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The predictive content of financial cycle measures for output fluctuations[1]

The financial cycle refers to fluctuations in perceptions and attitudes about financial risk over time. It is often marked by swings in credit growth, asset prices, terms of access to external funding, and other financial developments. A single measure that summarised such indicators would simplify analysis of the financial cycle, with benefits for both systemic risk assessment and stabilisation policy. It is not obvious, however, how best to select and combine the many potentially relevant indicators or how the usefulness of the resulting measure might be assessed. One criterion is predictive power. This special feature reviews the power of three differently composed measures to predict output fluctuations up to two years ahead. One of the measures is found to have substantial predictive content for output forecasting at short horizons. However, this result seems to arise mainly from the inclusion of indicators strongly related to actual financial system stress, rather than from swings in more generalised perceptions and attitudes about financial risk.

JEL classification: E32, E51.

The concept of the financial cycle is central to the study of systemic risk and stabilisation policy. It generally refers to swings in perceptions and attitudes about financial risk. These changes are often marked by corresponding swings in credit growth, asset prices, terms of access to external funding, and other indicators of financial behaviour.[2] Financial cycles contribute to output fluctuations both in normal times and during financial crises. The influence of interest rates on the financial cycle also makes it relevant to the study of the monetary policy transmission mechanism.

However, the financial cycle is not well defined empirically. No single variable corresponds closely in concept to the financial cycle. Instead, it is latent in quantities and prices set in many financial and non-financial markets. In practice, policymakers track the financial cycle by looking at a broad range

1 I am grateful to Claudio Borio, Stephen Cecchetti and Christian Upper for useful comments on earlier drafts of this article, and to Emir Emiray for able research assistance.

2 See the discussion of the financial cycle in, for example, Borio et al (2001).

of indicators.[3] A single measure that summarised these indicators would be useful in the same way that the output gap can represent the common movement in many economic indicators and embody the business cycle in macroeconomic analysis.

This article looks at issues related to the construction of financial cycle measures by studying three recently developed indicators of quarterly financial activity in the United States. These are the financial conditions index developed by Hatzius et al (2010; HHMSW);[4] the credit/GDP gap used in the countercyclical capital buffer guidance issued recently by the Basel Committee on Banking Supervision (2010; BCBS);[5] and the financial cycle measure from my earlier work with a co-author (Domanski and Ng (2011; DN)). Only DN was designed expressly to measure the financial cycle as defined here. However, HHMSW and BCBS have related aims, and it is worth noting the different design choices and their consequences.

The specific consequence explored here is for the predictive content of the three measures for US GDP growth (using final, not real-time, data) up to two years ahead. This is the main criterion used to address the question of which measure is "best" – though of course other criteria are possible and could result in different rankings.

Predictive content is assessed with a forecasting approach in which the observations to be forecast are not used in the estimation of the forecasting equations. The target period for testing predictive content is the six years to March 2010. This period features the run-up to the recent global financial crisis and deep recession. However, the analytical setup abstracts from crises as such and is instead cast more generally in terms of output fluctuations (up and down, large and small). This approach reflects policymakers' interest not only in predicting financial crises (which was the context in which BCBS was developed), but also in understanding the role of the financial cycle in output fluctuations unaccompanied by financial crises. The financial cycle's contribution to growth volatility even absent a crisis remains relevant for policy seeking to address financial imperfections.

The rest of the article proceeds as follows. The next section outlines the three measures in more detail. The subsequent section presents the results of the evaluation of the predictive content of the three measures for output growth. The final section discusses the results and draws conclusions.

Three financial cycle measures

Recent theoretical and empirical papers suggest candidate indicators for inclusion in summary financial cycle measures. These cover credit and asset prices (eg Claessens et al (2009)), credit spreads (Cúrdia and Woodford

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[3] See the review by Čihák (2006) of the typical contents of financial stability reports.

[4] HHMSW was downloaded from Mark Watson's website.

[5] I am grateful to Mathias Drehmann for providing the data for BCBS.

(2010), Gilchrist et al (2009)), leverage and liquidity (Adrian and Shin (2008), Geanakoplos (2010)), surveyed bank lending standards (Lown and Morgan (2006)) and banks' non-core liabilities (Shin and Shin (2011)).

