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# Uncertain Kingdom: nowcasting GDP and its revisions

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# Uncertain Kingdom: nowcasting GDP and its revisions

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## Abstract

We propose a Release-Augmented Dynamic Factor Model (RA-DFM) that allows to quantify the role of a country's data flow in nowcasting both early GDP releases, and subsequent revisions of official estimates. We use the RA-DFM to study UK GDP early revision rounds, and assemble a comprehensive and novel mixed-frequency dataset that features over 10 years of real-time data vintages. The RA-DFM improves over the standard DFM in real-time when forecasting the first release each quarter, and economic and survey data help forecasting the first revision round. Afterwards, the predictive content of the data flow is largely exhausted.

**Key words:** Nowcasting, data revisions, dynamic factor model.

**JEL classification:** C51, C53, C55.

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# 1 Introduction

Assessing a country's growth in real time can be thought of as a dual problem. The first difficulty lies in the fact that GDP figures, the key measure of economic activity, are typically quarterly, and released by the statistical offices only with delay relative to the period they refer to. A second complication arises from the fact that these initial official estimates rely on incomplete datasets, and undergo multiple revision rounds as time goes by and more data are incorporated in the calculations.

The first issue has been successfully addressed in the empirical literature, by devising nowcasting models that are able to exploit the comovement between GDP data and other indicators of economic activity that are instead available in a more timely fashion (see Evans, 2005; Giannone, Reichlin and Small, 2008, for earlier treatments). These models are able to deal with data that are sampled at different frequencies – quarterly, monthly, or even daily –, and that have asynchronous publication delays, to produce nowcasts of GDP growth that are both timely, and that can be updated in real-time in accordance with the data flow in any given country (see Bańbura, Giannone, Modugno and Reichlin, 2013, for a review). One particularly appealing feature of these models is that they are able to quantify how different pieces of information, e.g. the publication of a particular business survey, or the release of an official labor market report, contribute to change and refine the models' nowcasts (Bańbura and Modugno, 2010).

Dealing with data revisions is instead arguably more complex, primarily because it typically requires researchers to make assumptions on whether (e.g. Jacobs and van Norden, 2011; Aruoba, Diebold, Nalewaik and Schorfheide, 2016) and/or when (e.g. Kishor and Koenig, 2012; Cunningham, Eklund, Jeffery, Kapetanios and Labhard, 2012) 'true' values of GDP growth are observed. In nowcasting data subject to revisions, approaches have ranged from abstracting from the revisions altogether (e.g. Bańbura, Giannone, Modugno and Reichlin, 2013), to making very specific and potentially restrictive assumptions on when 'true' values are eventually revealed (e.g. Camacho and Perez-Quiros, 2010).

In this paper, we propose a Release-Augmented Dynamic Factor Model (or RA-DFM) that bridges the nowcasting and the data revision modelling literatures with a dual aim.

First, it provides a flexible way to explicitly incorporate GDP revisions in standard nowcasting models without having to resort to strong assumptions on their modelling, relaxing the framework devised in Camacho and Perez-Quiros (2010). Second, it allows to quantify how the data flow contributes to update the model's forecasts of the revisions themselves, extending the reach of Bańbura and Modugno (2010).

Specifically, in the RA-DFM successive release of quarterly GDP growth relative to the *same* quarter are modelled as separate but correlated observables in an otherwise standard mixed-frequency DFM. This allows us to exploit their intrinsic factor structure since they are effectively different estimates, potentially increasingly more accurate ones, of the same object. As a result, we can write GDP revisions as being the sum of two components. One that is a function of the common unobserved factors, and hence depends directly on the data flow. In the language of Mankiw and Shapiro (1986), this component captures *news revisions*, since the common factors updates are brought about by the availability of new information. Using the RA-DFM, we can forecast these types of revisions, and quantify the role played by the individual data being released. This is the novel feature that is introduced with the RA-DFM. The second component is instead entirely idiosyncratic, and captures data revisions that are due to reduction of measurement errors in earlier releases, that is, *noise revisions*.

The RA-DFM retains all the characteristics of the existing DFM used for nowcasting, including those estimated on real-time data. However, contrary to these models, it permits going beyond preliminary GDP estimates and understand how the real-time data flow informs the initial revision rounds with a straightforward extension of the 'data news' decomposition of Bańbura and Modugno (2010).

Our approach has a number of advantages compared to the previous literature. First, we are able to exploit the information content of a large number of economic and financial variables to predict the initial GDP revisions. This is in stark contrast with existing data revision models that allow for the inclusion of only a small number of indicators, if any at all (e.g. Kishor and Koenig, 2012; Cunningham, Eklund, Jeffery, Kapetanios and Labhard, 2012). Second, the state vector grows linearly in the number of revision rounds considered. This allows us to retain parsimony that facilitates estimation with real-time data, in contrast to the specification in Kishor and Koenig (2012) and Galvão (2017). Third, the model is not restricted only to data revisions led by reduction of measurement errors in earlier GDP estimates (Camacho and Perez-Quiros, 2010). We model news revisions by effectively allowing successive GDP estimate for the same quarter to load differently on the common unobserved factors, following an earlier suggestion in Evans (2005). We allow for serial and (weak) cross-sectional correlation among the idiosyncratic revision components, which accommodates the measurement error approach to data revisions and can improve forecasting performance as suggested by Clements and Galvão (2013a).

We use the RA-DFM to study early revision rounds of UK GDP growth in real-time. To this end, we assemble a comprehensive mixed-frequency real-time dataset that features over 10 years of real-time data vintages (2006-2016) with history going back to January 1990. The main source for the construction of our real-time dataset are the archives of the Bank of England, in which data released by the UK Office of National Statistics (ONS) have been carefully stored over the years. We make this dataset available to the broader research community. Our data covers the indexes of production and services, labour market indicators, macroeconomic aggregates such as consumption, investment, and international trade, as well as surveys, credit measures and financial variables. The complete list encompasses all the 'market movers' that feature in the most prominent economic calendars, such as those distributed by Bloomberg and Thomson Reuters. To the best of our knowledge, ours is the most comprehensive real-time mixed-frequency dataset for the UK economy in terms of breadth and coverage.[1]

Our results can be summarised as follows. First, we find that the data flow is informative for the first revision. The data that are mostly informative are, in decreasing order of contribution, business surveys, production data, and labor market statistics. Second, we find that following the first round of revisions, subsequent revisions to GDP official estimates seem to be mainly driven by the removal of measurement issues in previous estimates. Hence, there is less scope for using the data flow to predict them. Third, the RA-DFM produces forecasts for the first two revision rounds whose accuracy is comparable to that of model averages, as embedded in surveys of professional forecasters and

[1] The Bank of England maintains a real-time database that only covers quarterly variables, and details on its construction are in Castle and Ellis (2002) and Garratt and Vahey (2006). An early mixed-frequency real-time dataset for the UK economy was introduced in Egginton et al. (2002); this dataset, however, was only last updated at the end of 1999, and covered a smaller cross-section compared to ours.

market participants. Neither of them, however, improves consistently over a no-change forecast at all horizons.

In addition to data revisions, the RA-DFM can also be used for nowcasting GDP growth itself. When forecasting the first releases of UK GDP, we find that the RA-DFM yields statistically significant improvements against a standard mixed-frequency DFM estimated on real-time data. Finally, we evaluate the predictive performance of the RA-DFM for the latest vintage of GDP growth, arguably the best estimates of UK GDP currently available. We find that RA-DFM forecasts contain useful information for forecasting mature GDP vintages that is not included in early ONS estimates. Also, we find that RA-DFM predictive densities for the latest GDP estimates are correctly specified .

**Relation to the Literature** Our paper builds on the large body of literature on nowcasting GDP growth using Dynamic Factor Models (DFM), firstly introduced by Giannone et al. (2008). Numerous applications to point forecasts using (typically pseudo) real-time data have been proposed over the years, and for a number of different countries (see Bańbura et al., 2013, for a review). Aastveit, Gerdrup, Jore and Thorsrud (2014)'s evaluation includes a DFM for nowcasting US growth that uses fully real time data. Forecasting models with factors have been previously applied for predicting UK GDP growth (Artis, Banerjee and Marcellino, 2005; Mitchell, 2009; Miranda-Agrippino, 2012; Antolin-Diaz, Drechsel and Petrella, 2017; Anesti, Hayes, Moreira and Tasker, 2017), but these all used pseudo-real-time data vintages constructed from latest available estimates for all the variables included in the models.

Our paper is also related to the literature that has proposed methods for macroeconomic forecasting when dealing with data subject to revisions. The literature has typically approached the issue of data uncertainty in forecasting in three ways. The first one evaluates a model's forecasts using only the data that were actually available to a professional forecaster at each forecast origin (see e.g. survey in Croushore, 2006). The second one conditions forecasts only on data that have undergone the same number of revision rounds (Koenig et al., 2003; Clements and Galvão, 2013b). The third one requires the joint estimation of the forecasting model and of the data revision process, with the aim of predicting revised future values of the variable of interest (Kishor and Koenig, 2012; Cunningham, Eklund, Jeffery, Kapetanios and Labhard, 2012; Clements and Galvão, 2013a; Carriero, Clements and Galvão, 2015; Galvão, 2017). Our approach not only addresses the issue of how to compute short-term forecasts of data subject to revision, but it also provides a method to evaluate the effects of data announcements on the prediction of data revisions. In this respect, it is closest to the third branch of this literature.

The paper is organised as follows. Section 2 describes the RA-DFM model. The details of the UK real-time data flow are reported in Section 3, and we present our results in Section 4. Section 5 concludes. Additional details are reported in the Appendix.

# 2 A Nowcasting Model for Macroeconomic Data Subject to Revisions

In this section we describe the framework that we design to model and forecast subsequent GDP releases relative to the same quarter, the model-implied stochastic process for the revisions, and how we assess the relevance of 'data news' in forecasting GDP growth and revisions to early released GDP data.

## 2.1 The RA-DFM

In most advanced economies, statistical offices publish a first release of GDP based only on a partial coverage of the economy about a month after the end of the relevant quarter. This first and incomplete estimate is then updated as more data are collected and measurement issues are resolved. This process results in improved estimates for the same quarter being systematically released in the months and years that follow. We think of these successive estimates of GDP for the same quarter as separate but correlated observables. This allows us to exploit their intrinsic factor structure (i.e. they are all estimates of the same object) and to write successive revisions as the sum of two components: one that is linked to the underlying common measures of economic activity, and a residual idiosyncratic one.

**Factor Structure** Let $y_t$ denote quarterly GDP growth, and let $y_t^{(k)}$ denote the $k^{th}$ estimate for $y_t$ released by the statistical office, such that $y_t^{(1)}$ denotes the first release for $y_t$, $y_t^{(2)}$ the second release, and so on.[2] The timing of the publication can vary across countries, but it is typically the case that the statistical office publishes these releases for quarterly GDP following a monthly schedule. For example, for the first quarter of every year $y_t^{(1)}$ is available at the end of April, $y_t^{(2)}$ at the end of May, $y_t^{(3)}$ at the end of June.

The core intuition of our modelling strategy is to assume that $y_t^{(k)}$, for $k = 1, \dots, K$ have a factor structure

$$y_t^{(k)} = \bar{\mathbf{\Lambda}}^{(k)} F_t + \varepsilon_t^{(k)}, \tag{1}$$

where we use $\bar{\mathbf{\Lambda}}^{(k)}$ to denote the vector of loadings on the set of factors $F_t$, and $\varepsilon_t^{(k)}$ to denote the idiosyncratic component of each $y_t^{(k)}$. $F_t$ can be thought of as an underlying measure of real activity, which we define below as a function of a broader collection of mixed-frequency indicators.

The RA-DFM obtains from stacking Eq. (1) to the measurement equations of the mixed-frequency DFM of Bańbura et al. (2013). Formally:

$$x_t^M = \mathbf{\Lambda}_M f_t + \zeta_t^M, \tag{2}$$

$$x_t^Q = \bar{\mathbf{\Lambda}}_Q F_t + \zeta_t^Q, \tag{3}$$

$$y_t^{(k)} = \bar{\mathbf{\Lambda}}^{(k)} F_t + \varepsilon_t^{(k)}, \ \ k = 1, \dots, K. \tag{1}$$

$x_t^M$ is a generic $n_M \times 1$ vector of demeaned stationary monthly variables observed at $t = 1, 2, \dots, T$. Similarly, $x_t^Q$ denotes a $n_Q \times 1$ vector of quarterly zero-mean stationary variables observed at $t = 3, 6, \dots,$ T. We assume the same timing convention for $y_t^{(k)}$. $f_t \equiv (f_{1,t}, \dots, f_{r,t})'$ is an $r \times 1$ vector of zero-mean unobserved factors for $t = 1, 2, \dots, T$, and $F_t = (f_t', f_{t-1}', \dots, f_{t-4}')'$. We use $\mathbf{\Lambda}$ to denote generic matrices of factor loadings that we define below.

To combine the monthly and quarterly variables, we rely on the approximation for

[2] In the US, the Bureau of Economic Analysis refers to $y_t^{(1)}$, $y_t^{(2)}$ and $y_t^{(3)}$ as the Advance, Preliminary and Final GDP Estimate respectively.

flow variables of Mariano and Murasawa (2003). Specifically, let $X_t^Q$ denote the level of a quarterly variable, e.g. log level of consumption, and $x_t^Q$ its quarterly growth rate. Let $\widetilde{X}_t^M$ be its unobservable monthly counterpart, such that $X_t^Q \simeq \widetilde{X}_t^M + \widetilde{X}_{t-1}^M + \widetilde{X}_{t-2}^M$, and define $\tilde{x}_t^M \equiv \widetilde{X}_t^M - \widetilde{X}_{t-1}^M$. The approximation allows us to write

$$x_t^Q \simeq (1 + 2L + 3L^2 + 2L^3 + L^4)\tilde{x}_t^M, \tag{4}$$

where $L$ is the lag operator.[3]

Using Eq. (4), we can rewrite the measurement equation of the RA-DFM as

$$\underset{(n\times 1)}{x_t} \equiv \begin{pmatrix} x_t^M \\ x_t^Q \\ y_t^{(1)} \\ \vdots \\ y_t^{(K)} \end{pmatrix} \simeq \begin{pmatrix} \mathbf{\Lambda}_M & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{\Lambda}_Q & 2\mathbf{\Lambda}_Q & 3\mathbf{\Lambda}_Q & 2\mathbf{\Lambda}_Q & \mathbf{\Lambda}_Q \\ \mathbf{\Lambda}^{(1)} & 2\mathbf{\Lambda}^{(1)} & 3\mathbf{\Lambda}^{(1)} & 2\mathbf{\Lambda}^{(1)} & \mathbf{\Lambda}^{(1)} \\ \vdots & & \vdots & & \vdots \\ \mathbf{\Lambda}^{(K)} & 2\mathbf{\Lambda}^{(K)} & 3\mathbf{\Lambda}^{(K)} & 2\mathbf{\Lambda}^{(K)} & \mathbf{\Lambda}^{(K)} \end{pmatrix} F_t + \begin{pmatrix} \zeta_t^M \\ \zeta_t^Q \\ \varepsilon_t^{(1)} \\ \vdots \\ \varepsilon_t^{(K)} \end{pmatrix}. \tag{5}$$

In Eq. (5), the monthly variables load only on the contemporaneous values of the factors via the coefficients in the $n_M \times r$ matrix $\mathbf{\Lambda}_M$ (see Eq. 2). The loadings structure for the quarterly variables is instead inherited from the approximation in Eq. (4), such that $\bar{\mathbf{\Lambda}}_Q \equiv \begin{bmatrix} \mathbf{\Lambda}_Q & 2\mathbf{\Lambda}_Q & 3\mathbf{\Lambda}_Q & 2\mathbf{\Lambda}_Q & \mathbf{\Lambda}_Q \end{bmatrix}$, where $\mathbf{\Lambda}_Q$ is $n_Q \times r$. The same holds true for $\bar{\mathbf{\Lambda}}^{(k)}$, $k = 1, \dots, K$ with each $\mathbf{\Lambda}^{(k)}$ being $1 \times r$ (Eqs. 3 and 1).

