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Abstract

In this paper, we propose a component-based dynamic factor model for nowcasting GDP growth. We combine ideas from "bottom-up" approaches, which utilize the national income accounting identity through modelling and predicting sub-components of GDP, with a dynamic factor (DF) model, which is suitable for dimension reduction as well as parsimonious real-time monitoring of the economy. The advantages of the new model are twofold: (i) in contrast to existing dynamic factor models, it respects the GDP accounting identity; (ii) in contrast to existing "bottom-up" approaches, it models all GDP components jointly through the dynamic factor model, inheriting its main advantages. An additional advantage of the resulting CBDF approach is that it generates nowcast densities and impact decompositions for each component of GDP as a by-product. We present a comprehensive forecasting exercise, where we evaluate the model's performance in terms of point and density forecasts, and we compare it to existing models (e.g. the model of Almuzara, Baker, O'Keeffe, and Sbordone (2023)) currently used by the New York Fed, as well as the model of Higgins (2014) currently used by the Atlanta Fed. We demonstrate that, on average, the point nowcast performance (in terms of RMSE) of the standard DF model can be improved by 15 percent and its density nowcast performance (in terms of log-predictive scores) can be improved by 20 percent over a large historical sample.

JEL classification: C32, C38, C53
Key words: dynamic factor models, GDP nowcasting

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1 Introduction

Gross Domestic Product (GDP), the most important summary measure of economic activity, arrives with a considerable delay, creating an information gap in market participants' understanding of the current state of the economy. Having a reliable current-quarter estimate, also known as a 'nowcast', of GDP growth is therefore a crucial guide for households, firms and policymakers alike. One of the main challenges in constructing such an estimate is determining which series to monitor and how to effectively utilise these data, given that they are released at uneven intervals at different points throughout the quarter and are subject to constant revisions.

The focus of this paper is on automated judgment-free nowcast models; we abstract from judgmental forecasts, which lack a formal and systematic framework for continuously extracting signal from large amounts of complex information. There are two broad approaches in the literature on nowcast modelling. The first utilises dynamic factor (DF) models (e.g. Giannone, Reichlin, and Small (2008), Banbura, Giannone, and Reichlin (2010), as well as the model of Almuzara et al. (2023) currently used by the New York Fed) which are well-suited to adapt in real-time to handle a large-dimensional set of variables, mixed frequency, missing observations and uneven arrival of information in a parsimonious and model-consistent way that delivers uncertainty in the form of GDP nowcast probability density. DF models are well established in policy institutions around the world. See Cascaldi-Garcia, Luciani, and Modugno (2024b) for a recent review on DF models in nowcasting[1]. There is also a literature on other mixed-frequency models suitable for nowcasting, such as vector autoregressions (e.g., Schorfheide and Song (2015) and Carriero, Clark, and Marcellino (2015)). One disadvantage of existing DF and VAR nowcast models is that, since they do not impose the national income accounting identity, they are missing important restrictions linking key components to GDP, and, consequently, can produce counter-intuitive results. Moreover, while data on some aggregate GDP components arrive with GDP at quarterly frequency, data on others, such as consumption and trade, are released much earlier and at monthly frequency. Standard DF models use information in such early component releases revising their GDP estimate through the model's factors and loadings; however, DF model structure lacks key accounting restrictions on such monthly components, which, if utilised effectively, can improve the accuracy of the GDP estimate.

The second approach in the literature, sometimes referred to as a 'bottom-up' approach, attempts to mimic as closely as possible the accounting formula that the Bureau of Economic Analysis (BEA) uses when constructing the GDP estimate (e.g. the model of Higgins (2014) currently used by the Atlanta Fed or Baffigi, Golinelli, and Parigi (2004)). This involves utilising early, realised data on some GDP components and nowcasting all other components (typically through a set of auxiliary methods such as simple time-series models, bridging equations, or MIDAS models) and then combining all pieces into a GDP estimate via the national accounting identity. The disadvantage of this approach is that it lacks

[1]For nowcast performance of DF models in the context of different countries, see Cascaldi-Garcia, Ferreira, Giannone, and Modugno (2024a) for the Eurozone, Anesti, Galvão, and Miranda-Agrippino (2022) for the UK, Bragoli and Modugno (2017) for Canada and Hayashi and Tachi (2023) for Japan.

the capacity to *jointly* process the data in a statistically rigorous way based on formal likelihood and filtering through a single model. Moreover, since GDP components are often modelled using separate methodologies, it cannot produce a model-consistent probability density around the nowcast estimate.

In this paper, we develop a new component-based dynamic factor (CBDF) nowcast model that combines ideas from both existing approaches in the literature by utilising a dynamic factor model to effectively process in real-time the flow of information from a wide range of macroeconomic and financial indicators, while at the same imposing the national accounting identity on six aggregate GDP components in order to closely mimic the formula used by the BEA to construct GDP. The resulting DF model produces nowcast densities for each sub-component, which are then combined through the accounting identity to obtain nowcast density for GDP growth. We make use of market-moving indicators on manufacturing, labour market, financial conditions, and soft data such as consumer sentiment and business outlook surveys, as well as series on the GDP components (consumption, investment, inventories, net exports, and government spending). The new model processes these data by combining Bayesian dynamic factor modelling, Kalman filtering techniques, and 'bottom-up' methods, delivering a number of advantages over existing approaches.

First, it imposes the national accounting identity, used by the BEA, weighting the model-implied nowcasts of individual GDP components by their respective nominal shares, in contrast to existing dynamic factor models. Second, it models all GDP components jointly, in contrast to existing 'bottom-up' approaches, through a single dynamic factor model, inheriting its desirable properties: (i) effective real-time handling of mixed frequency, missing observations and unbalanced arrival of new data; (ii) dimensionality reduction through the use of the factors designed to capture component-specific as well as common co-movements. Third, it provides a transparent reading of the incoming data releases through the impact decomposition of the nowcast revisions to both GDP and its components. Finally, it generates probability density for the nowcast of each component, combined to deliver a nowcast of GDP growth, along with a full probability density quantifying the uncertainty around it. This is achieved through time-varying volatility[2] as well as variance outliers in the factors and idiosyncratic terms of the DF model, providing a more accurate account of the data and parameter uncertainty around each component and the GDP estimate.

We experiment with ways to improve the nowcast performance of the CBDF approach through various specifications. We study the historical performance of the resulting model through a comprehensive real-time forecasting exercise, where we evaluate the model's performance in terms of point and density nowcasts and we compare it to existing models (e.g. the model by Almuzara et al. (2023) currently used by the New York Fed, and the model by Higgins (2014), currently used by the Atlanta Fed, as well as judgement-based professional forecasts such as SPF and Blue Chip). We demonstrate that the new CBDF model performs well and can improve on average the point nowcast performance (in terms of RMSE) of the current NY Fed Staff Nowcast model by 15% and its density nowcast performance (in terms of log-predictive scores) by 20% over a large historical sample.

[2]See, for example, Del Negro and Otrok (2008) or Mumtaz and Surico (2012) for DF models with stochastic volatility.

The remainder of the paper is organised as follows. In Section 2.1, we provide a motivation for the development of the new model demonstrating how it can resolve some issues with existing DF nowcast models. In Section 2.2 we illustrate the differences between the new CBDF and the standard DF approaches through the lens of the most recent quarter (2025:Q1). The technical details on the new model can be found in Section 3; the forecast evaluation exercise is presented in Section 4. Section 5 concludes and the Appendix (A) contains details on the Gibbs Sampling algorithm and prior distributions, as well as some additional empirical results.

