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Financial conditions and economic activity: a statistical approach[1]

How do conditions in the financial sector affect the macroeconomy? We summarise the common variation in a large array of financial variables into a small set of statistical factors and examine the information content of these factors when forecasting GDP and inflation in four economies. We find that financial factors contain information that is independent of and complementary to that in real variables. This information accounts for a larger proportion of the movement in real and nominal GDP, but a smaller proportion of the variability of inflation.

JEL classification: G00, C65, C530.

Macroeconomists have often taken a simplistic approach to addressing the interactions between the financial sector and the real economy. Models that incorporate financial variables rarely venture beyond the yield curve and/or the price of assets such as equity or property. However, as the experience of the recent crisis underscored, the channels of transmission between the real and financial sectors can be very strong and diverse, working through asset prices as well as the balance sheets of financial institutions, households and firms. Thus, the identification of stable patterns in the joint dynamics of the real and financial sectors could provide the basis for improving our understanding of the mechanisms at work.

This article examines lead-lag statistical relationships between financial and real sector variables. No specific economic model underpins the exercise. Rather the idea is to outline the connections between a wide array of financial variables and two key macro variables: GDP and inflation. To do so, we extract a small set of factors that summarise conditions in the financial sector and select those with the highest information content for forecasting the real variables. Based purely on statistical criteria, the selection is intended simply to establish stylised empirical regularities about the dynamic links between the two sets of variables. There is no attempt to explain or characterise them. Our approach adds to the literature by examining the information content of a large group of variables in the context of output and inflation and for a number of countries.

Our results show that, consistently across countries, financial factors do contain information about macroeconomic variables. This is most evident in the case of

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output. The inclusion of financial factors and their lags in the forecasting equations for real and nominal GDP growth significantly improves their explanatory power compared to using past values of real variables only. The financial factors also improve the fit of the forecasting regressions for inflation, but their contribution is weaker.

The rest of the article consists of four sections. The first section introduces the exercise with reference to the existing research literature on the relationship between macroeconomic activity and financial sector variables. The second section is methodological, and describes the statistical approach we use for the construction of the financial factors. The third section presents the results of the forecasting regressions and discusses the contribution of the financial factors to GDP and inflation. The concluding section outlines the points that could be taken up in future research.

Financial conditions and the real economy

Historically, macroeconomic modelling abstracted from financial sector activity, focusing primarily on the interactions of real variables such as GDP, prices, unemployment and components of aggregate expenditure. Money and interest rates were the main financial variables used in models as they related to the stabilisation tools available to central banks. Even these variables were omitted in descriptions of macroeconomic dynamics provided by the real business cycle literature.[2]

This modelling shortcut does not mean that economists have disregarded the influence of financial factors in shaping macroeconomic outcomes. On the contrary, several important works have focused on the interactions between the business and financial cycles, albeit adopting a narrative rather than a formally quantitative approach. The works of Kindelberger and Minsky are cases in point. That said, macroeconomists have yet to converge on a set of key variables that summarise the financial sector's behaviour. The resulting lack of parsimony stands in the way of empirical or theoretical modelling, representing a stumbling block to further quantitative analysis.

Yet a number of empirical exercises use financial variables to forecast real sector developments. Motivated by the observation that financial contracts are forward-looking and that asset prices reflect market participants' expectations about the future, research has looked into variables that can help to predict future changes in the real economy. Another practical advantage of financial variables, especially asset prices, is that they are observed in real time. The literature focuses on the role of interest rates and asset prices in explaining developments in output and inflation (Goodhart and Hofmann (2000)). The term structure is used as the predictor of economic activity in Estrella and Hardouvelis (1991) and for inflation in Mishkin (1991). The interest rate spread between risky and safe debt issues was used by Friedman and Kuttner (1992). Researchers have also examined the information content of financial variables other than prices for economic activity. For example, Borio and Lowe (2002) looked at bank credit, while Kashyap et al (1993) examined shifts in the composition of credit to the private sector from banks

[2] Two seminal papers in this strand of the literature are Kydland and Prescott (1982) and Long and Plosser (1983).

and market sources as a gauge of the tightness of credit conditions that can affect future output.

The recent crisis has given new impetus to efforts to include a substantial financial sector in macroeconomic models (see Borio (2011) for a discussion). Recently the literature has focused on changes in the monetary transmission mechanism. It assumes that monetary conditions influence the real sector by affecting the financial conditions that have direct links to economic behaviour. For example, Boivin et al (2009) and Gertler and Karadi (2010) study unconventional monetary policies in models that incorporate financial intermediaries. Gertler and Kiyotaki (2010), and Christiano et al (2011) study the influence of financial sector activity in shaping the business cycle.

Our work is also closely related to a budding literature on how indicators for financial conditions might be devised. With the aim of developing metrics for financial stability, researchers have proposed different indicators of varying composition and complexity that summarise aspects of financial sector activity. Examples include Bordo et al (2000), Illing and Liu (2006) and Holló et al (2012). Our approach follows closely, and expands, the work of English et al (2005) and Hatzius et al (2010).

