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A new Banque de France Financial Conditions Index for the euro area

Financial conditions matter for the conduct of monetary policy. Over time, the scope of financial variables with a significant impact has increased, calling for the creation of an aggregate indicator – the financial conditions index (FCI) – that would summarise the information. The need for an aggregate indicator has gained even further traction since the 2008 global financial crisis as the usual monetary policy reference for financial conditions – the short-term interest rate – has become much less informative once stuck at its lower bound. This article presents a new FCI for the euro area with time-varying component weights. It is based on a set of financial series regularly monitored by the Banque de France and which pinpoints the sources of changes in financial conditions. Since 2014, financial conditions have loosened substantially thanks to the implementation of the European Central Bank's non-standard monetary policy measures.

Anna Petronevich and Jean-Guillaume Sahuc
Monetary and Financial Analysis Directorate
Financial Economics Research Division

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Six factors
rates, credit, equity, uncertainty, inflation, and exchange rates make up the financial conditions index (FCI) of the Banque de France

Since 2014
financial conditions have loosened substantially thanks to the implementation of the European Central Bank's non-standard monetary policy measures

At the start of 2019
looser financial conditions come mainly from the depreciation of Asian currencies against the euro

Dynamics of the Banque de France FCI for the euro area

Sources: Bloomberg and authors' calculations.

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A financial conditions index (FCI) can be seen as a barometer of the health of financial markets. Economists and market analysts have therefore constructed such indices as a way of analysing the effects of changes to financial conditions on the real economy. However, tracking developments in the financial sector has become increasingly difficult and there is still no consensus among experts about the correct way to estimate FCIs. The purpose of this article is to explain the construction of an alternative FCI that relies on a principal component analysis and on time-varying component weights. We compare its evolution with other FCIs and discuss the way in which it can be used for policy purposes (bearing in mind some well-known caveats with FCIs).

1 Key technical challenges in the calculation of financial conditions indices

The key advantage of our framework compared to other methodologies is threefold: (i) it is based on a broader dataset; (ii) it is transparent; and (iii) it tracks the contribution of the main drivers of the Banque de France FCI (uncertainty, rates, credit, exchange rates, etc.). Furthermore, it is able to adjust to the rapidly changing environment of the financial sector through the time-varying weights attributed to each driver (see Box for details about the underlying methodology).

Data selection

Financial conditions are important because they influence current and future economic activity in ways that are not fully captured by the short-term interest rate, especially in times of crisis. For instance, asset prices are prime determinants of changes in the valuation of private sector portfolios, and therefore changes in private wealth, which affect the future spending behaviour of the private sector. Consequently, an FCI should cover a wide spectrum of data in order to keep track of various sources of complications in the financial sector. Our FCI is based on 18 daily series divided into 6 main components: rates, credit, equity, uncertainty, inflation, and exchange rates (the Appendix provides the details on the underlying data). The use of 18 financial series makes the Banque de France FCI the broadest index among established FCIs.

Traceability and tractability

Most FCIs do not report the underlying datasets and estimation procedures, and are therefore difficult to replicate and, sometimes, interpret. The Banque de France FCI is calculated using a clear and tractable methodology, which makes the index transparent and replicable.

Aggregate index with time-varying weights

An FCI should also be able to adjust to the rapidly changing environment of the financial sector. More precisely, it should give more importance to a currently more problematic component so that its signal does not get mitigated by the overall good state of the other components. The weights in the Banque de France FCI are based on conditional volatility, so that greater instability increases the weight of the corresponding component in the FCI. In this way, our FCI uses two types of information: (i) the actual level of indicators and (ii) their volatility.

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BOX

Methodology

The construction of our FCI is performed in two steps. In the first step, the 18 initial financial series[1] are combined into six main factors with the help of the principal component analysis. This methodology reduces the dimensionality (number of variables) of a large number of interrelated variables, while retaining as much of the information as possible. New variables, referred to as principal component scores, are constructed as weighted averages of the original variables, so that, geometrically, the initial individual series can be interpreted as projections onto the principal components.

More precisely, if we denote by Y an $t \times n$ matrix of observables, where t corresponds to time and n corresponds to the number of financial series under consideration (in our case, $n = 18$), we can transform it using the singular value decomposition as follows:

$$Y = U\Psi V',$$

where U and V are unitary matrices of size $t \times n$ and $n \times n$, respectively, and Ψ is a txn rectangular diagonal matrix. V is computationally equivalent to the eigenvectors of the covariance matrix Σ of Y, while the singular values on the diagonal of the matrix Ψ are equivalent to the square root of the eigenvalues of Σ.

The principal component scores S are then computed as $S = U\Psi$. The columns of the matrix S correspond to the 18 principal components ranked by their informativeness with respect to Y. Each of the components can be interpreted by the corresponding vector of loading, which shows the weight of each individual series in the factor. Multiplying Y by V also gives the principal components scores. Indeed,

$$S = U\Psi = U\Psi V'V = YV.$$

Therefore, V is a projection matrix, also referred to as a matrix of loadings in this context, as it gives the coefficients of the linear combinations used to compute the scores.