2 Motivation

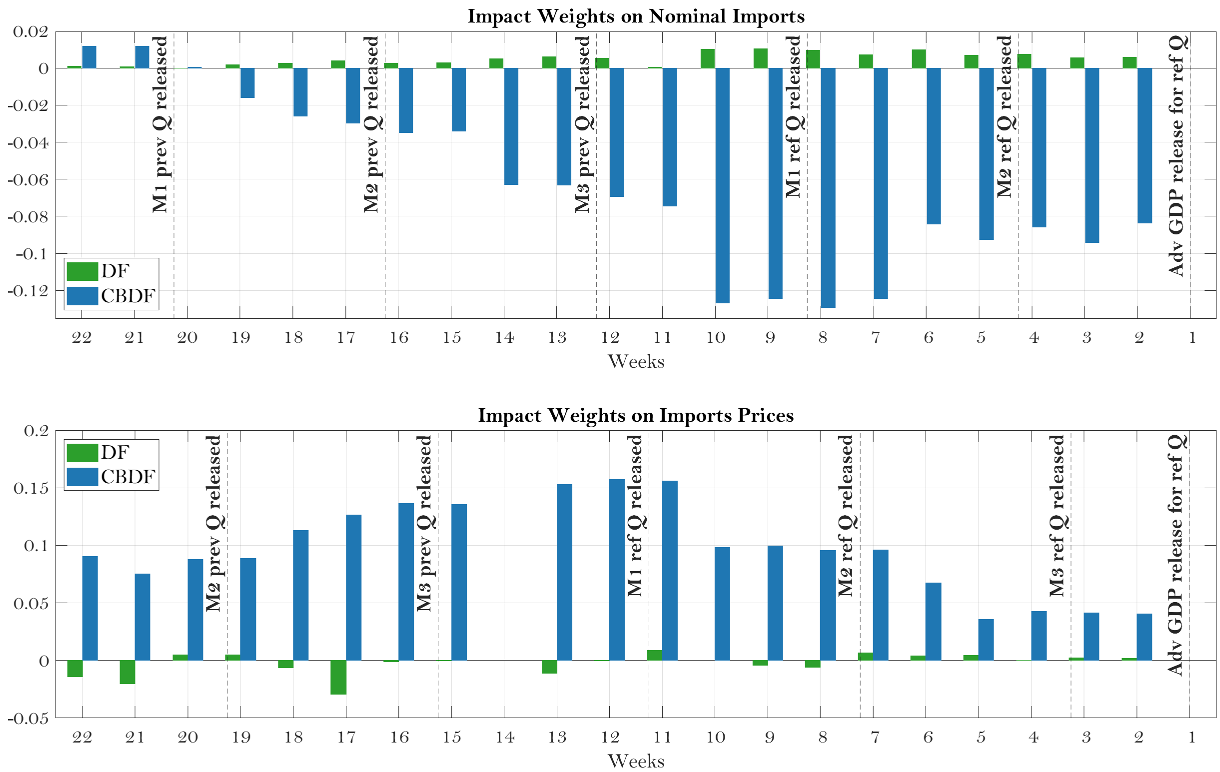
2.1 What moves the GDP Nowcast

Standard DF nowcast models, which do not impose the accounting identity, can sometimes generate contradictory outputs. We illustrate this point below through the model-implied impact analysis, which decomposes each weekly GDP nowcast revision into impacts stemming from surprises in data releases (relative to the model's prediction), as well as data and parameter revisions. For technical details on how these impacts are computed, refer to Section 3.5; here we provide intuition and some empirical illustrations. In the context of the new CBDF model, the forecast revision of GDP from one week to another is a weighted average of the forecast revisions of each component, which in turn are weighted averages of 'news' during the week, with news' being defined as the difference between released data that week and the model's prediction.

The resulting CBDF models's impact weights assigned to news (surprises) in monthly component series are the result of three modelling choices: (i) the nominal shares each component receives in the accounting equation, (ii) the disproportionate weights each month receives in the computation of the QoQ growth rate for each component (and hence GDP), and (iii) the joint dynamic structure stemming from the underlying factor model. Standard DF models' impact weights only feature in the model structure through the factors, loadings and idiosyncratic terms, missing the first two effects due to the absence of an imposed national accounting structure. The first issue leads to muted impact weights on surprises in component series that matter greatly for the computation of GDP growth, relative to what the nominal shares in the national accounting identity would imply. In fact, in some cases, e.g. import growth, the weights generated by the standard DF model have a counter-intuitive sign. While positive surprises in import series may affect all other series in the multivariate DF model through various channels and in different directions via the factor structure, their aggregate effect on GDP growth is largely expected to be negative, since imports enter the accounting identity with a negative sign. The new CBDF model is designed to address this by allowing the import series to affect all other series through the common factor structure, but crucially imposing it to enter the GDP equation with negative sign and weight given by the nominal share of imports.

In Figure 1, we display the weekly impact weights that nominal monthly import growth and import

FIGURE 1. Average GDP impact weights of nominal imports (top) and import prices (bottom) across a quarter



inflation surprises receive when revising the QoQ GDP nowcast for the model by Almuzara et al. (2023) (currently used by the New York Fed), which we label DF model, and our new CBDF model[3] (the figure displays weekly weights within a quarter averaged across 75 quarters from 2006:Q2-2024:Q4). Since these monthly series are released with a lag, the figure also indicates approximately when each monthly observation is released in the quarter. As is clear from Figure 1, in contrast to the standard DF model, the new CBDF model features negative impact weights on surprises from releases of nominal import growth and positive weights on import prices (consistent with the GDP accounting identity).

The second issue with the standard DF model is that the resulting shape of the impact weights for important monthly GDP components throughout the quarter does not reflect the formula for computing QoQ growth rate in which some months receive more weight than others (see equation 1 in Section 3.1 for details on the exact formula). Hence, surprises in more important months receive equal weights to surprises in less relevant months. In contrast, our CBDF model addresses this issue, since our GDP nowcast is computed by imposing the national accounting identity on the QoQ growth rates for the components, which for components arriving at monthly frequency (such as consumption and trade data) are computed from the MoM growth rate releases. In Figure 1, the impact weights of the CBDF model reflect closely the QoQ formula evolving throughout the quarter. As expected, the impact weights peak when the series for the first month of the reference quarter arrives, in line with the formula for

[3]Technical details on the model's equations, data and factor structure can be found in Section 3.

FIGURE 2. Average GDP impact weights of consumption

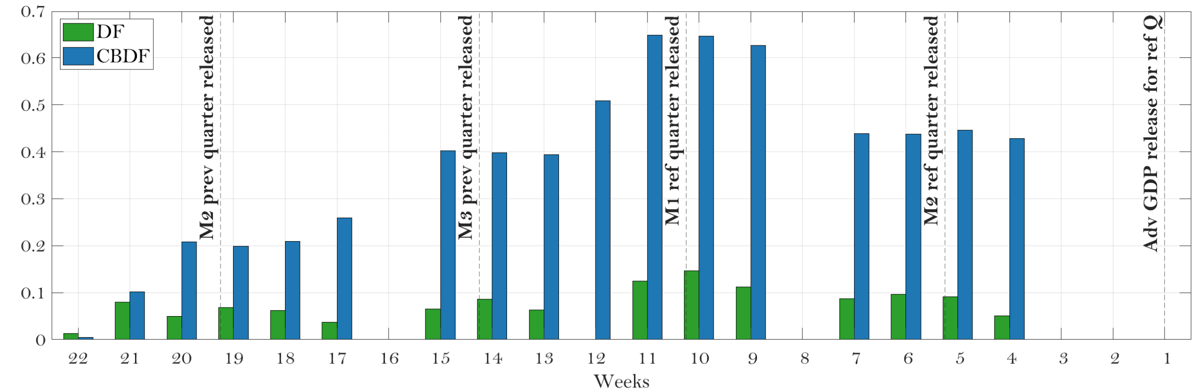
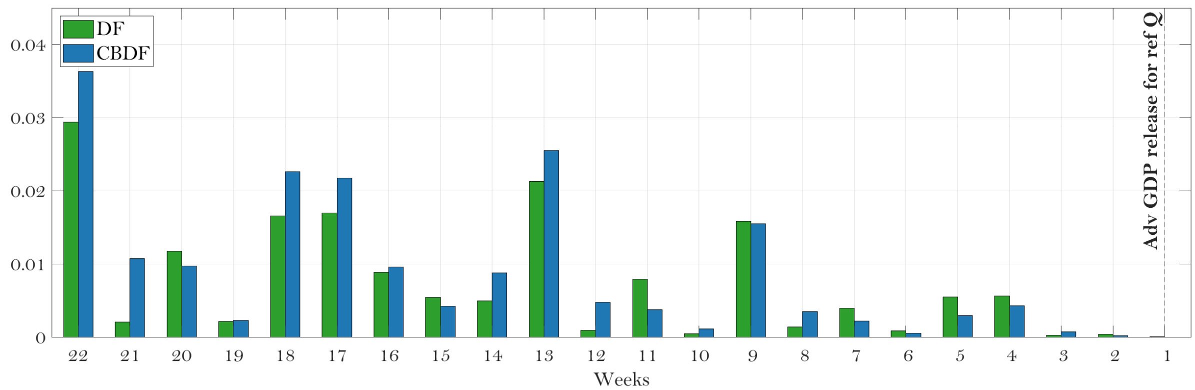


FIGURE 3. Absolute sum of soft data impact weights on GDP

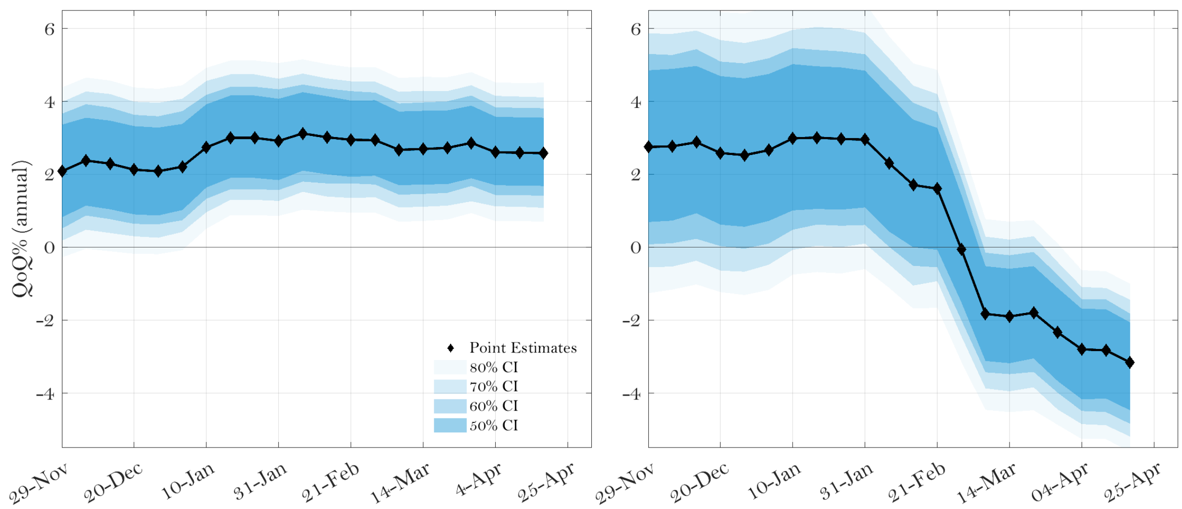


QoQ growth rate which gives this month the largest weight. Since the import price data arrive a month earlier, the corresponding weights peak earlier, in line with the formula. We illustrate the above points with another example: the impact weights on surprises in monthly personal consumption expenditure (PCE), which, with a nominal share of around 70% of GDP, provides an early and invaluable signal for current quarter GDP. In Figure 2, we display the weekly impact weights on GDP from surprises in PCE growth data. The standard DF model attributes positive weights for the series, however, these are small and do not correctly reflect the great importance of this component on GDP. Moreover, surprises in different monthly releases receive similar weights. In contrast, the CBDF model assigns large positive weights to surprises in consumption releases, in line with the nominal share of consumption, and as expected, assigns larger weights to the first month of the reference quarter, in line with the QoQ formula.

