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Output gaps, inflation and financial cycles in the United Kingdom

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Abstract

This paper aims at constructing potential output and output gap measures for the United Kingdom which are pinned down by macroeconomic relationships as well as financial indicators. The exercise is based on a parsimonious unobserved components model which is estimated via Bayesian methods where the time-paths of unobserved variables are extracted with the Kalman filter. The resulting measures track current narratives on macroeconomic cycles and trends in the United Kingdom reasonably well. The inclusion of summary indicators of financial conditions leads to a more optimistic view on the path of UK potential output after the crisis and adds value to the model via improving its real-time performance. The models augmented with financial conditions have some inflation forecasting ability over the monetary policy relevant two to three-year horizon during the last fifteen years, although this ability diminishes in a real-time setting. Finally, we also introduce a new approach to constructing financial conditions indices, with emphasis on their real-time performance and ability to track the evolution of macrofinancial imbalances. Our results can be relevant from both monetary and macroprudential policy perspectives.

Key words: Bayesian estimation, business cycle, forecasting, financial conditions, real-time data, unobserved components model.

JEL classification: C11, C32, E31, E32, E52.

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1. Introduction

The concept of the output gap, based on pioneering papers like Okun (1962), corresponds to the difference between observable actual and unobservable potential output, where the latter can be subject to various theoretical or empirical restrictions. Consequently there exist numerous views on what output gap measures actually mean. On the one hand, the output gap can be seen as the difference between actual output and a long-term, steady state output path, without any reference to inflation. On the other hand, the measure can be interpreted as the difference between actual output and hypothetical level of output achieved when nominal rigidities in the economy are absent, implying an output gap which is a measure of (dis)inflation. Typically, the latter interpretation is more meaningful from the perspective of monetary policy which has a focus on achieving an inflation target over the medium term. For empirical business cycle analysis or from a macro-prudential policy perspective different concepts of the output gap may be suitable. In the current paper, we do not put a strict theoretical restriction on the concept of the output gap, since we build our measures on a handful of relevant macroeconomic and financial variables, with a focus on plausibility, real-time performance and forecasting ability.

Given the link between output gaps and inflation, measures of the output gap carry crucial relevance for monetary policy. The stance of monetary policy in the UK, as in most other advanced economies, is set with reference to expected inflation and the actual cyclical position of the economy (i.e. the output gap). Despite their policy relevance, output gaps are notoriously difficult to measure (especially in the vicinity of a large shock like the recent financial crisis), and there is no consensus in the profession on the best method for estimating them. This uncertainty is related to the inherently unobservable nature of potential output. Because of this, the level of potential output needs to be inferred by decomposing observable output (real GDP) subject to various assumptions on, for example, the frequency of cyclical fluctuations, the smoothness of the trend representing potential output, and the co-movement between cyclical fluctuations and other, possibly observable variables.

Different approaches for estimating potential output and output gaps have been developed, ranging from simple time-series methods to more complex structural model based decompositions.[1] One of the most widely used methodologies is the production function approach, where observable output is first decomposed into the contribution of production factors (capital, labour) and a residual (representing total factor productivity (TFP)). These variables are then de-trended individually subject to certain assumptions and methods[2]. Potential output is subsequently constructed as a weighted sum of trend components, with weights corresponding to factor shares. In this sense, the production function approach is not a methodology in itself, but an "umbrella term" covering the underlying

[1] For an analysis of some current methods used for policy purposes in the UK, see OBR (2014).

[2] TFP and labour input can be detrended, for example, with the help of univariate statistical filters like the Hodrick-Prescott filter or band-pass type filters.

methodologies which are used for decomposing production factors into trend and cyclical components[3].

The aim of this paper is to strike a balance between simple time series and more complex structural methods by providing a semi-structural time series framework for estimating output gaps and inflation dynamics in the UK. In particular, we explore the relevance of financial variables for the estimation of the output gap in the spirit of Borio et al. (2014). Furthermore, we study both the real-time performance and medium-term inflation forecasting properties of our models and examine their general ability to conform to macroeconomic theory and empirics of the UK economy.

Our approach makes a number of contributions to the well-established literature on macroeconomic cycles. First, the main results of the analysis suggest that it is possible to construct output gap measures which track actual narratives on macroeconomic cycles and trends of the UK reasonably well, and at the same time are able to signal the pre-crisis build-up of macroeconomic imbalances in real time. Second, we show that augmenting a basic model with financial variables adds value through improving its real-time performance. In particular, financial variables help to identify the pre-crisis boom and also signal a more optimistic view on UK potential output after the financial crisis, as through their inclusion a larger part of the crisis-related downturn is attributed to cyclical rather than structural factors. Third, the models, especially the one augmented with financial conditions, have had some statistically significant inflation forecasting ability over a monetary policy relevant 2 to 3 year horizon during the last 15 years, suggesting that these types of models can have important information content for the conduct of monetary policy. However, this forecasting ability diminishes in a real-time forecasting experiment, highlighting the uncertainty related to monetary policy decisions taken in real time. And finally, as a by-product of the analysis, we also introduce a new approach to constructing financial conditions indices, with emphasis on their real-time performance and ability to track macroeconomic cycles.

The paper is structured as follows. The next section describes the model used for the analysis. Section 3 presents the results, concentrating on output gap measures and inflation, both from an *ex post* and real time perspective. Section 4 concludes. Technical details are relegated to the appendices.

2. The model

The core of the proposed framework[4] is a relatively small semi-structural unobserved components model (UCM), which is used to pin down the paths of the unobserved variables by casting it in state space form and applying the Kalman filter. The Kalman filter is also used to evaluate the likelihood function of the model, and thus it is a crucial element in estimating the parameters.[5] Bayesian

[3] For an example of this type of a method, see Fernald (2012).

[4] See Appendix 1 for technical details of the modelling framework. See also Tóth (2015).

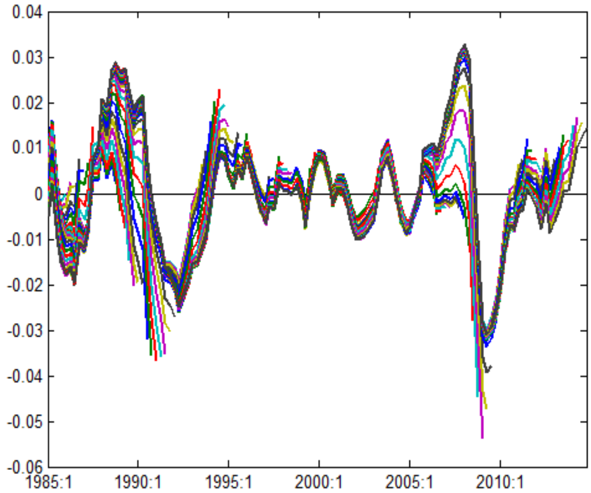
[5] For more details on state space models and the Kalman filter, see e.g. Kalman (1960) and Durbin and Koopman (2001).

estimation methods are used to combine prior assumptions and the information content in the data with regard to the parameters of the model.

The UCM is based on well-established macroeconomic relationships in order to simultaneously decompose a vector of observable variables (GDP, unemployment rate, inflation) into unobservable trend and cyclical components. Our model builds on the framework introduced by Kuttner (1994), and also has similarities with the model of Benes et al. (2010). One special feature of our model is the way in which the path of trend unemployment rate is pinned down by economic relationships connecting cyclical and trend components of unemployment and output as well as by developments in the long-term unemployment rate. The resulting unemployment trend measure is thus somewhat different from the established NAIRU/NAWRU concepts. This assumption not only helps the estimation of the equilibrium unemployment rate but can be considered as a shortcut for capturing possible labour market hysteresis effects.

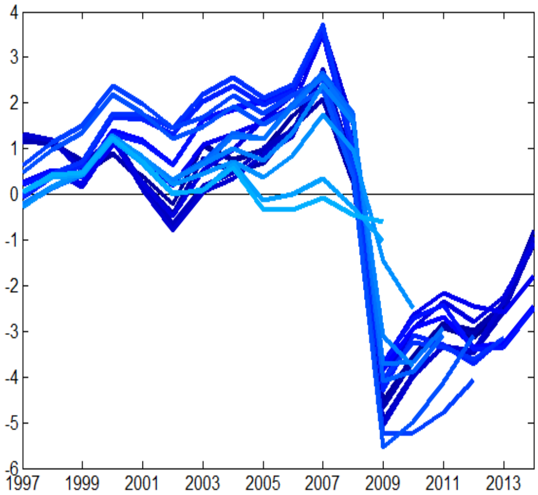
With regard to features of filter-type models, it is well established in the literature[6] that simple, univariate filters used for trend-cycle decomposition tend to have an "end-point" problem, meaning that with incoming data estimates close to the end of the sample get revised significantly. This property renders decomposition approaches relying on standard univariate filters unsuitable for real-time policy analysis. As an example, the size of the pre-crisis output gap estimated using the popular Hodrick-Prescott (HP) trend-cycle decomposition changed substantially as new data became available (Chart 1).

Chart 1 Revisions of UK output gaps: Hodrick-Prescott filter (lambda=1600)



Expanding window estimation over 1985q1 – 2014q4

Chart 2 Revisions of UK output gaps: vintages of the European Commission's estimates (2007 – 2014)

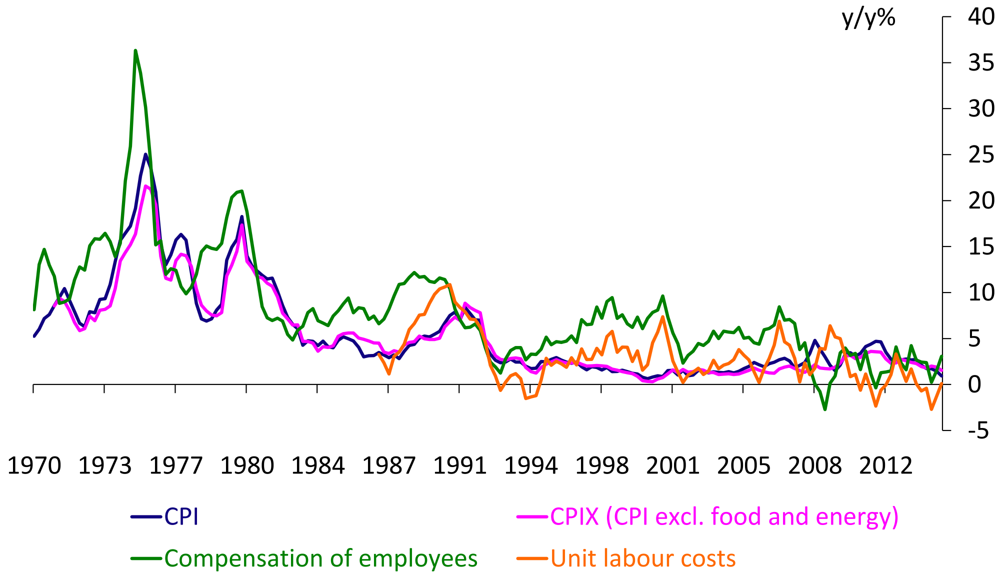


Annual data, including 2 year ahead forecasts. The examined period includes multiple methodological changes.
Source: Eurostat – Ameco database

[6] See e.g. Orphanides and van Norden (2002).

