Nowcasting Using Mixed Frequency Methods: An Application to the Scottish Economy*

"...some of our statistics are too late to be as useful as they ought to be. We are always, as it were, looking up a train in last year's Bradshaw [timetable]"

Harold MacMillan
UK Chancellor of the Exchequer, 1956.

Abstract: The delays in the release of key economic variables mean that policy-makers do not know their current values. Quickly produced, high frequency, indicators are essential in understanding economic performance in a timely fashion. Thus, there is a need for nowcasts, which are estimates of the current values of such variables (e.g. GDP, employment, etc.). This paper nowcasts economic growth in Scotland. Nowcasting the Scottish economy is complicated because the government statistical agency treats Scotland as a region within the UK. This raises issues of data timeliness and availability. For instance, key nowcast predictors such as industrial production are unavailable at the sub-national level. Accordingly, we use data on some non-traditional variables and investigate whether UK aggregates, and indicators for neighbouring regions of the UK, can help nowcast Scottish GDP growth. Similar considerations hold for other regions in other countries. Thus, we show that these models and methods can be successfully adapted for use in a regional setting, and so produce timely macroeconomic indicators for other regional economies.

Keywords: nowcasting, mixed frequency data, regional economics

JEL codes: C13, C53, O18, R11

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1 Introduction

For some purposes, policymakers are interested in future values of macroeconomic variables and, thus, forecasting is an important activity. However, for other purposes, policymakers are interested in the values of macroeconomic variables *now*. For many variables (e.g. asset and commodity prices), obtaining current values of variables is trivial. But for other variables, and particularly for key economic variables such as GDP or employment, data must be collected and processed before release and, thus, the policymaker does not know their current values, in some cases for a substantial period of time. While timeliness can certainly be an issue at the national level, it is especially acute and problematic for sub-national data and sub-national policy making.

A good example of this difficulty is evident in Scotland, which is classified as a region within the UK according to the European Union's NUTS 1 classification scheme. The initial estimate of Scottish GDP[1] for the second quarter of 2014 was released on 19 October, 2014 (and even this initial estimate is liable to be revised in upcoming months). Thus, a policymaker in 2014Q2 did not know the current value of GDP when making decisions and would not find out what it was until 15 weeks after the end of the quarter. Such concerns motivate regional interest in the growing field of *nowcasting*: providing current estimates of key macroeconomic variables such as GDP.

Nowcasts of major macroeconomic aggregates are currently produced for many countries. For instance, the online nowcasting service (www.now-casting.com) produces nowcasts for the major OECD countries as well as Brazil and China. There are no nowcasts for Scottish GDP growth and very few for other sub-national regions. There is some work on developing indicators which can provide timely warnings of recession. For instance, Chung & Hewings (2014) develop an intuitive and timely measure of the probability that particular regional economies within the US will enter recession. These probabilities are contingent on the performance of the aggregate national economy, and in this sense includes the idea of regional economies being nested within national economies. Our work, in contrast, focuses on producing a timely point estimate of the quarterly change in economic activity at the regional level which may be a more useful measure to guide economic policymaking.

Generating nowcasts at the sub-national level raises its own particular issues. These include the reduced range of data series available about the regional economy and data

[1]In fact, it is gross value added (GVA) which we nowcast, but we use the term GDP here for consistency with the national literature on nowcasting. GVA is one component of GDP. The Office of National Statistics describe the relationship between GVA and GDP as follows: "GVA (at current basic prices; available by industry only) plus taxes on products (available at whole economy level only) less subsidies on products (available at whole economy level only) equals GDP (at current market prices; available at whole economy level only)" `http://www.ons.gov.uk/ons/guide-method/method-quality/specific/economy/national-accounts/gva/relationship-gva-and-gdp/gross-value-added-and-gross-domestic-product.html`. GVA, and not GDP, is what is released for the UK Government Office Regions.

being released in a less timely manner than at the national level. These issues are shared by many regions and sub-national entities. The most obvious of these is in the United States, where State level quarterly real personal income is released with a delay of around 3 months, while State level quarterly GDP is released with a lag of approximately 5 months from the end of the quarter[2]. The purpose of this paper is to try to tackle these issues in the context of implementing sub-national nowcasting models, and to illustrate their potential usefulness to policymakers. In order to do so, we develop a nowcasting model for Scotland and evaluate its performance. Using data from 1998[3] to 2014, we nowcast the growth in Scottish GDP in pseudo real-time. That is, we provide nowcasts at each point in time (say time τ) using the data available at time τ and compare the nowcasts to the actual values for GDP growth in time τ (which would not have been known until much later than time τ).

In this paper, we describe the methods we use to produce nowcasts and carry out the pseudo real-time nowcasting exercise. To achieve the former, this paper begins by surveying existing nowcasting methods. Subsequently, we describe the distinctive challenges which occur when nowcasting economic activity for a regional economy such as Scotland. These include the short time span for which data is available, the lack of many key variables commonly used in other nowcasting methods and the greater time delays in the release of data. We then discuss how we construct nowcasts in light of these challenges. The penultimate part of this paper contains the pseudo real-time forecasting exercise, with forecast evaluation measures, before we conclude this paper with reflections on how we might develop our methodology in future work.

2 Nowcasting: an overview

Several excellent surveys of nowcasting (or closely related topics such as short-term forecasting) have recently appeared. These include Banbura, Giannone and Reichlin (2011), Banbura, Giannone, Modugno and Reichlin (2013), Camacho, Perez-Quiros and Poncela (2013) and Foroni and Marcellino (2013). This section will first discuss the general issues that arise in constructing timely estimates of economic aggregates, before outlining in more detail the key methodological approaches which have been taken to construct nowcasts at the national level, which we extend to the regional case.

2.1 Key issues

At the most general level, nowcasting techniques (like most forecasting methods) seek to find explanatory variables/predictors which are useful for predicting the dependent

[2]This is clear from the schedule of data releases for the regional economic accounts, available here: https://www.bea.gov/newsreleases/news_release_sort_regional.htm.

[3]Before 1998, quarterly Scottish GDP data is unavailable.

variable to be nowcast. Nowcasts are based on an econometric model linking the predictors to the dependent variable. For GDP growth there are a myriad of such predictors. For instance, Banbura, Giannone, Modugno and Reichlin (2013) use 23 predictors in their nowcasting model of US GDP growth including both "hard" variables such as industrial production and "soft" variables such as surveys of businesses.

Important econometric issues arise when nowcasting because nowcasters want their predictors to be as timely as possible. For instance, when nowcasting Scottish 2014Q2 GDP growth, having a predictor for which data becomes available in May or June, 2014 is very useful. A predictor which is not available until October 2014 (when the initial estimate of Scottish 2014Q2 GDP is released) is virtually useless. Furthermore, nowcasters typically update their nowcasts throughout the quarter as new information becomes available. The desire for timeliness and frequent updating of nowcasts leads to two econometric issues which are treated in different ways by the different nowcasting approaches. These are: i) the dependent and explanatory variables have different frequencies and ii) the nowcaster's data set typically has a "ragged edge".

The mixed frequency issue arises since GDP is observed quarterly whereas many potential predictors for GDP e.g. industrial production, some labour force statistics and Purchasing Managers' Indices (PMIs) are available monthly. In this paper, we will use MIDAS methods (described below) to address the mixed frequency issue, but several other methods exist (see, in particular, Foroni and Marcellino (2013) for a survey of the various econometric methods used with mixed frequency data).