Finally, in Figure 3 we display the weekly impact weights that both the standard DF and the novel CBDF models assign to soft survey data revisions; these include the Michigan Consumer Sentiment survey as well as ISM, the Philadelphia Fed and the Empire State manufacturing surveys[4]. In the figure, we display the sum of absolute values of impact weights for all survey data series[5], in order to access

[4]For the full list of the series in this category, refer to Table 1 in Section 3.4.
[5]We take absolute value to avoid cancellation since weights can move in opposite directions.

FIGURE 4. 2025:Q1 Evolution for DF (left) and new CBDF models (right)



how important they are for the two models, given that they do not enter the accounting identity but can provide early signal on the state of the economy. We find that both models have similar impact weights, suggesting that the CBDF model, by imposing the GDP accounting identity, does not mute the effect that such important leading indicators may have on GDP through the factor structure of the model. Crucially, we find that surprises in soft data matter considerably more at the beginning of each quarter and their impact weights decline to zero towards the end of the quarter when hard data become available.

2.2 Recent Example 2025:Q1

Having discussed how key components affect the novel GDP nowcast, we now focus on a concrete example: the most recent quarter (2025:Q1), in order to illustrate how the output of the new CBDF model differs from that of the standard DF model. In Figure 4, we display the 2025:Q1 nowcast for the annualised QoQ GDP growth of the component-based approach (right) against the standard DF model by Almuzara et al. (2023) currently used by the New York Fed (left). From the figure, it is clear that, as of Friday 04/18/2025, the nowcast of the CBDF model is -3.16 which is not as optimistic as the DF model's estimate of 2.58.

Ordinarily both models perform similarly (see Section 4 for historical evaluation of their relative nowcast performance). However, the divergence between the two in 2025:Q1 is a result of sizeable drops in the realised monthly component contributions (consumption, exports and imports in particular), which in the CBDF model are directly imposed on GDP through the accounting identity, while in the DF model can only indirectly affect the GDP estimate through the factors and loadings.

In Figure 5, we include plots of the 2025:Q1 nowcasts for the annualised QoQ growth rate of each of the six GDP components (the inventory contribution to GDP growth is modelled directly). It is worth providing a brief discussion of how these QoQ component growth rates are computed. In particular, for series like consumption and trade, which arrive at a monthly frequency, the QoQ growth rate for 2025:Q1 is computed as:

$$2025{:}Q1\% \approx \frac{1}{3}2024{:}M11\% + \frac{2}{3}2024{:}M12\% + \frac{3}{3}2025{:}M1\% + \frac{2}{3}2025{:}M2\% + \frac{1}{3}2025{:}M3\%. \tag{1}$$

To provide a concrete example, on 02/28/2025 when 2025:M1 series for consumption arrives, our model uses this number together with the numbers for 2024:M11 and 2024:M12 directly in the formula above combining them with the model-implied nowcasts for 2025:M2 and 2025:M3 to compute the QoQ consumption growth nowcast for 2025:Q1. This QoQ nowcast is then weighted by the nominal share of consumption and combined with the other components through the national accounting identity to produce the nowcast for GDP (see Section 3.4 for technical details). This not only contributes to more timely and accurate nowcasts for monthly components but also reduces the model's GDP nowcast uncertainty as more of these monthly component series arrive.

In order to understand the evolution of the CBDF model's nowcast throughout the quarter, we make use of the impact decomposition analysis (see Section 3.5 for technical details) which allows us to directly trace the source of each weekly movement of the nowcast throughout 2025:Q1. In particular, the largest weekly impacts on the component-based GDP estimate are:

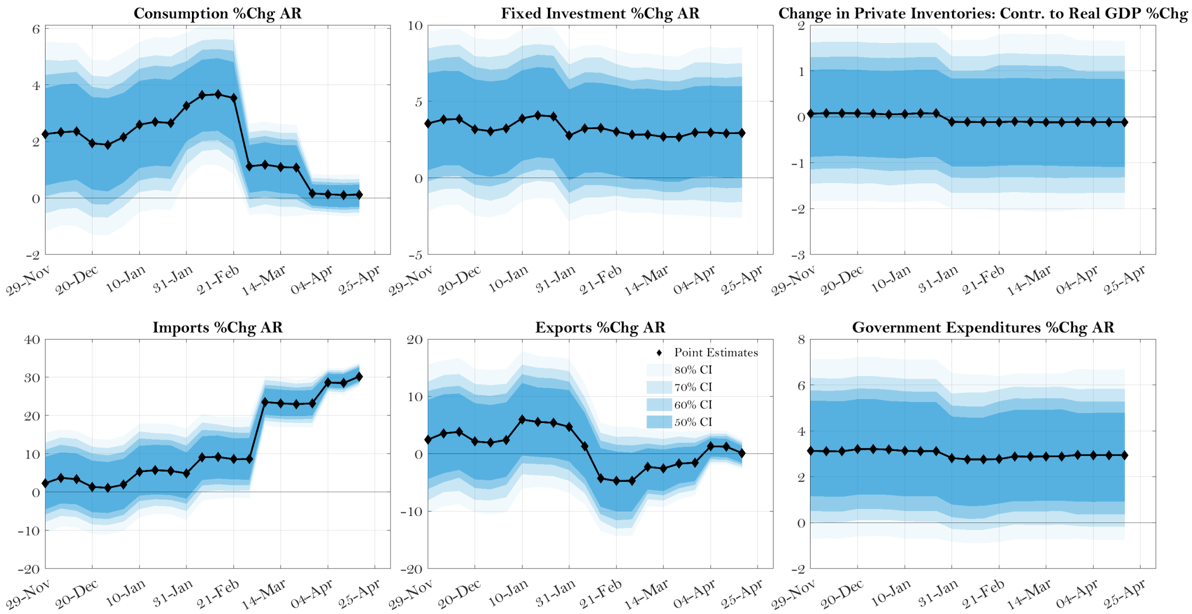
- 02/07/2025: –0.53% due to 2024:M12 nominal export growth[6] and –0.36% due to 2024:M12 nominal import growth
- 02/14/2025: -0.55% due to 2025:M1 export price growth
- 02/28/2025: -1.84% due to 2025:M1 consumption growth
- 03/07/2025: -2.01% due to 2025:M1 nominal import growth.

The exceptionally strong import growth in 2024:M12 and 2025:M1, responsible for the sizeable downward revisions of the component-based GDP nowcast, could be due to recent tariff uncertainty and companies stockpiling on goods prior to tariffs taking effect. Some of these imported goods, if neither consumed nor used in production in 2025:Q1, will likely end up as a one-to-one increase in inventories either in 2025:Q1 or in future quarters, dampening the negative effect of import growth on GDP. While it is difficult to know exactly what proportion of import growth's effect on final GDP may be cancelled through higher inventories[7], the impact decomposition of the CBDF model allows us to quantify precisely these effects and conduct counterfactual analysis by 'switching off' some channels. For example, if we were to assume that import growth surprises in 2024:M12 and 2025:M1 were driven solely by stockpiling and would be fully offset in the final GDP number, and we therefore entirely remove their impact on our GDP estimate (which are –0.36 for 2024:M12 and –2.01 for 2025:M1), our 2025:Q1 GDP nowcast would be -0.79 instead of -3.16.

[6] The export and import data from Census is adjusted for non-monetary gold, since gold is not included in the BEA's calculation of quarterly real exports and imports, refer to Table 1 for details on the data and transformations.

[7] At the time of writing, we do not have the 2025:Q1 BEA Advance GDP release or the Advance release for inventories, which become available on 30 April 2025.

FIGURE 5. 2025:Q1 Evolution of the Nowcasts for GDP Components



3 Methodology

3.1 The State Space Dynamic Factor Model

The dynamic factor model specification follows closely the model of Almuzara et al. (2023) currently used by the New York Fed, which builds on the Legacy Staff Nowcast of Bok, Giannone, Caratelli, Sbordone, and Tambalotti (2018); we include details of the state space model for reference below. The main state equation of the model is given by

$$y_t = \mu + \iota g_t + \Lambda f_t + e_t, \tag{2}$$

where y_t is an $n \times 1$ vector of monthly series $y_t = [y_{1,t}, ..., y_{n,t}]'$, f_t is an $n_f \times 1$ vector of common factors, $e_t = [e_{1,t}, ..., e_{n,t}]'$ is an $n \times 1$ vector of idiosyncratic terms, g_t is an $n_g \times 1$ vector of time-varying trends[8], μ, ι and Λ are $n \times 1$, $n \times n_f$ and $n \times n_g$ parameters respectively. The trend g_t (scalar process in our setup) follows a simple random walk equation of the form:

$$g_t = g_{t-1} + \gamma_g v_{g,t}, \; v_{g,t} | \mathcal{F}_{t-1} \sim \mathcal{N}(0, 1).$$

The factors follow a VAR(p) model of the form:

$$f_t = \sum\nolimits_{j=1}^{p} \Phi_j f_{t-j} + \Omega_t S_t \epsilon_{f,t}, \; \epsilon_{f,t} | \mathcal{F}_{t-1} \sim \mathcal{N}\left(0, I_{n_f}\right),$$

[8] For our final CBDF model, the trend g_t is a scalar process and loads only on the equation for government spending; see Appendix A.2 for alternative specifications.

where Φ_j are $n_f \times n_f$ autoregressive matrices for $j = 1, ..., p$, Ω_t is an $n_f \times n_f$ p.d. diagonal matrix with time-varying diagonal elements given by $\sigma_{i,f,t}$ and S_t is an $n_f \times n_f$ p.d. diagonal matrix with discrete outlier terms given by $s_{f,t} = diag(S_t)$.