The same approximation extends to the idiosyncratic components of all the quarterly variables in the system, including the subsequent GDP releases $y_t^{(k)}$. This allows us to write $\zeta_t^Q \equiv R(L)\tilde{\zeta}_t^M$, where $R(L) \equiv 1 + 2L + 3L^2 + 2L^3 + L^4$ and $\tilde{\zeta}_t^M$ denotes the idiosyncratic component of $\tilde{x}_t^M$. Also, $\varepsilon_t^{(k)} \equiv R(L)\tilde{\varepsilon}_t^{(k)}$, $k = 1, \dots, K$.

[3] $x_t^Q \equiv X_t^Q - X_{t-3}^Q = (1 - L^3)X_t^Q \simeq (1 - L^3)(\widetilde{X}_t^M + \widetilde{X}_{t-1}^M + \widetilde{X}_{t-2}^M) = (1 - L^3)(1 + L + L^2)\widetilde{X}_t^M = (1 - L)(1 + L + L^2)^2\widetilde{X}_t^M = (1 + L + L^2)^2\tilde{x}_t^M$, see Mariano and Murasawa (2003).

**Model Dynamics** For the factors and the idiosyncratic terms in Eq. (5) we assume the following

$$f_t = \mathbf{A}_1 f_{t-1} + \ldots + \mathbf{A}_p f_{t-p} + \eta_t \qquad \eta_t \sim \mathcal{N}(0, \mathbf{\Sigma}), \tag{6}$$

$$\zeta_t \equiv \begin{pmatrix} \zeta_t^M \\ \tilde{\zeta}_t^M \end{pmatrix} = \mathbf{D}\zeta_{t-1} + \epsilon_t \qquad \epsilon_t \sim \mathcal{N}(0, \mathbf{\Xi}), \tag{7}$$

$$\tilde{\varepsilon}_t \equiv \begin{pmatrix} \tilde{\varepsilon}_t^{(1)} \\ \vdots \\ \tilde{\varepsilon}_t^{(K)} \end{pmatrix} = \mathbf{\Phi}\tilde{\varepsilon}_{t-1} + \nu_t \qquad \nu_t \sim \mathcal{N}(0, \mathbf{\Gamma}). \tag{8}$$

In Eq. (6) $\mathbf{A}_i,\ i \ldots, p$ denote $r$-dimensional matrices of autoregressive coefficients, and $p$ is the VAR lag order. As is standard in the literature (e.g. Bańbura et al., 2013), we allow for some residual autocorrelation in the idiosyncratic terms $\zeta_t$; this applies to both the idiosyncratic of the monthly variables $\zeta_t^M$, and the unobserved monthly idiosyncratic of the quarterly variables $\tilde{\zeta}_t^M$. $\mathbf{D}$ and $\mathbf{\Xi}$ are diagonal matrices, and $\mathbb{E}[\epsilon_{i,t}\epsilon_{j,s}] = 0\ \forall i \neq j$ and $t \neq s$.

Eq. (8) specifies the dynamics for the (unobserved monthly) idiosyncratic components of the GDP releases. Here we assume as follows. First, as done for $\zeta_t$, we allow $\tilde{\varepsilon}_t$ to display some degree of autocorrelation (i.e. serial correlation within the same vintage – $\mathbb{E}\left[\tilde{\varepsilon}_t^{(k)}\tilde{\varepsilon}_{t-1}^{(k)\prime}\right] \neq 0$). However, because successive GDP releases for the same quarter are effectively different estimates of the same object, the elements of the idiosyncratic vector $\tilde{\varepsilon}_t$ may also be correlated across vintages – i.e. $\mathbb{E}[\tilde{\varepsilon}_t^{(j)}\tilde{\varepsilon}_t^{(k)}] \neq 0$ for $j \neq k$. If GDP-specific information is correlated across releases, systematic correlation may persist beyond that accounted for by the common factors in $f_t$ (i.e. correlation across all variables in the same data vintage, $\mathbb{E}[x_t x_t']$). To account for these features, in Eq. (8) we specify both $\mathbf{\Phi}$ and $\mathbf{\Gamma}$ as full matrices.

An equivalent way of formulating these properties would be to specify a common factor for the vector $\tilde{\varepsilon}_t$. This would amount to essentially impose restrictions on the loading matrices $\mathbf{\Lambda}_M$ and $\mathbf{\Lambda}_Q$, on the autoregressive coefficients in $\mathbf{\Phi}$, and on the covariance matrix of the residual terms $\mathbf{\Gamma}$. A simple factor structure would in fact obtain by imposing zero restrictions on the off-diagonal elements of both $\mathbf{\Phi}$ and $\mathbf{\Gamma}$, and by replacing $f_t$ with an

$(r+1)$-dimensional vector of common factors $\tilde{f}_t = (f_t' \; g_t')'$ where $g_t$ is a univariate factor common only to the GDP releases (i.e. the $(r+1)$-th columns of $\mathbf{\Lambda}_M$ and $\mathbf{\Lambda}_Q$ are vectors of zeros).[4]

Evans (2005) and Camacho and Perez-Quiros (2010) consider successive monthly GDP releases within a dynamic factor model by assuming that data revisions remove measurement errors in earlier releases. Their data revision structure leads to contemporaneous correlation among GDP idiosyncratic components, similar to Eq. (8), but they assume that the last release, $y_t^{(K)}$ for some $K$, includes no measurement errors, that is, true values of GDP are eventually observed. Because in our framework the loadings of each $y_t^{(k)}$ for $k = 1, ..., K$ on the common factors in $F_t$ are allowed to differ, we are implicitly assuming that true GDP may never be observed as in Jacobs and van Norden (2011) and Aruoba et al. (2016). Camacho and Perez-Quiros (2010) constraint loadings and idiosyncratic terms to be the same across GDP releases, as any difference is only due to measurement error; as a consequence, their model is a restricted version of the RA-DFM in Eqs. (5-8).

**Revisions to Early GDP Estimates** We define the $k^{th}$ GDP revision as

$$rev_t^{(k)} = y_t^{(k+1)} - y_t^{(k)}, \tag{9}$$

that is, in terms of the difference between consecutive publications for the same reference period. Combining Eq. (9) with Eq. (1) implies the following stochastic process for the GDP revisions:

$$rev_t^{(k)} = \left[\bar{\mathbf{\Lambda}}^{(k+1)} - \bar{\mathbf{\Lambda}}^{(k)}\right] F_t + \left[\varepsilon_t^{(k+1)} - \varepsilon_t^{(k)}\right], \tag{10}$$

where, as before, $\bar{\mathbf{\Lambda}}^{(k)} \equiv \left[\mathbf{\Lambda}^{(k)} \quad 2\mathbf{\Lambda}^{(k)} \quad 3\mathbf{\Lambda}^{(k)} \quad 2\mathbf{\Lambda}^{(k)} \quad \mathbf{\Lambda}^{(k)}\right]$ , $\forall k$.

The term $\left[\bar{\mathbf{\Lambda}}^{(k+1)} - \bar{\mathbf{\Lambda}}^{(k)}\right] F_t$ captures the fact that GDP revisions may change the link between the observed GDP and the underlying monthly factors. As we allow the factors loadings to differ across GDP releases, we are able to capture news revisions, that is, revisions that add new information and are correlated with the 'true' underlying measure of real activity. This follows Evans (2005), who suggests to model news-revisions by allowing the way in which each release links to true values to differ across releases.

[4]We evaluate the performance of the model specified in these terms in Figure D.2 in the Appendix.

The second term in Eq. (10) captures differences in the serial correlation of the idiosyncratic term across releases, but can also capture the impact of noise-revisions (later releases remove measurement errors of earlier releases) since $\mathbb{C}ov\left(\varepsilon_t^{(j)}, \varepsilon_t^{(k)}\right)$ is non-zero, as in Camacho and Perez-Quiros (2010). In this sense, the model-implied revision process in Eq. (10) can in principle accommodate both noise and news revisions in the GDP data (see e.g. Mankiw and Shapiro, 1986; Faust et al., 2005; Jacobs and van Norden, 2011). We return to this point more in detail in the next subsection.

Cunningham et al. (2012) assume that the variability of each successive revision declines with the data maturity $k$. We do not impose such restrictions, but empirically, depending on the values of $\mathbf{\Lambda}^{(k)}$ and of the idiosyncratic errors variances, we could have that $\mathbb{V}ar\left(rev_t^{(k+1)}\right) \leq \mathbb{V}ar\left(rev_t^{(k)}\right), \ \forall k$.

**Baseline Specification & Estimation** Stacking the vectors $x_t$ $\forall t = 1, \dots, T$ yields an unbalanced monthly panel. Variables may have a different start date, may contain systematically missing values as in the case of the quarterly indicators, and they may display the 'ragged-edge' that is typical of real-time data vintages whose entries are not released in a synchronous manner. All these features of the data can be broadly characterised by allowing for an arbitrary pattern of missing data in each vintage of $x_t$, and efficiently dealt with by estimating the RA-DFM using the EM algorithm of Bańbura and Modugno (2014).

In order to facilitate the interpretation of the factors, zero restrictions can be imposed on any of $\mathbf{\Lambda}_M$, $\mathbf{\Lambda}_Q$ and $\mathbf{\Lambda}^{(k)}$ such that group-specific factors are defined (see Bańbura et al., 2013). For example, one may want to aggregate the information in surveys in a specific 'soft-information' factor by restricting the loadings of all other variables to this factor to zero.

Our baseline specification sets the number of factors to 3. All variables load on the first factor, that can be interpreted as a synthetic indicator for economic activity in the UK. The second factor only loads on economic activity measures computed by the statistical office, such as GDP and components, and labour market indicators. The third factor summarises information of business surveys. We choose the number of factors to balance between model complexity, interpretability of the factors, and accuracy of the out-of-sample estimates (RMSFE).[5] We set $p = 1$ in Eq. (6); a higher lag order adds complexity to the system without any appreciable improvement in terms of RMSFE, as suggested by the results in Table C.1. We model each $\zeta_t$ as an independent AR(1) process, and the vector of GDP idiosyncratic terms $\tilde{\varepsilon}_t$ as a VAR of order 1.

The RA-DFM can handle an arbitrary number of subsequent GDP releases. In our empirical application we focus only on the first four release rounds (i.e. we set $K = 4$) for a number of reasons. First, the first revision rounds are those more likely to be originated by the availability of new information relative to the reference quarter. Second, and related, these are those typically regarded as being 'market movers' (see e.g. Bloomberg/Econday economic calendars). Third, the publication of the fourth update ($y_t^{(4)}$) typically coincides with the publication of the first release relative to the following quarter ($y_{t+3}^{(1)}$) – hence, for what concerns real-time nowcasting, at that point in time the relevant forecast target switches to $y_{t+3}$, and subsequent revisions to past quarters become less relevant. It is worth stressing that because we estimate the model on fully real-time vintages, revisions to all the data in $x_t$ are accounted for, and contribute to the estimation and update of the common factors $f_t$. However, we only explicitly model revisions in GDP estimates since this is the main focus of our application.

The model is estimated on 25 monthly measures of economic activity and financial conditions, and 8 quarterly activity variables, including GDP components and $K = 4$ GDP releases. Prior to estimation, where necessary the variables are transformed to achieve stationarity (see Table B.1 for details on transformations) and standardised. We report details on the estimation procedure in Appendix A.

## 2.2 The Role of Data News

**Contribution to Forecast Updates** In order to address the contribution of all the different data announcements to GDP forecasts updates we first rewrite the RA-DFM

[5] Alternative criteria based on different loss functions are those in e.g. Coroneo, Giannone and Modugno (2016) that suggest a modified version of the Bai and Ng (2002) criterion to determine the number of factors. Comparing the performance of our baseline specification with alternative factor structures supports our choice. Results are not reported for space considerations but are available upon request.

model in its state-space form

$$x_t = \mathbf{C}s_t + e_t \qquad e_t \sim \mathcal{N}(0, \mathbf{R}), \tag{11}$$

$$s_t = \mathbf{A}s_{t-1} + u_t \qquad u_t \sim \mathcal{N}(0, \mathbf{Q}), \tag{12}$$

where $x_t$ is defined as in Eq. (5), and the vector of unobserved states is $s_t \equiv \left(f_t', \ldots, f_{t-4}', \zeta_t^{M'}, \zeta_t^{Q'}, \ldots, \zeta_{t-4}^{Q'}, \varepsilon_t, \ldots, \varepsilon_{t-4}\right)'$.[6]

Let $\Omega_v$ denote the information set in a data vintage $v$ – i.e. a snapshot of $x_t$ at a particular date, and $\Omega_{v-1}$ and $\Omega_v$ denote the information set in two consecutive $x_t$ vintages. Note that consecutive data vintages are not generally equally spaced, i.e. they may be a few hours apart in the case of data being released at two different times within the same day, or they may be days or even weeks apart depending on the characteristics of the release calendar. With real-time data, $\Omega_v \setminus \Omega_{v-1}$ will contain first releases of some of the variables in $x_t$, and revisions to older data, such that $\Omega_{v-1} \notin \Omega_v$.

For simplicity, and without loss of generality, consider the case in which only one variable $x_\tau^*$ is released between $\Omega_{v-1}$ and $\Omega_v$. Between consecutive vintages, the forecast for $y_t^{(k)}$ is updated as follows

$$\mathbb{E}\left[y_t^{(k)} | \, \Omega_v\right] - \mathbb{E}\left[y_t^{(k)} | \, \Omega_{v-1}\right] = \mathbb{E}\left[y_t^{(k)} | \, I_v\right] + \mathbb{E}\left[y_t^{(k)} | \, O_v\right]. \tag{13}$$

Using the terminology in Bańbura and Modugno (2010), we refer to $I_v \equiv x_\tau^* - \mathbb{E}(x_\tau^* | \, \Omega_{v-1})$ as *data news*, or the news component in the release of $x_\tau^*$. That is, $I_v$ constitutes an element of surprise with respect to the model's forecast $\mathbb{E}(x_\tau^* | \, \Omega_{v-1})$, i.e. it is an innovation with respect to $\Omega_{v-1}$. Following Bańbura and Modugno (2010); Bańbura et al. (2013), data news are attributed to an expansion of the information set, that is, to a new observation. $O_v$ contains instead revisions to past data that are released together with $x_\tau^*$ and, potentially, a term which relates to the correlation among these. For example, in the likely case in which $x_\tau^*$ is released together with a revised value for $x_{\tau-1}^*$, $O_v = \left[x_{\tau-1}^{*(2)} - \mathbb{E}\left(x_{\tau-1}^{*(1)} | \, \Omega_{v-1}\right)\right] + \mathbb{E}\left(x_\tau^* \left[\left(x_{\tau-1}^{*(2)} - \mathbb{E}\left(x_{\tau-1}^{*(1)} | \, \Omega_{v-1}\right)\right]'\right)$. In the analysis of the contribution of data news, while we allow revisions in past $x_\tau^*$ to inform the forecast

[6]Details on the state-space representation of the RA-DFM are reported in Appendix A.

updates (i.e. we use Eq. (13) to update the forecasts for $y_t^{(k)}$), we evaluate only the impact of new observation surprises, included in $I_v$. Using the properties of the conditional expectation, we obtain

$$\mathbb{E}\left[y_t^{(k)}|\ I_v\right] = \underbrace{\mathbb{E}\left[y_t^{(k)} I_v'\right]\mathbb{E}\left[I_v I_v'\right]^{-1}}_{\text{weight}} \underbrace{\left[x_\tau^* - \mathbb{E}(x_\tau^*|\ \Omega_{v-1})\right]}_{\text{data news}}. \tag{14}$$

The elements in Eq. (14) are obtained from the Kalman smoother,

$$\mathbb{E}\left[y_t^{(k)} I_v'\right] = \mathbf{C}_{(k)}\mathbb{E}\left[\left(s_t - \mathbb{E}[s_t|\ \Omega_v]\right)\left(s_\tau - \mathbb{E}[s_\tau|\ \Omega_v]\right)'\right]\mathbf{C}_{x^*}', \tag{15}$$

$$\mathbb{E}\left[I_v I_v'\right] = \mathbf{C}_{x^*}\mathbb{E}\left[\left(s_\tau - \mathbb{E}[s_\tau|\ \Omega_v]\right)\left(s_\tau - \mathbb{E}[s_\tau|\ \Omega_v]\right)'\right]\mathbf{C}_{x^*}' + \mathbf{R}_{x^*,x^*} \tag{16}$$

where $\mathbf{C}_j$ denotes the $j$-th row of $\mathbf{C}$, and we refer to $\mathbb{E}\left[y_t^{(k)} I_v'\right]\mathbb{E}\left[I_v I_v'\right]^{-1}$ as the news weights.

