notes. The white line represents the mean impact of FCIs changes on the 5th percentile of industrial production, while the shaded areas represent the 95 percent confidence intervals around it. The country specific sample varies according to data availability, see Appendix E.

To test how our simple indices compare against these two alternatives, we repeat the quantile regression analysis for the US and the EA including also the NFCI and the CISS as potential competitors. The results of this exercise, shown in Figure 7, indicate that both the NFCI for the US as well as the CISS for the euro area have lower in-sample information content than the indices obtained via simple average.

Next, we test the out-of-sample predictive accuracy of each of the financial indicators in the quantile regression framework. Following Adrian et al. (2018), we compute predictive scores as the predictive distribution generated by the model and evaluated at the realized value of the time series.[15] The higher the predictive scores, the more accurate the out-of-sample prediction. To provide a compact view of the results, we summarize them in a heatmap (Figure 8) where the rows represent the countries and the columns the different FCIs. The darker the color, the better the average out-of-sample performance, so the dark cells indicate the best performing FCI.[16]

It is pretty evident that the TVP-FCI is the worst performing indicator, as it ranks last or next to last in most cases, apart from Sweden, Brazil and Mexico. Overall, the WA-FCI outperforms the other measures in terms of out-of-sample accuracy for a significant number of countries (i.e Euro Area, Canada, United Kingdom, France, Germany, Norway, Australia, Turkey, Korea, China). For other countries the WA-FSI performs well too (i.e United States, Italy, Japan, New Zealand, Russia, India). We include in this comparison also the VIX and the Chicago Fed NFCI for the US and the CISS for the euro area.[17] None of these indicators ever ranks best in our out-of-sample comparison.

4.2 FCIs and crisis probability

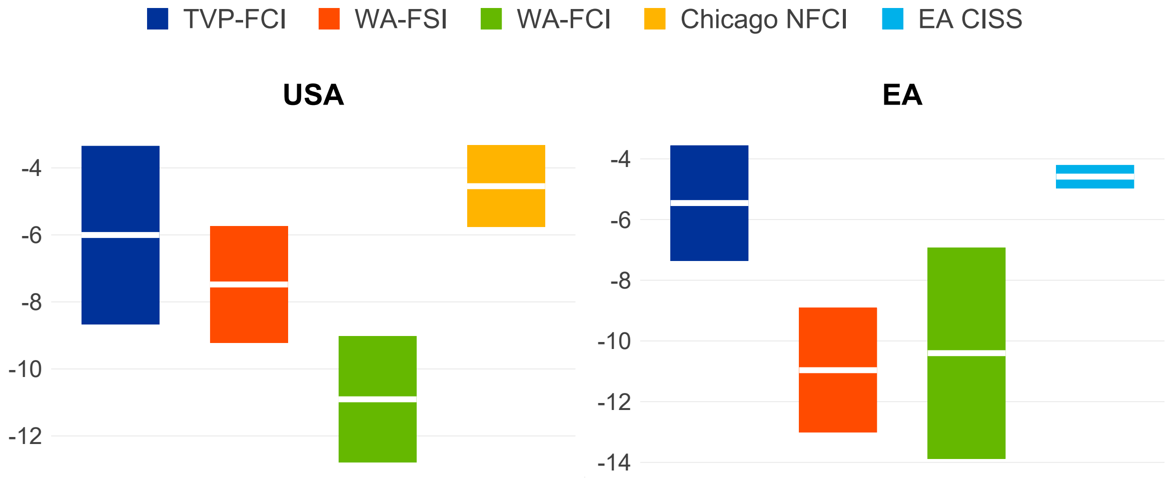
As a second criterion for assessing the informational content of the three competing indices, we consider their ability to predict a set of crises, specifically systemic banking

[15]In a nutshell, we re-estimate the quantile regressions using expanding windows, then fit the skewed t-density into the estimated quantiles and evaluate the predictive density score of this density at the actually realized value. Following Adrian et al. (2018), we fit the skewed t-distribution developed by Azzalini and Capitanio (2003) in order to recover a probability density function.

[16]We use an ordinal criterion to measure performance, i.e. the best performing model is the one that attains the highest score in most months.

