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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 use four criteria to assess the performance of these indicators, namely quantile regressions, Structural Vector Autoregressions, the ability of the indices to predict banking crises and their response to US monetary policy shocks. We find that averaging across the indicators of interest, using judgemental but intuitive weights, produces financial condition indices that are not inferior to, and actually perform better than, those constructed with more sophisticated statistical methods.

JEL codes: E32, E44, C11, C55.

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

Non-technical summary

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 periods of tranquillity, characterized by cheap borrowing rates, high asset prices, low volatility and compressed spreads, during which imbalances build-up. In this context, financial condition indices (FCIs) provide valuable information regarding future risks to economic activity and can be used to appropriately calibrate macro-prudential tools. Financial condition indices are also actively used by monetary policy makers to study the broad effects of monetary policy on financial markets.

But which indicators should a financial condition index include and how should these indicators be weighed? Part of the econometric literature has explored different methods, more or less sophisticated, for answering these questions. In this paper we show that simply averaging across a handful of indicators, using judgemental but intuitive weights, produces financial condition indices that are not inferior to, and actually perform better than, those constructed with more sophisticated statistical methods that have gained popularity after the global financial crisis.

We start our analysis by constructing a sophisticated type of financial condition index, based on a Bayesian dynamic factor model with time varying coefficients and drifting volatilities (TVP-FCI). We then construct two simpler weighted average (WA) measures. One, more akin to a financial stress index, in which spreads and volatilities have a preponderant role (WA-FSI), and one that gives a predominant role to the level of interest rates and stock valuations (WA-FCI). Our analysis is based on data for 18 advanced and emerging economies at a monthly frequency from January 1995 to May 2020. These countries represent about 70% of the world's GDP.

We use four criteria to formally assess the performance of the three indices of financial conditions. First, we use quantile regressions to examine their predictive content for the lower quantiles of the distribution of industrial production growth. This analysis reveals that the WA-FSI, that is the financial stress index constructed via simple averaging, provides the strongest signal for exceptional downturns of economic activity. For the euro area and for the US, the WA-FSI strongly outperforms also 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. Second, by means of a panel probit model we analyze the ability of these indices to predict banking crises. Again, the WA-FSI emerges as the index that is more strongly correlated with subsequent turmoil in the banking sector. Third, using simple Bayesian Vector Autoregression models we study their response to a financial shock on economic activity. The outcome of this analysis is not clear-cut, as all the indices respond in similar fashion to the identified shock. Fourth, we examine their reaction to monetary policy shocks. We find that the WA-FCI, which loads more on interest rates and stock prices, portrays more sensibly the effects on US monetary policy on global financial conditions.

In sum, our empirical analysis sends two key messages. First, in order to construct some measure of financial conditions for international policy analysis the lack of a large information set for some countries should not be seen as a major obstacle. For the US and the euro area, for which a comparison between large and small datasets is feasible, we do not find evidence that going "large" is really beneficial. Second, the use of complicated methods makes these indicators hard to interpret and does not provide important value added.

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 tranquillity, 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 centre of the transmission mechanism of monetary policy. Even small movements in short 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 behaviour 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 that was developed in the 2000s (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 these indices has increased over time. For instance, Koop

[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 more closely related to measuring credit conditions in the economy.

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 behaviour. Interest rates, for instance, have been falling historically for some decades now. Corporate spreads or equity volatility, on the other hand, are stationary process with occasional jumps. Finally, exchange rates show pronounced cyclicality. To make this point more concrete, 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. 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. Out of the 36 correlations that fill the off-diagonal elements of the table, only 3 are higher than 0.3 in absolute value, namely the correlation of equity volatility with stock returns and sovereign spreads, and the correlation between inter-bank and sovereign spreads.

Given this heterogeneity and the lack of collinearity, it is very likely that the final composite index is largely going to reflect the behaviour 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, for instance, 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.[2] The different colours illustrate the block to

[2]The Chicago Fed's NFCI provides a comprehensive weekly update on U.S. 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 F reports the series that are included in the index.

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

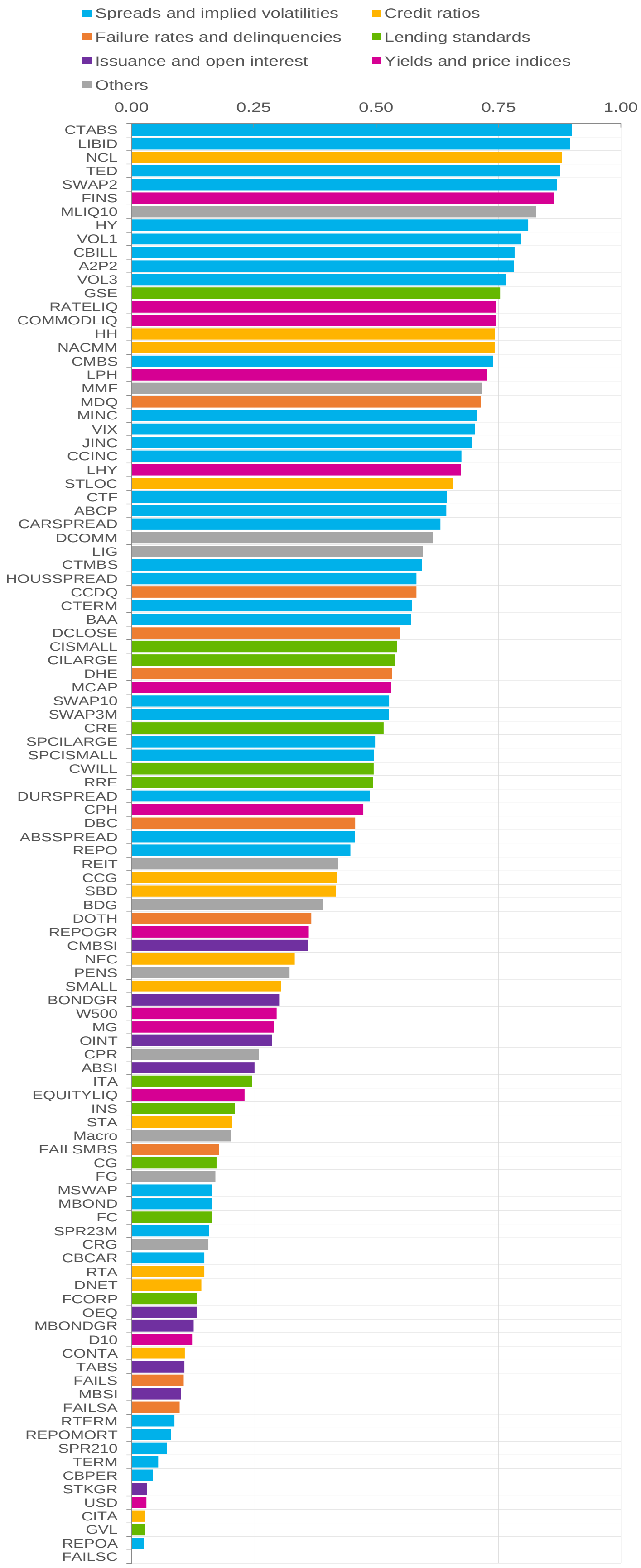
Notes. Correlations are unweighted averages across countries. Countries' specific correlations are computed over the period January 1995-February 2020 for a sample of 18 countries including China, United States, India, Japan, Germany, Russia, Brazil, United Kingdom, France, Mexico, Italy, Turkey, South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

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 dominance of blue bars at the high end of the correlation spectrum. Some yields are also represented, but most of the yields 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*.