The ragged edge problem refers to the fact that the variables in the nowcaster's data set typically have different release dates and, thus, at the end of the sample missing observations will exist for some of them. Consider, for instance, nowcasting 2014Q2 Scottish GDP growth at the end of July 2014. By this time, the value of June's Bank of Scotland's PMI was released and the nowcaster would wish to update the 2014Q2 nowcast. But data on UK exports and imports for June will not be released until mid-August. Again, there are several ways of addressing this ragged edge problem, and these are surveyed in the papers cited earlier, but we will address them using MIDAS methods as detailed later in this paper.

A final data issue worth noting, of relevance to both forecasters and nowcasters working in real time, is that GDP is revised over time as new information is collected, leading to different vintages of data (i.e. the first vintage of GDP data is the initial release 15 weeks after the end of the quarter, the second vintage follows a quarter after that, etc.). For instance, the initial estimate of 2012 Q3 Scottish GDP growth was 0.6%, but three months later this was revised to 0.4%, later revisions occurred such that at present GDP growth in this quarter is estimated as 0.1%. In the present paper, our pseudo real-time nowcasting exercise does not address this issue since we use final vintage data.

2.2 Competing nowcasting approaches

This section provides a brief overview of three competing methods of producing nowcasts; and hence overcoming the mixed frequency and jagged edge issues in nowcasting which were discussed in the previous section. A reader in search of more details should refer to the survey papers cited at the beginning of the preceding sub-section. Here we outline the general concepts underlying nowcasting before describing the particular set of methods that we use in this paper in section 2.3. We use notation where y_{t_Q} is the quarterly variable we are interested in nowcasting (in our case GDP growth) for $t_Q = 1, .., T_Q$ quarters and X_{t_M} is a monthly predictor for $t_M = 1, .., T_M$.

One way of over-coming the frequency mismatch between dependent variable and predictor, would be to transform the higher frequency explanatory variables to the lower frequency. For the case of monthly and quarterly variables, this would mean creating:

$$X_{t_Q}^{Q} = \frac{X_{3\left(t_Q-1\right)+1} + X_{3\left(t_Q-1\right)+2} + X_{3\left(t_Q-1\right)+3}}{3}$$

and then using a standard regression model:

$$Y_{t_Q} = \alpha + \beta X_{t_Q}^{Q} + \varepsilon_t.$$

Such an approach, which underlies bridge sampling methods, can be thought of as taking an average of recent values of the monthly variables and using the result as a predictor. An example of this would be creating a quarterly Purchasing Managers' Index (PMI) variable by averaging across the three monthly values of the PMI and then using this average to nowcast quarterly GDP. It is this approach that is taken by Smith (2013) who uses univariate autoregressive forecasting models to 'fill in the gaps' caused by the jagged edge, before applying a bridging equation approach to transform the higher frequency data into explanatory variables to be used in a regression involving the lower frequency dependent variable being nowcast.

This is a simple and easily implemented approach, but at the cost of losing potentially useful information. By taking a simple average, recent and past values are weighted equally (possibly an undesirable feature, since we may want to weight recent values more heavily) and the impact of a single good (or bad) month in the quarter can be ameliorated. While bridging approaches provide an intuitive and straightforward solution to the difficulties posed by mixed frequency data, in recent years more complex models have been developed with an aim to improve nowcast accuracy.

Factor models are a major alternative to bridging equations. Factor methods take a large number of explanatory variables and extract a small number of variables called factors which contain most of the information in the explanatory variables. These factors can then be used in the nowcasting regression. The methods developed in Giannone et al (2008) allow for the factors to be at a higher frequency than the lower frequency variable being nowcast. Thus, this approach also deals with both of the issues identified earlier.

The third main alternative, and the one we use in this paper, is MIxed DAta Sampling (MIDAS). This is also a regression-based method, initially introduced by Ghysels (2004). We will explain MIDAS in more detail in the next section. But, before doing so, we note here that it addresses both of the issues raised above. Under MIDAS, no forecasting of missing values is necessary (so the first difficulty noted above disappears) and the models are set up (as the name suggests) to deal with mixed frequency data (addressing the second issue raised above).

Within the MIDAS approach there are a number of different specifications that are possible, and a literature has built up which walks the reader through these. It is worth noting that much of the MIDAS literature is focussed on using very high frequency explanatory variables (e.g. daily financial data) to forecast a monthly or quarterly dependent variable. In such a case, if the researcher uses each daily observation as an explanatory variable in a regression, then the number of explanatory variables can be enormous. This creates econometric problems which MIDAS surmounts by placing restrictions on the coefficients. The different MIDAS specifications arise from the nature of these restrictions.

Below we will discuss the practical details of using MIDAS methods. For the reader interested in the econometric theory, Andreou, Ghysels and Kourtellos (2013) is a recent survey. Much pioneering work in the field was done by Eric Ghysels in several papers including Ghysels, Sinko and Valkanov (2007). Bai, Ghysels and Wright (2013) shows the close relationship between MIDAS methods and the factor methods used by nowcasters such as Giannone, Reichlin and Small (2008). The next section provides a more in-depth treatment and explanation of the MIDAS methods that we use in this paper.

2.3 MIDAS

GDP data (and some of the predictors we use) are available at quarterly intervals, whereas most of our predictors are available at monthly intervals.[4] One thing that can be done to address some of the criticisms of bridge equation modelling, outlined earlier, is to allow for unequal weights so as to have more recent data receive more weight than data from the more distant past.[5] This suggests working with a regression model of the form:

[4]We are focussed on providing monthly updates of our nowcasts and, hence, work at this frequency in this paper. Some nowcasters work at the daily frequency, providing daily nowcasts so that, e.g., on 13 January, 2014, when the value of December's Bank of Scotland's PMI was released, the nowcast of GDP could be updated on 13 or 14 January. Given we are updating nowcasts monthly, we would use this PMI release in our 1 February nowcast and treat all of our predictors as though they are end of month values.

[5]Andreou, Ghysels and Kourtellos (2013) also show some econometric problems of the equal weight specification used in bridge sampling, including the potential for asymptotic bias or inefficiency.

$$y_{t_Q} = \alpha + \beta \sum_{j=0}^{p_{M-1}} w_j X_{3t_Q - j} + \varepsilon_t, \tag{1}$$

where the weights, w_j, sum to one and depend on unknown parameters which are estimated from the data and p_M are the number of monthly lags. This is a MIDAS model. Non-linear least squares can be used to estimate a MIDAS model.

Given the importance of timing issues in nowcasting, we elaborate on what exactly MIDAS nowcasts involve for the Scottish case. Note that, for any quarter's GDP growth, there are several nowcasts of interest. In our empirical work, we produce five nowcasts. Consider, for instance, GDP growth in 2014Q2. During this quarter, we do not know its value and, thus, nowcasts made on 1 May and 1 June, 2014 will be needed. But the initial estimate of GDP growth in 2014Q2 will not be released until mid October and, hence, nowcasts[6] made on 1 July , 1 August and 1 September, 2014 are also required. These nowcasts can be produced using a slight alteration to (1) by introducing an index h to denote these five nowcasts through the following specification:

$$y_{t_Q} = \alpha + \beta \sum_{j=0}^{p_M - 1} w_j X_{3t_Q - j - h} + \varepsilon_t. \tag{2}$$

To understand the properties of this specification, we will continue using 2014Q2 as an example. If $h = 0$, then the explanatory variables are all dated June 2014 (or earlier). Given a one month delay in releasing data on the explanatory variables, this data would be available by the end of July 2014. Thus, nowcasts of 2014Q2 GDP growth made on 1 August, 2014 can be obtained by setting $h = 0$. By similar reasoning, setting $h = 1$ produces nowcasts using explanatory variables dated May 2014 which come available during June. This is what we would want when making nowcasts on 1 July, 2014, etc. We can even set h to be a negative number. This is called MIDAS with leads. Setting $h = -2, -1, 0, 1, 2$ will produce the five nowcasts referred to at the beginning of this paragraph.