As those papers do, we follow Stock and Watson (2002) in condensing the common components in the dynamics of a large group of financial sector variables into a small set of statistical principal components (factors) and then use these to forecast economic activity variables at a one- to two-year horizon.

In contrast to most of the financial conditions literature, we firmly link the financial factors to future developments in the real economy. This is motivated by our interest in highlighting the interactions between the two sectors, an area of inquiry that remains underdeveloped in current macroeconomic analysis despite its importance for monetary and financial stability policy. We also draw lessons from the common features of the results across four countries with a view to adding robustness to the analysis.

Construction of financial factors

The approach we adopt in this article is purely statistical. The absence of an established formal model that describes the workings of the financial sector would rule out a structural empirical investigation of the interactions with the real sector. Instead, our atheoretical approach condenses the information content of a broad array of variables into a set containing a few representative factors that could then be feasibly used in a forecasting exercise. Starting with a wide array of financial variables gives ample room to select the more pertinent relationships between real and financial variables. The forecasting framework sets the criterion for this selection. It assigns a premium to those factors that have the closest relationship with future macroeconomic developments.

The construction method for these factors follows Stock and Watson (2002). It relies on principal components analysis (PCA) to distil the common movements in a large array of variables into a small set of uncorrelated factors. The input to the PCA is a set of normalised variables. The box gives more detail on the preparatory work for the financial sector variables that enter the PCA. These variables are then

Principal component analysis on an unbalanced panel with mixed frequencies

PCA requires that the input data series have certain properties. Variables must be stationary (ie without deterministic or stochastic trends), they should be of a comparable range of variation (ie have similar means and volatilities), and they should be defined over a common range of dates. Not all the original series we use (see Web Appendix for a list) fulfil these criteria. Most series are quarterly, but a few are observed only annually. Most series start in 1980 but some begin later. Finally, there is considerable variation across variables in terms of their units and amplitude. We deal with these problems through a series of adjustments that are fairly standard in the literature.

As a starting point, all the series are checked for stationarity by performing a battery of unit root tests: these are the Philips-Perron test, as well as autoregressive and trend-stationary Augmented Dickey-Fuller tests. The lag choice for the tests is based on the procedure suggested by Ng and Perron (1995) and the rule-of-thumb suggested by Schwert (1989). The variables that exhibit unit roots are then differenced in the final set. All variables are normalised by dividing by their standard deviation.

In order to fill in missing observations due to the use of annual series or to extrapolating quarterly series beyond their observed range, we apply the EM algorithm proposed by Stock and Watson (2002). The algorithm is embedded in the process estimating the PCs and it comprises two steps. The first step involves the linear projection (regression) of those variables with missing observations on a balanced panel of PCs estimated on the basis of the quarterly series observed over the entire sample period. This projection is used in the second step to fill in the missing observations before a new set of PCs is estimated on the basis of the complete and projected series. The procedure is repeated until the process converges, namely the subsequent estimates of PCs are sufficiently close between iterations. In our case, this occurred after four to five iterations. As prescribed in Stock and Watson (2002), the details of the algorithm are slightly different depending on whether the interpolated series refers to a stock or flow variable, and whether it is in levels or first differences.

The final, balanced panel of variables at a quarterly frequency together with a one-quarter lag was used to calculate a final set of factors that were used in the forecasting exercise for the real variables. Stock and Watson (2002) argue that the inclusion of a one-period lag can go some way towards capturing the time dynamics of the financial variables in the estimated factors.

transformed into a set of uncorrelated variables: the principal components (PCs), or factors as we alternatively refer to them below. By construction, the number of estimated PCs can be as high as the number of the initial set of (correlated) financial variables. Since, by construction, the PCs are ordered in declining importance in terms of their ability to capture the overall variability in the group of input variables, we focus only on the first few that capture the bulk of this variability.

The approach in this paper has similarities also with the weighted average approach used by Dudley et al (2005) or Guichard and Turner (2008). They construct an indicator of financial conditions as the weighted sum of several financial variables with weights that reflect their relative impact on real GDP. A key difference with our paper is that they obtain the weights on the basis of simulations using large macroeconomic or vector-autoregressive models.

We conduct our exercise for four countries: Canada, Germany, the United Kingdom and the United States. For each country we collected around 90 financial variables that belong to different groups (see the Web Appendix for a detailed list of the variables). We group them into four categories: (i) interest rates and spreads; (ii) asset prices; (iii) credit and debt aggregates; and (iv) indicators of performance for the banking system.

The interest rate category includes short- and long-term interest rates on government and private sector bonds, as well as interest rate spreads that capture credit and liquidity risk premia. These measure primarily the cost of borrowing for consumers and investors but also reflect expectations about future inflation and the monetary policy stance.

