Analysis and Prediction of the UK Economy

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Declaration:

This thesis is a presentation of the work I have undertaken, every effort has been made to recognise any contributions and reference literature appropriately. As well as recognise the results of collaborative discussions or work.

This thesis was completed under the guidance of Professor Jagjit Chadha and Dr. Katsuyuki Shibayama.

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Table of Contents

Accounting for the Great Recession in the UK: Real Business Cycles and Financial Frictions.*

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Abstract

Using the business cycle accounting (BCA) framework pioneered by Chari, Kehoe and McGratten (2006, Econometrica) we examine the causes of the 2008-09 recession in the UK. There has been much commentary on the financial causes of this recession, which we might expect to bring about variation in the intertemporal rate of substitution in consumption. However, the recession appears to have been mostly driven by shocks to the efficiency wedge in total production, rather than the intertemporal (asset price) consumption, labour or spending wedge. From an expenditure perspective this result is consistent with the observed large falls in both consumption and investment during the recession. To assess this result we also simulate artificial data from a DSGE model in which asset price shocks dominate and find no strong role for the intertemporal consumption wedge using the BCA method. This result does not imply that financial frictions did not matter for the recent recession but that such frictions do not necessarily impact only on the intertemporal rate of substitution in consumption.

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1 Introduction

In the second quarter of 2008, the U.K. economy slid into its deepest postwar recession. The proximate cause has frequently been reported as the global financial crisis and that year's failure of large US 'bulge bracket' investment banks: Bear Stearns and, with powerful ramifications, Lehman brothers. Following the collapse of Lehman Brothers a number of UK commercial banks were placed into majority public ownership. As every schoolboy knows, the increase of systemic risk in the banking system led to the increase in the cost of loans to households and firms and coupled with a fall in global demand, led to a sharp fall in investment and consumption. GDP fell sharply with output as much as 10-12% below trend in the first quarter of 2009 by some estimates. Over this period central banks were forced to look for alternative instruments to stimulate economic activity, as the main tool of monetary policy makers - the short run interest rate - was constrained to the zero lower bound. There has been a hesitant and faltering recovery as expansionary fiscal policy has also reached its limits. In this paper we will attempt to assess this demand-side story as the cause of the 'great recession' with reference to a supply side model.

A useful way of thinking about a deep recession is that it represents a persistent deviation in output from its natural, or flex-price, level. And so we can use Chari, Kehoe and McGrattan's (2007) Business Cycle Accounting (BCA) framework. The BCA framework decomposes the deviation in the economy from its flex price equilibrium into four sets of residuals (henceforth wedges) which act like time varying taxes on: labour supply; productive efficiency, investment and total expenditure. Within this framework these wedges correspond to a whole host of distortions used widely in the DSGE literature, such as sticky wages and prices (for the labour wedge), external finance premia (the investment wedge) or distortionary taxes (expenditure wedge). As such the BCA framework appears to be a natural candidate to assess the ultimate causes of the recent recession in terms of these distortionary wedges.

To assess the results, we also provide a simple demand decomposition of the recession period, which uncovers each components of individual growth to overall output growth. The results of this decomposition provide a clear characterisation of this recession, as consumption and investment-led, and points researchers as to how shocks from more complex models should move economic variables. Finally, we shall also provide some insight to how financial shocks from an extended version of the Bernanke Gertler and Gali model (Bernanke and Gali (1999)) which includes an asset price (or bubble) shock map into the BCA analysis. We run the model with a high degree of asset price variation and then extract the simulated data and re-estimate using the BCA estimation process and assess whether an investment wedge is then found to have driven the asset price bubble economy.

As a result we have some clear measure on the recent UK recession: the shocks that drove the recession reduce both consumption and investment, according to our expenditure decomposition, and hence are either according to the BCA methodology efficiency or labour wedges. This is because the investment wedge drives consumption and investment in opposite directions and the expenditure wedge does not have sufficient variation. Our estimation of the BCA model clearly suggests that the main cause of the 'great recession' is variation in the efficiency wedge of production, which on its own provides significant explanation of the variation in output, rather than the other wedges.[1] To check this finding our Monte Carlo analysis of the BCA experiment, using a version of the BGG model including a dominant asset price bubble shock, finds that this shock also does not appear as an investment wedge in the BCA analysis. This implies that it is entirely possible for asset price shocks to show up in other wedges in the BCA framework and that ascribing a causal role to efficiency or labour wedges may not strictly imply that the shocks emanated from those sectors alone. At one level we therefore argue that DSGE modellers may have to continue to think about how asset pricing equations and the role of asset prices affect the wider economy, as their impacts in general equilibrium may be to shift labour supply or the ratio of outputs to inputs.

The structure of the paper is as follows, section 2 introduces the BCA literature and some of the recent papers focusing on the 'great recession', section 3 outlines the methodology behind BCA and the estimation strategy employed. Section 4 outlines the results and section 5 provides a summary.

2 Literature Review

The BCA framework introduced by Chari, Kehoe and McGrattan (2007), sought to decompose the economy into wedges which affected the equilibrium allocations of labour supply, intertemporal efficiency and productive allocations. They showed that it was possible to map defined distortions from complicated models into a simple growth model and

[1] The investment wedge provides a secondary role falling slightly at the time of the recession, pari passu it however would exaggerate the movements of GDP over the projected recovery period. The labour wedge plays little to no role in explaining the recession as it remains relatively constant throughout the recessionary period and then falls through the projected recovery. There is also little role for the expenditure wedge.

that these distortions would map one on one into a particular wedge. The underpinning idea of these wedges was equivalence results, the examples they gave were that the effects of sticky prices or unionisation would appear as a labour wedge through the disconnect between the marginal product of labour and the marginal rate of consumption, labour. Financial accelerator type mechanisms would appear through the investment wedge, the disconnect between the intertemporal rate of substitution, consumption and marginal product of capital. Finally they showed that input financing constraints would show up as an efficiency wedge a total factor productivity parameter. The applied the methodology to the U.S. for the great depression era and the recession in the 1980s, after the wedges had been measured, they then simulated counter factual economies where only one wedge or a combination of wedges were allowed to vary over time while all others were held constant at their steady state values. Their results suggested that for both recessionary periods that the efficiency and labour wedges were the most important causes of the recessions.

In terms of the most recent recession much of the recent discussion has focused around the role that financial frictions, falls in investment and asset prices can lead to wider effects on the economy. One such example is given by Martin (2010) who provides an in-depth look at the factors that caused the U.K. economy to be weak before concentrating on the causes of the 'great recession'. Martin argues that the main drivers of the recession were a large collapse in world trade, falls in private wealth due to the collapse in the housing market and the stock market as well as the financial crisis. He argues that bank lending may have reached a shortfall of around 8% around the peak of the crisis. He notes however there appears to be a delayed impact from the onset of financial crisis to the wider economy, he notes two contributing factors; firstly that there may have been expectational effects due to the failure of Lehmans leading to an increase in percautioanry saving for the future. A second explanation for the depletion of liquidity cushions for households and non-financial firms, essentially at the beginning of the financial crisis given the constrained credit conditions households and firms reduced their holdings of liquid assets in order to maintain pre-crisis levels of consumption once these liquid assets had run out households and firms had to cut spending.

Chari, Christiano and Kehoe (2008), provide a dissenting view as to the 'great recession', it is important to note that they do not argue that there is no existence of a large financial shock, rather they argue that the financial crisis may not be the main cause of the recession and that rather it may appear as an effect, their analysis focus' on the change (or the lack thereof) in the spreads. They note that the interest rate on commercial paper had not increased by much for AA rated non-financial companies whereas it had risen markedly for the financial companies. They note that the on aggregate non-financial firms can cover their capital costs entirely through retained earnings and that 80% of all of the borrowing from non-financial firms happens outside of the banking system. The also argue that the increase in spreads that occurred could just be due to an increase of perceived risk and a rebalancing of banks balance sheets as opposed to any underlying large scale market failure around lending and borrowing. Essentially under this view non-financial firms ability to source investment funds appear to be unaffected by the problems in the financial sector, furthermore the small rise in spreads that we have seen may just be the result of normal reactions to a recession.

Chadha and Warren (2011) used a log-linearised version of the BCA model to show the impulse responses from shocks affecting each of the wedges. This provides some background into what type of wedge is likely to be able to explain the recessionary period. The efficiency and labour wedges are common to Real Business Cycle models and their properties are well known, shocks which affect these wedges will lead to co-movements in consumption and investment. Alternatively the investment wedge will lead to a divergence in these two determinants of GDP, the intuition behind this result is that any shock which increases the investment wedge in the first period will increase the value of current consumption against the value of future consumption in todays value, thus increasing current consumption and reducing investment.

Kersting (2006) has applied BCA for the 1980's recession and recovery for the U.K. Kersting's results found that the most important cause was the labour wedge while the efficiency wedge played a secondary role in understanding the business cycle episode. The investment wedge over this period moves in a counter-cyclical fashion, suggesting that the alleviation of financial frictions actually stopped the U.K. economy from being in a steeper recession.

There have been two interesting extensions to the BCA methodology, while outside of the scope of this paper highlight the flexibility and usefulness of the framework, firstly Otsu (2010) who provides an open economy version and concludes that efficiency and labour wedges are the most important cause of the increased output correlation between countries. Sustek (2010) provides a nominal extension to BCA, and shows through equivalence results complicated nominal models can also be mapped into a growth model adjusted for nominal effects as, monetary wedges and bond price wedges, the nominal business cycles accounting exercise finds that the nominal wedges have little to no effect on real variables but can help to explain puzzles in the bond market.

Christiano and Davies (2006) criticise the flexibility of the BCA framework as they suggest that without placing identifying restrictions on the reduced form of the VAR estimations it is impossible to gauge the effects of spillovers between wedges. They place restrictions on the primitive shocks and estimate a rotation decomposition, they create a statistic which shows the importance of each wedge. Their findings show that different identification restrictions will lead to the same values of the likelihood function but indicate different levels of importance of the investment wedge. While Christiano and Davies (2006) are beyond the scope of this paper, it is an important point to note, subsequently when assessing the importance of each wedge it does not rule out models in which financial shocks could lead to movements in other wedges and vice-versa.

In this paper we shall provide the background to the recession by showing the contributions of the determinants of demand, followed by decomposing the economy by the BCA methodology. Our final exercise in this paper is to use artificial data created via a modified version of the Bernanke, Gali and Gertler financial accelerator model (Bernanke and Gerter (1999)) This follows on from CKM (2006) original paper where they showed that through equivalence results that frictions which appear explicitly in complicated models will appear as only one wedge in the proto-type growth model.We are interested in how the "bubble shock" in the modified BGG model, a shock which effects the net worth of entrepreneurs and therefore the external finance premium (the financial distortion) will manifest itself in the BCA methodology. We do this firstly as a robustness check of the CKM equivalence results and secondly the results from this exercise may provide us with an alternative view of the causes of the current recession.

2.1 Decomposing supply and demand

This subsection provides the background for the later discussion about the results of the BCA decomposition, we calculate two simple decompositions using the determinants of supply and demand. These two decompositions provide both some background to the recession, but also may highlight some important points for the results of the BCA decomposition presented later.

For our simple demand decomposition we take advantage of the expenditure definition of output shown by (1), to which we calculate the year on year changes of each of the expenditure components and scale them by their relative contributions to over all output ((2) provides an example for how this would be done for consumption).

$$Y_t = C_t + X_t + G_t + (EX_t - IM_t), \tag{1}$$

$$\frac{C_{t-4}}{Y_{t-4}} \times \frac{C_t - C_{t-4}}{C_{t-4}}. \tag{2}$$

In order to decompose supply we calculate a simple growth accounting exercise. Given data on output, labour hours and the capital stock. We assume a simple Cobb-Douglas production function with the form:

$$Y_t = K_t^{\alpha}(Z_t L_t)^{1-\alpha}, \tag{3}$$

taking logs and defining growth as $g_y = \frac{Y_t - Y_{t-1}}{Y_t}$, (which follows for g_k and g_l) we get the following;

$$g_y = \alpha g_k + (1-\alpha) g_l + (1-\alpha) g_z \tag{4}$$

by re-arranging we can calculate the solow residual and uncover the contributions of the factor inputs to the production function.

The main contributions of the expenditure components of growth to the overall level of GDP growth were investment and consumption, with the contribution of investment providing the largest fall in GDP. It is important to note that investment falls to negative levels just before the beginning of the recession in 2008 Q1 while the contribution of consumption to overall output growth begins after the onset of the recession by a quarter in 2008 Q3. Both investment and consumption are negative throughout the recession and are slow to return to positive growth, the main driver in the recovery period appears to be investment, while consumption growth remained sluggish through the recession and the subsequent recovery. This point is re-iterated in Table (1) which quantifies the contributions of the expenditure components as an average for both the period of the recession and the preceding years back to 1971 Q1. Average growth for the U.K. is 2.26% over this sample period, the main contribution to growth is supplied by consumption with investment and government expenditures making up the rest, over this period net exports contributed slightly negatively to average growth. The recessionary period highlights how sharp the fall in GDP was the average over the period was around 4.5%, reaching a trough in 2009 of approximately 5.9%. The table shows that the fall in investment was equally as sharp falling over 4% while consumption fell by roughly 3.5% in comparison to average before the recession. GDP growth was slightly held up by net exports which grew by over 1%, government spending decreased slightly over this period. Overall, the expenditure decomposition shows that the recession was investment and consumption led and importantly that the two series co-move throughout the whole recession with the exception of the quarter before the recession.

For the supply side decomposition we find that during normal periods of growth that TFP contributes to most of the growth of GDP contributing around 60% which the capital stock contributes towards around 30% of GDP growth, the contribution of labour is relatively small and provides the final 10%. During the recession the main driver of GDP growth is TFP which fell of 4% and contributed to 80% of the fall in GDP, the labour input fell around 1.75% which equates to a contribution in the fall of GDP of around 40%. The contribution of capital over this period remained relatively constant to the pre-recession levels and even increase a fraction, it contributed positively to GDP around 15 %.

3 Methodology

In this section we will explain the underlying model behind the BCA methodology while explaining the meaning behind the theoretical underpinnings of these wedges, we shall also outline the estimation procedure while highlighting other options which can be used as alternatives to the ones that we employ in this paper. We finally explain the method used to decompose the business cycle episodes in to the contributions of the wedges.

3.1 Model

The model is the standard form of the general equilibrium with time varying wedges included, consumers maximise utility given the choice of consumption and labour;

$$\max_{c_t l_t} E_0 \sum_{t=0}^{\infty} \beta^t U(c_t, l_t) N_t, \tag{5}$$

subject to the budget constraint,

$$c_t + (1 + \tau_{xt}) x_t = (1 - \tau_{lt}) w_t l_t + r_t k_t + T_t, \tag{6}$$

where c_t is consumption at time t x_t is investment, τ_{xt} and τ_{lt} are the time varying tax rates on investment and labour, w_t is the wage rate, r_t is the real interest rate T_t are lump sum taxes, N_t is population, β is the discount factor, and k_t is the capital stock, firms try to maximise profits.

$$\max_{k_t l_t} A_t F(K_t, (1+\gamma)^t l_t) - w_t l_t - r_t k_t, \tag{7}$$

where A_t represents the efficiency wedge and like standard real business cycle models this parameter is exogenously determined from the model the parameter $(1 + \gamma)$ is the rate of labour augmenting technical progress. The law of motion of capital is given by;

$$(1+\lambda)k_{t+1} = (1-\delta)k_t + x_t, \tag{8}$$

Where $(1+\lambda)$ is the growth rate of the population which is a constant and δ is the depreciation rate.

The equilibrium conditions of the economy are as follows (for derivation of the log linearised model and technical notes about the maximum likelihood estimation see Appendix);

$$c_t + x_t + g_t = y_t, \tag{9}$$

$$y_t = Z_t F(K_t, (1+\gamma)^t l_t), \tag{10}$$

$$-\frac{U_{lt}}{U_{ct}} = (1-\tau_{lt})A_t(1+\gamma)^t F_{lt}, \tag{11}$$

$$U_{ct}(1+\tau_{xt}) = \beta E_t U_{ct+1}\left[Z_{t+1}F_{kt+1} + (1-\delta)(1+\tau_{xt+1})\right]. \tag{12}$$

The wedges thus can be described as the following, the parameter A_t is the efficiency wedge at time t, the efficiency wedge will capture any distortion which causes firms to allocate resources inefficiently. The labour wedge is described by $(1-\tau_{lt})$, this captures any effects which separate the marginal rate of labour from the marginal rate of substitution of consumption and labour. The investment wedge is given by $\frac{1}{(1+\tau_{xt})}$ which captures anything which separates the consumption and the asset pricing kernel. It is important to note that the wedges do not pick out a single type of distortion within the wedge rather it is captures all possible distortions which may affect labour, investment and efficiency.

3.2 Estimation Strategy

It is possible to calculate the labour and the efficiency wedge from their first order conditions once the functional forms of the production and the utility are chosen. As with CKM (2003, 2006), Kersting (2008) both choose Cobb-Douglas productions function and a log linear utility function with the form $U(c,l) = logc_t + \psi log(1-l_t)^2$ where ψ is the time allocation parameter. The following expressions are the calculations for the efficiency wedge and the labour wedge.

$$Z_t = \frac{\left(\frac{y_t}{k_t^\alpha}\right)\frac{1}{1-\alpha}}{l_t}, \tag{13}$$

$$(1-\tau_{lt}) = \frac{\psi}{(1-\alpha)}\frac{c_t}{y_t}\frac{l_t}{(1-l_t)}, \tag{14}$$

The investment wedge can also be calculated with the following expression:

$$\beta E_t \frac{1}{c_{t+1}}\left(\frac{\alpha k_{t+1}}{y_{t+1}} + (1+\tau_{xt+1})(1-\delta)\right) = (1+\lambda)(1+\tau_{xt})\frac{1}{c_t}. \tag{15}$$

As a result of the expectational component of equation (15) the calculation of the investment wedge is more difficult. There are two strategies employed in order to estimate this wedge. The simplest way to achieve this is to assume that agents have perfect foresight about the wedges and the underlying stochastic process of the economy as CKM (2003) and Kobayashi and Inaba (2006). Using these assumptions allows the researcher to ignore the expectational component and move all of the time dependant variables back a period, for which (15) can then be re-arranged for $(1+\tau_{xt})$ calculated as a backward looking difference equation. This does however require an initial value of τ_{xt} in order to start the series, for this the steady state values of the investment wedge can be used.

The other method which is more commonly used and favoured here ((for instance Chakraborty (2004), Kersting (2008), Ahearne et al (2006) and CKM (2007)) is to estimate the wedges using the Kalman filter and a maximum likelihood procedure. To do this the decision rules and the steady states are worked out. The reduced form of the system equation is then worked out and estimated, in this case the reduced form of the structural system corresponds to the following VAR (1) system.

$$s_{t+1} = P_0 + Ps_t + Q\varepsilon_t, \tag{16}$$

[2] There are other choices within the CES group of production which are consistent with Real Business Cycle models the advantage of using Cobb-Douglas functional forms is the tractability of the problems. Klump and Priessler (2000) provide a discussion about the CES group of production functions.

where $s_t = \left[Z_t \, \tau_{lt} \, \tau_x \, g_t \right]'$[3]. Following CKM the model is solved using the method of undetermined coefficients[4] and the likelihood function is then maximised using the one step ahead predictions of the Kalman filter.

