FEATURE

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Forecasting GDP using external data sources

SUMMARY

The Office for National Statistics (ONS) is the official provider of National Accounts data in the UK. However, business surveys and financial markets also provide a large number of other possible indicators of economic activity. This article outlines how ONS might use this 'external' data in compiling gross domestic product (GDP) estimates. A study of the literature suggests that these indicators may be useful predictors of economic activity, but their forecast performance in 'real time' is not proven. As a result ONS uses this data cautiously and only as an informal guide and a check on its own statistics. As there are a large number of potential indicators, this article describes how principal components analysis can be used to construct an alternative estimate of GDP which aims to summarise the external data 'view of the world' for comparison purposes.

In the UK, the Office for National Statistics (ONS) produces a succession of different vintages of quarterly gross domestic product (GDP). The first of these is the preliminary estimate which is an output-based measure and is published no more than 25 days after the end of the reference quarter. Due to the timeliness of the release, information for many of the components of GDP is incomplete, particularly for the final month of the quarter. Skipper (2005) estimates the data content of the preliminary estimate to be just 44 per cent, with the missing information at this stage replaced by forecasts and imputations.

Over time ONS publishes later vintages of the same data. Revisions reflect the arrival of new survey information, not only for the output measure of GDP but also for the income and expenditure measures. By the time the Quarterly National Accounts are published around 85 days after the end of the reference quarter, the data content of the GDP estimate increases to 80 per cent. Data-driven revisions can continue for up to two years as data from annual surveys and administrative sources such as HM Revenue & Customs (HMRC) become available. In the longer run, revisions can also result from methodological changes representing attempts to measure the evolving economy more accurately.

The presence of revisions is clear evidence of a 'timeliness versus accuracy' trade-off between different vintages of GDP. Although preliminary estimates are available almost immediately, being based on low data content also means they are likely to be superseded by later vintages that more accurately measure the growth path of the economy. This trade-off is a prominent issue where policy is set in a pre-emptive fashion, such as the operation of monetary policy, because short-term forecasts may be affected by relatively immature and unrevised data. This issue is outlined by Croushore and Stark (2002), and Nelson and Nicolov (2003) discuss the implications of output gap mismeasurement for UK inflation during the 1970s and 1980s. The analysis of 'real time' data and their impact on (monetary) policy setting has been a hot topic in the recent economics literature.

Although mature ONS data are generally accepted as the best measure of GDP, given the low data content of the preliminary estimate, it is sensible to investigate the possibility of reducing the likelihood of subsequent revisions by using other timely data. There are two main sources of alternative data. Business surveys are conducted by trade associations and industry groups in the UK such as the Confederation of British Industry (CBI), the Chartered Institute of Purchasing and Supply (CIPS) and the British Chambers of Commerce (BCC). These data are more qualitative, but are available in a timely fashion and on a broad range of indicators. Financial market variables are available in 'real time' and may also have predictive power over the level of GDP.

A recent paper by Ashley *et al* (2005) describes how the Bank of England uses business surveys in an attempt to deal with the 'data uncertainty' in early estimates of GDP. Although ONS does not use formal methods to incorporate business survey data into its estimates, it is not oblivious to the story being told by other data sources. Compilers of economic statistics in ONS pay attention not just to business survey and financial market data, but also to a large amount of specific industry data and use these in the process of quality assuring data from official sources. ONS also monitors the views reported by business surveys as a check on its own data, and attempts to account for any differences in the story being told.

This article has two main aims. The first is to review the recent literature on using business surveys and financial market data as indicators in forecasts of GDP. If found to have strong predictive content, then there is a rationale for using these data to guide early estimates. The conclusion of this article is that there are likely to be significant technical difficulties with the use of such indicators in this way, and that other considerations must also be taken into account, notably the independence of official estimates, and their grounding in international standards. Therefore an informal use of these data is the most appropriate and then simply as a guide and a check on official estimates. Second, the number of potential indicator variables is very large. Although some of these warrant more consideration than others, it is useful to extract common factors which may be interpreted as shared underlying trends in order to give a single 'external data' view of the economy. This can be done using principal components analysis which works as a data reduction technique. Using this approach, for each quarter, an alternative estimate of GDP is constructed for comparison purposes with the official estimate.