The asset prices category includes the total return of the general stock price index as well as a financial sector sub-index, and the growth of residential and commercial property prices. There are several channels through which asset prices can be connected to future real sector developments. One channel reflects the fact that they embody market participants' collective information and expectations about future macroeconomic developments. By contrast, the credit channel has a more causal impact on aggregate demand as higher asset prices increase the borrowing capacity of households and corporates, helping to support higher levels of expenditure. Finally, higher asset prices increase wealth, which arguably leads to increased consumption through the wealth channel.

Credit and debt aggregates include measures of credit to households, the government and non-financial corporations. Increases in credit often precede increases in fixed investment and thus growth. In addition, periods of booming credit typically go hand in hand with optimism on the part of economic decision-makers and with positive attitudes towards risk-taking that fuel investment and consumption. We include in this category credit extended by banks to various sectors and for various purposes (consumer credit, mortgages etc).

The category of banking system performance indicators includes measures of the financial health of the banking system, based on banks' balance sheet and income statements. We include also profitability metrics such as net interest margins, return on equity and on assets, as well as capitalisation ratios.

By construction, the estimated factors are mutually uncorrelated and are ranked in reverse order of their ability to capture the overall variance of the broad dataset of financial variables (see Table 1). Among the four countries in our analysis, three exhibit a similar pattern in terms of the importance of the first few factors. In the United States, Germany and Canada, the first factor explains about one seventh of the total variance, with the proportion falling gradually to about one twentieth for the fifth factor. The first five factors explain about half of the total variance while the next five add a little less than 20%. The pattern in the United Kingdom is slightly different as the first three factors (and the first one in particular) have greater information content. As a result, the explanatory power in terms of overall variance of the first five and 10 factors is about 10 percentage points stronger than for the other three countries. We have no obvious explanation for this difference.

Financial factors – percentage of total variance explained | Table 1

	United States	Germany	Canada	United Kingdom
First factor	13.5	15.1	15.2	23.0
Second factor	12.2	8.6	11.3	14.2
Third factor	8.9	8.1	8.2	9.9
Fourth factor	7.6	7.3	6.5	7.9
Fifth factor	5.6	6.7	6.0	4.9
First 10 factors	68.5	65.9	68.8	76.3

Source: Authors' calculations.

Information content of financial factors for real sector

Forecasting regressions with four-quarter horizon; quarterly data 1980–2011 Table 2

Variables	United States			United Kingdom			Germany			Canada		
	Real GDP growth	Nominal GDP growth	Inflation	Real GDP growth	Nominal GDP growth	Inflation	Real GDP growth	Nominal GDP growth	Inflation	Real GDP growth	Nominal GDP growth	Inflation
GDP_t	1.82 (4.94)	2.18 (5.11)	0.44 (3.00)	1.57 (4.34)	4.04 (7.76)		3.10 (4.65)	3.67 (5.08)	0.54 (1.74)	1.98 (3.64)	0.68 (0.85)	0.42 (5.88)
GDP_{t-1}	–1.99 (–4.29)	–2.13 (–4.14)	–0.19 (–1.10)	–1.62 (–3.82)	–5.96 (–6.24)		–4.57 (–4.00)	–5.55 (–4.63)	–0.83 (–1.67)	–1.95 (–3.48)	–0.76 (–0.65)	
GDP_{t-2}					2.74 (5.36)		1.70 (2.78)	2.29 (3.92)	0.37 (1.47)		0.18 (0.27)	
GDP_{t-3}												
GDP_{t-4}	1.56 (4.97)	1.47 (3.84)		1.16 (3.01)						1.60 (3.78)		
GDP_{t-5}	–1.19 (–4.90)	–0.84 (–2.55)		–0.79 (–2.62)						–1.24 (–3.91)	0.08 (0.65)	
$INFL_t$	–1.54 (–3.10)	–2.05 (–3.74)	1.01 (2.89)		–0.30 (–4.16)	1.81 (3.51)			1.70 (6.61)	–0.22 (–1.53)	–1.18 (–1.84)	1.65 (5.85)
$INFL_{t-1}$	1.67 (3.11)	2.36 (3.99)	–0.68 (–1.74)			–1.81 (–1.84)			–1.28 (–4.64)		1.23 (2.25)	–1.22 (–3.92)
$INFL_{t-2}$				–0.42 (–1.62)		0.69 (1.15)				0.22 (1.72)		
$INFL_{t-3}$				0.33 (1.46)								
$INFL_{t-4}$	–1.66 (–3.37)	–2.39 (–3.95)		0.96 (2.29)								1.21 (3.19)
$INFL_{t-5}$	1.26 (3.28)	1.92 (3.97)		–0.65 (–2.54)		–0.14 (–1.14)			0.13 (1.41)			–0.81 (–2.74)
$FF1_t$	–0.28 (–3.95)	–0.26 (–3.42)		–0.53 (–2.61)		1.15 (3.95)				–0.23 (–5.06)	–0.62 (–6.36)	
$FF1_{t-1}$				–1.13 (–2.81)	–0.06 (–4.84)	2.28 (3.92)				0.26 4(.74)	0.28 (2.09)	
$FF1_{t-2}$				–1.28 (–3.24)		1.18 (3.90)			–0.04 (–2.17)			
$FF1_{t-3}$	0.19 (2.76)	0.19 (2.72)		–0.66 (–3.49)								0.11 (3.83)
$FF2_t$	–0.15 (–4.26)	–0.20 (–3.97)	–0.12 (–3.59)		–0.42 (–4.99)	–0.58 (–5.08)	0.80 (4.66)	0.92 (4.84)				
$FF2_{t-1}$	0.10 (2.09)						–0.41 (–3.51)	–0.45 (–2.96)				
$FF2_{t-2}$										–0.15 (–3.60)		0.12 (4.49)
$FF2_{t-3}$		0.13 (2.43)	0.11 (3.26)	–0.29 (–4.20)	0.27 (4.57)	0.72 (4.94)						
$FF3_t$				–0.59 (–2.85)	–0.13 (–3.08)	0.91 (3.28)						
$FF3_{t-1}$							–0.35 (–3.51)	–0.32 (–3.61)				
$FF3_{t-2}$						–1.32 (–4.19)						
$FF3_{t-3}$	–0.15 (–2.05)		0.09 (1.87)	0.74 (3.74)					0.08 (3.06)		–0.09 (–1.52)	
$FF4_t$				0.17 (1.99)		0.41 (4.19)				–0.18 (–4.14)	–0.35 (–4.32)	
$FF4_{t-1}$						–0.34 (–3.94)	–0.28 (–2.96)	–0.40 (–3.13)			0.27 (2.68)	
$FF4_{t-2}$										–0.08 (–2.11)		
$FF4_{t-3}$	–0.12 (–4.01)			–0.12 (–2.23)					–0.08 (–3.02)			
R^2 adj	0.79	0.79	0.84	0.78	0.92	0.86	0.72	0.79	0.74	0.76	0.61	0.85