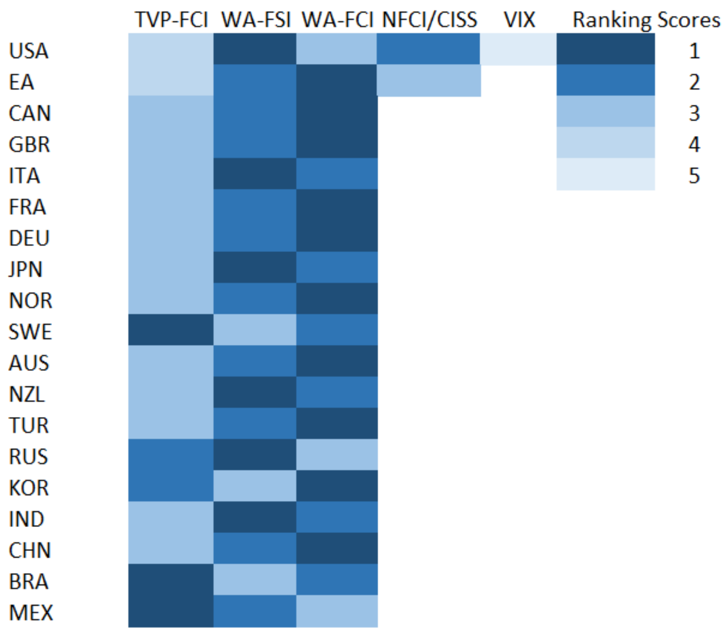
[17]Since the VIX performs poorly in case of US, its out-of-sample performance was not tested for the other countries employed in the analysis.

Figure 7: Impact of FCIs on the lower quantile of Industrial Production distribution for US and EA - Comparison with Chicago NFCI and EA CISS



Notes. The white line represents the mean impact of FCIs changes on the 5th percentile of industrial production, while the shaded areas represent the 95 percent confidence intervals around it. The EA indicators are obtained by aggregating country FCIs for Germany, France and Italy using GDP PPP annual shares as weights (see Figure 3, for 2019). For EA the data sample covers January 2000 - December 2019.

Figure 8: Rank of predictive scores of out-of-sample performance



Notes. The figure reports the predictive scores of the probability integral transform. The out-of-sample predictive scores of the predictive distribution for industrial production growth are conditioned on each FCI at a time, a constant and persistence of industrial production growth. The color coding defines the score ranking: the index that performs best the highest number of times is colored dark blue and ranked 1, the next one lighter blue and ranked 2, and so on with the lowest number of cases being colored the lightest blue and ranked 5.

and currency crises.[18] For this purpose, we collect data on the timing of these crises from Laeven and Valencia (2020)[19] and estimate the following panel probit model[20] for each set of crises:

$$\Pr(Y_t = 1 \mid X_{t-1}) = \int_{-\infty}^{X'_{t-1}\beta} \phi(t)dt = \Phi(X'_{t-1}\beta) \tag{1}$$

where $\Pr$ denotes the outcome probability, Y is a binary variable equal to 1 when a crisis occurs and 0 otherwise, and X is a vector of explanatory variables that influence the outcome. We estimate four different specifications. In the first three, we include each of the competing indicators of financial conditions separately. In the fourth, we include all of them. We also include a set of standard control variables (X_t), namely the growth rate of inflation and of real GDP, the level of real credit from banks to the private non-financial sector and the growth rate of real domestic and foreign credit.[21] Since we are more interested in the predictive power rather than in the contemporaneous relationship of the variables, we lag all the regressors by one period.

Table 5 reports the results. Let us look first at banking crises (panel A). Except for the TVP-FCI, the coefficients associated with the FCIs have a positive sign (i.e. a tightening in financial conditions at time t-1 increases the probability of a banking crisis at time t). However, the only FCI that combines statistical and economic significance is the WA-FSI. In addition, the magnitude of the coefficients, as well as the value of the log-likelihood, suggest that the WA-FSI is the best performing measure. This result is confirmed by the fact that when we include all the indicators simultaneously (column 4), only the coefficient associated with the WA-FSI remains statistically and economically significant. For a graphical comparison of the models, Figure 9 plots the Receiver Operating Characteristic (ROC) curves for each of the model in Table 5 and a model including only controls and excluding any type of FCI (i.e. model 5). Conceptually, the ROC compares the true positive, i.e the probability of a crisis according to the model when there is a crisis (known

[18] Laeven and Valencia (2020) define a banking crisis as an event combining significant signs of financial distress in the banking system and significant banking policy intervention measures in response to significant losses in the banking system. They define a currency crisis as a sharp nominal depreciation of the domestic currency against the US dollar. We do not consider sovereign debt crises because there is only one debt crisis matching our sample (Russia, 1998).

[19] The database only specifies the exact quarter the crisis started for a subset of episodes. Whenever the starting quarter is unknown we assign a value of 1 to the dummy for the entire year, while we assign the value of 1 only to the exact quarter when available.

[20] Due to data constraints the model is estimated using quarterly data on the sample 1995-2017.

[21] The last three variables are expressed in US Dollars.