Another issue that we need to address is the role played by lags of the dependent variable. That is, it is common, even after controlling for explanatory variables, for macroeconomic aggregates such as GDP growth to exhibit autocorrelation. Thus, including lags of the dependent variable has the potential to improve nowcast performance. This can easily be accommodated by adding lags of the dependent variable to the MIDAS model:

$$y_{t_Q} = \alpha + \sum_{j=1}^{q} \rho_j y_{t_Q - j} + \beta \sum_{j=0}^{p_M - 1} w_j X_{3t_Q - j - h} + \varepsilon_t. \tag{3}$$

This is what we do in this paper. However, we have to be careful since Scottish GDP figures are released with around a 15 week delay. Consider, again, the five nowcasts of

[6] One could call these "backcasts" instead of nowcasts.

2014Q2 GDP growth obtained by setting $h = -2, -1, 0, 1, 2$ in (3). For the first three (made on 1 May, 1 June and 1 July 2014), the initial release of 2014Q1 GDP figures would not be available. Thus, we would not yet know what y_{t_Q-1} is and it cannot be used as a predictor. Accordingly, the lags must begin with y_{t_Q-2} (or, equivalently, we must set $\rho_1 = 0$ in (3) for the first three out of the five nowcasts). Table 1 summarizes the timing of the data[7] for each of our nowcasts.

MIDAS is commonly used with financial data where daily data is used to forecast monthly or quarterly variables. In such a case, parsimony is a major concern since there can be so many weights to estimate. That is, instead of our three months in a quarter (leading to three weights in the case where we lag variables up to a quarter), there are 31 days in a month and 122 days in a quarter. This has led to wide range of distributed lag specifications being proposed. However, for our relatively parsimonious case, we do not consider such specifications but, instead, work with the unrestricted MIDAS specification of Foroni, Marcellino and Schumacher (2013). Foroni, Marcellino and Schumacher (2013) show that U-MIDAS performs better than other MIDAS specifications for this type of mixed data sampling. The interested reader is referred to, e.g., Andreou, Ghysels and Kourtellos (2013) for a discussion of other specifications.

2.4 Parsimony and Model Combination

Our previous discussion is all framed in terms of the basic MIDAS model involving a single high frequency explanatory variables. However, in many applications, including the present one, we will have many explanatory variables. In our case, we have 40. Given that our data span is very short, beginning in 1998Q1, simply including all of them would lead to a very non-parsimonious model. There are several methods that could be used to deal with this problem. In this paper, we adopt Bayesian model averaging (BMA) methods. That is, we use a model space involving 40 models, each with a single high frequency predictor and produce nowcasts which average over all these small (parsimonious) models. A similar strategy is used in Mazzi, Mitchell and Montana (2014).

Bayesian statistics provides a formal methodological justification of this approach. Let M_r for $r = 1, .., R$ denotes R different models. The Bayesian treats models as random variables and posterior model probabilities, $p(M_r|y)$ can be obtained for each. If y^* is a nowcast, then the rules of probability imply:

$$p\left(y^*|y\right) = \sum_{r=1}^{R} p\left(y^*|y, M_r\right) p\left(M_r|y\right). \tag{4}$$

Thus, the posterior for y^* is the average of its posterior in each individual model with

[7] This timing is relevant for monthly variables which are released within a month. As noted in the appendix, a small number of our variables are released with a delay of more than a month and, for these, the timing convention is adjusted appropriately.

weights proportional to $p\left(M_r|y\right)$. Note that such a strategy allows for a formal treatment of model uncertainty.

Conventional BMA methods use posterior model probabilities which are proportional to marginal likelihoods as weights. Since the Bayesian Information Criterion (BIC) is asymptotically equivalent to the log of the marginal likelihood, one approach we adopt is to construct weights using BIC. However, we also consider alternative weighting schemes. In particular, if we have N models and p_{it} is the weight attached to model i at time t for $i = 1, .., R$, then we considered:

- Equal weights:
$$p_{it} = \frac{1}{R}$$

- BIC based weights:
$$p_{it} = \frac{\exp\left(BIC_{it}\right)}{\sum_{j=1}^{R} \exp\left(BIC_{jt}\right)}$$

- MSFE based weights:
$$p_{it} = \frac{\left(MSFE_{it}\right)^{-1}}{\sum_{j=1}^{R} \left(MSFE_{jt}\right)^{-1}}.$$

In these weights BIC_{it} stands for Bayesian information criterion of model i at time t and MSFE is mean squared forecast error. Both are calculated using the data available at time t. MSFE is a measure of forecast performance, so using MSFE based weights results in more weight being put on models which have forecast well in the past.

Having identified the key contributions in the literature, outlined what nowcasting involves, and how we tailor the empirical specification that exist in the literature to our application nowcasting Scottish GDP, the next section outlines the data that we will use to produce our nowcasts for Scotland, which are presented in the section after.

3 Nowcasting in Scotland

For the reasons outlined in Section 2.1, the goal of the nowcaster is to find variables which: i) help predict GDP growth, ii) are timely and iii) are updated frequently (e.g. at a monthly frequency). Typically, this has led researchers to use a variety of hard and soft predictors. Industrial production (and its components) is commonly used as one of the main hard variables. Variables reflecting the labour market, employment, sales and consumption are also popular hard variables. Soft variables are based on surveys of various sorts (i.e. surveys of business, consumers, etc.). However, many of these (and, in particular, many of the hard variables) are unavailable for Scotland. This is a problem facing many regions.

Accordingly, we have collected a data set of predictors containing some traditional nowcasting predictors, but also some non-traditional ones. In addition, we include some conventional hard nowcasting variables for the UK as a whole to investigate whether these have enough explanatory power to help improve nowcasts of Scottish GDP growth. Furthermore, it is possible that there is information in other UK regions which our nowcasts can exploit. For this reason, some of our predictors are for the other regions of the UK.

The specific variables that we have collected and used are briefly described below, in addition we explain why these have been chosen. Full details on each variable (including definitions, timeliness, sources, any data transformations applied and release dates) are given in the Data Appendix.

Some of these are available for Scotland alone, while others are for other regions of the UK or the UK as a whole. For the reasons described above we have taken the stance that data which may be a useful predictor of Scottish economic activity should be included, even if the data relates to a wider geographic grouping, such as the UK. Additionally, many of the data used in nowcasting at a national level are simply either not available for regions, or are only available for the regions with a greater lag.

We should note that quarterly Gross Value Added (GVA) for Scotland was first available for 1998Q1 and (at the time of writing) runs to 2014Q2 (produced on the 19th of October 2014). It is the change in this index of economic activity which we are seeking to nowcast. We are especially keen to include variables which would be available over the same period, and have not included some series that are available only for part of this time period. Quarterly variables included therefore run from 1998Q1 to 2014Q2, while monthly variables run from January 1998 to September 2014 (although as the Data Appendix explains, some of the monthly variables are released with longer delays and so are only currently available for earlier months).