In the analysis of the contribution of data news of Section 4, we make use of average impacts for each variable $x_\tau^*$. These are defined as the product of average weights times the average standard deviation of data news. Specifically, the average impacts for each variable $x_\tau^*$ are constructed as

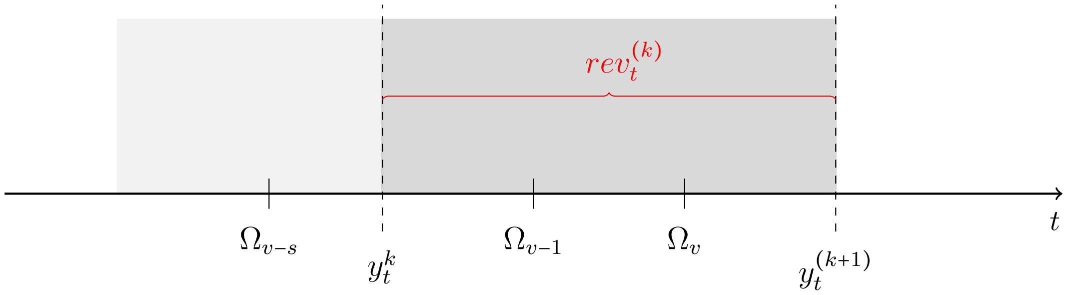
$$i_{x^*} = \frac{1}{V}\sum_{v=1}^{V} b_{x^*}\bar{\sigma}_{x^*}, \tag{17}$$

where $V$ is the number of data vintages in which $x_\tau^*$ is released, $b_{x^*}$ are the weights in Eq. (14), and $\bar{\sigma}_{x^*}$ denotes the average standard deviation of the model's forecast errors (i.e. the data news, $I_v$) for $x_\tau^*$.

**Contribution to Forecast of GDP Revisions** The RA-DFM can accommodate both news and noise revisions in GDP data as discussed earlier. Here we formalise this aspect further, and also consider how *data news* may affect the model's expectation for the revision of early releases of GDP, which is the main novelty introduced with the RA-DFM.

Conditional on having observed $y_t^{(k)}$, and extending the argument in Bańbura and Modugno (2010), we can decompose the real-time forecast update for $rev_t^{(k)}$ with a

FIGURE 1: DATA NEWS IN GDP REVISIONS



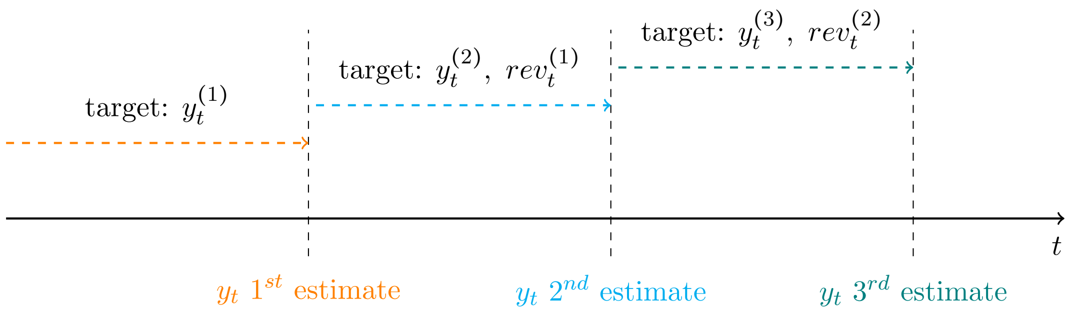

straightforward generalisation of Eq. (13)

$$\begin{aligned}\mathbb{E}\left[rev_t^{(k)}|\ \Omega_v, y_t^{(k)}\right] - \mathbb{E}\left[rev_t^{(k)}|\ \Omega_{v-1}, y_t^{(k)}\right] &= \mathbb{E}\left[y_t^{(k+1)}|\ \Omega_v, y_t^{(k)}\right] - \mathbb{E}\left[y_t^{(k+1)}|\ \Omega_{v-1}, y_t^{(k)}\right] \\ &= \mathbb{E}\left[y_t^{(k+1)}|\ I_v, y_t^{(k)}\right] + \mathbb{E}\left[y_t^{(k+1)}|\ O_v, y_t^{(k)}\right]. \quad (18)\end{aligned}$$

As before, in determining the contribution of data news, we focus on $\mathbb{E}\left[y_t^{(k+1)}|\ I_v, y_t^{(k)}\right]$. By doing so, we analyse the impact of an expansion in the observables data set that reflects on the expected values of GDP revisions. Expected values are updated if the new information is incorporated into the estimates of the unobserved common monthly economic activity factors.

Consider now the news and noise GDP revisions as defined by Mankiw and Shapiro (1986), and the timing of events summarised in Figure 1. 'News revisions' are triggered by new information accumulated between $y_t^{(k)}$ and $y_t^{(k+1)}$ (dark grey area in the figure), and are orthogonal to the information set at the time of the release of $y_t^{(k)}$ (light grey area). In our real-time nowcasting environment, we account for the contribution of new information in forecasting $y_t^{(k+1)}$ insofar as $\bar{\boldsymbol{\Lambda}}^{(k+1)}$ is non-zero, and in forecasting $rev_t^k$ if $\left[\bar{\boldsymbol{\Lambda}}^{(k+1)} - \bar{\boldsymbol{\Lambda}}^{(k)}\right]$ is non-zero. In contrast, as discussed earlier, 'noise revisions' are mainly captured by the idiosyncratic terms. Because only GDP releases move the vector $\varepsilon_t$ and, by construction, there are no GDP releases between any $\Omega_{v-1}$ and $\Omega_v$ in the dark grey area of Figure 1, the evaluation of the impact of the data flow on predictions of GDP revisions characterises effects associated to 'news revisions'.

Figure 2: Time-Varying Forecast Targets



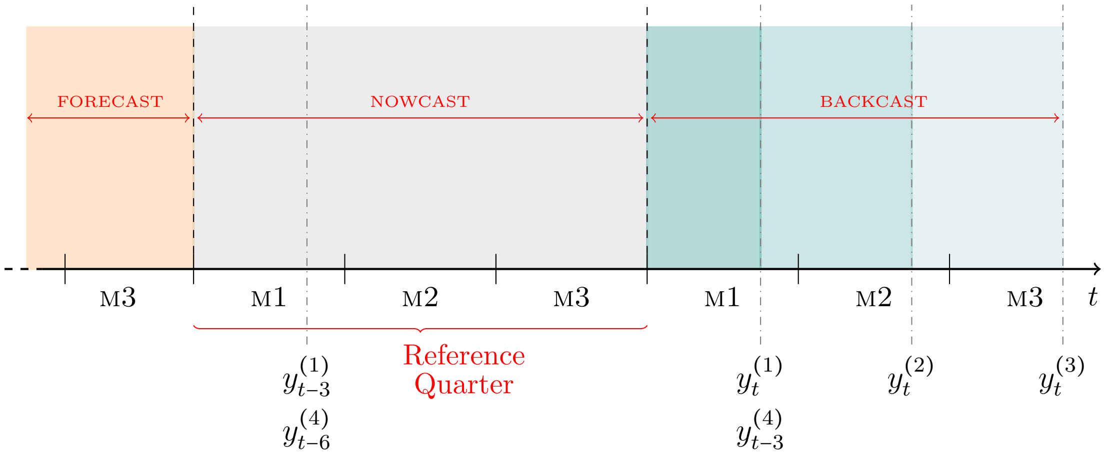

*Note:* Example of time-varying forecast targets for the RA-DFM.

## 2.3 Time-Varying Forecast Targets and Forecast Horizons

Traditional models such as e.g. Bańbura et al. (2013) have a unique forecast target, typically either the first GDP release, or the latest available vintage. Conversely, the RA-DFM allows us to switch forecast targets as time goes by, and in accordance with the publication calendar of the statistical agency. Prior to the publication of any official GDP data for the reference quarter, the target is the first estimate of GDP – $y_t^{(1)}$. Once this number is published, the target shifts to the second estimate for the same reference quarter – $y_t^{(2)}$. As noted, conditional on having observed $y_t^{(1)}$, targeting $y_t^{(2)}$ is the same as targeting the first revision round $rev_t^{(1)}$. With the publication of $y_t^{(2)}$, the target moves to be $y_t^{(3)}$ (or, equivalently, $rev_t^{(2)}$) and so on. We sketch the intuition in Figure 2.

We use the following convention for the forecast horizons, summarised in Figure 3. If the timing of the data vintage $v$ falls within the current/reference quarter (grey area), conditional on $\Omega_v$ we nowcast $y_t^{(1)}$ and forecast next quarter GDP $y_{t+3}^{(1)}$. Similarly, if it falls within the first month following the reference quarter, but still before the publication of the first release (dark teal area), we backcast $y_t^{(1)}$, and nowcast $y_{t+3}^{(1)}$. Once $y_t^{(1)}$ is released (teal area), we drop it from the set of active targets and substitute with $y_t^{(2)}$, which is then further substituted with $y_t^{(3)}$ once the release for $y_t^{(2)}$ is out (light teal area), as in Figure 2. We track each quarter for a total of roughly 270 days. The first 90 are a pure forecast; i.e. the forecast horizon relative to the reference quarter and expressed in quarters, is $h = 1$ (orange area). The second set of 90 days corresponds to the nowcast period ($h = 0$, grey area), and we generally refer to the backcast period as the sum of the

Figure 3: Tracking Window




*Note:* The figure sketches the convention for the forecast horizons in the RA-DFM. The orange area is the forecast period, where the forecast horizon, expressed in quarters and relative to the reference quarter, is $h = 1$. The grey area is the nowcast period, with $h = 0$. The backcast period is the sum of the teal areas ($h = -1$).

three teal areas ($h = -1$).

## 3 The UK Real-Time Data Flow

The UK real-time dataset built to support the empirical analysis in this paper contains real-time vintages for output and its components, production, domestic and international trade, and labor market statistics, as well as business surveys and financial market indicators. The data start in January 1990 and real-time vintages are available from September 1st, 2006 until January 26th, 2017. We describe our dataset in detail in Appendix B.

In the context of real-time forecasting, addressing the timeliness and publication calendar of the different indicators is as important as assembling the relevant data. We recovered the actual date and time of official data releases for all the variables in our dataset by combining information provided by the original data suppliers with the economic calendar of data releases distributed by Bloomberg. The latter is populated by all the 'market movers', most of which appear in our set.

The data flow within a typical month in the UK is summarised in Table 1. The first column reports the average publication day for each indicator, while in the fifth column we report the period the release refers to. These two pieces of information are

Table 1: The UK Data Flow

| Release Day | Code | Variable Name | Frequency | Reference Period | Publication Delay |
|---|---|---|---|---|---|
| 1 | PMIM | PMI Manufacturing | M | m-1 | 1 |
| 1 | CIPSEM | CIPS-E-Manufacturing | M | m+3 | -89 |
| 3 | PMIC | PMI Construction | M | m-1 | 3 |
| 3 | CIPSEC | CIPS-E-Construction | M | m+3 | -87 |
| 5 | PMIS | PMI Services | M | m-1 | 5 |
| 5 | CIPSES | CIPS-E-Services | M | m+3 | -85 |
| 9 | IOP | Industrial Production | M | m-2 | 39 |
| 9 | MPROD | Manufacturing Production | M | m-2 | 39 |
| 10 | BOPEXP | BOP Total Exports (Goods) | M | m-2 | 40 |
| 10 | BOPIMP | BOP Total Imports (Goods) | M | m-2 | 40 |
| 17 | CCOUNTR | Claimant Count Rate | M | m-1 | 17 |
| 17 | LFSE | LFS Number of Employees | M | m-2 | 47 |
| 17 | LFSU | LFS Unemployment Rate | M | m-2 | 47 |
| 20 | RSI | Retail Sales Index | M | m-1 | 20 |
| 20 | CBIORDER | CBI Industrial Trends | M | m | -10 |
| 22 | IOS | Index of Services | M | m-2 | 52 |
| 22 | GDP | Either GDP1, GDP2 or GDP3 | Q | q-1 | 22, 52, 82$^{\dagger}$ |
| 22 | QCONSTR | Construction Output | Q | q-1 | 22, 52, 82$^{\dagger}$ |
| 22 | CONS | Private Consumption | Q | q-1 | 52 and 82$^{\dagger}$ |
| 22 | INV | Total Business Investment | Q | q-1 | 52 and 82$^{\dagger}$ |
| 22 | HINV | Housing Investment | Q | q-1 | 52 and 82$^{\dagger}$ |
| 23 | CBISALE | CBI Distributive Trade | M | m | -7 |
| 26 | LLOYBB | Lloyds Business Barometer | M | m | -4 |
| 30 | ASCORE | Agents' Score | M | m | 0 |
| 30 | UKBASKET | UK Focused Equity Index | M | m | 0 |
| 30 | SERI | Sterling Effective Exchange Rate | M | m | 0 |
| 30 | TERMSP | Term Spread | M | m | 0 |
| 30 | CORPSP | Corporate Bond Spread | M | m | 0 |
| 30 | MTGAPP | Mortgages Approved | M | m-1 | 30 |
| 30 | CREDIT | Net Consumer Credit | M | m-1 | 30 |

*Note:* The table sketches the data flow within a typical month. The first column is the average release day for each variable. Column five reports the reference period: $m$ and $q$ denote the current month and current quarter; hence, $m + 3$ refers to three months ahead, and $q - 1$ to the previous quarter. The last column reports the average publication delay (in days) from the end of the reference period. $^{\dagger}$ The publication delay of quarterly variables varies depending on which month in the quarter is considered (i.e. 25 days for preliminary estimates, 85 days for the third estimate).

combined in the last column of the table where we report the typical publication delay for each variable, expressed in days from the end of the reference period. For example, Manufacturing PMI is released on the first day of each month for the previous month. The publication delay in this case is only one day. Within the same release, Markit/IHS also publishes a forward looking index that summarises expectations relative to the next quarter (CIPSEM). Hence, in this case the publication delay is negative, as the number refers to the following 90 days.

Production and international trade data are published in the second week of each month, and refer to two months prior to the one in which they are published. E.g. the index of industrial production (IOP) for March is released on the 9th of May, with a publication delay of 39 days counting from the end of the reference month (Mar). Hence, in each quarter, the first production data relative to that quarter are only released in the third month of the quarter. This constitutes a considerable delay, particularly when compared to US production data which are published only two weeks after the reference period. A similarly long publication delay characterises labour market statistics. These get published by the ONS on the third week of every month. The timeliest labour market data are those relative to the Claimants Count: these count the number of unemployment benefits claims every month, and have the shortest publication delay. Conversely, the unemployment rate and employment data, part of the same release, have an extra 30 days of delay. The scarcity of timely 'hard' data in the UK makes nowcasting the UK economy a much tougher exercise when compared to other countries, since most of the information at early stages of each quarter only comes from either surveys or credit and financial markets data. The majority of UK surveys are releases towards the end of each month for the current month, with zero (negative) delay. Since we use monthly averages for asset prices, we assume that they become available at the end of the month for the current month, similar to surveys. Contrary to the latter, we assume that their release time is the end of the trading day on the last day of the month.