Table 5: Panel Probit results

A. Systemic Banking Crises				
	(1)	(2)	(3)	(4)
TVP-FCI_{t-1}	-0.007			-0.214*
	(0.944)			(0.054)
WA-FSI_{t-1}		0.197***		0.333***
		(0.002)		(0.005)
WA-FCI_{t-1}			0.095	-0.025
			(0.309)	(0.810)
Observations	1,454	1,454	1,454	1,454
Log likelihood	-95	-93	-95	-91

B. Currency Crises				
	(1)	(2)	(3)	(4)
TVP-FCI_{t-1}	0.170**			0.054
	(0.050)			(0.526)
WA-FSI_{t-1}		0.205**		0.229**
		(0.021)		(0.013)
WA-FCI_{t-1}			-0.060	-0.199***
			(0.277)	(0.003)
Observations	1,454	1,454	1,454	1,454
Log likelihood	-36	-35	-37	-35

Notes. Robust p-values in parentheses. Statistical significance levels: *** p<0.01, ** p<0.05, * p<0.1.

as *sensitivity*), against false positives, i.e. the estimated probability of a crisis when there is not a crisis (known as *specificity*). The ROC curve of a random choice model is the 45 degrees line. The area below the ROC curve (AUROC) can be interpreted as a measure of accuracy of a binary model. The higher the AUROC, the better the model. The chart confirms that the best performing model is the fourth one (in green). This conclusion is supported also by formal tests on the statistical significance of the differences between the AUROC of the best model and the AUROCs of the other models (see Appendix F).

Moving to currency crises (panel B), the best predictor seems to be again the WA-FSI. In fact, this is the only indicator whose coefficient remains statistically and economically significant when all the FCIs are included in the model. In this case, however, formal tests do not detect statistically significant differences across the alternative models.

5 Conclusions

In this paper we evaluate alternative measures of financial conditions indicators for a large number of advanced and emerging economies.

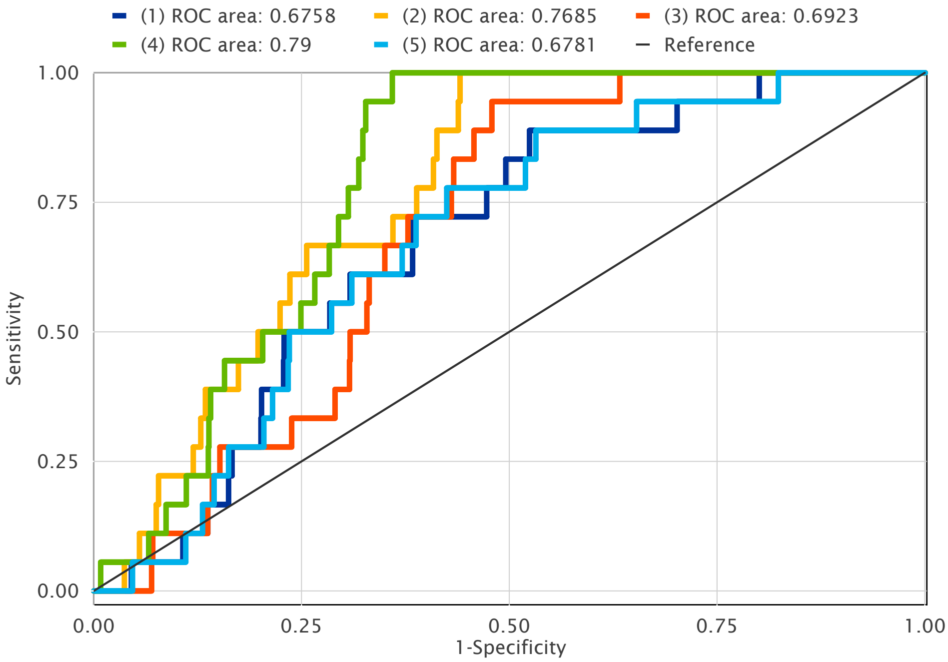
We argue that indices based on sophisticated factor models with time varying parameter do not offer any significant comparative advantage in terms of signalling risks for economic activity nor predicting financial crises. Indices constructed on the basis of alternative data reduction methods, like principal component analysis suffer from similar problems. In Appendix G we show that, indeed, principal component based indices and TVP based indices, are strongly correlated with each other.

A better alternative is simply averaging across the indicators of interest, using judgmental but reasonable weights. Indicators based on simple averages have some obvious benefits. Decomposition into the underlying drivers is simpler and more transparent. Moreover, the sign of some variables, like for instance the exchange rate, can be judgmentally decided, based on information on the financial structure of the economy.