In all, we employ a total of forty predictors, across a range of hard and soft indicators. We begin by describing the (thirty-three) monthly variables available. We have twelve Purchasing Managers Index (PMI) variables for the government office regions of the UK, including Scotland.[8] These are a widely used– including by the Bank of England – tracker of economic activity, also produced for nations and national groupings outside the UK (such as the Eurozone). Recent evidence suggests that the UK PMI measure has closely tracked recent UK economic performance, suggesting it may also be useful for nowcasting Scottish performance. Additionally, the short publication lag for the UK regional PMI variables– typically produced around 10 days after the end of the month

[8]The Scotland PMI series are reported by Bank of Scotland, part of the Lloyds Banking Group, whose commercial banking arm also produces the England and Wales Regional PMI. Ulster Bank provide PMI data for the Northern Ireland PMI

– merits their inclusion in our analysis. We include PMI measures for other regions of the UK (PMILON, PMISE, PMISW, PMIEAST, PMIWALES, PMIWMID, PMIEMID, PMIYORK, PMINE, PMINW AND PMINI) in addition to Scotland (PMISCOT). These variables are timely and may be good predictors since the rest of the UK is the primary and principle destination for Scottish exports. Additionally, we include three more PMI variables which are for the UK, Eurozone and world respectively (PMIUK, PMIEZ and PMIWORLD).

We include eight monthly variables related to VAT receipts for the UK. Such figures are likely to track with the level of spending, and, with consumption spending a significant portion of GDP, it is useful to include these measures. Five variables (VATPAY, VATREPAY, VATRCPT, IMPVAT and TOTALVAT) will track such receipts on a monthly basis. A further three variables relate to the number of firms registered for VAT purposes (NEWVATREG, VATDEREG and TRADEPOP).

There are a further ten monthly variables. The paucity of regional data means that only three soft monthly variables – GFKCC, a measure of Scottish consumer confidence, and BOSJOBS_PL and BOSJOB_ST – relate to Scottish activity specifically. Consumer confidence measures are widely used as nowcasting predictors as they give an indication about the direction of travel for consumption spending. They are often good predictors of sales revenues which are critical for economic activity in service-dominated economies. The two other measures mentioned above are monthly measures of the labour market in Scotland for job placements and staff demand, respectively. As such, these may both be useful predictors of employment growth and economic activity. The only other hard Scottish data series comes as the (claimant count) unemployment rate for Scotland (UNEMP).

As UK-wide hard predictors we use industrial production (UKIP) and the services-output index (IOSG). IOSG might be a good predictor as this shows the movements in gross value added for the service industries, which overall account for 78 per cent of UK GDP. UKCPI is the rate of inflation for the UK as a whole which is also typically included in nowcasting analysis. Two predictors refer to the level of exports (UKEXPORTS) and imports (UKIMPORTS) for the UK economy as a whole. Both these series could be useful predictors, in particular as Scotland is likely to contribute a greater share of UK exports than its share in UK GDP, through specific products such as whisky and refined petroleum. For this latter product, we also additionally include a (UK) measure of total throughput of refined petroleum – UKREFINE.

Turning to the (seven) quarterly variables, each of these specifically relate to Scotland. Firstly, we have as hard indicators the Scottish government-produced Retail Sales Index for Scotland (RSI) and HMRC data on total Scottish exports and imports to the rest of the world (EXP and IMP respectively).[9] The RSI data series is likely to be a useful predictor

[9]There are only annual surveys of total exports from Scotland, while the quarterly survey of exports

of retail and consumer spending, while both trade variables may be important for the strength of external (and domestic) demand and Scottish economic activity. We include four survey variables drawn from two respected quarterly surveys of the Scottish economy: the Scottish Business Monitor and Scottish Chambers Business Survey. From the former we use a measure of output by Scottish firms (SBM). From the latter, we use variables which measure the volume of business by firms in the manufacturing, construction and tourism sectors (SCBSMAN, SCBSCON and SCBSTOUR, respectively).

4 Nowcasting in Pseudo Real-Time

To evaluate the performance of our nowcasting methods we use predictive likelihoods and MSFEs as diagnostics. MSFEs are a common metric to evaluate the quality of point forecasts with lower values indicating better performance. However, policymakers are increasingly interested in moving beyond point forecasts and doing density forecasting. To evaluate the quality of our density nowcasts we use predictive likelihoods. Predictive likelihoods are a common metric for evaluating the quality of the entire predictive distribution with higher values indicating better nowcast performance. A predictive likelihood is the predictive density produced by a nowcasting model, evaluated at the actual outcome. Our MIDAS methods produce a predictive mean (the point nowcast) and a predictive standard deviation. We use a Normal approximation to the predictive density to produce our predictive likelihoods.

Our nowcasts are recursive, i.e. each nowcast is calculated using data from the beginning of the sample to the time the nowcast is made. We experimented with the use of rolling methods, but these performed slightly worse than recursive methods. Tables 2 and 3 contain our nowcast diagnostics for the nowcasts for the five different months (labelled $h = -1, 0, 1, 2, 3$ as described above). To be specific, for each realization (i.e. GVA value in a particular month) our method will provide five different nowcasts of it corresponding to different values of h. We evaluate these five different nowcasts separately in the different columns of the table.

Each nowcast is produced using the specification given in (3) with two lags of the dependent variable and a single explanatory variable. There are 40 such nowcasts for our 40 explanatory variables. We also present nowcasts which average over all models using the 3 weights schemes of sub-section 2.4. The different rows of these tables correspond to these different nowcasts. Lag length choices were made using BIC. Our results use two lags of the dependent variable ($q = 2$) and, thus, all our models add to the AR(2) process commonly used with GDP growth. For the monthly explanatory variables MIDAS is done over the three quarters in the month ($p_M = 3$). For the quarterly explanatory variables

produced by the Scottish government covers only manufacturing exports, which constitute a declining share of total exports.

we use a single lag which is the most recent value of the variable which is available at the time the nowcast is made. We evaluate the nowcasts beginning with the first month of 2005.

Tables 2 and 3 presents the MSFEs and sums of log predictive likelihoods, respectively. The row of Table 2 labelled "No change nowcasts" contains MSFEs for a benchmark we hope to beat. It simply uses as the nowcast the most recent value of GDP growth that is available. Given delays in release of data, this will be GDP growth two quarters ago for the three months of the quarter ($h = 3, 2, 1$) and last quarter's GDP growth for the first two months of the following quarter ($h = 0, -1$).

MSFEs and sums of log predictive likelihoods are telling similar stories and there are two main stories that emerge. First, we are finding that what we might call current quarter nowcasts ($h = 1, 2, 3$, e.g. nowcasts for 2014Q2 made on 1 July or earlier) are substantially better than no change nowcasts. Results for what can be called following quarter nowcasts ($h = -1, 0$, e.g. nowcasts for 2014Q2 made on 1 August and 1 September) are less encouraging. Second, model averaging is a great help in improving nowcast performance. We elaborate on these stories and offer some additional details in the following material.