Source: Authors' calculations.

Statistical links between real and financial sectors

The idea behind the forecasting exercise is to identify the factors that have the greatest information content for the future dynamics of the three macroeconomic variables we analyse: real and nominal GDP growth, and inflation. We set up equations of the following form over the period 1980–2011:

$$y_{t+k} = \sum_{i\in\{0,\dots,5\}} a_i y_{t-i} + \sum_{i\in\{0,\dots,5\}} \beta_i x_{t-i} + \sum_{I\in[1,\dots,n]} \sum_{i\in\{0,\dots,n\}} \gamma_{I,i} F_{I,t-i} + \varepsilon_{t+k} \ ,$$

where the variable to be forecast is either real GDP growth, nominal GDP growth or inflation over a four- or eight-quarter horizon (ie k is equal to either 4 or 8). There are two groups of predictors. The first group consists of current and lagged values of GDP growth and inflation, which provide the benchmark for the information content of the financial factors. We based the selection of the lags in each group of predictors on a procedure that balances the regression's goodness of fit, on the one hand, with parsimony, measured by the number of explanatory variables, on the other hand. This balance is achieved by minimising the Bayesian Information Criterion (BIC) due to Schwartz (1978).

The second group of predictors is selected among the financial variables and their lags. The selection is based on the same statistical criterion as the selection of the real set of predictors but treating the latter set as fixed. In other words, different combinations of the financial factors and their lags are added as additional predictors to the best specification that includes only real sector variables. We then select the model with the lowest BIC. That is the specification that offers the best balance between forecasting ability and parsimony.

The choice of forecast horizon corresponds to the typical horizon used in policy. In order to reduce noise coming from the high-frequency dynamics of the macro variables, we use four-quarter averages as the dependent variable.

Empirical results

Tables 2 and 3 present the results of the final forecasting regressions characterised by the lowest BIC. Each table shows results for all four countries and for the three macro variables. Table 2 refers to the one-year forecast horizon and Table 3 to the two-year horizon.

A number of patterns emerge from looking at the results across countries and forecasted variables. The performance of forecasting regressions is overall quite good, although it deteriorates as expected at the longer horizon. For the four-quarter horizon the adjusted R^2 ranges between 72% and 92%, with the exception of the Canadian nominal GDP growth regression, where it is only 61%. For the eight-quarter horizon the range is 31% to 88%, with the exception of the same variable as before, for which it is a very low 5%.

In all cases, the financial factors do have information content for future values of the macroeconomic variables. They enter the forecasting regressions at conventional significance levels contributing to the fit of the forecasting regression. Generally, when we forecast real and nominal GDP growth, more factors enter the regressions with multiple lags, therefore showing that factors do have a lagged and more complex influence on the variables. Regressions for inflation typically contain fewer financial factors and very often each factor enters only with one lag.