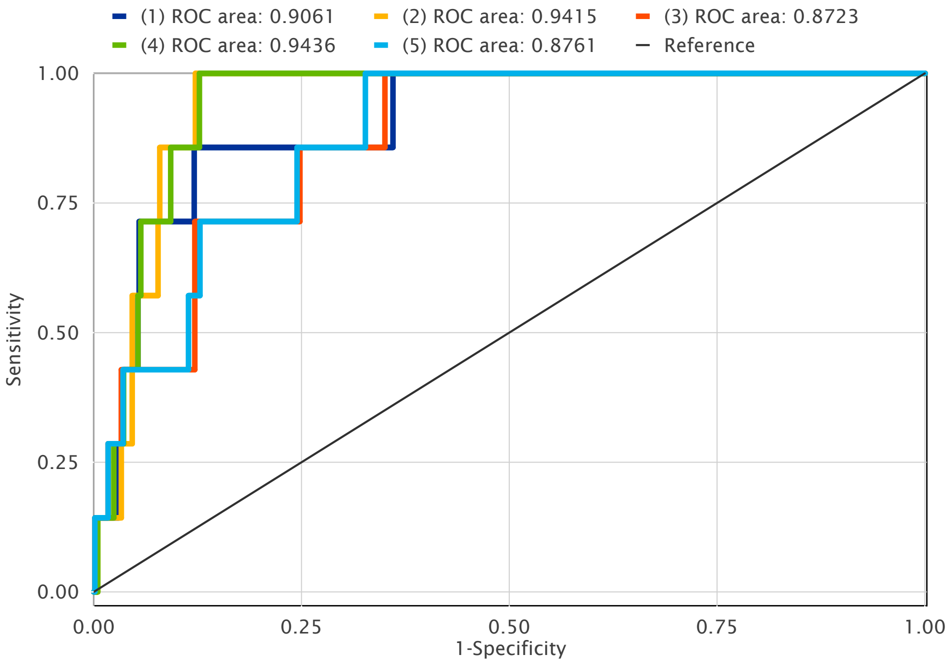
Our econometric evaluation, based on a large sample of countries, shows that simple averaging produces financial condition indices that are not inferior to, and actually perform better than those constructed with more sophisticated statistical methods. These results hold both in the context of quantile regressions, where they prove useful in

Figure 9: Comparison of ROC curves for each model

A. Systemic Banking Crises



B. Currency Crises



Notes. The numbers in brackets refer to the different models reported in Table 5. Lines represent the ROC curves for each of the models. The blue line refers to the model including TVP-FCI, the red line to the model including WA-FSI, the green line to the model including WA-FSI, the yellow line to the model including all three FCIs, and the light blue line to the model including only controls and excluding any type of FCIs (the latter is not included in Table 5).

anticipating downside risks to economic activity, as well as in probit models, where they show a stronger correlation with future banking and currency crises. Importantly, for the euro area and for the US our simple indices outperform popular alternatives based on larger information sets and on different econometric methods, namely the Composite Index of Systemic Stress (CISS) for the euro area and the National Financial Conditions Index (NFCI) published by the Chicago Fed for the US.

An indicator that gives more weight to measures of financial stress, which we term WA-FSI, emerges as the best indicator for anticipating banking crisis, and is therefore better suited for financial stability. At the same time the index seems quite suitable also for detecting downside risks to economic activity. For the latter criteria, an index of financial conditions that gives more weight to interest rates and to equity valuations and that is potentially available at the daily frequency (which we term WA-FCI) seems also appropriate. Nevertheless given its composition the WA-FCI index might be more appropriate for monitoring the effects of monetary policy.

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A The spillovers of a US financial shock

To estimate the effects of an exogenous tightening of financial conditions in the US on Mexico and Canada, we follow a two step strategy. First, we estimate a small Vector Autoregression (VAR) on US economy using domestic variables (Consumer Price Index, Industrial Production and the Excess Bond Premium) and global variables (the price of oil and global industrial production). We then identify a shock to financial conditions by assuming that the EBP reacts contemporaneously to slow moving variables (CPI, IP and the global variables), but that the latter only react with at least one month delay to an EBP shock. Admittedly with this crude identification assumption we are capturing a wide array of shocks (uncertainty, financial and credit supply shocks, just to name three) that impact contemporaneously financial conditions and that affect the business cycle with some delay. The exact definition of this shock is not crucial, as the purpose of the exercise is indeed to confirm that there is an important interplay between financial conditions and the business cycle *conditional on a wide array of shocks*.[22] We then use the estimated shocks as exogenous variables in VAR-X framework to study the effects on individual economies. This two step procedure has been widely used, see for instance Cesa-Bianchi et al. (2018) and Bhattarai et al. (2020), and rests on the assumptions that US and global shocks are exogenous with respect to developments in the small economies (like Canada and Mexico).

The effect of the shock on individual countries is examined using the following VAR-X model:

$$Y_t^i = \sum_{j=1}^{p} B_j Y_{t-j}^i + \Gamma^i s_t + \varepsilon_t^i \tag{A.1}$$

where Y_t^i is a vector of macro/financial variables for country i and s_t is the shock to financial conditions estimated in the first step. Both VARs are estimated with Bayesian methods using standard Minnesota priors. In this way we take into account all the sources of uncertainty when estimating the effects of the shocks on individual countries. In practice, conditioning on a draw of s_t from the posterior of the US/global VAR we take a draw from the country specific VARs and estimate the IRFs. The IRFs shown in

[22]This identification assumption follows Gilchrist and Zakrajsek (2012). Bhattarai et al. (2020) use the same methodology to study the spillovers of US uncertainty shocks.

Figure 2 are obtained from this model.