With current quarter nowcasts, averaging over all models is producing MSFEs which tend to be much lower than individual nowcasts using a particular predictor. Furthermore, MSFEs are being reduced by roughly a quarter relative to no change nowcasts. But most of these gains are driven by a small number of our predictors. This illustrates an advantage of our approach: we can include a large number of potential predictors, most of which provide little explanatory power, and let the econometric methodology decide which ones should be used to form the nowcasts. In our case, it is sometimes the case that non-obvious variables receive a lot of weight. For instance, PMI for Northern Ireland is the best predictor for Scottish GDP growth for several nowcasts. A careful examination of the data reveals the reason: Northern Ireland's PMI fell much further after the financial crisis than PMI for the other regions. This improved the nowcasts after the financial crisis when actual GDP growth fell dramatically. In general, some of the PMI variables do tend to be good predictors. Among the PMI variables, one would expect Scottish PMI to be the best predictor for Scottish GDP growth. It does often nowcast well. However, as noted, at some nowcast horizons Northern Ireland's PMI is a better predictor. And for $h = 0$ (i.e. nowcasts released on the first day of the second month of the following quarter (e.g. on the 1st August) using data from the third month of the previous quarter (so e.g. June)), PMI for the UK as a whole is a very good predictor.

Among the remaining soft variables (which often nowcast better for the current quarter), GFKCC (a survey of consumer confidence) tends to nowcast well. Variables from the Bank of Scotland's Report on Jobs, are also often reasonably good predictors.

Some of the hard variables nowcast well in the following quarter. Given that hard variables are often released more slowly than soft variables this is not surprising. For instance, the index of services for the UK as a whole (IOSG) is released with nearly a two-month delay, but is often an excellent nowcasting variable. For our final nowcast before the new GDP data release ($h = -1$) the IOSG and PMINI are the best predictors.

Most of the other predictors rarely nowcast well and obtain little weight in most of our averaged nowcasts. But most of them at least occasionally make an impact. For instance, most of our variables relating to VAT do not nowcast well, but for one nowcast horizon ($h = 0$) new VAT registrations is a good predictor. Our methods can automatically adjust to such findings, giving substantial weight to the nowcasting model with NEWVATREG when $h = 0$, and giving very little weight to this model for other values of h.

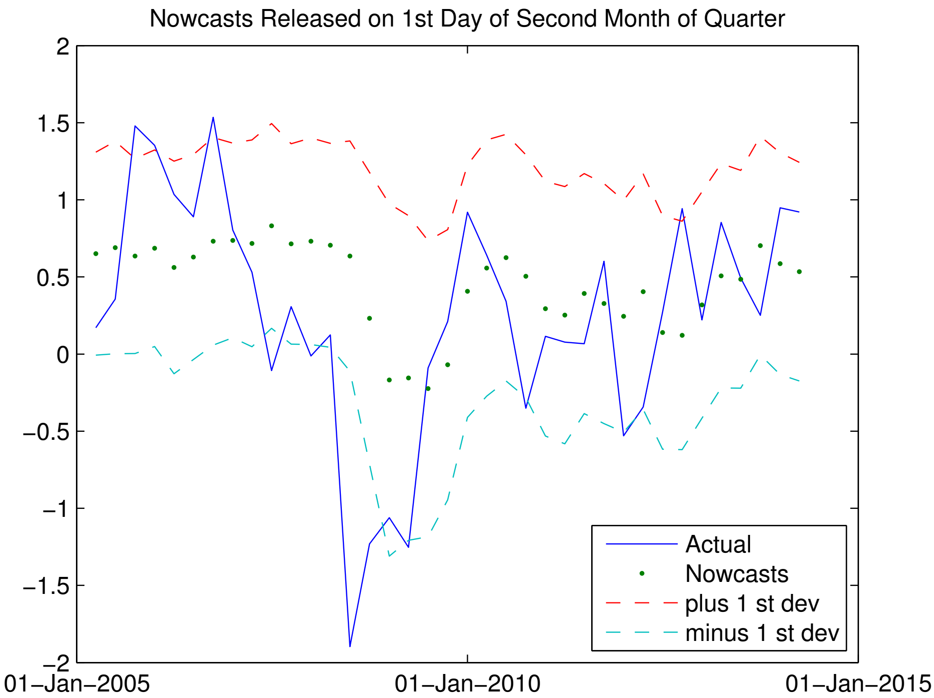
Tables 2 and 3 present forecast metrics averaged over the entire period from 2005 through the end of the sample. To gain insight into how our nowcasts perform over time, figures 1 through 5 plot nowcasts for our preferred approach (averaged nowcasts using MSFE weights) over time for the five nowcast horizons. On the whole, our nowcasts match the actual outcomes quite well. The Great Recession began in the middle of our nowcast evaluation period. It can be seen that our methods were slightly late in capturing the fall in GDP growth and never quite predicted its magnitude. Perhaps this is unsurprising given the short sample that was being used to estimate the models and the fact that the Great Recession was quite different than anything else seen previously in our data.

Another pattern is that the nowcasts, as expected, tend to improve over time. For instance, if one examines the stuttering recovery which began in 2010, it can be seen that the first nowcasts we produce tended to be below the eventual realization of GDP growth. However, by the second quarter of the months, the nowcasts were tracking the actual realizations much better.

5 Conclusions

In this paper, we have discussed the challenges facing the researcher interested in nowcasting within a sub-national region such as Scotland. These include the longer delays in release of key variables, the lack of data on variables commonly-used to nowcast at the national level and the shortness of the time span for which data is available. To try and overcome these challenges, we have collected a large dataset containing a wide variety of variables. We find that, by using MIDAS methods and averaging over results for our many models, we can nowcast fairly successfully, particularly in the quarter being nowcast. In this paper we have demonstrated how nowcasting methods can be implemented in a regional setting, and we have demonstrated how well these methods can perform, even with more limited data being available at the regional level. There is clear scope, and in our experience interest, in implementing these methods for regions, and we hope that this paper will bring these methods to the attention of regional policymakers. For us, our plan is to use these variables and econometric methods in the future to nowcast Scottish GDP growth and release monthly updates of the current state of the economy in Scotland.

Figure 1:



Nowcasts Released on 1st Day of Second Month of Quarter
2
1.5
1
0.5
0
−0.5
−1
−1.5
−2
01−Jan−2005
01−Jan−2010
01−Jan−2015
Actual
Nowcasts
plus 1 st dev
minus 1 st dev

Figure 2:

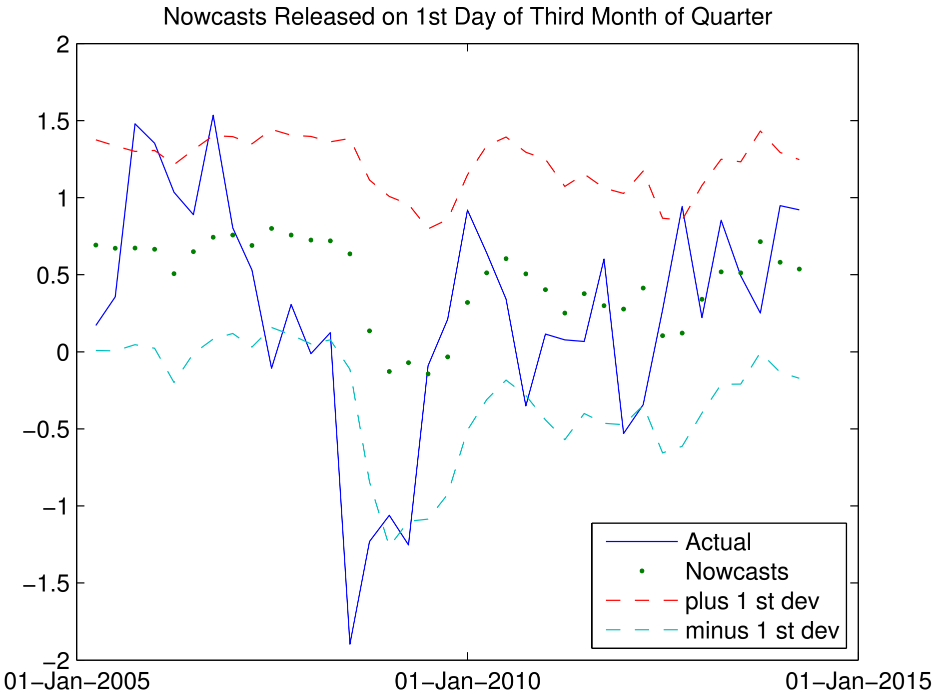


Figure 3:

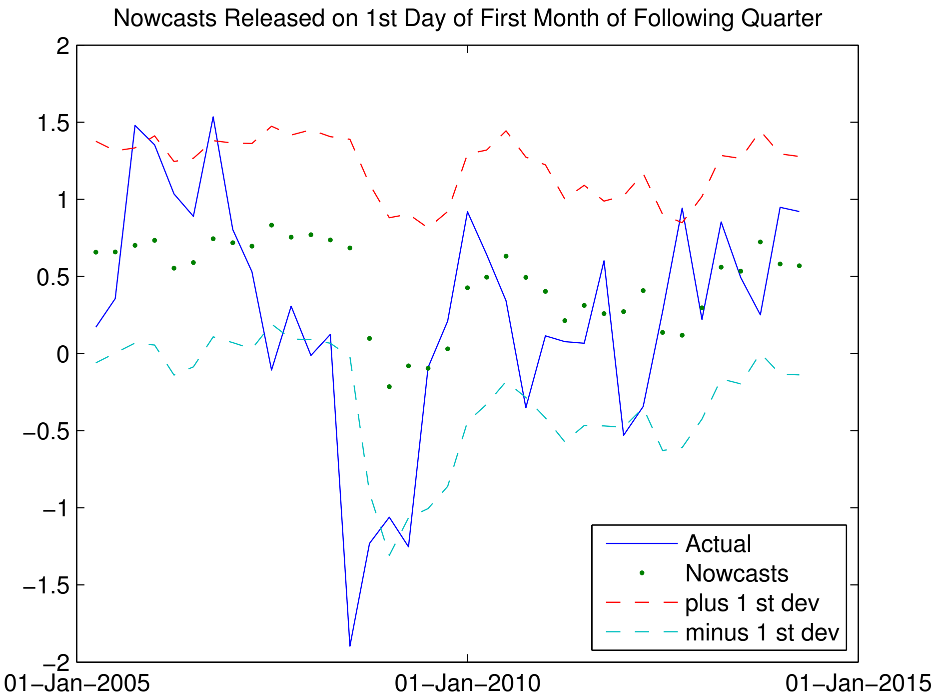


Figure 4:

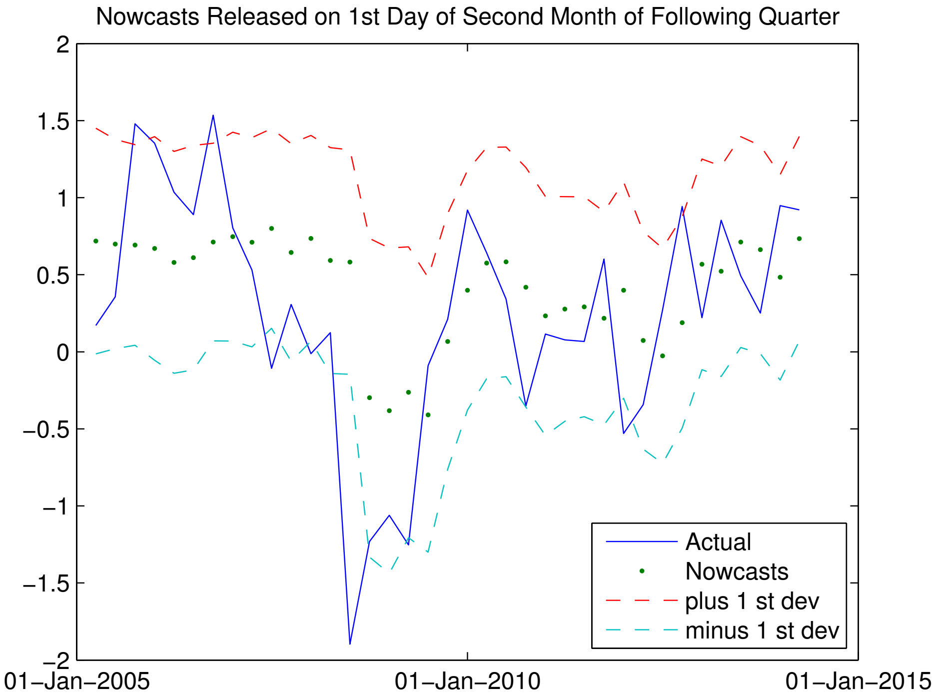


Figure 5:

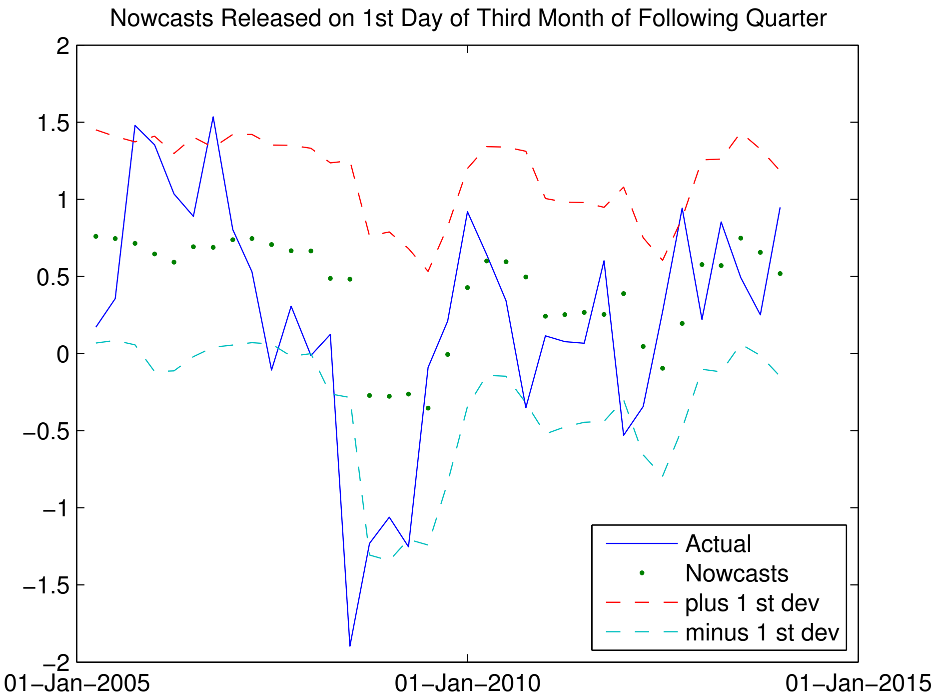


Table 1: Timing of Data and Nowcast Releases

h	Month data relates to:	e.g. for Q2 GDP	Nowcast released on 1st day of	e.g. for Q2 GDP
-2	Second month of Q_{+1}	August	First month of Q_{+2}	October
-1	First month of Q_{+1}	July	Third month of Q_{+1}	September
0	Third month of Q	June	Second month of Q_{+1}	August
1	Second month of Q	May	First month of Q_{+1}	July
2	First month of Q	April	Third month of Q	June
3	Last month of Q_{-1}	March	Second month of Q	May