Financial cycle measures can be based on broad …

Of the three measures considered here, HHMSW uses variables covering the broadest range of financial concepts (see Table 1 for a list). This broad approach is related to its creators' intention to measure "the current state of financial variables that influence economic behavior" (Hatzius et al (2010, p 1)), rather than the fluctuations in perceptions and attitudes about financial risk that lie at the heart of the definition of the financial cycle used in this article.[6] In particular, HHMSW includes financial variables that one would expect to be significantly affected by the emergence of acute financial system stress, such as the Libor-OIS spread, the TED spread (spread between interbank and short-term US government debt interest rates) and idiosyncratic bank stock price volatility. It also includes the real effective exchange rate, which is likely to be affected by monetary policy. However, unlike some other financial conditions indices, it does not include short-term interest rates other than in spread form.[7]

Financial concepts represented in HHMSW and DN

Concept represented	HHMSW	DN
Intermediated credit growth	X	X
Equity prices	X	X
Property prices	X	X
Corporate credit spreads	X	X
Commodity prices	X	X
Term spread – short-term	X	
Term spread – medium- to long-term		X
Lending standards	X	X
Loan-to-deposit ratio		X
Securities issuance	X	
Aggregate money	X	
Exchange rate	X	
Acute financial system stress indicators:		
VIX	X	
TED spread	X	
idiosyncratic bank stock price volatility	X	
Libor-OIS spread	X	
bank CDS spread	X	
Others	X	

Table 1

[6] Some other examples of financial conditions indices in the same spirit are those of Beaton et al (2009), Brave and Butters (2011), Guichard et al (2009) and Swiston (2008).

[7] FCIs that include short-term interest rates seem to aim at a concept more akin to the general availability and cost of funding, which is clearly strongly driven by monetary policy, rather than at the financial cycle concept as defined here.

HHMSW is the least-squares estimate of the single underlying financial "factor" assumed to underlie their chosen variables.[8] The factor model statistical framework is a popular approach to summarising the common variance in many variables (see Box 1). It offers the promise of condensing the information in dozens or hundreds of variables into a few summary variables (or, as here, into one). The technique essentially weights each underlying variable according to the similarity of its fluctuations to those of the other variables. Variables that have overlapping cycles are weighted more heavily. This corresponds to the aim of constructing financial cycle measures that summarise the common cycle in a range of financial variables. HHMSW accounts for about 40% of the variance in the variables it summarises.

… or narrow sets of underlying financial indicators

The second measure, DN, is computed from variables whose fluctuations would, in its authors' judgment, mostly reflect ebbs and flows in risk sentiment rather than other influences. In particular, it excludes any variables likely to reflect acute financial system stress or be heavily influenced by monetary policy. The variables meeting these criteria represent a narrower set of financial concepts than those in HHMSW (Table 1). They were combined using a factor approach similar to that for HHMSW.

In principle, if the factor model specification correctly characterises the relationship between the financial variables and the financial cycle, this tighter judgmental preselection should add information (provided the judgment is correct) and result in a more accurate estimate of the financial cycle. The resulting financial cycle measure should then be a better variable for testing the relationship between the financial cycle and output fluctuations, as is done in the next section.

DN accounts for about 50% of the variance in its underlying variables, a higher proportion than for HHMSW. This result is consistent with the preselection of a more homogeneous set of variables than those for HHMSW. The higher explained variance indicates that a single underlying cycle is statistically more evident in the variables used for DN, compared with those used for HHMSW. The source documents for DN and HHMSW report the factor model estimates of the relative weights on the respective underlying variables, and show that although both DN and HHMSW have high weights on credit spreads, lending standards, stock prices and credit, HHMSW also has high weights on indicators of acute financial system stress.