The idiosyncratic elements $e_{i,t}$ for $i = 1, ..., n$ follow univariate AR(q) processes[9] of the form:

$$e_{i,t} = \sum_{j=1}^{q} \phi_j e_{i,t-j} + \sigma_{i,e,t} s_{i,e,t} \epsilon_{i,e,t},\ \epsilon_{i,e,t} | \mathcal{F}_{t-1} \sim \mathcal{N}(0, 1),$$

where ϕ_j are AR coefficients for $j = 1, ..., q$, $\sigma_{i,e,t}$ are time-varying volatilities and $s_{i,e,t}$ are discrete outlier terms. Distributional assumptions on $\epsilon_{f,t}$ and $\epsilon_{i,e,t}$ are required for full information Bayesian estimation; we impose Gaussianity for convenience[10].

The stochastic volatility in the innovations of the factors and the idiosyncratic terms are modelled as smooth geometric random walks of the form:

$$\begin{aligned}
\log\left(\sigma_{i,f,t}\right) &= \log\left(\sigma_{i,f,t}\right) + \gamma_{i,f} v_{i,f,t},\ v_{i,f,t} | \mathcal{F}_{t-1} \sim \mathcal{N}(0, 1) \text{ for } i = 1, ..., n_f \\
\log\left(\sigma_{i,e,t}\right) &= \log\left(\sigma_{i,e,t}\right) + \gamma_{i,e} v_{i,e,t},\ v_{i,e,t} | \mathcal{F}_{t-1} \sim \mathcal{N}(0, 1) \text{ for } i = 1, ..., n.
\end{aligned}$$

The discrete outlier terms $s_{f,t}$ and $s_{i,e,t}$ in the factor and idiosyncratic terms are equal to one in most periods and are designed to switch to values higher than one in unusual periods, in order to allow for more abrupt changes in the error volatility, facilitating periods characterised by outliers and large data spikes, such as the Covid-19 pandemic, for example. Finally, the measurement equation is given by

$$Y_{i,t} = \begin{cases} y_{i,t} \text{ if } Y_{i,t} \text{ is monthly} \\ Hy_{i,t} \text{ if } Y_{i,t} \text{ is quarterly,} \end{cases} \tag{3}$$

where $H = \frac{1}{3}\left(1 + 2L + 3L^2 + 2L^3 + 1L^4\right) y_{i,t}$ and L denotes the lag operator $Ly_{i,t} = y_{i,t-1}$. The formula above is a linear approximation of the QoQ growth rate as a weighted sum of MoM growth rates to the exact nonlinear formula (see Mariano and Murasawa (2003)). The model is estimated with Bayesian methods through a standard Gibbs sampling algorithm. Details on the sampling algorithm as well as priors distributions of the parameters can be found in Appendix A.1.

3.2 The Data and Factor Structure

[9] For our final CBDF model, the choice for the number of lags is $p = 1$ and $q = 1$, but we have experimented with various lag orders; see Appendix A.2 for alternative specifications.

[10] Posterior inference on the conditional mean parameters continues to be valid for large samples even if the true distribution of the innovations is non-Gaussian, as long as the first two conditional moments of the innovations are correctly specified (see, e.g. Petrova (2022)).

TABLE 1. Data Series that enter the Components-Based Dynamic Factor Model

Data Series	Block g	Block G	Block C	Block I	Block T	Block Cv	Transformation
All employees: Total nonfarm	□	■	■	□	□	■	Level change (thousands)
JOLTS: Total job openings	□	■	■	□	□	■	Level change (thousands)
Civilian unemployment	□	■	■	□	□	■	Ppt. change
ADP nonfarm private payroll employment	□	■	■	□	□	■	Level change (thousands)
Nonfarm business sector: Unit labor cost	□	■	□	□	□	■	QoQ % change (annual)
ISM mfg.: PMI composite index	□	■	□	■	□	■	Index
ISM non-mfg.: NMI composite index	□	■	□	■	□	■	Index
ISM mfg.: Prices index	□	■	□	■	□	□	Index
ISM mfg.: Employment index	□	■	□	■	□	■	Index
Empire State Mfg. Survey: General business conditions	□	■	□	□	□	■	Index
Philly Fed Mfg. Business Outlook: Current activity	□	■	□	□	□	■	Index
University of Michigan: Consumer sentiment	□	■	■	□	□	□	Index
Industrial production index	□	■	□	□	□	■	MoM % change
Manufacturers' new orders: Durable goods	□	■	□	■	□	■	MoM % change
Merchant wholesalers: Inventories: Total	□	■	□	■	□	■	MoM % change
Total business inventories	□	■	□	■	□	■	MoM % change
Manufacturers' shipments: Durable goods	□	■	□	■	□	■	MoM % change
Manufacturers' unfilled orders: All industries	□	■	□	□	□	□	MoM % change
Manufacturers' inventories: Durable goods	□	■	□	■	□	□	MoM % change
Real Private Nonresidential Fixed Investment: Structures	□	■	□	■	□	■	QoQ % change
Real private non-residential fixed investment: Equipment	□	■	□	■	□	■	QoQ % change
Real private non-residential fixed investment: IPP	□	■	□	■	□	■	QoQ % change
Real private residential fixed Investment	□	■	□	■	□	■	QoQ % change
Real private fixed investment	□	■	□	■	□	■	QoQ % change
Change in private inventories: Contribution to real GDP	□	■	□	■	□	■	QoQ % Level
New single-family houses sold	□	■	□	□	□	■	MoM % change
Housing starts	□	■	□	■	□	■	MoM % change
Value of construction put in place	□	■	□	□	□	■	MoM % change
Building permits	□	■	□	■	□	■	Level change (thousands)
Retail sales and food services	□	■	■	□	□	■	MoM % change
Real personal consumption expenditures	□	■	■	□	□	■	MoM % change
Real government consumption & investment	■	■	□	□	□	■	QoQ % change
Real disposable personal income	□	■	□	□	□	■	MoM % change
Real gross domestic income	□	■	■	□	□	■	QoQ % change (annual)
Exports: Goods and services*	□	■	□	□	■	■	MoM % change
Imports: Goods and services*	□	■	□	□	■	■	MoM % change
Import price index	□	■	□	□	■	□	MoM % change
Export price index	□	■	□	□	■	■	MoM % change
S&P GSCI commodity index	□	■	□	□	■	■	MoM % change
Real FRB trade-weighted dollar index	□	■	□	□	■	□	MoM % change
CPI-U: All items	□	■	■	□	□	■	MoM % change
PCE: Chain price index	□	■	■	□	□	□	MoM % change
Moody's seasoned BAA corporate bond yield relative to 10-Year	□	■	□	■	□	□	Level

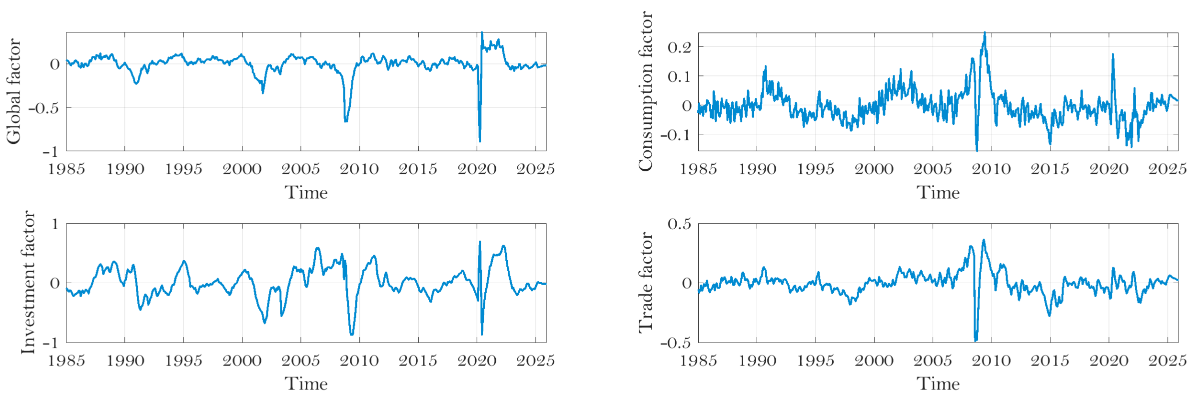
Labor · Production · Construction · Income · Surveys · Consumption · Trade · Prices

The colour-coded squares refer to the category each series belongs to. Filled squares in the "Block" column indicate each series' restrictions on the factor loadings, with g, G, C, I, T, and Cv indicating the trend, global, consumption, investment, trade, and Covid-19 factors, respectively. Series used in the accounting identity are highlighted in bold.

*We subtract balance of payments based non-monetary gold data, released monthly by the BEA, from nominal levels of exports and imports before computing MoM growth rates which enter into the model directly.

