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A Monthly Indicator of Economic Activity for Ireland

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Deciphering the pace of growth in economic activity using standard National Accounts aggregates has become increasingly difficult in recent years. At the same time, a wide range of other high-frequency official data are published that shed light on the performance of the economy. This *Economic Letter* demonstrates how a single indicator can be extracted from a large monthly dataset to provide a timely assessment of economic activity. In line with reliable measures such as employment, the indicator shows that the economy moved into an expansionary phase around early 2013. The most recent data suggest that economic activity continues to grow at a robust pace, underpinned by improvements in the labour market. Based on a nowcasting framework, we describe how the indicator can be used to derive a real-time estimate of the rate of growth in underlying domestic demand.

This *Economic Letter* demonstrates how a single indicator of economic activity can be extracted from a large monthly dataset to provide a timely assessment of the current state of the economy.

1. Introduction

Movements in macroeconomic indicators reflect both underlying changes in the economy as well as short-run idiosyncratic fluctuations. The latter are noise and can occur, for example, due to measurement errors. To assess the state of the economy, it is important to abstract from these noisy fluctuations which cloud the underlying trends in the data. One of the challenges in interpreting macroeconomic data is how to isolate these underlying changes from fluctuations that are due to noise. Another challenge relates to the timeliness of macroeconomic data. Key macroeconomic data (such as national accounts data on consumer spending and investment) are released with a lag. For example, data for the current quarter typically becomes available around three months after the end of the quarter. These two issues can make it difficult to provide a timely assessment of current economic developments. In this *Economic Letter*, we construct a Business Cycle Indicator (BCI) for Ireland that aims to overcome these problems.

The indicator is constructed from a monthly dataset of Irish economic activity and the purpose of the indicator is to capture the comovement in this set of data. Underlying changes in the data are separated from movements due to noise using an approach known as Principal Component Analysis (PCA). PCA allows us to extract a single factor from the data (known as the first principal component) which summarises the variation across a range of indicators of Irish economic activity. The BCI can be thought of simply as the single factor, common to all of the series, that explains most of the variation across the data. We find that the BCI captures well the different phases of the Irish economy over the last 20 years. This part of

[1] Irish Economic Analysis Division. An overview of the analysis in this *Letter* was published in Box C of the Bank's July 2018 Quarterly Bulletin. This paper is an extended version of that work. The views expressed are those of the authors and do not necessarily reflect those of the Central Bank of Ireland or the European System of Central Banks. We would like to thank Stephen Byrne, Mark Cassidy, John Flynn, Reamonn Lydon, Terry Quinn, Gerard O'Reilly and Diarmaid Smyth for comments.

the analysis largely updates similar previous work for Ireland by Conefrey and Liebermann (2013).

In a 1991 article on forecasting inflation, using a similar methodology to that employed in this *Economic Letter*, Stock and Watson found that a single index constructed from the first principal component of 85 economic activity series forecasted inflation as well as or better than several standard models. Since 2001, the Federal Reserve Bank of Chicago has published a National Activity Index, similar to the BCI we estimate. They find that the index performs reasonably well as a real-time indicator of economic activity in the US. In the second part of our analysis, we test whether the BCI is useful as a leading indicator of changes in domestic economic activity using an approach known as "nowcasting".

Nowcasting is a technique used to produce timely estimates of macroeconomic variables, such as gross domestic product (GDP) or domestic demand. Defined by Bańbura, Giannone, and Reichlin (2011) as "the prediction of the past, the very near future, and the very recent past," nowcasting methods provide early estimates of target variables, typically measured at quarterly frequency, by using information contained in monthly data. One of the key issues that nowcasting tries to address is the fact that National Accounts data for the current quarter becomes available only after the fact, yet policymakers and analysts are required to evaluate the state of the economy in the present moment as developments unfold. For example, a nowcast model can use monthly data released in the first three months of the year to produce a first quarter tentative estimate of GDP ahead of the publication of the National Accounts. In fact, a nowcast model can generate a sequence of nowcast estimates throughout the quarter as the flow of monthly information becomes available.

There are a number of challenges to nowcasting. To begin with, statistical data releases are not published in a synchronous manner, and this gives rise to the jagged-edge problem. In other words, the model input is an unbalanced panel of data. Second, the panel of data usually contains a large number of variables and this creates a so called "curse of dimensionality" problem, with the number of variables close to the number of observations. These two technical issues can be solved by using modern econometric techniques, such as the state-space form, and by adopting a principle of parsimony. In the Irish case, there are further complications due to the volatile nature of the data, the extent of data revisions, and, more recently, the problems with using GDP and other National Accounts series as indicators of economic activity in Ireland.

This *Economic Letter* addresses the nowcast problem by building on previous research at the Central Bank. Unlike the previous research in Ireland, which focused on GDP, this *Economic Letter* turns the attention to the domestic component of Irish economic activity. We find that the indicator is a better predictor of domestic activity when compared to both a benchmark statistical model and an econometric model based on employment.