We also include in our dataset the Agents' Score, a survey compiled by the regional agents of the Bank of England. This survey is based on questions relative to both current and expected economic conditions that the regional agents ask firms and businesses during their regular visits, and its timing is tied to the Bank of England's monetary policy cycle.[7]

The UK's Office of National Statistics (ONS) measures GDP using three approaches: output, expenditure, and income. There are three official publication stages for the quarterly GDP estimates: Preliminary ($y_t^{(1)}$), Second Estimate ($y_t^{(2)}$), and the UK Quarterly National Accounts (QNA, $y_t^{(3)}$).[8] In its current schedule (May 2018), the ONS's preliminary GDP estimate is published 4 weeks after the end of the reference quarter and is based on 44% of actual output data.[9] The second estimate, published 8 weeks after the

[7] https://www.bankofengland.co.uk/about/people/agents

[8] https://www.ons.gov.uk/economy/grossdomesticproductgdp/methodologies/grossdomesticproductgdpqmi

[9] Since July 2018, the ONS has introduced the publication of a monthly GDP estimate, while the first GDP release is now delayed by another 10 days. Our model can easily be generalised to formally link

reference quarter, is based on information from all three approaches (80% of output, 50% of income, and 60% expenditure). At this point in the data cycle the ONS also releases preliminary data on the consumption and investment components of GDP. The UK QNA are published 13 weeks after the end of the reference quarter, and are based on 90% of the data for the output approach, 70% for the expenditure approach, and 70% for the income approach. These first two rounds of revisions are primarily due to the inclusion of information that was not available at the time of the preliminary estimate.[10]

## 4 Nowcasting UK GDP Growth in Real-Time

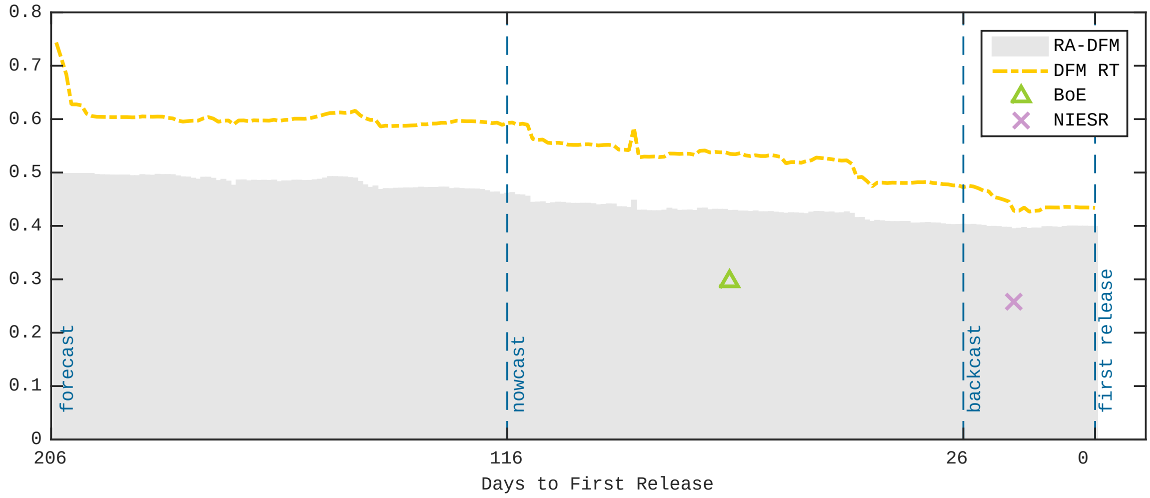
In this section we take the RA-DFM to the data. We start with a brief assessment of the overall forecasting performance of the RA-DFM in terms of accuracy with respect to the first release of GDP ($y_t^{(1)}$), as is standard in the nowcasting literature. We then move to analyse the forecasting accuracy with respect to subsequent releases for the same quarter ($y_t^{(k)},\ k = 2, 3, 4$), and the contribution of data news to revisions in early GDP estimates ($rev_t^{(k)},\ k = 1, 2, 3$), which constitute the core of our results. We conclude the section by evaluating how the model performs against the latest available estimates of GDP – presumably a more accurate measure of GDP growth – in terms of both point and density forecasts.

**Setup of the Out-Of-Sample Forecasting Exercise** To recap from Section 2, the benchmark RA-DFM specification includes all the variables listed in Table 1. Monthly variables enter the model either in levels (e.g. surveys), or in month-on-month growth rates. Quarterly variables all enter in quarter-on-quarter growth rates. We combined the real-time dataset with the actual publication day and time of all the data between 2006 and 2016; the procedure delivers over 1,500 real-time data vintages over which the

monthly to quarterly GDP releases, following the intuition in Bragoli and Modugno (2017).

[10]Following these initial revision rounds, annual revisions are published as part of the Blue Book publication (https://www.ons.gov.uk/economy/grossdomesticproductgdp/compendium/unitedkingdomnationalaccountsthebluebook/2017). After three years from the initial publication, GDP numbers computed under the income and expenditure approaches are revised to yield the same value in (chained) British Pounds.

Figure 4: Forecasting Performance (2006-2016): First Release




*Note*: RMSFE over the evaluation sample. Numbers on the $x$ axis denote days since the beginning of the tracking window for the average reference quarter until the first GDP release is published.

performance of the model is evaluated.[11]

The parameters of the model – i.e. $\mathbf{C}, \mathbf{R}, \mathbf{A}, \mathbf{Q}$ in Eqs. (11 - 12) –, are estimated at the beginning of every new calendar year in the evaluation sample (2006-2016) using an expanding time window that always starts on Jan 1st, 1992 and the EM algorithm of Bańbura and Modugno (2014).[12] Forecast updates at each forecast origin within the year are then computed using the parameters estimated at the beginning of the year. Real-time out-of-sample forecast, nowcast and backcasts (see Figure 3) for the first four releases of real quarter-on-quarter UK GDP growth are produced for the 10-year period between Q4 2006 and Q4 2016.

## 4.1 Nowcasting the First Release

Figure 4 summarises the average point forecasting performance of the benchmark RA-DFM specification over the forecast, nowcast and backcast periods. We compare the predictions of the RA-DFM with those of a standard DFM estimated on real-time data vintages (DFM RT). The DFM RT is specified on the same set of variables and the same factor structure of the RA-DFM. The only difference between the two is the way in which

[11]See Section 3 for additional details on the construction of the real-time vintages and assumptions on release dates for financial variables. Release date/times for the variables in the dataset are retrieved from the original sources or from the Bloomberg ECO Calendar.

[12]Estimation details are reported in the Appendix.

GDP vintages enter the specification: the DFM-RT uses full real-time vintages for GDP data, while the RA-DFM only the first four releases and models them as in Eqs. (5) and (8).[13] Figure 4 also reports the forecasts obtained from two institutional forecasters: the Bank of England, and the National Institute for Economic Research (NIESR) aligned at the time when their forecasts become publicly available.

In the figure, RMSFEs are all computed over the 41 quarters in the out-of-sample period. Numbers on the vertical axis are quarter-on-quarter percentage points. On the horizontal axis we report the number of days since the beginning of the tracking window for each quarter (see Figure 3) measured in terms of distance from the release of the target variable $y_t^{(1)}$. The first 90 days are a pure forecast period, the subsequent 90 days are the nowcast quarter and the backcast starts after 180 days, until the first GDP estimate is published.

A few elements are worth highlighting. First, the RMSFE associated with the DFM models declines over time, as more high-frequency data are published. This is well known in the literature (e.g. Giannone et al., 2008) and we document a similar finding for the UK as well. Second, although institutional forecasts seem to be more accurate on average over our sample, it is worth noting here that essentially all the accuracy gains of the institutional forecasters (including the BSE discussed in what follows) are realised in those quarters when the use of judgement, absent from the RA-DFM by construction, was instead crucial. Examples of these instances are the onset of the 2008/2009 recession and one-off episodes such as the 2012 London Olympic Games. Indeed, if we abstract from these events and remove the last two quarters of 2008 and the last three of 2012 from the evaluation period, we find that the Bank of England RMSFE is now 0.30 and that of the NIESR changes to 0.26, while the equivalent RA-DFM value is 0.33, implying a difference of only 3-7% in favour of the professional forecasters. Hence, the RA-DFM is effectively as accurate as the best institutional forecasters if one compares the performance over those period when the forecasts can all be thought to be conditional on approximately the same information set, or, equivalently, when the use of judgement was less essential. Moreover, institutional forecasters only report their forecasts once over

[13] We report further comparisons with alternative RA-DFM specifications in Appendix C. The comparison confirms that results reported in this section are robust to the specification of the RA-DFM.

the tracking period, in contrast with statistical models that are designed to monitor economic conditions continuously. Third, the RA-DFM improves the accuracy of forecasts, nowcasts and backcasts for the first GDP release over the standard DFM estimated on real-time vintages. The reduction in RMSFE is 23% at the beginning of the nowcast period, 15% as the backast period starts and 7% the day before the publication of the first release. The improvements in accuracy are in general statistically significant at 1% level during the forecast and nowcast windows, and at the 5% level during the backcast window.[14]

## 4.2 Nowcasting the Revisions to Early GDP Releases

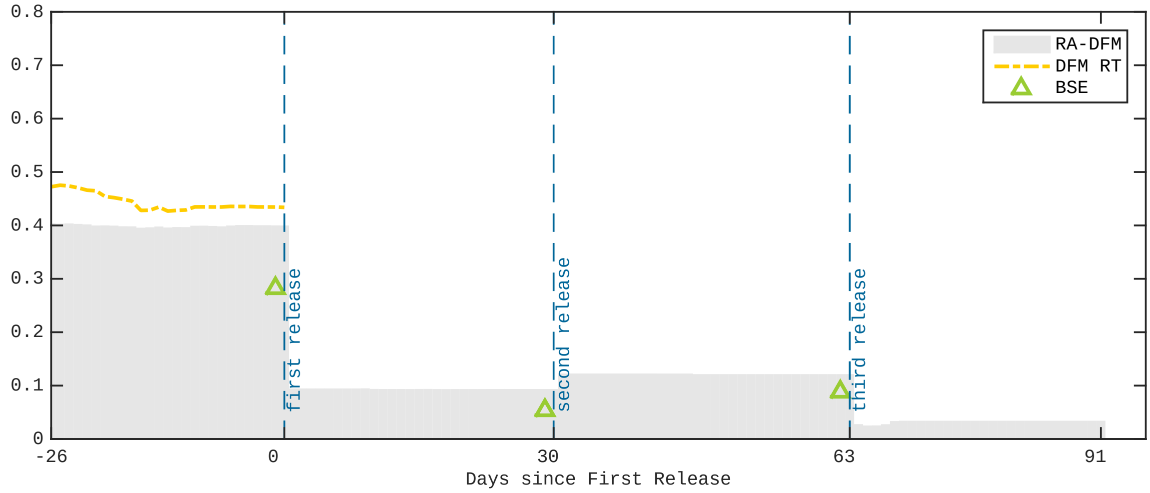
The added value of the RA-DFM relative to a standard DFM with real-time data is its ability to forecast beyond the first release, and to provide a framework to evaluate how the data flow informs future revisions to early released GDP data.

Figure 5 reports the forecasting performance (measured by the RMSFE over the out-of-sample period) of the RA-DFM for the backcast horizons as described in Figure 3. After the publication of the first release, our modelling approach will be effectively forecasting GDP revisions. The time span covered in the chart goes from the beginning of the backcast period to the day of the publication of $y_t^{(4)}$. Numbers on the vertical axis are again quarter-on-quarter percentage points. The markers in the figure denote the RMSFE of the Bloomberg Survey of Economists (BSE). The survey collates responses from economists and market participants prior to the publication of the first, second, and third release relative to each quarter.

After the first release, Figure 5 indicates a large decline of the RA-DFM RMSFE, partially explained by the small size of initial UK data revisions as reported in Appendix B. The performance of the RA-DFM in predicting GDP revisions is also explained by our VAR modelling of the idiosyncratic components of the GDP releases (see Eq. (8)), as Figure D.2 (in the Appendix) suggests that this specification performs better than adding a common factor to GDP releases, which is a restricted version of RA-DFM benchmark

[14]This statement relies on the computation of a test for equal forecast accuracy between the RA-DFM and the DFM RT for each forecasting horizon over the tracking period in Figure 4. We computed the statistic under a quadratic loss function with the small sample correction in Harvey et al. (1997). The significance levels reported in the text refer to one-sided test with the RA-DFM under the alternative.

Figure 5: Forecasting Performance (2006-2016): Subsequent Releases




*Note*: Point forecast performance measured by the RMSFE. Numbers on the $x$ axis denote days since the beginning of the backcast period for the average reference quarter until the fourth GDP release is published.

specification. Figure 5 suggests that RA-DFM performance is similar to the BSE survey.

A natural question that arises from inspection of Figure 5 is whether the RA-DFM adds any additional information for forecasting the subsequent releases to instead simply using any $y_t^{(k-1)}$ as a forecast for $y_t^{(k)}$, that is, a random walk forecast.[15] We provide results for this exercise in Table 2. The table reports the RMSFE for predicting the first and the second GDP revisions using three methods: using the previous ONS release, the RA-DFM predictions computed the day before each release, and the Bloomberg Survey (BSE) predictions. We also include p-values for two tests of equal accuracy between the random walk forecast and either the RA-DFM or the BSE predictions. In Table 2, values in parentheses are p-values for the Diebold-Mariano statistics assuming a quadratic loss function and applying the small sample correction in Harvey, Leybourne and Newbold (1997). Values in brackets are asymptotic p-values for the MSE-P adjusted test in Clark and West (2007), which is equivalent to a forecasting encompassing test. The advantage of the latter test statistic is that takes into account that the forecasting model under the null (a random walk model) requires no parameter estimation.

The statistics in Table 2 indicate that on average over our sample the real-time RA-DFM forecasts are as accurate as the previous ONS releases in predicting revised GDP

[15]We thank an anonymous referee for suggesting this comparison.