The third measure, BCBS, is intended to help "gauge the build-up of system-wide risk" (BCBS (2010, p 8)), rather than to measure the financial cycle as defined here, although the two ideas are clearly related. BCBS is the deviation from trend of the credit-to-GDP ratio, constructed using a filter and selected as the most suitable guide to the build-up of system-wide risk of a range of variables tested. The construction and selection techniques are documented in Drehmann et al (2010). Its design emphasised simplicity and

[8] The impact of past output and inflation on the financial variables is stripped out by linear regression prior to their use in the factor model. In practice, this step seems to make little difference to the profile of the estimated factor.

Box 1: Factor models

Factor models exploit the fact that variables co-move. They are valid under conditions that are in practice not difficult to satisfy for many interesting economic questions (Stock and Watson (2005)), and are often used in empirical business cycle studies (eg Kose et al (2003)) and in forecasting (eg Stock and Watson (2002)).

A factor model

$X_t = A'F_t + e_t$

decomposes the variance of each of N variables (collected in X_t) into a component due to r common factors (collected in F_t and weighted by A), and an idiosyncratic component (collected in e_t) capturing the rest of the variance. Because the point of the exercise is to (drastically) reduce the number of variables one has to deal with, r is assumed or expected to be much less than N. The common and idiosyncratic components are orthogonal by construction. The factors are also contemporaneously orthogonal to each other. The idiosyncratic components can be serially correlated and cross-correlated "weakly" as defined by Chamberlain and Rothschild (1983). In a general "approximate dynamic" factor model framework (Bai and Ng (2002)), lags of factors can appear in F_t and F_t can follow a vector autoregressive process.

Both HHMSW and DN were estimated assuming a simple static model where F_t comprises a single factor that impacts X_t contemporaneously only and corresponds to the financial cycle.[①] The variables in X_t were rendered stationary where necessary by differencing, and then standardised.[②] With a balanced panel as in DN, F_t can then be estimated as the first principal component of X_t. With an unbalanced panel, as in HHMSW, it can be estimated iteratively.

In principle, the factor model framework allows as many variables in X_t as desired as long as the conditions on the serial and weak cross-correlation of the e_t are satisfied. But in the practical reality of small samples, preselection of variables (and other factor modelling choices) can make a difference to forecasting performance (Eickmeier and Ng (2010)). The results in the main text suggest, for example, that the use of a single static factor model to characterise the common variance in the variables in HHMSW is too restrictive, and better forecasting performance is achieved if the variables measuring acute financial system stress are split out.

① Bai and Ng (2002) provide formal information criteria for choosing r. Hatzius et al (2010) tested for r and other structural features in an approximate dynamic factor model framework, and found that the one-factor static model performed best in out-of-sample forecasting compared with more complicated specifications. ② A non-trivial issue is that different ways of achieving stationarity emphasise variance at different frequencies in the raw data. This is particularly relevant for financial variables such as credit, which in almost all economies exhibits a strong upward trend (even as a ratio to GDP). The simple differencing approach has the advantage of transparency, but tends to emphasise higher-frequency variance.

transparency, which meant a strong preference for parsimony (only two variables ultimately used) compared with the more numerous variables and concepts used for HHMSW and DN.[9] A further difference was that the selection process involved not only judgment about the likely relevance of the candidate variables (as in DN and HHMSW) but also quantitative testing for

9 That said, the Basel Committee guidance on the buffer also cautions that BCBS should be supplemented with other aggregate indicators such as asset prices, credit spreads and macro variables, on the basis that using a wider range of variables helps in judging whether developments in BCBS are consistent with financial stability. Such a caveat underscores the desirability of a systematic and transparent way of combining the financial cycle information in a wide range of variables, even if such comprehensiveness in the indicator needs to be traded off against transparency and simplicity.

predictive content for financial crises.[10] However, as with DN but not HHMSW, the variance of none of the candidate variables considered during the process of construction and selection of BCBS was likely to be dominated by the state of a crisis actually in progress. BCBS is thus closer in spirit to the concept of the financial cycle than HHMSW, at least in terms of the upswing phase of the financial cycle. For the downswing phase under stress conditions, Drehmann et al (2010) emphasise that BCBS tends to lag the emergence of actual financial system stress, meaning that other variables are needed to measure this phase.

Preselection of underlying indicators can make a big difference to the resulting measures ...