The rest of this *Economic Letter* is organized as follows. Section 2 describes the dataset. Section 3 outlines the methodology. Section 4 contains the empirical results. Section 5 reports the results of a forecast exercise. Section 6 concludes.[2]

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[2] Appendix A provides a literature review.

2. Dataset

The monthly dataset used to construct our indicator draws on a number of publications and sources; see Table 1. The majority of the data come from the Central Statistics Office (CSO) statbank database. The other publicly available data are retrieved from the Department of Public Expenditure and Reform databank containing Exchequer Returns data. There are some proprietary time-series in the dataset, such as the Purchasing Managers' Index (PMI), and the ESRI/KBC Consumer Sentiment Index; these are available from IHS Markit / Datastream, and the Economic and Social Research Institute (ESRI) / KBC Bank, respectively.

The purpose of the analysis is to derive an indicator of underlying economic activity – i.e. economic activity carried out in Ireland that affects the employment and incomes of Irish residents. The individual time-series used to calculate the indicator are carefully selected to ensure that they provide meaningful information on economic conditions in Ireland. For example, although overall industrial production is a highly relevant indicator of economic activity for most countries, we do not use this series in computing the monthly indicator for Ireland. This is because headline industrial production data for Ireland include the impact of goods produced abroad under contract manufacturing arrangements.[3] For the purposes of calculating the indicator, we instead use industrial production in the traditional sector as this better reflects trends in output produced by firms in Ireland.

Table 1 | Overview of the Dataset

Block	No.	Publication	Source	Transformation
Output	1	Purchasing Managers Index	IHS Markit	Annual Change
	2	Industrial Production Volumes	CSO	Annual Percent Change
Labour	3	Live Register	CSO	Annual Change
	4	Monthly Unemployment Rate	CSO	Annual Change
Trade	5	Merchandise Trade Volumes	CSO	Annual Percent Change
Consumption	6	Retail Sales	CSO	Annual Percent Change
	7	Consumer Sentiment	KBC / ESRI	Annual Change
	8	Vehicle Licenses	CSO	Annual Change
Fiscal	9	Exchequer Returns	PER Databank	Annual Change
Financial	10	ISEQ Index	CSO	Log Difference
	11	Exchange Rates	CSO	Log Difference
	12	Interest Rates	CSO	Level
Housing	13	House Prices	CSO	Annual Change
	14	New House Guarantee Registrations	CSO	Annual Change
Prices	15	Consumer Prices	CSO	Annual Percent Change

The methodology we use is applicable to stationary data. Therefore, the raw data in the dataset, if non-stationary, are transformed to stationary and standardised. The

[3] Contract manufacturing occurs where a company in Ireland engages a company abroad to manufacture products on its behalf. Even though the goods never pass through Ireland, the sale of the good is recorded as an Irish export of goods, while the contracted production is considered an import of services.

transformations that are applied to the raw data are shown in Table 1. Our final dataset consists of a panel of 62 data series (see Appendix B for a detailed description of the dataset). Due to data availability, the coverage of activity in the services sector is less comprehensive than for industry. The panel is balanced at the start from 2001M01, although the majority of series are available back to the mid 1990s. About half of the dataset starts in the 1980s. The end of the panel has a jagged edge structure, i.e. the series have different end dates.[4]

3. Methodology

The indicator is derived using a popular dimensionality reduction technique called principal components analysis (PCA). This technique produces a number of "factors". These factors are linear combinations (weighted averages) of the data, and together they explain all of the variation in the dataset. However, a small number of factors usually capture the majority of the variation. The first principal component is the most important factor because it explains most of the variation. The first factor represents the indicator.

Technically, the indicator, or the first principal component, is a linear combination of the variables in the dataset, where the weights are the eigenvectors associated with the largest eigenvalue obtained from the principal component analysis.[5] The indicator can be written as

$$BCI_t = \lambda_1 x_{1,t} + \lambda_2 x_{2,t} + \cdots + \lambda_N x_{N,t}$$

where the λ's denote the eigenvectors, the x's denote the stationary variables, t denotes time, and N is the number of variables in the dataset.

The indicator alone does not produce an estimate of economic growth, but it does play a useful role as a qualitative measure of the economic cycle and as a summary measure of a large amount of data. The indicator has the following interpretation: values of the indicator below zero imply below average growth while values above zero imply above average growth. By construction, the indicator has a mean of zero and standard deviation of one.