The loading vectors can thus be used to interpret the corresponding scores. However, since the loadings are a product of a statistical transformation, their reading is not straightforward and sometimes without clear economic meaning. To improve the interpretability of the loadings, we use the property that the matrices of principal components and principal component loadings are defined up to a linear transformation, i.e. up to a matrix. This allows us to redefine the principal components by multiplying the loading matrix by a rotation matrix R, so that:

$$Y = U(RR')\Psi V' = \tilde{S}\tilde{V}'.$$

1 It is important to note that, in order to reconcile the effect of the variation of each series on the overall state of financial conditions by sign, some indicators (Euro Stoxx and Euro Stoxx Banks indices) were mean inverted.

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The rotated principal component scores are then computed as:

$$\tilde{S} = UR\sqrt{n-1} = Y(\tilde{V})^+,$$

where

$$\tilde{V} = \frac{V\Psi R}{\sqrt{n-1}},$$

and $(\tilde{V})^+$ is the pseudo inverse of matrix $\tilde{V}$.

Note that we require that the new loading matrix $\tilde{V}$ have a particular pattern, which would give greater weight to a group of series of similar nature (for example, series corresponding to rates of sovereign bonds of different maturity) and little weight to the others. This can be done by imposing constraints on matrix R. Besides, we retain only the first six principal components, which altogether explain 95% of the total variance of the original series Y, and omit the last 12 as uninformative. To simplify the notation we denote the individual series of the estimated rotated principal components as $f_{i,t}$, $i \in (1:6)$, and call them factors. In addition, we denote by y_t the matrix of observables Y at time t.

In the second step, for each of the factors $f_{i,t}$, we estimate a generalised autoregressive conditional heteroscedasticity model – GARCH(1,1) – and compute the estimates of the resulting conditional volatilities $\sigma_{i,t}$: [2]

$$f_{i,t} = c_i + \varepsilon_{i,t},$$
$$\varepsilon_{i,t}|f_{i,t-1} \sim N(0, \sigma_{i,t}^2)$$
$$\sigma_{i,t}^2 = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2.$$

The Banque de France FCI is then calculated as follows:

$$ICF_t = \sum_{i=1}^{6} w_{i,t} f_{i,t}, i = 1, ...,6,$$

where the weights $w_{i,t}$ sum up to one in each period t and are computed as:

$$w_{i,t} = \frac{\hat{\sigma}_{i,t}}{\sum_{i=1}^{6} \hat{\sigma}_{i,t}}.$$

[2] We choose the GARCH(1,1) model for its flexibility and because the empirical distributions of the demeaned factors are symmetrical, with the coefficient of skewness comprised between -1 and 1. To make sure the asymmetry is indeed negligible, we compare the FCI based on GARCH(1,1) with the FCI based on the exponential generalised autoregressive conditional heteroscedasticity model, EGARCH(1,1), and the Threshold GARCH model, TGARCH(1,1). Given that the difference between the resulting FCIs is minor, we retain the most parsimonious GARCH(1,1) model to model the factor weights. The results are available on request.

2 Dynamics of the financial conditions index of the Banque de France and decomposition of its monthly changes

Charts 1 and 2 show the dynamics of the Banque de France FCI and its weights. The index is scaled to be zero-mean, so that only FCI's dynamics are informative (and not the absolute level). On average, the weight of the equity component is about 28%, whereas all the other components account for 12% to 16.1% of the weight (see Chart 2). We observe that the weights are relatively volatile and can vary significantly depending on the period.

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C1 Dynamics of the Banque de France FCI for the euro area

↑ Tighter

Sources: Bloomberg and authors' calculations.

The Banque de France FCI compares well to the widely-used Goldman Sachs Euro Area FCI with a correlation of 93%, and much less to the Bloomberg FCI, with a correlation of 66% (see Chart 3). The largest deviations from the Goldman Sachs FCI in most cases appear during major financial disruptions and take the form of more pronounced peaks and troughs, rendering them more detectable. The largest deviations are observed at the start of 2010 due to an abrupt decline on the stock market, throughout 2012 during the sovereign debt crisis (seemingly undervalued by the Goldman Sachs FCI), during the sudden depreciation of the euro in 2015 following the announcement of the expanded Asset Purchase Programme, and during the slump in Euro Stoxx 50 in June 2016 and February 2018.

The advantage of our methodology is that we can decompose the period-to-period changes of the FCI into changes of its main components, which makes it possible to identify the reason for the overall improvement or the deterioration in financial conditions. The contribution $C_{i,\Delta t}$ of changes in each of the factors is:

$$C_{i,\Delta t} = \Delta f_{i,\Delta t}\, w_{i,t} + f_{i,t}\, \Delta w_{i,\Delta t}.$$

For the sake of interpretability, it is more useful to analyse the monthly contributions of each of the factors and not the daily contributions, since the daily data contain too much uninformative noise.