The new CBDF model features four factors[11], as well as a temporary Covid-specific factor which is switched on for the periods 2020:M3-2020:M9. The data consists of 43 series and the restrictions we impose on the factor loadings of these series allow us to label the factors as component-specific. We choose to label one of the factors as 'global', loading all 43 series on it. In addition, we allow for consumption-specific, investment-specific and trade-specific blocks. The full list of the series, as well as the applied data transformation and details on the precise factor loading restrictions can be found in Table 1. PCE, labour series as well as consumer sentiment data and retail sales load on the consumption factor. Investment sub-component series, as well as manufacturing data and surveys, and corporate bond spread load on the investment-specific factor. In alternative specifications, we experimented with adding stock market returns, various bond yields and spreads, as well as mortgage rates to the investment block, but we found that these add more noise than signal to the resulting GDP nowcast; see Appendix A.2 for further details. Inventories (measured as contribution to GDP) also load on the investment block. Monthly trade data load on the trade-specific block, alongside effective USD exchange rate and commodity price inflation. The quarterly series for government spending loads on the global and Covid factors only. Figure 6 and 7 display the Kalman-smoothed factors of our model and their corresponding volatilities over time.

FIGURE 6. Factors



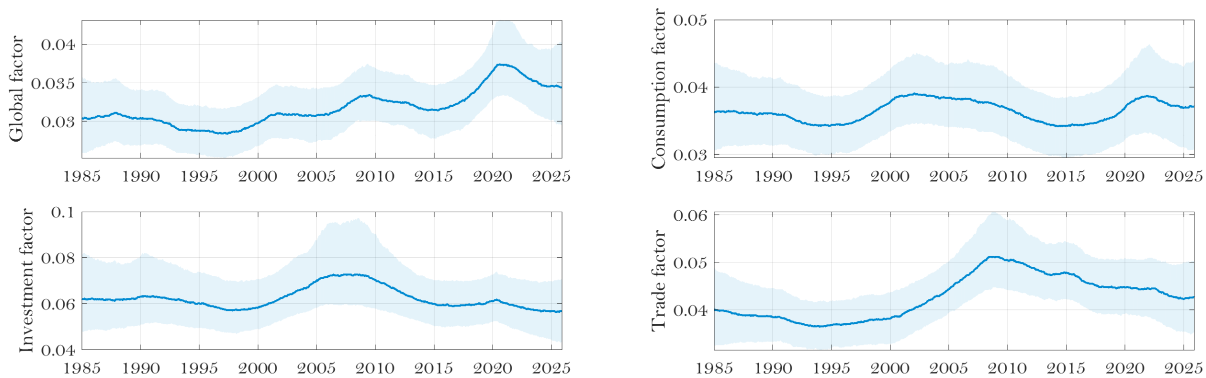
3.3 The GDP Nowcast Constructed via the Accounting Identity

The novel idea behind our component-based approach is to remove the series for GDP growth from the state and measurement equations (2) and (3) and construct the nowcast for GDP through the model-implied nowcasts of individual GDP components via the use of the national accounting identity. In particular, denoting by N_t^{GDP} nominal GDP, the national identity is given by:

$$N_t^{GDP} = N_t^C + N_t^I + N_t^G + N_t^X - N_t^M + \Delta N_t^V \tag{4}$$

[11]We have experimented with the number of factors as well as the structure of the loadings, see Appendix A.2 for alternative specifications.

FIGURE 7. Volatilities with 68% probability band



where $N_t^C, N_t^I, N_t^G, N_t^X, N_t^M$ and $\Delta N_t^V = N_t^V - N_{t-1}^V$ denote nominal quantities for consumption, investment, government spending, exports, imports and change in inventories[12]. Denoting the corresponding real quantities and prices of each component k by Q_t^k and P_t^k respectively, the usual identity holds $Q_t^k = N_t^k/P_t^k$. We let $G_t^k = Q_t^k/Q_{t-1}^k$ and denote the corresponding nominal shares by $w_{k,t} = N_t^k/N_t^{GDP}$. Since inventories enter (4) in first difference, we have $w_{V,t} = \Delta N_t^V/N_t^{GDP}$ and $G_t^V = \Delta Q_t^V/\Delta Q_{t-1}^V$ instead. Additionally, since imports enter with a negative sign, we define $w_{M,t} := -N_t^M/N_t^{GDP}$. The Laspeyres equation for real GDP is given by:

$$G_t^{GDP,L} = \sum\nolimits_{k=1}^{6} w_{k,t-1} G_t^k. \tag{5}$$

Since the nominal shares sum up to one by construction, $\sum_{k=1}^{6} w_{k,t-1} = 1$, the Laspeyres equation for the real GDP growth rate is given as a weighted sum of the real growth rates of the individual components:

$$g_t^{GDP} = \sum\nolimits_{k=1}^{6} w_{k,t-1} g_t^k, \tag{6}$$

where $g_t^k = \left(Q_t^k - Q_{t-1}^k\right)/Q_{t-1}^k = G_t^k - 1$ is the real rate of growth for each component.

The GDP formula used by the BEA combines the Laspeyres weighting in (5) with a Paasche weighting

$$\left(G_t^{GDP,P}\right)^{-1} = \sum\nolimits_{k=1}^{6} w_{k,t} \left(G_t^k\right)^{-1}$$

via a geometric mean, in order to compute the Fisher equation

$$G_t^{GDP,F} = \sqrt{G_t^{GDP,L} G_t^{GDP,P}}.$$

Notice that the nominal component shares used in the Laspeyres equation are lagged while the nominal shares used in the Paasche weighting are timed at t rather than $(t-1)$. Since nominal shares are very persistent and approximately constant over time, and since our DF model is not suitable to nowcast such

[12] The negative sign on nominal imports ensures that imported goods and services that may be included in domestic consumption or production are subtracted from GDP.

persistent quantities, we choose to use previous period weights, setting $\hat{w}_{k,t} = w_{k,t-1}$. The Laspeyres, Paasche and Fisher weighting equations result into nearly identical values for G_t^{GDP} with $w_{k,t} = w_{k,t-1}$; we therefore limit our attention to the Laspeyres equation, due to its convenience and linearity.

Since the nominal shares are available at $(t-1)$, using equation (6), we can construct a QoQ GDP growth nowcast $\hat{g}_t^{GDP}$ as a weighted sum of the QoQ growth nowcast for each component $\hat{g}_t^k$:

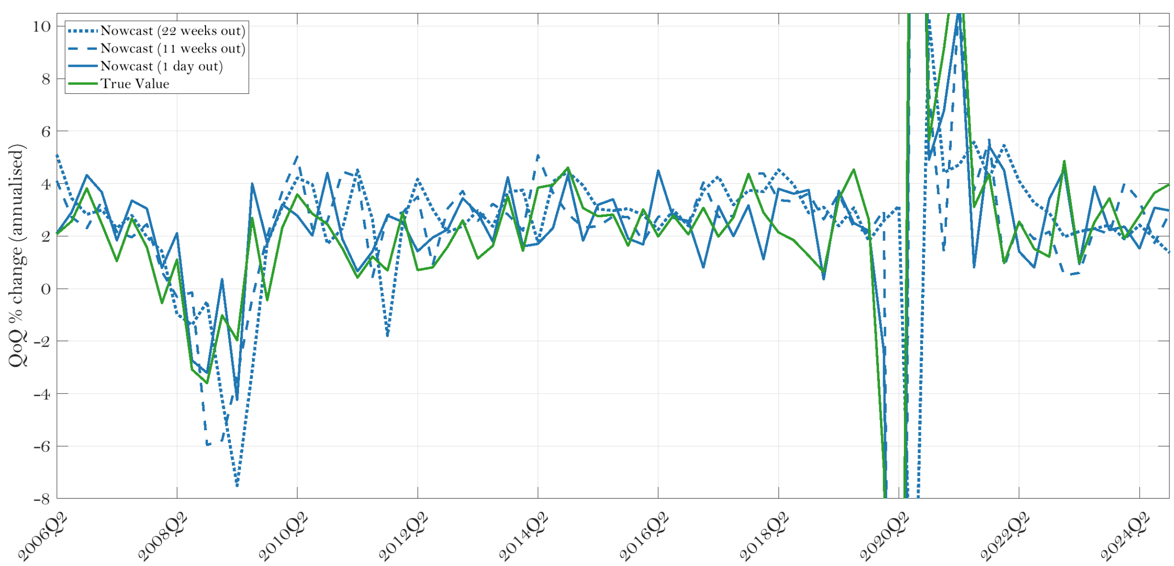
$$\hat{g}_t^{GDP} = \sum\nolimits_{k=1}^{6} w_{k,t-1}\hat{g}_t^k, \tag{7}$$

where $\hat{g}_t^k$ are obtained through the dynamic factor model in (2) and (3). In practice, for each draw from the posterior of the model-implied component nowcasts, a posterior draw for GDP is obtained through equation (7), giving rise to a full posterior distribution of GDP nowcast draws, reflecting parameter and data uncertainty around the GDP estimate.