This motivational empirical analysis is naturally subject to some caveats. More sophisticated identification schemes could strengthen the case for a causal relationship going from the financial sector to the real economy. This has been done elsewhere in the literature. Caldara et al. (2016), for instance, show that financial shocks have been an important source of cyclical fluctuations since the 80s and that uncertainty shocks that cause a tightening of financial conditions are equally damaging for the business cycle.

B Data Sources

Table A1: Data sources and descriptions

Variable	*Detailed description*	*Source*
Credit◇, m-o-m growth rate	Credit to households and non-profit institutions serving households provided by all sectors. Adjusted for breaks, market value	Bank for International Settlements
Long term government bond yields	10-years nominal government bond yields. For TVP-FCI and WA-FSI yields are transformed in real terms by subtracting the annual growth rate of inflation	National sources via Refinitiv Datastream
Short term government bond yields	3/6 months or 1 year short term nominal government bond yields, according to country's best availability	National sources via Refinitiv Datastream
Sovereign spread	If available, we use the JPM EMBI stripped spreads. Otherwise we construct it as 10-years government bond yields minus the benchmark country's 10 years yield (US, UK, Germany, Japan, Switzerland)	Refinitiv Datastream, JP Morgan Chase
Inter-bank spread	Constructed as 3-months government benchmark bid yield minus 3-months inter-bank offered rate	National sources via Refinitiv Datastream
Term spread	Constructed as short minus long term government bond yields	National sources via Refinitiv Datastream
Equity volatility	30-days historical volatility of national stock indices	National sources via Refinitiv Datastream
Equity prices, m-o-m growth rate	Price indices of national stock exchange	National sources via Refinitiv Datastream
Real residential house prices◇, m-o-m growth rate	National residential property prices indices, deflated by consumer price indices	Bank for International Settlements, Oxford Economics, Cesa-Bianchi et al. (2015)
Bilateral exchange rate with the US Dollar	Market exchange rates, expressed as national currency per US Dollar	Refinitiv Datastream, International Monetary Fund, Federal Reserve Board, Haver
Price/Earning ratio	Price to earning ratios on national stock exchange	National sources via Refinitiv Datastream
NEER	Nominal effective exchange rates	Refinitiv Datastream
Corporate spread°	Constructed as redemption yields of corporate indices minus government bond yields with the same maturity	Merrill Lynch, Barclays and Refinitiv Datastream
Industrial production	Industrial production indices, standardized	National sources via Refinitiv Datastream
Headline inflation	Consumer price indices	International Monetary Fund and Bank for International Settlements
Real GDP	Real GDP in local currency, seasonally adjusted at annual rate	Organisation for Economic Co-operation and Development, Haver
Real domestic banks credit	Real domestic credit from banks to non-financial sector in US Dollar	Bank for International Settlements
Real foreign banks credit	Computed as a weighted average of domestic banks credit using country specific GDP PPP weights, US Dollars	Bank for International Settlements, International Monetary Fund

Notes. ◇ Since these data are originally quarterly, when used monthly we keep the value constant over the relative months of the quarter. ° In some cases, to extend series of corporate spreads when not available, we extend them using equity volatility and standardize the combined series.

Figure A1: Correlations with FCIs from Arregui et al. (2018)

Mexico	92.6%
Germany	92.2%
China	91.5%
Turkey	89.8%
Australia	88.3%
Japan	83.9%
France	83.1%
Norway	82.9%
Brazil	82.0%
United Kingdom	76.7%
Italy	76.1%
United States	74.3%
India	72.1%
Canada	70.1%
New Zealand	54.3%
South Korea	52.1%
Sweden	25.3%
Russia	-10.0%

Notes. Due to the public availability of the data for the FCIs from Arregui et al. (2018) correlations are computed over the period January 1995 - September 2016.

Figure A1 shows the correlation between the FCIs from Arregui et al. (2018) and our TVP-FCI. As expected, the replication using the factor model leads to a good match for almost all the countries.

C The dynamic factor model with time-varying parameters

Let $x_{it} = (x_{1t}, ..., x_{nt})'$ be an $n-$dimensional vector of variables that follows a dynamic factor model of the form:

$$x_{it} = \lambda_{it} f_t + \epsilon_{it} \tag{C.1}$$

$$f_t = B_t f_{t-1} + \eta_t \tag{C.2}$$

where f_t is the $k \times 1$ vector of factors, λ_{it} is the $n \times k$ factor loadings, B_t is a $k \times k$ matrix of $VAR(1)$ coefficients and ϵ_{it} and η_t are disturbance terms. It is further assumed that $\epsilon_t \sim N(0, V_t)$ and $\eta_t \sim N(0, Q_t)$ where V_t and Q_t are the $n \times n$ and $k \times k$ diagonal covariance matrices respectively. Note that the ϵ_{it} are uncorrelated with both f_t and η_t at all leads and lags. In order to complete the description of the TVP-DFM model we need to define how the time-varying parameters evolve. We allow λ_t and β_t to evolve as driftless random walks:

$$\lambda_t = \lambda_{t-1} + u_t \quad u_t \sim N(0, R_t) \tag{C.3}$$

$$\beta_t = \beta_{t-1} + \nu_t \quad \nu_t \sim N(0, W_t) \tag{C.4}$$

The model ha a standard state space representation where equation C.1 is the measurement equation and C.2 to C.4 are the state equations. The state vector f_t, λ_t, β_t are estimated via the Kalman smoother, provided that an estimate of the covariances, V_t, Q_t, R_t, W_t is available. We assume that errors across blocks of equations are uncorrelated, i.e. that u_t and ν_t are *i.i.d.* errors, with each other as well as with ϵ_t and η_t at all leads and lags.[23] The model covariances are estimated using a standard forgetting factor algorithm. First, R_t and W_t evolve as follows:

$$R_t = \left(\frac{1-\theta_R}{\theta_R}\right) P^{\lambda}_{t-1/t-1}$$
$$W_t = \left(\frac{1-\theta_W}{\theta_W}\right) P^{\beta}_{t-1/t-1}$$

where $P^{\lambda}_{t-1/t-1}$ and $P^{\beta}_{t-1/t-1}$ are the estimated covariance matrices of the unobserved state vectors λ_t and β_t in the model. The smoothing parameters θ_R and θ_W are set at 0.96. The matrices V_t and Q_t are estimated by suitably discounting past squared one step ahead prediction errors:

$$\widehat{V}_t = \kappa_\nu \widehat{V}_{t-1} + (1-\kappa_\nu)\epsilon_t\epsilon_t' \tag{C.5}$$
$$\widehat{Q}_t = \kappa_Q \widehat{Q}_{t-1} + (1-\kappa_Q)\eta_t\eta_t'$$

where ϵ_t is the vector that collects the measurement errors in equation C.1 and κ_ν and κ_Q are also set at 0.96.

[23]See, for instance, Cooley, 1971; Koop and Korobilis, 2010.

D Quantile regression framework

In our exercise, a quantile τ for h quarters ahead of the distribution of industrial production growth (y) is modeled as a function of current financial conditions (or other financial measures/vulnerability indicators), a constant and the current industrial production growth:

$$y_{t+h,\tau} = \beta_c + \beta_{FCI} FCI_t + \beta_{y_t} y_t + \epsilon_{t+h,\tau} \tag{D.1}$$

where τ is the τ_{th} conditional quantile. In a quantile regression the slope β is chosen so as to minimize the quantile weighted absolute value of errors. The predicted value is the quantile of $y_{(t+h)}$ conditional on the vector of regressors. In the paper we consider h=1 (month).

E Data sample for quantile regressions

The sample of data that we use for quantile regressions differs between countries due to data availability of industrial production. Table A2 reports the country specific data sample.

Table A2: Data sample for quantile regressions

CHN: Jan 1995-Nov 2019	GBR: Jan 1995-Dec 2019	KOR: Jan 1995-Dec 2019
USA: Jan 1995-Dec 2019	BRA: Jan 1995-Dec 2019	CAN: Jan 1995-Nov 2019
IND: May 2005-Dec 2019	FRA: Jan 1995-Dec 2019	AUS: Jan 1995-Aug 2019
JPN: Jan 1995-Dec 2019	MEX: Jan 1995-Dec 2019	SWE: Jan 2000-Dec 2019
DEU: Jan 1995-Dec 2019	ITA: Jan 1995-Dec 2019	NOR: Jan 1995-Dec 2019
RUS: Jan 1999-Mar 2019	TUR: Jan 2010-Dec 2019	NZL: Jan 1995-Nov 2019

Notes. Countries are ordered by GDP shares at purchasing parity power.

F Test for difference of Probit models' AUROCs

We formally test whether the AUROC associated with model 4 (benchmark model) is statistically different from the AUROC of every other model in pairwise comparisons. Table A3 shows the results. For systemic banking crises we can reject the null hypothesis and conclude that AUROCs are statistically different from the AUROC of model 4. Not surprisingly, the only exception is that the AUROC for model 2 is not statistically different from the AUROC for model 4. With regard to currency crisis, the AUROCs are not statistically different from the AUROC of the best model.

Table A3: Test for statistical difference of AUROCs

A. Systemic Banking Crises		
H_0	χ^2	$Pr > \chi^2$
AUROC(4)=AUROC(1)	3.9752	0.0462**
AUROC(4)=AUROC(2)	0.4360	0.5091
AUROC(4)=AUROC(3)	4.2909	0.0383**
AUROC(4)=AUROC(5)	3.7352	0.0533*

B. Currency Crises		
H_0	χ^2	$Pr > \chi^2$
AUROC(4)=AUROC(1)	0.6803	0.4095
AUROC(4)=AUROC(2)	0.1530	0.6957
AUROC(4)=AUROC(3)	2.0605	0.1512
AUROC(4)=AUROC(5)	2.0450	0.1527

Notes. *** p<0.01, ** p<0.05, * p<0.1. If $Pr > \chi^2$ is significant we can reject H_0, i.e. the AUROC is statistically different from the AUROC of the benchmark model.