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. For instance, after the global financial crisis new pockets of vulnerability in the global economy have emerged, like for instance the rise of debt in emerging markets as well as the increased relevance of cross-border portfolio flows and corporate debt in the US

Figure 1: Correlation of NFCI subcomponents with the final index



Notes. For variables definitions and details see Figure A.2 in Appendix F. Due to data availability, correlations are computed over the period 3 June 2005 - 29 May 2020 on a weekly frequency.

(IMF, 2019).

We argue that simply averaging across the indicators of interest, using judgemental 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 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 four such criteria to evaluate the performance of our financial indicators. First, we examine across the 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). Second, and related to the first, we examine how the various alternatives are correlated with future banking crises. Banking crises are somewhat related to deep recessions, so we see this exercise as complementary to the previous one. Third, we model simple Structural Vector Autoregressions in which financial condition indices interact with other macroeconomic variables. Impulse response functions to a shock to financial conditions should convey some information on their *causal* impact on economic activity. Fourth, we examine how different candidate measures of financial conditions respond to US monetary policy shocks. In this context, the literature on monetary policy spillovers provides some guidance on plausible results that we can use to benchmark those obtained with financial condition indices.

We take as a benchmark a "sophisticated" type of financial condition index, constructed as in Koop and Korobilis (2014). This index is at the highest level of the sophistication spectrum, since it is based on a Bayesian dynamic factor model with time varying coefficients and drifting volatilities 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.[3] The index can be easily replicated for a large number of countries. This broadens the analysis outside of the US, the economy for which the largest number of financial condition indices has been developed. In the rest of the analysis we will refer to this index as 'TVP-FCI'. We contrast this benchmark with two simple alternatives based on simple weighted averages. The choice of the weights is deliberately naive, and reflects the purpose of the index. First, we construct an index that measures the level of stress in the economy, by assigning half of the weight to spreads and to stock market volatility. The level of interest rates, the exchange rate, as well as stock returns and house prices, account with approximately equal weights for the rest of the index. We call this index the 'WA-FSI', to reflect the fact that it is based on a weighted average (hence WA) and that it reflects more heavily measures of stress than financial conditions in normal times (hence FSI). The second alternative is geared more towards capturing the actual cost of financing for economic agents, and gives a predominant role to the level of interest rates, as well as to equity valuations. We call this second alternative the 'WA-FCI'. Although all our analysis is based on monthly data, the WA-FCI relies on indicators that would be available also at at very high (daily) frequency. We see these latter two indices as complementary. The former, loading more heavily on indicators that signal strains in the financial system, could be more useful in the context of financial stability analysis. The latter, being more representative of the level of credit costs and being available at higher frequency, could be of greater interest for monetary policy monitoring.

Our findings show that the measure of financial stress based on weighted averages (WA-FSI) is a more powerful predictor of banking crises and better captures growth at risk. The WA-FCI, which loads more on interest rates and stock returns, portrays more sensibly the effects on US monetary policy on global financial conditions. Overall, the more sophisticated alternative, the TVP-FCI, never emerges as the preferred option in any of the empirical applications.[4]

All these financial condition indices are based on a limited information set. This

[3] Growth at risk is the time varying estimate of the 5th quantile of GDP growth, and provides a probabilistic assessment of macro-economic vulnerability; much like value at risk measures the vulnerability of a portfolio of assets in the context of financial analysis. The concept was popularized by Adrian et al. (2019) and adopted by the IMF as the main quantitative criterion to gauge global financial stability risks. See also Section 3.

[4] Using principal components results in indices very similar to the TVP-FCI, see Appendix E, so that all the criticisms directed to the TVP-FCI are also valid for principal components.

choice is dictated by the desire to provide a benchmark index for a large number of countries, useful for policy analyses and based on a homogeneous information set. A natural question one might want to raise is whether "large data" alternatives, available for large advanced economies like the US or the euro area, outperform our simple indices. To answer this question we use our quantile regression framework to perform a horse race between the TVP-FCI, the WA-FCI, the WA-FSI and two popular alternatives, namely the Chicago Fed 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. In both cases the WA-FSI comfortably outperforms both the NFCI and the CISS.

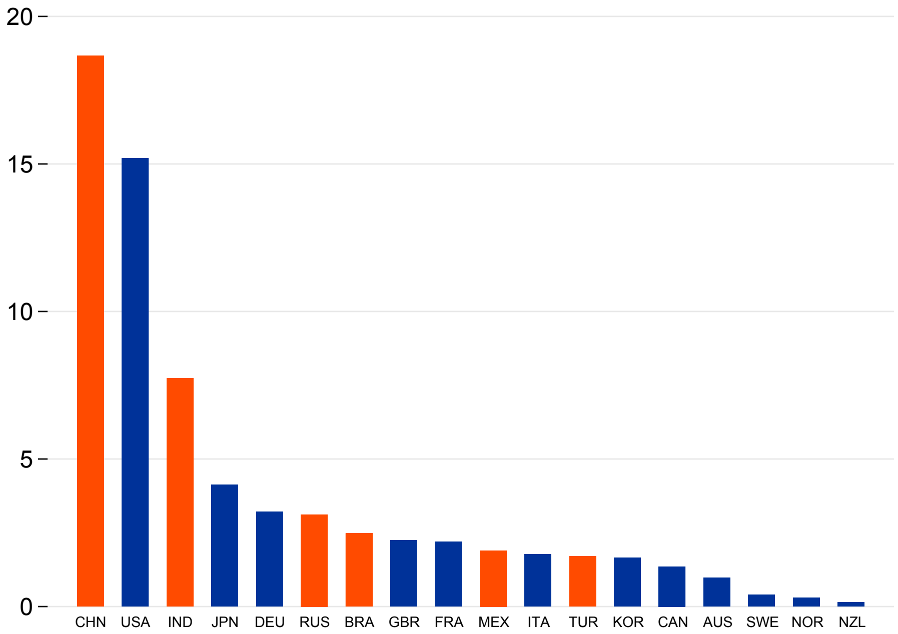
In sum, our empirical analysis sends two key messages. First, in order to construct some measure of financial conditions for international policy analysis, the lack of a large information set for some countries should not be seen as a major obstacle. For the US and the euro area, for which a comparison between large and small datasets is feasible, we do not find evidence that going "large" is really beneficial. Second, the use of complicated methods makes these indicators hard to interpret and does not provide important value added.

The paper is organized as follows. Section 2 provides a description of the data and details on the construction of the indices. Section 3 describes the four criteria that we employ to assess the performance of our financial condition indices and discusses the empirical results. Section 4 concludes.

2 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 2 shows, these countries represent about 70% of the world's GDP at Purchasing Power Parity.

Figure 2: Countries 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, 2018 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 A.