4. Results

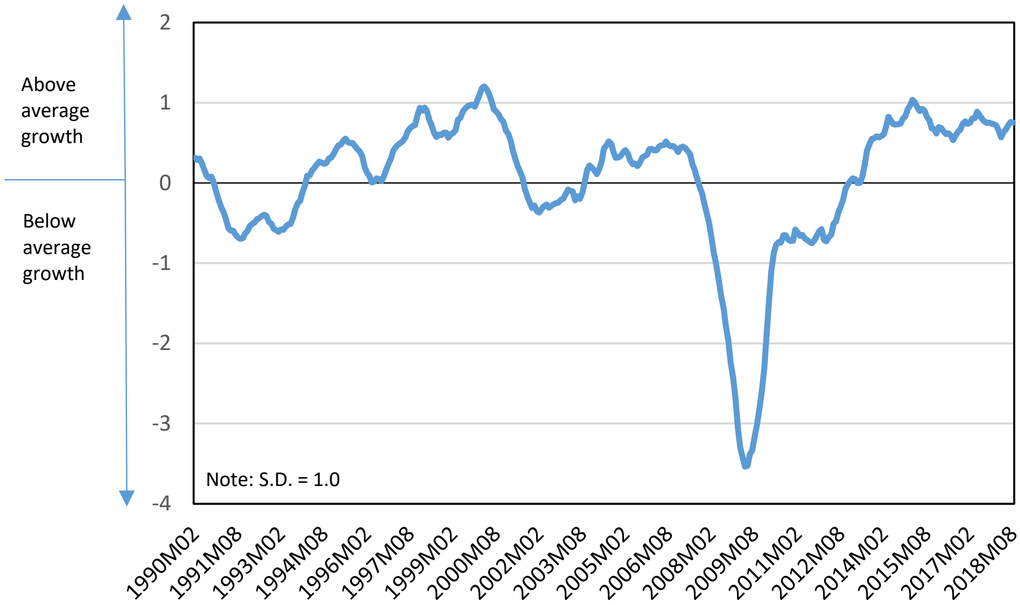
The BCI is shown in Figure 1. The indicator points to above average growth from the mid 1990s before turning below trend following the collapse of the dot-com bubble. The indicator remained positive from 2003 up until 2008. The impact of the crisis is reflected in a sharp drop in the indicator in 2009 with growth remaining below trend until around 2013. Since then, the indicator signals that there has been a strong rebound in economic activity with above average growth. It is noticeable that, in contrast to some headline National Accounts aggregates such as GDP, the indicator does not show an exceptional increase in economic activity in 2015. This reflects the choice of data used to compile the indicator which excludes series affected by globalisation activities of large multinational enterprises. These activities have driven volatile changes in GDP that are unrelated to developments in the domestic employment and incomes. When this activity is excluded, the

[4] For the purpose of nowcasting, the jagged edge problem is handled using a dynamic factor model and Kalman smoother.

[5] Eigenvalues and eigenvectors are measures computed from the covariance matrix of the dataset. The eigenvalues are used to rank the factors from first to last. The eigenvectors are the weights attributed to each variable in every factor. For more details see Crawley (2013, Chapter 25).

remaining data indicate stable and robust growth in domestic economic activity since 2013.

Figure 1 | Business Cycle Indicator



To help explain the factors which drive movements in the indicator, Figure 2 shows a historical decomposition.[6] The decomposition shows the contribution of different data series (grouped into eight blocks of related variables) to movements in the overall indicator over time. Figure 2 shows that in the late 1990s, the main contributions to economic activity were from consumer spending (green) and improvements in the labour market (red) as unemployment fell. A change is evident in the mid 2000s with the expansion in housing market activity (grey) and consumer spending (green) explaining most of the variation in the indicator.

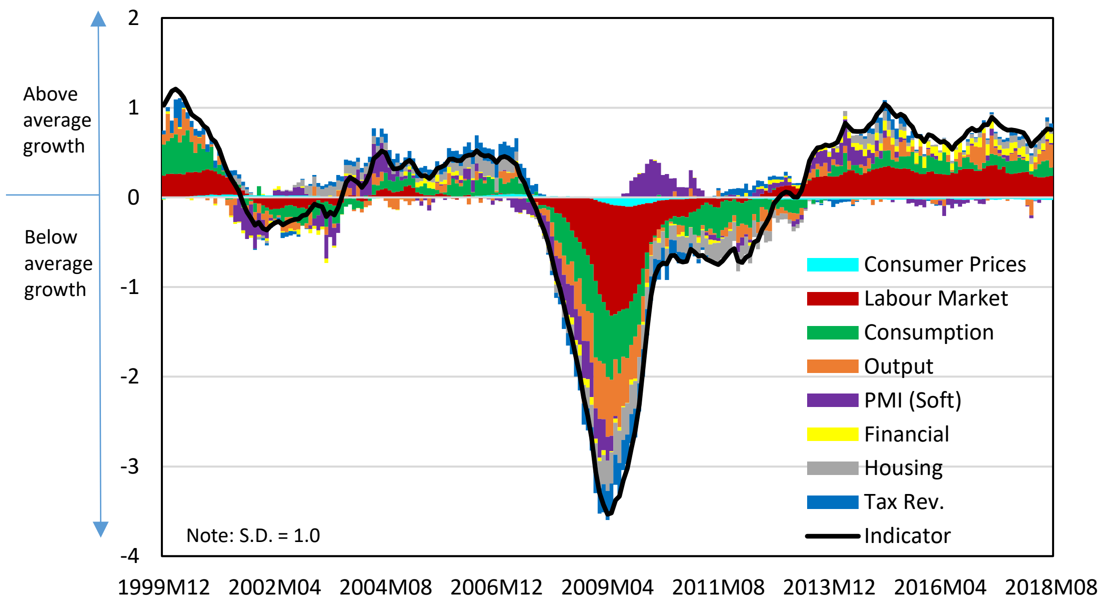
In the 2008-13 downturn, Figure 2 shows that there was a broad-based contraction in most indicators of economic activity. The rapid rise in unemployment and reduction in economic output resulted in lower spending by both consumers and firms. Consumer spending remained below trend around 2011-2012. Since 2014, there have been significant improvements in labour market conditions. The labour market is a key driver of the indicator today, as it was during the 1990s. However, unlike the 1990s, there are relatively smaller contributions from consumer spending. The more significant contribution of output (orange) to the recent growth in the economy is also noticeable. This indicates than increases in output by Irish and foreign-owned firms have played an important role in driving the recovery in the economy since the crisis. It also points to a more balanced composition of growth currently, compared to position in 2005-07.

