A UK financial conditions index using targeted data reduction: Forecasting and structural identification

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\section*{A B S T R A C T}

A financial conditions index (FCI) is designed to summarise the state of financial markets. Two are constructed with UK data. The first is the first principal component of a set of financial indicators. The second comes from a new approach taking information from a large set of macroeconomic variables weighted by the joint covariance with a subset of the financial indicators (a set of spreads), using multivariate partial least squares, again using the first factor. The resulting FCIs are broadly similar. They both have some forecasting power for monthly GDP in a quasi-real-time recursive evaluation from 2011 to 2014 and outperform an FCI produced by Goldman Sachs. A second factor, that may be interpreted as a monetary conditions index, adds further forecast power, while third factors have a mixed effect on performance. The FCIs are used to improve identification of credit supply shocks in an SVAR. The main effects relative to an SVAR excluding an FCI of the (adverse) credit shock IRFs are to make the positive impact on inflation more precise and to reveal an increased positive impact on spreads.

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1. Introduction

Financial variables have desirable features for policymakers who wish to assess the current state of the economy (nowcast) and forecast the future, and especially so for central bankers. There are several reasons for this. The data are intrinsically forward looking and likely to incorporate market expectations about macro data. They may in themselves directly influence the future state of the economy. They are timely and available at high frequencies, so even if ex post they contain no information not available in other data that will eventually be published, they may still be useful in real time when attempting to understand and forecast macroeconomic developments. Moreover, since the onset of the financial crisis in 2007 the monetary transmission mechanism has arguably altered. In the United Kingdom, as in other economies, once policy rates hit the effective lower bound, policy involved asset purchases on a large scale, intended to impact asset yields. While conceivably it used to be the case that a small set of differently-dated interest rates was able to capture relevant financial conditions, that is no longer likely. For example, spreads over Bank and risk-free rates have altered, and credit rationing has been prevalent.

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For all these reasons, there has been a renewed interest in financial conditions indices (FCIs). These include for example Angelopoulou et al. (2013) for the EU, Hatzius et al. (2010) for the USA, Gauthier et al. (2004) for Canada and Guichard et al. (2009) and Paries et al. (2014) for variously euro area and some OECD countries, although they were largely developed and published before the onset of the crisis. Regularly produced FCIs include those from Bloomberg, Deutsche Bank, Goldman Sachs, the OECD and the Federal Reserve Bank of Kansas City Financial Stress Index. In this paper we use a hitherto untried method (multivariate partial least squares; MPLS) to construct a new FCI for the UK, as well as a more standard method using principal components (PC).

This innovation combines the insight that large data sets contain a rich set of information about underlying drivers in the economy with the desirable feature of FCIs that they are focussed on or informative about the financial sector. Our approach produces a summary of financial conditions that, uniquely, uses information from a separate large macroeconomic dataset. This is useful in itself as a summary measure, but also turns out to help forecast a variable of interest, namely an interpolated monthly series of GDP, with an advantage over the PC method in a recursive exercise using the longest possible estimation sample. And beyond that we can use the FCI to better identify credit supply shocks in a small structural vector autoregression (SVAR). Using the new FCI makes a material difference to some key impulse responses.

2. Constructing FCIs

The history of FCIs is well described elsewhere, so we will be brief. They grew out of an earlier cottage industry that was in the business of producing Monetary Conditions Indices (MCIs). MCIs combine a set of monetary indicators such as money stocks, interest rates and the exchange rate with weights obtained by various means, which are used as summary measures of monetary tightness and to nowcast or forecast. Arbitrary weights may be used, but data-driven methods are generally preferred. A frequently used method, pioneered by the Bank of Canada in the 1990s, is to weight series using the correlation with or regression coefficients in an equation explaining a variable of interest (typically inflation), on the grounds that this increases the usefulness of the indicator in this context. In a similar spirit, some recent FCIs (e.g. Swiston, 2010) have been constructed using VARs. One reason why the regression based MCIs fell out of fashion at some central banks was the difficulty in interpreting them, a point made forcefully in Ericsson et al. (1998), who point out that MCIs are not underpinned by a structural model derived from stable underlying microeconomic foundations (a critique that carries over to FCIs). As such, their stability and predictive power is questionable. They are certainly vulnerable to the Lucas critique: policy changes (or, more precisely, policy regime changes) reduce their utility. The issue is essentially one of identification.

Structural models, by contrast, allow us to understand the primitive shocks driving all aspects of the economy, including the monetary and financial sectors. In principle it would be possible to estimate such models, identify financial shocks and construct impulse responses that describe the dynamics of those shocks as they are transmitted through the economy. However, structural (DSGE) models with a role for a credit sector and for unconventional monetary policy are only now beginning to be explored, with a variety of financial frictions included and as yet no candidate for the canonical model. Moreover, many of the frictions that have been introduced have small effects on the monetary transmission mechanism. And in the standard New Keynesian model, central bank balance sheet operations have no effect due to a neutrality result discussed in Curdia and Woodford (2011), and the additional mechanisms used there that make asset purchases useful allow no role for government securities. Features such as market segmentation, preferred habitats, costs of adjusting portfolios or heterogeneity among different agents are needed, and DSGE models including them are in their infancy (e.g. Andrés et al., 2004; Gertler and Kiyotaki, 2010; Harrison, 2012). So although it would be desirable to have identifiable structural shocks, at present structural models are insufficiently well developed to deliver them.

An alternative might be to use an SVAR using some looser theoretical structure. For example, Swiston (2010) estimates an SVAR and constructs impulse responses from the estimated financial shocks, and examines the cumulated impact on GDP growth. But the approach inevitably pivots around the question of how to identify the shock of interest, which as the discussion above indicates, remains uncertain. Swiston (2010) employs a Cholesky decomposition, which may be appropriate in some cases (e.g. identifying a monetary shock in a simple VAR with interest rates and, say, growth and inflation) but in general is arbitrary. An alternative approach is to use sign restrictions to identify shocks as is done in Barnett and Thomas (2013), as the restrictions are rooted in theory but do not require a tight specification. The problem then becomes one of timeliness, as typically models are quarterly. Furthermore results are inevitably subject to model and parameter uncertainty, which equally applies to estimated DSGE models. Despite these reservations we identify credit supply shocks using sign restrictions below, but to check the usefulness of our approach rather than to generate an FCI. Nevertheless, FCIs may be useful as descriptive statistics and for forecasting. And from a practical point of view reduced-form statistical techniques may be the only means available to assess the impact of financial shocks and unconventional policy instruments (which work through financial and credit markets). Thus we take it as given it is worthwhile constructing such indices.

As with MCIs, some commonly reported FCIs simply average variables to provide an atheoretical summary measure. Regression techniques are not widely used. Recent data-driven methods use principal components to extract common factors from a group of financial variables, which is then interpreted as an FCI. Methods also allow time variation in the weights and the relationship with the macroeconomic variables of interest (e.g. Koop and Korobilis, 2013). It should be clear that we too accept that reduced form techniques like these are useful. But there is an alternative that has not yet been explored. Namely, aggregating indicators via multivariate partial least squares.
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