G Principal component analysis

An alternative, widely used, technique to compute synthetic financial condition indices is Principal Component Analysis (PCA). We select the first principal component, that is the one explaining the largest fraction of the variance of the original variables, to be our PCA-FCI. Results reported in table A4 show that this method delivers financial conditions indices that closely mirror those obtained with the TVP-DFM. Correlations indicate that, except for Russia, there are no major differences between using the factor model or the PCA. Indeed, for 12 out of 18 countries the correlation is larger than 90%, suggesting that the two approaches produce almost identical results.

Table A4: Correlations between TVP-FCI and PCA-FCI

France	98.6%	Australia	96.4%
Germany	98.2%	New Zealand	95.4%
Norway	98.2%	Italy	94.3%
Canada	98.1%	Brazil	88.5%
United States	98.0%	Mexico	85.9%
Sweden	98.0%	India	80.8%
Japan	97.9%	South Korea	78.7%
China	97.9%	Turkey	76.3%
United Kingdom	97.6%	Russia	29.5%

H NFCI subcomponents explainer

Figure A2: NFCI components and categories

1	Spreads and implied volatilities
2	Credit ratios
3	Failure Rates and delinquencies
4	Lending standards
5	Issuance and open interest
6	Yields and price indices
7	Others

Mnemonic	Financial indicator	Category	Mnemonic	Financial indicator	Category
A2P2	1-mo. Nonfinancial commercial paper A2P2/AA credit spread	1	INS	Total Assets of Insurance Companies/GDP	4
ABCP	1-mo. Asset-backed/Financial commercial paper spread	1	ITA	Fed funds and Reverse Repurchase Agreements/Total Assets of Commercial Banks	4
ABSI	Nonmortgage ABS Issuance (Relative to 12-mo. MA)	5	JINC	30-yr Jumbo/Conforming fixed rate mortgage spread	1
ABSSPREAD	BofAML Home Equity ABS/MBS yield spread	1	LHY	Markit High Yield (HY) 5-yr Senior CDS Index	6
BAA	Moody's Baa corporate bond/10-yr Treasury yield spread	1	LIBID	3-mo. Eurodollar spread (LIBID-Treasury)	1
BDG	Broker-dealer Debit Balances in Margin Accounts	7	LIG	Markit Investment Grade (IG) 5-yr Senior CDS Index	7
BONDGR	New US Corporate Debt Issuance (Relative to 12-mo. MA)	5	LPH	CoreLogic National House Price Index	6
CARSPREAD	UM Household Survey: Auto Credit Conditions Good/Bad spread	1	MBOND	20-yr Treasury/State & Local Government 20-yr GO bond spread	1
CBCAR	Commercial Bank 48-mo. New Car Loan/2-yr Treasury yield spread	1	MBONDGR	New State & Local Government Debt Issues (Relative to 12-mo.h MA)	5
CBILL	3-mo. Financial commercial paper/Treasury bill spread	1	MBSI	Total MBS Issuance (Relative to 12-mo. MA)	5
CBPER	Commercial Bank 24-mo. Personal Loan/2-yr Treasury yield spread	1	MCAP	S&P 500, NASDAQ, and NYSE Market Capitalization/GDP	6
CCDQ	S&P US Bankcard Credit Card: 3-mo. Delinquency Rate	3	MDQ	MBA Serious Delinquencies	3
CCG	Consumer Credit Outstanding	2	MG	Money Stock: MZM	6
CCINC	S&P US Bankcard Credit Card: Excess Rate Spread	1	MINC	30-yr Conforming Mortgage/10-yr Treasury yield spread	1
CG	Commercial Paper Outstanding	4	MLIQ10	On-the-run vs. Off-the-run 10-yr Treasury liquidity premium	7
CILARGE	FRB Senior Loan Officer Survey: Tightening Standards on Large C&I Loans	4	MMF	Total Money Market Mutual Fund Assets/Total Long-term Fund Assets	7
CISMALL	FRB Senior Loan Officer Survey: Tightening Standards on Small C&I Loans	4	MSWAP	Bond Market Association Municipal Swap/20-yr Treasury yield spread	1
CITA	Commercial Bank C&I Loans/Total Assets	2	NACMM	NACM Survey of Credit Managers: Credit Manager's Index	2
CMBS	BofAML 3-5 yr AAA CMBS OAS spread	1	NCL	Commercial Bank Noncurrent/Total Loans	2
CMBSI	CMBS Issuance (Relative to 12-mo. MA)	5	NFC	Nonfinancial business debt outstanding/GDP	2
COMMODLIQ	COMEX Gold/NYMEX WTI Futures Market Depth	6	OEQ	S&P 500, S&P 500 mini, NASDAQ 100, NASDAQ mini Open Interest	5