To test whether the indicator tracks movements in other measures of economic activity, we calculate the correlation between the indicator and underlying domestic demand and employment. We also repeat the analysis for GDP. The results show that the indicator is highly correlated with reliable measures of economic activity

[6] Note that this is not a historical decomposition in terms of structural shocks as found in the VAR literature. Figure 2 shows the contributions to the indictor which are based on variable weights. In contrast, VAR historical decompositions are based on model shocks.

such as underlying domestic demand ($\rho = 0.86$) and employment ($\rho = 0.87$). It is less correlated with GDP ($\rho = 0.67$), especially from 2011 onwards. This is not surprising given the well-known problems for Ireland with using GDP as a measure of domestic economic activity.

Figure 2 | Contributions to the Business Cycle Indicator



5. Forecast Exercise

In this section, we report the results of a forecast exercise, the aim of which is to investigate the usefulness of the indicator for producing early estimates of underlying domestic demand. In the forecast exercise, we evaluate the forecast performance of a number of models based on their 1-step ahead forecasts.[7] We use a range of forecast evaluation statistics, which are standard in the literature, to rank the different models.

Since the indicator is measured at monthly frequency and underlying domestic demand is measured at quarterly frequency, these type of data are called mixed-frequency data. Modelling mixed-frequency data is non-standard, so a brief overview of the methods and models that we have used in the forecast exercise can be found in Appendix C. Among the models we use are bridge models and MIDAS models. To benchmark the exercise, we consider a number of statistical models as well as models based on employment growth (an alternative indicator).

The forecast exercise considers the 1-step ahead forecasts for the range of models over the sample 2006Q1 to 2018Q2.[8] The results of the exercise are shown in Table 2. The best performing model is highlighted in the green cells in Table 2. The results show that the dynamic bridge equation with the BCI (model 2) is the best performing model across a range of measures. The results also show that the dynamic bridge equation with employment growth (model 6) has a similar

[7] The 1-step ahead forecasts are equivalent to nowcast estimates. In practice, these models would only be used for their 1-step ahead prediction, so we limit our forecast exercise to this particular case.
[8] As a sensitivity check, we report the results of the exercise where we restrict the sample to the recent expansionary period only, i.e. 2013Q1 to 2018Q2. The results are similar and can be found in Appendix D.

performance. The statistical benchmark models are the worst performing models and the more complicated MIDAS models do not offer an improvement to the simpler bridge equations.