The end-point problem does not necessarily disappear when using more complex trend-cycle decomposition procedures, such as a production-function based methodology[7] (Chart 2). Nevertheless, real-time performance can possibly be improved by exploiting the information content of variables which – based on economic theory or empirical findings – tend to co-move strongly with the business cycle. Nominal variables, such as inflation or wage inflation are often used to help to pin down the path of the output gap, through Phillips-curve type relationships. However, there are reasons to believe that the cyclicality of these nominal variables has decreased over recent decades. Inflation may have become less sensitive to the cycle due to better anchored inflation expectations ("the great moderation") and for a small open economy like the UK, fluctuations in inflation have sometimes been independent of business cycles. Indeed, one lesson of the recent financial crisis is that nominal variables, usually thought of as good indicators of overheating, were less able to signal any pre-crisis boom (Chart 3).

Chart 3 CPI inflation in the UK



Source: Bank of England, ONS

Instead of relying only on traditional macroeconomic variables, as shown by Borio et al. (2014), some financial and asset price indicators can capture (and possibly cause) fluctuations in the output gap, and can thus help make the end-point problem less severe. In this paper we also make an attempt to use a number of financial variables to create a financial cycle measure which is used to inform the output gap measure of our model. A key (and to our knowledge, unique) feature of our model is the inclusion of a summary indicator of financial conditions in the modelling framework. The recent financial crisis has proved how important financial sector shocks can be in driving macroeconomic variables, and hence, there is value in examining how financial sector variables can be included in a more traditional unobserved components model. The information content of financial variables can be expected to be

[7] See Havik et al. (2014).

especially important in a country like the UK, where the weight of the financial sector is much larger than in most other advanced economies.

Our approach is thus very similar in spirit to that of Borio et al. (2013) and (2014), who used variables such as real credit growth and residential property price indices to capture the impact of the financial cycle in a small scale unobserved components model of the output gap. Within this conceptual framework the financial cycle can be interpreted as fluctuations transmitted by or coming form the financial system, e.g. in the fashion of the financial accelerator model of Kiyotaki and Moore (1997).

Apart from including these proxy variables, there are various other ways in which financial sector variables could be included in our models; one could, for example, use the current account balance as a proxy for overall financial imbalances (see Darvas and Simon (2015)), although this approach is likely to be more suitable for emerging economies, where capital in- and outflows play a key role in boom/bust cycles. Our chosen way is the inclusion of a relatively parsimonious financial conditions index, where we include a small number of key financial variables and then use a dynamic-factor model approach[8] to elicit the financial conditions index for the UC model. In this way one avoids the arbitrariness of choosing one single credit or financial indicator to pin down the financial cycle, whilst remaining relatively agnostic about the exact sources of financial sector shocks in the economy.

There is also ample evidence in the existing literature on the effects of financial conditions on macroeconomic cycles. For example, Darracq-Paries et al. (2014) find that manufacturing production responds negatively to shocks leading to tighter financial conditions in the euro area, and Guichard et al. (2009) detect negative responses of GDP and output gap to negative shocks in the UK in the aftermath of the financial crisis. The effects of shocks to financial conditions on GDP typically propagate through lower asset prices, higher price volatility, higher spreads between risky and less risky debt, as well as lower credit flows. Hence, particularly given our interest in post-crisis dynamics, taking into account the cyclical effects – with the correct signs for the propagation mechanisms for individual members of the financial conditions index – appears to be a crucial element of any output gap estimation framework.

Based on the above justifications, our model is estimated in three versions:

1) A basic "bare bones" model (henceforth, the B1 model) with GDP, inflation and unemployment rate;
2) Another version of the basic model (B2 model) with B1 model augmented with a long-term unemployment rate;
3) B2 model augmented with a financial conditions index (FCI model). Given the nature of FCIs and the difficulties in selecting the appropriate group of financial indicators, we report the

[8] For an introduction to dynamic factor models of this type, see e.g. Stock and Watson (1991). In fact, we experiment with two different financial condition indices (see details below).

results for two different FCIs for robustness. The FCI specifications are based on financial condition indices, where the scope of the underlying indicators differs. While the FCI1 specification is based on eight financial market variables selected on a priori grounds, the FCI2 model is based on five key financial market variables, which were selected on the basis of statistical properties. Both FCIs are extracted using a factor model approach.[9]

Given the focus of the current study on monetary policy, the key variables of interest in our analysis are the output gap and inflation. One key question is to see whether the FCI model implies a larger positive output gap in the UK during the 2000's before the financial crisis (as suggested by Borio et al. (2013)) than the basic models. More generally, we explore output gap dynamics and compare them with a simple Hodrick-Prescott (HP) filter, both *ex post* and in real time.

We also test the models for their inflation forecasting capabilities. The intuition for the forecasting experiment is that if the models can reveal something fundamental about output gaps and the relationship between GDP and inflation, they might also be helpful in forecasting inflation. It is worth noting that our interest in the inflation variable is a key departure from the approach taken by Borio et al. (2013) and (2014), who argue against forcing a link between inflation and output gaps in these types of models. However, the parsimonious one-equation multivariate filters introduced by these authors do not allow for their financial cycle augmented models to be checked for their endogenous inflation forecasting performance, and hence they lack macroeconomic structure which is crucial for an inflation-targeting central bank.

3. Results

This section reports the results of the UC model estimations.[10] We report the main results for B1, both long and short version of B2 as well as FCI1 and FCI2. For some of the more detailed results, we only report the results from B2, FCI1 and FCI2, as appropriate. The basic models are estimated over a sample of 1995q1 to 2014q4, and for comparison purposes, the B2 model also over a longer sample of 1985q1 to 2014q4.[11] The following subsections report the results for i) the full-sample potential output and output gap estimates and ii) real-time output gap and inflation forecasting experiments.

[9] For details of the FCIs, see Appendix 3.

[10] For details of the estimation procedure, see Appendix 1, and for details of the data, see Appendix 2.

[11] All sample length choices are driven by data availability, in particular with regard to the financial conditions index, as well as the stability of the monetary policy environment. The sample of 1995q1 to 2014q4 can be regarded as relatively short for this type of an analysis, but this problem is mitigated by the Bayesian nature of the modelling strategy. Quarterly changes in seasonally adjusted core inflation (CPI excluding food and energy) are used in the model, as this measure captures domestic inflation pressures better than the headline one. However, all results are qualitatively very similar when using headline CPI inflation.

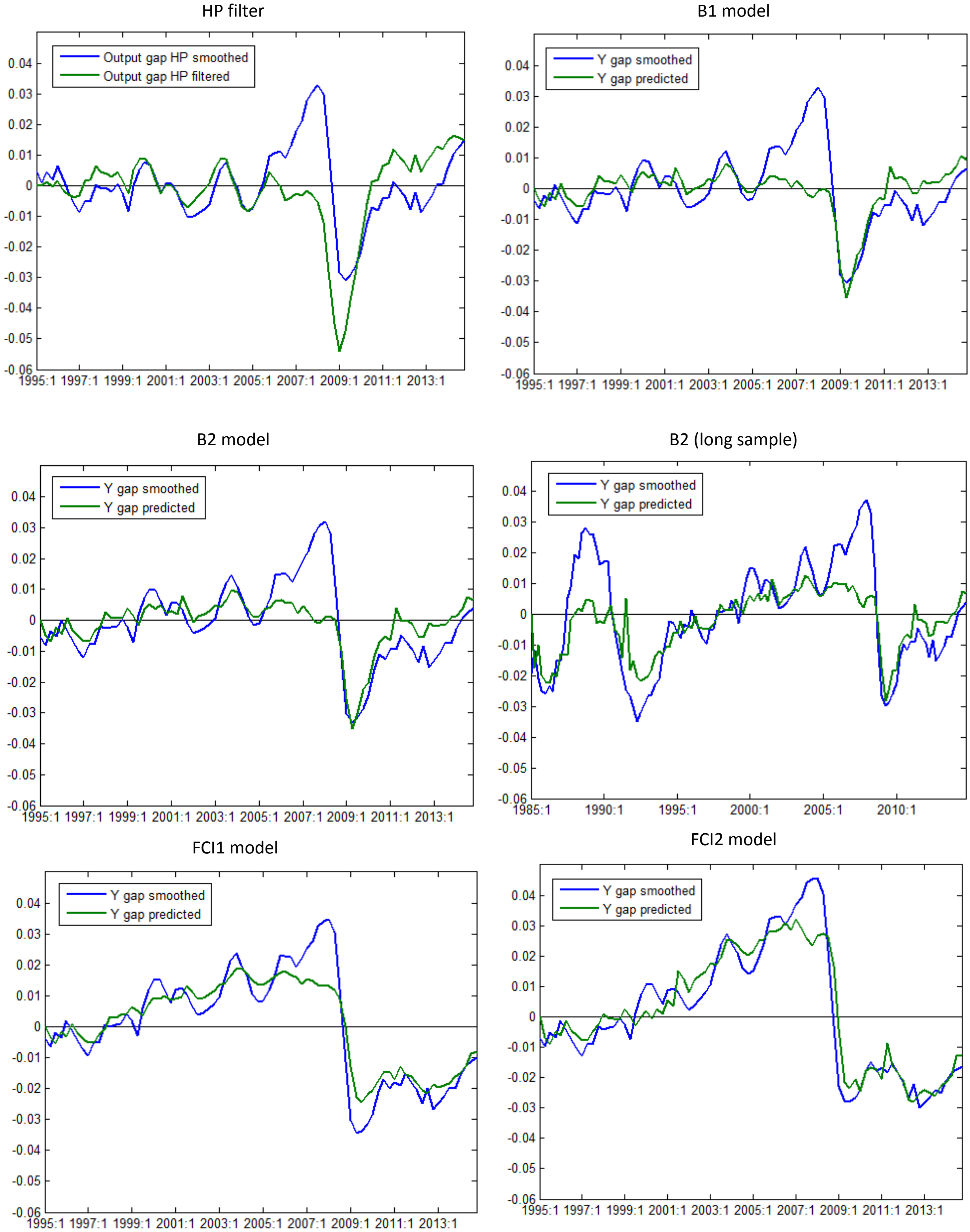
3.1 Full-sample output gaps

Chart 4 compares the output gaps of the UC models (as well as those of a Hodrick-Prescott (HP) filter) for pseudo real-time[12] filtered (one-sided) and smoothed (two-sided) estimates. The charts for the HP filter provide evidence for the (well-known) poor real-time performance of this simple measure, especially over the past 10 years. The pseudo real-time performance of basic models is better, although both the long and the short version of the B2 model struggle to capture the volatile pre- and post-crisis dynamics of recent years. The FCI models offer an improvement in terms of their pseudo real-time performance; they have detected the recent fluctuations relatively well, at least according to this simple filtering exercise.

All the filters detect (ex post) a relatively large and persistent positive output gap before the recent financial crisis. While there is significant uncertainty about the extent of and reasons behind the pre-crisis "boom" in the UK, this result is qualitatively similar with other estimates produced, for example, by the OECD and the IMF. It is also noteworthy how close the dynamics of the output gap estimates of the two FCI models are to each other, which increases the robustness of these results.

[12] We define pseudo real-time as filtered real-time estimation of the models, using latest vintage (2014Q4) data. In Section 3.2, we use vintage real-time GDP data and quarterly re-estimation of the models to test the fully fledged real-time performance of the models.

Chart 4 Output gap - smoothed and predicted



The charts show output gaps as measured in real time (one-step ahead Kalman filter predictions) and taking into account the entire sample (Kalman smoother).

The basic and the FCI models imply a very different view on the size of the UK output gap at the end of the sample (2014q4). According to the basic models, the output gap was around 0.5% positive, whereas the FCI models indicate a negative output gap of about 1 to 1.5%. These differences reflect the different views the two models offer on potential output (Chart 5); the basic model is more pessimistic on the level of potential output, as the dynamics of the macroeconomic variables in the model during the crisis period have dragged down the trend path. This is not surprising in the light of the lack of disinflationary pressures in most of the post 2008 period. In contrast, the FCI model is more optimistic on potential output; the level of actual output has been temporarily depressed by the weakness in cyclical financial conditions, the improvement of which should allow for a return to a higher path of output without immediately triggering inflationary pressures.