CONTA	Commercial Bank Consumer Loans/Total Assets	2	OINT	3-mo. Eurodollar, 10-yr/3-mo. swap, 2-yr and 10-yr Treasury Open Interest	5
CPH	FRB Commercial Property Price Index	6	PENS	Total Assets of Pension Funds/GDP	7
CPR	Counterparty Risk Index (formerly maintained by Credit Derivatives Research)	7	RATELIQ	CME Eurodollar/CBOT T-Note Futures Market Depth	6
CRE	FRB Senior Loan Officer Survey: Tightening Standards on CRE Loans	4	REIT	Total REIT Assets/GDP	7
CRG	S&P US Bankcard Credit Card: Receivables Outstanding	7	REPO	Fed Funds/Overnight Treasury Repo rate spread	1
CTABS	ICE BofAML ABS/5-yr Treasury yield spread	1	REPOA	Fed Funds/Overnight Agency Repo rate spread	1
CTERM	3-mo./1-wk AA Financial commercial paper spread	1	REPOGR	Repo Market Volume (Repurchases+Reverse Repurchases of primary dealers)	6
CTF	ICE BofAML Financial/Corporate Credit bond spread	1	REPOMORT	Fed Funds/Overnight MBS Repo rate spread	1
CTMBS	ICE BofAML Mortgage Master MBS/10-year Treasury yield spread	1	RRE	FRB Senior Loan Officer Survey: Tightening Standards on RRE Loans	4
CWILL	FRB Senior Loan Officer Survey: Willingness to Lend to Consumers	4	RTA	Commercial Bank Real Estate Loans/Total Assets	2
D10	10-yr Constant Maturity Treasury yield	6	RTERM	3-mo./1-wk Treasury Repo spread	1
DBC	ABA Value of Delinquent Bank Card Credit Loans/Total Loans	3	SBD	Total Assets of Broker-dealers/GDP	2
DCLOSE	ABA Value of Delinquent Consumer Loans/Total Loans	3	SMALL	NFIB Survey: Credit Harder to Get	2
DCOMM	Commercial Bank Total Unused C&I Loan Commitments/Total Assets	7	SPCILARGE	FRB Senior Loan Officer Survey: Increasing spreads on Large C&I Loans	1
DHE	ABA Value of Delinquent Home Equity Loans/Total Loans	3	SPCISMALL	FRB Senior Loan Officer Survey: Increasing spreads on Small C&I Loans	1
DNET	Net Notional Value of Credit Derivatives	2	SPR210	10-yr/2-yr Treasury yield spread	1
DOTH	ABA Value of Delinquent Noncard Revolving Credit Loans/Total Loans	3	SPR23M	2-yr/3-mo. Treasury yield spread	1
DURSPREAD	UM Household Survey: Durable Goods Credit Conditions Good/Bad spread	1	STA	Commercial Bank Securities in Bank Credit/Total Assets	2
EQUITYLIQ	CME E-mini S&P Futures Market Depth	6	STKGR	New US Corporate Equity Issuance (Relative to 12-mo. MA)	5
FAILS	Treasury Repo Delivery Fails Rate	3	STLOC	Federal, state, and local debt outstanding/GDP	2
FAILSA	Agency Repo Delivery Failures Rate	3	SWAP10	10-yr Interest Rate Swap/Treasury yield spread	1
FAILSC	Corporate Securities Repo Delivery Failures Rate	3	SWAP2	2-yr Interest Rate Swap/Treasury yield spread	1
FAILSMBS	Agency MBS Repo Delivery Failures Rate	3	SWAP3M	3-mo. Overnight Indexed Swap (OIS)/Treasury yield spread	1
FC	Total Assets of Finance Companies/GDP	4	TABS	Total Assets of ABS issuers/GDP	5
FCORP	Total Assets of Funding Corporations/GDP	4	TED	3-mo. TED spread (LIBOR-Treasury)	1
FG	Finance Company Owned & Managed Receivables	7	TERM	1-yr/1-mo. LIBOR spread	1
FINS	S&P 500 Financials/S&P 500 Price Index (Relative to 2-yr MA)	6	USD	Advanced Foreign Economies Trade-weighted US Dollar Value Index	6
GSE	Total Agency and GSE Assets/GDP	4	VIX	CBOE Market Volatility Index VIX	1
GVL	FDIC Volatile Bank Liabilities	4	VOL1	1-mo. BofAML Option Volatility Estimate Index	1
HH	Household debt outstanding/PCE Durables and Residential Investment	2	VOL3	3-mo. BofAML Swaption Volatility Estimate Index	1
HOUSSPREAD	UM Household Survey: Mortgage Credit Conditions Good/Bad spread	1	W500	Wilshire 5000 Stock Price Index	6
HY	BofAML High Yield/Moody's Baa corporate bond yield spread	1	Macro	Macroeconomic adjustment due to activity and inflation	7

Notes. The choice of macro-categories and the allocation of components to them is based on the judgment of the authors.

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