The rationale for using external data in official estimates

Both the ONS preliminary estimate of GDP and the alternative estimate constructed using external data sources can be viewed as nowcasts of GDP. That is, they are essentially forecasts of later vintages of the same data. Following Granger and Ramanathan (1984), there is an extensive literature on the potential benefits of reducing forecast errors by combining forecasts. Noting that forecast errors in this context refer to data revisions, it is worth exploring the potential scope for a combination of preliminary and alternative estimates to produce a better timeliness-accuracy trade-off for early GDP estimates.

Let the preliminary estimate of GDP for period t be defined as y^p_t, and a mature estimate as y^M_t. If the preliminary estimate is simply a nowcast of the later estimate then:

$$y^m_t = y^p_t + \varepsilon_t \qquad (1)$$

The error term ε_t is the associated forecast error. The revision from the preliminary to the mature estimate is simply $R_t = y^m_t - y^p_t$, so from (1) it is clear that revisions are just forecast errors between different vintages of the same data. Mincer and Zarnowitz (1969) argue that if the preliminary estimate is an efficient forecast then it must fully incorporate all the information available at the time of its compilation. Therefore, the forecast error or the revision should be unpredictable, implying that future revisions are driven solely by information that will only become available in the future. This statement forms what is known as the efficient forecast hypothesis (EFH).

A test of the EFH can be formed by estimating

$$R_t = a + by^p_t + \mathbf{X}_t\boldsymbol{\varphi}' + \varepsilon_t \qquad (2)$$

Where $\mathbf{X}_t = [x_{1t}, x_{2t}, \ldots\ldots\ldots\ldots, x_{mt}]$ is the vector of m indicators and $\boldsymbol{\varphi} = (\phi_1, \phi_2, \ldots\ldots\ldots, \phi_m)$ an associated vector of coefficients. In this case the null hypothesis of accepting the EFH requires

$$a = b = \phi_1 = \phi_2 = \ldots\ldots\ldots\ldots = \phi_m = 0 \qquad (3)$$

Acceptance of this null would imply that revisions are unpredictable and that the EFH holds. However, a rejection of the null would infer the opposite, that the current forecast is inefficient and making use of the added information will on average reduce revisions.

The form of (2) is fairly easy to justify and gives an indication from where extra information might be found. If a ≠ 0 then it implies that there is a systematic component or bias to the revisions. For example, if $a>0$, it implies that revisions have a positive mean, suggesting that the preliminary estimate on average underestimates the latest estimate. This could be corrected by simply adding a bias adjustment of the size a to the preliminary estimate.

It might also be the case that $b \neq 0$ which suggests that the preliminary estimate itself is a predictor of future revisions. For example, if $b < 0$, revisions are inversely related to the preliminary estimate. This would mean that if the preliminary estimate is positive (perhaps overestimated) then the subsequent revision is likely to be downwards, whereas if the preliminary estimate is negative (perhaps underestimated) then future revisions are likely to be upwards. Alternatively, if $b > 0$, then the implication is that preliminary estimates under-record the strength of a growing economy and the weakness of a shrinking economy.

When one or more components in the coefficient vector $\boldsymbol{\varphi}$ are significantly different from zero, it means that the associated indicators have predictive power over revisions. In this case, the preliminary estimate can be improved if it is adjusted to incorporate the part of the revision that is predicted by the indicators.

The concept of forecast efficiency is very similar to the notion of combining forecasts outlined by Granger and Ramanathan (1984). The optimal forecast of GDP is its expected value given the full available information set (I_t), $y^*_t = E[y_t/I_t]$. The preliminary estimate in turn is the expected value of GDP growth given the information available to ONS $y^p_t = E[y_t/I^p_t]$. Because these are based on surveys of samples rather than populations, the information set will only be a subset of the total $I^p_t \subset I_t$. Likewise, the alternative estimate is based on the information available to the forecaster from business survey and financial market data $y^A_t = E[y_t/I^A_t]$, which is again a subset of all the information available $I^A_t \subset I_t$. The combined forecast represents the estimate based on the union of the two information sets $y^C_t = E[y_t/I^p_t \cup I^A_t]$.

Combining information or data sets is difficult though, especially if they are large and not measured in the same units. For example, in the ONS survey, the response by a firm will represent a point estimate of quarterly output movements, whereas in an business survey they would simply reply 'up', 'down' or 'no change'. Quantitative and qualitative data cannot be easily combined. Therefore, combining forecasts provides an easy approximation to combining information sets $y^c_t = \hat{\lambda} y^p_t + \hat{\omega} y^A_t$. The optimal weights λ and ω can be identified as the estimated coefficients from the regression:

$$y^M_t = \lambda y^p_t + \omega y^A_t + \varepsilon_t \qquad (4)$$

It is often the case that the weights are constrained to sum to one. There is no econometric rationale as to why the restriction $\omega = (1-\lambda)$ in (4) needs to be applied; in fact, unrestricted estimation is likely to produce a better fitting equation. However, imposing the restriction makes it easier to judge the relative contribution of each forecast in the optimal combination.