Table 2: MSFEs for nowcasts

	$h=3$	$h=2$	$h=1$	$h=0$	$h=-1$
No change nowcasts	0.611	0.611	0.611	0.405	0.405
Ave. MSFE weights	0.510	0.515	0.507	0.442	0.439
Ave. BIC weights	0.517	0.521	0.511	0.445	0.445
Ave. equal weights	0.517	0.521	0.512	0.445	0.445
PMISCOT	0.535	0.520	0.470	0.482	0.565
PMILON	0.641	0.629	0.655	0.564	0.596
PMISE	0.633	0.608	0.538	0.527	0.548
PMISW	0.576	0.590	0.605	0.512	0.555
PMIEAST	0.557	0.546	0.520	0.531	0.491
PMIWALES	0.631	0.676	0.622	0.574	0.571
PMIWMID	0.711	0.634	0.613	0.545	0.499
PMIEMID	0.611	0.639	0.619	0.507	0.486
PMIYORK	0.687	0.657	0.595	0.550	0.556
PMINE	0.675	0.650	0.681	0.511	0.545
PMINW	0.668	0.632	0.607	0.578	0.542
PMINI	0.463	0.457	0.588	0.422	0.366
VATPAY	0.705	0.702	0.671	0.570	0.586
VATREPAY	0.734	0.704	0.661	0.532	0.593
VATRCPT	0.639	0.694	0.668	0.549	0.498
IMPVAT	0.575	0.683	0.731	0.573	0.546
TOTALVAT	0.611	0.711	0.706	0.540	0.493
NEWVATREG	0.652	0.612	0.573	0.456	0.547
VATDEREG	0.656	0.604	0.559	0.522	0.555
TRADPOP	0.685	0.555	0.530	0.545	0.531
UKIP	0.641	0.672	0.651	0.484	0.532
UKCPI	0.683	0.646	0.588	0.520	0.529
UNEMP	0.618	0.674	0.682	0.541	0.462
IOSG	0.510	0.549	0.570	0.444	0.385
GFKCC	0.498	0.516	0.537	0.660	0.636
UKREFINE	0.544	0.647	0.598	0.475	0.504
UKEXPORTS	0.651	0.648	0.624	0.557	0.558
UKIMPORTS	0.616	0.608	0.594	0.537	0.553
RSI	0.592	0.592	0.592	0.488	0.488
EXP	0.551	0.551	0.551	0.488	0.488
IMP	0.517	0.517	0.517	0.452	0.452
SBM	0.541	0.551	0.551	0.415	0.426
SCBSMAN	0.573	0.573	0.573	0.480	0.480
SCBSCON	0.519	0.519	0.519	0.472	0.472
SCBSTOUR	0.559	0.559	0.559	0.507	0.507
PMIUK	0.529	0.536	0.502	0.432	0.427
PMIEZ	0.562	0.571	0.558	0.468	0.441
PMIWORLD	0.530	0.551	0.518	0.454	0.453
BOSJOBS_PL	0.538	0.575	0.574	0.444	0.494
BOSJOBS_ST	0.569	0.555	0.528	0.464	0.475

Table 3: Sums of log Predictive Likelihoods for nowcasts

	$h=3$	$h=2$	$h=1$	$h=0$	$h=-1$
Ave. MSFE weights	130.73	130.64	130.09	132.74	129.92
Ave. BIC weights	130.57	130.48	129.99	132.67	129.72
Ave. equal weights	130.56	130.47	129.98	132.66	129.70
PMISCOT	129.16	130.45	132.24	131.88	127.13
PMILON	125.63	125.78	125.50	128.66	126.83
PMISE	126.55	126.07	127.65	131.60	128.80
PMISW	127.90	128.10	125.98	128.68	127.87
PMIEAST	129.70	130.02	127.92	130.00	127.37
PMIWALES	129.66	127.60	127.75	130.86	128.33
PMIWMID	127.21	127.05	123.76	129.04	128.46
PMIEMID	124.19	126.31	127.03	130.26	130.53
PMIYORK	123.13	123.27	126.56	128.40	126.04
PMINE	122.30	125.92	125.39	131.42	130.73
PMINW	127.60	127.56	125.40	130.50	129.35
PMINI	132.86	133.31	128.44	135.67	130.85
VATPAY	124.40	123.35	123.48	125.83	126.13
VATREPAY	120.65	120.62	122.54	127.22	127.19
VATRCPT	124.27	123.63	124.08	128.03	129.53
IMPVAT	125.62	122.39	119.86	125.48	126.84
TOTALVAT	125.42	124.13	124.41	129.51	129.36
NEWVATREG	124.65	126.05	127.88	132.03	129.82
VATDEREG	126.17	128.15	126.85	128.72	127.76
TRADPOP	126.37	129.67	129.60	129.25	130.79
UKIP	124.18	124.96	125.57	130.51	131.03
UKCPI	126.54	126.53	127.45	130.55	130.89
UNEMP	126.83	126.63	125.60	131.58	133.85
IOSG	131.02	129.28	129.34	132.36	135.53
GFKCC	131.65	131.24	131.39	127.73	128.32
UKREFINE	127.34	124.06	125.88	130.23	128.64
UKEXPORTS	124.97	123.95	123.99	128.12	127.38
UKIMPORTS	121.55	122.18	123.60	127.76	127.03
RSI	125.50	125.50	125.50	129.89	129.89
EXP	127.05	127.05	127.05	130.25	130.25
IMP	127.56	127.56	127.56	131.76	131.77
SBM	129.40	127.21	127.21	135.61	131.09
SCBSMAN	126.47	126.47	126.47	130.07	130.07
SCBSCON	128.29	128.29	128.29	131.15	131.15
SCBSTOUR	127.74	127.74	127.74	130.98	130.98
PMIUK	129.04	128.91	129.72	133.42	130.08
PMIEZ	126.52	126.43	127.17	130.83	129.80
PMIWORLD	128.00	127.33	129.09	131.73	129.87
BOSJOBS_PL	127.21	126.15	126.35	131.56	129.63
BOSJOBS_ST	125.94	126.42	127.80	130.73	129.36