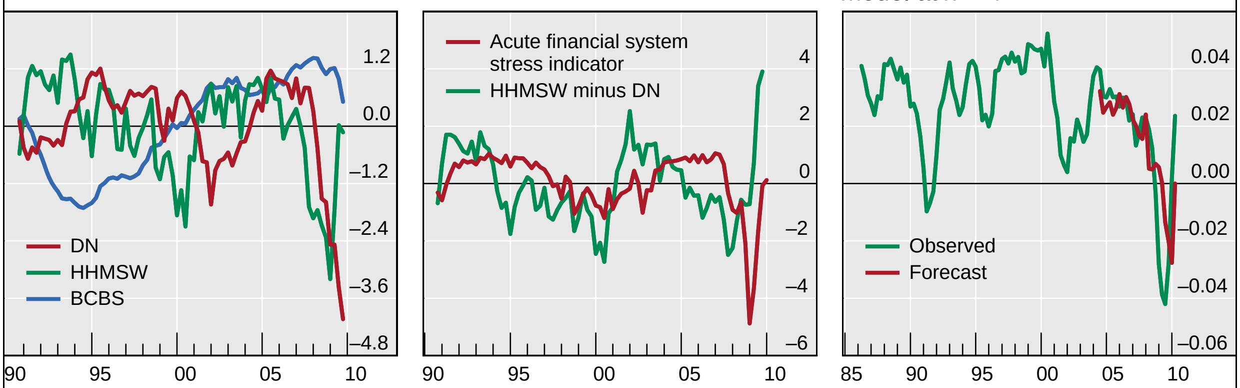
The choices about design and underlying variables make a big difference to the profiles of the resulting measures (Graph 1, left-hand panel). DN matches quite well the documented episodes of financial cycles in the United States, such as the aftermath of the savings and loan crisis (early 1990s), the dotcom euphoria and bust (1998–2001) and the period leading up to and including the latest financial crisis (2004–). HHMSW exhibits a little more high-frequency volatility, probably owing to its inclusion of variables such as the VIX that are volatile at high frequencies. The effect of using a high degree of smoothing in the filter used to construct BCBS is evident in its much longer periodicity, of about 20 years, compared with about eight or nine years for DN and HHMSW. This reflects the calibration of BCBS to the frequency of financial crises.

... especially if variables related to acute financial system stress are included

Although DN and HHMSW differ materially over the whole sample, they diverge most obviously at the end (Graph 1, centre panel). This is the consequence of the inclusion in the latter of variables relating to acute financial system stress. The centre panel of Graph 1 plots an acute financial system stress indicator constructed as the first principal component of the TED spread, idiosyncratic bank stock price volatility and the VIX, all of which ranked within

Financial cycle measures, their composition and their predictive content

Financial cycle measures[1]	Gap between HHMSW and DN	Forecasting performance of best model at $h = 4$



[1] All measures normalised such that an increase indicates greater risk-seeking tendency.

Sources: Basel Committee on Banking Supervision (2010); Hatzius et al (2010); author's calculations. Graph 1

[10] The testing for predictive content for large, relatively rare events (crises) meant, among other things, that the smoothing parameter was set to extract cycles that are long relative to typical business cycle lengths.

the top eight by weight of the 45 variables used in HHMSW.[11] The acute financial system stress indicator is clearly able to explain the large pickup in HHMSW at the end of the sample, when these variables recovered (following massive policy intervention) from their large and sharp increases during the crisis. By contrast, at the end of the sample, DN indicates the financial cycle at extreme and increasing levels of pessimism about financial risk, consistent with reports of the general sentiment at the time. Differences between the two measures over the rest of the sample indicate, though, that there is still a major component to be explained by concepts represented in HHMSW but not in DN.

Evaluation of predictive content

A pertinent question for those who might use the three measures in policymaking is how the different choices of design and underlying variables affect their predictive content for output. Earlier work by English et al (2005) found that financial conditions indices had predictive content for the output gap, but all of these indices, like HHMSW, drew on rather broad sets of underlying financial indicators (including some heavily influenced by monetary policy, such as short-term interest rates). The purpose here is to see what difference it makes to exclude such variables, consistent with a narrow definition of the financial cycle.