Once the wedges have been estimated the next step is to do the accounting procedure, to do this we pass the wedges back through the model one by one holding the other wedges fixed at a steady state levels[5]. This procedure then shows us the path the economy would have taken had only one wedge been active through the time series.

3.3 Model Solution

The labour and efficiency wedges can be calculated from the first order conditions (6) and (7), however the investment wedge depends on expectations of the future levels of consumption, labour, capital stock and the wedges, as such the decision rules on the model depend on the future values of these variables. In order to measure the investment wedge we estimate the underlying stochastic process of the model. We assume that the wedges follow an AR (1) process such as that described in (12) and use Kalman filtering and maximum likelihood methods to solve for the decision rules. Once we have estimated the underlying stochastic process we then have all of the measured wedges we can write the decision variables as a function of s_t and k_t. We can then proceed with the decomposition, as mentioned before if we put the time series for each of the wedges jointly through the model it will replicate output exactly. In order to asses the contribution of each of the wedges we pass the measurements of the wedges back through the decision rules for the economy but restrict the other wedges to remain at their steady state levels. For example if we wished to view the contribution of the efficiency wedge to output we would apply the following (taking a steady state value of 2006); $s_{eff} \left[z_t \, \tau_{l2006} \, \tau_{x2006} \, g_{2006} \right]$ and k_t would then give us, y_{eff}, x_{eff} , more explicitly the contribution to the fluctuations of fundamental variables due to only fluctuations in the efficiency wedge.

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[3] For details of the deriviation of the state space estimatable equation as well as the deriviation of the capital stock see the Appendix 1.

[4] The more commonly used perpetual inventory method is equally usable here.

[5] Note: Koybayashi and Inaba (2005) found evidence that the choice of the steady state may be important to the results. In this paper we choose 2006 Q1 to fix our steady states, this period incorporates low volatility and therefore this period should not be too far from a theoretical steady state. We also considered Kerstings (2008) steady state of 1979 the results were robust to these choices. However, setting the steady state before the 1992 recession changed the results for this period.

3.4 Data

In order to estimate the stochastic process and create the time series for the wedges we use per capita data on output, investment, labour hours and government spending[6], we use the available series for the dates between 1974 Q2 to 2010Q4. As is common with estimation involving filters there may be problems with the estimation due to a series finishing below trend and therefore skewing the results. In order to avoid this we use forecasted series for the mentioned variables which extends the sample through to 2015 Q4. We use the forecasted values as made available by the *Office for Budgetary Responsibility*[7] which covers the main parts of the data series used in the construction of the data set needed for the BCA experiment. For the series of output, government consumption and gross capital formation we calculated the year on year growth level for the forecasted series and then using these growth rates we extend the series. For the labour hours, we use the forecasted for total hours and trend population 16+, as the population does not exactly match that used in our original series the resulting calculation will be smaller, in order to make these compatible we adjust the values upwards so that the final non-forecasted point in the *OBR* series is at the same value as our data set, and the average difference between the two data sets is used to increase the forecasted values.

4 Results

4.1 Business Accounting for the Great Recession

Figures (2) and (3) present the results of the decomposition states using the data for the U.K. economy. Figure (2) shows the counter factual paths the economy would have taken had only one wedge been active while all other wedges are held at their steady state values. Figure (2) shows that both the investment and efficiency wedges fall around the beginning of the recession at the same time as output and that they both add negative pressure on output. The investment wedge only falls a small amount while the efficiency wedge provides an almost exact characterisation of the variation of output over this period. The labour wedge remains relatively constant throughout the recession and only begins to fall once output growth picks up and returns towards its normal trend levels. As the simulation with only the efficiency wedge and

[6]See Data annex for more details

[7]The data sets are available as supplementary materials from the *Economic and Fiscal Outlook 2011* and are available from the *Office for Budgetary Responsibility* website, http://budgetresponsibility.independent.gov.uk/economic-and-fiscal-outlook-march-2011/.

the realised path of output are almost the same, this suggests that any class of friction which works through the efficiency wedge are the most important in explaining the most recent recession. While we see evidence that a shock has affected the investment wedge the overall effects are not large enough to cause such a large fall as seen in the actual data series, we also see that during the recovery period the investment wedge grows much faster that output growth contributing positively to the movements in output. Subsequently we can say that frictions which work through an investment wedge may have a minor secondary role in explaining the 'great recession, while those that work through the labour wedge are largely unimportant.

Figure (3) shows simulations of the counter factual economies had all the wedges except one been allowed to vary over time. The results here reinforce those from figure (2), the combination of the investment wedge and efficiency wedges provide a good characterisation of output. It is interesting to note that around the recovery period as output is increasing there is a fall in the simulation of the combined efficiency wedge and investment wedge. This supports the results presented by Martin (2010) who suggested that there was a delay in the effect of the financial shock affecting the wider economy through the financial channels. The secondary importance of the investment wedge and the irrelevance of the labour wedge are confirmed through the simulations which exclude the efficiency wedge, in which although there is a fall in the simulated level of output it is small and remains relatively constant throughout the whole business cycle.

4.2 Explaining the Business Cycle Accounting results

The impulse responses for BCA were shown by Chadha and Warren (2011), while the IRFs for the efficiency and the labour wedges are standard and well known in RBC theory, that a shock to either of these wedges will lead to positive co-movements in consumption and investment as an effect of a positive shock. A positive shock to the investment wedge mentioned previously will lead to a divergence between consumption and investment due to increasing the present value of consumption over the present value of future consumption. These impulse responses along with the expenditure decomposition can help to explain the results from the BCA simulations. Firstly from figure (1) there is only one period at the beginning and one at the end of the recession where consumption and investment have diverged and in both cases the corresponding consumption growth is very close to 0%. There are two likely periods where we can shock affecting the investment wedge and as the size of the divergence isn't large the size of the shock is likely to be small. As is also shown throughout the rest of the recession and recovery, consumption and investment positively co-move leaving the candidate explanations as being either the labour of efficiency wedges (or a combination of the two). Overall, the expenditure decomposition provides an insight in to why for the most recent recession the investment wedge is unlikely to provide a good explanation for the variation in output.

4.3 Business Cycle Accounting for the BGG model

In order to investigate where the shocks which are investment related in nature appear in the BCA methodology we propose to use the a log linearised version of the Kansas City federal reserve version of the BGG model (see Bernanke and Gertler (1999))[8], from which we create an artificial data series by using Monte Carlo simulations[9]. The data series is then scaled to appropriate steady state levels and then passed through the estimation procedure and then the counter factual levels of output for the artificial series are simulated. The BGG model is a standard New Keynesian model with the added extension of the existence of credit markets which are subject to frictions, the frictions lead to a financial accelerator (FA) mechanism which leads to it costing firms more to source loans externally rather than internally, as such this will then affect investment otherwise termed as the external finance premium. The external finance premium is inversely related to the net worth of the borrowers, as such the external finance premium will be counter cyclical, as such shocks to fundamental which increase (decrease) output will magnify the response of investment and also therefore output. The key extension of the KC fed version is to include bubble shock which allows the market value of net worth to deviate from the fundamental values of net worth, and therefore affect real activity through the decrease in the external finance premium.

While we would expect to see the bubble shock of the model appear through the Euler equation as an investment wedge figure (4) highlights a rather surprising result, that the bubble shock appears almost entirely as a labour wedge. The investment wedge moves weakly and countercyclically to the movements in output[10]. The result is

[8]The key loglinearised equations are presented in the appendix along with the parameterisations used.

[9]We allow the bubble shock to be both positive and negative.

[10]We tested all of the shocks within the BGG framework, these are a shock to government spending, efficiency and monetary policy. None of these shocks would deliver an investment wedge as a primary cause of movements in output.

particularly surprising as the bubble shock would represent a similar story to a fall in the quality of collateral which could be viewed as a similar story to the fall in asset prices as with our experiments with the actual data series we see very little effects on the investment wedge our candidate explanation. The disconnect here between financial frictions and the investment wedge suggest that researchers may have to rethink the role of the financial frictions working through the asset pricing equation as a transmission mechanism for financial shocks and develop models which affect the real economy in alternative methods, such as through the TFP parameter and the labour supply equation. The results from the Monte Carlo and those of the BCA experiment for the great recession suggest that if we are to believe that the much of the debate around the causes of the recession being due to a large shock to investment, falls in asset prices is correct we must look outside of frictions which affect the Euler equation for answers of how falls in asset prices and investment frictions may affect the wider economy.

5 Conclusion

In this paper, we examine look at the UK Great Recession via a simple demand decomposition and through the lens of Chari Kehoe and McGratten (2007) Business Cycle Accounting methodology. The demand decomposition clearly shows that the recession was primarily caused by large falls in investment and consumption, with investment contributing the most throughout the recession, the demand decomposition also showed that the fall in investment led the fall in output. The results of the BCA experiment suggested that the efficiency wedge could explain the variations in output almost perfectly, and that the investment wedge had a very minor secondary role. To further investigate these findings we use simulated data from the BGG model which contains a well defined financial friction in the form of the external finance premium and only included a bubble shock to create the series, the results showed that the bubble shock would appear almost entirely as a labour wedge with the investment wedge moving counter cyclically to output. We interpret this result as telling us that financial frictions may not appear only in the investment wedge.

The results of the Monte Carlo analysis does not necessarily contradict the results from the BCA experiments rather it questions the way in which shocks and frictions to financial markets affect the real economy. In other words, just because a shock may emanate from financial markets, it does not imply that it will necessarily impact on the marginal rate of substitution in consumption. In the case of the BGG model, the shock to asset prices leads to greater variation in labour supply over the business cycle - as increases (decreases) in collateral value induce more (fewer) working hours in general equilibrium. We need therefore to understand better the implications of financial frictions for general equilibrium outcomes.

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Appendix
Data Annex

All data can be found on the office for national statistics website, under the time series data section unless otherwise specified.

Output per capita = (GDP + Services from consumer durables + depreciation from consumer durables - V.A.T) / Working age population

GDP = GDP chained volume measure, seasonally adjusted, 2005 prices £ million. Accronym: ABMI

Services from consumer durables = The service from the stock of consumer durables, in order to create the stock of consumer durables, the series consumption of consumer durables is cumulated assuming a 16.5 depreciation rate. An added assumption is that in 1964, all purchases of consumer durables were for replacement purposes. Services from the stock of consumer durables are then assumed to be 4%.

Total expenditure on durables = Chained Volume measure, Seasonally adjusted, 2005 prices £million. Acronym: UTID

Working age population = 16-59/64 Seasonally adjusted, thousands. Acronym: YBTF

Labour input per Capita = (Total weekly hours worked / Working age population)/100

Total weekly hours worked = Total actual weekly hours worked, Millions, Seasonally adjusted. Acronym:YBUS

The labour input per capita is divided by 100, to account for the total possible hours workable in one week.

Investment per capita = (Gross fixed capital formation + changes in private inventories +Total expenditure on durables - Sales Tax × Share of durables in total consumption) / Working age population

Gross fixed capital formation = Chained volume measure, seasonally adjusted, 2005 prices £ million. Acronym: NPQT

Changes in private inventories = Chained Volume measure, seasonally adjusted, 2005 prices £ million. Acronym: CAFU

Sales Tax = Central Government: Taxes on production & Imports receivable: VAT: £ million, current prices not seasonally adjusted Acronym: NZGF.

In order to make the sales tax series consistent with the rest of the data series, it had to be seasonally adjusted and also deflated so that there were constant prices. To seasonally adjust the data a 4 Quarter average was taken. The data series was deflated using the retail price index (RPI), which can be found in full on the *ecowin* programme.

RPI = Retail price index rebased so that 2005 = 100. Ecowin code: ew:gbr11800, NSO Accronym: CHAW.

Share of consumer durables in total consumption = Total expenditure on durables / (Total expenditure on durables + Total expenditure on non-durables + Total expenditure on services).

Total expenditure on non-durables = Chained volume measure, seasonally adjusted, 2005 prices £ million. Acronym: UTIL

Total expenditure on services = Chained volume measure, seasonally adjusted, 2005 prices £ million. Acronym: UTIP.

Government spending per capita = (Total government spending + Net exports) / Working Age population.

Total Government spending = Chained volume measure, seasonally adjusted, 2005 prices £ million. Acronym: NMRY.

Net exports = (Exports - Imports)

Exports = Goods and Services, Chained volume measure, seasonally adjusted, 2005 prices £ million. Acronym: IKBK

Imports = Goods and Services, Chained volume measure, seasonally adjusted 2005 prices £ million. Acronym:IKBL.

We used series from the *Economic and Fiscal Outlook* published by the Office for Budgetary Responsibility (published on the 23rd of march) in order to create the series leading past those which are available from the ONS.

Annex 2

Log Linear conditions for the BGG model with a bubble shock

Resource constraint,

$$y_t = \frac{C}{Y}c_t + \frac{C^e}{Y}c_t^e + \frac{I}{Y}i_t + \frac{G}{Y}g_t, \tag{17}$$

Euler equation,

$$E_t c_{t+1} = c_t + \sigma r^n, \tag{18}$$

Euntrepreneurial consumption,

$$\begin{aligned} c_t^e = &\frac{K}{N}r_t^q - \left(\frac{K}{N}(1-\frac{K}{N})\psi\right) r_{t-1} - \left(\frac{K}{N}(1-\frac{K}{N})\psi\right) k_{t-1} - \\ &\left(\frac{K}{N}(1-\frac{K}{N})\psi\right) q_{t-1} + \left(\frac{K}{N}\left\{(1-\frac{K}{N})\psi + \frac{N}{K}\right\}\right) n_{t-1}, \end{aligned} \tag{19}$$

Production function,

$$y_t = z_t + \alpha k_{t-1} + (1-\alpha)l_t, \tag{20}$$

Labour supply equation,

$$y_t + x_t + \frac{1}{\sigma}c_t = \gamma_l h_t \tag{21}$$

Phillips curve,

$$E[\pi_{t+1}] = \lambda E[x_{t+1}] + \gamma_f E[\pi_{t+2}] + \gamma_b \pi_t, \tag{22}$$

Relationship between asset valuations and investment,

$$q_t = \phi(i_t - k_t), + \varepsilon_{q,t} \tag{23}$$

Net worth accumulation,

$$\begin{aligned} n_t = &\chi r_t^k - \chi\left(1-\frac{N}{K}\right) r_{t-1} - \chi\left(1-\frac{N}{K}\right)\psi k_{t-1} - \chi\left(1-\frac{N}{K}\right)\psi q_{t-1} \\ &\left(\chi\left(1-\frac{N}{K}\right)\psi + \frac{N}{K}\right) n_{t-1} + \left(\chi(1-\gamma rkss) + \frac{N}{K}/\gamma\right) y_t, \end{aligned} \tag{24}$$

Ex-post price of external funds,

$$E[r_{t+1}^k] = (1-\epsilon)(x_t + y_t - k_{t-1}) + \epsilon q_t - q_{t-1}, \tag{25}$$

Relation of external price of funds and the interest rate,

$$E[r_{t+1}^k] - r_t = -\psi(n_t - q_t - k_{t-1}), \tag{26}$$

External finance premium,

$$s_t = E[r_{t+1}^k] - r_t, \tag{27}$$

Monetary policy,

$$r_t^n = \rho_n r_{t-1}^n + \rho_\pi \pi_t + \rho_y y_t + \varepsilon_{i,t}, \tag{28}$$

Real interest rate,

$$r_t = r_t^n - E[\pi_{t+1}], \tag{29}$$

Law of motion for capital,

$$k_t = \delta i_t + (1-\delta)k_{t-1}, \tag{30}$$

Driving process for government and technology;

$$g_t = \rho_g g_{t-1} + \epsilon_{g,t}, \tag{31}$$

$$z_t = \rho_z z_{t-1} + \epsilon_{z,t}. \tag{32}$$

Estimates of the Stochastic process

Below are the estimates of the stochastic process as described in (16)

$$P_0 = \begin{bmatrix} 0.149 \\ (0.005) \\ 0.349 \\ (0.002) \\ 0.645 \\ (0.014) \\ -1.21 \\ (0.003) \end{bmatrix} \quad P = \begin{bmatrix} 0.971 & 0.075 & 0.013 & -0.020 \\ (0.009) & (0.012) & (0.005) & (0.004) \\ -0.135 & 1.189 & 0.089 & -0.091 \\ (0.004) & (0.010) & (0.008) & (0.006) \\ 0.194 & -0.309 & 0.854 & 0.134 \\ (0.009) & (0.029) & (0.020) & (0.016) \\ -0.193 & 0.120 & 0.071 & 0.879 \\ (0.023) & (0.012) & (0.013) & (0.008) \end{bmatrix}$$

$$Q = \begin{bmatrix} 0.010 & & & \\ (0.001) & & & \\ 0.000 & 0.006 & & \\ (0.000) & (0.000) & & \\ 0.002 & -0.013 & 0.012 & \\ (0.001) & (0.001) & (0.002) & \\ 0.004 & 0.006 & 0.017 & 0.005 \\ (0.001) & (0.001) & (0.000) & (0.000) \end{bmatrix}$$

BCA for the recession.

$$P_0 = \begin{bmatrix} -0.191 \\ -0.384 \\ 0.580 \\ -1.488 \end{bmatrix} \quad P = \begin{bmatrix} -0.011 & 0.062 & 0.615 & 0.242 \\ 0.568 & 0.915 & -0.633 & -0.631 \\ 0.530 & -0.056 & 0.437 & -0.01 \\ -0.199 & 0.014 & 0.137 & 1.055 \end{bmatrix}$$

$$Q = \begin{bmatrix} 0.005 & & & \\ -0.004 & 0.162 & & \\ 0.007 & -0.018 & 0.004 & \\ 0.005 & -0.002 & -0.000 & 0.000 \end{bmatrix}$$

BCA for the simulated BGG data.

As mentioned in CKM (2006) the estimates of the stochastic processes don't appear to make too much difference to the simulation and decomposition parts of the BCA experiment. For the stochastic process we find that the diagonal elements of the P matrix are high correlations which are close to 1, and even larger than one in the case of the labour supply. The possible reason for this is that the per capita labour hours over this period is downward sloping over our sample period, which may lead to the greater than 1 coefficient on labour. For the artificial data we find that the cross correlations are much greater than that found in the real data and that the coefficient on the efficiency and investment wedges are much smaller.

Tables

Parameterisations for the BCA estimations and the BGG model

	1975 Q1 - 2008 Q3	2008 Q4 - 2009 Q4	BGG Model
Output	2.26	-4.43	2.32
Demand % Contribution			
C	1.60	-1.93	-1.11
I	0.40	-3.80	3.43
G	0.36	0.24	N/A
NX	-0.10	1.05	N/A
Supply % Contribution			
K	0.67	0.70	
L	0.08	-1.67	
TFP	1.37	-3.45	

Table 1: Demand and Supply contributions for the recession and artificial data created from the BGG model with a bubble shock.