Chart 5: Trend and actual output estimates

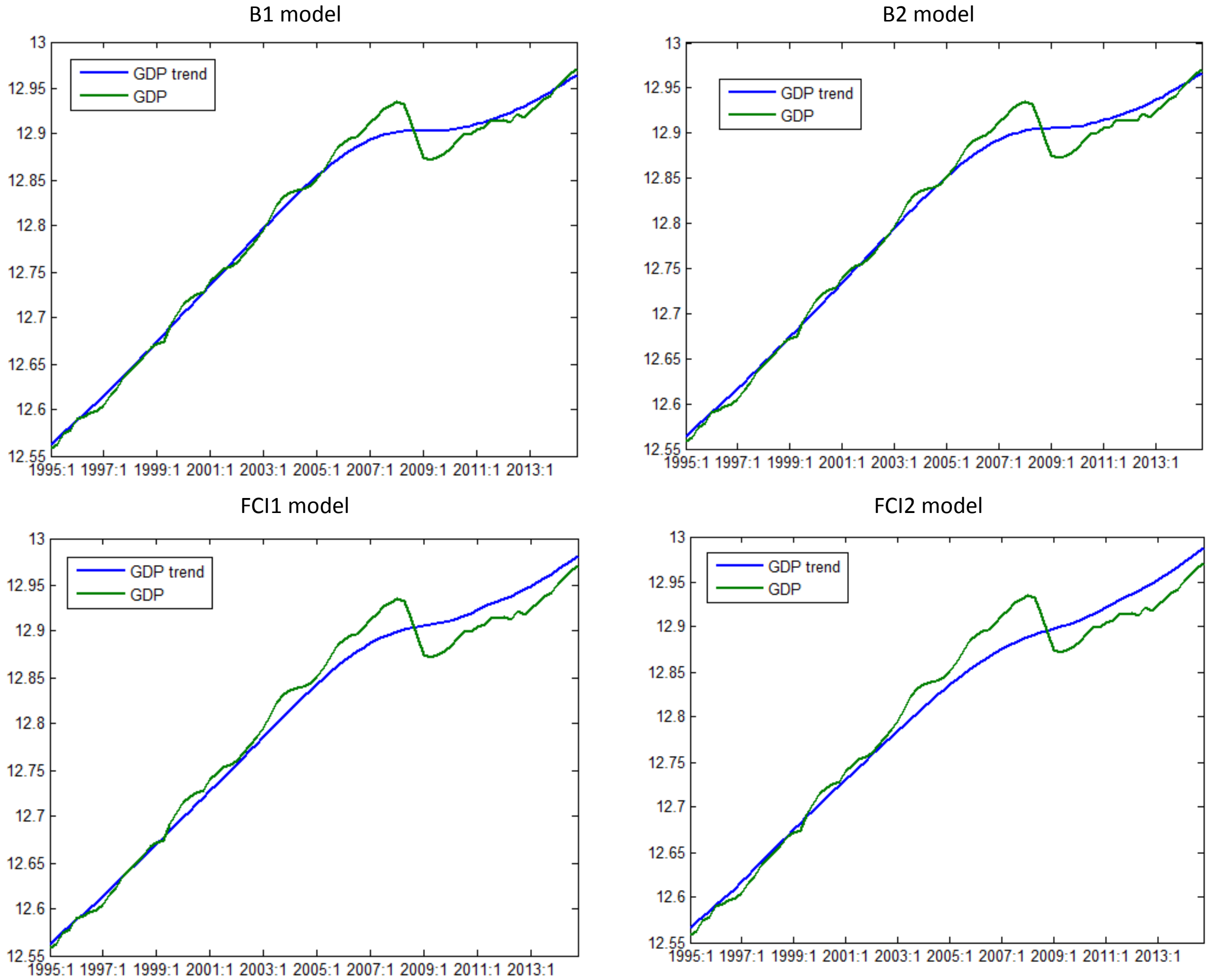


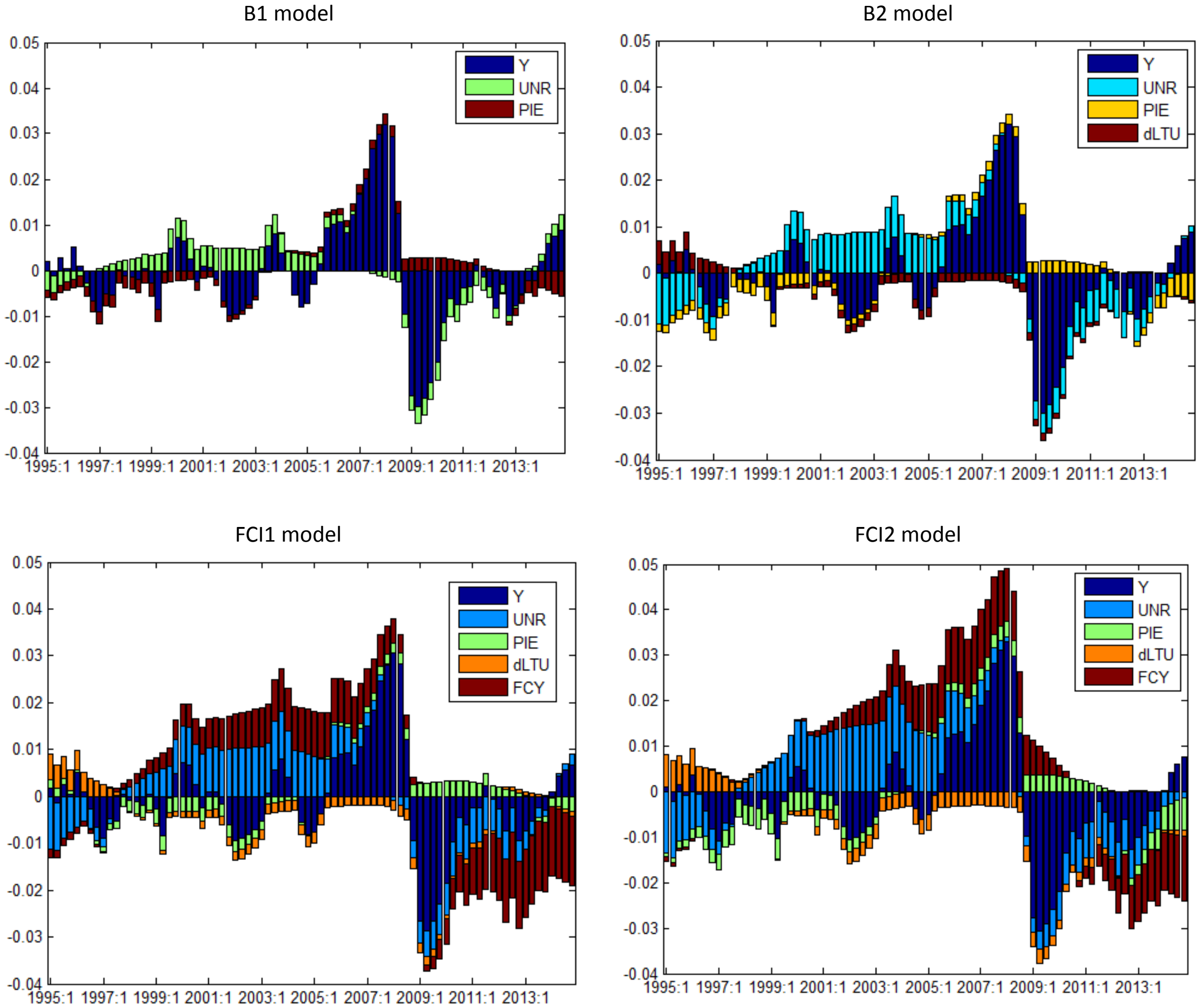
Chart 6 presents the decomposition of the smoothed output gap in the different models into contributions (in terms of what helps in identifying the unobservable output gap measure) from the different observable variables in the models. These decompositions are largely intuitive. As expected, the main driver of the output gap in all models in recent years has been output itself, while the unemployment rate has also made a significant contribution. As is typical in these types of models, the contribution of inflation to the output gap has been relatively limited, although there is a fairly large negative contribution from the low recent inflationary pressures. Interestingly, the FCI variable makes a significant contribution in both of the FCI models, and this contribution was still very strongly negative at the end of the sample, despite marked improvement in financial market conditions in the UK[13].

The dynamics of other unobservable trend variables in the models also appear intuitive (see Appendix 4, Charts A2-A4), and they are relatively close to each other. According to the B2 and the FCI models, trend GDP growth hovered around 2.5-3% before the crisis and was just around 1.5-2% at the end of the sample. This is also in line with estimates from other, more complex models and forecasting institutions[14]. The estimates for the unemployment rate are very similar for the three models, and suggest a relatively sluggish reaction of trend unemployment to fluctuations in actual unemployment. From a monetary policy perspective it is reassuring to see that the models imply relatively steadily anchored trend inflation at around 2%, although the FCI1 model suggests an increase to above 2% since 2008.

[13] However, it is notable how weak net lending and credit dynamics (an important variable in the FCIs) remained at the end of the sample.

[14] For example, OECD, in its June 2015 Economic Outlook, estimated the trend output in the UK at between 2 and 2.5% 2004 to 2006, and at 1.8% in 2014.

Chart 6 Decomposition into observable variables of output gap estimates[15]



Y is real GDP, UNR is the unemployment rate, PIE is core CPI,FCI is the financial conditions index, and dLTU is the change in long term unemployment rate.

3.2 Real-time results

Given the uncertainties in using the models for policy-making purposes in real-time, apart from the full sample results presented above, it is crucial to examine the real-time performance of the models. This section presents the results of both pseudo and actual[16] real-time performance for output gap measures and inflation forecasting. For the purposes of measuring the performance, the sample is split

[15] Calculations are conducted in a similar vein to Andrle (2013)

[16] The difference between pseudo and actual real-time is a subtle but an important one. In the current study, pseudo real-time refers to one-sided (filtered) estimates based on a state space where parameters are estimated on the latest date vintage (2014Q4), whereas actual real time refers to two-sided smoothed estimates based on an expanding sample with real-time GDP data vintages (as of 2000Q1) and real time parameter estimation. Even actual real time, as defined here, is used loosely, since no account is taken of actual vintage inflation and unemployment rate data (for which revisions are relatively small, however), nor of the uncertainty related to availability of current modelling techniques at each point in time.

in half; the model is first estimated from 1995Q1 to 2004Q4 (40 observations), and the different real-time experiments are then run on the second half of the sample (2005Q1 to 2014Q4).

For the actual real-time experiment, we need real-time GDP data for the UK. Based on publically available data from the Bank of England and the ONS, we construct real-time GDP data vintages from 1999Q4 onwards (see Appendix 4, Chart A2 RHS). The chart suggests that revisions to the UK GDP data have been relatively large over the past 15 years, so achieving good real-time performance will be challenging. It is also worth noting that the introduction of real-time GDP vintages adds another layer of complexity to the models. The models need to be estimated each quarter, and a new GDP dataset (both current and past quarters) needs to attached to the model (replacing the previous one) at each point of estimation.

We also introduce a forward-looking element to the real-time experiment in the spirit of Blagrave et al. (2015). In particular, we add 12 quarters of Bank of England GDP and CPI forecasts to the end of the sample at each quarter as noisy signals on the (future) path of output and inflation (see Appendix 3 for details). As it turns out, the CPI forecasts do not significantly improve the medium-term inflation forecasts of the UC models, but the GDP forecasts somewhat improve the inflation forecasting performance of the FCI2 model. Hence, all the results reported below for the FCI2 model are of a version that includes the GDP forecasts[17].