There is a clear link between the concept of forecast efficiency and the motivation underlying forecast combinations. The alternative estimate can be formed from a set of indicators using a two-stage process. First, estimate a relationship between a mature estimate of GDP and the set of m indicator variables:

$$y_t^M = \alpha + \mathbf{X}_t\boldsymbol{\theta}' + \varepsilon_t \qquad (5)$$

where $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots\ldots, \theta_m)$ is a set of m coefficients. The alternative estimate can then be formed using the estimated parameters from (5). As all the elements in $\mathbf{X}$ for time t are available before the preliminary estimate is published, the alternative GDP forecast can be constructed using the coefficients from (5) estimated at time t-1:

$$y_t^A = \hat{\alpha} + \mathbf{X}\hat{\boldsymbol{\theta}}' + \varepsilon_t \qquad (6)$$

Essentially the forecast efficiency (2) and forecast combination (4) models are just reparamaterisations of each other, where $a = \omega\hat{a}$, $b = -\lambda$, $\boldsymbol{\varphi} = \omega\hat{\boldsymbol{\theta}}$ and $\hat{a}$ and $\hat{\boldsymbol{\theta}}$ are the estimated coefficients in (6). The two models are therefore equivalent. If the preliminary estimate is an inefficient estimate of mature data, it implies that it fails to incorporate available and relevant information. If this information is reflected in an alternative estimate, then combining forecasts leads to a more efficient outcome (that is, lower forecast errors or revisions on average).

This forecast combination approach is advocated by the Bank of England in Ashley *et al* (2005). ONS has investigated the potential improvement to revisions performance but has stopped short of using formal combination methods for a number of reasons.

The success of forecast combination models, like any forecast models, is best assessed by testing out-of-sample performance. As will be seen in the next but one section, there is a substantial literature showing that indicators that work well in-sample can form poor forecasts when the sample is extended. The best-fitting equation is not necessarily the best forecasting model. This is partly because the relationship between indicators and official data is unstable over time. Certain indicators are found to work well but only in certain periods. The relationships are further complicated by ongoing improvements to National Statistics, such as the development work on measuring the service sector (see Tily (2006)). All in all, a relationship that worked well in the past will not necessarily perform so well in the future.

Tests should also be conducted using 'real time' data. These are the unrevised data available at the time the forecast was produced. Failure to do so gives the forecaster an informational advantage that he would not enjoy in actuality. It is much easier to select the relevant variables if you have some knowledge of where the data being forecast will gravitate towards in the future. As yet there is little published evidence that external indicator variables have performed well in out-of-sample tests on real time data. These points are generally accepted in Ashley *et al* (2005).

As a National Statistics institution, ONS has an obligation to meet international standards on the formulation of National Accounts, and produce estimates in a transparent way so that users can be confident that quality benchmarks are being maintained. Combining official estimates with indicators would certainly compromise this. Many business surveys are based on very small samples compared with those used by ONS, and purport to measure something other than a point estimate of GDP. A difficulty in separating out the different data sources might also hamper users who could just as well combine the data themselves if considered necessary.

ONS recognises that external data sources are potentially useful in helping to interpret and validate its data but, based on the above considerations, it is better to use indicator data in a strictly informal way rather than incorporating them into official estimates using combination models.

Indicators of GDP

There are two main sources of information on which an alternative estimate of GDP can be based.

Business and consumer surveys

There are many industry groups and trade associations that administer surveys on certain sectors of the economy. These business surveys are based on smaller samples than those conducted by ONS and tend to be more qualitative. For example, the ONS survey would seek to measure how output changed in a certain industry over the quarter. The external surveys on the other hand would simply ask firms to respond as to whether their output went 'up', 'down' or was 'unchanged', with the results published as a balance statistic between the total number of 'ups' and 'downs'.

There are a large number of these types of surveys in the UK recording a rich variety of firm and consumer behaviours, experiences and expectations. These do not just apply to recent output, but factors that are otherwise difficult for National Statistics institutions to collect such as expected future output, capacity constraints, confidence, cost and availability of finance, skill and labour shortages, order books and uncertainty of demand.