3.4 The Components

3.4.1 Monthly Components

FIGURE 8. Consumption

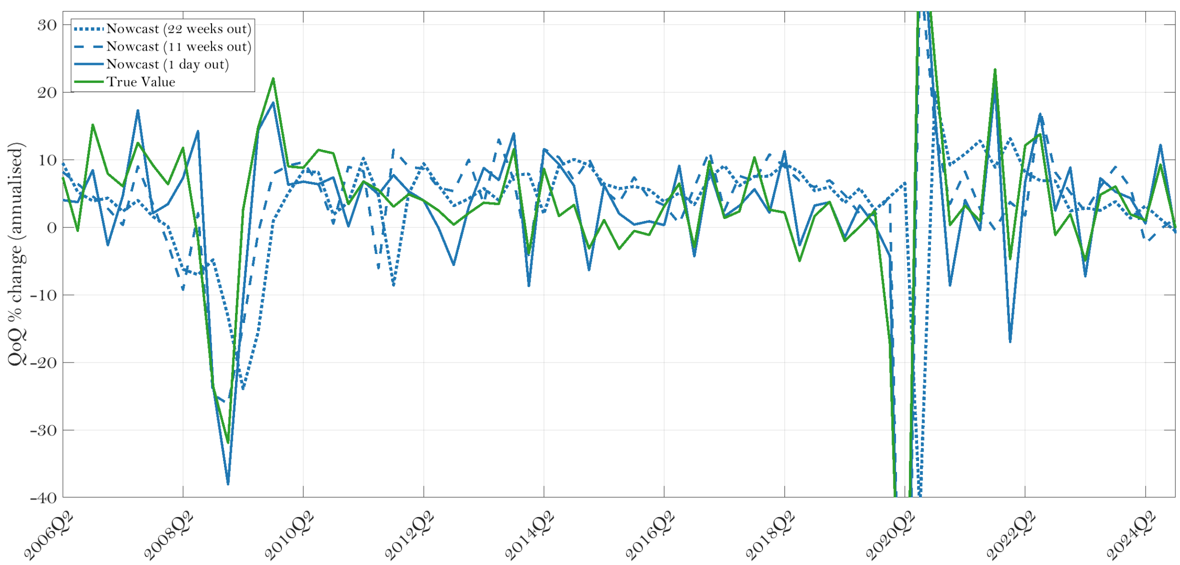


We provide a brief discussion on the modelling choices we impose on the six components in our component-based approach. For consumption, we use monthly series, which are expected to give the CBDF model an informational advantage towards the end of the quarter, since QoQ growth rates can be more accurately pinned down. In particular, we use the linear approximation of QoQ growth rate of consumption as a sum of weighted MoM growth rates[13]:

$$\hat{g}_t^C = h'\tilde{\hat{Y}}_{C,t} \tag{8}$$

where $h = \frac{1}{3}[1,2,3,2,1]'$, $\tilde{\hat{Y}}_{C,t} = \left[\hat{Y}_{C,t}, ..., \hat{Y}_{C,t-4}\right]'$ and $\hat{Y}_{C,t}$ are the DFM-implied monthly nowcasts for PCE MoM growth, which enter the measurement equation (3) directly. Notice that, at the end of a given quarter, $\hat{Y}_{C,t-1}, \hat{Y}_{C,t-2}, \hat{Y}_{C,t-3}$ and $\hat{Y}_{C,t-4}$ are already available and so the model uses these realised values to compute the nowcast for the QoQ growth rate for consumption $\hat{g}_t^C$ in equation (8). This not only improves $\hat{g}_t^C$ and, hence, the nowcast for GDP, but also reduces the posterior uncertainty around it as we get close to the end of the quarter.

FIGURE 9. Exports



In Figure 8 we display the QoQ PCE nowcast at three different points in the quarter based on a real-time forecasting exercise for the period 2006:Q2-2024:Q4 against the realised series[14]. From the figure, it is clear that as we get closer to the end of the quarter, the nowcast for consumption becomes more accurate; for example, the root mean squared error (RMSE) for the annualised QoQ growth of PCE twenty-two weeks before the BEA release is 2.3 whereas at the end of the quarter (a day before the release), it drops to 1.3.

Similarly, we use monthly series for exports and imports to calculate the corresponding nowcasts for the QoQ growth rates required for the nowcast accounting identity (7). In particular, monthly nominal export and import growth series and monthly export and import inflation series enter the measurement equation (3) of the DF model directly (see Table 1 for details). Next, we use the same formula as in (8) to compute the corresponding nominal QoQ growth rates of exports and imports, which we deflate with

[13] We experimented with using the exact (non-linear) instead of the approximate (linear) formula; the performance of the model is nearly identical; we choose to work with the linear formula since linearity simplifies further the impact analysis in Section 3.5.

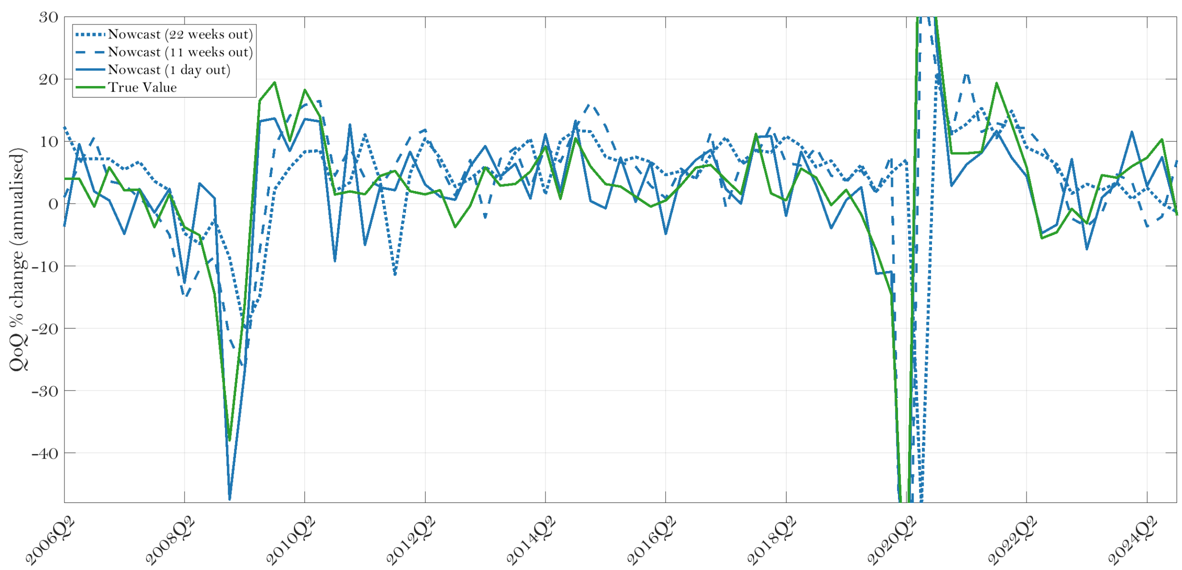
[14] For realised series, here and throughout the paper, we use the latest available vintage as of 18/04/2025; in Appendix A.3 we also report comparisons against the Advance release.

the corresponding QoQ inflation to obtain the real QoQ growth rate required for the accounting identity (7). For example, for exports, we compute the nowcast $\hat{g}_t^X$, which enters the GDP nowcast in (7) as

$$\hat{g}_t^X \quad = \quad \hat{g}_t^{X_N} - \hat{\pi}_t^X = h'(\tilde{\hat{Y}}_{X,t} - \tilde{\hat{Y}}_{P_X,t}),$$

where $\hat{g}_t^{X_N}$ and $\hat{\pi}_t^X$ are the QoQ growth rates of nominal exports and export prices respectively, $\tilde{\hat{Y}}_{X,t} = \left[\hat{Y}_{X,t}, ..., \hat{Y}_{X,t-4}\right]'$, $\tilde{\hat{Y}}_{P_X,t} = \left[\hat{Y}_{P_X,t}, ..., \hat{Y}_{P_X,t-4}\right]'$, and $\hat{Y}_{X,t}$ and $\hat{Y}_{P_X,t}$ are the model-implied nowcasts for MoM growth rates of nominal exports and export prices respectively, coming from the measurement equation of the DF model (3) directly.

FIGURE 10. Imports



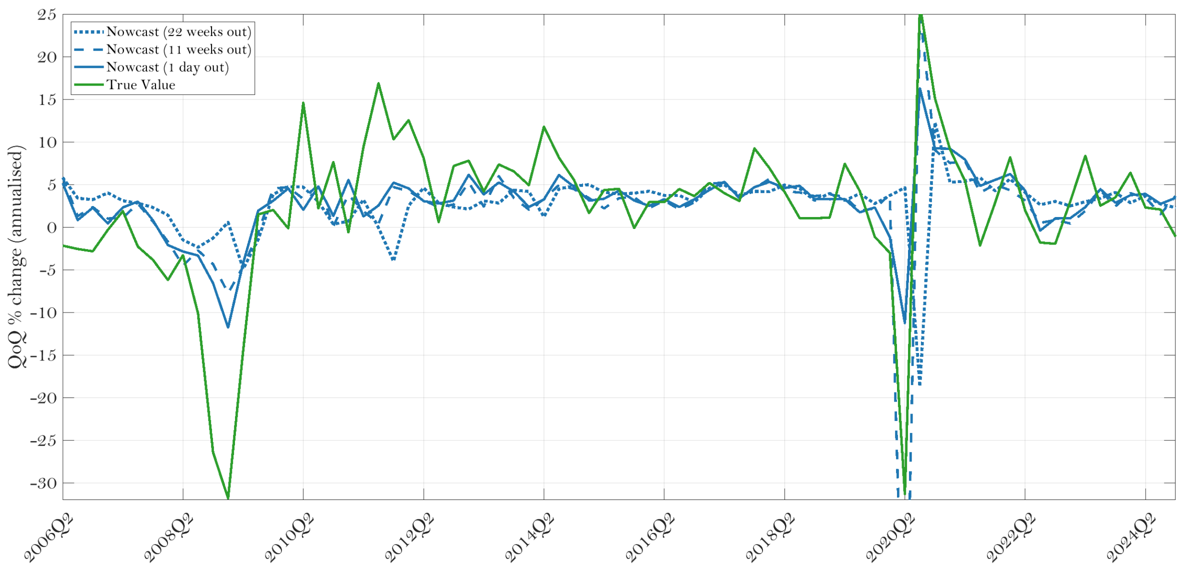
Figures 9 and 10 display our QoQ real exports and imports nowcasts for the period 2006:Q2-2024:Q4 against the realised series. As expected, nowcasts for both series become more accurate as we get closer to the release date (e.g. the RMSE for the annualised QoQ growth of exports and imports drops from 8.9 to 4.8 and from 7.5 to 5.0 respectively, as we move from twenty-two months to one day before the release).