3.2.1 Output gaps

Chart 7 shows the actual real-time performance of the output gap measure for the B2 and FCI models. As was already suggested by Chart 4, the FCI models capture the dynamics relatively well in real time, also including the pre-crisis "overheating", especially for the FCI1 model. To put a numerical value on the relative real-time performance, we calculate the absolute value of the mean deviation of the full sample output gap estimate from the end-point of the real-time estimate (the dashed lines in Chart 7) at each quarter from 2005Q1 to 2014Q4, and divide this by the standard deviation of the full sample gap. This gives a measure of standardised average errors for the different models.

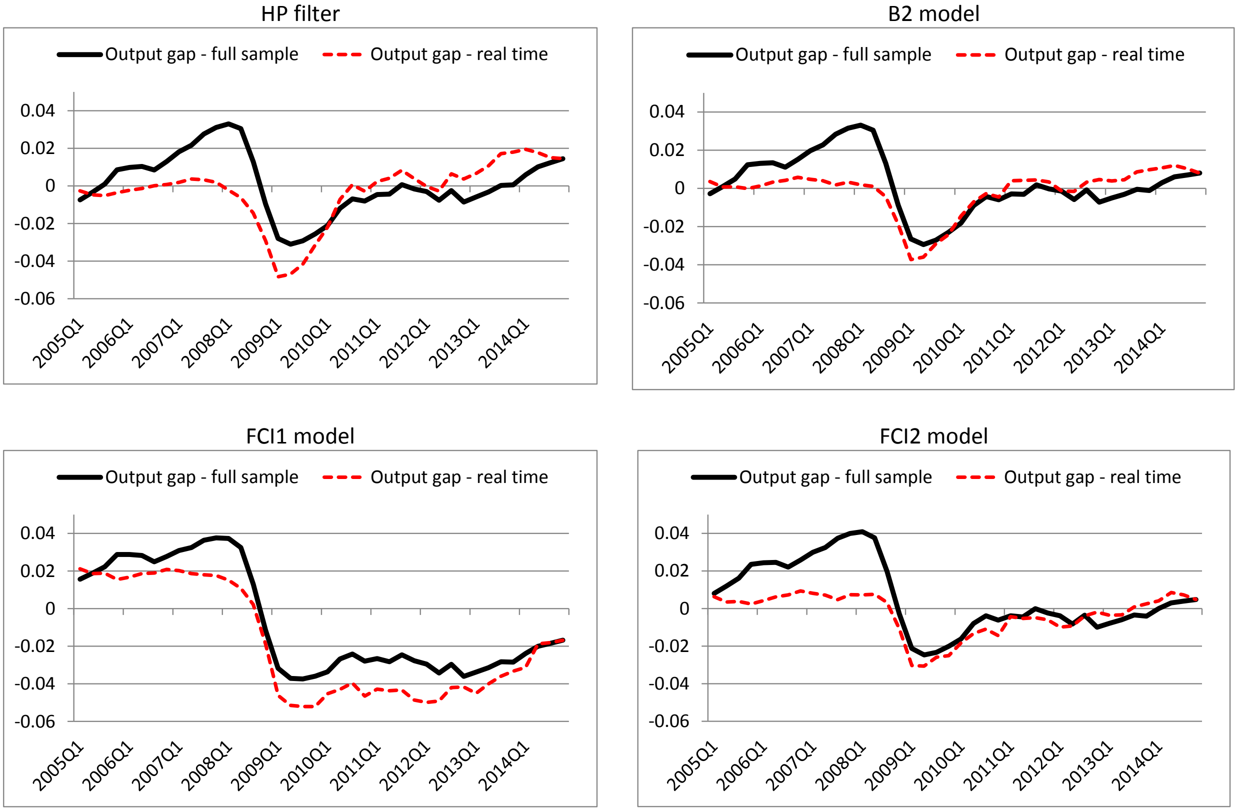
Table 1: Relative real-time performance based on standardised average errors (SAE)

Model	SAE
HP filter	0.78
B2	0.59
FCI1	0.42
FCI2	0.57

[17] The inclusion of the forward-looking element does not have a large effect on the real-time output gap estimates nor the performance of these estimates, although it does have some effect on the level of the gap at the end of the sample. The results for the B1 model are not reported in this section, as they are very close to the B2 model

The results are reported in Table 1 and suggest that the real-time performance of the UC models' gap measure clearly improves the performance[18] compared to the HP filter and more crucially, the financial conditions index provides vital information for the model, further improving the performance compared to the B2 model. This is a key result of our analysis and emphasises the importance of using relevant modelling techniques in real time to avoid the types of policy mistakes discussed, for example, by Orphanides (2003). It is also encouraging to see how well the FCI models (FCI1 model in particular) are able to pick up the high volatility in output experienced during the financial crisis period, which also suggests a larger role played by financial variables as a cause for macroeconomic fluctuations than traditionally claimed.

Chart 7: Output gaps in real time



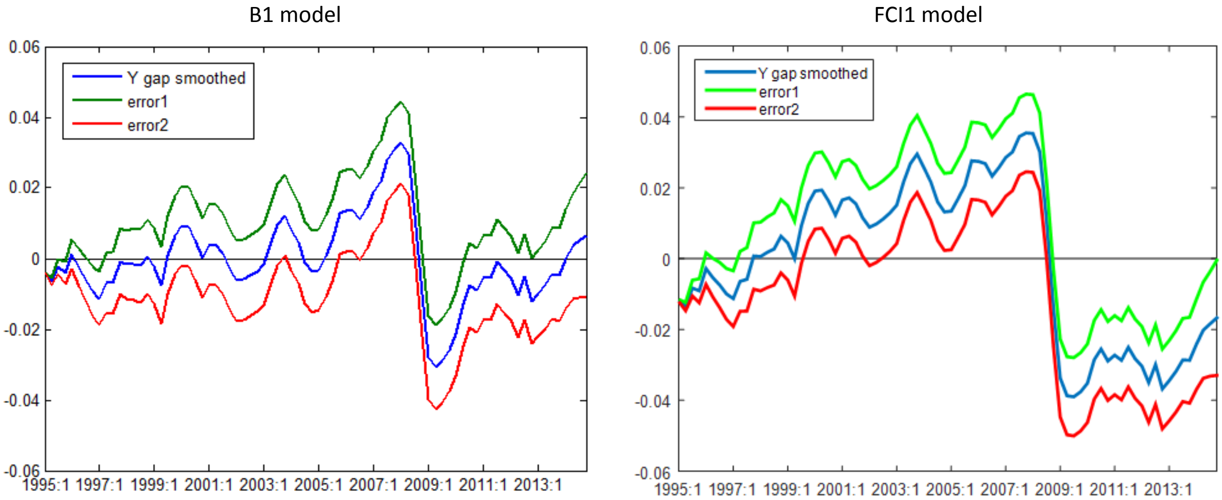
The charts show estimates with the full sample along with real-time estimates with rolling end-points for estimation (with real time FCI and GDP data) at different points in time.

As a more conventional cross-check on the real-time analysis, Chart 8 shows the confidence intervals around the output gap forecasts of the B1 model and the FCI1 model. A casual reading of the charts would suggest that one can have more confidence in the results of the B1 model compared to the FCI1 model, as the confidence intervals of the former are narrower. However, this is not the correct conclusion; as shown above, the real-time performance of the B1 and B2 models is significantly worse than that of the FCI1 model. The FCI1 model is better specified than the B1 model and hence captures the uncertainties related to the output gap measure more realistically than the B1 model. This

[18] This is also true for the estimates of trend unemployment, but we do not report the results here, as this is not the focus of our study.

further emphasises the importance of conducting real-time performance analytics in these types of models instead of relying on traditional confidence interval type measures of the full sample results.

Chart 8: Output gap estimates with 90% confidence intervals



3.2.2 Inflation forecasting experiments

For the output gap measure in our models to be more relevant for monetary policy, a desired feature would be for them to be able to forecast inflation with at least some degree of accuracy over a monetary policy relevant horizon. The inflation forecasting performance of the UC models was tested in a rolling pseudo as well as actual real-time forecasting experiment[19]. This was done for five different models; the B2, the long B2, the FCI1, the FCI2 and for comparison purposes, a simple 3-variable (GDP, inflation and unemployment) vector autoregressive (VAR) model. For the long model, the experiment was initialised in 1993Q1, because this coincides with the introduction of inflation targeting in the UK (in October 1992). For the shorter B2 and FCI models, the forecast experiment was initialised in 2005q1, both due to availability of GDP forecast data as well as to strike a balance between the size of estimation and forecasting samples.

The results, presented in Table 2 (showing Theil U statistics together with statistical significance based on the Diebold-Mariano test), suggest that the models do not perform particularly well in the short-term (apart from the 3-quarter horizon for the shorter sample). Interestingly, however, they perform consistently well in the pseudo real-time experiment over the 2-3 year horizon (although the improvement against a random walk of the long B2 model is not statistically significant), which is also the most relevant from a monetary policy perspective. The UC models also clearly beat the VAR

[19] The models are first estimated with data up to 2004q4 (in the case of the long B2 model, up to 1992q4), and then a forecast is produced for each quarter for a three-year period forward. The estimation period is then rolled forward quarter by quarter. Forecasting performance against a simple random walk assumption can then assessed with standard tools, like root mean square errors (RMSE) and Theil U (the relative RMSE of a UC model versus that of a random walk assumption). It is also worth noting that in the FCI models, the dynamic factor model for the FCI is executed in real time also for the pseudo (as well as for the actual) real-time experiment to allow only for financial markets data up to the examined point in time to affect the FCI estimate.

model, which performs quite poorly relative to a random walk assumption. The FCI2 model performs slightly better than the short B2 model, although this difference is not statistically significant. In the actual real-time experiment, the forecast performance worsens, as expected. The FCI2 and B2 models, however, still have some statistically significant ability to forecast the quarterly inflation rates over the 2 to 2½-year horizon.

Table 2: Theil U statistic for real time forecast experiments

		Pseudo real-time					Real-time		
	Model	FCI 1	FCI 2	B2	B2	VAR	FCI 1	FCI 2	B2
	Sample	short	short	short	long	short	short	short	short
Quarters	1	1.15	1.24	1.24	1.02	1.15	1.02	0.94	0.97
ahead	2	0.91	1.00	1.00	1.14	1.12	1.04	0.89**	0.94
	3	0.79**	0.74**	0.74**	1.05	1.17	1.09	0.87**	0.90
	4	0.92	0.95	0.97	1.62	1.23	1.15	0.87**	0.92
	5	0.96	0.94	0.98	1.65	1.27	1.27	0.91	0.93
	6	1.19	1.08	1.15	1.89	1.65	1.60	1.09	1.11
	7	1.11	1.08	1.15	1.04	1.74	1.52	1.05	1.04
	8	0.80**	0.78**	0.83**	1.06	1.42	1.19	0.86**	0.89**
	9	0.75**	0.66***	0.74**	0.96	1.42	1.13	0.84**	0.84**
	10	0.77**	0.69***	0.77**	0.91	1.43	1.12	0.84**	0.85**
	11	0.79*	0.74**	0.82*	0.87	1.41	1.14	0.88	0.90
	12	0.75**	0.69***	0.77**	0.84	1.28	1.08	0.86	0.86
	Avg	0.91	0.88	0.93	1.17	1.36	1.19	0.91	0.93
y/y	8	1.22	0.96	1.09				1.16	1.19
inflation	10	1.00	0.76**	0.94				1.10	1.11
	12	0.88	0.61***	0.86*				1.07	1.07

Theil U statistics of the model against a random walk (RW). A number lower than 1 indicates the model beats RW.
Short sample is forecast experiment with the sample of 2005q1 to 2014q4, long is 1993q1 to 2014q4.
Statistical significance: * 10%, ** 5%, *** 1%.