TABLE 2: RELATIVE ACCURACY OF RA-DFM FOR UK GDP REVISIONS

| | ONS PREVIOUS RELEASE (RW Forecast) | RA-DFM | BSE |
|---|---|---|---|
| Second Release (First Revision) | 0.077 | 0.093<br>(0.228)<br>[0.599] | 0.055<br>(0.091)<br>[0.055] |
| Third Release (Second Revision) | 0.108 | 0.119<br>(0.086)<br>[0.203] | 0.088<br>(0.332)<br>[0.181] |

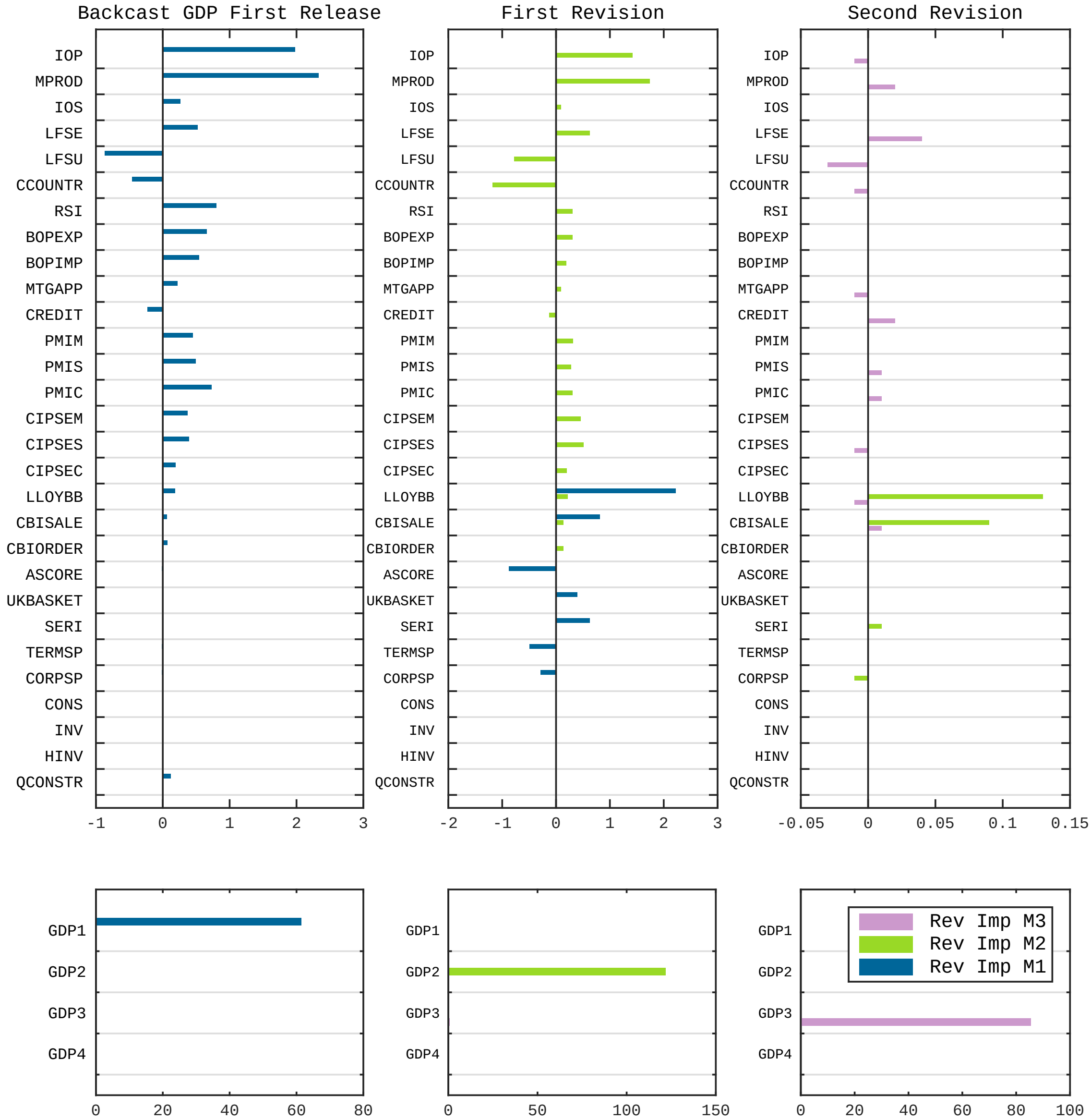
*Note:* Entries are RMSFE over the evaluation period (2006-2016). The values in parentheses are p-values of the Diebold and Mariano test of equal accuracy using a quadratic loss function with the small sample correction suggested in Harvey et al. (1997). The values in brackets are the asymptotic p-values of the forecast encompassing test computed as ECN-T in Clark and McCracken (2001). P-values < 10% suggest that the null of equal accuracy between random walk forecast and alternative model is rejected at 10% level.

values. In addition, however, the RA-DFM is able to exploit regularities between past releases and the data flow in order to forecast GDP revisions, and we discuss supportive evidence on the informativeness of the data flow for GDP revisions in the next section. Auroba (2008) and Clements and Galvão (2017) find similar difficulties in exploiting in-sample regularities to predict GDP data revisions out-of-sample using US data. The results in Table 2 also suggest that the BSE forecasts for the first revision significantly improve over the random walk forecast. Previous research suggested that survey predictions of US GDP revisions are hard to beat using statistical models (Clements and Galvão, 2017), so it is not surprising to find similar improvement for UK GDP revisions.

## 4.3 The role of data news in explaining data revisions

What do we learn from applying the RA-DFM to UK real time data? In order to answer this question, in this section we study how the data flow contributes to forecasting GDP revisions. Results reported are average impacts over the backcast window over the 2006-2016 period calculated using Eq. (17). Results are reported in Figure 6. The left panels of the figure report the average impacts on predictions for the first release, the middle panels those for the second release (first revision), and the right panels those for the third

Figure 6: Impact of Data News on Expected GDP Revisions




*Note*: Impact of data releases on the expected values for the first (left panels), second (middle panels) and third (right panels) GDP release. These impacts are computed by multiplying average weights by the average standard deviation of the specific data release, see Eq. (17).

release (second revision). In terms of timing, the panels of Figure 6 correspond (from left to right) to the three teal areas of Figure 3 respectively. We report the impacts of the GDP releases themselves on separate panels (at the bottom of the figure) to enhance readability. For ease of comparison, average impacts are scaled such that all the forecast targets ($y_t^{(1)}$,$y_t^{(2)}$ and $y_t^{(3)}$) have a standard deviation of 1, and M1, M2, M3 refer to the three months in the backcast window period.[16,17]

The average contributions reported in the upper left panel of the figure confirm the importance of hard data, and production in particular, in backcasting the initial estimates of GDP growth. The index of production (IOP) and the index of production in the manufacturing sector (MPROD) are the two most important variables in our dataset in informing the backcast of $y_t^{(1)}$. Unemployment figures (LFSU) are the second best predictors, but with impacts half the size of those of production data. PMIs do not contribute in a particularly significant way. The impact of the remaining business surveys in this period is zero: being released towards the end of the month, they fall outside of the tracking period for $y_t^{(1)}$ by construction.

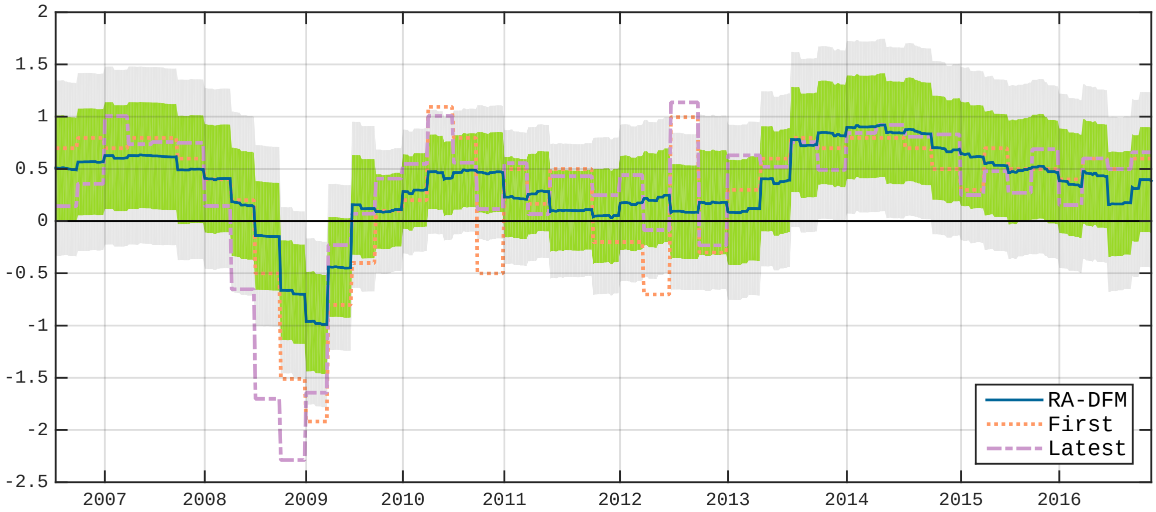
Business surveys, and particularly the Business Barometer distributed by Lloyds (LLOYBB), are as important as some of the more traditional data for predicting the second GDP release, that is, the first revision. In fact, impacts are comparable to those of both production and labor market statistics. As indicated in Table 1, both manufacturing production (MPROD) and unemployment (LFSU) are published with a two-month delay. This delay plays an important role here since the new observations published during the second backcast month refer to the last month of the reference quarter, explaining why the RA-DFM estimates suggest that these releases are linked to large updates of first revision predictions. Also somewhat relevant are financial market data such as the exchange rate (SERI) and the yield curve (TERMSP). This is in line with results for the US reported in Clements and Galvão (2017). The impacts reported in the figure corroborate the notion that the second release incorporates information from 'hard data', such as production and labor market indicators. This is also compatible with the fact that in this instance the ONS updates GDP estimates because new information becomes available, i.e. these are mainly *news revisions*.

The information content of data news is largely exhausted by the time the forecast target switches to the third release (second revision). This is a direct consequence of the

[16] M1, M2 and M3 correspond to Apr, May, Jun for each Q1, to Jul, Aug, Sep for each Q2 and so on. The bars are averages for each month over the evaluation period, such that M1 is the average of releases published in Jan, Apr, Jul, Oct, M2 averages over Feb, May, Aug, Nov, and M3 averages over Mar, Jun, Sep, Dec.

[17] Results for the forecast and nowcast of the first release largely confirm previous findings for other countries (surveyed in Bańbura et al., 2013), and are reported in Figure D.1 in the Appendix.

FIGURE 7: RA-DFM BACKCAST AGAINST FIRST AND LATEST GDP VINTAGES




*Note*: These predictions are computed over the backcast window period (horizons from 26 days to 0) for $y_t^{(1)}$ over the evaluation sample (blue line). The green and grey areas indicate 68% and 95% predictive intervals. Dashed yellow line is the first GDP release, and dashed lilac line is the latest GDP vintage (May 2018).

timeliness of the data included in our set – numbers published beyond the end of the second month after the end of the reference quarter start referring to the following one, and are hence little informative. In relative terms, an exception is labour market data. Due to their publication delay and the fact that unemployment (LFSE) and employment (LFSU) are published as rolling 3-month moving averages, they still have some impact for the second revision, but magnitudes in absolute terms are negligible.

In sum, our results show that revisions to early released GDP data are in part explained by data news. Mostly, however, the information content of new observations in the data flow is exhausted with the publication of the second GDP estimate.

## 4.4 Forecasting Later GDP Vintages

A standard way to think about subsequent GDP releases for the same quarter is as increasingly more accurate estimates of GDP growth values. In this sense, latest vintages of GDP data can be thought of as being the best available estimates of historical growth, given that the majority of observations have gone through many rounds of revisions. In this section we evaluate the RA-DFM predictions against the latest vintage of GDP data available at the time of writing (May 2018).

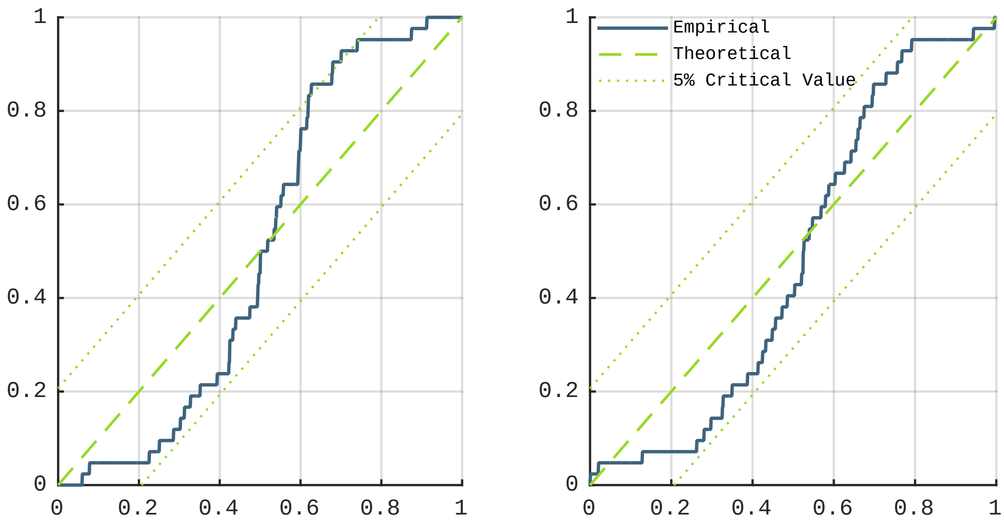
In Figure 7, we show that the RA-DFM can be applied to compute predictive intervals for the first release of GDP in real-time. The figure plots the point prediction for the first GDP release computed for the backcast window that comprises horizons from 26 to zero days (see Figure 4) together with 68% and 95% predictive intervals. These are computed under the assumption of a Gaussian predictive density, and a predicted variance that does not consider effects of parameter uncertainty, and it is computed with a closed-form solution. The plot also includes GDP growth realisations as observed in the first GDP release (dotted line) and the May 2018 GDP vintage (dash-dotted line).

An inspection of the chart reveals that the latest GDP growth estimate lies outside the 95% predictive interval only 3 times compared with the 5 of the first release, which implies a better fit to the latest vintage considering that the expected number of misses is 2. Of the three instances that the latest GDP growth estimate lie outside the predictive interval, two are entirely idiosyncratic, while the third is linked to the 2008/2009 recession. It is worthwhile to note that, as documented also in Galvão and Mitchell (2018), the GDP revisions have shifted the turning points in the recession phase such that the trough of the recession was anticipated to Q4-2008 from Q1-2009.

In order to evaluate whether the RA-DFM predictive densities are correctly specified we employ the test proposed by Rossi and Sekhposyan (2019). The test statistic relies on probability integral transforms (PITs), and it is robust to instability in predictive performance. The empirical CDF for PITs values computed over the evaluation sample are reported in Figure 8. The predictive densities evaluated are computed the day before the first GDP release is due. The PITs are computed using as realisations the values in the first GDP release in the left panel, and in the latest vintage in the right panel. If the predictive densities are well-specified, predicted probabilities are as the expected theoretical probabilities, and we should observe PITs values as near the 45 degree line as possible.

An inspection of the figure suggests that the PITs CDF lie within the interval computed using the Rossi and Sekhposyan (2019) procedure when actuals are obtained from the latest vintage, but not when using the first release. As a consequence, we confirm earlier results that RA-DFM predictive densities are better specified for best available historical estimates of GDP growth than for the first GDP release. Hence, it appears

Figure 8: Predictive Densities: Empirical CDF of RA-DFM PITs




*Note*: Predictive densities are computed the day before the first release assuming Gaussianity and using an estimate for the predictive variance that does not take into account parameter uncertainty. The dotted lines describe confidence intervals to test for the uniformity of probability integral transforms (PITs), and are computed using the statistic proposed by Rossi and Sekhposyan (2019). If the empirical CDF is outside the interval, we are able to reject the null of uniformity at 5% level.

that the model's forecasts are informative for an assessment of the state of the economy that goes beyond the initial estimates. We evaluate this claim more formally in Table 3.

Table 3 reports results of a forecast encompassing test that compares the predictive content of the official ONS estimates against RA-DFM forecasts in predicting latest GDP estimates (as of May 2018). The regression used to compute the test statistic is as follows:

$$y_t^{(2018M5)} = c + \lambda y_t^{(k)} + (1 - \lambda)\widehat{y}_t^{(k)} + \xi_t, \tag{19}$$

where $\widehat{y}_t^{(k)}$ is the RA-DFM predictions for $y_t^{(k)}$ dating a day before $y_t^{(k)}$ is due for publication, such that the information set of the RA-DFM and that of the ONS are aligned. The coefficient $\lambda$ determines the optimal forecast combination weights. If $\lambda = 0$, then the model's forecast encompasses the corresponding official release of the statistical office, i.e. given $\widehat{y}_t^{(k)}$, the information in $y_t^{(k)}$ can be dispensed with in order to forecast $y_t^{(2018M5)}$. We estimate the regression in Eq. (19) using out-of-sample predictions for all quarters between 2006 and 2016 and report the results for $k = 1, 2, 3$ in the columns of Table 3.