Parameter	Value	Definition
g_z	1.02	Growth rate of technology
g_n	1.015	Growth rate of population
δ	.0464	Depreciation rate
β	.9722	Discount factor
α	0.35	Capital share
ψ	2.24	Frisch Elasticity
σ	1.000001	Parameter of households risk aversion

Table 2: Parameterisations used for the BCA model give in an annualised basis

Parameter	Value	Definition
β	0.99	Discount factor
$\frac{C}{Y}$	0.568	Steady state level of household consumption
$\frac{C^e}{Y}$	0.0541	Steady state level of entrepreneurial consumption
$\frac{I}{Y}$	0.1779	Steady state level of Investment
$\frac{G}{Y}$	0.2	Steady state level of government consumption
σ	0.1	Elasticity of consumption in Euler equation
ϕ	1	Elasticity of asset prices to investment
δ	0.25	Depreciation rate
ψ	0.05	Scaling parameter (Tobin's Q)
α	0.35	Capital share
χ	2.1	Scaling parameter coefficient on output (Net Worth accumulation)
γ	0.9728	Scaling parameter coefficient on output (Net worth accumulation)
γ_b	0.9	Coefficient on contemporaneous inflation (Phillips curve)
γ_l	1.33	Coefficient on labour hours worked (Labour supply)
γ_c	$1/\sigma$	Coefficient on consumption (Labour supply)
γ_f	0.5	Coefficient on forward looking inflation (Phillips curve)
γ_y	0.5	Coefficient on output (Taylor Rule)
ρ_n	0.9	Persistence of interest rate
ρ_g	0.9	Driving process for government
ρ_z	0.9	Driving process for technology
λ	0.024	Coefficient on marginal cost
ϵ	0.99	Weighting parameter in return on asset equation

Table3: Parameterisations of the BGG model

Figures

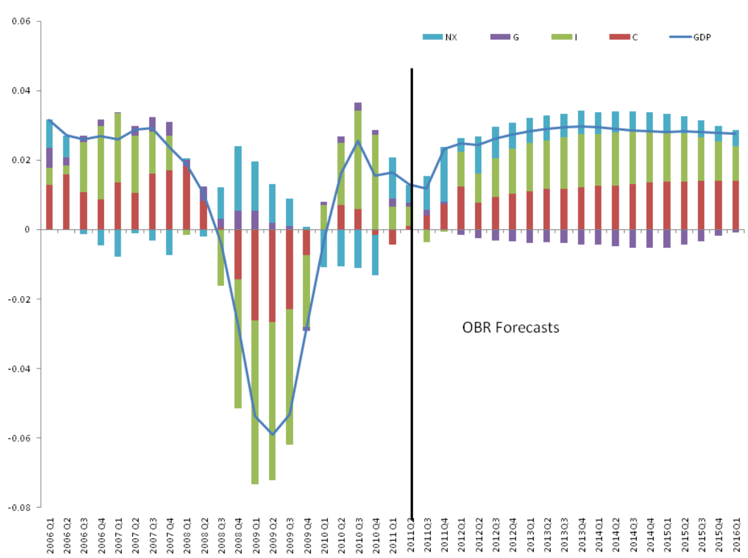

Figure 1: Expenditure decomposition

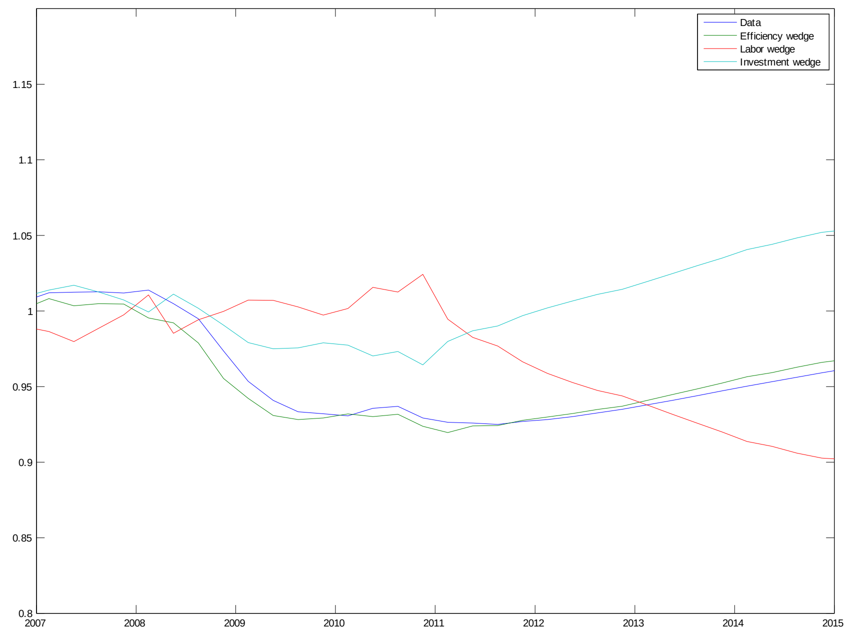

Figure 2: BCA decomposition with one wedge allowed to vary over time.

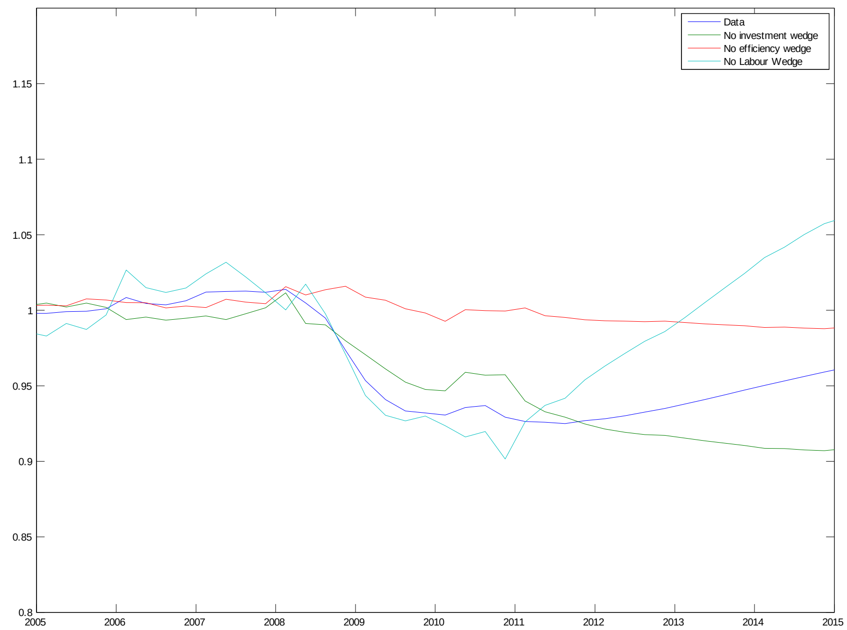

Figure 3: BCA decomposition with all but one wedge to vary over time.

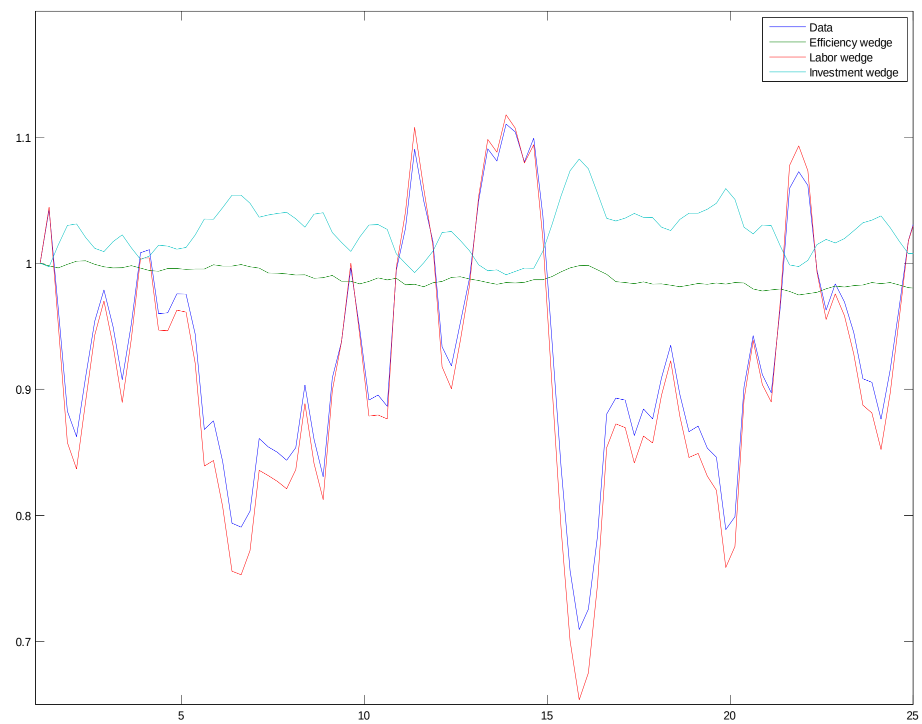

Figure 4: BCA decomposition for artificial data from the BGG model.

Predicting the UK Economy: A comparison of nowcasting methodologies

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24th February 2016

Abstract:

We investigate the ability of three standard nowcasting methodologies, bridge equations, unrestricted Mixed Data Sampling regressions and mixed frequency VARs, to nowcast the UK GDP. All three methodologies may have advantages over the other, bridge equations are the simplest to construct and are the most transparent. The direct forecasting approach of MIDAS may reduce errors in the face of model misspecification while remaining relatively simple to estimate and forecast with. The mixed frequency VAR allows for dynamics between the variables which may help to reduce the forecast error. We evaluate these methods using a final dataset which mimics the data availability at each period in time for 5 monthly indicators. We find that the VAR on average across all forecast horizons is the most consistent, while MIDAS has the best predictive power at the 1 step ahead horizon. The bridge equations do not appear useful until the final month of the quarter. Throughout the evaluation period the predictive accuracy of the methods varies, the MFVAR performs best during the 'Great Recession' period while MIDAS is better during normal growth periods.

JEL classifications: C11 C32 E17

Keywords: Forecasting, mixed frequency data, bridge equations, MIDAS, MFVAR

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1. Introduction

Nowcasting provides a useful tool for policymakers and market participants to gauge the current state of the economy before the release of official statistics which are generally released with a lag. A successful nowcasting model should have the ability to extract the information present in timely economic indicators and also be able to deal effectively with irregularly spaced release dates to provide estimates of a lower frequency series, most commonly GDP. In this paper we compare the effectiveness of the ability of three standard models capable of dealing with multiple frequencies to predict the growth rates of GDP for the UK economy, using a small set of monthly indicators.

Bridge equations are the simplest of the methodologies employed, these are commonly used in policy making institutions (see Bell et al (2014) for the Bank of England) due to the relative ease of their implementation and transparency. This class of model predicts the quarterly variable using contemporaneous and lagged instances of explanatory variables also specified in quarterly frequencies, the main prediction equation in its standard form can be estimated by OLS. While, the higher frequency variables enter the main equation in quarterly frequency, where data for these variables are not available to the appropriate quarter, these series are forecast forward at the monthly frequency and transformed into the quarterly frequency using a temporal aggregation function.

The two other methods forecast directly from the higher frequency to the quarterly frequency. The Mixed Data Sampling regressions (MIDAS) are an alternative approach to single equation nowcasting, see, for example, Ghysels, Sinko, and Valkanov (2007) and Ghysels, Santa-Clara, and Valkanov (2006) for applications to financial data and Clements and Galvao (2009) are an example of an application to macroeconomic series. Like the bridge equations MIDAS are a single equation approach, however, the higher frequency variables are linked directly to the quarterly series and the forecast is computed as a jump to the forecast horizon. These equations are often specified with a distributed lag polynomial (such as the exponential Almon lag polynomial in the case of Ghysels, Sinko, and Valkanov (2007)), to enforce parameter decay on the lag structure, but still, retain flexibility over the shape of such decay. Where a lag polynomial is used, estimation using nonlinear least squares (NLS) is required. Other than the simplicity and flexibility MIDAS predictions may have some advantages of those of the Bridge equation. Firstly, by computing the forecast as a h-step ahead procedure, in the presence of misspecification the forecasts are likely to be more accurate than iterative methods. Secondly, by projecting from the monthly variables directly onto the quarterly variables, if the monthly series contains useful information then this is directly exploited.

Our final methodology is the mixed frequency vector autoregression (MFVAR), implemented initially by Mariano and Murasawa (2004, 2010), which takes the form of a normal VAR, except that the monthly observations of the quarterly series are unavailable, and must be dealt with during estimation. In most cases, the VAR is cast into state space form and a forward filter/backward smoothing algorithm is employed in order to uncover the monthly series of the quarterly variables, given the parameterisation of the rest of the VAR. Estimation can either be achieved via frequentist methods such as the EM algorithm (Mariano and Murasawa (2004, 2010) or Bayesian methods (Schorfheide and Song (2015)) for which in this paper we follow the latter approach. Over the bridge models, the MFVAR has a similar advantage to MIDAS in that information from monthly data series is directly exploited. While the forecasting method is iterative like that of the bridge equations, the MFVAR explicitly imposes a structure between the variables and as a result may improve the forecasting ability, not just of the quarterly variable but the monthly variables as well.

In order to evaluate the effectiveness of each of these methods we create a pseudo real-time nowcasting exercise, we use final data for a small subset of economic indicators but preserve the availability of that data for each of the forecast horizons, therefore replicating the ragged edge nature of a real-time data set. Three forecasts are then created for each time horizon up to the preliminary release of GDP. From which we compare the predictive accuracy of each of the series against a naive benchmark model in a random walk and also against each other.

We find that both the predictive power of MIDAS regressions and the MFVAR improve throughout our forecast period. The MFVAR is the most consistent with a smaller mean absolute error and root mean squared error. The MIDAS regressions have the best predictive accuracy at the shortest horizon albeit marginally. The bridge equations are the worst performing across all horizons, for forecast horizons longer than one, we find that no improvement in the predictive accuracy of the bridge equations. At the single step ahead the bridge equations perform only marginally worse than the other two methodologies.

The structure of the paper is as follows, in section two we provide a survey of the current approaches to nowcasting including the prevalent extensions to the three standard methodologies presented in this paper. Section three outlines the structure of each of the models and their respective estimation techniques, as well as the construction of the dataset. Section four presents the results of the evaluation exercise and section five concludes.

2. Literature Review

Bridge models are a simple and popular type of nowcasting model used commonly across national and international policy making institutions (see, for example, Diron (2008), Sédillot and Pain (2003) Rünstler G. and Sédillot F. (2003)). These types of models comprise a set of linear regressions which forecast the low-frequency variable at their own frequency but incorporate the timelier high-frequency observations through forecasts and temporal aggregation. Given their relatively simplicity that they improve on more complicated single frequency models is impressive, for instance, Golinelli and Parigi (2007) find that for the G7 countries, bridge models provide improvements in nowcasting GDP over quarterly frequency VAR and AR models. Antipa et al (2012) compare bridge equations to a quarterly dynamic factor model and find that they generally have a smaller forecast error, furthermore, they find that adjusting the bridge equations so to incorporate new information when it is available, further improves the accuracy of the nowcast.

One key extension to the bridge models is to include large datasets in the high-frequency equations as Angelini et al (2008), estimated as dynamic factor models. They evaluate each methodology for Euro Area GDP and find that the factor Bridge model has a lower RMSE than the standard bridge model. Also, over a single nowcasting period, the forecast errors of the factor model reduce, whereas those for the standard models remained relatively constant. They attributed this result to soft indicators whose contribution to the improvement in accuracy was greater when there was the relative scarcity of new observations for the hard data. This result is also mirrored by Higgins (2014) for a large scale Factor bridge model of the US economy.

A useful feature of bridge models is that they are extremely flexible, for example, Camacho et al (2012) incorporate Markov switching into a dynamic factor based bridge model. They find that in general, the incorporation of mixed frequencies leads to an improvement in the identification of business cycle. However, the quality of the data is important, indicators which have a large signal to noise ratio are effective, as the noise to signal ratio gets worse the prediction error will get larger. Further extensions include incorporating heteroskedastic shock processes such as Marcellino et al (2012) who estimate a dynamic factor model with stochastic volatility and find that the density forecasts improve as a result.

A key criticism of the bridge equations are that information in the monthly series is not directly exploited. MIDAS regressions provide an alternative which avoids this problem as they directly project the monthly series onto the quarterly series. This is achieved by redefining each lag of the monthly series as a new variable which can then be regressed onto the quarterly series. Initial applications of MIDAS methodology were focused on forecasting financial time series, for instance, Ghysels, Sinko, and Valkanov (2007) and Ghysels, Santa-Clara, and Valkanov (2006), who used an exponential Almon lag polynomial to determine the lag structure of the model. Clements and Galvao (2009) applied these to forecasting inflation and GDP, they generalised the form by incorporating an autoregressive term. Overall, their findings indicated that the predictive accuracy of MIDAS was greater than that of quarterly frequency models. They note that as a result of directly mixing the monthly and quarterly series MIDAS avoids imposing restrictions on the parameterisations that occur from the temporal aggregation. Furthermore, the use of a lag polynomial avoids the issue of the lag selection as this occurs endogenously within the estimation procedure.

Given that MIDAS regressions are simple single equation models, any variation that can be applied to standard single equation model can also be applied to MIDAS. Marcellino and Schumacher (2010) compare factor MIDAS with other mixed frequency factor methods and found that all forms improved over single frequency quarterly models but also that the factor MIDAS has the greatest predictive accuracy amongst the mixed frequency models. Guèrin and Marcellino (2013) introduce Markov switching dynamics, found that this extension improved on the standard MIDAS models for one step ahead predictions but the standard MIDAS regressions perform better at the two step ahead predictions. They further found that in out of sample forecasting the MSMIDAS performed well in identifying recessionary periods. Foroni, Marcellino and Schumacher (2012), provide an interesting simplification of the AR-MIDAS by leaving the lag polynomial unrestricted. They conclude that for forecasting with monthly and quarterly variables, by not imposing a weighting scheme on the lag structure improves the predictive accuracy over standard MIDAS regressions. However, as the sampling frequency increases, this is reversed.

Schumacher (2014) provides an interesting empirical comparison between Bridge and MIDAS models, provides a set of auxiliary models which adjusts the MIDAS equations to reduce the difference between the two methodologies. Firstly, by leaving the lag polynomial unrestricted, and secondly they create a version of MIDAS which forecasting is computed iteratively. The empirical evaluations were undertaken over a large number of different specifications, over data as well as model specifications; the overall result is that the indicators chosen were more important than the model specifications. It was also noted, however, that the worst performing model was the unrestricted MIDAS model (U-MIDAS); this result was primarily due to the short sample over which the pre-evaluation estimations were conducted.

The MFVAR is a multivariate approach to forecasting, the estimation and forecasting are performed on the monthly series. Murasawa and Mariano (2004) create a single factor mixed frequency VAR to create a monthly series for GDP. They assume that the missing observations of GDP are missing draws from a normal distribution.