The three main business surveys are conducted by CIPS and the BCC, which cover the manufacturing and service sectors of the economy, and the CBI who survey the manufacturing and distribution sectors. Other important sources include the PricewaterhouseCoopers financial services survey, the British Retail Consortium survey of high street consumer spending, and consumer confidence indicators provided by MORI and GfK.

Monetary and financial data

Data from financial markets are generally available in 'real time' so there is only a very small delay between the end of the reference quarter and the availability of relevant data. Monetary and financial data consist of variables such as exchange rates, interest rates, yield curves, stock market indices, money supply and commodity prices. There are two ways in which these data are expected to be an indicator of GDP.

First, there is a direct economic association between financial data and the main aggregates of GDP. Movements in exchange rates affect imports and exports. Interest rates and stock market prices have an impact on both consumption and investment. Although conventional wisdom argues that monetary variables have no long run effects on real variables such as real GDP growth, the presence of nominal rigidities implies that they can have significant short-run effects.

Second, the prices of financial assets are largely governed by expectations about the future including GDP growth. If the economy is anticipated to grow strongly, then expectations of higher future profits will boost current stock market prices and perhaps the gradient of the yield curve would increase. The price of financial assets generally incorporates investors' expectations of the future; hence movements in asset prices might be an indicator of future economic growth.

Recent literature on the use of indicator variables

A large literature has grown up on how these indicators might be used to forecast GDP and its components.

Business surveys

Blake *et al* (2000) look at the short-term forecasting of EU industrial production using three business surveys and short-term interest rates as an indicator. The models are estimated recursively and out-of-sample performance is tested. The findings suggest that models with indicators generally do worse than simple autoregressive models. Naive models where output growth is equal to previous output growth are found to perform well so there is little role for indicator variables, particularly in quieter periods. They also report that the best-fitting model is not always the best forecasting model, and that performance was sensitive to the choice of starting date for the forecast evaluation stage.

However, Sedillot and Pain (2003) find that indicators such as business surveys and financial variables can outperform autoregressive time series models when forecasting GDP for a range of OECD countries. For most countries, the difference in forecasting errors is statistically significant, but different indicators tend to perform differently in different countries. Although their results are based on recursive testing, the underlying data are not 'real time' but the most recently published data set. Similar results were found by Mouougagne and Roma (2002) who investigate the use of confidence indicators for forecasting real GDP growth rates in a range of selected euro area countries. The results are based on a limited number of observations for out-of-sample assessments and found to be a useful improvement over ARIMA models. In addition, Garcia-Ferrer and Bujosa-Brun (2000) find that using qualitative survey data improves the detection of turning points in the economy for six OECD countries.

Consumer confidence

A number of researchers have investigated whether consumer confidence indicators can forecast consumer spending or GDP, but with very limited success. Howrey (2001) finds that measures of consumer sentiment sharpen predictions of recessions, but as a measure of quantitative GDP they only do marginally better than a distributive lag model. Furthermore, these results were not tested out-of-sample and the lead times between movements in confidence indicators and GDP are variable.

Bram and Ludvigson (1998), in forecasting consumer expenditure in the USA, show that adding extra information on consumer confidence reduced forecast errors but not by a statistically significant amount. They also note that models tend to fit better in-sample rather than out-of-sample and in 'real time'. This finding is supported by Croushore (2005), whose main conclusion is that, in 'real time', indexes of consumer confidence are not of significant value in forecasting consumer spending. In fact, in some cases they make forecasts significantly worse.

Financial variables

The significance of financial variables in forecasting GDP is also mixed. Forni *et al* (2003) state that financial variables are not significant leading indicators of industrial production. Estrella and Mishkin (1998), though, find that the yield curve spread holds some power in predicting recessions based on out-of-sample forecasting models. Finally, Stock and Watson (2001) investigate the use of financial variables in predicting output growth using out-of-sample estimation. They find that financial variables predict output movements for some countries in some periods, but overall it is difficult to predict what variables will work where and when.

Factor analysis and data reduction techniques

A useful technique for forecasting output movements when there are a large number of potential indicators was pioneered by Stock and Watson (1989). The underlying hypothesis is that the collection of indicators is driven by a common unobservable variable which might be interpreted as the state of the economy. This can be extracted using a dynamic factor model and used to forecast GDP. This approach was extended by Camba-Mendez *et al* (2001) who develop an automatic leading indicator (ALI) model of GDP. This is a two-stage process where latent variables are first extracted from a set of indicators which are then used to forecast GDP using vector autoregressive models. The ALI model has been used in several instances to generate flash estimates of GDP and industrial production in the euro area (see Buffeteau and Mora (2000) and Bruno and Lupi (2003)).