3.4.2 Quarterly Components

The series we use for aggregate investment and government spending are available quarterly, (see Table 1 for details) therefore, we use the measurement equation (3) of our DF model directly to compute the nowcasts for QoQ growth rates $\hat{g}_t^I$ and $\hat{g}_t^G$ required to compute the GDP nowcast through the accounting identity (7). Since our model is ill-equipped for predicting government spending, we add a random walk time-varying trend in the government spending equation in order to improve the model-implied nowcast.

Figures 11 and 12 display our model's nowcasts for the annualised QoQ growth of real investment

FIGURE 11. Private Investment



and government spending at three points throughout the quarter for the period 2006:Q2-2024:Q4 against the realised series. Figure 12 also displays the fitted time-varying trend in the government spending equation and the 68% posterior bands around it. It is clear from the figures that, while the nowcasts marginally improve as we get closer to the end of the quarter, such improvements are negligible; this is unsurprising, since both components are available in quarterly frequency and so do not benefit from large improvements due to timely data arrival, as is the case with the monthly components for consumption and trade.

Finally, our series for inventories is quarterly. While the change in inventories constitutes a small component of GDP, its volatility makes it difficult to forecast, hence it can play a disproportionately large role for nowcasting GDP. After much experimentation with the inventories component (see Section A.2 for the nowcast performance of a variety of inventory specifications), we found the best performing specification to be one in which the inventories contribution enters the DF model directly, i.e., we use quarterly series for $c_t^V = w_{V,t-1} g_t^V$ directly in the DF model and obtain a quarterly nowcast $\hat{c}_t^V$ through the measurement equation (3). Figure 13 displays the annualised inventories contribution nowcast $\hat{c}_t^V$ for the period 2006:Q2-2024:Q4 against the realised series.

3.4.3 Nowcast Error Decomposition

Subtracting (7) from (6) and rearranging terms, we can decompose the GDP nowcast error of our component-based model into a weighted sum of component-specific nowcast errors:

$$\hat{g}_t^{GDP} - g_t^{GDP} = \sum_{k=1}^{5} w_{k,t-1} \left(\hat{g}_t^k - g_t^k \right) + \hat{c}_t^V - c_t^V .$$

FIGURE 12. Government Expenditures with Time-Varying Trend

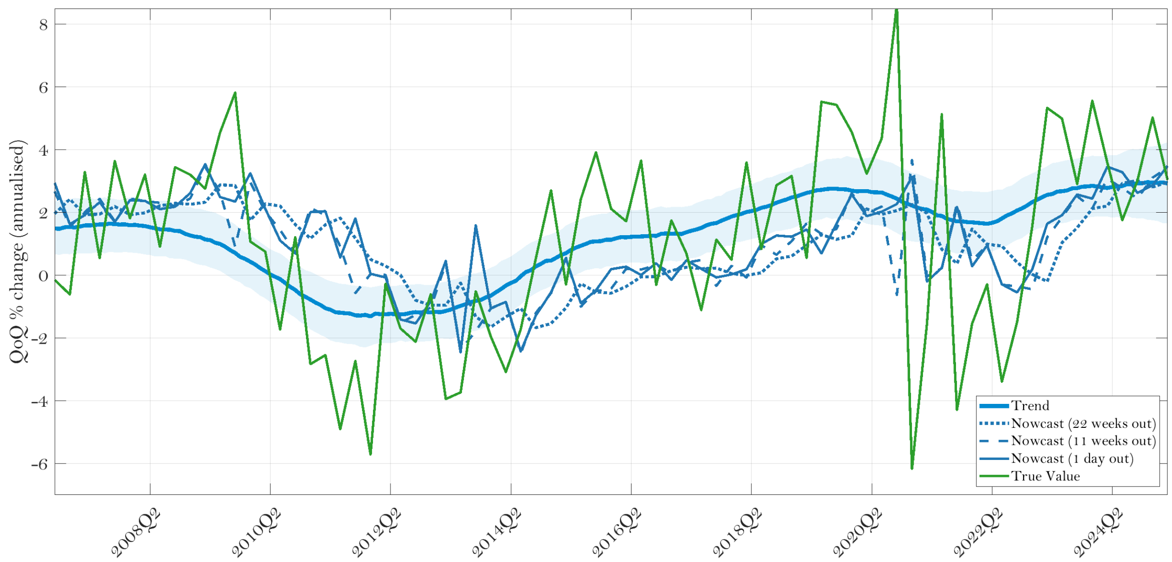


Figure 14 displays the GDP nowcast error decomposition (one day before the BEA release) for the period 2006:Q2-2024:Q4 into weighted component-specific errors. From the figure, it is clear that components such as inventories, while accounting for only a small share of nominal GDP (approximately 1%), can contribute considerably to the forecast error of our model due to its high volatility and unpredictability.

3.5 The Component-Based Impact Analysis

In this section, we show how impacts of data releases and revisions can be computed from the component-based approach. In particular, just like existing DF models, we can decompose the nowcast revisions for each component into impacts due to data releases, parameters and data revisions. Then, we can pass these impacts through the accounting identity nowcast equation (7) in order to obtain a decomposition for the component-based GDP nowcast.

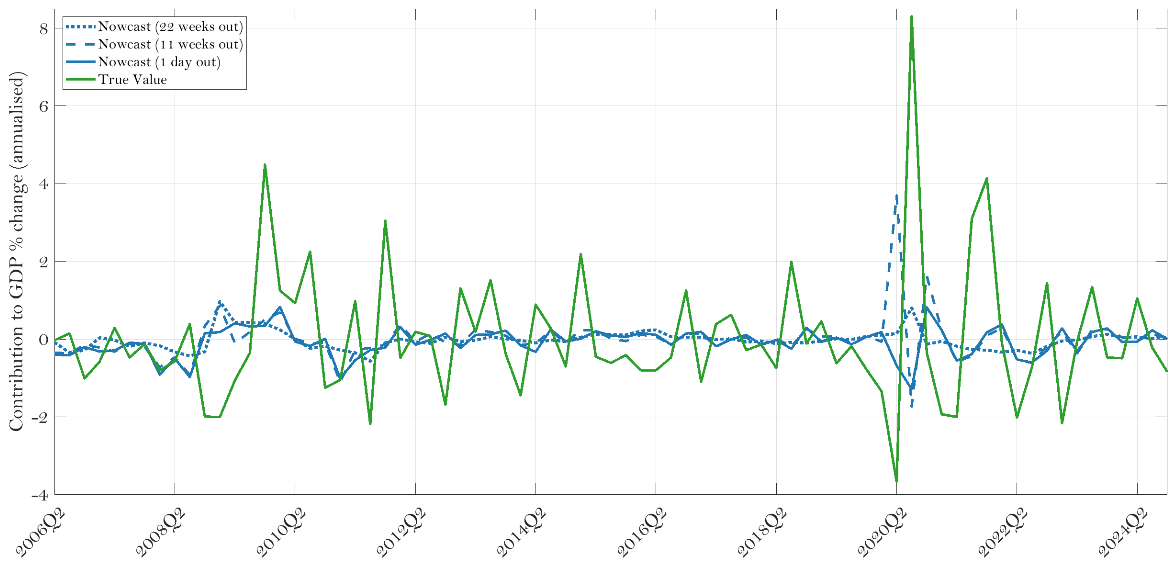
Given two information sets at different points in time $\mathcal{F}_{v'}$ and $\mathcal{F}_{v''}$, where $\mathcal{F}_{v''}$ can contain both data revisions of existing observations in the sample of $\mathcal{F}_{v'}$ and new releases, denoting by $\tilde{\mathcal{F}}_{v''}$ the sample augmented with new releases only, we can decompose the nowcast revision for each series $y_{i,t}$ in the DF model state equation (2) in impacts due to data releases, parameter and data revisions respectively as:

$$\begin{aligned} r_{i,t} &= \mathbb{E}\left(y_{i,t}|\mathcal{F}_{v''},\hat{\theta}_{v''}\right) - \mathbb{E}\left(y_{i,t}|\mathcal{F}_{v'},\hat{\theta}_{v'}\right) \\ &= I_{i,t} + I_{\theta,i,t} + I_{d,i,t} \end{aligned} \tag{9}$$

where $I_{i,t}$ are impacts due to new releases

$$I_{i,t} := \mathbb{E}\left(y_i|\tilde{\mathcal{F}}_{v''},\hat{\theta}_{v'}\right) - \mathbb{E}\left(y_i|\mathcal{F}_{v'},\hat{\theta}_{v'}\right),$$