These can be ignored by the Kalman filter algorithm by adjusting the observation equation. They then estimate the system of equations via the expectation maximisation algorithm. Schorfheide and Song (2015) provide a Bayesian implementation of the MFVAR for the US over a dataset of 11 variables. They impose a Minnesota prior and estimate the parameters of the equations using a Gibbs sampling algorithm. Against a comparable Quarterly frequency BVAR at short horizons, the MFBVAR provides large increases in predictive accuracy but at longer horizons there is no gain. They also provide an example using a smaller dataset against U-MIDAS, in which they find that the MFBVAR over all horizons performs no worse and improves over the other, but in general both utilise within quarter information equally well. Kuzin, Marcellino and Schumacher (2009) provide a comparison between the MIDAS regressions and the MFVAR, estimated using the EM algorithm. They conclude that the two methodologies are complementary, that MIDAS performs best over the forecasting horizons shorter than 6 months whereas the VAR was more accurate for those longer than this.

In regards to nowcasting in the UK, there are relatively few examples. Castle, Hendry and Kitov (2013) provide a wide-ranging guide to nowcasting methodology which culminates in an application of a suite of bridge equations using an autometric algorithm for estimation. They found that bridge models augmented with monthly indicators, estimated using autometric methods outperform that of official preliminary estimates and single equation benchmark models. Most importantly they found that correcting for locational shifts in variables lead to the most accurate results. Mitchell et al (2005) provide a novel approach to bridge equations, by manipulation of the lag operator they create a monthly bridge model, estimated by GMM with a constraint that the three monthly observations for GDP sum to the quarterly number. The approach is explicitly focused towards the preliminary release of GDP, using components from the more timely output approach to GDP. This model remains a live nowcasting model rather than academic example and the rolling one month ahead forecast for GDP are published by the *National Institute of Economic and Social Research,* who report a full sample RMSE of 0.22, which is larger for the while over the 'Great Recession' period it recorded a RMSE of 0.3 (see for example Kirby and Warren (2016)).

3. Methodology

3.1 Bridge Equations

The Bridge approach to nowcasting links the quarterly GDP growth with the quarterly values for of the timely predictor series using an ARDL model given in (1)

$$\boldsymbol{y_{t_q} = c_0 \sum_{i=1}^{j} \alpha^i(L) y_{it_q} + \sum_{i=0}^{j} \beta^i(L) x_{it_q} + u_{t_q}} \tag{1}$$

Where L is the lag operator, β is a lag polynomial of length k, y_{tq} is GDP at the quarterly frequency and x_{itq} is a vector of monthly variables aggregated to the quarterly frequency. We select the lag lengths for α and β using the Bayesian information criterion, testing all combination of models down from 4 lags to 1. This equation is re-estimated and the model selection is re-determined at the beginning of each new quarter. In estimation, we include contemporaneous variables but no leads. Where, the monthly variables are not available to the current quarter, these are forecast to the end of the quarter using a simple AR(p) process with the lag length again chose by the BIC from 6 lags down and re-estimated on a monthly basis.

For the variables which are specified in monthly growth rates these are then aggregated to quarterly values using the following aggregation function:

$$\boldsymbol{x_{t_q} = \frac{1}{3} x_{t_m} + \frac{2}{3} x_{t-1_m} + x_{t-2_m} + \frac{2}{3} x_{t-3_m} + \frac{1}{3} x_{t-4_m}} \tag{2}$$

Equation (2) applies only to quarterly variables specified in growth rates, of which we are concerned with in this application, for a fuller list of aggregation functions see, Stock and Watson (2002).

Our forecast is therefore created by a two-step procedure, we first forecast the monthly variables to the quarter relevant quarter, aggregate these to quarterly values and then create the one step ahead forecast for GDP. While we are only concerned with the immediate one step ahead forecast, if a forecast horizon greater than 1 was required, given the AR term present in 1, a forecast for y would have to be computed for each time period t until the forecast horizon.

The forecasting method of the bridge equations is, therefore, an iterative approach, for both the high-frequency variables and for the main equation for forecast horizons greater than one. A key weakness is that, if any of the forecast equations are misspecified, for each of the iterations of the forecast; the effect of the specification is to the power of t.

It is, therefore, worth noting that while an AR process is commonly chosen for the forecast equations of the high frequency any variety of models could be used here. For example, where available a second set of indicators could be used in an auxiliary ARDL as in Mitchell et al (2005) or even as a VAR in an effort to reduce the accumulation of misspecification errors.

3.2 MIDAS

MIDAS regressions are another form of single equation approach to nowcasting, they, however, differ from the Bridge equations as they link the monthly variables to quarterly GDP growth directly. A common form of these regressions is as follows;

$$\boldsymbol{y_{t_m} = c_0 + \lambda y_{t-3_m} + \beta_1 b(L_m;\theta)(1-\lambda L_m^3)x_{t_3-w-3} + \varepsilon_{t_m}} \qquad (3)$$

Where L is the lag operator, $b(L_m;\theta)$=$\sum_{k=0}^{K} d(k;\theta)$ which sets the parameterisations of the lagged monthly variables. In equation (3) the AR term is modelled as a common factor as without this, as Clements and Galvao (2009) note, there will be seasonal dynamics in the response of y regardless of whether x has any seasonal component. The monthly variables are linked directly to GDP, with each month of the quarter being modelled as a new variable, i.e. x_1 is the first month of each quarter, x_2 the second etc for each indicator.

The functional form of the parameterisations of the distributed lag polynomial are suitably flexible, the original application by Ghysels et al (2006) adopted the following 'exponential Almon lag' polynomial;

$$\boldsymbol{d(k;\theta)} = \frac{\mathbf{exp}\ (\boldsymbol{\theta_1}, \boldsymbol{k} + \cdots \boldsymbol{\theta_q}, \boldsymbol{k^q})}{\sum_{\boldsymbol{K=1}}^{\boldsymbol{K}} \mathbf{exp}\ (\boldsymbol{\theta_1}, \boldsymbol{k} + \cdots \boldsymbol{\theta_q}, \boldsymbol{k^q})} \tag{4}$$

However, alternative distributed lag polynomials, such as the beta lag polynomial, and stepwise functions are straight forward to incorporate, for a fuller list see Ghysels et al (2007). An alternative method is to estimate the equation without the imposition of the distributed lag polynomial, as proposed by Foroni et al (2012), termed U-MIDAS. This approach simplifies estimation, it is not needed to model the AR term as a common factor, furthermore, OLS can be used for estimation rather than NLS, as is required when (4) is chosen as the lag polynomial.

We follow the U-MIDAS approach, which as Foroni et al (2012) and Schumacher (2014) discuss, is likely to improve on versions of MIDAS which impose a polynomial lag structure as in (4). However, the converse is likely to be true where the sample period is short or the number of variables is large.

Forecasting using the MIDAS system is a direct multistep process, as a result for each new piece of information that becomes available, this represents a new model to be estimated. Therefore, we re-estimate the MIDAS regressions each period, we use OLS for estimation, with 6 monthly lags on the monthly variables and 2 on the AR term, as with the estimation of the bridge equations we use the BIC to determine model selection.

3.3 MFVAR

Like the bridge equations, the MFVAR is also an iterative method. However, the data is sampled the data at the monthly frequency. The forecasting equation can be written as a VAR(1), convenient for casting into state space;

$$\boldsymbol{x_{t_m}} = \boldsymbol{\mu_0} + \boldsymbol{B}\boldsymbol{x_{t-1_m}} + \boldsymbol{\varepsilon_{t_m}} \tag{5}$$

$$\boldsymbol{where}, \boldsymbol{\varepsilon}_{\boldsymbol{t_m}} \sim \boldsymbol{N}(\mathbf{0}, \boldsymbol{\Sigma})$$

x is an N ×1 vector of variables in the monthly frequency, B is an N ×M vector of parameters, and ε_{t_m} is a N ×1 vector of normally distributed shocks with mean 0 and variance Σ. To link the latent monthly series with quarterly GDP observations, a slightly modified form of the Kalman filter algorithm is employed to deal with missing data, this is given by the following familiar system of equations,

$$\boldsymbol{x}_{t|t-1} = \boldsymbol{\mu}_{0} + \boldsymbol{B}\boldsymbol{x}_{t-1|t-1} \tag{6}$$

$$\boldsymbol{P}_{t|t-1} = \boldsymbol{B}\boldsymbol{P}_{t-1|t-1}\boldsymbol{B} + \boldsymbol{\Sigma} \tag{7}$$

$$\boldsymbol{\eta}_{t|t-1} = \boldsymbol{y}_{t} - \boldsymbol{H}_{t}\boldsymbol{x}_{t|t-1} \tag{8}$$

$$\boldsymbol{where}, \boldsymbol{H}_t \begin{cases} \boldsymbol{if\ m = 3}, \begin{pmatrix} \mathbf{1} & \mathbf{0} & \mathbf{1} & \mathbf{0} & \mathbf{1} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{I}_{nm\times nm} & \mathbf{0} & \mathbf{0}_{nm\times nm} & \mathbf{0} & \mathbf{0}_{nm\times nm} \end{pmatrix} \\ \boldsymbol{else}, \begin{pmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{I}_{nm\times nm} & \mathbf{0} & \mathbf{0}_{nm\times nm} & \mathbf{0} & \mathbf{0}_{nm\times nm} \end{pmatrix} \end{cases} \tag{8a}$$

$$\boldsymbol{\gamma}_{t|t-1} = \boldsymbol{H}_{t}\boldsymbol{P}_{t|t-1}\boldsymbol{H}_{t} + \boldsymbol{R} \tag{9}$$

$$\boldsymbol{x}_{t|t} = \boldsymbol{x}_{t|t-1} + \boldsymbol{K}_{t}\boldsymbol{\eta}_{t|t-1} \tag{10}$$

$$\boldsymbol{P}_{t|t} = \boldsymbol{P}_{t|t-1} - \boldsymbol{K}_{t}\boldsymbol{H}_{t}\boldsymbol{P}_{t|t-1} \tag{11}$$

$$\boldsymbol{where, K_t = P_{t|t-1} H_t' \gamma_{t|t-1}^{-1}}$$

Overall the Kalman filter follows the standard form, the first two steps the prediction of the state equation and variance, the next two steps, the evaluation of the prediction and variance of the prediction error, while finally updating using the Kalman gain. The key difference from the standard Kalman filter is the loading matrix in the measurement equation, which, when quarterly GDP is observable includes an aggregation function. Mariano and Murasawa (2004, 2010) impose the same aggregation function as with the bridge equation, which represents the geometric mean of the quarter. However, we follow Schorfheide and Song (2015) and impose a simple within quarter average to aggregate the latent monthly GDP series to the quarterly frequency. By adjusting the measurement equation in such a way in effect integrates out the missing observations from the likelihood function.

The VAR as such can be estimated either using the expectation maximisation algorithm as with Mariano and Murasawa (2004, 2010), Kuzin et al (2009), or via Bayesian inference as with Schorfheide and Song (2015), we take the latter approach.

We estimate the parameters of B using a Gibbs sampling algorithm, following that proposed by Banbura, Giannone and Reichlin (2010), the priors for the system are set as follows,

$$\mathbf{E}[\![(\boldsymbol{A_k})_{ij}]\!] = \begin{cases} \boldsymbol{\delta_i \, if \, k = j} \\ \boldsymbol{0, otherwise} \end{cases} \tag{12}$$

$$\mathbf{V}[\![(A_k)_{ij}]\!] = \begin{cases} \dfrac{\lambda^2}{k^2} \textit{if } k = j \\ \vartheta \dfrac{\lambda^2}{k^2}\dfrac{\sigma_i}{\sigma_j}, \textit{otherwise} \end{cases} \tag{13}$$

The priors δ_i are set as the AR(1) co-efficients from a univariate regression, and σ_i *and* σ_j are error terms from the univariate OLS regression of the parameters in the VAR. ϑ governs how important other lags are in comparison to own lags, we set this co-efficient to 1. The hyperparameter λ controls the tightness of the prior which we set to 0.2 following Canova (2007). Following Banbura et al (2010) we include one further prior on the sum of the coefficients, τ, this controls the amount of shrinkage of the parameters, as τ goes to infinity shrinkage approaches 0, we set this 10λ. Finally the prior on the constant term, ϵ, is set as an uninformative prior we set the value at 1/1000. These priors are then implemented through the dummy observations approach of Banbura et al (2010);

$$y_d = \begin{pmatrix} diag(\delta_1\sigma_{1,\ldots\ldots}\delta_n\sigma_n)/\lambda \\ 0_{n\times p} \\ diag(\delta_1 \ldots\ldots \delta_n) \\ 0_{1\times n} \\ diag(\delta_1\mu_1 \ldots\ldots \delta_n\mu_n)/\tau \end{pmatrix} \tag{14}$$

$$x_d = \begin{pmatrix} diag(1,2..p) \otimes \dfrac{diag(\delta_1\sigma_{1,\ldots\ldots}\delta_n\sigma_n)}{\lambda}, 0_{np\times 1} \\ 0_{n\times np}, \quad 0_{n\times 1} \\ 0_1 \times np, \qquad \epsilon \\ 0_{1\times n} \\ diag(1,2..p) \otimes \dfrac{diag(\delta_1\mu_1..\delta_n\mu_n)}{\tau}, 0_{np\times 1} \end{pmatrix} \tag{15}$$

Therefore, for the Gibbs algorithm we now have $y^*=[y, y_d]$ and $x^*=[x, x_d]$ and $T^* = T+T_d$

The algorithm then repeatedly iterates through the following steps;

Step 1:

$$\boldsymbol{B_{i+1}}|\boldsymbol{B_i}\ \boldsymbol{\Sigma_i}, \mathbf{x_{i_m}} \sim \mathbf{N}(\mathbf{B_i}, (\mathbf{x_i}'\mathbf{x_1})^{-1} \otimes \boldsymbol{\Sigma_i}) \tag{16}$$

Step 2:

$$\boldsymbol{\Sigma_{i+1}}|\boldsymbol{B_{i+1,}}\mathbf{y_m} \sim \mathbf{IG}(\mathbf{T^d}, \mathbf{e_i}) \tag{17}$$

Step 3:

$$\boldsymbol{y_{i+1_m}}|\boldsymbol{B_{i+1}}, \boldsymbol{\Sigma_{i+1}} \tag{18}$$

This asserts that in the first step, conditional on the variance and the current draw of our latent variables, we take a new draw of the parameter matrix from the normal distribution with a mean of the parameter matrix and variance from the previous iteration of the Gibbs sampler. At this step we take a rejection sampling approach, at each iteration, we check that the roots of the parameter matrix lie inside the unit circle if they do not we discard the current draw and keep the previous draw. Conditional on the new draw of the parameter matrix we draw the new variance/covariance matrix where $e_i = (y^*_{i,t_m} - B_{i+1}x^*_{i,t_m})'(y^*_{i,t_m} - B_{i+1}x^*_{i,t_m})$. Finally, given the new parameters and variance, we use the Carter and Kohn (1994) forward filter, backward smoothing algorithm to take a new draw for the missing monthly observations of the quarterly frequency variable. Note: The forward step is given in the Kalman filter equations (6) – (11), while the smoothing step is standard. We repeat this repeat these steps 20, 000 times and burn the first 10, 000 iterations.

For lag selection, we follow both Mariano and Murasawa (2004) and Schorfheide and Song (2015) and estimate the state space system with 1 lag. We re-estimate the parameters every quarter as the new quarterly observation becomes available. For this exercise, we are not interested in the density forecast, at the conclusion of the estimation, we take the mean of the saved draws. Then for each of the monthly forecasts, given the posterior mean and variance we pass the dataset through the filter/smoother algorithm to fill in the missing observations and project forward to the quarterly horizon.

3.4 Data

For the UK, the preliminary release of GDP generally occurs around 25 days after the end of the quarter, and is based on the output approach, which aggregates four broad sectors of the UK economy; Agriculture (approximately 0.7 per cent), production industries (approximately 15 per cent), services (approximately 80 per cent) and construction (approximately 5 per cent).

From these sectors we use the index of production, while given that services represent the majority of the economy, they would appear a useful series. However, for our purpose, the time series starts at the beginning of 1997 which we adjudge to be too short for this exercise. Furthermore, services are the least timely of the sectors of the output approach to GDP, the monthly series lags the quarterly release of GDP and its own quarterly series by one month. Secondly, the Index of Services is liable to large revisions both of which may lead it to be an unreliable indicator for real-time nowcasting purposes. As a result we use the retail sales index a timelier subcomponent of the IoS as a proxy for services; furthermore, the retail sales index also provides a timely indicator of consumption from the expenditure approach to GDP contributing around 1/3 to overall final consumption.

In order to capture labour market conditions, we use the growth rate of total claimants of the claimant count; we chose this rather than the rate to exclude the labour force effect, it should be expected that the growth of the raw series will exhibit greater variation than the rate. Furthermore, at the monthly frequency, the inertia present in the rate will lead to multicollinearity in variables for the MIDAS regressions. It must be noted that a downside of the total claimants rather than the rate is that it can be affected by government policies which directly affect the welfare structure. This may lead to growth rates which are not reflective of overall labour market conditions.

We provide a simple proxy of financial conditions by using the spread between the LIBOR and Base rate. The more accurate representation of this spread is the spread between the 3-month LIBOR – OIS, however, the time series here is relatively short. As a result the spread used will include short-run expectations over the path of policy, however, this effect is likely to be small.

Our final indicator is the Halifax ‘All buyers’ house price index, primarily as the house prices and the business cycle tend to comove and turning points tend to coincide (see OECD(2005). A further advantage to this indicator is the timely nature, generally released between 4 to 6 days from the end of the month.

The series are all seasonally adjusted and are final datasets, for the index of production, retail sales, claimant count and house price series, we use the monthly growth rates, while the end of period value is used for the LIBOR-Base rate spread. For the estimation period, the sample ranges between the April 1983 to December 2006, the evaluation period is then from January 2007 through to March 2015. Our quarterly series is the final release of the seasonally adjusted, chain volume measure of GDP transformed into quarterly growth rates.

As with any selection of indicators for a nowcasting exercise, there may be a number of others which have been excluded, which inclusion could be argued for. We provide a short argument as to why some more obvious choices have been excluded in favour of our preferred indicators. We exclude the monetary policy rate from our set of indicators for a number of reasons, firstly, it is often quoted that the transmission mechanism of monetary policy operates over ‘long and variable’ lags, it is thought to be around 12 – 18 months (for example see Wheeler (2015)). While, monetary policy is generally forward looking in its conduct, the onset of the great recession saw reactive rather than predictive monetary policy, which would likely reduce the accuracy of nowcasts of GDP. Finally, the period post the ‘great recession’ has been characterised by historically low interest rates and periods where the transmission mechanism has been impaired, and may not reflect economic conditions. For these reasons monetary policy is excluded.

Exchange rates and inflation also represent timely indicators which could be included. We exclude these in both cases for similar reasons, namely that the movement in these series may provide mixed information. As noted by Kirby and Meaning (2014), the pass-through of exchange rates to the general economy crucially depends on the underlying cause of the change, for example, a change in risk premia will be a quantitatively different response to a productivity shock especially so in the short run. With regards to inflation, whether the underlying causes of inflation are as a result of a shock to underlying supply, whereby GDP and inflation would be expected to diverge or, a demand shock whereby inflation and GDP would co-move. In both cases, the informational content is likely to be more relevant to longer forecasting horizons rather than shorter.

Often confidence indices, both business, and consumer are included, however as noted in Carroll, Fuhrer and Willcox (1994), such surveys when considered as the only available indicator, can improve economic forecasts but when a larger array of available indicators are included this disappears, a result mirrored in Howrey (2001). As noted by Angelini et al (2011), confidence indicators are most effective in the absence of hard data; such series may be the most applicable within factor based models.