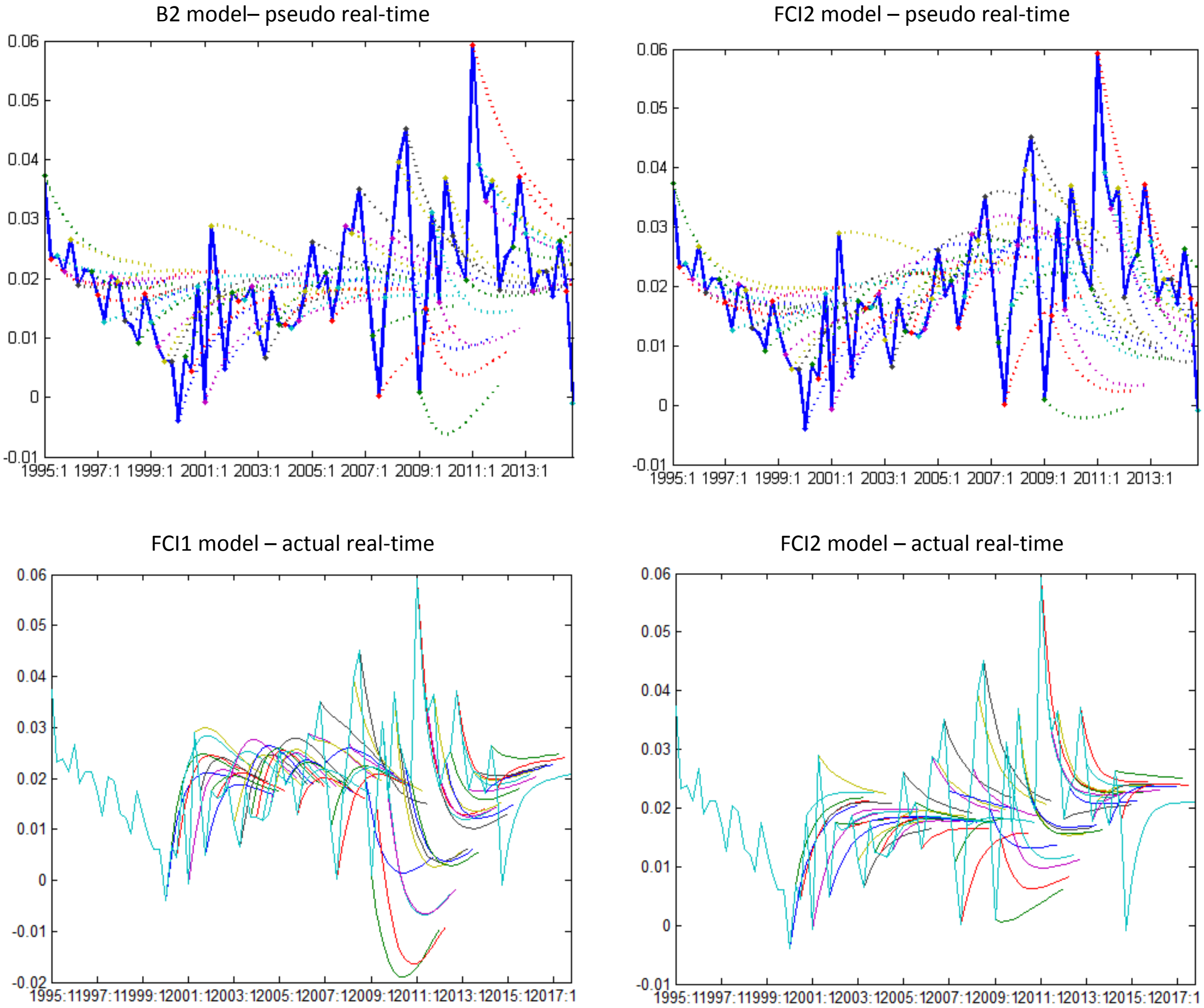
Given that the models include inflation in quarterly growth terms, the ability to forecast quarterly rates does not necessarily give much information about annual inflation. The results for the relevant annual inflation forecasts are presented in the lower panel of Table 2. They suggest that the FCI2 model has statistically significant forecasting power in the pseudo real-time experiment over the 2½ to 3 year horizon, but not the 2-year horizon. However, in the actual real-time experiment, this forecasting ability disappears. This is unsurprising, especially given the volatility in UK GDP data revisions, and is also in line with previous literature.[20]

It is interesting to note that, for the 2-year horizon, neither the random walk nor the FCI models can beat a constant 2% inflation rate assumption, even in the pseudo real-time experiment. This result can be interpreted as a reassuring outcome from monetary policy perspective; despite short-term fluctuations, inflation rates, on average, appear to have been relatively well anchored at 2% over the past 15 years in the UK. Overall, however, the UC models do seem to contain some policy-relevant

[20] See, for example, van Norden and Orphanides (2004).

information on inflation in the UK, at least given information we have now on the importance of financial conditions in estimating output gaps during the recent financial crisis.

Chart 9: Core CPI forecasts in real time



The charts show 12-quarter-ahead out of sample forecasts at different points in time.

The differences in forecasting performance between the different models is also apparent in Chart 9, which shows the forecast paths at different points in time (for as long a period as they are available), together with the actual data. While there are no significant differences between the basic and the FCI model in the pseudo real-time experiment, the latter appears to have performed somewhat better in recent years and when changes in the inflation rate have been large. There is also a large difference between the actual real-time performance of the FCI1 and the FCI2 models, where the latter beats the former. In fact, there appears to be a trade-off in the choice of the FCI models for the recent UK data; the FCI1 model, which produces a better-performing real-time output gap measure than the FCI2 model, performs worse in inflation forecasting. Nevertheless, there is clear overall evidence for the superiority of the FCI models compared to the basic B1/B2 type models.

4. Conclusions

This paper introduces a simple and robust econometric time series method for estimating potential output, output gaps and forecasting inflation. Despite the parsimonious structure of the models, they are able to track cycles and trends of the UK economy reasonably well, even through the volatile post-financial crisis period of recent years. The main result of the study is the empirical evidence provided on the importance of financial cycle variables in estimating output gaps in the UK. In particular, there is some evidence for the financial conditions augmented model to have a more optimistic view on UK potential output after the financial crisis than the model without the financial conditions index. This implies that cyclical variations as suggested by the model with financial conditions are larger. Furthermore, the importance of the financial cycle underlines the concept of sustainable output (see Borio et al. (2013)); even though an economy is growing at its potential, this does not necessarily mean the growth path is sustainable, if financial imbalances keep accumulating. In particular, the FCI models used in the current study would suggest that the pre-crisis growth period was much less sustainable than would be apparent by looking at more traditional output gap models relying only on macroeconomic variables.

Our work, along with a number of previous studies, highlights the relevance of these types of models for modern empirical policy analysis carried out in central banks. The models provide a useful tool for analysing the cyclical position of the economy, and, for the UK economy, our models, and especially the FCI model, have some inflation forecasting ability over a monetary policy relevant horizon. However, using real-time data, this forecasting ability diminishes, highlighting the importance of good quality data as well as the uncertainty related to monetary policy decisions in real time.

Given the importance of financial variables in our models, we also take a stance on how to construct useful measures of financial conditions for our analysis. We introduce a new approach to constructing financial conditions indices, with emphasis on their real-time performance and ability to track macro-financial cycles. This is in contrast with most of the existing literature on financial conditions indices, which appears to pay little attention to the real-time stability of the models.

Potentially, the models presented in this paper also provide useful information for the coordination of monetary and macroprudential policies. One important implication of the results is the emphasis on the effect of financial conditions on cyclical macroeconomic volatility. This implies there is a need for central banks to actively analyse both macroeconomic as well as financial market variables to be able to set monetary and macroprudential policies so that they are best suited to minimise risks to the economy. Further research on the links between financial and macroeconomic cycles, extending to a larger set of countries, different explanatory variables and different methods is needed to inform crucial future policy decisions that have to be taken when trying to mitigate the effects of macroeconomic crises.

Appendix 1: Technical details of the unobserved components model

Basic four-variable (B2) model[21]

Based on an unobserved components model (UCM) introduced by Kuttner (1994), key macroeconomic variables (GDP (y_t), inflation (π_t), unemployment (u_t) are decomposed into a cyclical (marked by hat above the variable name) and a trend (marked by bar) component according to equations (A1)-(A3). Long term unemployment rate (Δltu_t) – often used in empirical work as a proxy for structural unemployment rate – is also included in the UCM as an auxiliary observable variable. It is assumed that changes in the (unobservable) structural unemployment rate are proportional to the changes in (observable) long term unemployment rate, up to a measurement error (η_t^{ltu} in equation (A4)).

$$y_t = \bar{y}_t + \hat{y}_t \tag{A1}$$
$$u_t = \bar{u}_t + \hat{u}_t \tag{A2}$$
$$\pi_t = \bar{\pi}_t + \hat{\pi}_t \tag{A3}$$
$$\Delta ltu_t = \Delta\bar{u}_t + \eta_t^{ltu} \tag{A4}$$

Equations (A1) to (A4) correspond to the state (or transition) equations of the UCM. In order to decrease the dimensionality of the parameter space, state equations are introduced with a parsimonious lag structure. Cyclical components of observable variables are assumed to follow autoregressive processes, while trends are assumed to be stochastic.

The model structure for GDP is presented in equations (A5) to (A7). In line with a widely used practice, trend output is assumed to follow an I(2) process, i.e. a random walk with drift). This is sometimes referred to as a ‘smooth linear trend’ decomposition.[22] In equation (A6), which describes the evolution of the level of potential output, it is also assumed that changes in structural unemployment rate have an effect on the slope of potential output, which reflects a production function-type element. By using this specification, the time-variation in the slope of potential output (i.e. the changing nature of potential growth) can be better captured.[23]

$$\hat{y}_t = \alpha_1\hat{y}_{t-1} + \varepsilon_t^{\hat{y}} \tag{A5}$$
$$\bar{y}_t = \bar{y}_{t-1} + g_{t-1} - \iota\Delta\bar{u}_t \tag{A6}$$
$$g_t = g_{t-1} + \varepsilon_t^{g} \tag{A7}$$

where the ε's indicate i.i.d. error terms with a zero mean.

[21] The details of the B1 model are excluded for brevity. The B1 model is similar in structure apart from the exclusion of variables related to the long-term unemployment rate.

[22] See e.g. Harvey, Koopman and Penzer (1998).

[23] See Benes et al. (2010) for a similar approach.