The measures' predictive content for output fluctuations is one measure of their usefulness for policy

As noted earlier, the three measures considered were constructed for different purposes, so there is no a priori reason to suspect that they should perform well in the current context. Indeed, as discussed in Borio and Lowe (2004), the predictive content for output of measures based on the credit/GDP ratio, such as BCBS, could be expected to be highly non-linear and even non-monotonic. Nevertheless, given the apparent similarity of the concepts that the three measures are intended to represent, it is interesting to compare them side by side against the same criterion. If they turn out to perform well for a policy-relevant purpose different to the one for which they were designed, then so much the better.

Forecasting power is tested for GDP growth two, four and eight quarters ahead (see Box 2 for details). The root mean squared forecast errors (RMSFEs) of equations are calculated with the financial cycle measures and macroeconomic variables (output growth itself, inflation and the real federal funds rate) as predictors, and compared with benchmark specifications using macroeconomic variables only as predictors. The test period for forecasting performance is Q2 2004 to Q1 2010 (24 quarters), using equations estimated on data starting at the latest in Q3 1991 (depending on the specification) and not including data to be forecast.

[11] See the table of factor model weights in Hatzius et al (2010, p 40). Data for the VIX, the TED spread and idiosyncratic bank risk were obtained from Mark Watson's website.

Box 2: Setup for testing predictive content

Predictive content is tested for using simple quarterly time-series linear forecasting equations. Such a setup is simpler than the analysis by Borio and Drehmann (2009) of the predictive content of BCBS and other variables for a binary variable indicating the occurrence or not of a financial crisis. Among other things, the setup in this feature does not require a definition of crisis.

The target variable (the regressand in forecasting equations) Z_t in the forecasting exercise is four-quarter growth in GDP, that is, $Y_{t+h} - Y_{t+h-4}$, where Y_t is log GDP and h = 2, 4, 8 is the forecasting horizon.[①] The target period for forecasts is Q2 2004 to Q1 2010 (24 observations).

The forecasting exercise does not use observations to be forecast in the estimation of the forecasting equations. The forecast errors are generated by first estimating a forecasting model using data up to t–1, using the estimated model to forecast Z_t, and then repeating with an observation added to the end of the sample, until all the observations in the test period are used.

The forecasting models were estimated by OLS. All lags on the predictor variables (the regressors) up to p = 0 to 4 were included in alternative specifications. Starting dates for the estimation sample depend on p and on the predictor variables in the specification. Sample starting periods were set to maximise sample length, in the interests of improving the accuracy of the estimates in each case.[②] The latest estimation sample starting period was Q3 1991 and used at least 43 observations, depending on h, p and which observation from the test period was being forecast.

The benchmark forecasting model, a "macro only" model, featured as predictor variables annual growth itself, quarterly GDP deflator inflation and the ex post real federal funds rate. p for the benchmark model at each horizon was selected on the basis of best performance on the test period in terms of root mean squared forecast error (RMSFE), with a search from p = 0 to p = 4.

To the macro predictor variables was then added HHMSW, BCBS or DN either by themselves, or accompanied by the acute financial system stress indicator shown in the centre panel of Graph 1, with all lags up to p = 0 to 4.

Significance tests for lower model RMSFE compared with benchmark at a given horizon over the test period were conducted using a one-sided Diebold and Mariano (1995) (DM) test. The DM test was implemented using the procedure outlined in Sheppard and Patton (2009), estimating the variance of the DM test statistic using Newey and West's (1987) estimator with the number of lags set to h – 1. Diebold and Mariano (1995) view this usage of the Newey-West estimator as a "reasonable" benchmark for multi-step-ahead forecasting.

Note that this exercise is not a true out-of-sample test of the forecasting ability of models using the financial cycle measure designs examined here. For example, I used as predictors the full-sample estimates of both DN and HHMSW. A more realistic, and tougher, test would be to estimate the measures without using data from the period being forecast, before using them as predictors in the estimated forecasting equations. It would also be closer to a true out-of-sample test to use real-time output data, and to choose a single p for each iteration. These enhancements would, however, be more computationally intensive and add another dimension of complication to the interpretation of the results.