The estimated weights show that the RA-DFM predictions provide information for

Table 3: Official Estimates vs RA-DFM Predictions

| | FIRST | SECOND | THIRD |
|---|---|---|---|
| ONS GDP estimate | 0.664*** | 0.703*** | 0.723*** |
| | (6.05) | (4.817) | (5.67) |
| RA-DFM backcast | 0.453** | 0.404* | 0.284 |
| | (2.03) | (1.870) | (1.55) |

*Note:* Forecast encompassing test. Regressions include a constant. The dependent variable is UK GDP growth as per latest available vintage (May 2018). $t$ statistics are reported in brackets, robust standard errors, n=41 quarters. The columns report the coefficients of Eq. (19) estimated using the first, second, and third ONS releases respectively. Model's forecasts are aligned such that the timing of the information set of the RA-DFM and the ONS coincide.

the best estimate of GDP growth beyond what is contained in the official first estimates. This information is also sizeable, with estimated $(1 - \lambda)$ roughly equal to one half for the first and 0.4 for the second release.

# 5 Conclusions

In this paper, we have proposed a Release-Augmented Dynamic Factor Model, or RA-DFM, for nowcasting data subject to revision, and applied it to nowcasting UK real GDP growth in real-time. To this end, we have also compiled a rich and comprehensive real-time mixed-frequency dataset for the UK economy, assembled using official data stored over the years in the archives of the Bank of England.

The RA-DFM incorporates successive GDP estimates without making strong assumptions about the characteristics of their data revision process. The modelling allows for data revisions that arise from the inclusion of new information by the statistical office and from the removal of measurement errors in earlier estimates. An advantage of the RA-DFM approach is that it permits the evaluation of the impact of data news not only on GDP forecasts and nowcasts, as it is usual in this literature, but also on GDP revisions predictions. We assess gains from employing the RA-DFM for UK GDP growth real-time forecasting to show the model improves the accuracy of nowcasts, in particularly if we interested in predicting revised GDP values.

# References

Aastveit, K. A., K. R. Gerdrup, A. S. Jore, and L. A. Thorsrud (2014) "Nowcasting GDP in real time: a density combination approach," *Journal of Business and Economic Statistics*, Vol. 32, pp. 48–68.

Anesti, N., S. Hayes, A. Moreira, and J. Tasker (2017) "Peering into the present: the Bank's approach to GDP nowcasting," *Bank of England Quarterly Bulletin*, Vol. Q2, pp. 122–133.

Antolin-Diaz, Juan, Thomas Drechsel, and Ivan Petrella (2017) "Tracking the Slowdown in Long-Run GDP Growth," *The Review of Economics and Statistics*, Vol. 99, No. 2, pp. 343–356, May.

Artis, M. J., A. Banerjee, and M. Marcellino (2005) "Factor Forecasts for the UK," *Journal of Forecasting*, Vol. 24, pp. 279–298.

Aruoba, S. B., F. X. Diebold, F. Nalewaik, and F. Schorfheide (2016) "Improving GDP Measurement: A Measurement-Error Perspective," *Jounal of Econometrics*, Vol. 191, pp. 384–397.

Auroba, S. B. (2008) "Data revisions are not well-behaved," *Journal of Money Credit and Banking*, Vol. 40, pp. 319–40.

Bai, Jushan and Serena Ng (2002) "Determining the Number of Factors in Approximate Factor Models," *Econometrica*, Vol. 70, No. 1, pp. 191–221.

Bańbura, Marta and Michele Modugno (2010) "Maximum likelihood estimation of factor models on data sets with arbitrary pattern of missing data," Working Paper Series 1189, European Central Bank.

Bańbura, M. and M. Modugno (2014) "Maximum Likelihood estimation of factor models on datasets with arbitrary pattern of missing data," *Journal of Applied Econometrics*, Vol. 29, No. 133-160.

Bańbura, Marta, D. Giannone, M. Modugno, and L. Reichlin (2013) "Now-casting and the Real-Time Data Flow," in *Handbook of Economic Forecasting, volume 2A*: Elsevier, Chap. 4, pp. 195–237.

Bragoli, Daniela and Michele Modugno (2017) "A now-casting model for Canada: Do U.S. variables matter?," *International Journal of Forecasting*, Vol. 33, No. 4, pp. 786–800.

Camacho, M. and G. Perez-Quiros (2010) "Introducting the EURO-STING: Short-term indicator of euro area growth," *Journal of Applied Econometrics*, Vol. 25, pp. 663–694.

Carriero, A., M. P. Clements, and A. B. Galvão (2015) "Forecasting with Bayesian Multivariate Vintage-Based VARs," *International Journal of Forecasting*, Vol. 35, pp. 757–768.

Castle, J. and C. Ellis (2002) "Building a real-time database for GDP(E)," *Bank of England Quarterly Bulletin*, No. Spring, pp. 42–48.

Clark, Todd E and Michael W McCracken (2001) "Tests of equal forecast accuracy and encompassing for nested models," *Journal of Econometrics*, Vol. 105, No. 1, pp. 85 – 110. Forecasting and empirical methods in finance and macroeconomics.

Clark, T. E. and K. D. West (2007) "Approximately Normal Tests for Equal Predictive Accuracy in Nested Models," *Journal of Econometrics*, Vol. 138, pp. 291–311.

Clements, M. P. and A. B. Galvão (2013a) "Forecasting with Vector Autoregressive Models of Data Vintages: US output growth and inflation," *International Journal of Forecasting*, Vol. 29, pp. 698–714.

——— (2013b) "Real-time Forecasting of Inflation and Output Growth with Autoregressive Models in the Presence of Data Revisions," *Journal of Applied Econometrics*, Vol. 28, pp. 458–477. DOI: 10.1002/jae.2274.

Clements, M. P and A. B. Galvão (2017) "Predicting Early Data Revisions to US Output Growth and the Effects of Releases on Equity Markets," *Journal of Business and Economic Statistics*, Vol. 35, No. 591-604.

Coroneo, Laura, Domenico Giannone, and Michele Modugno (2016) "Unspanned Macroeconomic Factors in the Yield Curve," *Journal of Business & Economic Statistics*, Vol. 34, No. 3, pp. 472–485.

Croushore, D. (2006) "Forecasting with Real-Time Macroeconomic Data," in *Handbook of Economic Forecasting I*: Elsevier, pp. 961–982.

Cunningham, A., J. Eklund, C. Jeffery, G. Kapetanios, and V. Labhard (2012) "A state space approach to extracting the signal from uncertain data," *Journal of Business & Economic Statistics*, Vol. 30, pp. 173–80.

Egginton, Don M., Andreas Pick, and Shaun Vahey (2002) "'Keep it real!': a real-time UK macro data set," *Economics Letters*, Vol. 77, No. 1, pp. 15–20.

Evans, M. D. D. (2005) "Where are we now?" *International Journal of Central Banking*, Vol. 1, pp. 127–175.

Faust, J., J. H. Rogers, and J. H. Wright (2005) "News and Noise in G-7 GDP Announcements," *Journal of Money, Credit and Banking*, Vol. 37 (3), pp. 403–417.

Galvão, A. B. (2017) "DSGE Models and Data revisions," *Journal of Econometrics*, Vol. 196, pp. 215–232.

Galvão, A. B. and J. Mitchell (2018) "Measuring GDP Growth Data Uncertainty," *University of Warwick, mimeo.*

Garratt, A. and S. P. Vahey (2006) "UK real-time macro data characteristics," *Economic Journal*, Vol. 116, pp. F119–F135.

Giannone, D., L. Reichlin, and D. Small (2008) "Nowcasting GDP and Inflation: The Real-Time Informational Content of Macroeconomic Data Releases," *Journal of Monetary Economics*, Vol. 55, pp. 665–676.

Harvey, David, Stephen Leybourne, and Paul Newbold (1997) "Testing the equality of prediction mean squared errors," *International Journal of Forecasting*, Vol. 13, No. 2, pp. 281 – 291.

Jacobs, J. P. A. M and S. van Norden (2011) "Modeling Data Revisions: Measurement Error and Dynamics of 'True' Values," *Journal of Econometrics*, Vol. 161, pp. 101–109.

Kishor, N. K. and E. F. Koenig (2012) "VAR Estimation and Forecasting When Data are Subject to Revision," *Journal of Business and Economic Statistics*, Vol. 30, pp. 181–190.

Koenig, E. F., S. Dolmas, and J. Piger (2003) "The use and abuse of real-time data in economic forecasting," *The Review of Economics and Statistics*, Vol. 85(3), pp. 618–628.

Mankiw, N. G. and M. D. Shapiro (1986) "News or Noise: An Analysis of GNP Revisions," *Survey of Current Business (May 1986), US Department of Commerce, Bureau of Economic Analysis*, pp. 20–25.

Mariano, Roberto S. and Yasutomo Murasawa (2003) "A new coincident index of business cycles based on monthly and quarterly series," *Journal of Applied Econometrics*, Vol. 18, No. 4, pp. 427–443.

Miranda-Agrippino, Silvia (2012) "Nowcasting UK GDP,"Technical report, London Business School.

Mitchell, J. (2009) "Where are we now? The UK recession and nowcasting GDP growth using statistical models," *National Institute Economic Review*, Vol. 209, pp. 60–69.

Rossi, Barbara and Tatevik Sekhposyan (2019) "Alternative tests for correct specification of conditional predictive densities," *Journal of Econometrics*, Vol. 208, No. 2, pp. 638 – 657.

# A Estimation and State-Space Representation

## A.1 State Space Representation of the RA-DFM

The full RA-DFM of Section 2 with $n_K = 4$ is

$$\underset{(n\times 1)}{x_t} \equiv \begin{pmatrix} x_t^M \\ x_t^Q \\ y_t^{(1)} \\ \vdots \\ y_t^{(4)} \end{pmatrix} \simeq \begin{pmatrix} \mathbf{\Lambda}_M & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{\Lambda}_Q & 2\mathbf{\Lambda}_Q & 3\mathbf{\Lambda}_Q & 2\mathbf{\Lambda}_Q & \mathbf{\Lambda}_Q \\ \mathbf{\Lambda}^{(1)} & 2\mathbf{\Lambda}^{(1)} & 3\mathbf{\Lambda}^{(1)} & 2\mathbf{\Lambda}^{(1)} & \mathbf{\Lambda}^{(1)} \\ \vdots & & \vdots & & \vdots \\ \mathbf{\Lambda}^{(4)} & 2\mathbf{\Lambda}^{(4)} & 3\mathbf{\Lambda}^{(4)} & 2\mathbf{\Lambda}^{(4)} & \mathbf{\Lambda}^{(4)} \end{pmatrix} \begin{pmatrix} f_t \\ f_{t-1} \\ \vdots \\ f_{t-4} \end{pmatrix} + \begin{pmatrix} \zeta_t^M \\ \zeta_t^Q \\ \varepsilon_t^{(1)} \\ \vdots \\ \varepsilon_t^{(4)} \end{pmatrix}, \qquad (1)$$

$$f_t = \mathbf{A}_1 f_{t-1} + \ldots + \mathbf{A}_p f_{t-p} + \eta_t \qquad \eta_t \sim \mathcal{N}(0, \mathbf{\Sigma}), \qquad (6)$$

$$\zeta_t \equiv \begin{pmatrix} \zeta_t^M \\ \tilde{\zeta}_t^M \end{pmatrix} = \mathbf{D}\zeta_{t-1} + \epsilon_t^M \qquad \epsilon_{i,t} \sim \mathcal{N}(0, \varsigma_i^2), \qquad (7)$$

$$\tilde{\varepsilon}_t = \mathbf{\Phi}\tilde{\varepsilon}_{t-1} + \nu_t \qquad \nu_t \sim \mathcal{N}(0, \mathbf{\Gamma}). \qquad (8)$$

where $\mathbf{D}$ is diagonal, $\mathbf{\Psi}$ and $\mathbf{\Gamma}$ are full $4 \times 4$ matrices and we use $\tilde{\zeta}_t^M$ and $\tilde{\varepsilon}_t$ to denote the unobserved idiosyncratic components (see Section 2). We can rewrite the equations above in state-space representation

$$x_t = \mathbf{C}s_t + e_t \qquad e_t \sim \mathcal{N}(0, \mathbf{R}), \qquad (A.1)$$
$$s_t = \mathbf{A}s_{t-1} + u_t \qquad u_t \sim \mathcal{N}(0, \mathbf{Q}), \qquad (A.2)$$

where $x_t$ and $e_t$ are $n \times 1$, $\mathbf{C}$ is $n \times n_s$, $s_t$ and $u_t$ are $n_s \times 1$, $\mathbf{R}$ is $n \times n$ and $\mathbf{A}$ and $\mathbf{Q}$ are $n_s \times n_s$. Recall that $x_t^M$ and $x_t^Q$ are vectors of dimensions $n_M$ and $n_Q$ respectively. Let $q$ denote the number of lagged factors needed for the approximation in Eq. (4), i.e. $q = 4$, and $n_K$ denote the number of GDP releases the DFM is augmented with, also equal to 4 in our case. We define:

- $n = n_M + n_Q + n_K$: number of observables,
- $n_s = n_s^f + n_s^M + n_s^Q + n_s^K$: number of unobserved states,
- $n_s^f = r \max\{p, q+1\}$: number of states for factors,
- $n_s^M = n_M$: number of states for monthly idiosyncratic,
- $n_s^Q = n_Q(q+1)$: number of states for quarterly idiosyncratic.
- $n_s^K = 4(q+1)$: number of states for GDP releases idiosyncratic.

With $p < q$, $q = 4$, $K = 4$, and $n_Q = 1$ (i.e. there is one quarterly variable besides GDP):

$$\underset{(n_s\times 1)}{s_t} = \left(\begin{array}{c} \underset{\left(n_s^f\times 1\right)}{s_t^f} \\ \hdashline \underset{(n_s^M\times 1)}{s_t^M} \\ \hdashline \underset{(5\times 1)}{s_t^Q} \\ \hdashline \underset{(n_s^K\times 1)}{s_t^K} \end{array}\right) = \left(\begin{array}{c} \left(\begin{array}{ccc} f_t' & \dots & f_{t-4}' \end{array}\right)' \\ \hdashline \left(\begin{array}{ccc} \zeta_{1,t}^M & \dots & \zeta_{n_M,t}^M \end{array}\right)' \\ \hdashline \left(\begin{array}{ccc} \zeta_t^Q & \dots & \zeta_{t-4}^Q \end{array}\right)' \\ \hdashline \left(\begin{array}{ccc} \varepsilon_t & \dots & \varepsilon_{t-4} \end{array}\right)' \end{array}\right), \tag{A.3}$$

where $\varepsilon_t \equiv \left(\varepsilon_t^{(1)}, \dots, \varepsilon_t^{(4)}\right)'$ and the partitions identify (from top to bottom) the states referring to the factors $\left(s_t^f\right)$, and to the idiosyncratic for the monthly variables $(s_t^M)$, the quarterly variables $(s_t^Q)$, and the GDP releases $(s_t^K)$.

$$\underset{(n\times n_s)}{\mathbf{C}} = \left(\begin{array}{ccccc:c:c:ccc} \mathbf{\Lambda}_M & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbb{I}_{n_M} & \mathbf{0} & & \mathbf{0} & \\ \hdashline \mathbf{\Lambda}_Q & 2\mathbf{\Lambda}_Q & 3\mathbf{\Lambda}_Q & 2\mathbf{\Lambda}_Q & \mathbf{\Lambda}_Q & \mathbf{0} & \mathcal{R} & & \mathbf{0} & \\ \hdashline \mathbf{\Lambda}^{(1)} & 2\mathbf{\Lambda}^{(1)} & 3\mathbf{\Lambda}^{(1)} & 2\mathbf{\Lambda}^{(1)} & \mathbf{\Lambda}^{(1)} & & & \mathcal{R} & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{\Lambda}^{(4)} & 2\mathbf{\Lambda}^{(4)} & 3\mathbf{\Lambda}^{(4)} & 2\mathbf{\Lambda}^{(4)} & \mathbf{\Lambda}^{(4)} & & & \mathbf{0} & \mathbf{0} & \mathcal{R} \end{array}\right) \tag{A.4}$$

where $\mathbf{0}$ denotes matrices of zeros of conformable dimensions, $\mathbb{I}_m$ is the identity matrix of dimension $m$, and $\mathcal{R} = \left[\begin{array}{ccccc} 1 & 2 & 3 & 2 & 1 \end{array}\right]$.

$$\underset{(n\times n)}{\mathbf{R}} = \varrho \mathbb{I}_n, \tag{A.5}$$

where $\varrho$ is a very small number.

$$\underset{(n_s\times n_s)}{\mathbf{A}} = \left(\begin{array}{c:c:c:c} \begin{array}{ccc} A_1 \ \dots & A_p & \mathbf{0} \\ \mathbb{I}_{r(q-1)} & \mathbf{0} & \mathbf{0} \end{array} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \hdashline \mathbf{0} & \mathbf{D} & \mathbf{0} & \mathbf{0} \\ \hdashline \mathbf{0} & \mathbf{0} & \mathbf{\Psi} & \mathbf{0} \\ \hdashline \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{\Phi} \otimes \mathbb{I}_q \end{array}\right). \tag{A.6}$$

Finally,

$$\underset{(n_s\times n_s)}{\mathbf{Q}} = \left(\begin{array}{cc:c:c:c} \mathbf{\Sigma} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & & & \\ \hdashline \multicolumn{2}{c:}{\mathbf{0}} & \mathbf{Q}^M & \mathbf{0} & \mathbf{0} \\ \hdashline \multicolumn{2}{c:}{\mathbf{0}} & \mathbf{0} & \mathbf{Q}^Q & \mathbf{0} \\ \hdashline \multicolumn{2}{c:}{\mathbf{0}} & \mathbf{0} & \mathbf{0} & \mathbf{Q}^K \end{array}\right), \tag{A.7}$$

where $\mathbf{Q}^M$ is a diagonal matrix with the variances of the idiosyncratic monthly variables $\varsigma^2_{M,i}$, $\mathbf{Q}^Q$ is a block diagonal matrix with a block for each quarterly variable, and each block is all zeros except for the element (1,1) which equals the variance of the idiosyncratic quarterly variables $\varsigma^2_{Q,i}$. Finally, $\mathbf{Q}^K$ is a sparse matrix with the elements of $\mathbf{\Gamma}$ appropriately placed in correspondence of the contemporaneous covariances of the idiosyncratic terms for the GDP releases.