3.5 Evaluation exercise

In order to test the ability of our 3 models ability to nowcast GDP, we compute out of sample forecasts from for the first quarter of 2007 through to the first quarter of 2015. We define the forecasts throughout the quarter as follows:

$$Q_t = M_1 + M_2 + M_3$$

The nowcast period starts after the release of the preliminary GDP, and the cutoff period for new data is the release of the Index of Production, which in general occurs around ten to fifteen days before the preliminary release of GDP. While the publication of the indicators, in reality, varies throughout time, we assume that data availability remains static throughout each month of our evaluation period. For our data set this means that at our cut-off date, three of our monthly series are available at M_{t-1}, the Index of production, claimant count, and retail sales. The other two series, the All buyers house price index and the LIBOR/Base rate spread are available at M_t, implying that by our final nowcast of the quarter, M_3, these are fully available. Through each month of the quarter and for each quarter throughout the evaluation period we maintain this structure of data availability to broadly mimic an unbalanced real-time dataset. With this, we compute a forecast for each of these months.

4. Results

Table 1 presents a set of descriptive statistics pertaining to the accuracy of each of the nowcasts as well as the Diebold and Mariano parametric tests for predictive accuracy (henceforth, DM; see Diebold and Mariano (1995)). The root mean square errors (RMSE) and mean absolute error (MAE) for each of the models are presented relative to a simple random walk model. Our final statistic is the mean directional average, which for each time period assigns a 1 where the directional change is correct and a 0 otherwise and then averages over the binary outcomes.

In the first month of the nowcasting period, the MAE and the RMSE for the MIDAS regressions are around 1 suggesting no improvement on the random walk model, whereas the MFVAR is has a relative RMSE of around 9 per cent and an MAE of 12 per cent lower than that of the RW model. In the second period, the two distance measures are around the same magnitude albeit the RMSE is slightly larger for MIDAS. The discrepancy between the two measures itself contains information, as larger forecast errors will have a greater effect on the RMSE. The abnormal growth profile of the ‘Great Recession’ period is likely to be the main cause of this deviation between the two statistics, which as a result Willmott and Matsura (2005), suggest that overall the MAE represents a more accurate description of predictive accuracy. However, the discrepancy between the MAE and the RMSE here suggests that the MFVAR captures the recessionary period better of the two models, although, figure 1 shows a more nuanced view of this. Both series miss the turning point from the peak and the trough, but the VAR captures the recovery slightly better. In the final month of the nowcasting period, there is a marginal improvement in the predictive accuracy in the MFVAR and a greater improvement in the performance of the MIDAS regressions. At this horizon the MIDAS regressions are the most accurate, furthermore, the discrepancy between the RMSE and the MAE have all but disappeared. As shown in the bottom of the panel, the paths of the two models are now reversed, the MIDAS regressions are now less volatile than before but however, do not capture the depth of the recession but perform well in the recovery phase. The VAR conversely, is closer to capturing the depth of the recession but lags the recovery phase.

The final row of table 1 presents the DM tests using the RMSE to calculate the loss differential between the errors from a random walk model and our candidate models. At the 3-month horizon, neither of the models is a statistically better predictor of GDP than a simple random walk model, with the MIDAS regressions performing slightly worse. This becomes statistically significant for the MFVAR at the 2-month horizon and for both at the 1-month horizon. The results between the MIDAS and the MFVAR somewhat mirrors that of Kuzin et al (2009), that the VAR is better than MIDAS over longer forecasting horizons, albeit in this instance, shorter than their findings.

The bridge equations perform the worst amongst the three models presented, exhibiting a larger RMSE than the random walk model for the first two months within the evaluation period, albeit not statistically significant according to the DM statistic. The MAE is around the same magnitude as the random walk, the divergence, as mentioned in the comparison of the other two models being the ability to capture the crisis period as illustrated in figure 1. The final period prediction improves markedly, and both statistics are in line with the relative magnitudes of the other two models. Furthermore, the gap in the gap between the two distance measure disappears, implying a marked improvement in the ability to predict the crisis period.

The final statistic is the mean directional average, for both the VAR and MIDAS models these improve consistently, from on average predicting the correct directional movement of GDP two-thirds of the time at the three-month horizon, to three-quarters at the one-month horizon. In contrast, the bridge equations have the highest accuracy of predicting the direction at the three-month horizon. Albeit, given the poor forecasting performance of the bridge at the three and two-month horizons, this may purely co-incidence rather than a meaningful ability to predict the direction of GDP. At the one-month horizon, the bridge still performs worse than the other two models correctly predicting the direction two-thirds of the time.

Given that forecast accuracy is unlikely to be static, in the spirit of Giancomini and Rossi (2010), we look at the relative performance of the models over the evaluation period. We calculate a form of fluctuation statistic, by computing the relative MAE between candidate models over a rolling centred 5 quarter period. Where the statistic falls below 0, this indicates that for that period the candidate model improves over the benchmark. Figure 2 presents these for each of the three nowcasting models against each other, while figure 3 plots the models against the random walk to facilitate a more meaningful comparison.

Over the shortest forecast horizon, the ability of the models is similar, as suggested in table 1. Against the VAR, the MIDAS regressions perform better over the earlier part of the evaluation period, including the crisis period, after which the VAR performs slightly better. As shown in figure 2, these are marginal differences between the two forecasts. At the end of the evaluation period, there is a sharp increase relative accuracy of the MIDAS regressions, which corresponds to two quarters where the MIDAS regressions accurately predict GDP, whereas the VAR manages to get the direction but not the magnitude of the change. The story of MIDAS and the Bridge is broadly similar, however without such a dramatic increase in the relative accuracy of MIDAS. While the VAR performs reasonably well over the ‘Great Recession’ period, the volatile period of growth around the middle of 2012 is captured better by the single equation models.

In comparison with the random walk, an interesting feature is at the end of the evaluation period, for the longest forecasting horizon, against the random walk all three of the models perform badly. The primary cause of this is as a result of a sharp contraction in the total number of claimants of the claimant count, which corresponds to a contractionary fiscal policy period associated with the coalition government. During this period the claimant count rate is a better indicator of labour market conditions, as not all of the contraction seen in the number of claimants is indicative of economic activity and therefore not all of this fall would be transferred through to the labour market. This is illustrated in figure 4, which repeats the nowcast evaluation with the claimant count rate rather than the number of claimants. We present the final horizon period only as the differences between the two nowcasts are consistent across each horizon. As can be seen for the majority of the period there is little difference between the two sets of nowcasts, however toward the end of the evaluation period, for each of the models, the predictions are consistently closer to the outturns. The tradeoff here is, though; the magnitude of the ‘Great Recession’ period is less accurately forecast. Highlighting, as Castle et al (2013) note, the importance of identifying and dealing with structural shifts in indicators, and secondly as Schumacher (2014) identifies, the general importance of the indicators chosen.

It’s possible that the simple method of model selection employed in estimation could be the cause of the poor performance of the bridge equation. In order to investigate this, we create a set of ‘post hoc’ forecasts using the bridge methodology. To construct the three auxiliary examples we compare the outturn with the different combinations of lags and select the closest as our forecast, of which there are 3 combinations, the best possible result we could gain from the bridge equation is selecting the closest forecast from all combinations of both steps of the bridge. The two intermediate examples allow the either the AR parts or the main to be chosen by the BIC as in our pseudo real-time implementation while setting the other to the lowest absolute deviation from the realised outturn.

Obviously, these cannot be considered real nowcasts and furthermore the greater the number of possible combinations, the greater likelihood that there exists a combination of lags that encompasses the data outturn. However, these provide an interesting lens through which to view the possibilities of the bridge equations. The results for these synthetic nowcasts are presented in table 2, by construction these nowcasts will be more accurate than the real time examples. Interestingly like the real time example, there is no noticeable improvement in the predictive accuracy when moving from a forecast horizon of three and two months, suggesting there is a little informational gain at these horizons, this is in line with the findings of Angelini et al (2011). While, as with the real time example there a sharp improvement at the shortest forecast horizon. In each of the forecast horizons there still exists a discrepancy between the MAE and the RMSE given the combinations implied by the dataset, and maximum lag lengths the Bridge equations are not best suited to capturing periods of sharp contraction. We make no attempt here to comment on whether a more comprehensive model selection scheme such as the auto-metrics methodology of Hendry and Krolzig (2005) or modelling averaging methods such as forecast pooling (for example see Schumacher (2014)) could achieve these levels of predictive accuracy, it does at least hint at the limitations of Bridge equations.

5. Conclusion

In this paper, we assessed the ability of three simple nowcasting models at extracting the information from a small subset of timely economic indicators. On average across all horizons, the bridge methodology performed the worst and that until the closest forecasting horizons informational content of the nowcasts did not improve. While our relatively simple model selection method may have led a reduced predictive power in comparison to more sophisticated model selection schemes. Nonetheless, two points can be drawn for the Bridge equations; firstly at forecast horizons greater than one month, there is little informational gain. Secondly, the Bridge equations seem less able to predict severe contractionary periods, however, they perform with close predictive accuracy to the other two approaches.

The predictive power of the MIDAS and MFVAR methodologies improved throughout the forecast period, the MFVAR provided the most consistent of the methodologies improving on the random walk across all forecasting horizons, while the MIDAS methodology provided the best short term forecasts In terms of directional accuracy, both methodologies were equivalent over our sample.

Across the evaluation period, the accuracy of the models varied with the VAR providing a better a slightly better accuracy of the ‘great recession’ period compared with the MIDAS regressions, especially at the two and three-month forecast horizons. Although there was some evidence that the MIDAS equations, especially at the shortest forecast horizon are more likely to capture general volatility of GDP. For practical purposes both of these models could be used in tandem to inform short-term GDP forecasts, the MFVAR over longer horizons and MIDAS at the shortest horizons.

At the closet forecast horizon all three nowcasting methodologies over predicted growth rates, this was caused by the use of the total number of claimants as a labour market indicator rather than the rate. Although a trade off with using the latter series is a reduction in ability to capture the ‘great recession’. This highlights the important for a nowcaster in being able to identify and deal with structural changes in underlying data series. This particular case possibly suggests that using factor methods which incorporate allow for the use of wider range of information could be useful.

Finally, in this example, the largest component of the output approach to GDP, the index of services was excluded, this contributes around 80 per cent of the preliminary release of GDP. While this series is likely to extremely important for live nowcasting UK GDP, it represents a challenging series to include. Firstly as the revisions to this series can be relatively large and secondly the monthly series is the least timely of the components of preliminary GDP.

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Table1: Relative distance measures compared with Random Walk

	Bridge			MF VAR			MIDAS		
Horizon	3	2	1	3	2	1	3	2	1
MAE	1.00	0.98	0.72	0.88	0.74	0.70	0.97	0.73	0.66
RMSE	1.30	1.26	0.74	0.91	0.71	0.69	1.04	0.75	0.67
MDA	0.69	0.64	0.67	0.64	0.70	0.76	0.64	0.70	0.76
DM-		-					-		
test	-0.90	0.85	1.79	1.02	2.07	2.36	0.30	1.50	2.11

Note: A number smaller than 1 indicates an improvement on the random walk model. A positive Diebold and Mariano statistic indicates that the mixed frequency models improve on the random walk, the 5 per cent significance level is given by 1.96.

Table 2: Comparison of Real-time bridge equations against post hoc evaluations

	Real-time			Post Hoc Both			Post-Hoc AR			Post-Hoc Main		
Horizon	3	2	1	3	2	1	3	2	1	3	2	1
MAE	1.00	0.98	0.72	0.60	0.62	0.41	0.86	0.88	0.72	0.73	0.72	0.40
RMSE	1.30	1.26	0.74	0.96	0.96	0.51	1.10	1.11	0.74	1.15	1.09	0.50
DM-	-	-					-	-		-	-	
test	0.90	0.85	1.79	0.15	0.15	3.14	0.36	0.41	1.81	0.47	0.33	3.16

Note: The RMSE and MAE presented are relative to a random walk. A number smaller than 1 indicates an improvement on the random walk model. A positive Diebold and Mariano statistic indicates that the mixed frequency models improve on the random walk, the 5 per cent significance level is given by 1.96.

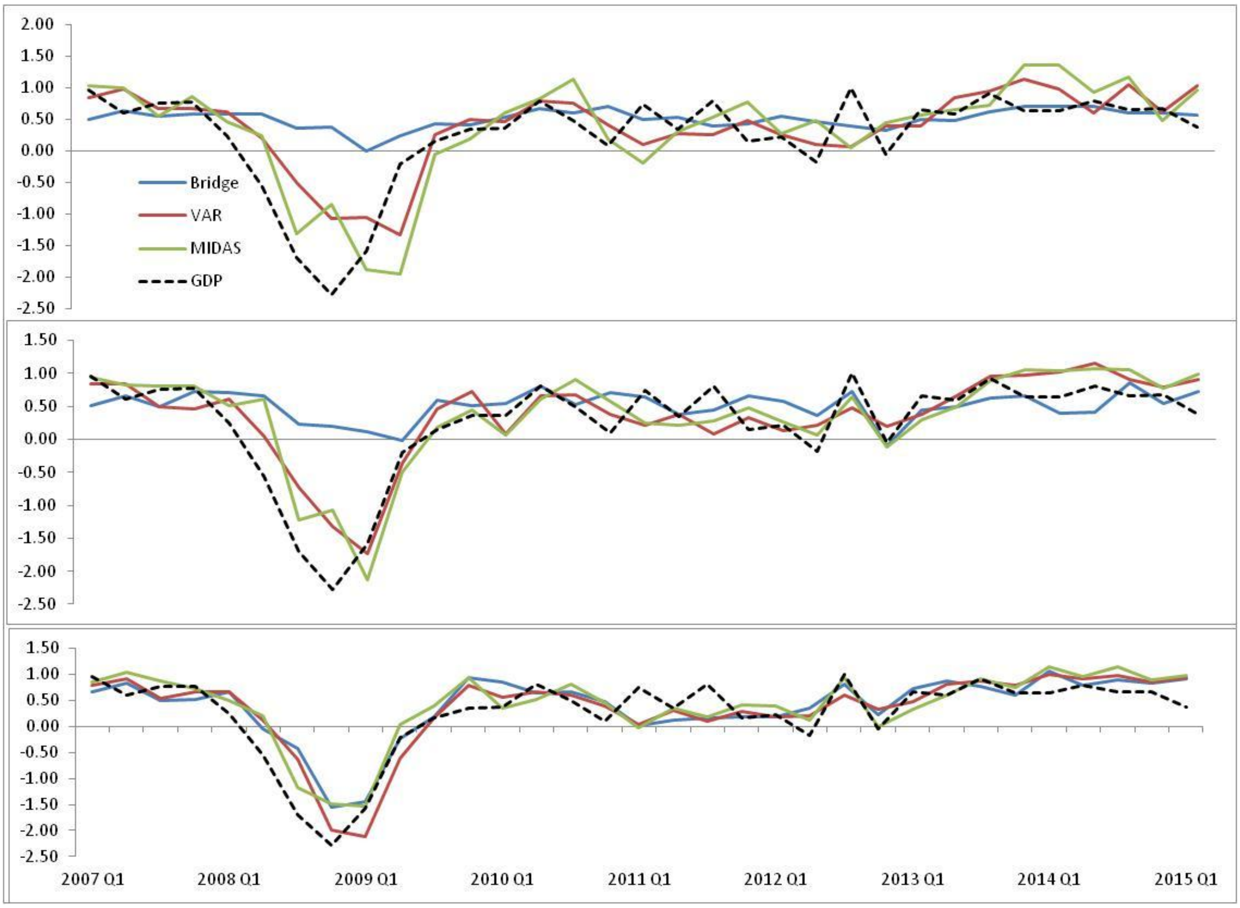

Figure 1: Quarterly nowcasts and quarterly GDP growth, from top to bottom; month 1, month 2 and month 3

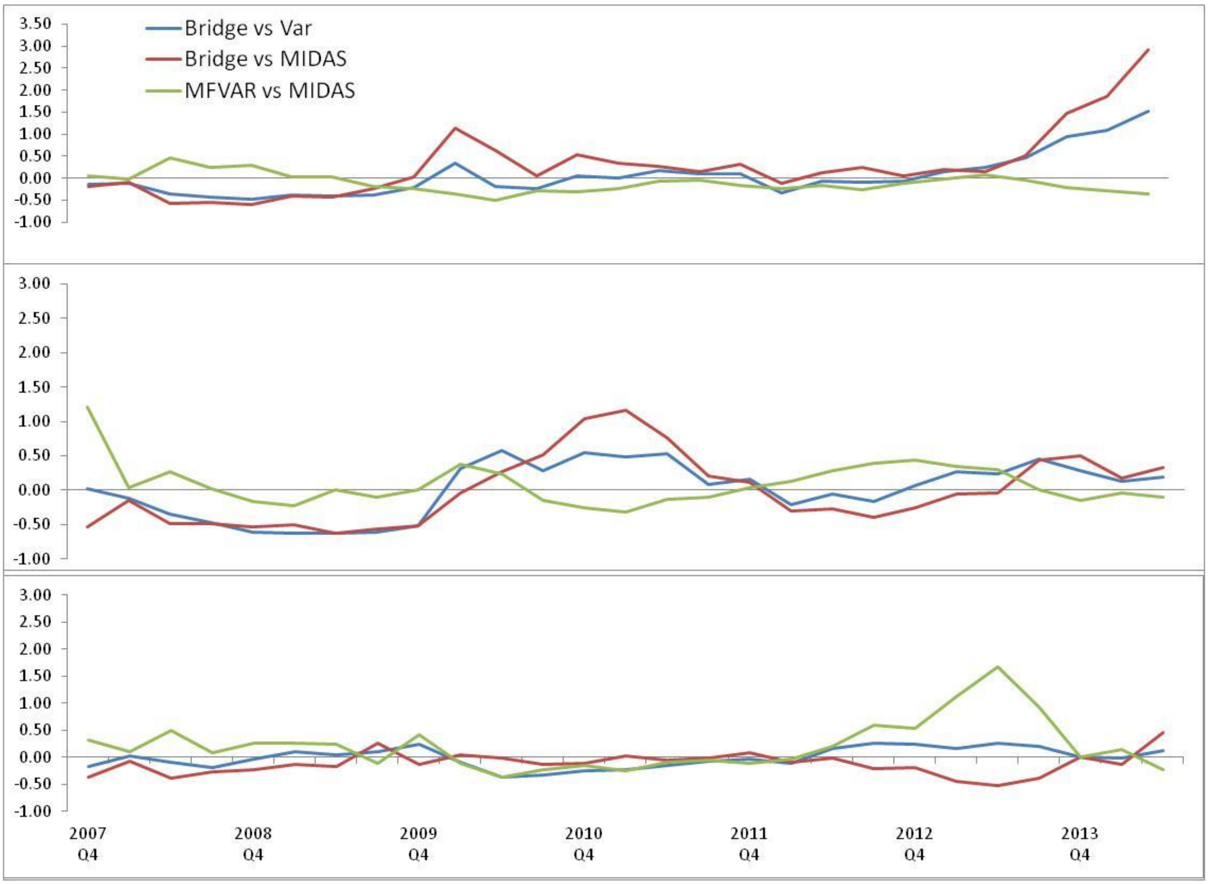

Figure 2: Fluctuation statistics, from top to bottom: Month 1, month 2 and ‘’’month 3 . A number greater than 0 represents greater accuracy of the nowcasts for the first model against the second, i.e. Bridge is more accurate than the VAR