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① Note that, because of the lags in the target variable definition, the effective lead on the instantaneous growth rate is h–2 rather than h. Hatzius et al (2010), who also assess their financial conditions indices for predictive content, use $Y_{t+h} - Y_t$ as the target, which also reduces the effective lead, by h/2. Such choices, while not ideal econometrically, help reduce noise in the target variable. ② The earliest possible sample start was 1977, reflecting the availability of the federal funds rate data. Going back this far raises issues of unstable parameters arising from structural change, undermining the goal of achieving better estimates in the forecasting equations (that assume no structural change). In practice, varying the sample starting periods from 1977 to 1991 (where that was possible) did not matter very much to the forecasting performance or to the relative ranking of the models.

The results (Table 2) make clear that output growth over the test period is difficult to forecast. The performance of the benchmark model is similar to that of a random walk model at all three horizons. The RMSFEs for the test period are large, with much of the sharp fall in output during the period remaining unexplained even by the best forecasting model (Graph 1, right-hand panel).

Including financial cycle measures in the prediction equations significantly improves forecast performance at very short, but not at longer, horizons. This is indicated in Table 2 by relative RMSFE below one. This means that, at the shorter horizons h = 2 and h = 4, financial cycle measures have some

GDP growth forecasting performance[1]

RMSFE relative to benchmark, except where indicated

Horizon h = 2					
Random walk RMSFE	0.019				
"Macro only" benchmark RMSFE	0.019				
	lags p allowed in forecasting model =				
Forecasting model predictors – macro plus:	0	1	2	3	4
HHMSW only	0.91	0.65**	0.84	0.93	0.87
DN only	1.21	0.99	1.12	1.16	1.15
BCBS only	1.05	0.91**	0.95	0.96	0.96
HHMSW, acute stress indicator	0.96	0.53**	0.51**	0.54**	0.58**
DN, acute stress indicator	0.84	0.77**	0.83**	1.04	1.24
BCBS, acute stress indicator	1.01	0.79***	0.83***	0.81**	0.87**
Horizon h = 4					
Random walk RMSFE	0.026				
"Macro only" benchmark RMSFE	0.030				
	lags p in forecasting model =				
Forecasting model predictors – macro plus:	0	1	2	3	4
HHMSW only	0.70	0.70	0.78	0.79	0.77
DN only	0.93	0.96	0.97	0.99	1.01
BCBS only	0.93	0.92	0.96	1.03	1.04
HHMSW, acute stress indicator	0.70	0.51*	0.58	0.64	0.73
DN, acute stress indicator	0.93	0.98	1.13	1.35	1.54
BCBS, acute stress indicator	0.91	0.88	0.86*	0.85	0.94
Horizon h = 8					
Random walk RMSFE	0.025				
"Macro only" benchmark RMSFE	0.028				
	lags p in forecasting model =				
Forecasting model predictors – macro plus:	0	1	2	3	4
HHMSW only	1.02	1.03	1.06	1.05	1.06
DN only	1.13	1.16	1.32	1.50	1.68
BCBS only	1.14	1.23	1.29	1.09	1.04
HHMSW, acute stress indicator	0.97	0.95	1.01	1.13	1.16
DN, acute stress indicator	1.22	1.37	1.46	1.49	1.66
BCBS, acute stress indicator	0.93*	0.95	1.02	1.16	1.31

[1] *, ** and *** indicate that the corresponding forecasting model achieved a significantly lower RMSFE than the benchmark model at the 10%, 5% and 1% levels, respectively.

Table 2

predictive content for the component of output fluctuations not explained by macroeconomic variables (though at h = 4 few of the RMSFE improvements are significant). In some cases, the improvement in forecasting performance is quite sensitive to p, suggesting that overfitting could be a concern.

By contrast, very few models improve forecasting performance relative to the benchmark at h = 8. The only model that is able to improve statistically (but not economically) significantly on the benchmark RMSFE at this horizon is the model using BCBS and the acute stress indicator with p = 0. This longer horizon is more relevant for policy actions (such as macroprudential interventions) that are needed to anticipate and mitigate the likelihood of medium-term output fluctuations due to upswings in the financial cycle, as opposed to actions reacting to events happening now or in the very short term of the next few quarters.