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Data Appendix

No.	Variable name	Definition	Source	URL for latest data	Transformation	Approximate release date	Monthly (M) or quarterly (Q)	UK, Scottish or other region
-	GVASCOT	Quarterly GVA series for Scotland, constant price, chained volume measure	Scottish Government	`http://www.scotland.gov.uk/Topics/Statistics/Browse/Economy/GDP/Findings`	$\ln(X_t)-\ln(X_{t-1})$	15 weeks after end of quarter	Q	Scotland
1	PMISCOT	Headline PMI (output) for Scotland	Bank of Scotland PMI Scotland	—	No transformation	10 days after end of month	M	Scotland
2	PMILON	Headline PMI (output) for London	Markit	—	No transformation	10 days after end of month	M	Other
3	PMISE	Headline PMI (output) for South East England	Markit	—	No transformation	10 days after end of month	M	Other
4	PMISW	Headline PMI (output) for South West England	Markit	—	No transformation	10 days after end of month	M	Other
5	PMIEAST	Headline PMI (output) for East of England	Markit	—	No transformation	10 days after end of month	M	Other
6	PMIWALES	Headline PMI (output) for Wales	Markit	—	No transformation	10 days after end of month	M	Other
7	PMIWMID	Headline PMI (output) for the West Midlands	Markit	—	No transformation	10 days after end of month	M	Other
8	PMIEMID	Headline PMI (output) for the East Midlands	Markit	—	No transformation	10 days after end of month	M	Other
9	PMIYORK	Headline PMI (output) for Yorkshire and the Humber	Markit	—	No transformation	10 days after end of month	M	Other
10	PMINE	Headline PMI (output) for North East England	Markit	—	No transformation	10 days after end of month	M	Other
11	PMINW	Headline PMI (output) for North West England	Markit	—	No transformation	10 days after end of month	M	Other
12	PMINI	Headline PMI (output) for Northern Ireland	Markit	—	No transformation	10 days after end of month	M	Other
13	PMIUK	UK Purchasing Managers Index Output for the UK	Markit	—	No transformation	10 days after end of month	M	UK
14	PMIEZ	Eurozone Purchasing Managers Index Output for the Eurozone	Markit	—	No transformation	10 days after end of month	M	Other
15	PMIWORLD	World Purchasing Managers Index Output for the World	Markit	—	No transformation	10 days after end of month	M	Other
16	VATPAY	(Home) Value Added Tax payments	HM Revenue and Customs (HMRC)	`https://www.uktradeinfo.com/Statistics/Pages/TaxAndDutyBulletins.aspx`	$\ln(X_t)-\ln(X_{t-12})$	21 days after end of month	M	UK
17	VATREPAY	(Home) Value Added Tax repayments	HM Revenue and Customs (HMRC)	`https://www.uktradeinfo.com/Statistics/Pages/TaxAndDutyBulletins.aspx`	$\ln(X_t)-\ln(X_{t-12})$	21 days after end of month	M	UK
18	VATRCPT	(Home) net VAT receipts	HM Revenue and Customs (HMRC)	`https://www.uktradeinfo.com/Statistics/Pages/TaxAndDutyBulletins.aspx`	$\ln(X_t)-\ln(X_{t-12})$	21 days after end of month	M	UK

19	IMPVAT	Import VAT receipts	HM Revenue and Customs (HMRC)	`https://www.uktradeinfo.com/Statistics/Pages/TaxAndDutyBulletins.aspx`	$\ln(X_t)-\ln(X_{t-12})$	21 days after end of month	M	UK
20	TOTALVAT	Total VAT receipts	HM Revenue and Customs (HMRC)	`https://www.uktradeinfo.com/Statistics/Pages/TaxAndDutyBulletins.aspx`	$\ln(X_t)-\ln(X_{t-12})$	21 days after end of month	M	UK
21	NEWVATREG	New registrations for VAT	HM Revenue and Customs (HMRC)	`https://www.uktradeinfo.com/Statistics/Pages/TaxAndDutyBulletins.aspx`	$\ln(X_t)-\ln(X_{t-12})$	21 days after end of month	M	UK
22	VATDEREG	Deregistrations for Value Added Tax	HM Revenue and Customs (HMRC)	`https://www.uktradeinfo.com/Statistics/Pages/TaxAndDutyBulletins.aspx`	$\ln(X_t)-\ln(X_{t-12})$	21 days after end of month	M	UK
23	TRADEPOP	Live (VAT-registered) trader population	HM Revenue and Customs (HMRC)	`https://www.uktradeinfo.com/Statistics/Pages/TaxAndDutyBulletins.aspx`	$\ln(X_t)-\ln(X_{t-12})$	21 days after end of month	M	UK
24	GFKCC	Monthly consumer confidence barometer	Markit	—	No transformation	Approximately 2 weeks after end of month	M	Scotland
25	BOSJOBS_PL	Index of permanent staff placements (seasonally adjusted)	Markit	—	No transformation	21 days after end of month	M	Scotland
26	BOSJOBS_ST	Index of permanent staff demand (seasonally adjusted)	Markit	—	No transformation	21 days after end of month		Scotland
27	UNEM	Claimant count rate (i.e. number of those receiving Jobseekers Allowance divided by those receiving JA plus the number of workforce jobs)	Office for National Statistics	`http://www.ons.gov.uk/ons/rel/subnational-labour/regional-labour-market-statistics/index.html`	$\ln(X_t)-\ln(X_{t-1})$	15 days after end of month	M	Scotland
28	UKIP	Index of Production	Office for National Statistics	`http://www.ons.gov.uk/ons/rel/iop/index-of-production/index.html`	$\ln(X_t)-\ln(X_{t-1})$	Approximately 5 weeks after end of month	M	UK
29	IOSG	UK Index of Services	Office for National Statistics	`http://www.ons.gov.uk/ons/rel/ios/index-of-services/index.html`	$\ln(X_t)-\ln(X_{t-1})$	Approximately 6 weeks after end of month	M	UK
30	UKCPI	UK consumer price inflation (CPI) index	Office for National Statistics	`http://www.ons.gov.uk/ons/taxonomy/index.html?nscl=Consumer+Prices+Index`	$\ln(X_t)-\ln(X_{t-1})$	Approximately 2 weeks after end of month	M	UK
31	UKEXPORTS	Total UK exports (million, seasonally adjusted)	Office for National Statistics	`http://www.ons.gov.uk/ons/rel/uktrade/uk-trade/index.html`	$\ln(X_t)-\ln(X_{t-1})$	Approximately 6 weeks after end of month	M	UK
32	UKIMPORTS	Total UK imports (million, seasonally adjusted)	Office for National Statistics	`http://www.ons.gov.uk/ons/rel/uktrade/uk-trade/index.html`	$\ln(X_t)-\ln(X_{t-1})$	Approximately 6 weeks after end of month	M	UK
33	UKREFINE	Throughput of crude and process oil at UK refineries, Table 3.12	Department of Energy and Climate Change	`https://www.gov.uk/government/statistics/oil-and-oil-products-section-3-energy-trends`	$\ln(X_t)-\ln(X_{t-12})$	Approximately 8 weeks after end of month	M	UK
34	RSI	Index of retail sales volume at basic prices	Scottish Government	`http://www.scotland.gov.uk/Topics/Statistics/Browse/Economy/PubRSI`	$\ln(X_t)-\ln(X_{t-1})$	Approximately 5 weeks after end of quarter	Q	Scotland

35	EXP	Total value of exports from Scotland (current prices)	HM Revenue and Customs (HMRC)	`https://www.uktradeinfo.com/Statistics/RTS/Pages/default.aspx`	$\ln(X_t)-\ln(X_{t-4})$	Approximately 9 weeks after end of quarter	Q	Scotland
36	IMP	Total value of imports to Scotland (current prices)	HM Revenue and Customs (HMRC)	`https://www.uktradeinfo.com/Statistics/RTS/Pages/default.aspx`	$\ln(X_t)-\ln(X_{t-4})$	Approximately 9 weeks after end of quarter	Q	Scotland
37	SBM	Index of trends in total volume of business	Scottish Business Monitor	—	No transformation	Approximately 4 weeks after end of quarter	Q	Scotland
38	SCBSMAN	Index of manufacturing orders	Scottish Chambers Business Survey	—	No transformation	Approximately 3 weeks after end of quarter	Q	Scotland
39	SCBSCON	Index of construction orders	Scottish Chambers Business Survey	—	No transformation	Approximately 3 weeks after end of quarter	Q	Scotland
40	SCBSTOUR	Index of tourism orders	Scottish Chambers Business Survey	—	No transformation	Approximately 3 weeks after end of quarter	Q	Scotland