Principal components analysis works in a similar way to factor analysis, aiming to select a small number of principal components which account for most of the variance in the larger original set of indicators. This approach is adopted by Klein and Park (1995) and Klein and Ozmucur (2001) who find that many indicators are helpful in improving statistical performance for forecasting but no single indicator can do the job by itself. The results from surveys covering consumers and producers are generally useful in forecasting major macroeconomic variables such as industrial production and retail sales, and qualitative data can be very responsive to changing economic conditions. Principal components are used to find common factors from a range of surveys which are subsequently used to forecast the components of GDP. Encouraging results were found in one-step-ahead forecasts using this method.

Neither of these models, though, is immune to general forecasting problems. Stock and Watson (1992) highlighted many of the difficulties in using indicators to forecast GDP: for example they failed to predict the 1991 US recession. Indicator selection can be difficult, as certain indicators can work well in some samples but not in others. Emerson and Hendry (1996) share the scepticism in using indicator (ALI) based models for forecasting. Different indicators tend to perform well at different times, which make out-of-sample testing crucial, as model stability may be otherwise taken for granted.

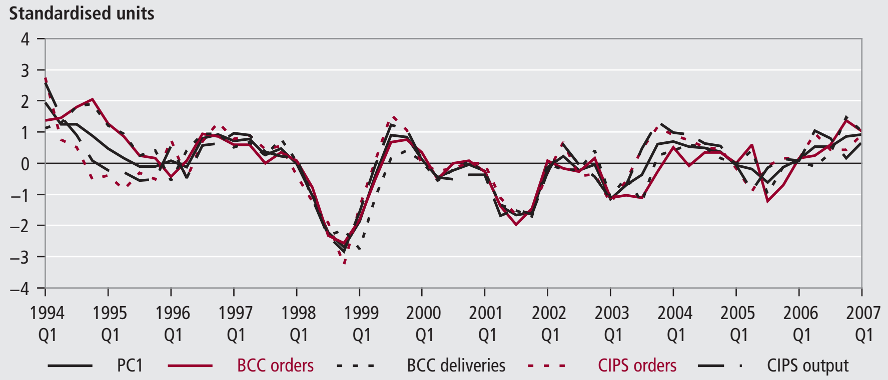
The general view from the literature is that indicator variables may offer some value in interpreting the economy, but whether they can make accurate forecasts of GDP on a consistent basis is unproved. ONS is therefore justified in taking a cautious approach in the use of external data sources.

An alternative estimate of GDP using principal components analysis

Equations (5) and (6) describe a two-stage process where an alternative estimate of GDP can be based on a set of indicator variables. This can then be used as a check against official measures. However, problems arise in estimating (5) because the potential set of external information is large relative to the sample size (T). The number m of available indicator variables amounts to several hundred, so because $T<m$, there is a major degrees of freedom problem and estimation of (5) is not possible. A further problem arises due to the high degree of correlation between many of the indicators. Estimation of (5) will then be subject to multicollinearity, and because it is then difficult to interpret the significance of the parameters in $\boldsymbol{\theta}$, model selection is hampered.

A solution to both these problems exists in using principal components analysis.

Figure 1
Four surveys of manufacturing activity and the first principal component



This essentially identifies the common factors in a set of data and, because the number of significant common factors is substantially below m, it works as a useful factor reduction technique. In addition, because principal components are designed to be orthogonal to each other, the collinearity problem that otherwise befits estimation of (5) is reduced. A full description of the principal components methodology can be found in Mitchell and Weale (2001).

For example, **Figure 1** plots four survey measures of activity in the UK manufacturing sector along with the first principal component of this data set. In **Table 1**, the relative variance accounted by each of the four principal components is displayed. The weights for the first principal component are designed so that the component accounts for the maximum variance of the four variables. The second principal component, in turn, accounts for the largest amount of variance not accounted for the first, and so on. It can be seen that, in this case, 83 per cent of the variance in the four manufacturing surveys can be accounted for by one principal component.