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), interbank 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 B. 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 (excluding Russia) own a non-negligible part of their debt in US dollars, when the local currency weakens against the dollar, the cost of debt express 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 averages of a smaller set of financial variables, which are potentially available at the daily frequency. This FCI could be used, for instance, for the high frequency 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 also 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[5]); and (iv) a measure of spread, namely corporate spreads for advanced economies and the JP Morgan EMBI stripped spreads for emerging markets.

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

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 (see WA-FCI paragraph), 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.

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

Comments and comparisons. Figures 3a and 3b 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

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.

prevalence of interest rates and equity valuations results in indices that are more cyclical and spike less during the GFC.

3 Empirical analysis

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

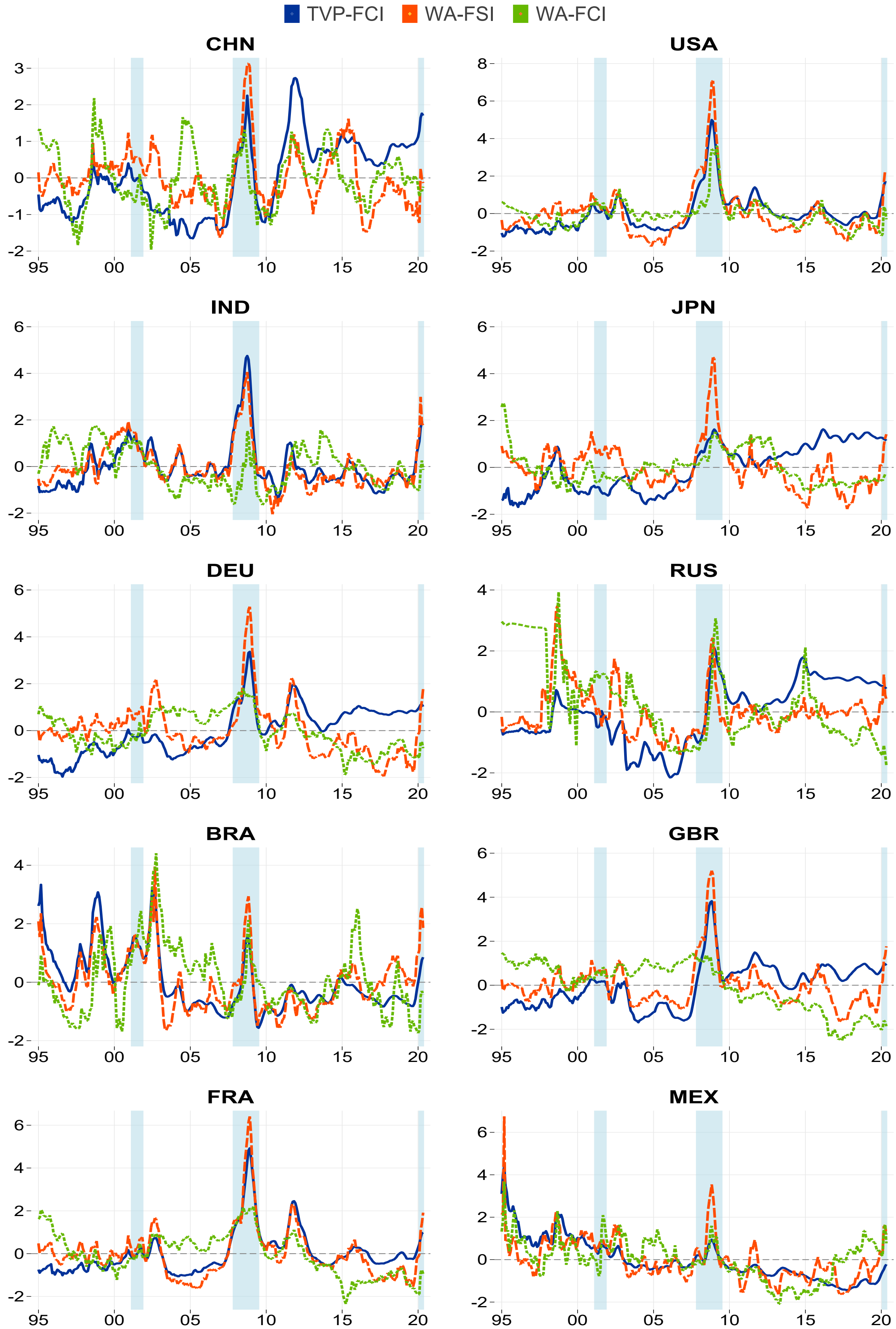
3.1 Quantile regressions

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 C 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 much more strongly over time and react more to developments in financial conditions than 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 2 (for data availability see Appendix D). The results are summarized in Figure 4. 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 is significantly more negative than either on the central tendency or on the upper tails. This implies that financial conditions convey

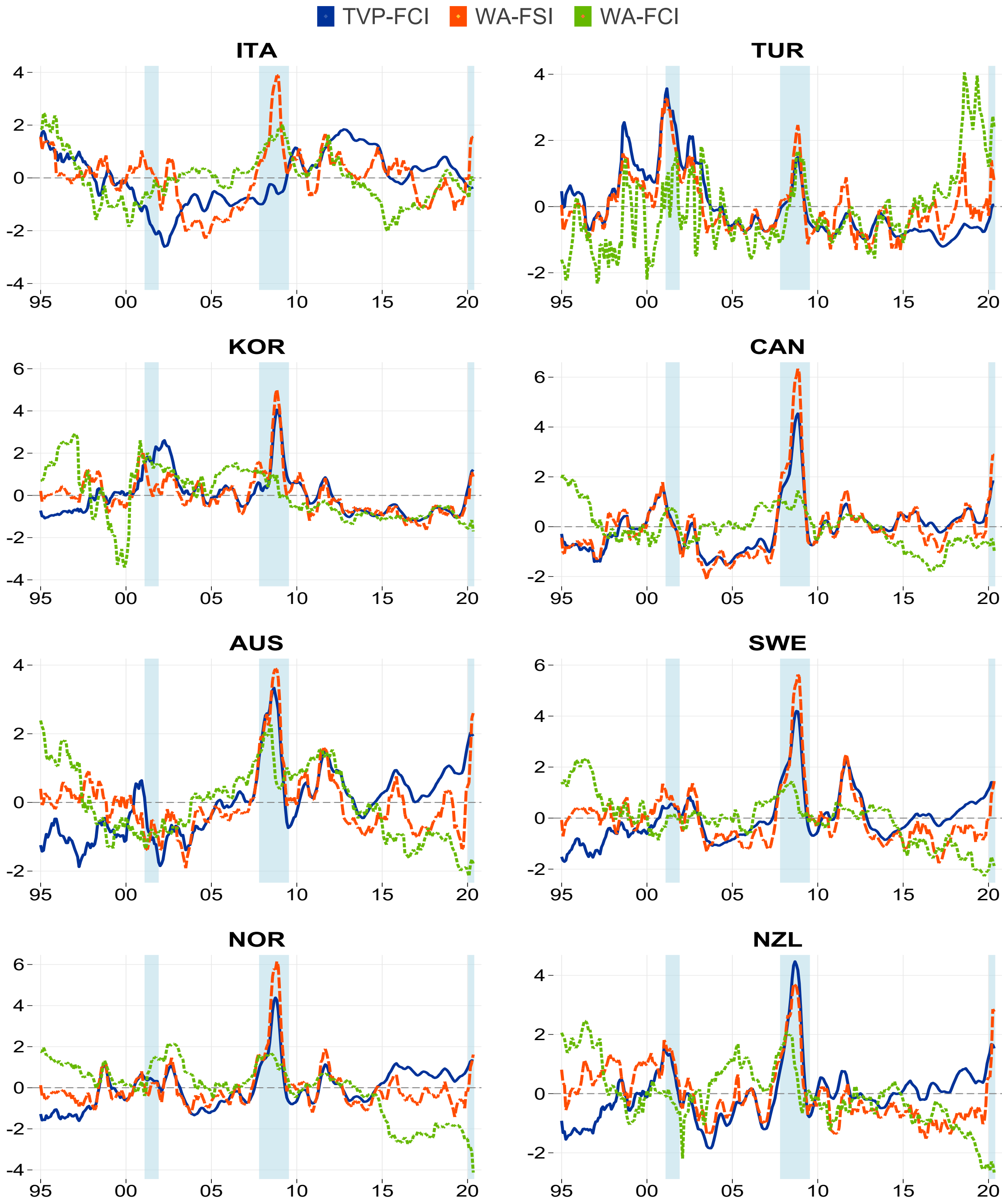
[6] For Italy the asymmetry in terms of the impact of the three financial indicators on industrial production distribution is only valid for WA-FSI and WA-FCI. For India and Norway the asymmetry is not so evident for any of the measures considered. For reasons of space we only report here the impact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