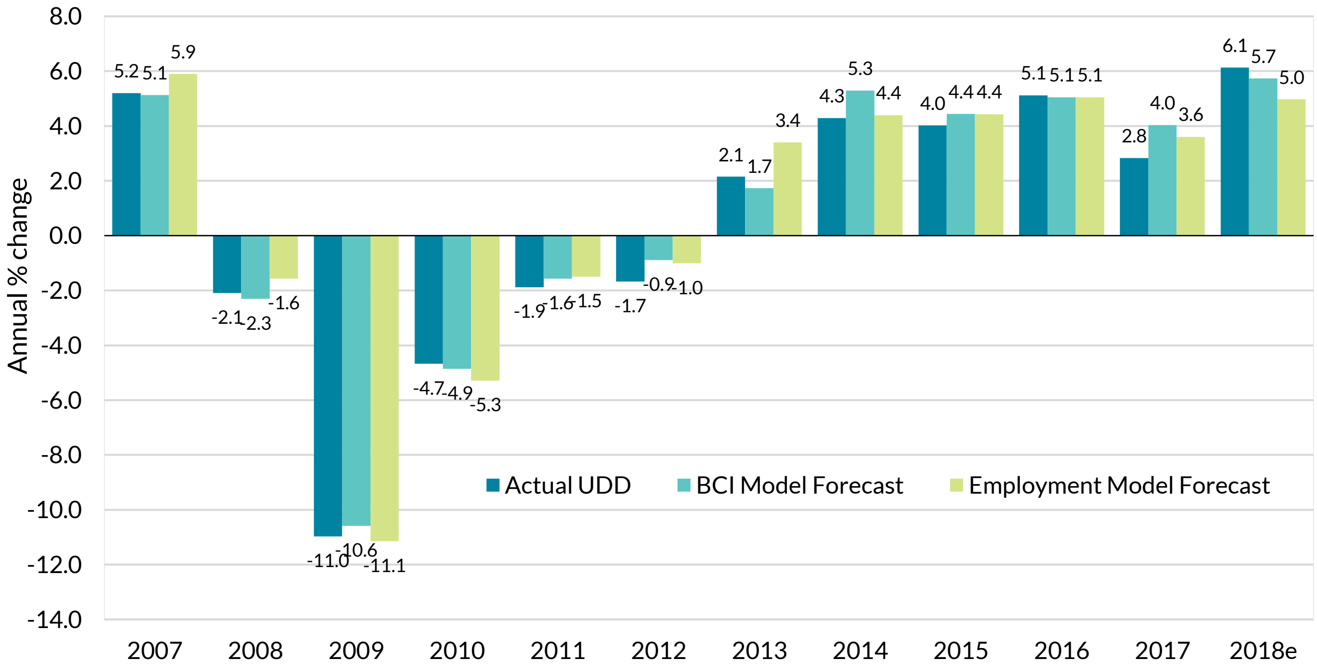
Table 2 | Forecast evaluation statistics

Model	Model Description	Predictor	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
1	Static Bridge Equation	BCI	2.37	1.97	87.94	77.42	0.23	1.93
2	Dynamic Bridge Equation	BCI	1.30	0.99	47.20	34.11	0.13	1.02
3	Statistical AR(1) Benchmark	1 Lag	1.87	1.41	65.21	51.24	0.19	1.08
4	Statistical AR(2) Benchmark	2 Lags	2.01	1.56	68.35	53.01	0.20	1.00
5	Static Bridge Equation	Employment	1.50	1.24	58.50	43.14	0.14	1.39
6	Dynamic Bridge Equation	Employment	1.33	1.07	49.03	40.16	0.13	0.97
7	PDL-MIDAS Model	BCI	1.77	1.44	57.29	53.23	0.17	1.19
8	U-MIDAS Model	BCI	1.70	1.35	55.86	50.68	0.16	1.20

Note: based on the sample period 2006Q1 to 2018Q2

Figure 3 compares the within-sample forecasts of underlying domestic demand from the two best models to the actual data. The chart shows that the dynamic bridge equation models using both the BCI and employment growth track the data quite well over the period. Interestingly, the actual data for 2017 appear weak compared to the implied growth rates from the models. This is due to the 2017Q1 observation (1.6 per cent) in the national accounts, which is out of line with the model estimates and may be subject to data revisions. For 2018, the indicator suggests annual growth in underlying domestic demand of 5.7 per cent. Published national accounts data for the first nine months of 2018 show annual growth in UDD of 6.1 per cent.

Figure 3 | Nowcast Model Estimates



Notes: Chart shows the actual outturn for underlying domestic demand (UDD) in each year in comparison to the forecast for UDD based on two models, one using employment growth as the predictor and one using the BCI. The data for 2018 are for the first nine months of the year.

6. Conclusion

In this *Economic Letter*, we derived an indicator of economic activity in Ireland. Our methodology allows us to use the most recent information from a range of monthly data releases to help decipher changes in economic activity. The monthly data on which the indicator is based are carefully selected to ensure they contain relevant and meaningful information on economic conditions in Ireland. In this way, the indicator helps to address two key difficulties faced by analysts in assessing current economic conditions – the fact that standard aggregates such as GDP no longer provide a meaningful measure of developments in the Irish economy and that key National Accounts data are only available with a lag. The methodology also differentiates between the noise component of various economic series and underlying changes which provide useful information on economic developments.

As well as shedding light on current economic conditions, we demonstrate how the indicator can be used in a nowcasting framework to provide early estimates of domestic demand. As new data become available, it in intended to update the indicator regularly and to use it as part of the Bank's forecasting framework to inform assessments of the current state of the economy, as well as to produce preliminary estimates of economic activity.