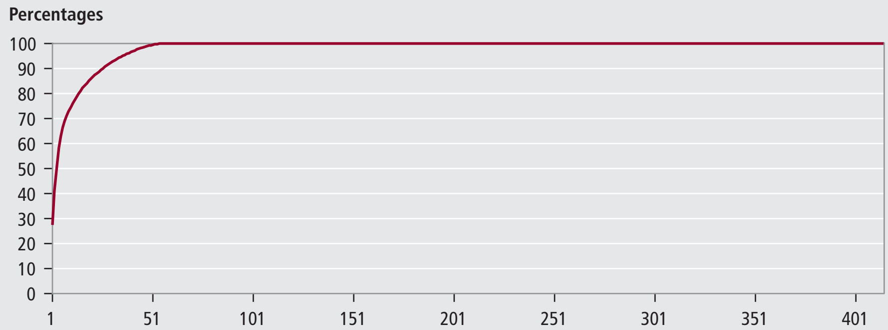
Table 1
Variance proportions of the four principal components relating to the four manufacturing surveys in Figure 1

Percentages

	PC1	PC2	PC3	PC4
Variance proportion	*83*	*15*	*1.1*	*0.9*
Cumulative variance	*83*	*98*	*99.1*	*100*

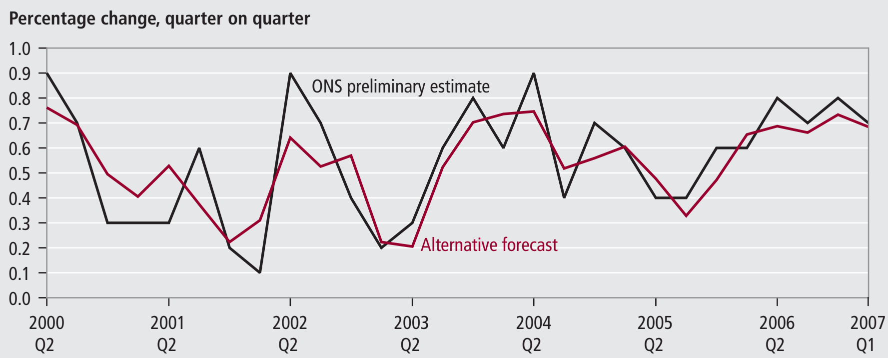
Figure 2 illustrates how principal components analysis can be useful as a factor reduction technique when the set of available indicators is very large. In forming an alternative GDP estimate for 2007 Q1, there are a total of 415 available indicators, so there will also be 415 corresponding principal components. However, the first five principal components account for 62 per cent of the total variation, whereas the first ten account for 75 per cent of the cumulative variance. Therefore, a relatively large number of indicators may be represented by a fairly small number of principal components. In fact, once the eighth principal component is exceeded, no individual principal component accounts for more than 2 per cent of the total variance.

Figure 2
Cumulative share of total variance accounted for by each principal component, 2007 Q1



The estimation of (5) now becomes feasible. Instead of using the set of m indicators, the vector **X** can be replaced with a vector **Z** of $n < m$ principal components. The only remaining consideration is the choice of mature data y_t^M onto which the principal components will be mapped. A mature vintage, such as data that have passed through at least two Blue Books, would have advantages, as the alternative estimate might then reflect where the preliminary estimate could end up. However, the Quarterly National Accounts (month 3) estimate is chosen for two reasons. First, this is the most mature data vintage that is available with a one-quarter lag, so the alternative estimate only requires a one-step ahead forecast. Second, given a reported bias between preliminary and post-Blue Book 2 data, alternative forecasts constructed using later data vintages are unlikely to be informative about the scale and trends in the preliminary estimate, and hence of little comparative value.

Figure 3
Preliminary and alternative early estimates of GDP



The alternative forecast of GDP is plotted in **Figure 3** along with the ONS preliminary estimate. Note that each of these forecasts has been generated out-of-sample using 'real time' data.

Conclusion

ONS takes a conservative approach to using external data sources in compiling its statistics. This is primarily due to the forecast reliability of indicators being unproven in 'real time', and that external data sources might not reach the same quality benchmarks required by the National Statistics label. However, there are a large number of available indicators from business surveys and financial markets which may help compilers in better understanding the current state of the economy and in interpreting their data. ONS is also taking steps to analyse and measure the coherence of official and external data.

This article introduces a simple approach to producing an early estimate of GDP using data collected from non-official sources. Principal components analysis is used to derive the common factors from a large number of available indicators, which is then used to form an alternative forecast/measure of GDP. This measure can help provide an informal check or guide when compiling official estimates.

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