Figure 3a: Comparison of the FCIs, 10 largest countries



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

Figure 3b: Comparison of the FCIs, continued



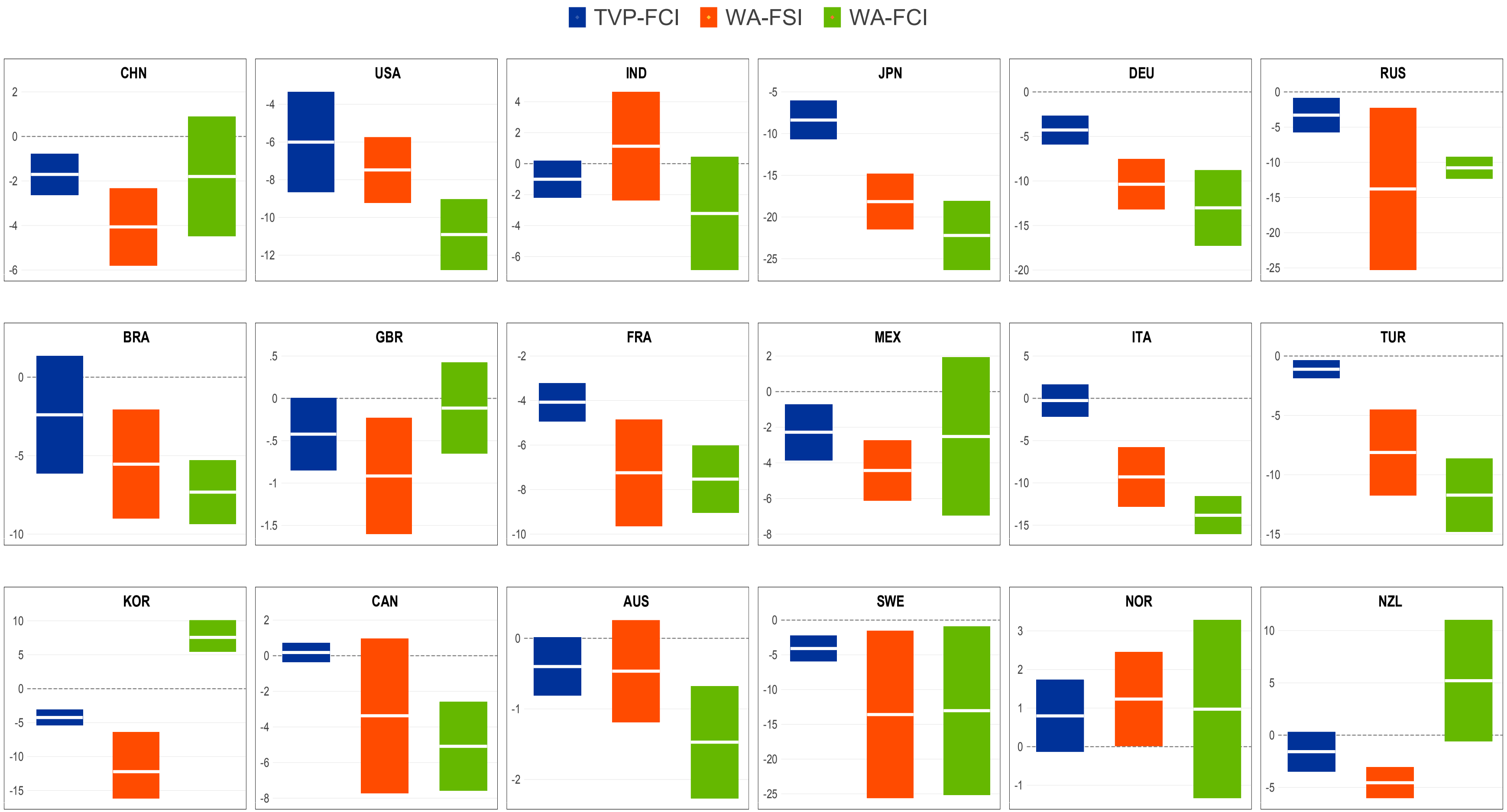
Notes. Shaded areas represent NBER recessions. All indicators are normalized.

powerful signals on downside risks to 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).[6]

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 US, Italy, Australia, Germany, India, Brazil, Turkey, France, Canada and Japan are better captured by developments in the WA-FCI.[7] 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 information on downside risks for future economic activity.

[7]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 4: Impact of FCIs on the lower quantile of 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 D.

The poor performance of the TVP-FCI could be due to the size of the information set. Factors models, after all, are designed to extract information from a large number of time series and existing measures of financial stress for the US rely indeed on many carefully chosen series. The Chicago Fed NFCI, for instance, includes 106 time series. Another possibility is that the particular method that we have picked (i.e. a factor model with time-varying parameters) is a poor choice. Other methods among those proposed in the literature, might work better. For instance, the CISS by Hollo et al. (2012), is estimated by aggregating 13 indicators of financial stress through a time varying correlation model. To test how our simple indices compare against these two alternatives, we repeat the quantile regression analysis for US and EA including also the NFCI and the CISS as potential competitors. The results of this exercise, shown in Figure 5, indicate that both the NFCI for the US as well as the CISS for the euro area perform much worse not only than the WA-FSI, but also than the TVP-FCI.