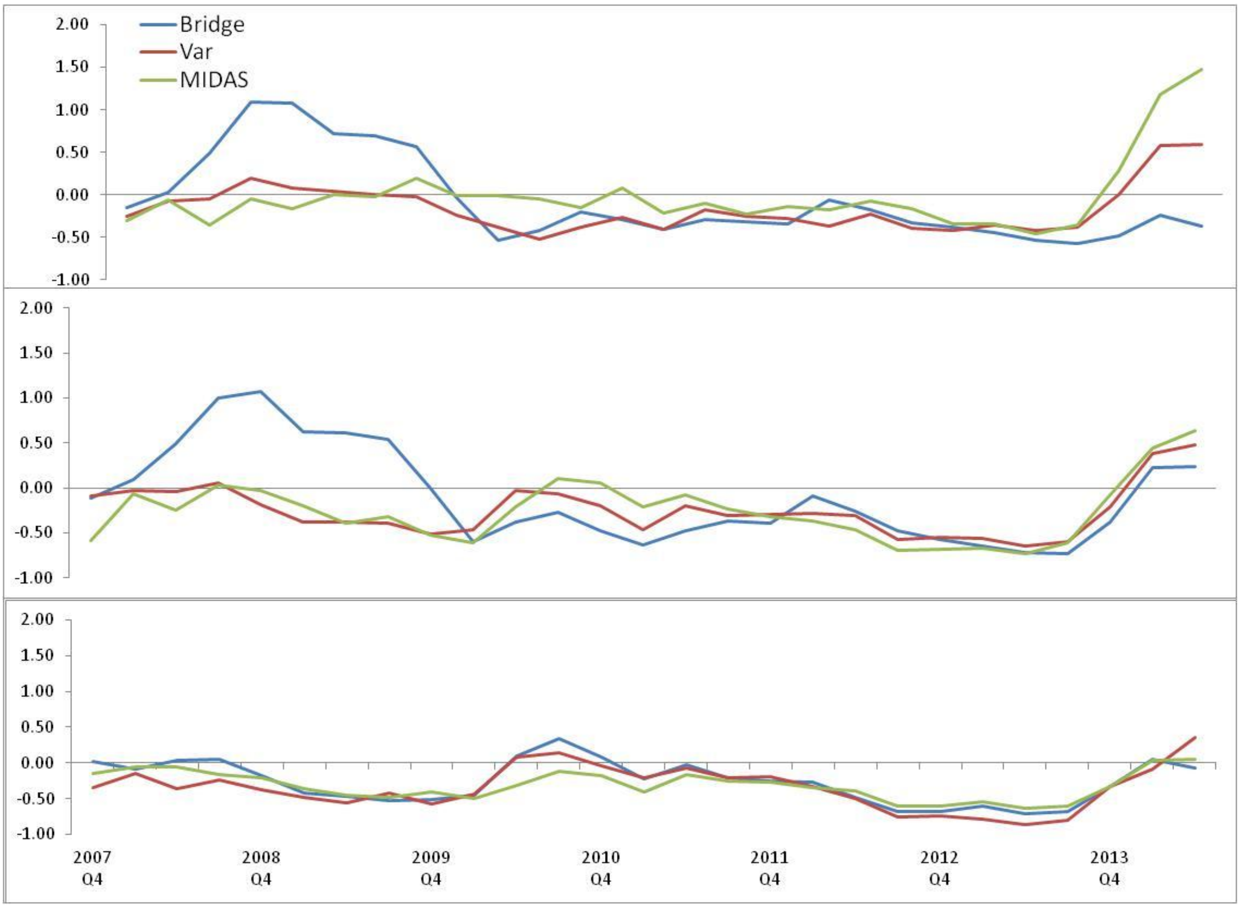

Chart 3: Fluctuation statistics against a Random walk, from top to bottom: Month 1, month 2 and month 3. A number greater than 0 indicates that the random walk was more accurate.

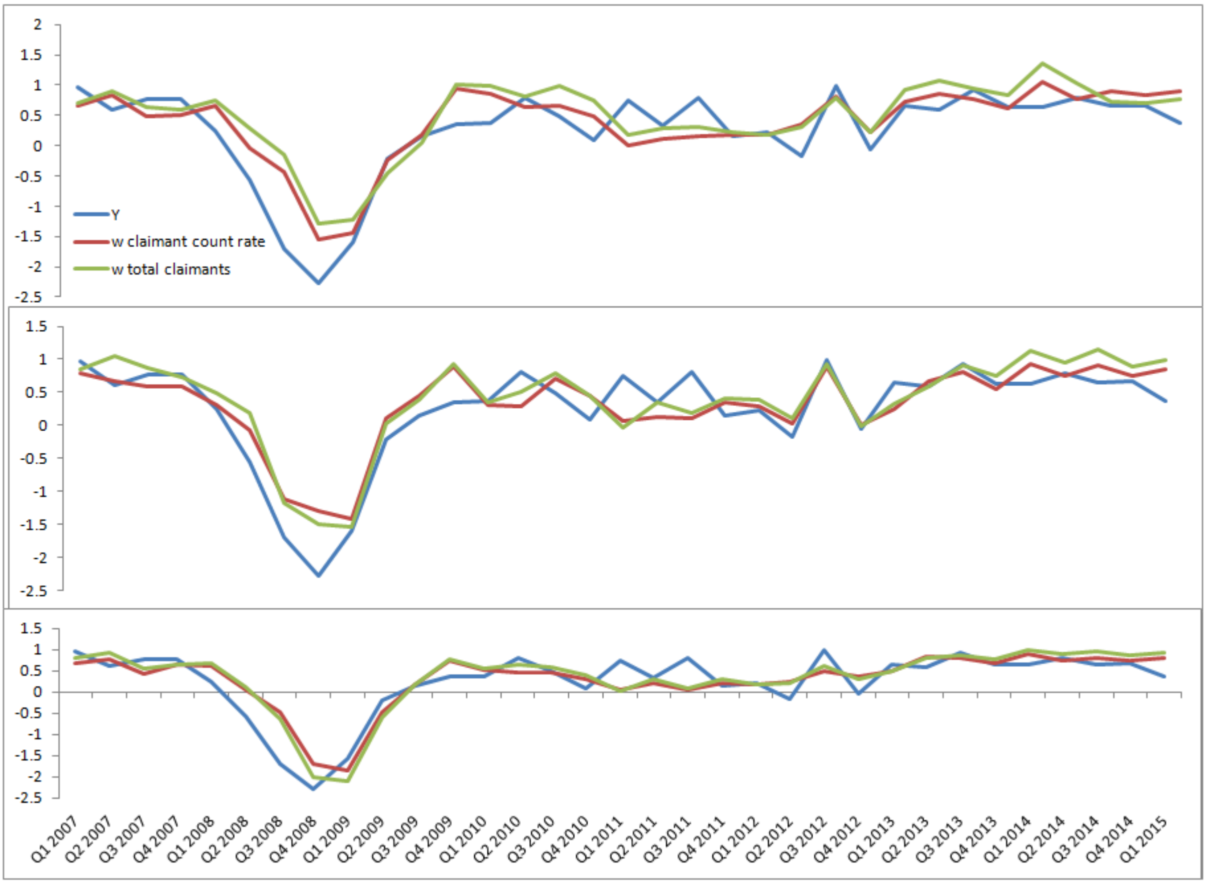

Chart 4: Comparison between 1 month ahead forecasts for each model with the claimant count rate and total number of claimants

Mixed Frequency VARs with Factors: An application to the US and the UK

James Warren[2]

20th March 2016Abstract:

In this paper, we apply the factor-augmented VAR of Bernanke, Boivin and Eliasz (2005) in the context of mixed frequencies for a US and a UK dataset. For the US we further extend the model to allow for regime switching dynamics, we compare the short-term predictive ability of the two models against the standard Mixed Frequency VAR of Murasawa and Mariano (2004, 2010). We find that in general, the MFVAR with factors performs slightly worse than the standard MFVAR for the US dataset, marginally so for forecast horizons greater than one and significantly worse at the single period ahead forecast. This result was broadly consistent for the UK dataset, except at the FAMFVAR performed slightly better at the single period ahead horizon. The Markov switching extension was the worst performing of all of the models. Studying the filtered probabilities for the recessionary regime indicated that only the deeper of the recessions were captured. Further work on dealing with the label switching problem may be required for better performance for the Bayesian treatment of MFVARs with regime switches.

JEL classifications: C11 C32 E17

Keywords: Forecasting, mixed frequency data, MFVAR, factor models, Markov switching

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1. Introduction

State space methods provide a natural way of dealing with ragged edge data which are inherent in nowcasting problems. With improvements in computational power and econometric methods, such approaches are now feasible and commonly employed. In this paper, we focus on the variants of one such approach, the mixed frequency VAR methodology of Mariano and Murasawa (2004, 2010). We compare the standard VAR with the factor based approach of Bernanke, Eliasz and Boivin (2005), in order to observe whether or not the inclusion of large datasets, which are condensed into a small number of unobservable common components can provide an improvement in the predictive accuracy of short-term forecasts. We further extend each of the VARs to include regime switching dynamics, the approaches are compared across two datasets, the US which has a large amount of timely monthly data series and the UK which has fewer and less timely information available.

There are two main nowcasting methodologies associated with state space systems, firstly, dynamic factor models, which commonly link (often a large) a number of observable indicators with a small number of unobservable latent variables. Factor models can be used to forecast GDP in the form of a bridge equation generally embedded within the state space structure, (see for example, Gianonne, Reichlin and Small (2008)), or to use a group of factor models to forecast the components of demand and aggregate upwards, for example the GDPNow model (Higgins 2014) used by the Federal Reserve Bank of Atlanta.

The other alternative approach is to forecast using a mixed frequency vector autoregression, in which a smaller subset of economic indicators is included, the Kalman filter is then used to interpolate the missing variables given a temporal aggregation scheme. An initial application of the MFVAR was from Mariano and Murasawa (2004), who use a small group of monthly indicators alongside GDP and create a single factor which represents a composite coincident index for activity. A practical nowcasting implementation of this model was employed by Schorheide and Song (2013), who use Bayesian methods to estimate and a larger subset of variables, to predict the level of GDP, an augmented version of this model is used by the Federal Reserve Bank of Minneapolis.

Both approaches are similar in their execution, the Kalman filter, and an intertemporal aggregation function is used to interpolate the missing values for the lower frequency variable, and given the state space structure, missing data, due to the information flow at any given time is forecast within the system of equations. This contrasts with the single equation approaches such as MIDAS regressions (see for example Ghysels, E., Sinko, A. and Valkanov, R. (2007)), where each new information point represents a new forecast equation, or standard bridge equations (see for example Schumacher (2009)) where missing data is dealt with by forecasting to the quarterly horizon.

A suggested advantage of factor models, however, is that by extracting the common component from a large number of economic indicators, the idiosyncratic or noisy movements are discarded and just the unobservable drivers of the economy are captured in a parsimonious way. As a result, the data dilemma for the econometrician is somewhat reduced. Conversely, the VAR methodology has been used widely in general forecasting applications. Compared to factor based methods the VAR is less parsimonious, with the inclusion of new variables size of the parameter matrix increases by N^2, therefore placing an upper limit on the number of parameters which can be included. Albeit, an approach to ameliorate the curse of dimensionality for the VAR not considered in this application exploits, Bayesian shrinkage (see for example Banbura et al (2010) Koop (2013)), therefore allowing the inclusion of a larger number of indicators, at the cost of the prior distribution becoming increasingly important for the determination of the parameter values. For policy makers and private institutions, which may be required to explain the changes in the nowcast as a result of new information, the transparency is likely to be preferable. Secondly, the idiosyncratic movements which are filtered from the unobservable factors may themselves be important for predictive accuracy.

The inclusion of regime switching dynamics provides a second area of interest, whether or not nowcasting methods can identify in advance recessions. Within the MFVAR literature, this has previously been applied using state space methods by Foroni et al (2015), estimated by using the EM algorithm and Viefers (2011) using Bayesian methods. In this paper we follow the latter approach, we note that as with single frequency Bayesian Markov Switching models careful consideration to solving the label switching problem remains the key difficulty in their implementation.

Finally, the comparison between two data sets provides an interesting contrast; the US is commonly used in comparisons of nowcast models. Given the data availability from both the output and expenditure approaches to GDP, the length of time series available and the timeliness of the data which is generally released within four to five weeks after the conclusion of the month, it constitutes a best case scenario. The UK conversely provides a larger number of challenges for nowcasting models, many of the relevant time series are available only from 1997, data from the components of GDP are available only from the output approach and the data is less timely. The most important component of the output approach to GDP, the index of services, which contributes around 80 per cent to the overall aggregate, is released with up to almost a 3-month lag. In fact, the preliminary release of GDP occurs before the full quarter for monthly services has been released.

We find that in general the FAVAR and the MFVAR have comparable performance, with the standard VAR being slightly more accurate up to three-month horizons. The MSVAR was the worst performing model, in accuracy. Checking the probabilities of being in the recessionary regime, over the whole sample showed that model was only identifying the deeper of the recessions. We suggest revisiting the approach to dealing with the label switching problem may help with improving the MS variant of the mixed frequency VAR

The paper is split into the following sections, section two comprises of a literature review providing a brief overview factor and VAR-based nowcasting methods, and section three describes the methodology for the regime switching FAVAR. Section 4 presents the results and section 5 concludes and suggests further directions for research.

2. Literature review

Vector autoregressions were introduced to the field of economics by Sims (1980), as a way to simultaneously describe the dynamics of a variety of time series without the imposition of spurious *a priori* restrictions common to the large-scale structural economic models of the era. Given the structure of VARs, the initial applications were constrained by the number of variables which could be included, as the number of parameters increased by N^2 for each extra variable. As such, initial applications were implemented over small subsets of data and therefore not ideal for forecasting purposes. An important contribution to making VARs suitable for forecasting was Littermann (1986), who, imposed Bayesian priors to enforce parameter shrinkage, thus allowing the inclusion of a larger number of variables, subsequently, VARs have become a commonly used tool in forecasting and economic inference.

The MFVAR is an extension of the standard VAR, while applications of this VAR are relatively recent, the initial approach can be traced back to Zardozny (1988), who proposed a method to directly estimate the parameters of a VARMA model in the presence of different frequencies. The initial application to business cycles was by Mariano and Murasawa (2004, 2010), who used a small number of important economic indicators to cast GDP into a single factor to create a composite coincident indicator representing activity. They estimated the parameters of the model via an adjusted version of the expectation maximisation algorithm in order to deal with the missing variables. Kuzin, Marcellino and Schumacher (2009) apply the same methodology to a nowcasting comparison with a simple single equation approach in form of mixed data sampling regressions (MIDAS, Ghysels, E., Sinko, A. and Valkanov, R. (2007)),) for the Euro Area. They found that the two methodologies were complements of each other, that the VAR was a better forecaster at longer horizons whereas the MIDAS regressions have better predictive accuracy at the shorter horizons.

A Bayesian treatment of the MFVAR is provided by Schorfheide and Song (2015), who impose a Minnesota prior (Littermann (1986)) and estimate the parameters of the model on the level of all variables included. They find results converse to those of Kuzin et al (2009), in that the VAR outperforms that of an unrestricted MIDAS regression. It is worth applying a caveat to the previous result, as the forecast comparison is performed over a much smaller subset of variables than is included in the main component of the paper.

While the literature remains relatively new, there have been a number of extensions to the standard MFVAR. Foroni, Guerin and Marcellino (2015) extend the mixed frequency VAR to include regime shifts, estimated using maximum likelihood methods via the expectation maximisation algorithm. As a result, their implementation requires that the Kalman and Hamilton filters are approximated at each time period following Kim and Nelson (1998) in order to avoid the rapid proliferation of states through the iterative process. They compare the MFVAR with regime switches to a number of alternative models, with and without switching dynamics for the Euro Area. They find that in terms of predictive accuracy the MSVAR performs poorly, however as an indicator of the state of the business cycle it performs relatively well.

A Bayesian algorithm for the MFVAR with switching is developed by Viefers (2011), who assesses the ability of the VAR to capture movements between regimes both on a Monte Carlo data set and an application to the US. They find that the model performs reasonably well. Viefers (2011) however notes that the label switching problem, inherent in the Bayesian treatment of mixture models must be dealt with in an appropriate way.

Gotz and Hausenberger (2015), extend the MFVAR to include time-varying parameters, by splitting the estimation into two steps, the first which deals with the missing observations, in the same manner as that of Schorfheide and Song (2015) and the second which then deals with the time variation. They find an improvement in the predictive accuracy over the standard MFVAR even in the presence of minor parameter instabilities.

While, the approaches mentioned above all focus on the state space implementation of the MFVAR, an alternative is to approach it as a stacked (or blocked) regression (Eraker et al 2011). This approach is akin to a VAR-based approach of the single equation MIDAS regressions. The monthly indicator variables are transformed into the same frequency as the low-frequency variable by splitting them into three separate variables dependent on the month they correspond to. The main advantage of such an approach is that estimation via the state space can be avoided; however, this is also less parsimonious than the state space representation. Furthermore, when forecasting using such models, each new data point represents a new model and therefore the VAR must be re-estimated. Secondly, the forecasting approaches differ, the standard MFVAR forecasts via iterative methods whereas forecasts from the stacked VAR are computed as an h-step ahead forecast. Foroni et al (2015), find in their application of the MFVAR with regime switching that the blocked equation performs significantly worse in the identification of the the business cycle.

An alternative approach to forecasting macroeconomic variables is the dynamic factor models, first developed by Geweke (1977) and Sargent and Sims (1977). The underlying assumption of such models is that a large number of macroeconomic variables are driven by a small number of common factors and idiosyncratic shocks. The latter authors showed empirically that a large proportion of activity and inflation could be described by just two factors. By condensing down the dataset into a smaller subset of variables, dynamic factor models remain parsimonious but can still claim to exploit information from larger datasets than those available to standard VARs.

There are now a large number of empirical applications using factors for forecasting a large number of macroeconomic time series simultaneously. In general the estimation of DFMs can be split into three approaches, Stock and Watson (2002) used static principal components to estimate a dynamic factor model with up to 215 variables, they found that the forecasts from large scale models improved over a variety of benchmark models including small VARs, in the prediction of real and nominal variables over a variety of forecast horizons. Forni, Hallin, Lippi and Reichlin (2001), find such a similar result for the Euro Area while estimating a DFM with dynamic principal components. Finally, Kapetenaios and Marcellino (2004), use a subspace algorithm, where the factors are estimates of linear combinations of the contemporaneous lags and leads, and find comparable accuracy to the previous two methods.