Equations (A8) to (A9) represent the inflation structure of the model. The notation is analogous to the GDP equations. Note that the equation for the cyclical inflation component (A8) can be interpreted as a simple backward looking Phillips curve, where current inflation is dependent on past inflation and output gap (i.e., the cyclical GDP component).

$$\hat{\pi}_t = \beta_1 \hat{\pi}_{t-1} + \beta_2 \hat{y}_{t-1} + \varepsilon_t^{\hat{\pi}} \tag{A8}$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \varepsilon_t^{\bar{\pi}} \tag{A9}$$

Equations (A10) to (A11) represent the labour market structure, with a simple Okun's law relationship in the cyclical equation (A10).

$$\hat{u}_t = \gamma_1 \hat{u}_{t-1} - \gamma_2 \hat{y}_{t-1} + \varepsilon_t^{\hat{u}} \tag{A10}$$

$$\bar{u}_t = \bar{u}_{t-1} + \varepsilon_t^{\bar{u}} \tag{A11}$$

State space form gathers the structure of the model into a form consisting of a measurement equation and a state equation. The state space form can be easily handled by the Kalman filter:

$$Y_t = C'X_t + V_t \qquad V_t \sim N(0, R)$$

$$X_t = AX_{t-1} + FW_t \qquad W_t \sim N(0, Q)$$

Based on the structure introduced above, the measurement equation consists of the following matrices:

$$\begin{bmatrix} y_t \\ \pi_t \\ u_t \\ \Delta ltu_t \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 \end{bmatrix} \begin{bmatrix} \hat{y}_t \\ \bar{y}_t \\ g_t \\ \hat{\pi}_t \\ \bar{\pi}_t \\ \hat{u}_t \\ \bar{u}_t \\ \bar{u}_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ \eta_t^{ltu} \end{bmatrix}$$

And state equation consists of the following matrices:

$$\begin{bmatrix} \hat{y}_t \\ \bar{y}_t \\ g_t \\ \hat{\pi}_t \\ \bar{\pi}_t \\ \hat{u}_t \\ \bar{u}_t \\ \bar{u}_{t-1} \end{bmatrix} = \begin{bmatrix} \alpha_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \beta_2 & 0 & 0 & \beta_1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ \gamma_2 & 0 & 0 & 0 & 0 & \gamma_1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \hat{y}_{t-1} \\ \bar{y}_{t-1} \\ g_{t-1} \\ \hat{\pi}_{t-1} \\ \bar{\pi}_{t-1} \\ \hat{u}_{t-1} \\ \bar{u}_{t-1} \\ \bar{u}_{t-2} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -i & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\hat{y}} \\ 0 \\ \varepsilon_t^{g} \\ \varepsilon_t^{\hat{\pi}} \\ \varepsilon_t^{\bar{\pi}} \\ \varepsilon_t^{\hat{u}} \\ \varepsilon_t^{\bar{u}} \\ 0 \end{bmatrix}$$

Five-variable model with financial conditions index

This version of the model augments the basic version with a financial conditions index. Measurement equations are as follows:

$$y_t = \bar{y}_t + \hat{y}_t \tag{A12}$$
$$u_t = \bar{u}_t + \hat{u}_t \tag{A13}$$
$$\pi_t = \bar{\pi}_t + \hat{\pi}_t \tag{A14}$$
$$\Delta ltu_t = \Delta\bar{u}_t + \eta_t^{ltu} \tag{A15}$$
$$fci_t = \overline{fci}_t + \varepsilon_t^{fci} \tag{A16}$$

The transition equation for GDP is similar to the basic model, with the exception of an additional term in the cyclical term that takes into account the financial cycle. Hence, the intuition is that the output gap is affected not only by its own autoregressive terms, but also by financial dynamics. This allows for unsustainable financial market dynamics (bubbles) to have an effect on the output gap measure.

$$\hat{y}_t = \alpha_1\hat{y}_{t-1} + \alpha_2\overline{fci}_{t-1} + \varepsilon_t^{\hat{y}} \tag{A17}$$
$$\bar{y}_t = \bar{y}_{t-1} + g_{t-1} - \iota\Delta\bar{u}_t \tag{A18}$$
$$g_t = g_{t-1} + \varepsilon_t^{g} \tag{A19}$$

The corresponding transition equations for inflation are as follows:

$$\hat{\pi}_t = \beta_1\hat{\pi}_{t-1} + \beta_2\hat{y}_{t-1} + \varepsilon_t^{\hat{\pi}} \tag{A20}$$
$$\bar{\pi}_t = \bar{\pi}_{t-1} + \varepsilon_t^{\bar{\pi}} \tag{A21}$$

Unemployment:

$$\hat{u}_t = \gamma_1\hat{u}_{t-1} - \gamma_2\hat{y}_{t-1} + \varepsilon_t^{\hat{u}} \tag{A22}$$
$$\bar{u}_t = \bar{u}_{t-1} + \varepsilon_t^{\bar{u}} \tag{A23}$$

Financial conditions index:

$$\overline{fci}_t = \rho\overline{fci}_{t-1} + \varepsilon_t^{\overline{fci}} \tag{A24}$$

State space form is similar to the basic form:

$$Y_t = C'X_t + V_t \qquad V_t \sim N(0, R)$$
$$X_t = AX_{t-1} + FW_t \qquad W_t \sim N(0, Q)$$

Measurement equation is the following:

$$
\begin{bmatrix} y_t \\ \pi_t \\ u_t \\ \Delta ltu_t \\ fci_t \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \hat{y}_t \\ \bar{y}_t \\ g_t \\ \hat{\pi}_t \\ \bar{\pi}_t \\ \hat{u}_t \\ \bar{u}_t \\ \bar{u}_{t-1} \\ \overline{fci}_t \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ \eta_t^{ltu} \\ \varepsilon_t^{fci} \end{bmatrix}
$$

State equation is the following:

$$
\begin{bmatrix} \hat{y}_t \\ \bar{y}_t \\ g_t \\ \hat{\pi}_t \\ \bar{\pi}_t \\ \hat{u}_t \\ \bar{u}_t \\ \bar{u}_{t-1} \\ \overline{fci}_t \end{bmatrix} = \begin{bmatrix} \alpha_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \beta_2 & 0 & 0 & \beta_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ \gamma_2 & 0 & 0 & 0 & 0 & \gamma_1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \hat{y}_{t-1} \\ \bar{y}_{t-1} \\ g_{t-1} \\ \hat{\pi}_{t-1} \\ \bar{\pi}_{t-1} \\ \hat{u}_{t-1} \\ \bar{u}_{t-1} \\ \bar{u}_{t-2} \\ \overline{fci}_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \alpha_2 \\ 0 & 0 & 0 & 0 & 0 & 0 & -i & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\hat{y}} \\ 0 \\ \varepsilon_t^{g} \\ \varepsilon_t^{\hat{\pi}} \\ \varepsilon_t^{\bar{\pi}} \\ \varepsilon_t^{\hat{u}} \\ \varepsilon_t^{\bar{u}} \\ 0 \\ \varepsilon_t^{\overline{fci}} \end{bmatrix}
$$

Conditional forecast information

The actual real-time versions of the FCI models are also augmented with Bank of England CPI and GDP forecasts to examine whether this improves the real-time performance. The forecasts are added to the models in a similar fashion as in Blagrave et al. (2015):

$$
Y_{t+j}^F = Y_{t+j} + \varepsilon_{t+j}^{Yf}
$$
$$
\pi_{t+j}^F = \pi_{t+j} + \varepsilon_{t+j}^{\pi f}
$$

for $j = 1, \dots, 12$, for the level of GDP and rate of (quarterly) inflation, respectively. Hence, the forecasts are seen as imprecise estimates of future GDP and inflation, with error terms ε_{t+j}^{Yf} and $\varepsilon_{t+j}^{\pi f}$ accounting for the noise and forecast errors. The forecast variables are added to the models in three formats: pure GDP, pure and CPI and both forecasts. As detailed in the main text, the pure GDP format adds the most information.

Estimation methodology

In order to conduct the filtering exercise which will yield the path of unobservable variables, the UCM needs to be cast in state-space form and its parameters have to be estimated. Kalman-filter recursions can be used to evaluate the log likelihood function of the UCM and thus, in principle, maximum likelihood estimation of the parameters is possible. However, in practice, the 'curse of dimensionality' cannot be avoided even in this fairly small UCM, particularly in view of the relatively short sample and the unobservable nature of the key variables of interest. Unsurprisingly, conventional likelihood methods based on numerical optimization algorithms struggle to identify certain regions of the parameter space, and can easily yield nonsensical parameter values. In order to regularize the likelihood surface and make estimation of parameters feasible in a real-time context a Bayesian approach is adopted.[24]

In order to conduct Bayesian estimation, prior distributions need to be specified for the parameters of the model. It is assumed that AR(1) processes governing cyclical components are fairly persistent, while the output gap is a key driver behind cyclical inflation and the unemployment gap, in line with well-established economic relationships, such as the Phillips curve and Okun's law. Furthermore, fluctuations in observable variables are assumed to be mostly driven by cyclical rather than trend shocks. These translate to beta-type prior distributions on AR(1) parameters, with mean 0.7 and standard deviation 0.2. Other coefficients are assumed to have a gamma type prior distribution with mean 0.5 and standard deviation 0.3. By using gamma prior distributions with identical hyper-parameters, we essentially force the data to obey the proposed macroeconomic relationships. However, the relative strength of these forces is determined by the data. Standard deviations of cyclical (trend) shocks are assumed to have an inverted gamma shaped prior, with hyper-parameters 1 (0.01) and ∞ respectively[25] (Table A1). The covariance matrix of the state equations is assumed to be diagonal, implying that fluctuations in cyclical components beyond what is explained by the output gap are idiosyncratic. Parameter ι, connecting trend output to changes in the structural unemployment rate cannot be identified from the data (i.e., the posterior remains very close to the prior). Therefore, consistently with a production function approach, it is calibrated to 0.7, which roughly corresponds to the average labour share historically in the UK.

Table A1 lists the median[26] posterior values of the Bayesian parameters for both FCI1 and FCI2 models; these values are sensible from a theoretical perspective and quite similar between the two FCI model options. In order to check robustness to the inclusion of financial variables, we estimate the augmented models also with uninformative (i.e. flat) prior on parameter α_2, which governs the impact of the financial cycle on the output gap. We find the results to be very similar. In the real-time exercise, however, we stick to a gamma prior distribution on this parameter, in line with our prior view that macroeconomic variables in themselves were not able to pick up the pre-crisis boom period in and of themselves in real time.

[24] Estimation and filtering have been implemented in Matlab with the help of the Iris-toolbox, see: J. Benes, M. K. Johnston, and S. Plotnikov, IRIS Toolbox Release 20150318 (Macroeconomic modelling toolbox). The software is available at http://www.iris-toolbox.com

[25] To avoid the so-called pile-up problem (see Stock and Watson (1998)), we also experimented with larger values for the hyper-parameters of trends and cycles, whilst holding their relative values constant. The results are very similar.

[26] Median values are very close to mode and mean values, so there is not qualitative difference between the results using any of these measures. However, using median values is more robust to the "tail behaviour" of posterior distributions.