3.2 FCIs and banking crises

As a second criterion for assessing the informational content of the three competing indices, we consider their ability to predict systemic banking crises. For this purpose, we collect data on the timing of systemic banking crisis from Laeven and Valencia (2018) and estimate a panel probit model specified as follows:

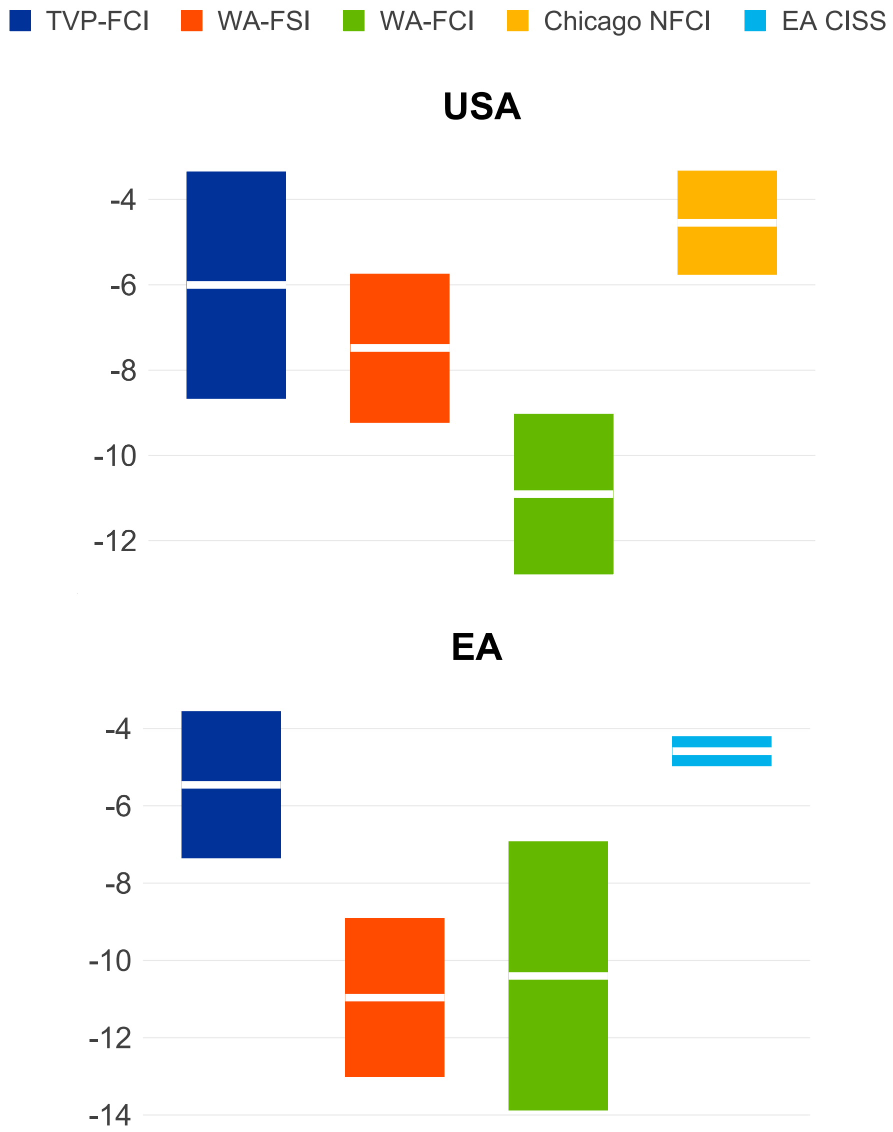
$$Pr(Y_t = 1 \mid X_{t-1}) = \int_{-\infty}^{X'_{t-1}\beta} \phi(t)dt = \Phi(X'_{t-1}\beta), \tag{1}$$

where Pr denotes the outcome probability, Y is a binary variable equal to 1 when a banking 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 three competing indicators of financial conditions separately. In the fourth, we include all of them. We also include a set of standard control variables, namely the growth rate of inflation, 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.[8] 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.[9] Table 5 reports the results.

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

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

Figure 5: 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 2). For EA the data sample covers January 2000 - December 2019.

Table 5: Panel Probit

	(1)	(2)	(3)	(4)
TVP-FCI$_{t-1}$	0.495***			0.128
	(0.001)			(0.414)
WA-FSI$_{t-1}$		0.583***		0.555***
		(0.000)		(0.000)
WA-FCI$_{t-1}$			0.197	-0.092
			(0.190)	(0.559)
Observations	1,454	1,454	1,454	1,454
Log likelihood	-397.56	-371.09	-429.47	-368.47

Notes. Robust p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

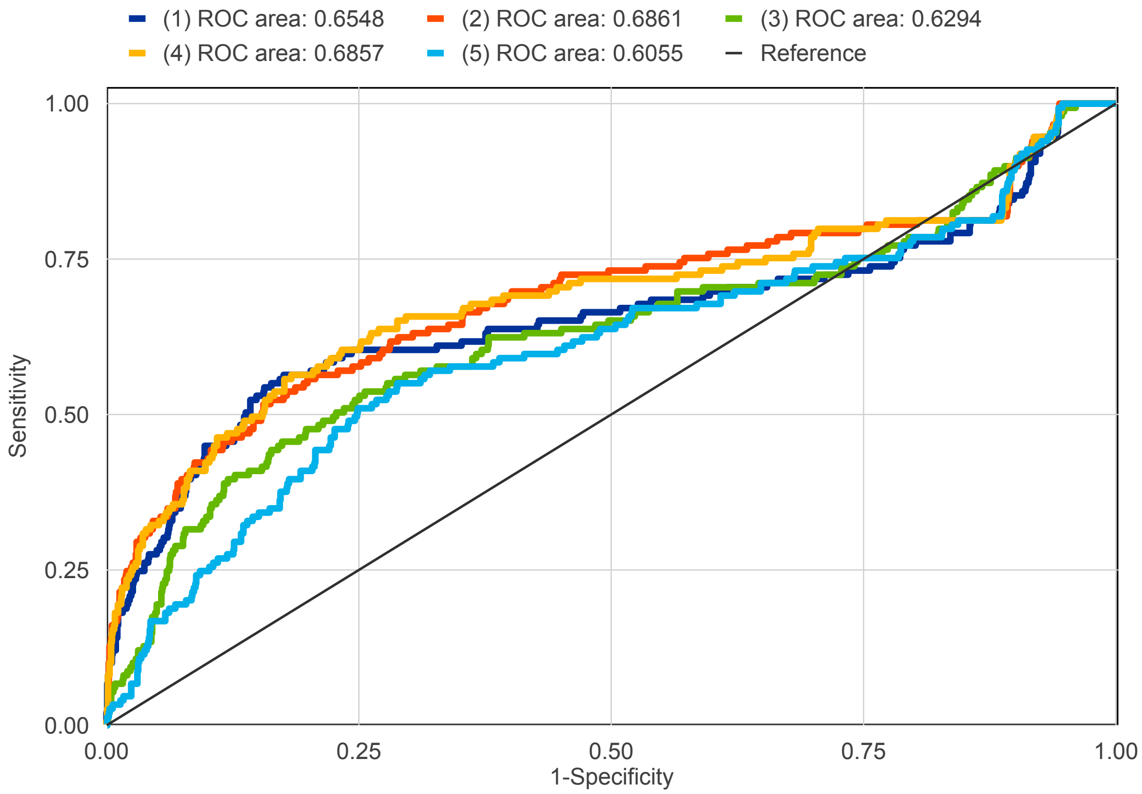
As expected, all the coefficients associated with the financial conditions indicators have a positive sign (i.e. a tightening in financial conditions at time t-1 increases the probability of a banking crisis at time t) and, with the exception of the WA-FCI, are highly statistically significant. The magnitude of the coefficients, as well as the value of the likelihood, suggests that the WA-FSI is the best performing measure. This result is confirmed by the fact that including all the indicators simultaneously, only the coefficient associated with the WA-FSI is statistically significant.