Acute financial system stress variables have material predictive content at very short, but not longer, horizons

The inclusion of the acute financial system stress indicator shown in the centre panel of Graph 1 as an additional predictor generally improves forecasting performance further at horizons h = 2 and h = 4. This is the case even for HHMSW, which already includes these variables in its construction. There could be two reasons for this result. First, the timing of the effects of acute financial system stress on growth may not be the same as that of the other variables included in HHMSW. Second, their relative predictive content may differ from the weights obtained from the factor estimation.

The results from including the acute financial system stress indicator also suggest that some of the greater predictive content at short horizons of HHMSW relative to the other two measures may be due to it capturing (however imperfectly) acute financial system stress. These variables are likely to be relevant for confirming that a crisis is, in fact, emerging and will lead within one or two quarters to a recession. The results suggest that they shed less light on the likelihood of output fluctuations more than a year ahead (before any systemic financial stress has actually appeared). That said, it is notable that the inclusion of the acute financial system stress indicator can generate a small improvement in forecasting performance at h = 8 with models including BCBS.

Discussion and conclusions

The results reported in the previous section suggest that choices about the types of variables to include in a summary measure of the financial cycle can make a big difference to the profile of the resulting measure. That said, there is little difference in the predictive content of the three measures for output fluctuations more than a year ahead. Given the lags in policy implementation and transmission, this longer horizon is the most relevant for policy seeking to prevent financial crises and their associated large output losses. Of course, such policy need not be predicated on indicator variables that have a linearly stable relationship with output fluctuations. BCBS, for example, is intended to support policy to build defences against the build-up of system-wide risk, rather than to head off actual crises or their output consequences within precisely defined time frames.

Indicators for acute financial stress should be treated separately from those for general financial risk sentiment

The relatively good short-term forecasting performance of HHMSW compared with the other two measures appears to reflect the influence of the indicators of acute financial system stress that it incorporates. At least for the purposes of understanding the consequences of financial developments for output, it is therefore worth treating acute stress indicators separately from variables reflecting more general financial risk sentiment. However, while such short-term predictive content might be useful for confirming the likely adverse growth consequences of a financial crisis already in progress, it is less useful for preventing crises in the first place.

The (marginally) best performance of forecasting models that use BCBS for medium-term forecasting is somewhat surprising, given the simplicity of the measure and the different objectives for which it was tailored. But the result nevertheless underscores the importance of credit in macroeconomic dynamics. DN was designed to capture a broader set of indicators for general financial risk sentiment (while not as broad as HHMSW), but forecasting models using DN performed very poorly relative to the others.

The generally poor forecasting performance of all of the models suggests that any relationship between the financial cycle and output fluctuations is unlikely to be as simple as the linear relationship assumed here (for simplicity and generality). It is widely accepted that financial crises contribute to very large output fluctuations, and the short-term forecasting results presented here are consistent with that proposition. However, they shed little light on the relationship between output fluctuations and financial cycles that do not lead to crises, for which better models are needed that can forecast the output fluctuations due to the financial cycle a year or more ahead. Models could take account of, for example, non-linearities, state dependence and the possibility that the relationship between output fluctuations and the financial cycle might have changed over time due to increasing global economic and financial integration.

The choice of a test period that includes the recent extreme global recession sets the bar high. This period may be so untypical that it is a poor test for the predictive content of financial cycle measures in more normal business and financial cycles. This proposition should be tested using more data on normal cycles.

Better financial cycle measures with predictive content over longer horizons are still needed

Finally, the finding that preselection matters for the predictive content for output fluctuations of factor model-based financial cycle measures suggests that it is worth continuing to try to refine such measures. Better measures would facilitate the study of how financial cycles behave. Structural empirical models that bring financial cycles and macroeconomic dynamics together would assist in determining the right responses to financial cycle developments. For example, financial cycle developments due to shocks emanating from the financial system itself might require different responses to those that are simply propagations of shocks from elsewhere in the economy.

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