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Appendix A: Literature Review

The initial work on nowcasting Irish macroeconomic data at the Central Bank begins with D'Agostino, McQuinn, and O'Brien (2012), who used the methodology of Giannone, Reichlin, and Small (2008) to nowcast GDP. Using a pseudo real-time out-of-sample simulation, they found that the nowcast model was an improvement over a benchmark model. They also found that the accuracy of the nowcast estimates improved throughout the quarter as more monthly information became available. Liebermann (2012) extended this work by introducing a number of new variables into the model. Using the same framework, Conefrey and Liebermann (2013) derived a business cycle indicator of the Irish economy from a smaller set of indicators. Keeney, Kennedy, and Liebermann (2012) performed a forecasting exercise to illustrate the value of both soft and hard data over the course of the nowcasting cycle. Byrne, Morley, and McQuinn (2014) provide an update to D'Agostino, McQuinn, and O'Brien (2012). Most recently, using the same technique as this latter paper, Casey (2018) estimates real-time nowcasts of components of domestic demand for Ireland. He finds that nowcasts perform well as a predictor of final National Accounts outturns.

In the United Kingdom, The National Institute of Economic and Social Research (NIESR) has published its own monthly estimates of UK GDP for more than twenty years using the methodology of Mitchell et al. (2005). Recently, however, the Office for National Statistics (ONS) has started to publish official monthly estimates.[9] At other Central Banks around the world, nowcasting has become a standard practice, although different methodologies have been used. At the Bundesbank, Kuzin et al. (2009) investigated MIDAS models and mixed frequency VAR models. At the European Central Bank (ECB), Modugno (2011) used a dynamic factor model to nowcast inflation. Anesti et al. (2017) explain that nowcast estimates at the Bank of England (BOE) are judgemental and draw on a range of models, including MIDAS models and dynamic factor models, as well as other information. A survey of nowcasting in economics can be found in Banbura et al. (2011).

[9] https://www.ons.gov.uk/economy/grossdomesticproductgdp/articles/introducinganewpublicationmodelforgdp/2018-04-27

Appendix B: Detailed Dataset

Table B.1 | The Monthly Indicators

Block	Description	Start	Source	Table / Code
Output	Ind. Prod. Vol., Traditional sector (05 to 17,181,19,22 to 25,28 to 31,321 to 324,329,33,35)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Food products (10)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Mining and quarrying (05 to 09)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Tobacco: leather; petroleum; transport equipment; furniture; repair of machinery (12, 15, 19, 29 to 31,33)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Paper and paper products, printing and reproduction of recorded media (17,18)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Transport equipment (29,30)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Other foods (102 to 104,108)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Grain mill and starch products; prepared animal feeds (106,109)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Meat and meat products (101)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Dairy products (105)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Bakery and farinaceous products (107)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Beverages (11)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Wood and wood products, except furniture (16)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Rubber and plastic products (22)	1981M01	CSO	MIM03
	Ind. Prod. Vol., Other non-metallic mineral products (23)	1981M01	CSO	MIM03
PMI	IR INVESTEC PMI: MANUFACTURING SADJ	1999M05	IHS Markit	IRPMIM..Q
	IR INVESTEC PMI: MANUFACTURING - OUTPUT SADJ	1999M05	IHS Markit	IRPMIMOUQ
	IR INVESTEC PMI: MANUFACTURING - NEW ORDERS SADJ	1999M05	IHS Markit	IRPMIMNOQ
	IR INVESTEC PMI: MANUFACTURING - EMPLOYMENT SADJ	1999M05	IHS Markit	IRPMIMEMQ
	IR INVESTEC PMI: SERVICES - NEW BUSINESS SADJ	2001M05	IHS Markit	IRPMISNBQ
	IR INVESTEC PMI SERVICES - BUSINESS ACTIVITY SADJ	2001M05	IHS Markit	IRPMIS..Q
	IR INVESTEC PMI: SERVICES - EMPLOYMENT SADJ	2001M05	IHS Markit	IRPMISEMQ
	IR ULSTER BANK PMI CONSTRUCTION - ALL ACTIVITY SADJ	2001M06	IHS Markit	IRPMIC..Q
	IR ULSTER BANK PMI: CONSTRUCTION - HOUSING ACTIVITY SADJ	2001M06	IHS Markit	IRPMICHAQ
	IR ULSTER BANK PMI: CONSTRUCTION - COMMERCIAL ACTIVITY SADJ	2001M06	IHS Markit	IRPMICCAQ
	IR ULSTER BANK PMI: CONSTRUCTION-CIVIL ENGINEERING ACTIVITY SADJ	2001M06	IHS Markit	IRPMICCEQ
	IR ULSTER BANK PMI: CONSTRUCTION - NEW ORDERS SADJ	2001M06	IHS Markit	IRPMICNOQ
	IR ULSTER BANK PMI: CONSTRUCTION - EMPLOYMENT SADJ	2001M06	IHS Markit	IRPMICEMQ
Labour	Persons on the Live Register (Seasonally Adjusted) (Number), All Ages, Both Sexes	1968M01	CSO	LRM02
	Persons on the Live Register (Seasonally Adjusted) (Number), All Ages, Male	1968M01	CSO	LRM02
	Persons on the Live Register (Seasonally Adjusted) (Number), All Ages, Female	1968M01	CSO	LRM02
	Seasonally Adjusted Monthly Unemployment Rate (%), 15 - 74 years, Both Sexes	1999M01	CSO	MUM01
	Seasonally Adjusted Monthly Unemployment Rate (%), 15 - 74 years, Male	1999M01	CSO	MUM01
	Seasonally Adjusted Monthly Unemployment Rate (%), 15 - 74 years, Female	1999M01	CSO	MUM01
Consumption	Consumer Sentiment	1997M02	KBC/ESRI	IRCNFCONR
	Consumer Confidence Indicator	1985M01	DG ECFIN	IRCNFCONQ
	Vehicles Licensed, All Vehicles	1997M07	CSO	TEM01
	Vehicles Licensed, New Vehicles	1997M07	CSO	TEM01
	All retail businesses, excluding motor trades	1997M01	CSO	RSM05
	Department stores (4719)	1997M01	CSO	RSM05
	Retail sale of pharmaceutical, medical and cosmetic articles (4773 to 4775)	1997M01	CSO	RSM05
	Retail sale of hardware, paints and glass (4752)	1997M01	CSO	RSM05
	Retail sale of electrical goods (4741 to 4743,4754)	1997M01	CSO	RSM05
	Retail sale of books, newspapers and stationery (4761,4762)	1997M01	CSO	RSM05
Fiscal	Tax Revenue, Total	1985M12	DOF	Databank
	Tax Revenue, Stamps	1985M12	DOF	Databank
	Tax Revenue, Income Tax	1985M12	DOF	Databank
	Tax Revenue, Valued Added Tax	1985M12	DOF	Databank