Information content of financial factors for real sector

Forecasting regressions with eight-quarter horizon; quarterly data 1980–2011 — Table 3

Variables	United States			United Kingdom			Germany			Canada		
	Real GDP growth	Nominal GDP growth	Inflation	Real GDP growth	Nominal GDP growth	Inflation	Real GDP growth	Nominal GDP growth	Inflation	Real GDP growth	Nominal GDP growth	Inflation
GDP_t				0.17 (1.12)	0.71 (4.68)			–0.42 (–2.39)	0.36 (1.83)		–0.7 (–0.83)	1.24 (5.47)
GDP_{t-1}	–0.13 (–0.77)								–0.35 (–1.59)		0.73 (0.65)	–1.13 (–4.27)
GDP_{t-2}											–0.21 (–0.36)	
GDP_{t-3}												0.58 (5.87)
GDP_{t-4}						0.31 (1.61)						
GDP_{t-5}					0.57 (3.23)				0.03 (0.36)	–0.31 (–2.67)	–0.07 (–0.29)	
$INFL_t$	–2 (–3.65)			–0.52 (–2.69)	–1.06 (–4.14)		–0.17 (–0.68)		0.04 (0.36)		–0.9 (–0.81)	0.51 (3.81)
$INFL_{t-1}$	2.13 (3.36)										1.2 (1.42)	
$INFL_{t-2}$												
$INFL_{t-3}$												
$INFL_{t-4}$	–2.65 (–3.99)	–1.34 (–2.96)										
$INFL_{t-5}$	2.17 (4.68)	1.47 (3.3)	0.09 (2.06)	0.3 (2.24)		0.15 (1.43)						0.14 (1.62)
$FF1_t$		–0.28 (–2.18)								0.23 (3.98)	–0.15 (–0.9)	
$FF1_{t-1}$											–0.04 (–0.25)	
$FF1_{t-2}$		0.32 (1.93)						–0.22 (–2.58)	–0.08 (–3.24)			0.08 (2.59)
$FF1_{t-3}$										–0.18 (–3.32)		
$FF2_t$			–0.07 (–1.44)	–0.18 (–1.8)	–0.17 (–2.07)	–0.13 (–1.35)	0.52 (2.8)	0.73 (3.08)				
$FF2_{t-1}$										–0.41 (–4.71)		
$FF2_{t-2}$												
$FF2_{t-3}$	–0.23 (–2.62)						–0.45 (–2.73)					0.09 (2.58)
$FF3_t$							0.36 (3.04)					
$FF3_{t-1}$		–0.28 (–2.12)							0.07 (3.04)			0.07 (2.3)
$FF3_{t-2}$									0.1 (3.74)	0.15 (1.94)		
$FF3_{t-3}$	–0.26 (–1.8)						–0.17 (–1.86)		0.07 (2.9)		–0.04 (–0.37)	0.13 (3.59)
$FF4_t$							–0.27 (–1.84)			–0.19 (–3.77)	–0.07 (–0.71)	
$FF4_{t-1}$								–0.54 (–2.62)	–0.11 (–3.67)	–0.12 (–1.84)	0.09 (0.74)	
$FF4_{t-2}$		–0.15 (–2.44)										0.09 (2.82)
$FF4_{t-3}$					–0.13 (–1.89)					–0.2 (–2.96)		
R^2 adj	0.52	0.49	0.74	0.31	0.75	0.66	0.33	0.41	0.69	0.57	0.05	0.88

Source: Authors' calculations.

To assess the information content of each group of variables, we have calculated two statistics. The first is due to Hellwig (1982) and it provides a measure of the contribution to the explanatory power of a regression by subgroups of regressors based on correlations across these variables and correlation with dependent variable. The second is a metric of the reduction in the sum of squared regression residuals achieved by the inclusion of a group of variables. It is the ratio of the gain in terms of a reduction in the sum of squared residuals of the regression that results from the addition of the given group of variables, and the sum of squared residuals of the regression that excludes that group. Both statistics were calculated separately for the group of real variables and the group of the selected financial factors for the optimal regression specification. A higher value of the statistic would imply a higher contribution of the specific group in explaining the future dynamics of the macroeconomic variable.

The results for both forecast horizons are shown in Tables 4 and 5. They highlight two key points for our analysis. The first point is that financial factors have overall as much explanatory power as lagged real variables. This result is strongest for the two GDP variables, for which the Hellwig statistic (Table 4) is practically unanimous across countries and forecast horizons. For inflation, the case is weaker. Financial variables make a stronger contribution to the forecasting exercise than financial variables at the two-year horizon, but the opposite is true for the one-year prediction. Moreover, it seems that the forecasting ability of financial factors is generally weak for Canadian inflation at both horizons. The second point that emerges from the comparison of the Hellwig statistics is that the overall predictive strength of the regressions is weaker for the longer-horizon forecasts; the ability of the financial factors is less affected than that of the real variables. The statistics that relate to the real variables deteriorate much faster with the forecast horizon than those relating to the financial variables, pointing to the possibility that the influence of financial factors on macroeconomic developments may have a longer fuse.