Posterior modes (see Charts A4-A5) and medians are found via a numerical optimization algorithm based on the Newton-Raphson procedure. The algorithm aims at finding the (possibly local) minima of the negative of the combined log-prior and log-likelihood functions, where the latter is evaluated with the help of the Kalman filter. As a robustness-check, numerical optimisation is repeated with a particle swarm optimisation algorithm. Posterior distributions are generated via MCMC simulations, based on an adaptive random walk Metropolis algorithm.[27]

Table A1: Parameter prior and posterior values

Parameter	Prior density type	Hyper-parameters	Posterior median (FCI1)	Posterior median (FCI2)
α_1	Beta	[μ=0.7, σ=0.2]	0.8468	0.9050
α_2	Flat/Gamma	[μ=0.5, σ=0.3]	0.1010	0.3522
β_1	Beta	[μ=0.7, σ=0.2]	0.6079	0.5991
β_2	Gamma	[μ=0.5, σ=0.3]	0.1233	0.1339
γ_1	Beta	[μ=0.7, σ=0.2]	0.7872	0.8243
γ_2	Gamma	[μ=0.5, σ=0.3]	0.1219	0.1068
$\sigma_t^{\hat{y}}$	Inv. gamma	[μ=1, σ=∞]	0.0146	0.0147
σ_t^{g}	Inv. gamma	[μ=0.01, σ=∞]	0.0016	0.0018
$\sigma_t^{\hat{u}}$	Inv. gamma	[μ=1, σ=∞]	0.0130	0.0131
$\sigma_t^{\bar{u}}$	Inv. gamma	[μ=0.01, σ=∞]	0.0007	0.0007
$\sigma_t^{\hat{\pi}}$	Inv. gamma	[μ=1, σ=∞]	0.0183	0.0181
$\sigma_t^{\bar{\pi}}$	Inv. gamma	[μ=0.01, σ=∞]	0.0026	0.0024
σ_t^{fci}	Inv. gamma	[μ=0.01, σ=∞]	0.0042	0.0020
$\sigma_t^{\overline{fci}}$	Inv. gamma	[μ=1, σ=∞]	0.0354	0.0126
η_t^{ltu}	Inv. gamma	[μ=0.01, σ=∞]	0.0007	0.0007

[27] One alternative to this approach, sometimes used in the literature, would have been using a Gibbs sampling algorithm with normal priors. However, taking into account that Gibbs sampling is a special case of the more general Metropolis-Hastings algorithm (see e.g. Robert and Casella (2004)), we did not find it useful to restrict ourselves to normal priors and the Gibbs sampler.

Appendix 2: Data

All data are quarterly, logarithmic scale is used for GDP data and underlying CPI level data, actual levels for unemployment data.

- GDP: ESA2010 chain linked volumes, seasonally and working day adjusted (Source: ONS)
- Unemployment rate: LFS unemployment rate of 16-64 year olds. (ONS)
- Inflation: CPI excluding food and energy. Seasonally adjusted annualised q/q rate (Bank of England/ONS)
- Long term unemployment rate: proportion of the labour force that has been unemployed for more than 12 months. Based on claimant count statistics for the UK (for details of the construction of the time series, see Speigner (2014)). (Bank of England/ONS)
- Financial conditions indices (details in Appendix 3).

Appendix 3: Financial conditions indices

It is not obvious which variables should be included in a financial conditions index (FCI), nor is there agreement on which estimation method should be used to derive the index. There is a wide existing literature on the estimation of FCIs[28]. In these studies, FCI's are typically derived by using simple averages, principal components analysis or vector autoregressions. The main focus of many of these studies is to examine the ability of FCI's to predict near-term GDP dynamics. However, there is surprisingly little (if any) analysis in the literature on the real-time performance of FCI models, which is a crucial metric for our purposes. Consequently, we refrain from using any of the existing FCI's for the UK due to our different emphasis on the construction of the FCI, as well as to avoid having to re-estimate and update FCI's introduced in earlier studies. We are also primarily interested in building a financial conditions index with relevant information on the business cycle rather than just financial markets, which is a slightly different aim compared to more traditional FCI studies.

For the current study, 22 financial indicators for the UK were collected. Different combinations of these indicators were tested, and given the uncertainty related to the estimation of FCIs, we use two different FCIs (denoted FCI1 and FCI2), derived by different methods from different variable sets.

<u>FCI1</u>

For FCI1, eight key UK financial market indicators are combined using a simple factor model structure, where the FCI is the only state variable, the eight indicators are the observable variables with eight idiosyncratic single shock terms. The model is estimated sing a sample from 1988 to 2014, and the resulting FCI1 index relevant for the sample of the current study (i.e., from 1995 to 2014) is presented in Chart A1. FCI1 performs well in real time and the contributions of the different indicators to it are intuitive (see bottom panel of Chart A1). The choice of the relevant indicators depends on the real-time performance of the model. The financial indicators (all demeaned and divided by their respective standard deviations) in the model are:

- Mortgage spread (2-year fixed mortgage rate (75% LTV) minus Bank Rate) (y/y growth rate). (Source: Bank of England) (mgage_spread)
- Sterling effective exchange rate index (ERI) (Bank of England) (eri)
- FTSE All-Share Index (Bloomberg) (ftse)
- Composite UK house price index (average of the Halifax and Nationwide House Price Indices) (y/y growth rate) (Bank of England/Halifax/Nationwide) (houseprice)
- Gold bullion spot price in sterling (Bank of England/Datastream) (goldprice)
- Net lending to the private sector (monthly changes of monetary financial institutions' sterling M4 net lending to private sector) (Bank of England) (lendflow_privsector)

[28] See, for example, Guichard et al. (2009), Matheson (2012), and Darracq-Paries et al. (2014).

- Credit to households in real terms (monetary financial institutions' sterling net lending to the household sector deflated by CPI) (y/y growth rate). (Bank of England/ONS) (rcred_hhold)
- Credit to firms in real terms (monetary financial institutions' sterling net lending to the non-financial corporate sector deflated by CPI) (y/y growth rate). (Bank of England/ONS) (rcred_firms)

FCI2

For FCI2, a slightly more mechanical approach was taken. First, the performance of different (parsimonious) combinations of the most relevant financial indicators was examined to find the best performing indicator in real time. In practice, the following procedure was followed:

1) The general suitability and lengths of available samples was examined for all the series. Based on this analysis, nine of the 22 series were dropped either because the time series were too short or bore no relation to macroeconomic cycles.
2) Real-time performance of all possible combinations of the remaining 13 variables was examined by running a real-time experiment from 2001 to 2014, recording the sum of standard deviations of the different vintages of the resulting FCI series at every quarter, and then the combinations were ranked based on this sum. This experiment was carried out for an FCI consisting of four, five and six variables. Based on this analysis, it was decided that concentrating on 5-variable FCI's would strike an optimal balance between the best real-time performance and maintaining as parsimonious a model as possible.
3) The 13 variables entering into the 5-variable FCI's were further ranked by their average position in terms of the standard deviations of the models that a particular variable entered in. The prevailing selection (above) was then made based on the best-performing variables, but also at the same time ensuring that the index would include interest rate spread variables, volatility variables and lending variables.

For the calculation of the index, the variables were first detrended and demeaned, and then smoothed with a 4-quarter moving average measure of them.[29] The resulting index is again shown in Chart A1 (top LHS). A dynamic factor model for FCI2 was then derived using the following variables:

- Net credit flow to households (monetary financial institutions' sterling net lending to the household sector) (y/y growth rate). (Bank of England)
- Net credit flow to non-financial corporations (monetary financial institutions' sterling net lending to private non-financial corporations) (y/y growth rate). (Bank of England)
- Money market spread (3-month GBP LIBOR minus Bank Rate) (Bloomberg/Bank of England)

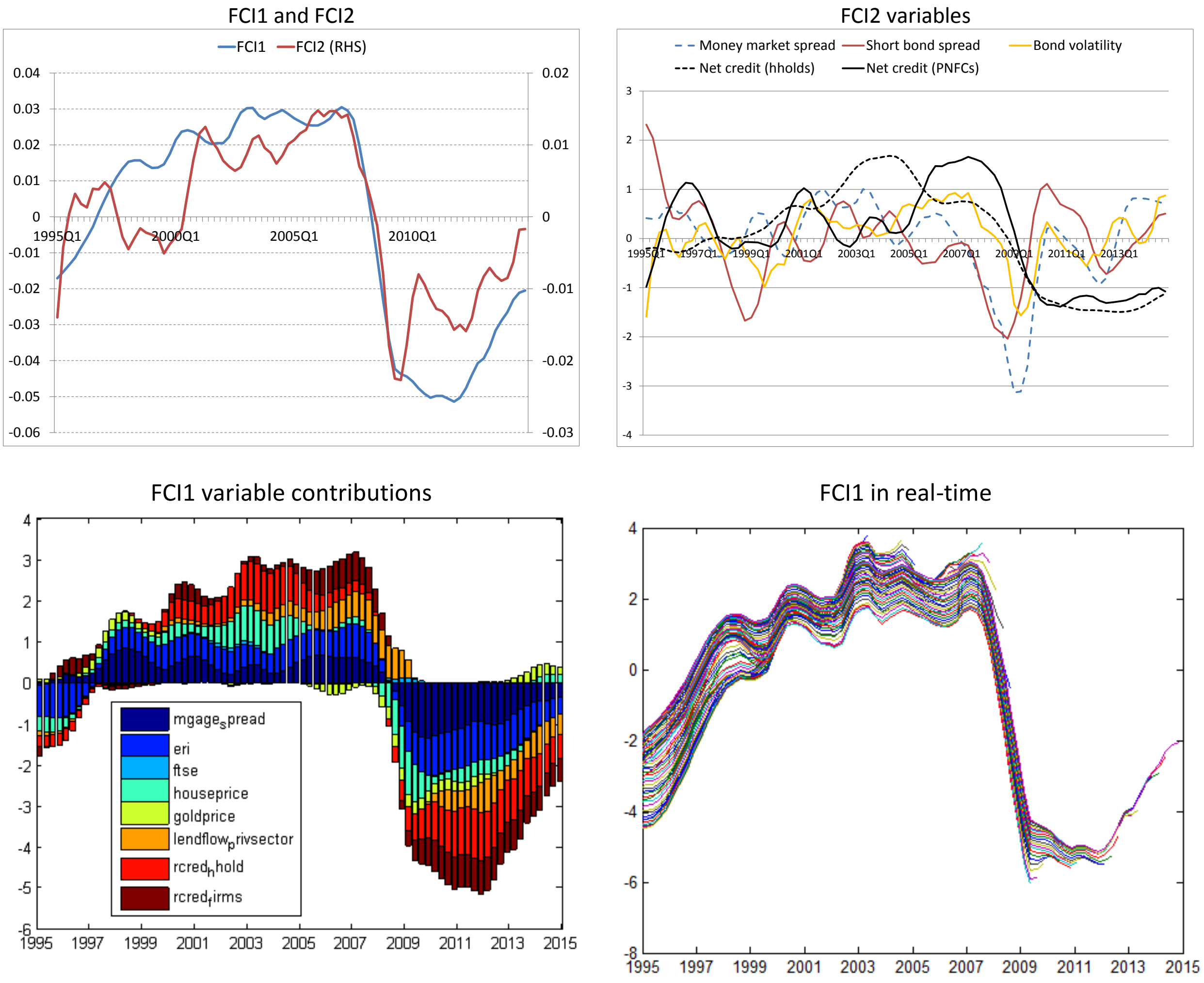
[29] The smoothing is not crucial for the results of the FCI model presented in this paper, but it slightly improves the real-time performance of the FCI as well as smoothing the short-term volatility.

- Short gilt spread (2-year UK Gilt yield minus 3-month GBP LIBOR) (Bloomberg/Bank of England)
- Bond market volatility (3-month rolling volatility of 10-year UK Gilt yield) (Bloomberg/Bank of England)

<u>Summary</u>

While the selection of any FCI is always contentious and is not the main focus of the current study, we believe that our FCI indices strike a balance between a very good real-time performance, parsimoniousness and the inclusion of relevant variables. The FCIs are also not only relatively close to each other, but also relatively close over the relevant time horizon to the UK FCI introduced by OECD (see Guichard et al. (2009)).

Chart A1: FCI indices and variables

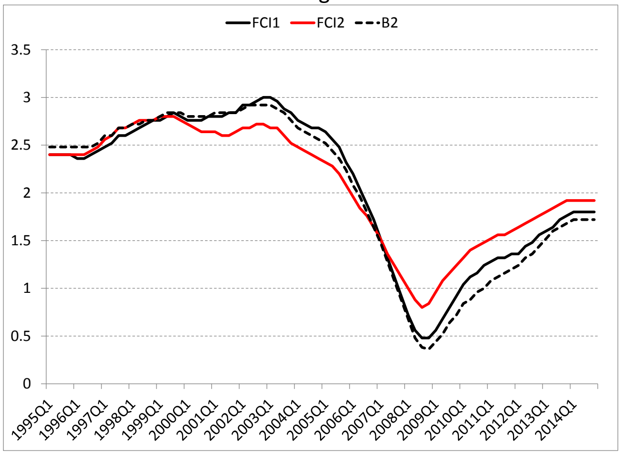


The chart shows demeaned series. Series are normalised so that a tightening of conditions is a negative movement.