Given the noisy nature and sometimes large information sets available with monthly economic indicators, it is perhaps unsurprising that the DFM methodology has been embraced in nowcasting methodologies. A common approach to the prediction of GDP of short forecasting horizons is to estimate dynamic factor models which are then used as inputs into a bridge equation, with both the bridge onto output and the dynamic factor model cast into a state space system. This can then be estimated either via the two-step procedure of Gianonne, Reichlin and Small (2008) whereby the factors are derived by using principal components. The Kalman filter/smoother is then applied to the entire dataset to re-estimate the factors over the unbalanced panel; or more efficiently in a single step using the expectation maximisation algorithm as with Doz, Giannone, and Reichlin (2012). Gianonne, Reichlin and Small (2008), apply the dynamic factor bridge to a large scale US dataset and find that as new information is released there is an improvement in the accuracy of the prediction of the nowcast. This has been further replicated for a large number of countries (for example, see Bessec and Doz (2014) for France, Marcellino and Schumacher (2010) for Germany, D'Agostino, McQuinn and O'Brien (2008) for Ireland).

In a similar but distinct approach, Higgins (2014) employs a set of dynamic factor models in order to predict the components of the expenditure approach to GDP. He then uses to aggregate to a GDP prediction given the weightings of the components within the overall aggregate. As with the DFM bridge models, he also finds that the new release of information consistently improves the predictions.

Camacho, Perez-Quiroz and Poncela (2012) extend the DFM-bridge nowcasting approach by adding Markov switching dynamics using the EM algorithm. They note that without approximation, given the intertemporal aggregation function used in Mariano and Murasawa (2004, 2010) the number of states required to be tracked by the Hamilton filter, expands dramatically. They suggest approximating the process by only computing the filtered probabilities over the observables at any time t, that the DFM with Markov switching performs reasonably well in tracking the business cycle for the US.

While not used for in applications of nowcasting, an important extension of the dynamic factor models is the Factor-Augmented VAR methodology of Bernanke, Boivin and Eliaz (2005). In their application, they estimated a VAR model with the interest rate alongside two factors interpreted as economic activity and prices. Their motivation was to improve the ability to draw inference from impulse responses to a monetary policy shock. However, variants of the FAVAR have been used in forecasting, including time varying parameters (see Eickmeier, Lemke and Marcellino (2015)), and factor error correction models (see, Banajee, Marcellino and Masten (2009) amongst others, all of which tend to improve on their non-factor counterparts.

In general, DFMs perform well in forecasting environment, however as noted by Eickmeier and Ziegler (2006), there tends to be a variety in the performance across countries and over the relative methods used. However, while not applied in this paper an alternative approach to handling large datasets in VAR form is to rely on Bayesian shrinkage, Banbura et al (2010), provide an example in extremis, they include up to 130 variables in a VAR and show that there is a general improvement in forecasting accuracy when compared to a small monetary VAR. Koop (2010) finds that generally, across different prior choices, a VAR of around 20 variables provides the best predictive accuracy after which additional variables only leads to marginal gains or a reduction in forecast accuracy. However, they find that large BVARs nonetheless tend to outperform factor based methods.

3. Methodology

3.1 Model and Estimation methodology

In this section we present the structure and estimation methodology for the Markov Switching, factor augmented VAR, noting that the alternative methodologies employed, evolve a subset of the algorithm described. The MSVAR comprises of a dynamic system of equations given by the following;

$$\begin{pmatrix} \boldsymbol{M_t} \\ \boldsymbol{Y_t} \end{pmatrix} = \boldsymbol{B}(\boldsymbol{L})_{\boldsymbol{S_t}} \begin{pmatrix} \boldsymbol{M_{t-1}} \\ \boldsymbol{Y_{t-1}} \end{pmatrix} + \boldsymbol{\varepsilon_t} \tag{1}$$

$$\boldsymbol{X_t} = \boldsymbol{\Lambda}^{\boldsymbol{M}} \boldsymbol{M_t} + \boldsymbol{\Lambda}^{\mathbf{Y}} \mathbf{Y_t} + \mathbf{v_t} \tag{2}$$

Equation (1) describes the transition equations, where B is a conformable lag polynomial of finite order p, Y is a vector of variables observed at the quarterly frequency but specified at the monthly frequency. M is a vector of K unobservable factors. The error term is given by the following moments $\varepsilon \sim N(0, Q)$, and S_t is an unobservable state variable which evolves according to a first order Markov process with transition probabilities $\Pr[S_t = J \mid S_{t-1} = I] = p_{ij}$ for i,j = 1,2. The measurement equation (2), describes how the observable indicators relate to the unobservable factors, Λ^M and Λ^Y are factor loadings with dimensions $N \times K$ and $N \times 1$, the idiosyncratic error term v_t has mean zero. We generate the factor loadings by the two step procedure described by Bernanke, Boivin and Eliasz (2005), which involves calculating by principal components; they note that as the loadings are generated via the observation equation only, they are econometrically unidentified, and therefore we apply a normalisation in the form of C'C/T.

We estimate the model via Bayesian methods, using a Gibbs sampler. We implement the priors in the same manner as Banbura et al (2010) who suggest creating a set of dummy observations which reflect the moments of a Minnesota prior. We apply the same priors to each of the regimes, i.e. we do not *a priori* assume different priors to reflect different regimes, as noted later this creates some complications in estimation.

$$\boldsymbol{y_d} = \begin{pmatrix} \boldsymbol{diag(\delta_1\sigma_{1,\ldots\ldots}\delta_n\sigma_n)/\lambda} \\ \boldsymbol{0_{n\times p}} \\ \boldsymbol{diag(\delta_1 \ldots\ldots \delta_n)} \\ \boldsymbol{0_{1\times n}} \\ \boldsymbol{diag(\delta_1\mu_1 \ldots\ldots \delta_n\mu_n)/\tau} \end{pmatrix} \tag{3}$$

$$\boldsymbol{x_d} = \begin{pmatrix} \boldsymbol{diag(1,2..p)} \otimes \dfrac{\boldsymbol{diag(\delta_1\sigma_{1,\ldots\ldots}\delta_n\sigma_n)}}{\boldsymbol{\lambda}}, \boldsymbol{0_{np\times 1}} \\ \boldsymbol{0_{n\times np}}, \quad \boldsymbol{0_{n\times 1}} \\ \boldsymbol{0_1 \times np}, \qquad \boldsymbol{\epsilon} \\ \boldsymbol{0_{1\times n}} \\ \boldsymbol{diag(1,2..p)} \otimes \dfrac{\boldsymbol{diag(\delta_1\mu_1..\delta_n\mu_n)}}{\boldsymbol{\tau}}, \boldsymbol{0_{np\times 1}} \end{pmatrix} \tag{4}$$

We set the priors to standard values from the literature as described by Canova (2007). The hyperparameter λ, which controls the tightness of the prior is set to 0.2; τ which determines the shrinkage applied to the sum of the coefficients, where, the smaller the value the greater the shrinkage, following Banbura et al (2010) we set the value of this to 10 λ. The hyperparameter ϵ is the prior for the constant, we set this to 1/1000, this represents an uninformative prior. Finally, the values of $\delta_1 \ldots\ldots \delta_n$ are set to the values of AR (1) coefficients estimates from single equation regressions for each of the variables in the VAR.

We largely follow the outline suggested by Viefers (2011), our Gibbs sampling algorithm subsequently cycles through the following steps:

Step 1: Draw the missing observations and the factors: Y_t and M_t | S_{t-1}, p, q, $B_{s=i}$, $B_{s=j}$, $Q_{=i}$, $Q_{=j}$

As noted in Kim and Nelson (1998), as the Gibbs sampling Bayesian implementation of Markov switching models samples from the joint conditional probabilities, the system of equations collapses a simple set independent linear regressions, where S_t acts as a dummy variable. As a result, unlike frequentists applications, approximations to the Kalman filter in order to stop the proliferation of the number of states is not required. Furthermore, as noted by Frühwirth-Schatter (2001), for each possible labeling scheme the interpolated series from the Kalman filter is equivalent. Therefore, the filter/smoother algorithm takes the standard for as described by Carter and Kohn (1994), however, one change is applied in order to deal with the missing quarterly observations. Mariano and Murasawa (2004, 2010) suggest that the missing quarterly observations can be replaced with draws from a normal distribution which are independent of the parameters of the models.

However, in practice this is unnecessary, practical approaches adjust the measurement equation so that these missing observations are either ignored or excluded. Angelini et al (2011) implement the former option, in the months not corresponding to a quarter; they set the variance of the measurement equation to infinity so that the observed value is ignored in the updating step. Schorfheide and Song (2015) and Mariano and Murasawa (2004, 2010), adjust the size of the observable vector and the loading matrix of the measurement equation, to the same effect. Here, we follow the latter approach, as such the measurement equation takes the following form;

$$\boldsymbol{\eta_{t|t-1} = y_t - H_t x_{t|t-1}} \tag{5}$$

$$\boldsymbol{where, H_t} \begin{cases} \boldsymbol{if\ m = 3} \begin{pmatrix} \boldsymbol{\Lambda^f} & \boldsymbol{\Lambda^y} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{1} & \boldsymbol{0} & \boldsymbol{1} & \boldsymbol{0} & \boldsymbol{1} \end{pmatrix} \\ \boldsymbol{else}, (\boldsymbol{\Lambda^f} \quad \boldsymbol{\Lambda^y}) \end{cases} \tag{6}$$

Where for the month that corresponds with the quarter we temporally aggregate the monthly predictions by summing growth rates across the quarter.

Step 2: Sampling the states, S_t|, p, q, $B_{s=i}$, $B_{s=j}$, $Q_{=i}$, $Q_{=j}$, Y_t and M_t

We follow Kim and Nelson (1998), given the joint density:

$$\boldsymbol{f(S_T|y_t) = \prod_{t=1}^{T-1} (S_T|S_{t+1}, y_t)} \tag{7}$$

$f(S_T|y_t)$, t = 1, 2,.....T, is calculated from the final iteration of the Hamilton filter, where the output from step one is treated as data. Then S_t is calculated conditional on y, they show that g$(S_T|S_{t+1}, y_t)$α g(S_{t+1}|S_t)g(S_t|y_t) where g(S_{t+1}|S_t) is the transition probability, using this we calculate the probability of being in state 1, as the following.

$$\mathbf{Pr}[\boldsymbol{S_{t=1}}|\boldsymbol{S_{t+1}}, \boldsymbol{y_t}] = \frac{\mathbf{g(St + 1|St = 1)g(S_t = 1|y_t)}}{\sum_{j=0}^{1} \mathbf{g(St + 1|St = j)\, g(S_t = j|y_t)}} \tag{8}$$

Then to generate S_t, we draw a number from a uniform distribution, between 0 and 1, if the generated number is less than or equal to $\Pr[S_{t=1}|S_{t+1}, y_t]$, then $S_t = 1$, otherwise $S_t = 0$.

Step 3: Sampling the parameter matrix for each regime, $B_{s=i}$, $B_{s=j}$ |, p, q, S_t, Q ,Y_t and M_t

$$\boldsymbol{B}_{S=1,i}|\boldsymbol{B}_{s=1,i-1}\ \boldsymbol{\Sigma}_{\mathbf{i}}, \mathbf{x}_{\mathbf{i_m}} \sim \mathbf{N}(\mathbf{B}_{\mathbf{i-1}}, (\mathbf{x}_{\mathbf{S=1}}{}'\mathbf{x}_{\mathbf{S=1}})^{-\mathbf{1}} \otimes \mathbf{Q}_{\mathbf{S=1,i-1}})$$

(9)

$$\boldsymbol{B}_{S=2,i}|\boldsymbol{B}_{s=2,i-1}\ \boldsymbol{\Sigma}_{\mathbf{i}}, \mathbf{x}_{\mathbf{i_m}} \sim \mathbf{N}(\mathbf{B}_{\mathbf{i-1}}, (\mathbf{x}_{\mathbf{S=2}}{}'\mathbf{x}_{\mathbf{S=2}})^{-\mathbf{1}} \otimes \mathbf{Q}_{\mathbf{S=2,i-1}})$$

The posterior distribution for the parameter matrix follows the standard approach, however, the data by which the posterior is drawn from has been split given the regime indicator given in the previous step. At this step we adopt a rejection sampling approach to ensure that the system is stable, we check that the roots of each of the parameter matrices lie within the unit circle. If this condition does not hold we discard the current draw and redraw until it is met.

Step 4: Draw the covariance for each regime, $Q_{s=i}$, $Q_{s=j}$,|, p, q, S_t, $B_{s=i}$, $B_{s=j}$ Y_t and M_t

$$\mathbf{Q_s}|\boldsymbol{B}_{S=1,}\mathbf{y}_{\mathbf{S=1}} \sim \mathbf{IG}(\mathbf{T^d}, \mathbf{e_i})$$

(10)

$$\mathbf{Q_s}|\boldsymbol{B}_{S=2,}\mathbf{y}_{\mathbf{S=2}} \sim \mathbf{IG}(\mathbf{T^d}, \mathbf{e_i})$$

As with the draws for the parameters the variance/covariance matrix is drawn with the state that it corresponds to.

Step 5: Draw the transition probabilities, p, q,| $Q_{s=i}$, $Q_{s=j}$, S_t, $B_{s=i}$, $B_{s=j}$, Y_t and M_t

As in Viefers (2011) we draw the transition probabilities from the following beta distribution;

$$p_{11} \sim Beta(a11 + N(S_{t-1}=1, S_t=1\ , a12 + N(S_{t-1}=1, S_t=2\ )) \qquad (11)$$

$$p_{12} \sim Beta(a11 + N(S_{t-1}=2, S_t=1\ , a12 + N(S_{t-1}=2, S_t=2\ ))$$

Where, a_i is a hyperparameter which we set to 1, this represents a diffuse prior. The operator N (A, B) is an indicator which counts the number of times the event happens.

A key problem with Bayesian inference on mixture models is the so-called label switching problem. Given that the priors (3) and (4) are imposed symmetrically on the parameters for each regime, subsequently, any given permutation of the parameter matrix can lead to an alternative with different implications for the inference of regimes, but exactly the same marginal likelihood. Subsequently, if estimated in an unconstrained manner the model is unidentified. A common approach in the economic literature is to apply an *a priori* identification constraint; this can be applied on either/both the unconditional means of the parameter matrix or the variance-co-variance matrix, see for example Albert and Chib (1993). After which there is a rejection step is applied, if this constraint is violated, the draw is discarded and repeated until the condition is met. We deviate from this slightly, while we impose an identification constraint if this is violated we follow Frühwirth-Schatter (2001) and compute a random permutation of the regime labels and recalculate steps 3 and 4 of the Gibbs sampler until we can accept the constraint. Furthermore, following Groen and Mumtaz (2008), where a draw from steps 3 and 4 imply that one of the two states is uninformative we reject the draw and repeat steps 3 and 4, we define an uninformative draw as N*L + 3.

To estimate the model we iterate over the above steps 10, 000 times, we burn the first 8000 draws of the sample and keep the final 2000. Given the computational burden of these models, especially those with switching dynamics, we choose to re-estimate the parameters once every 5 years for the US and given the short data sample, only once for the UK. For the factor models, a key choice is whether to retain factors from blocks of data, i.e. restrict the factor loadings to zero for the data which does not belong to the specified data block, or to approach this as in the original implementation by Bernanke et al (2005) and include all information in the factors. We choose the latter approach, and like the authors there we chose to extract two factors from the large cross-sectional dataset, these can be broadly interpreted as activity and prices (a larger number of factors was trialed but did not generally improve the forecasting performance). For lag selection, we chose 2 lags for the FAVARs and 1 lag for the standard VARs. The motivation behind the shorter lag structure for the standard VAR pertains to it's less parsimonious nature. With each additional lag, the state space grows at N^2, where N is the number of variables. This lag length was also chosen in applications from Schorfheide and Song (2015) and Mariano and Murasawa (2004, 2010), the former through the same motivation as here and the latter via model selection using the Bayesian information criterion.

To forecast we take the posterior mean of the saved draws, apply the Kalman filter algorithm to interpolate the missing observations and then using the state equation (1), project forward to the forecast horizon, aggregating the monthly values for GDP using the aggregation function. This implies that we are focusing entirely on the accuracy of the point forecasts. As Koop (2010) notes, it is preferable to look both at the point forecasts and the density distributions, as each provides interesting information about the predictive accuracy of models. This is beyond the scope of this paper.

3.2 Dataset and forecasting structure

We apply these methods to two separate datasets, a US dataset, which comprises of 77 variables monthly variables and GDP. The historical part of the dataset is balanced so backcasting is not required. These indicators encompass variables related to activity, prices, employment and financial data, and is an updated subset of the large dataset used by Stock and Watson (2002). For the standard VAR, we pick 9 variables from this aiming to cover the blocks of data implied by the larger dataset. For both the FAVAR and the standard VAR we treat the data in the same manner, first, we transform the data so that it is stationary and then normalise in the standard way. A full list of the data and the transformations used can be found in the appendix. US datasets like this one are an often trodden path in the nowcasting literature, this is largely because of the breadth and timeliness of the data available for the econometrician, as well as the relative importance of the economy within the global schema.

We contrast this dataset with a UK dataset, which has a smaller breadth and a shorter time series, which for the most part less timely. For example, the preliminary release of GDP in the UK is based on the output approach, for which the most important indicator is the index of services. This is released with a 3-month lag and the monthly series which completes the quarter is released after the publication of the preliminary estimate of GDP. However, a monthly number can be inferred from the quarterly estimates published and therefore for our example, we treat this series as available but with no further update in the month immediately following the quarter. We use a small subset of data comprising of 16 series, mostly based on the main components of the output approach to GDP, employment, and financial data. As with the US dataset, we transform the data so that it is stationary and normalise.

The dataset used for both estimation and evaluation in both examples are final vintages. However, as is common in nowcasting exercises, we mimic the real-time flow of data. For the US dataset used here, we compute the nowcasts in the following order: firstly, the financial data such as exchange rates and equity prices are available, immediately at the end of the month, employment data follows and subsequently the federal reserve data on money and credit, producer prices, industrial production and consumer prices are then released within days of each other, the personal income and consumption release is last. As a result, we compute 5 forecasts for each month within the quarter. We compute the out of sample nowcasts for the period of 2001 Q1 through to 2015 Q1.

For the UK, given that the flow of data is smaller, we only compute a single nowcast in each of the months within the quarter, which corresponds which the release of the index of production. While in real time the release of data sets is likely to vary by days we keep to the same structure throughout the evaluation period. For the UK, given the shorter data period, we compute the out of sample nowcasts for the period of 2005 Q1 to 2015 Q1.

4. Results

Table 1 presents the mean absolute error and the root mean squared errors for the three models, and for comparison the same statistics for a random walk. For the US these metrics suggest that the standard mixed frequency VAR is the best performing of the models, albeit the FAVAR is close over both metrics. Throughout the month in both the FAVAR and the MFVAR there is a general decline in the MAE and the RMSE as would be expected. However, the forecasts corresponding to the second and third releases of each month coincide with a slight worsening for both models, which is associated with the incorporation of the new labour market and money and credit data releases. It remains true that when compared to the same period as the month previous there is an improvement. This is somewhat in contrast to examples of factor-based models in the general literature, for example, Higgins (2014) finds that comparing nowcasts from a set of DFM's which are aggregated up to GDP, that the RMSE falls throughout the forecasting period.