Relative information content of real and financial variables

In percentage points of total explanatory power of forecast regression — Table 4

	Four-quarter forecasting horizon											
	United States			United Kingdom			Germany			Canada		
Variables	Real GDP	Nominal GDP	Inflation	Real GDP	Nominal GDP	Inflation	Real GDP	Nominal GDP	Inflation	Real GDP	Nominal GDP	Inflation
Real	12.1	12.9	38.4	15.9	45.1	42.2	7.9	23.7	39.3	7.2	5.4	46.5
Financial	40.2	32.6	20.3	25.3	64.2	29.5	25.9	46.2	22.4	45.4	29.8	6.4
	Eight-quarter forecasting horizon											
	United States			United Kingdom			Germany			Canada		
Variables	Real GDP growth	Nominal GDP growth	Inflation	Real GDP growth	Nominal GDP growth	Inflation	Real GDP growth	Nominal GDP growth	Inflation	Real GDP growth	Nominal GDP growth	Inflation
Real	3.3	17.6	7.6	3.6	23.9	6.0	1.4	5.4	15.9	4.7	2.6	27.4
Financial	24.1	17.0	8.9	15.0	48.4	22.6	11.5	24.8	40.3	14.5	0.5	7.4

Note: The table shows the value of the integral capacity of a set of predictors proposed by Hellwig (1968). The value of this metric corresponds to the percentage of the overall variation of the forecasted variable that is accounted for by a given set of the predictor variables.

Source: Authors' calculations.

Relative contribution to explanatory power of regression

In percentage points of unexplained residual — Table 5

	Four-quarter forecasting horizon											
Per cent	United States			United Kingdom			Germany			Canada		
Variables	Real GDP	Nominal GDP	Inflation	Real GDP	Nominal GDP	Inflation	Real GDP	Nominal GDP	Inflation	Real GDP	Nominal GDP	Inflation
Real	45.9	37.9	14.9	55.9	47.4	48.2	35.5	41.0	22.5	50.1	42.6	38.1
Financial	50.0	54.6	62.1	39.2	61.4	57.2	45.2	44.0	59.1	40.3	12.2	72.4
	Eight-quarter forecasting horizon											
Per cent	United States			United Kingdom			Germany			Canada		
Variables	Real GDP	Nominal GDP	Inflation	Real GDP	Nominal GDP	Inflation	Real GDP	Nominal GDP	Inflation	Real GDP	Nominal GDP	Inflation
Real	23.6	23.5	5.7	16.1	21.0	8.1	36.7	39.9	37.4	54.5	4.3	52.8
Financial	32.8	16.7	33.5	26.7	35.3	25.0	1.3	10.7	7.3	14.9	7.4	71.3

Note: The values refer to the difference between the sum of squared regression residuals of the full regression and that of a regression that excludes the variables corresponding to the specific row, divided by the latter figure. A higher value for the ratio indicates a higher information content.

Source: Authors' calculations.

A gauge of financial conditions?

The form of the forecasting regressions lends itself to another interpretation of the results. The linear combination of the financial factors can also be seen as a gauge of financial conditions. Taken literally, it represents the specific combination of financial variables that has the highest contribution in predicting future values of the real sector variables over and above the information contained in lagged values of output and inflation. We will label this combination of the financial factors in the forecasting regressions an index of financial conditions (FCI) and define it in terms of the notation used above as:

$$FCI_t = \sum_{I\in[1,\dots,4]} \sum_{i\in\{0,\dots,3\}} \gamma_{I,i} F_{I,t-i} \; ,$$