Appendix 4: Additional charts

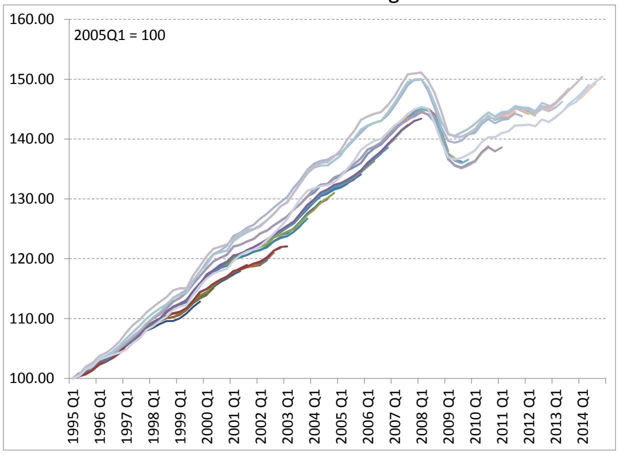
Chart A2: GDP trend growth rates and real-time vintages

GDP trend growth



The chart shows y/y change in %.

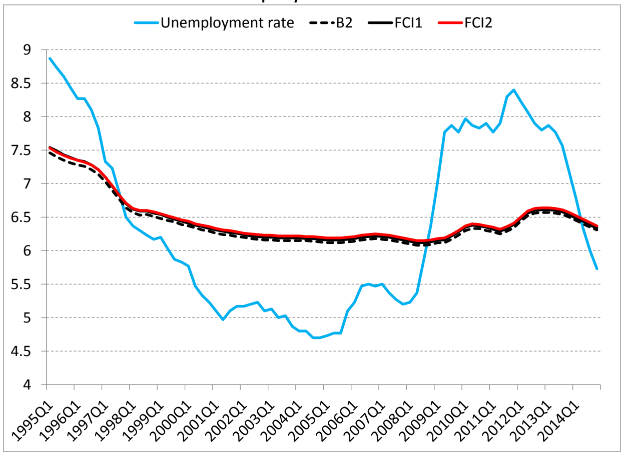
GDP real-time vintages



The chart shows indexed level of GDP volumes for different vintages at each quarter from 1999Q4 to 2014Q4.

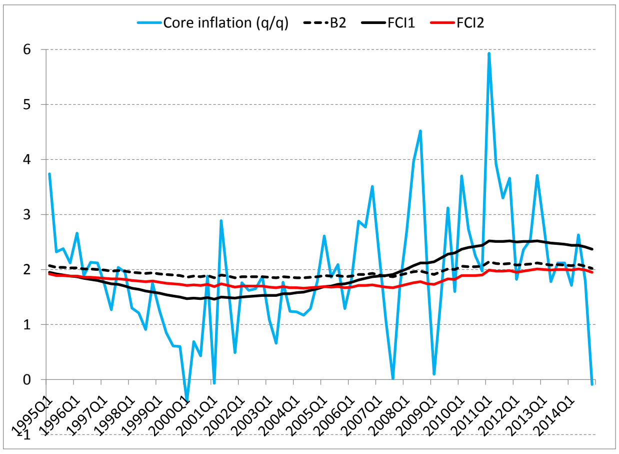
Chart A3: FCI model – trend unemployment rate and trend core CPI

Unemployment rate



The chart shows unemployment rate as %.

Core inflation



The chart shows q/q change in %.

Chart A4: Prior and posterior distributions of the FCI1 model

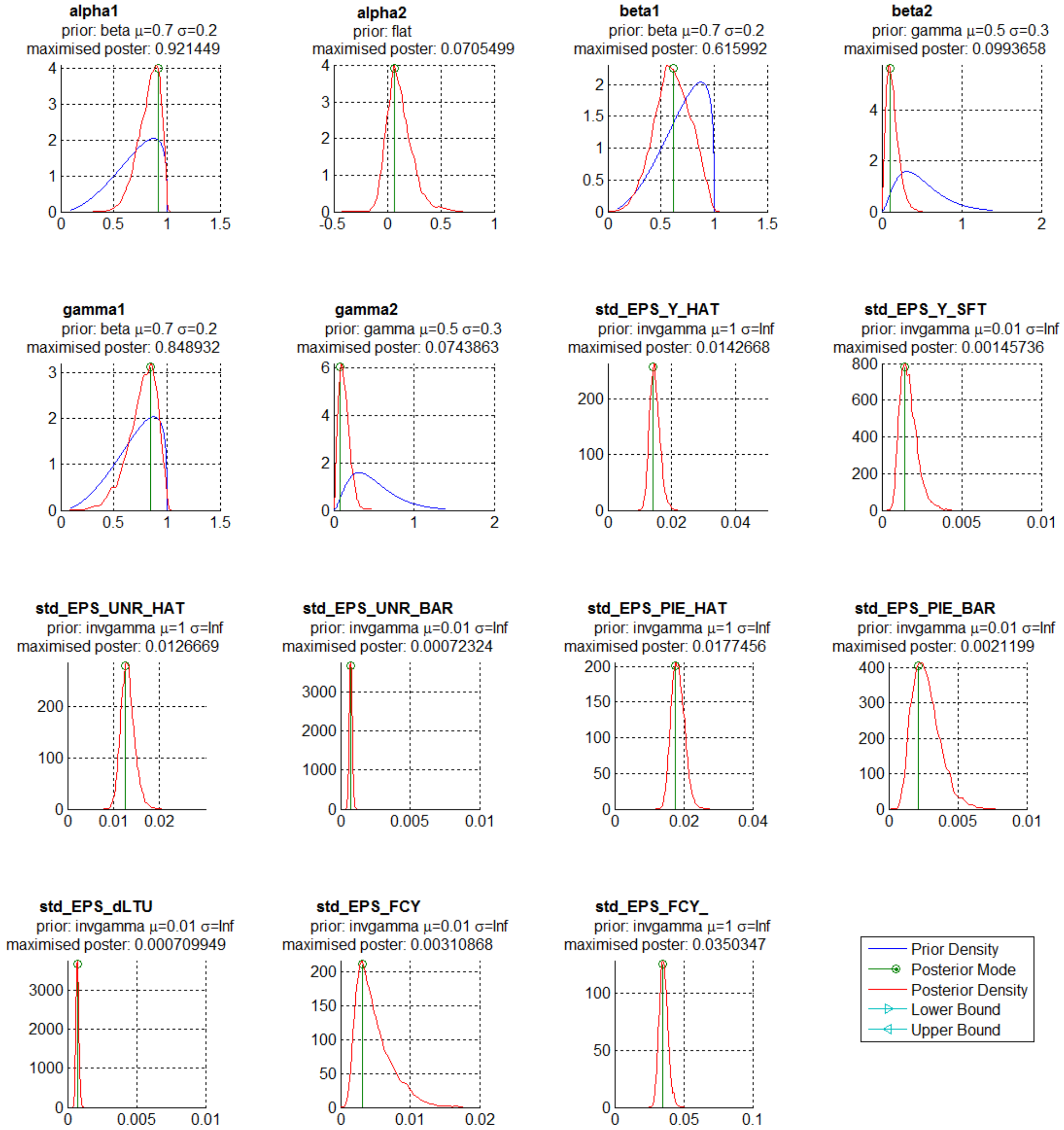
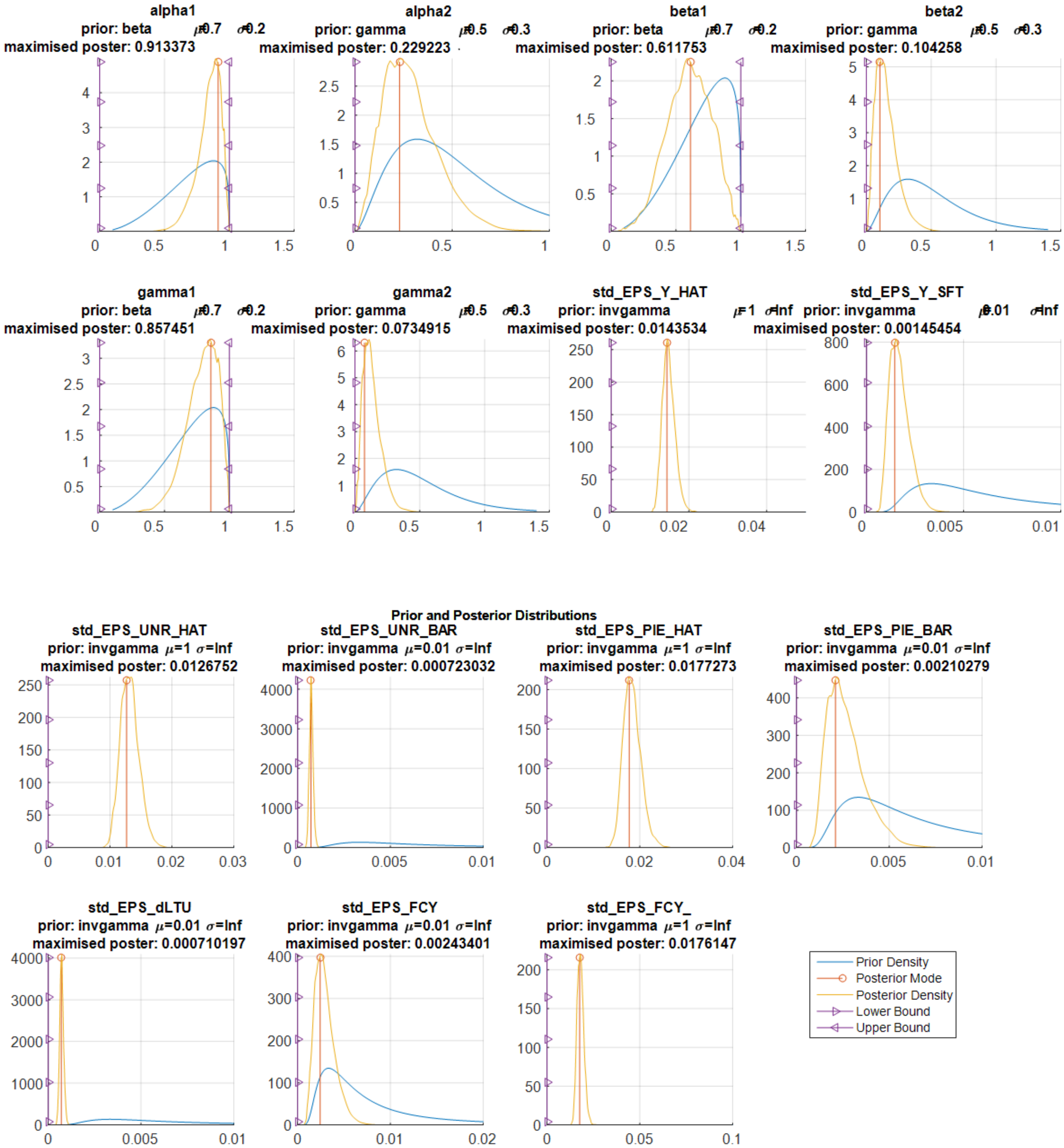


Chart A5: Prior and posterior distributions of the FCI2 model



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