Financial	US Dollar per Euro	1999M02	CSO	FIM02
	Pound Sterling per Euro	1999M02	CSO	FIM02
	Price Index of Ordinary Stocks and Shares (ISEQ) (Base 4th Jan1988=1000)	1988M02	CSO	FIM04
	ECB - marginal lending rate	1979M06	CSO	FIM08
	Government 10 year bond yield	1993M06	CSO	FIM08
	Interbank market rate 3 months fixed	1993M03	CSO	FIM08
Housing	ESB Connections (Number)	1976M01	CSO	HSM01
	Residential Property Price Index (Base Jan 2005 = 100), National - all residential properties	2006M01	CSO	HPM06
	Residential Property Price Index (Base Jan 2005 = 100), National - houses	2006M01	CSO	HPM06
	Residential Property Price Index (Base Jan 2005 = 100), National - apartments	2006M01	CSO	HPM06
	New House Guarantee Registrations (Number)	1980M01	CSO	HSM10
Prices	Consumer Price Index (Base Dec 2016=100), All Items	1976M11	CSO	CPM01
	Consumer Price Index (Base Dec 2016=100), Goods	1983M11	CSO	CPM03
	Consumer Price Index (Base Dec 2016=100), Services	1983M11	CSO	CPM03

Appendix C: Nowcast Models

Bridge Models

One of the earliest approaches to modelling mixed-frequency data is called the bridge model. Bridge models are linear regressions that link high frequency data to low frequency data. The link is created by aggregating the high frequency data. For example, a simple bridge equation linking the indicator to domestic demand can be written in static form as

$$DD_t = \alpha + \beta BCI_t^Q + \epsilon_t$$

where MEI_t^Q represents the monthly indicator aggregated to quarterly frequency, DD_t denotes domestic demand, α is a constant, β is the coefficient on the indicator, and ϵ_t is an error term.[10] The aggregation scheme is usually a simple average of the monthly values within the corresponding quarter.[11]

Bridge models are not standard macroeconometric models, since they do not specify a causal relationship; rather, they are justified by the statistical fact that the indicator contains timely updated information. For this reason, the bridge model technique allows early estimates of the low-frequency variable to be computed (as a 1-step ahead forecast). In other words, bridge equations are a tool for nowcasting.

The general bridge model that we consider can be written in autoregressive distributed lag (ARDL) form as

$$DD_t = \alpha + \sum_{i=0}^{q} \beta_i BCI_{t-i}^Q + \sum_{j=0}^{p} \phi_j DD_{t-1-j} + \epsilon_t$$

where the β's are the contemporaneous and lagged coefficients on the indicator, and the ϕ's are the lagged coefficients on domestic demand.

MIDAS Models

A more modern approach to modelling mixed-frequency data, introduced by Ghysels et al. (2004), is called the mixed data sample model, known as MIDAS. The MIDAS approach directly relates high frequency data to low frequency data using frequency alignment rather than aggregation. Frequency alignment is an advantage of the MIDAS approach because aggregating high-frequency data can throw away potentially relevant information. For example, a simple MIDAS model can be written as

$$DD_t = \alpha + \sum_{i=1}^{q} \beta_i BCI_{t-i}^M + \epsilon_t$$

where MEI_t^M represents the monthly indicator appropriately aligned to quarterly frequency. The MIDAS model can be freely estimated or a polynomial lag structure can be imposed, instead. It has been shown that the unrestricted MIDAS (U-MIDAS) model is particularly suited to nowcasting quarterly variables using monthly indicators. In contrast, the polynomial restriction is more suitable when modelling daily and weekly data. For example, see Forini et al. (2011).