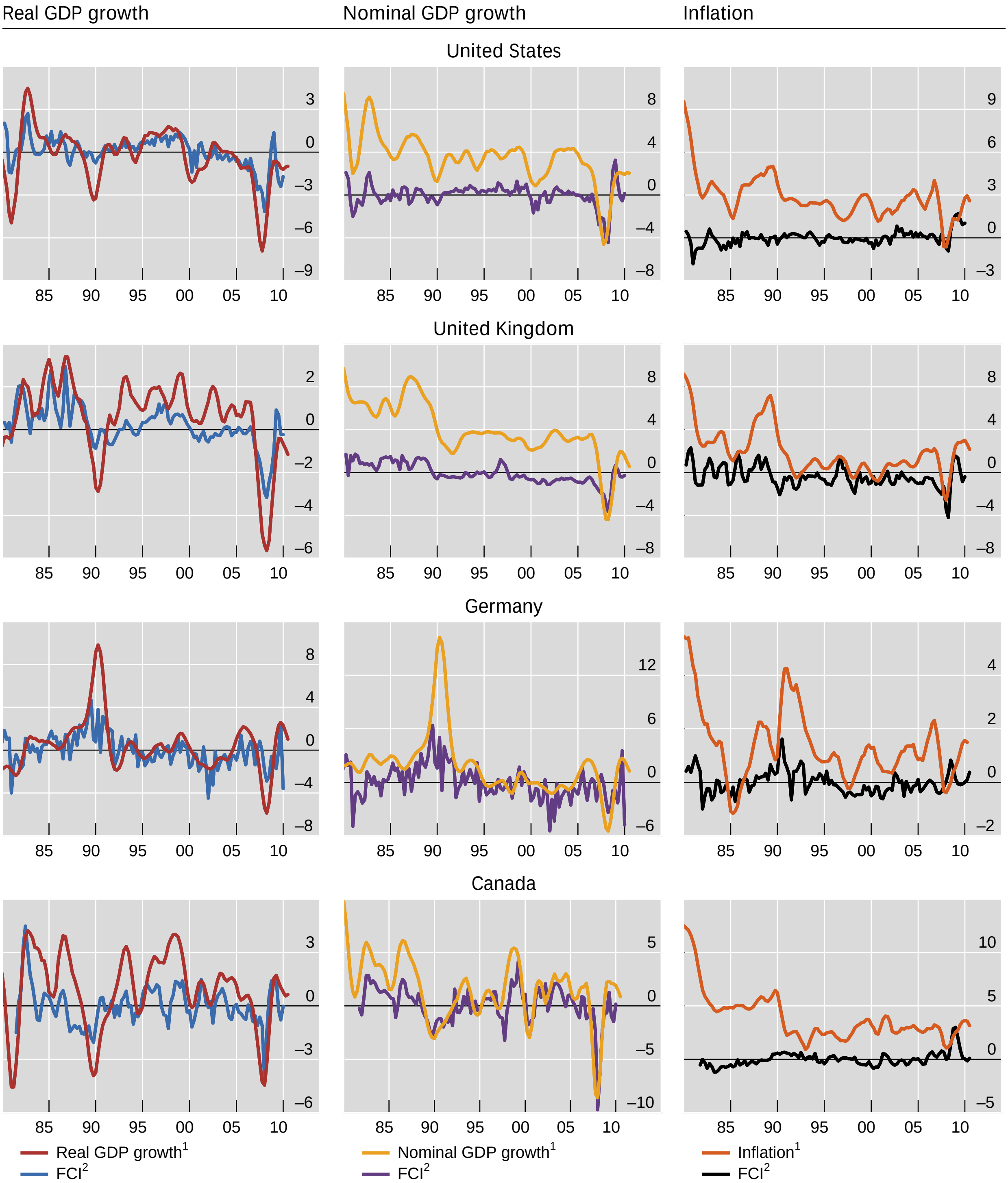
where the coefficients are those estimated in the forecasting regressions reported in Tables 2 and 3.

Two points are worth noting in interpreting the FCI. First, the FCI is a composite indicator drawing information from current and past values of all the financial variables in the dataset. Each estimated factor is constructed as a linear combination of all the variables and their lag. In addition, the selection procedure that determined the specification of the forecasting regression produced a combination of current and lagged values of some factors. Second, the interpretation of the FCI is most straightforward in the case of GDP. Positive values of the combined factors are associated with a boost to GDP growth in addition to what would have been predicted on the basis of the recent history of GDP and inflation. The converse holds for negative values of the combined factors. To the extent that greater economic activity is associated with accelerating inflation, we can also give a similar interpretation to positive values of the FCI in the inflation-forecasting equation.