For the FAVAR with switching, the MAE coinciding with the first release is of the same magnitude as a simple random walk, although, throughout the releases, through the months there is a gradual improvement in the predictive ability of this model. The same is largely true for the RMSE, which is larger than that of the random walk at the 3-month horizon but reduces as new information becomes available however by these statistics it still remains below those of the other models.

On the other hand, the evidence for the MSFAVARs ability to incorporate new information efficiently as it is release is less strong than the two alternative models presented. While a general improvement across the forecasting horizon exists as we get closer to the release of GDP; the predictive accuracy within the months displays a greater variety. The employment release in the first two months leads to on average, a marginal improvement in the predictive accuracy, while this is reversed in the final month. The money and credit releases in the first two months provide the least accurate predictions, while in the final month they improve the predictive ability. Furthermore, the most accurate nowcast for the MSVAR doesn't coincide with the final release date in each month. In the first two of the months, the release associated the greatest predictive accuracy across both the RMSE and the MAE corresponds with the release of the industrial production data. While, the final month, the nowcast which includes just the updated exchange rates and interest rates provides the greatest predictive accuracy, the CPI release is the second closest.

To provide an alternative indication of the comparison between these three models, in chart 1 we plot the nowcasts corresponding to the final release of the month for each of the months against GDP. This shows that across all three months the nowcasts by the FAVAR and the MFVAR are extremely close, as is implied by the statistics in table one and for the most part appear to co-move. The main point of difference between these models is the ability to capture the 'Great Recession', in all examples of the nowcast the MFVAR is closer to the data outturn, while neither model captures the timing of the recovery. As the charts further show neither model captures the volatility of GDP well, while the final nowcasts have a greater variation that those of the initial data releases, this is still well below that observed in the actual data outturn. The nowcasts, when taken as a series, appear to capture the general trend of output growth quite well but not the idiosyncratic movements.

The MSVAR, while beset with the same problems associated with the other models also captures the 'great recession' period less well. It would have predicted a more severe and more persistent, while also suggesting the same for the brief recession in 2001. All three models predict a slight downturn in 2003, however, the effect is exacerbated in the MSVAR, and the subsequent nowcasts remain well below the outturn of GDP. While the other two models largely do not capture the volatility of GDP, this effect is amplified in the MSVAR, which has the smoothest of the predicted paths. The result found here is in contrast to that of Camacho et al (2012) who found in their application of a DFM with two regimes and that at the shortest forecasting horizon the model with switching dynamics performed best, while afterwards marginally worse than single regime equivalents. Though, this is somewhat more in line with that of Foroni et al (2015) who found conversely, that the MSVAR was the worst performing of their nowcasting models.

In order to provide some indication as to why the MSVAR performs the worst out of the three models, chart 2 plots the filtered probabilities of being in recession evaluated over the whole sample period, alongside the NBER recession dates. This shows the models does not capture recessions particularly well. At the beginning of the sample, there are a number of false positives. It is worth noting that the sample begins just at the end of the recession which lasted between November 1973 and March 1975, which the model appears to identify the end of. Although, after this period there is immediately a false positive in 1978, while the two recessions that are followed are generally captured by the model. The in between periods remain at an elevated chance of recession, without entirely switching between regimes. The two brief recessions which in the 90's and early in 2001 are not captured, while the 'great recession' leads to a shift between regimes, however, at either the peak or the trough it fails to capture the turning points.

Table 2 presents the forecast accuracy metrics for the UK example, as with the US across the first two months both metrics, the RMSE and the MAE show a general improvement in the predictive accuracy of both models. The MAE indicates that the VAR is slightly more accurate over these horizons whereas the RMSE suggests the FAVAR is slightly more accurate, although in either case, the differences are marginal. However, interestingly while the predictive ability of the standard VAR continues to improve, the predictive accuracy FAVAR reduces across both of the metrics.

Chart 3, shows the plots between the predictions and the outturns, for the forecast horizons one and two, the FAVAR tends to outperform that of the standard VAR. Broadly speaking the two models perform similarly afterward over predicting growth. There are two points of interest, firstly compared to the forecasts from the US, the nowcasts produced for the UK version are more volatile, and this is likely to be caused by a combination of reasons. A smaller subset of variables is employed, allowing greater idiosyncratic effects, secondly, at the end of the sample period where the standard VAR consistently overpredicts, the FAVAR tends to pin down the predicted growth rate to around that of the outturn. As can be seen both the ability to predict the recession and the end of the evaluation period are reversed for the one month ahead prediction, overstating the former and for the latter, the forecasts are around of the same magnitude of the standard VAR.

5. Conclusion

We compared the short-term forecast performance of a standard and factor augmented and Markov Switching FAVAR in the presence of mixed frequencies, we found that for a large US dataset the FAVAR and the standard VAR were about comparable in their ability to predict GDP. While both series tracked the general trend of GDP neither method could accurately replicate the volatility of the data outturns. The FAVAR with regime switching was the worst performing of the VARs, it tended to miss the turning points for both the recessions and the recovery period was far slower in both examples of recessions in the evaluation period.

For the UK the relatively small factor model was around comparable to the standard VAR over the forecast horizons 2 and 3. It provided better predictions over the recessionary period and at the end of the evaluation period where the VAR consistently over-predicted growth. In the one period ahead forecast period the predictive accuracy of the FAVAR reduced dramatically, losing the gains seen in both previously horizons.

Across the forecasting periods, the improvements in predictive accuracy as a result of increased information from extra releases through the month were lumpy, this is in contrast with the general literature on Dynamic Factor Models. Some releases such as those associated with employment and money and credit marginally reduced the predictive power of the nowcast. However, the final release of each month was still the most accurate, suggesting that a general gain from information still existed.

There are two areas which may prove interesting for future work; firstly splitting the factors into relative blocks may provide some gains. While this moves the model more towards that of the standard VAR, having the extra variables representing the specific blocks but in a form but without the idiosyncratic movements of a single series may provide an approach to get closer to capturing the volatility of the outturns of GDP.

Finally, applying alternative approaches to dealing with the label switching problem may be worth investigating in order to see whether or not the identification of regimes can be improved using alternative algorithms to deal with the label switching problem especially when dealing with mixed frequencies.

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Release	1	2	3	4	5	6
MS FAVAR						
MAE						
M1	0.58769	0.57594	0.62662	0.55793	0.61156	0.56682
M2	0.55174	0.53936	0.59708	0.50558	0.57460	0.50831
M3	0.47119	0.52648	0.49366	0.4973	0.47431	0.49795
RMSE						
M1	0.81145	0.79530	0.88138	0.76320	0.85112	0.77250
M2	0.74330	0.73002	0.81564	0.67929	0.76591	0.68092
M3	0.60582	0.68517	0.64718	0.64401	0.61488	0.64459
FAVAR						
MAE						
M1	0.48094	0.45734	0.47624	0.44526	0.44136	0.43287
M2	0.44662	0.46897	0.48293	0.42601	0.42570	0.42206
M3	0.41647	0.43235	0.44250	0.41601	0.41395	0.41332
RMSE						
M1	0.65778	0.60488	0.62330	0.58546	0.58247	0.57245
M2	0.60034	0.58661	0.60480	0.53283	0.52949	0.52624
M3	0.53550	0.54085	0.55272	0.52623	0.52246	0.51833
MFVAR						
MAE						
M1	0.45632	0.43743	0.43714	0.41150	0.41258	0.41783
M2	0.42073	0.44695	0.43763	0.40845	0.40636	0.38421
M3	0.37389	0.37248	0.37338	0.40023	0.40054	0.38584
RMSE						
M1	0.57552	0.56109	0.56205	0.52621	0.5293	0.52748
M2	0.53445	0.55120	0.54339	0.50752	0.50839	0.49861
M3	0.49004	0.49172	0.49360	0.51713	0.51909	0.49011

Random Walk	
MAE	0.60995
RMSE	0.73865

Table 1: Descriptive statistics

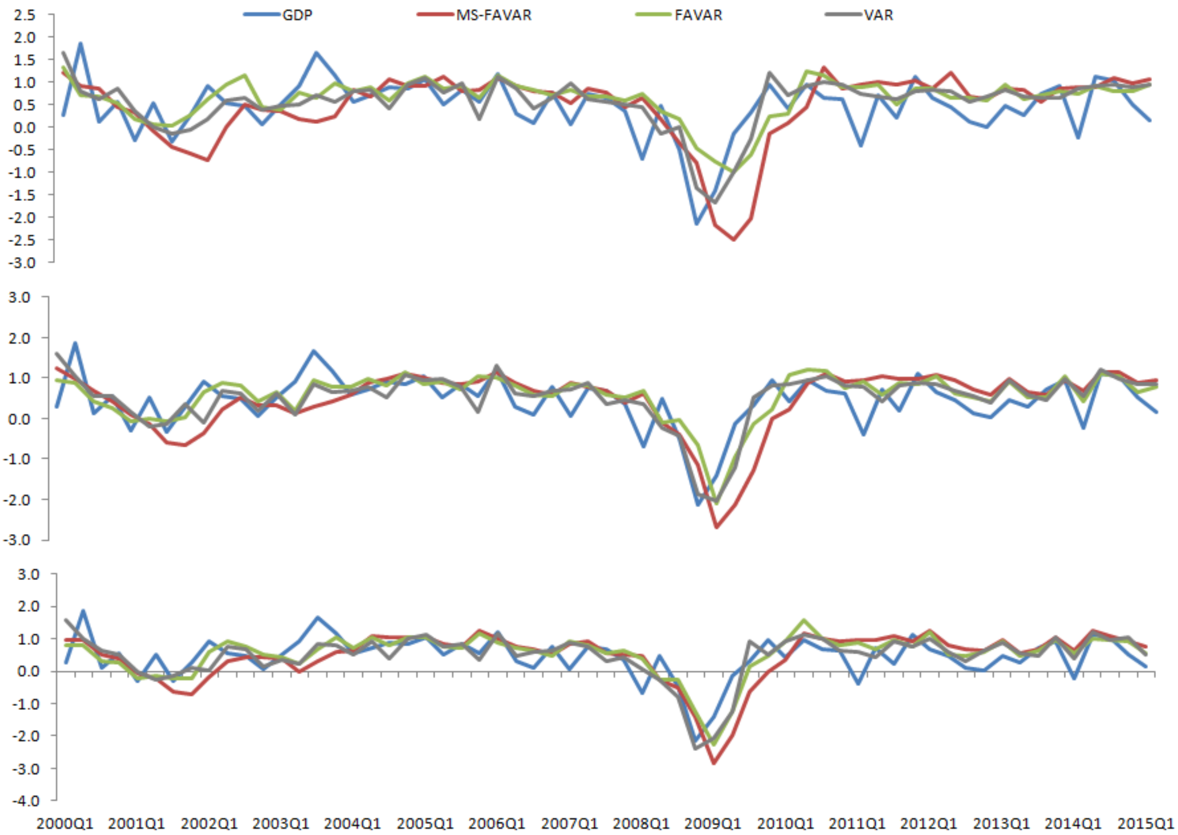

Chart 1: Final data release for each nowcasting model, top panel month 1, middle panel month 2 bottom panel month 3

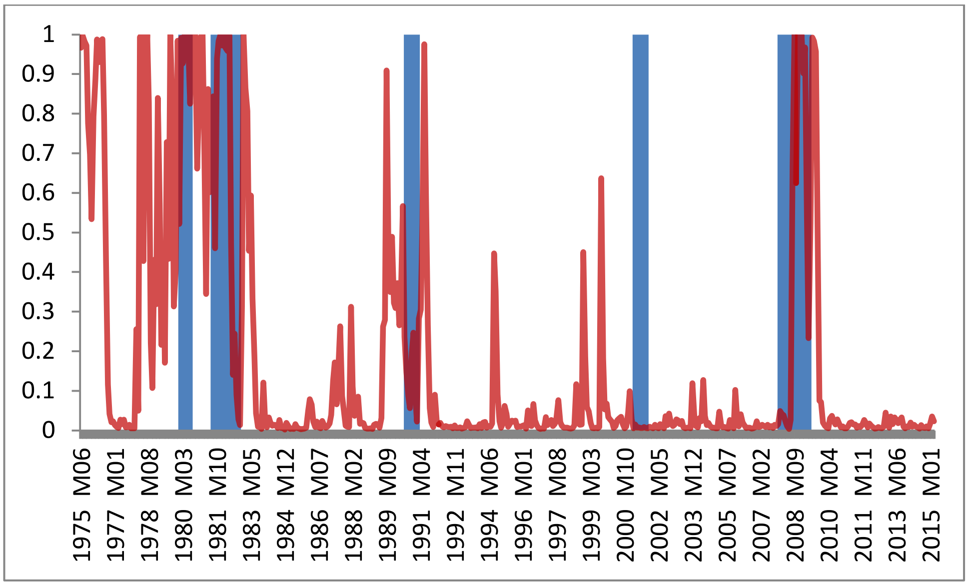

Chart 2: Filtered probabilities of being in recession

MFVAR			
MAE	0.40885	0.380307	0.33772
RMSE	0.584928	0.485653	0.430866

FAVAR			
MAE	0.438023	0.400708	0.34688
RMSE	0.574196	0.462722	0.528545

Table 3: Forecast Accuracy metrics for the UK

Chart 3: Predictions vs Outturns, month 1 to month 3, top to bottom.

Appendix – US dataset

Transformation key: 1 – log first difference (quarterly variable), 2 – Three-month difference (levels), 3- Three month, log difference, 4. Three-month difference of the twelve month logs difference

Money and Credit	
Total Assets, all commercial banks, SA	3
Bank Credit, all commercial banks, SA	3
Treasury and agency securities, all commercial banks, SA	3
Commercial and Industrial loans, all commercial banks, SA	3
Real estate loans, all commercial banks, SA	3
Consumer loans, all commercial banks, SA	3
M1, SA	3
M2, SA	3
Financial	
US Broad index of Dollar foreign value	3
Euro to Dollar exchange rate	3
US dollar to Japanese Yen, exchange rate	3
UK Pound sterling to US dollar, exchange rate	3
Canadian dollar to US dollar, exchange rate	3
London Gold price index	3
NYSE composite index	3
S&P 500 price index	3
Wiltshire 5000 total price index	3
Surveys	
US consumer confidence survey, SA	2
US consumer confidence indicator, SA	2
US ISM PMI, MFG, SA	2
US Chicago PM Business Barometer, SA	2
US ISM MFG survey:Production index, SA	2
US ISM manufacturers survey, new orders, SA	2

US ISM manufacturers survey: Supplier delivery	2
Consumer Prices - CPI index	
All urban	4
Food and Beverages	4
Housing	4
Apparel	4
Transportation	4
Medical care	4
Commodities	4
Durables	4
Services	4
All items less food	4
All items less food and energy	4
All items less shelter	4
All items less medical care	
Producer prices - PPI index	4
Finished goods less food and energy	4
Goods for final demand	4
Personal consumption goods less food	4
Personal consumption goods (finished consumer goods)	4
Finished goods	4
Interest Rates	
FREDDIE MAC 30 YEAR FIXED RATE	2
FEDERAL FUNDS RATE (MONTHLY AVERAGE)	2
TREASURY BILL RATE - 3 MONTH (EP)	2
TREASURY BILL SECONDARY MARKET RATE ON DISCOUNT BASIS-6 MONTH	2
TREASURY YIELD ADJTED TO CONSTANT MATURITY - 1 YEAR	2
TREASURY YIELD ADJTED TO CONSTANT MATURITY - 5 YEAR	2
TREASURY YIELD ADJTED TO CONSTANT MATURITY - 7 YEAR	2

TREASURY YIELD ADJTED TO CONSTANT MATURITY - 10 YEAR	2
CORP BONDS MOODYS SEASONED AAA (W) - MIDDLE RATE	2
CORP BONDS MOODYS SEASONED BAA (W) - MIDDLE RATE	2
Labour Market	
Other services	3
Leisure and hospitality	3
Education and health services	3
Professional and business services	3
Financial activities	3
Utilities	3
Transportation and warehousing	3
Wholesale trade	3
Private service-providing	3
Nondurable goods	3
Durable goods	3
Manufacturing	3
Construction	3
Mining	3
Goods-producing	3
Total private	3
Total nonfarm	3
Retail trade	3
Government	3
Hours	
Total private	3
Manufacturing	3
Overtime	
Manufacturing	3
Hourly Earnings	
Total Private	4

Construction	4
Manufacturing	4
Private service-providing	4
Wholesale trade	4
Retail trade	4
Transportation and warehousing	4
Financial activities	4
Professional and business services	4
Education and health services	4
Other services	4
Other Labour	
Civilian labor force participation rate	2
Unemployment rate	2
Unem <5	3
Unem 5-14	3
Unem15-26	3
Unem 15 +	3
Income and Output	
GDP	1
Sales	3
Manufacturing and trade	3
Manufacturing	3
Durable Goods	3
Nondurable goods	3
Merchant wholesale	3
Durables	3
Non-Durables	3
Retail Trade	3
Inventory Sales	3
Manufacturing and trade	3
Manufacturing	3

Durable goods	3
Nondurable goods	3
Merchant wholesale	3
Durable goods	3
Nondurable goods	3
Retail trade	3
US DISPOSABLE PERSONAL INCOME CVM	3
US PERSONAL CONSUMPTION EXPENDITURES CVM	3
US PERSONAL CONSUMPTION EXPENDITURES CVM	3
US PERSONAL CONSUMPTION EXPENDITURES CVM	3
US PERSONAL CONSUMPTION EXPENDITURES CVM	3
Industrial Production	
Total index; s.a. IP	3
Mining (NAICS = 21); s.a. IP	3
Manufacturing (NAICS); s.a. IP	3
Durable manufacturing (NAICS); s.a. IP	3
Nondurable manufacturing (NAICS); s.a. IP	3
Energy, total; s.a. IP	3
Computers, communications eq., and semiconductors (NAICS = 3341,3342,3344); s.a. IP	3
Final products; s.a. IP	3
Consumer goods; s.a. IP	3
Durable consumer goods; s.a. IP	3
Nondurable consumer goods; s.a. IP	3
Business equipment; s.a. IP	3
Materials; s.a. IP	3
Durable goods materials; s.a. IP	3
Nondurable goods materials; s.a. IP	3
Motor vehicles and parts (NAICS = 3361-3); s.a. IP	3
Total index; s.a. CAPUTL	2
Mining (NAICS = 21); s.a. CAPUTL	2

Appendix – UK dataset

Prices	
RPI: Retail Price Index	4
CPI: Consumer Prices Index	4
Index of Production	3
IOP: C:MANUFACTURING: CVMSA	3
IOP: B-E: PRODUCTION: CVMNSA	
Exchange rates	
Sterling Efex	3
Retail Sales	
RSI:Volume Seasonally Adjusted:All Retailers ex fuel:All Business Index	3
RSI:Non-specialised stores (vol sa):All Business Index	3
RSI:Household goods stores (vol sa):All Business Index	3
RSI:Other non-food stores (vol sa):All Business Index	3
Labour Market	
Unemployment rate	2
Total Claimant count SA (UK) - thousands	3
LFS: In employment: Full-time: UK: Male: Thousands: SA	3
LFS: In employment: Full-time: UK: Female: Thousands: SA	3
LFS: In employment: Full-time: UK: All: Thousands: SA	3
Other	
House Prices	3