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[10] The bridge equation does not have to take this simple form; for example, a number of indicators can be included in the model, so too can lags of variables.

[11] One of the factors that influences the aggregation scheme is whether the data represents a flow variable or a stock variable.

Benchmark Models

We use statistical autoregressive models as a benchmark in the forecast exercise. These models can be written as

$$DD_t = \alpha + \sum_{j=0}^{p} \phi_j DD_{t-1-j} + \epsilon_t$$

where the ϕ's are the lagged coefficients on domestic demand.

Nowcast models based on employment provide a more challenging benchmark. These can be written in ARDL form as

$$DD_t = \alpha + \sum_{i=0}^{q} \beta_i EMP_{t-i} + \sum_{j=0}^{p} \phi_j DD_{t-1-j} + \epsilon_t$$

where the β's are the contemporaneous and lagged coefficients on employment, and the ϕ's are the lagged coefficients on domestic demand.

Dynamic Factor Model

In order to produce nowcasts, the jagged-edge at the end of the dataset must be filled in. This is done using the two-step estimator of Doz, Giannone and Reichlin (2011), which involves setting up a dynamic factor model – a type of state-space model. The model is calibrated using the estimated coefficients from the PCA and then a Kalman smoother is run on the model. The smooth state variable can be used to update the nowcast estimate throughout the quarter as more monthly information becomes available.

Signal Equations

$$\begin{gathered} x_{1,t} = \lambda_1 BCI_t^U + \xi_{1,t} \\ \vdots \\ x_{N,t} = \lambda_N BCI_t^U + \xi_{N,t} \end{gathered}$$

State Equation

$$BCI_t^U = A_1 BCI_{t-1}^U + \cdots + A_p BCI_{t-p}^U + u_t$$

Appendix D: Forecast Exercise Sensitivity

Sub-Sample Forecast Exercise

As a sensitivity check on the forecast exercise presented in Section 6, the results shown in Table 3 below repeat the exercise over a sub-sample ranging from 2013Q1 to 2018Q2. This period marks the recent expansionary phase suggested by the indicator. The best performing model is highlighted in green. The ranking of the models is quite similar to before. The dynamic bridge equation with the BCI again has the best performance. The dynamic bridge equation with employment growth also performs well. Compared to the full sample exercise, the statistical AR(1) model performs significantly better than before.

Table 3 | Forecast evaluation statistics

Model	Model Description	Predictor	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
1	Static Bridge Equation	BCI	1.87	1.54	70.13	41.98	0.20	0.83
2	Dynamic Bridge Equation	BCI	1.33	0.94	34.88	30.64	0.15	0.55
3	Statistical AR(1) Benchmark	1 Lag	1.34	1.06	36.22	39.02	0.16	0.83
4	Statistical AR(2) Benchmark	2 Lags	1.46	1.18	40.20	45.25	0.18	0.92
5	Static Bridge Equation	Employment	1.65	1.32	66.49	38.53	0.18	1.28
6	Dynamic Bridge Equation	Employment	1.39	1.04	55.87	32.82	0.16	0.68
7	PDL-MIDAS Model	BCI	1.95	1.67	64.52	44.71	0.20	0.78
8	U-MIDAS Model	BCI	1.88	1.56	67.84	42.82	0.20	0.95

Note: based on the sample period 2013Q1 to 2018Q2

Alternative Demand Variable Forecast Exercise

We perform a further sensitivity check by investigating how well the models forecast an alternative (official) measure of domestic demand, namely, modified final domestic demand. The results from this exercise are shown in Table 4 and are consistent with the findings presented earlier. The dynamic bridge equations with the BCI and employment growth are the two best models. Similar results are found by repeating this exercise over the sub-sample ranging from 2013Q1 to 2018Q2.

Table 4 | Forecast evaluation statistics

Model	Model Description	Predictor	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
1	Static Bridge Equation	BCI	2.53	1.97	65.78	69.37	0.24	0.82
2	Dynamic Bridge Equation	BCI	1.69	1.34	48.08	41.94	0.16	0.51
3	Statistical AR(1) Benchmark	1 Lag	2.33	1.77	58.18	52.62	0.23	1.05
4	Statistical AR(2) Benchmark	2 Lags	2.40	1.82	61.43	52.61	0.24	1.06
5	Static Bridge Equation	Employment	1.83	1.57	54.63	46.10	0.17	0.86
6	Dynamic Bridge Equation	Employment	1.79	1.52	53.02	44.67	0.17	0.83
7	PDL-MIDAS Model	BCI	2.01	1.54	48.52	51.19	0.19	0.64
8	U-MIDAS Model	BCI	1.96	1.53	49.03	51.57	0.18	0.60

Note: based on the sample period 2006Q1 to 2018Q2

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