Predictive ability of financial factors for real sector developments

Forecasting regression with four-quarter horizon

Graph 1



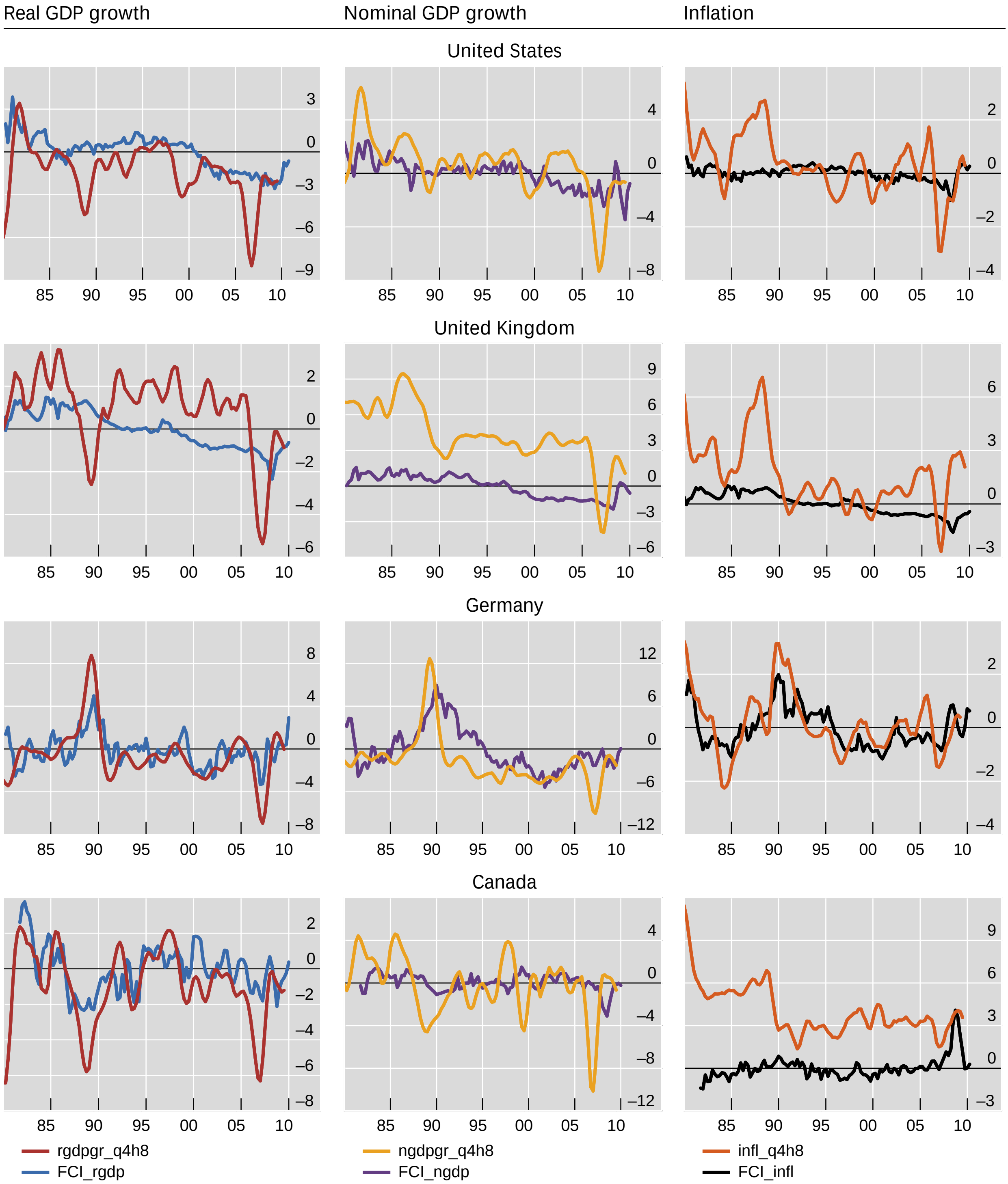
[1] Four-quarter trailing averages of annual growth; in per cent. [2] Combination of factors and their lags based on the best-fitting regressions.

Source: Authors' calculations.

Predictive ability of financial factors for real sector development

Forecasting regression with eight-quarter horizon

Graph 2



[1] Four-quarter trailing averages of annual growth; in per cent. [2] Combination of factors and their lags based on the best-fitting regressions.

Source: Authors' calculations.

Graphs 1 and 2 plot the values of the FCI estimated by each forecasting equation against the values of the variable being forecasted. The latter variable has been lagged by four or eight quarters in order to align the dates shown for the two plotted variables. The messages are very similar to those of the forecasting regressions. The FCI does a better job in accounting for future variation in the real and nominal GDP variables than it does for that of inflation. Moreover, while the forecasting ability of the financial factors deteriorates at a longer horizon, it remains significant, especially for GDP.

Another aspect of the relationship between real and financial variables highlighted by these graphs is that financial factors tend to pick up larger swings in the macroeconomic variables. This is most clearly the case with the sharp declines in GDP during the recent crisis, but also with the business cycle turns in the early 1990s (on a four-quarter horizon basis, see Graph 1). Given that the time scale of the two lines in each graph is shifted, this means that financial factors signalled the swings one year ahead of time. This observation points to the possibility that the relationship between the financial and real variables might be non-linear, in the sense that financial factors may be most pertinent in shaping macroeconomic outcomes if they exceed their usual range of fluctuation. But this must remain a topic for future analysis as it goes beyond the scope of the linear framework we use in this article.

Conclusions

This article explored the linkages between financial and real sector variables that are revealed by purely statistical techniques. We condensed the information of a broad array of financial variables into a small set of statistical factors and used those to forecast future GDP and inflation. The results are relevant for both macroeconomists seeking to understand the links between the two sectors and for policymakers who wish to build more robust policy on the basis of this understanding.

Financial variables have significant information content for future realisations of real variables over the typical planning horizon for monetary policy. They consistently contribute to the information contained in real variables in all the countries we studied. Moreover, the information they contain tends to have a significant lag and to be more pertinent in the case of larger cyclical swings, suggesting that these variables may be able to provide earlier signals for more extreme movements in real variables. That said, the predictive ability of financial factors is stronger and more reliable for measures of economic activity than for inflation.

These messages suggest that policy frameworks aiming at macroeconomic stability can benefit from the information in financial sector variables. In forecasting exercises, financial variables can add predictive power that maintains its strength even at longer horizons. Additionally, the weaker information content of financial variables for inflation suggests that economic processes that work through the financial sector may not influence economic activity through the inflation channel. This may weaken the information content of inflation as a guide to monetary policy when economic shocks originate in the financial sector. Exploring these conjectures would require a more elaborate analytical framework that can focus directly on structural linkages between the real and financial sectors.

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