For a graphical comparison of the models, Figure 6 plots the Receiver Operating Characteristic (ROC) curves. Conceptually, the ROC compares the true positive, i.e the probability of a banking crisis according to the model when there is a crisis (known as *sensitivity*), against false positives, i.e. the estimated probability of a banking crisis when there is not a crisis (known as *specificity*). The ROC curve of a random choice model is a 45 degrees line. The area below the ROC curve but above the 45 degree line can be interpreted as a measure of accuracy of a binary model. The chart confirms that the best performing model is the one including the WA-FSI alone (model 2, in red).

3.3 Structural Vector Autoregressions

As a third criterion we use Structural Vector Autoregressions (SVARs) to analyse the macroeconomic consequences of an exogenous financial tightening shock on economic activity. A potential advantage of the VAR models as compared to the quantile regression approach is that it better takes into account the feedback between all variables, which

Figure 6: Comparison of ROC curves for each model



Notes. The numbers in brackets refer to the different models reported in Table 5. Lines represent the ROC curves for each of the models. Specifically, 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 finally the light blue line to the model including only controls and excluding any type of financial conditions (the latter is not included in Table 5). The legend also reports a measure of the area between the respective ROC curve and the 45 degrees line.

may be particularly important when dealing with financial variables. A wave of papers on FCIs, Guichard and Turner (2008) and Swiston (2008), use VARs to examine the impact of financial conditions on economic activity in the United States (US). Gilchrist and Zakrajšek (2012) examine the macroeconomic consequences of shocks to the excess bond premium in US using a recursive identification scheme. The identifying assumption implied by their recursive ordering is that shocks to the excess bond premium affect economic activity and inflation with a lag, while the risk-free rates and stock prices can react contemporaneously to this financial shock. They find that an increase in the excess bond premium triggers a reduction in credit supply, with negative effects on economic activity.[10]

We broadly follow the same approach. For each country we construct a tri-variate VAR including financial conditions (each indicator at a time), industrial production and headline inflation. We order financial conditions first and, in line with Gilchrist and Zakrajšek (2012) we identify a shock to financial conditions using a recursive ordering.[11]

Figure 7 reports the trough response of industrial production to one standard deviation shock in each of the three financial indicators we constructed. The results are qualitatively similar to the ones obtained for quantile regressions. In particular, for none of the countries examined except Brazil, the TVP-FCI signals a stronger impact of an exogenous shock to financial conditions on economic activity than the alternative simple indicators. No clear-cut ranking emerges between the WA-FSI and the WA-FCI.

[10] Darracq Pariès et al. (2014) construct a financial conditions index for the euro area and use it in a VAR to identify bank lending supply shocks. According to their results, credit supply shocks accounted for one fifth of the decline in manufacturing activity during the euro area sovereign debt crisis.

[11] We estimate the models in levels with Bayesian methods and a standard Minnesota prior.

Figure 7: SVARs, Impact of FCIs on Industrial Production

Notes. The VAR model comprises financial conditions, industrial production and CPI inflation. The white line represents the impact of one standard deviation in FCI on industrial production, while the shaded areas represent the 95 percent confidence intervals around it. The results are reported for the through response of industrial production to a shock of one standard deviation in financial conditions. The country specific sample varies according to data availability, see Appendix D.

3.4 Spillover analysis

The fourth and final question that we ask is which measure of financial conditions better reflects the effects of monetary policy. It is well known that the relationship between financial conditions and monetary policy goes in two directions. First, monetary policy affects directly and indirectly financial conditions. By controlling the supply of reserves, either via repo operations or via open market operations of short-term government bonds, central banks determine the interest rate at which liquidity is exchanged in the inter-bank market and, starting from this, affect the broader spectrum of interest rates in the economy. This reverberates more generally on stock prices and on credit spreads (Gertler and Karadi, 2015). Yet, financial conditions are also an important element of the information set on which central banks condition their decisions. The reference to tighter financial conditions, for instance, has marked Fed's communication in occasion of two historical turnarounds in their policy stance, in January 2016 and in January 2019.

To check how our indices reflect monetary policy shocks we draw on the global financial cycle literature. Financial conditions have a strong global component, which is tightly linked to US monetary policy, see Miranda-Agrippino and Rey (2015) and Powell (2018), partly due to the importance of the dollar in global intermediation of credit and in trade invoicing. US monetary policy then responds to financial conditions and also affects financial conditions (Ammer et al., 2016). Spillovers operate mainly via three channels, namely exchange rate adjustments, import demand in the home economy and financial conditions. From a theoretical standpoint a US monetary expansion leads to a dollar depreciation. As a result, exports to the US become more expensive, imports from the US become cheaper and global demand is reallocated toward US goods. Yields and borrowing costs abroad also fall, credit in foreign economies rises, and asset prices increase. Evidence from monetary surprises in times of conventional and unconventional monetary policies indicates that the spillover effects are significant, albeit quantitatively small, and are likely to differ across recipient countries depending on various country-specific features, including how monetary policy reacts to US shocks, the exchange rate regime, and the degree of vulnerability to external shocks. Given this background, a useful index of financial conditions should properly respond to US monetary policy, reflecting the role of the US financial system in the global economy. We examine the response to US shocks in the context of panel local projections (Jordà, 2005) of the type:

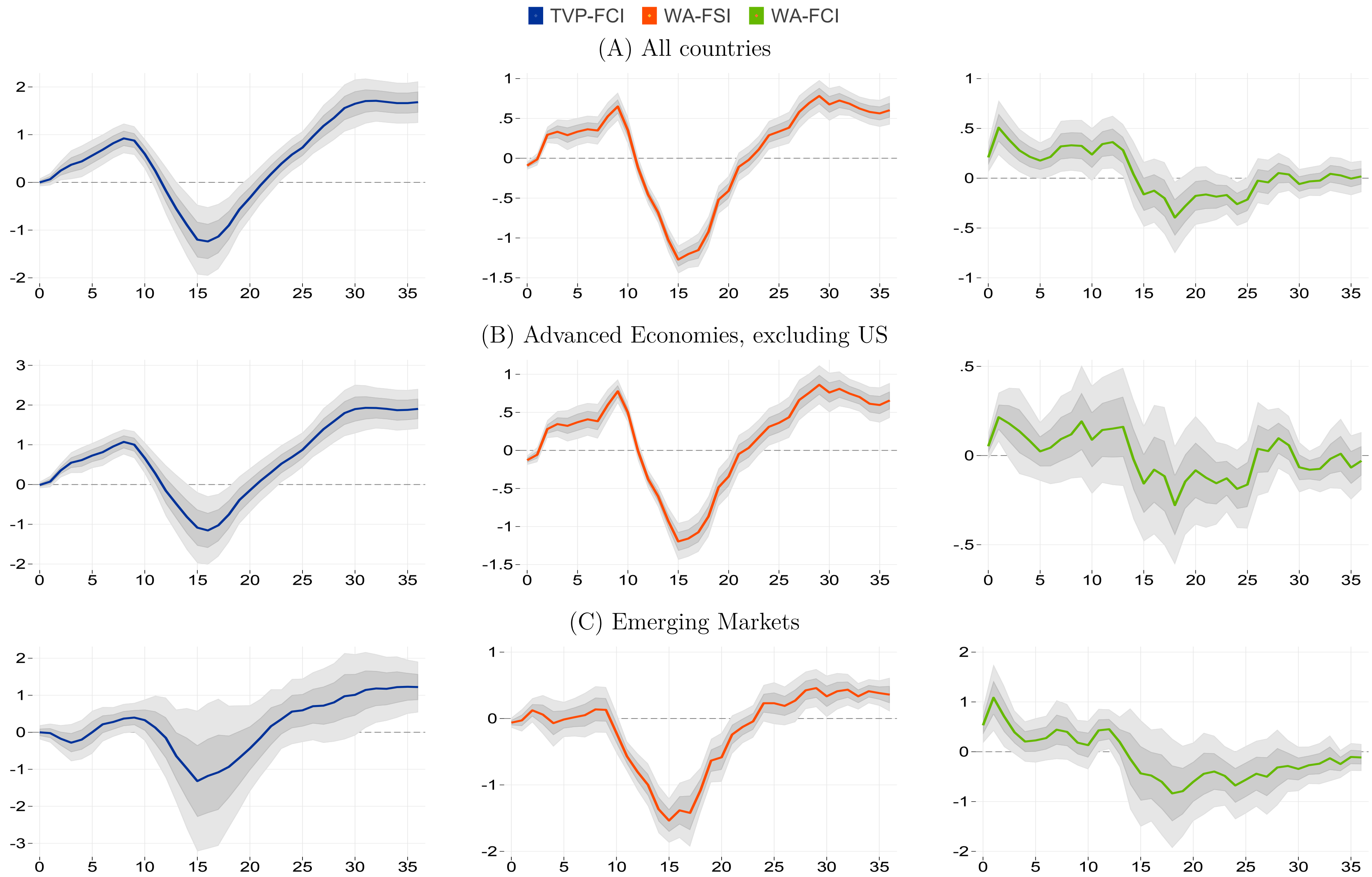
$$FCI_{i,t+h} - FCI_{i,t-1} = \alpha_{i,h} + \Xi_h Shock_t + \Omega_h FCI_{i,t} + \boldsymbol{\Psi_h}(L)\boldsymbol{X_{i,t}} + \varepsilon_{i,t+h}, \qquad (2)$$

where $Shock_t$ denotes structural US monetary policy shocks identified using high frequency data as in Jarocinski and Karadi (2019). $\mathbf{X}$ is a vector of controls including both country specific and common factors (computed as cross-country averages) of the growth rates of industrial production and inflation. These enter the model with up to two lags. A country fixed effect $\alpha_{i,h}$ is included. The estimation sample is January 1995 - December 2017. We also look at different cuts of the data, by running separate estimations for (a) all countries, (b) advanced economies (excluding US), and (c) emerging markets.

Results are reported in Figure 8. Local projections suggest that only the WA-FCI reacts immediately and significantly to a FED tightening shocks whilst the other two indicators' responses are insignificant within a period up to 2-3 months. Moreover, while the response for the WA-FCI is unequivocal and economically meaningful, the TVP-FCI and the WA-FSI do not react in a clear way as they revert their course after a few months. An analysis of the behaviour of the individual time series (not reported for brevity) indicates that the response of inter-bank spreads and equity volatility seems to account for the puzzling shape of the response of the WA-FSI index to monetary policy shocks. The WA-FCI, loading more heavily on variables that are directly connected to monetary policy, like rates and price to equity valuations, better captures the effects of US monetary policy on financial conditions.

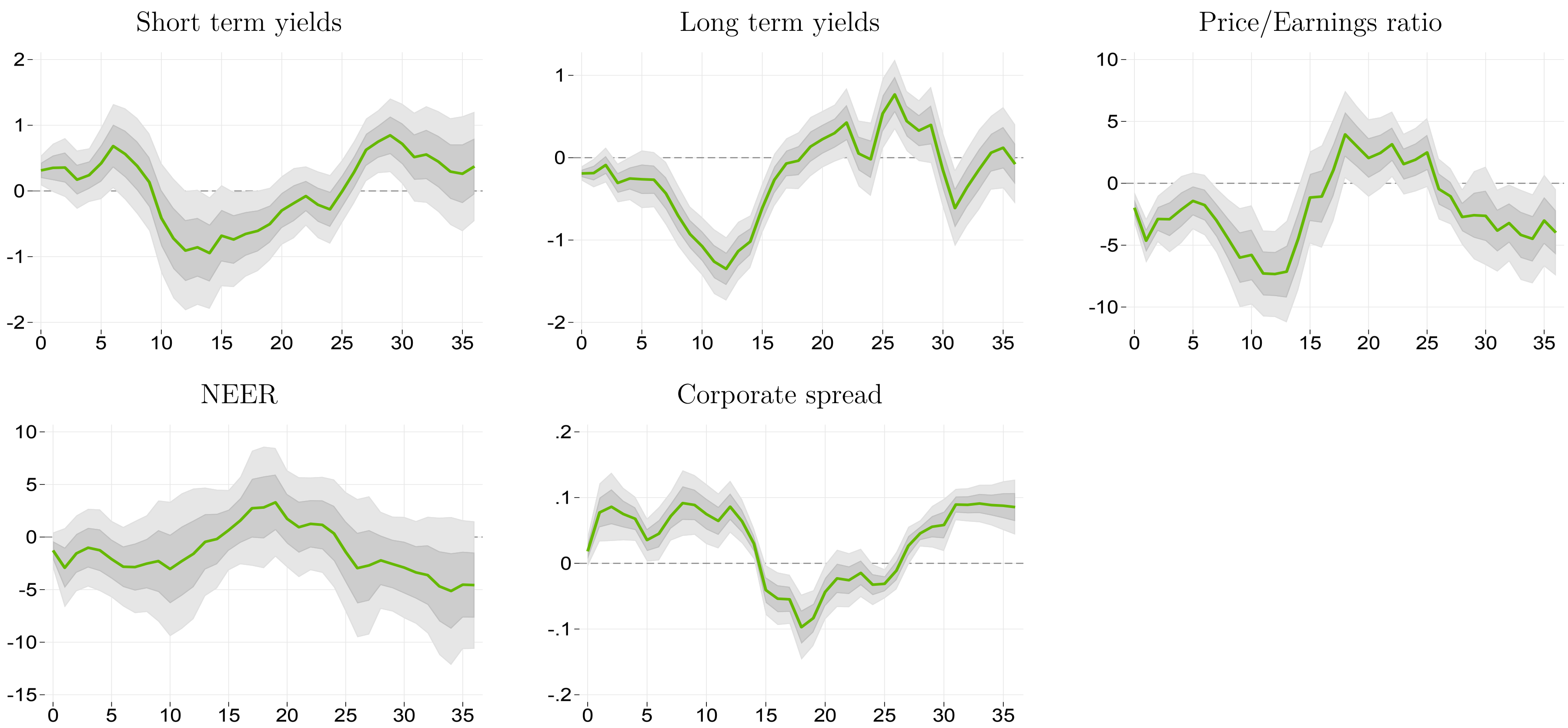
To better illustrate this last point, we analyze the response of the sub-components of the WA-FCI to the MP shocks. We start from advanced economies excluding the US (Figure 9). A US monetary policy tightening induces a significant fall of equity evaluations and a widening of the corporate spreads in advanced economies. Short term interest rates initially increase and the NEER depreciates. However, central banks in advanced economies react by easing monetary policy (Degasperi et al., 2020) and interest rates fall, cushioning the negative spillover from the US. As a result, the tightening in financial conditions in advanced economies is relatively short-lived. In emerging markets (Figure 10), on the other hand, spillovers are larger. The fall of equity valuations, the appreciation of the exchange rate and the widening of sovereign spreads are accompanied by a rise in long-term yields leading to a more pronounced tightening of financial conditions.