The structure in Eqs. (A.4 - A.7) is easily extended to accommodate the presence of block structures in the specification of $f_t$, by appropriately modifying the relevant matrix partitions.

## A.2 Estimation

Maximum Likelihood estimation of the RA-DFM can be carried using the EM Algorithm, where the Kalman Filter is used to calculate the expected conditional likelihood, and the Kalman Smoother updates the estimates of the states vector and relevant autocovariance matrices at each iteration. The presence of missing values in $x_t$ is handled by appropriately modifying the two algorithms such that the weight assigned to the missing observations vanishes at each $t \in [1, T]$ (see Bańbura and Modugno, 2014).

Let $\mathbf{C}_{[\iota]}$, $\mathbf{R}_{[\iota]}$, $\mathbf{A}_{[\iota]}$, $\mathbf{Q}_{[\iota]}$ denote the system matrices estimated at iteration $\iota$ of the EM. Moreover:

- $\Theta_{[\iota]}$: collects all parameters at iteration $\iota$,
- $\Omega_v$: information set at data vintage $v$,
- $\mathbb{E}_{\Omega,\iota} \equiv \mathbb{E}[\,\cdot\,|\Omega_t, \Theta_{[\iota]}]$: expectation conditional on all data and parameters at $\iota$,
- $s_{t|T,\iota} \equiv \mathbb{E}_{\Omega,\iota}[s_t]$: smoothed states,
- $P_{t|T,\iota}$: smoothed states variance,
- $P_{t,t-1|T,\iota}$: smoothed states first order autocovariance.

Further, partition $\mathbf{C}_{[\iota]}$, $\mathbf{A}_{[\iota]}$, $\mathbf{Q}_{[\iota]}$ such that

$$\mathbf{C}_{[\iota]} = \left[\begin{array}{c|cc} \mathbf{C}^M_{[\iota]} & \mathbb{I} & \mathbf{0} \\ & & \\ \mathbf{C}^Q_{[\iota]} & \mathbf{0} & \mathbb{I}_{k+1} \otimes \mathcal{R} \end{array}\right], \tag{A.8}$$

$$\mathbf{A}_{[\iota]} = \begin{bmatrix} \mathbf{A}^f_{[\iota]} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{A}^M_{[\iota]} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{A}^Q_{[\iota]} \end{bmatrix}, \tag{A.9}$$

$$\mathbf{Q}_{[\iota]} = \begin{bmatrix} \mathbf{Q}^f_{[\iota]} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{Q}^M_{[\iota]} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{Q}^Q_{[\iota]} \end{bmatrix}. \tag{A.10}$$

The matrices $\mathbf{C}^M_{[\iota]}$ and $\mathbf{C}^Q_{[\iota]}$ in Eq. (A.8) contain, respectively, zero restrictions that enforce the monthly variables only loading on the contemporaneous values of the factors, and the restrictions on the coefficients imposed by Eq. (4). In Eqs. (A.9 - A.10), $\mathbf{A}^M_{[\iota]} = \mathbf{D}_{[\iota]}$, $\mathbf{Q}^M_{[\iota]}$ collects the variances of the idiosyncratic terms for the monthly variables along the main diagonal, and with GDP the only quarterly variable $\mathbf{A}^Q_{[\iota]} = \mathbf{\Phi}_{[\iota]} \otimes \mathbb{I}_q$ and $\mathbf{Q}^Q_{[\iota]} = \mathbf{\Gamma}_{[\iota]} \otimes \mathbb{I}_q$. With the states being non observable, for each partition of $s_{t|T,\iota}$ the set of relevant sufficient statistics is given by:

$$\begin{aligned} \mathbb{E}_{\Omega,\iota}[s^j_t s^{j\prime}_t] &= s^j_{t|T,\iota} s^{j\prime}_{t|T,\iota} + P^j_{t|T,\iota}, & \quad (A.11)\\ \mathbb{E}_{\Omega,\iota}[s^j_{t-1} s^{j\prime}_{t-1}] &= s^j_{t-1|T,\iota} s^{j\prime}_{t-1|T,\iota} + P^j_{t-1|T,\iota}, & \quad (A.12)\\ \mathbb{E}_{\Omega,\iota}[s^j_t s^{j\prime}_{t-1}] &= s^j_{t|T,\iota} s^{j\prime}_{t-1|T,\iota} + P^j_{t,t-1|T,\iota} \qquad j \in \{f, M, Q\}. & \quad (A.13) \end{aligned}$$

Lastly, if at any $t \in [1, T]$ $x_t$ contains missing observations, define $W_t$ to be an $n \times n$ diagonal matrix of logical identifiers which singles out the available information discarding the unknowns.

The components in Eqs. (A.8 - A.10) at iteration $\iota + 1$ are the maximizers of the expected log likelihood conditional on $\Omega_t$ and $\Theta_{[\iota]}$. For the measurement equation:

$$\text{vec}\left(\mathbf{C}^M_{[\iota+1]}\right) = \left[\sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s^f_t s^{f\prime}_t] \otimes W_t\right]^{-1} \left[\text{vec}\left(\sum_{t=1}^{T} W_t \left(x_t s^{f\prime}_{t|T,\iota} - \mathbb{E}_{\Omega,\iota}[s^f_t s^{f\prime}_t]\right)\right)\right], \tag{A.14}$$

$$\text{vec}\left(\mathbf{C}^Q_{[\iota+1]}\right) = \left[\sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s^f_t s^{f\prime}_t] \otimes W_t\right]^{-1} \left[\text{vec}\left(\sum_{t=1}^{T} W_t \left(x_t s^{f\prime}_{t|T,\iota} - \mathbb{E}_{\Omega,\iota}[s^f_t s^{f\prime}_t]\right)\right)\right]. \tag{A.15}$$

When restrictions on the quarterly loadings are active, then those are enforced using the standard constrained least squares formula on the relevant partition of the parameters $\left(\mathbf{\Lambda} \in \mathbf{C}^Q_{[\iota+1]}\right)$. In our case, restrictions are in place to bridge the monthly and quarterly observations. Write the restrictions implied by Eq. (4) as $\mathbf{B}\mathbf{\Lambda} = \mathbf{b}$, where $\mathbf{\Lambda}$ is the partition of $\mathbf{C}^{Q}_{[\iota+1]}$ which is subject to the restriction, and $\mathbf{b}$ is a vector of zeros. The restricted loadings are given by:

$$\mathbf{\Lambda}_c = \mathbf{\Lambda} - \left[ \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_t^f s_t^{f\prime}] \right]^{-1} \mathbf{B}' \left[ \mathbf{B} \left( \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_t^f s_t^{f\prime}] \right)^{-1} \mathbf{B}' \right]^{-1} (\mathbf{B}\mathbf{\Lambda} - \mathbf{b}), \tag{A.16}$$

and Eq. (A.15) is adapted conformably.

For the parameters of the state equation:

$$\mathbf{A}^{f}_{[\iota+1]} = \left[ \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_t^f s_{t-1}^{f\prime}] \right] \left[ \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_{t-1}^f s_{t-1}^{f\prime}] \right]^{-1}, \tag{A.17}$$

$$\mathbf{A}^{\forall j \in \{M\}}_{[\iota+1]} = \left[ \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_t^j s_{t-1}^{j\prime}] \right] \left[ \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_{t-1}^i s_{t-1}^{j\prime}] \right]^{-1}, \tag{A.18}$$

$$\mathbf{A}^{Q}_{[\iota+1]} = \left[ \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_t^K s_{t-1}^{K\prime}] \right] \left[ \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_{t-1}^K s_{t-1}^{K\prime}] \right]^{-1}, \tag{A.19}$$

and

$$\mathbf{Q}^{f}_{[\iota+1]} = \frac{1}{T} \left[ \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_t^f s_t^{f\prime}] - \mathbf{A}^{f}_{[\iota+1]} \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_t^f s_{t-1}^{f\prime}] \right], \tag{A.20}$$

$$\mathbf{Q}^{\forall j \in \{M\}}_{[\iota+1]} = \frac{1}{T} \left[ \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_t^j s_t^{j\prime}] - \mathbf{A}^{j}_{[\iota+1]} \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_t^j s_{t-1}^{j\prime}] \right], \tag{A.21}$$

$$\mathbf{Q}^{Q}_{[\iota+1]} = \frac{1}{T} \left[ \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_t^K s_t^{K\prime}] - \mathbf{A}^{Q}_{[\iota+1]} \sum_{t=1}^{T} \mathbb{E}_{\Omega,\iota}[s_t^K s_{t-1}^{K\prime}] \right]. \tag{A.22}$$

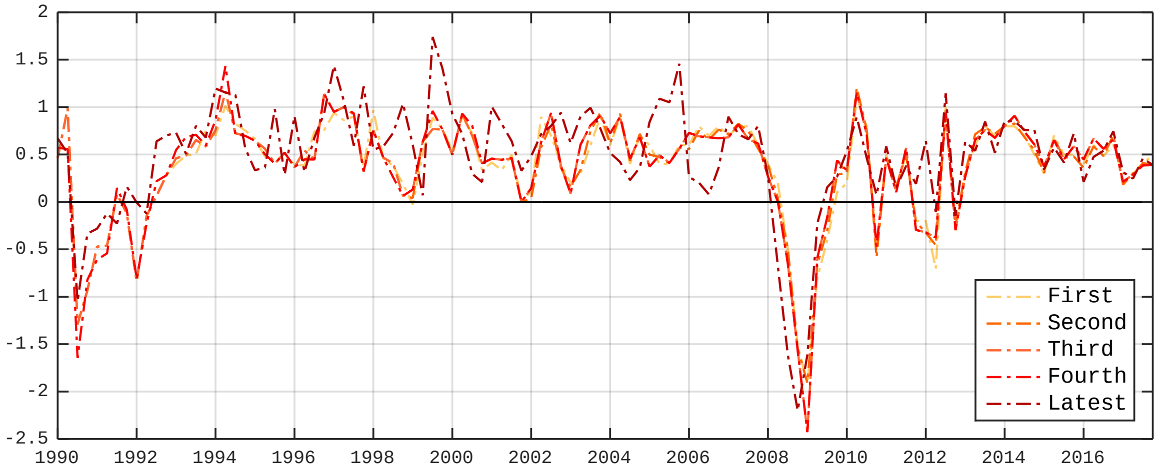
# B Real-Time Mixed-Frequency Dataset for the UK

We assembled a mixed-frequency dataset counting 8 quarterly and 25 monthly indicators.[18] These variables are listed in Table B.1, and are grouped into six types: economic activity, labour market statistics, business and output surveys, credit and financial data. Price data, available in the dataset, are not included in the model following results in Giannone et al. (2008). The data span the years from 1990 to 2017 with full real-time vintages since September 2006.

Quarterly variables include the first four GDP releases and some of the output and

[18] The number of monthly indicators that we consider is comparable to that in Bańbura et al. (2013), but smaller than that in other applications such as Artis et al. (2005).

Figure B.1: UK GDP Releases for the Same Quarter




expenditure components of GDP: Construction, Business Investment, Housing Investment and Private Consumption. The selection of monthly indicators is based on their relevance for policy makers, statistical agencies, and market participants. In order to construct real-time vintages for the variables that are subject to revision (column 7 of Table B.1) we used the archives of the Bank of England, where vintages of data released by the ONS data have been stored over the years. These data are available in their original release unit, and we were able to reconstruct real-time vintages for these variables from 2006-Q4 (Table B.2).

Other monthly indicators such as surveys, prices and labour market statistics can get lightly revised. These revisions are almost exclusively due to re-basing and/or changes in measurements or seasonal adjustment rather than to the addition of extra information. For these variables, we construct real-time vintages by starting from the latest available vintage available at the time of the assembly of the dataset (July 2017), and work backward using the actual release calendar of each of these data. The same procedure is used for credit and financial market variables that are also not revised. Asset prices enter the dataset in monthly averages and we assume they are released at close of markets on the last business day of each month.

**UK GDP: Releases and Revisions** The first four monthly releases of real UK GDP growth for all quarters since 1990 are charted in Figure B.1, together with the latest available vintage at the time of writing (May 2018). Table B.3 reports summary statistics for the first four GDP estimates for each quarter and the implied revisions relative to the first estimate. The table reports the sample mean, standard deviation and the first order serial correlation AC(1) for all quarters between 1990-Q1 and 2016-Q4. For the revisions, we also report the Lyung-Box Q(4) test for 4th order serial correlation, and a measure of the signal-to-noise ratio (SNR) computed as $SNR = 1 - \left[\mathbb{V}ar\left(y_t^{(k+1)} - y_t^{(1)}\right)/\mathbb{V}ar\left(y_t^{(k+1)}\right)\right]$. A SNR near 1 implies that the noisiness of the revision is small.