C2 Dynamics of the weights of the Banque de France FCI
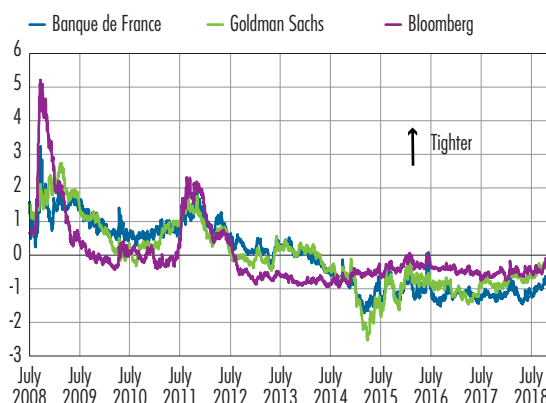
(%)
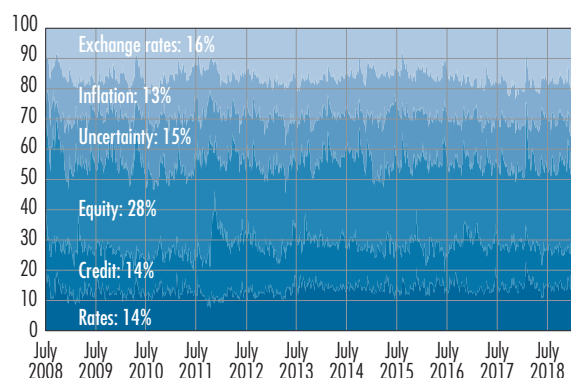
Note: The values indicated in white represent the average weight over the sample.
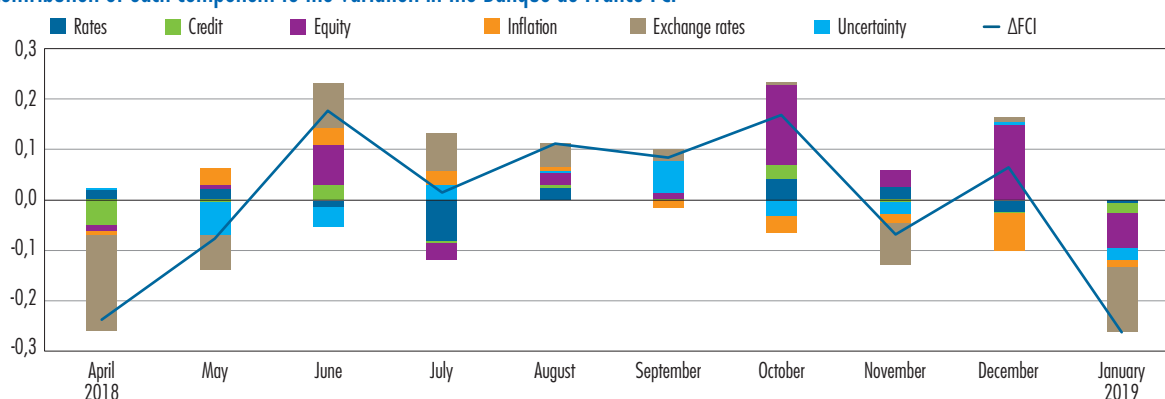Sources: Bloomberg and authors' calculations.

C3 Banque de France FCI versus alternative FCIs

Sources: Bloomberg and authors' calculations.

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C4 Contribution of each component to the variation in the Banque de France FCI

Sources: Bloomberg and authors' calculations.

As an illustration, Chart 4 shows the decomposition for the April 2018-January 2019 period. The decomposition reflects the contribution of each of the six factors to the monthly variation in the FCI of the Banque de France, where the variation is taken as the difference between the monthly averages of two consecutive months. According to the estimates, the loosening of financial conditions in April and May was due to the favourable situation on the foreign exchange market. The deterioration in the conditions in June 2018 was caused by the strengthening of the euro and a stock market decline, pulled back by the fall in rates in July. In October and December 2018, the important tightening in the FCI resulted essentially from the stock market decline (e.g. the Euro Stoxx 50 fell by around 6% in October), somewhat softened by the depreciation of the euro in November. Euro area equities were driven down by a combination of disappointing growth and worrying political news flow. At the start of 2019, looser financial conditions stem mainly from the depreciation of Asian currencies against the euro and, to a lesser extent, from the improvement in the stock market situation.

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Appendix
Composition of the Banque de France FCI: daily financial data

Rates	Euro area 1-year OIS[1] Euro area 2-year OIS Euro area 10-year OIS United-States 10-year OIS 10-year German bond yield EURIBOR 3-month
Credit	France yield spread to euro area 10-year OIS Italy yield spread to euro area 10-year OIS Spain yield spread to euro area 10-year OIS Euro area corporate spread of the AAA 10-year bonds
Equity	Euro Stoxx (broad) index Euro Stoxx Banks index
Uncertainty	Euro Stoxx implied volatility Citigroup Surprise index for the euro area
Inflation	Inflation-linked swap rate 5-year Inflation-linked swap rate 10-year
Exchange rates	Euro/dollar NEER 38 group of euro area trading partners

1 Overnight indexed swap.