Figure 8: Responses of FCIs to a FED's monetary policy tightening shock



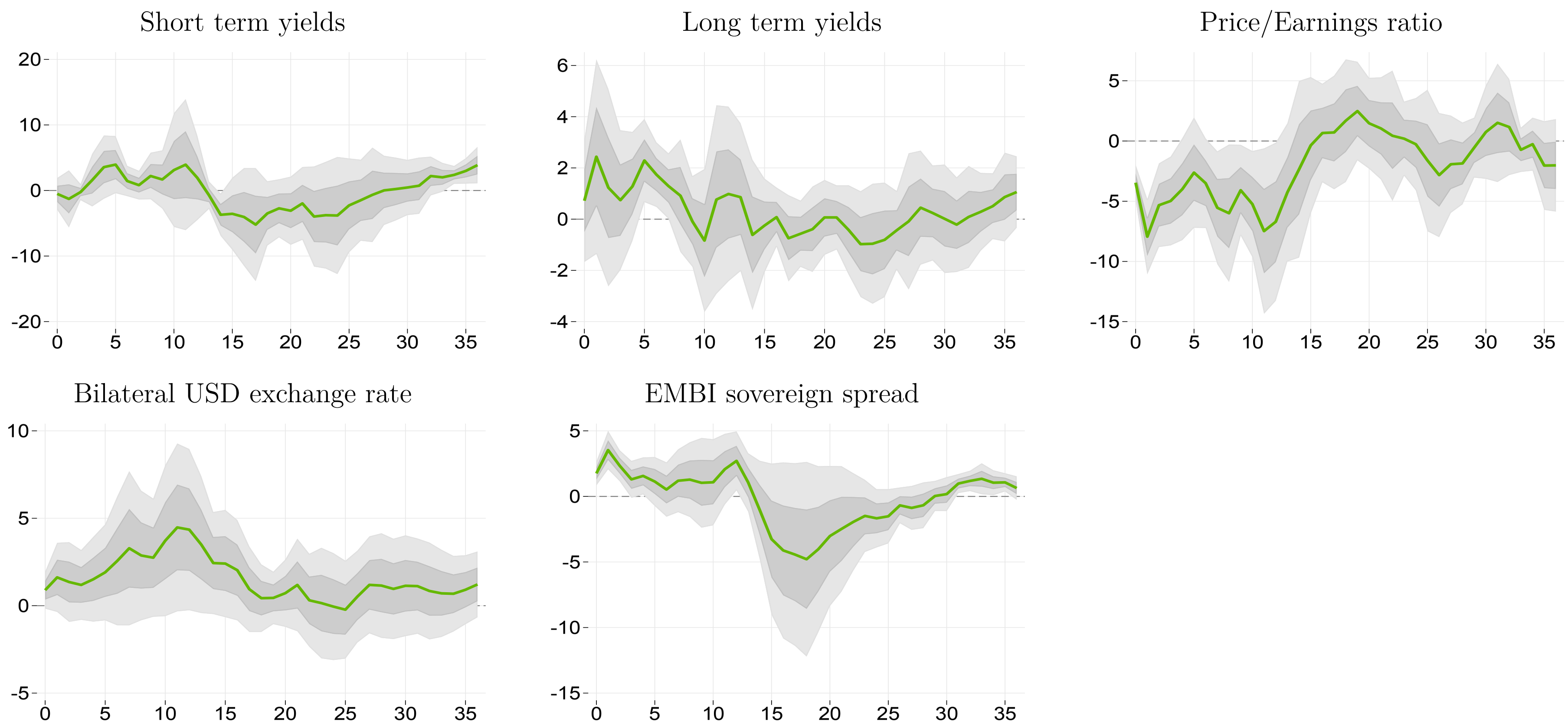
Notes. Months on the x-axis. The light grey shaded area denotes the 95% confidence interval, while the dark grey shaded area the 68% one. The line is the median response.

Figure 9: Responses of sub-components of WA-FCI to a FED's tightening shock: AEs excluding US



Notes. Months on the x-axis. The light grey shaded area denotes the 95% confidence interval, while the dark grey shaded area the 68% one. The line is the median response.

Figure 10: Responses of sub-components of WA-FCI to a FED's tightening shock: EMEs



Notes. Months on the x-axis. The light grey shaded area denotes the 95% confidence interval, while the dark grey shaded area the 68% one. The line is the median response.

4 Conclusions

In this paper we evaluate alternative measures of financial conditions indicators for financial stability and monetary policy monitoring 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, predicting banking crises, nor analyzing the spillovers of US monetary policy. Indices constructed on the basis of alternative data reduction methods, like principal component analysis suffer from similar problems. In Appendix E 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 judgemental but reasonable weights. Indicators based on simple averages have some obvious benefits. Decomposition into the underlying drivers is simpler and more transparent, 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 also 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. An indicator that gives more weight to measures of financial stress, which we term WA-FSI, emerges as the best indicator for anticipating downside risks to economic activity and banking crises, and is therefore better suited for financial stability monitoring. 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) is instead more appropriate for monitoring the effects of monetary policy.

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A Data Sources

Table A1: Data sources and descriptions

Variable	*Detailed description*	*Source*
Credit$^{\diamond}$, 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$^{\diamond}$, 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$^{\circ}$	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. $^{\diamond}$ Since these data are originally quarterly, when used monthly we keep the value constant over the relative months of the quarter. $^{\circ}$ In some cases, to extend series of corporate spreads when not available, we chain it them equity volatility and standardized the combined series.

Figure A.1: 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 A.1 shows the correlation between the FCIs from Arregui et al. (2018) and our TVP-FCI. As expected, the replication using the factor models leads to a good match for almost all the countries.

B 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:

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

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

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:

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

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

The model ha a standard state space representation where equations B.1 are the measurement equations and B.2 to B.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 v_t are *i.i.d.* errors, uncorrelated with each other as well as with ϵ_t and η_t at all leads and lags.[12] 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:

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

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

C Quantile regression framework

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

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

duction growth:

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

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:

$$\hat{Q}_{y_(t+h)/FCI_t, y_t} = \beta_c + \beta_{FCI} FCI_t + \beta_{y_t} y_t. \tag{C.2}$$

In the paper we consider h=1 (month).

D Data sample for quantile regressions and SVARs

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

Table A2: Data sample

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.

E 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 A3 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 A3: 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%

F NFCI subcomponents explainer

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

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