Table B.1: Real-Time Dataset for the UK Economy

| | Code | Variable Name | Source | Type | Freq | Revised | Transf |
|---|---|---|---|---|---|---|---|
| 1 | GDP1 | Gross Domestic Product, 1st rel | ONS | Activity | Q | ✓ | LD |
| 2 | GDP2 | Gross Domestic Product, 2nd rel | ONS | Activity | Q | ✓ | LD |
| 3 | GDP3 | Gross Domestic Product, 3rd rel | ONS | Activity | Q | ✓ | LD |
| 4 | GDP4 | Gross Domestic Product, 4th rel | ONS | Activity | Q | ✓ | LD |
| 5 | QCONSTR | Quarterly Construction Output | ONS | Activity | Q | ✓ | LD |
| 6 | CONS | Private Consumption | ONS | Activity | Q | ✓ | LD |
| 7 | INV | Total Business Investment | ONS | Activity | Q | ✓ | LD |
| 8 | HINV | Housing Investment | ONS | Activity | Q | ✓ | LD |
| 9 | IOP | Industrial Production | ONS | Activity | M | ✓ | LD |
| 10 | MPROD | Manufacturing Production | ONS | Activity | M | ✓ | LD |
| 11 | IOS | Index of Services | ONS | Activity | M | ✓ | LD |
| 12 | BOPEXP | BOP Total Exports (Goods) | ONS | Trade | M | ✓ | LD |
| 13 | BOPIMP | BOP Total Imports (Goods) | ONS | Trade | M | ✓ | LD |
| 14 | RSI | Retail Sales Index | ONS | Trade | M | ✓ | LD |
| 15 | CCOUNTR | Claimant Count Rate | ONS | Labour | M | | D |
| 16 | LFSE | LFS Number of Employees | ONS | Labour | M | | LD |
| 17 | LFSU | LFS Unemployment Rate | ONS | Labour | M | | D |
| 18 | MTGAPP | Mortgages Approved | BOE | Credit | M | | LD |
| 19 | CREDIT | Net Consumer Credit | BOE | Credit | M | | LD |
| 20 | CPI | CPI All Items | ONS | Prices | M | | LD |
| 21 | RPI | RPI All Items | ONS | Prices | M | | LD |
| 22 | PPII | PPI Input | ONS | Prices | M | | LD |
| 23 | PPIO | PPI Output | ONS | Prices | M | | LD |
| 24 | AWE | Average Weekly Earnings | ONS | Prices | M | | LD |
| 25 | UKBASKET | UK Focused Equity Index | BOE | Fin'l | M | | LD |
| 26 | SERI | Sterling Effective Exchange Rate | LSE | Fin'l | M | | LD |
| 27 | TERMSP | Term Spread | BOE | Fin'l | M | | D |
| 28 | CORPSP | Corporate Bond Spread | ML | Fin'l | M | | D |
| 29 | PMIM | PMI Manufacturing | IHS Markit | Survey | M | | L |
| 30 | CIPSEM | CIPS-E-Manufacturing | IHS Markit | Survey | M | | L |
| 31 | PMIC | PMI Construction | IHS Markit | Survey | M | | L |
| 32 | CIPSEC | CIPS-E-Construction | IHS Markit | Survey | M | | L |
| 33 | PMIS | PMI Services | IHS Markit | Survey | M | | L |
| 34 | CIPSES | CIPS-E-Services | IHS Markit | Survey | M | | L |
| 35 | CBIORDER | CBI Industrial Trends | CBI | Survey | M | | L |
| 36 | CBISALE | CBI Distributive Trade | CBI | Survey | M | | L |
| 37 | LLOYBB | Lloyds Business Barometer | Lloyds | Survey | M | | L |
| 38 | ASCORE | Agents' Scores | BOE | Survey | M | | L |

*Note:* Sources are the Office for National Statistics (ONS), the Bank of England (BOE), Bank of America Merril Lynch (ML), IHS Markit/CIPS, the Confederation of British Industries (CBI), LLoyds Bank. Revisions in survey data occur primarily due to rebasing and are hence treated as unrevised. Transformation codes: LD = log difference, L = levels, D = first difference.

Table B.2: Real-Time Vintages

| Variable Name | ONS Code pre 2011 | ONS Code post 2011 | Earliest Vintage | Earliest Data Point | Units |
|---|---|---|---|---|---|
| GDP | ABMI.Q | ABMI.Q | 04-1990 | 1990Q1 | £ million, CVM, SA |
| CONS | ABJR.Q+ HAYO.Q | ABJR.Q+ HAYO.Q | 11-2006 | 1990Q1 | £ million, CVM, SA |
| INV | NPEL.Q | NPEL.Q | 11-2006 | 1990Q1 | £ million, CVM, SA |
| HINV | DFEG.Q+ L635.Q+ L637.Q | DFEG.Q+ L635.Q+ L637.Q | 11-2006 | 1990Q1 | £ million, CVM, SA |
| QCONSTR | L2N8.Q | L2N8.Q | 10-2006 | 1993Q1 | |
| IOP | CKYW.M | K222.M | 09-2006 | 01-1990 | Index, SA |
| MPROD | CKYY.M | K22A.M | 09-2006 | 01-1990 | Index, SA |
| IOS | FVQQ.M | S2KU.M | 09-2006 | 01-1995 | Index, SA |
| BOPEXP | BOKG.M | BOKG.M | 09-2006 | 01-1990 | £ million, SA |
| BOPIMP | BOKH.M | BOKH.M | 09-2006 | 01-1990 | £ million, SA |
| RSI | EAPS.M | J5EK.M | 09-2006 | 01-1990 | Index, SA |

*Note:* The table summarised the availability of real-time data. The Variable Name is the same used in Table B.1. The second and third column report the official ONS identifiers. The Earliest Vintage refers to the timing of first available real-time vintage. The Earliest Data Point indicates the starting point of the time series and the Units correspond to the exact format in which the series is stored in the Bank of England internal database. CVM stands for Chained Volume Measures.

Table B.3: Summary Statistics for GDP Releases and Revisions processes

| RELEASES | First | Second | Third | Fourth |
|---|---|---|---|---|
| Mean | 0.370 | 0.375 | 0.378 | 0.379 |
| Stdev | 0.534 | 0.533 | 0.555 | 0.571 |
| AC(1) | 0.606 | 0.610 | 0.616 | 0.628 |
| REVISIONS | | First | Second | Third |
| Mean | | 0.005 | 0.003 | 0.002 |
| Stdev | | 0.092 | 0.077 | 0.074 |
| AC(1) | | -0.206 | 0.027 | 0.165 |
| Q(4) | | 7.414 | 1.136 | 12.13 |
| p-values | | [0.116] | [0.889] | [0.02] |
| SNR | | 0.970 | 0.980 | 0.983 |

*Note:* Revisions are defined with respect to the previous release. Summary statistics are computed for over the period 1990-2016 (i.e. for the lines in Figure B.1). AC(1) is the first order autocorrelation coefficients. Q(4) denotes the Lyung-Box Q(4) test for a serial correlation of order 4 with p-values reported in square brackets. $SNR = 1 - \left[\mathbb{V}ar\left(y_t^{(k+1)} - y_t^{(k)}\right) / \mathbb{V}ar\left(y_t^{(k+1)}\right)\right]$.

# C Robustness

Table C.1 compares the point forecast accuracy of the RA-DFM across different specifications at selected forecast horizons in the tracking window. Numbers in the table are average RMSFEs over the out-of-sample period (Q4 2006-Q4 2016). The models in each column of the table are:

(a) RA-DFM baseline specification: 25 monthly variables, 4 quarterly variables, 4 GDP releases, 3 factors (global, ONS variables, surveys), VAR(1) for the factors, VAR(1) for the GDP idiosyncratic, full real time vintages for all quarterly and monthly variables with the exception of GDP (only first 4 releases).

(b) GDP idiosyncratic terms share a common factor instead of a VAR(1). All other features are equal to the baseline.

(c) Standard DFM in real-time (DFM RT). Uses full real-time vintages of GDP as opposed to the most recent four releases of the RA-DFM. All other features are equal to the baseline.

(d) Uses only the first release of all the monthly and quarterly variables, and the most recent four GDP releases. All other features are equal to the baseline.

(e) Replaces $y_t^{(k)}$, $k = 1, \ldots, 4$ with $y_t^{(1)}$, $y_t^{(6)}$ and $y_t^{(12)}$ (more mature GDP estimates). All other features are equal to the baseline.

(f) VAR(4) for the factors rather than VAR(1). All other features are equal to the baseline.

(g) Baseline RA-DFM specifications, but parameters are estimated using a 10-year rolling window at every forecast origin rather than an expanding window from 1992.

The results in the Table C.1 suggest that alternative RA-DFM specifications usually do not improve over the benchmark, and when improvements are found, they are small. The DFM RT has worse forecasting performance than all RA-DFM alternatives.

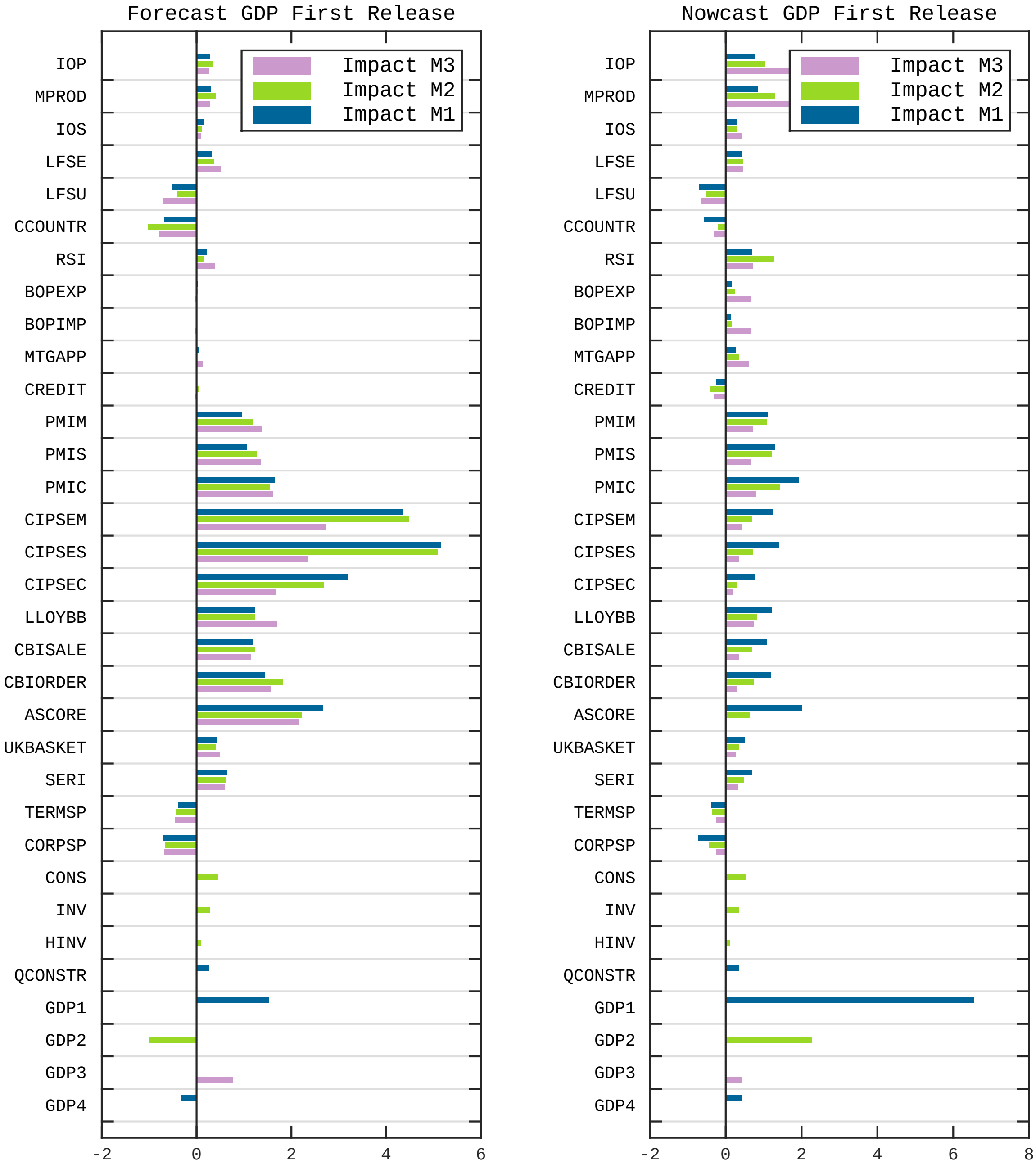
## Table C.1: Average RMSFE Across Specifications

| Position in tracking window (days☆) | Models (a) | (b) | (c) | (d) | (e) | (f) | (g) |
|---|---|---|---|---|---|---|---|
| forecast starts (-206) | 0.497 | 0.525 | 0.744 | 0.502 | 0.498 | 0.488 | 0.544 |
| nowcast starts (-116) | 0.458 | 0.454 | 0.594 | 0.455 | 0.461 | 0.451 | 0.486 |
| backcast starts (-26) | 0.402 | 0.425 | 0.476 | 0.385 | 0.416 | 0.403 | 0.410 |
| $y_t^{(1)}$ released (0) | 0.093 | 0.121 | 0.139 | 0.096 | 0.086 | 0.089 | 0.101 |
| $y_t^{(2)}$ released (30) | 0.121 | 0.107 | – | 0.125 | – | 0.119 | 0.139 |
| $y_t^{(3)}$ released (63) | 0.026 | 0.050 | – | 0.123 | – | 0.023 | 0.024 |
| $y_t^{(4)}$ released (91) | 0.032 | 0.065 | – | 0.030 | – | 0.031 | 0.021 |
| gdp targets | 4 | 4 | 1 | 4 | 4 † | 4 | 4 |
| factors VAR lags | 1 | 1 | 1 | 1 | 1 | 4 | 1 |
| VAR idiosyncratic | ✓ | | | ✓ | ✓ | ✓ | ✓ |
| gdp factor | | ✓ | | | | | |
| real-time | ✓ | ✓ | ✓ * | | ✓ | ✓ | |
| diagonals | | | | ✓ | | | |
| rolling | | | | | | | ✓ |

*Note:* Entries are average RMSFEs computed over the OOS span 2006-2016. ☆ negative numbers denote days before the First Release is available. † includes more mature GDP releases. * denotes a specification which also includes real-time data for the GDP data (DFM RT).

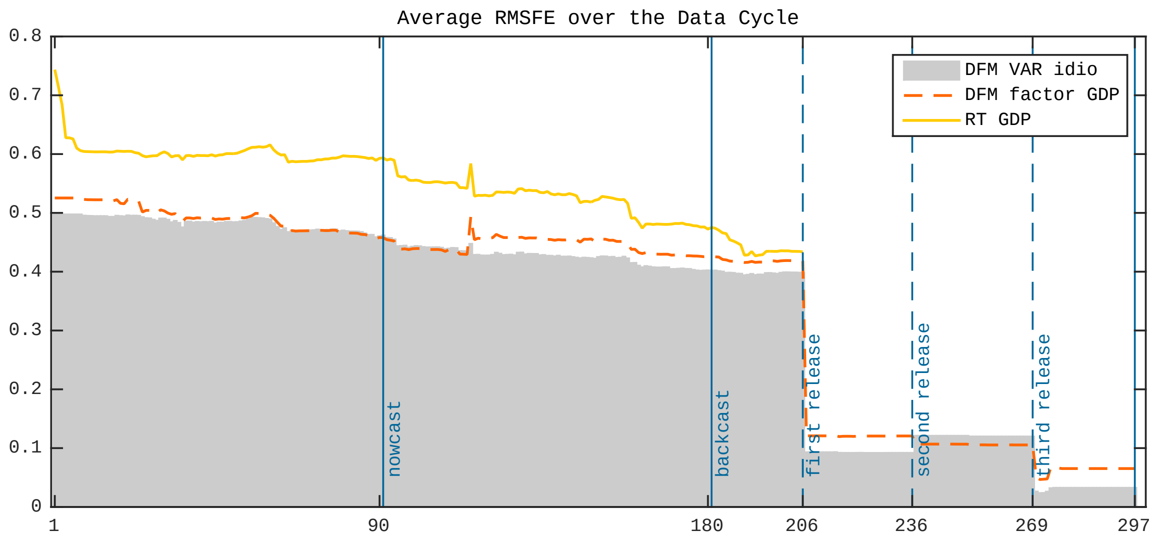
# D Additional Charts

Figure D.1: Impact of Data News – Forecast and Nowcast Tracking Periods




*Note*: Impact of data releases for the forecast (left panel) and the nowcast (right panel) of the first GDP release. These impacts are computed by multiplying average weights by the average standard deviation of the specific data release, see eq. (17).

Figure D.2: RA-DFM: VAR for the Idiosyncratic vs GDP-Specific Factor




*Note*: RMSFE over the evaluation sample (2006-2016). Benchmark RA-DFM (area), RA-DFM with GDP-specific factor (dashed line), standard DFM with RT data (solid line).