FIGURE 13. Inventories



where the estimates of the parameters $\hat{\theta}$ are based on information set $\mathcal{F}_{v'}$. The impact on the nowcast revision for each variable i due to parameter revisions is captured in the term $I_{\theta,i,t}$ given by

$$I_{\theta,i,t} = \mathbb{E}\left(y_{i,t}|\mathcal{F}_{v''}, \hat{\theta}_{v''}\right) - \mathbb{E}\left(y_{i,t}|\mathcal{F}_{v''}, \hat{\theta}_{v'}\right)$$

and impacts due to data revisions are included in the term $I_{d,i,t}$ given by

$$I_{d,i,t} = \mathbb{E}\left(y_i|\mathcal{F}_{v''}, \hat{\theta}_{v'}\right) - \mathbb{E}\left(y_i|\tilde{\mathcal{F}}_{v''}, \hat{\theta}_{v'}\right).$$

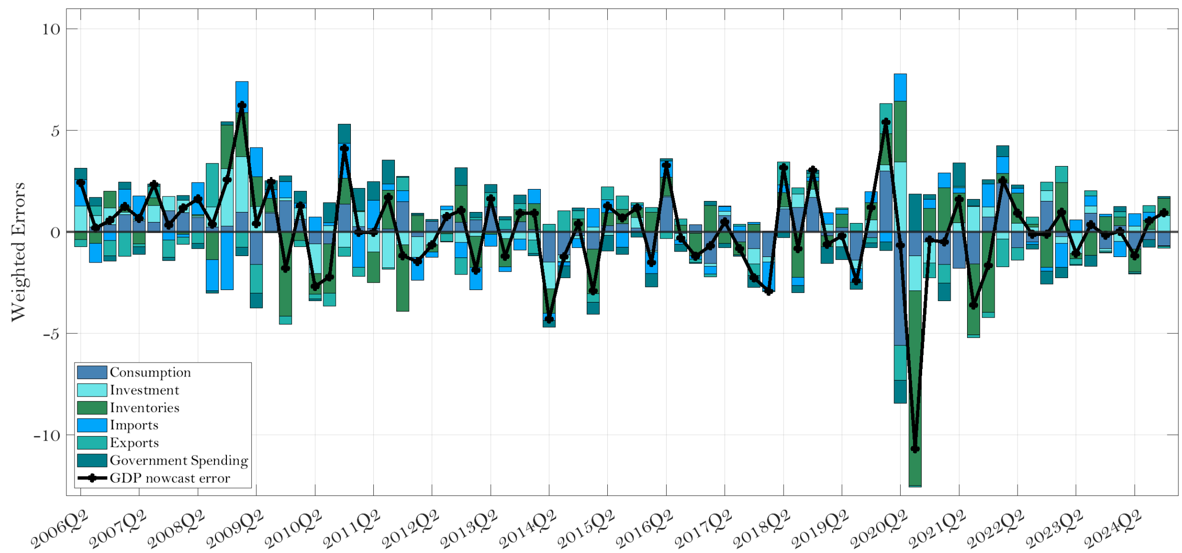
The decomposition in (9) follows directly by adding and subtracting the terms $\mathbb{E}\left(y_i|\tilde{\mathcal{F}}_{v''}, \hat{\theta}_{v'}\right)$ and $\mathbb{E}\left(y_i|\mathcal{F}_{v''}, \hat{\theta}_{v'}\right)$ from $r_{i,t}$ and re-arranging. The conditional expectation terms above can be computed as point nowcasts from the model, conditioning on different samples and parameter estimates. Since the focus is on specific data releases, the impact from such data releases can be further decomposed into impacts coming from individual variables $j \in (1, ..., n)$ as:

$$I_{i,t} = \sum_{j=1}^{n} b_{i,j} r_{j,t},$$

where the coefficients $b_{i,j}$ that can be computed through linear projection of nowcast revisions of other variables $r_{j,t}$ on $I_{i,t}$ (e.g. see Banbura et al. (2010) and Banbura and Modugno (2014)). This analysis can be further passed through the linear measurement equation (3) to obtain impacts for each observable in the DF model. Defining $h = \frac{1}{3}[1, 2, 3, 2, 1]'$ and $\tilde{r}_{i,t} = \left[r_{i,t}, ..., r_{i,t-4}\right]'$, we have

$$R_{i,t} := \mathbb{E}\left(Y_{i,t}|\mathcal{F}_{v''}, \hat{\theta}_{v''}\right) - \mathbb{E}\left(Y_{i,t}|\mathcal{F}_{v'}, \hat{\theta}_{v'}\right) = \begin{cases} r_{i,t} \text{ if series } i \text{ is monthly} \\ h'\tilde{r}_{i,t} \text{ if series } i \text{ is quarterly.} \end{cases} \tag{10}$$

FIGURE 14. Component Error Decomposition (against latest release)



The decomposition in (9) and (10) is standard and commonly used in the DF model literature (e.g. see Hayashi and Tachi (2021)). Since our component-based nowcast for GDP uses the national accounting identity (7), we can decompose revisions of our GDP nowcast as a weighted sum of revisions in each of the components:

$$
\begin{aligned}
& \mathbb{E}\left(g_t^{GDP}|\mathcal{F}_{v''}, \hat{\theta}_{v''}\right) - \mathbb{E}\left(g_t^{GDP}|\mathcal{F}_{v'}, \hat{\theta}_{v'}\right) \\
= & \sum_{k=1}^{6} w_{k,t-1}\left[\mathbb{E}\left(g_t^{k}|\mathcal{F}_{v''}, \hat{\theta}_{v''}\right) - \mathbb{E}\left(g_t^{k}|\mathcal{F}_{v'}, \hat{\theta}_{v'}\right)\right] \\
= & \sum_{k=1}^{6} w_{k,t-1} h' \tilde{r}_{k,t} = \sum_{k=1}^{6} w_{k,t-1} h'\left(\tilde{I}_{k,t} + \tilde{I}_{\theta,k,t} + \tilde{I}_{d,k,t}\right) \\
= & \underbrace{\sum_{j=1}^{n} \underbrace{\sum_{k=1}^{6} w_{k,t-1} b_{k,j} h'}_{\text{new CB impact weights}} \tilde{r}_{j,t}}_{\text{impacts due to releases}} + \underbrace{\sum_{k=1}^{6} w_{k,t-1} h' \tilde{I}_{\theta,k,t}}_{\text{impacts due to parameter revisions}} + \underbrace{\sum_{k=1}^{6} w_{k,t-1} h' \tilde{I}_{d,k,t}}_{\text{impacts due to data revisions}}
\end{aligned}
$$

where $\tilde{r}_{k,t} = \left[r_{k,t}, ..., r_{k,t-4}\right]'$ denote the nowcast revisions for the corresponding series of the six components $k \in \{C, I, X, M, G, V\}$ and $\tilde{I}_{k,t}$, $\tilde{I}_{\theta,k,t}$ and $\tilde{I}_{d,k,t}$ are similarly defined. Since the accounting identity (7) is based on QoQ growth rates, we pass the monthly components through the h transformation, which the measurement equation achieves directly for the quarterly components. For inventories, since we model the contribution directly, the nominal share weights are already included in the data g_t^V and we set $w_{V,t} = 1$ above, with a slight abuse of notation.

We provide a brief discussion about how the component-based approach changes the traditional impact analysis of the DF model. In the standard approach, where GDP is just one of the variables modelled directly, the impact weights for computing the GDP nowcast revision due to a specific data release for variable j depend on the model-implied coefficients $b_{GDP,j}$. In the new component-based

FIGURE 15. Average Impact by Category Across All Quarters (excluding 2020:Q2 and 2020:Q3)

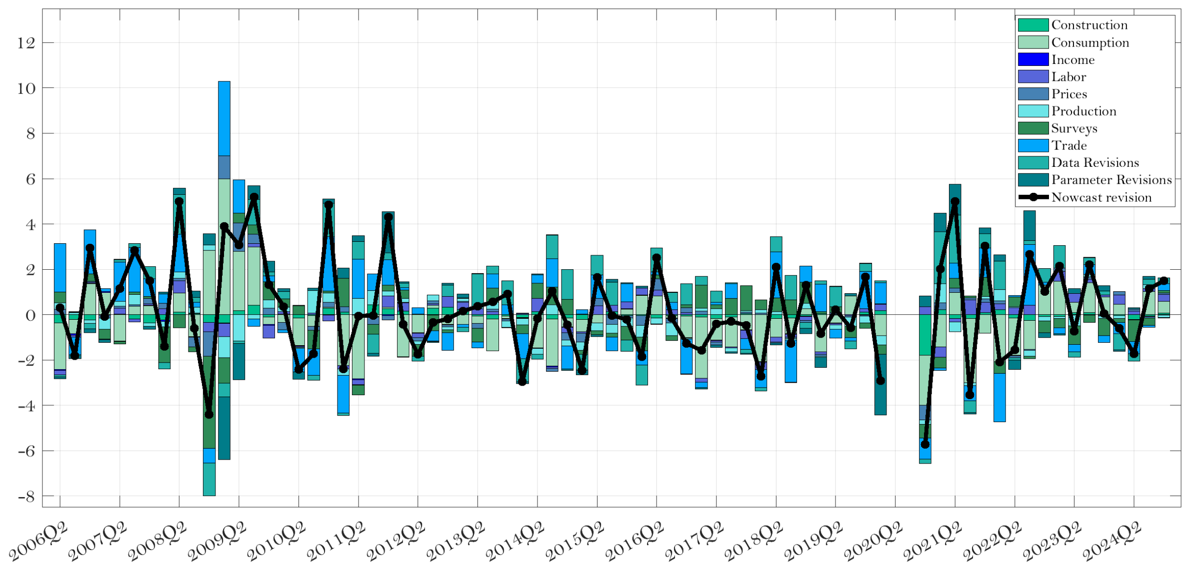
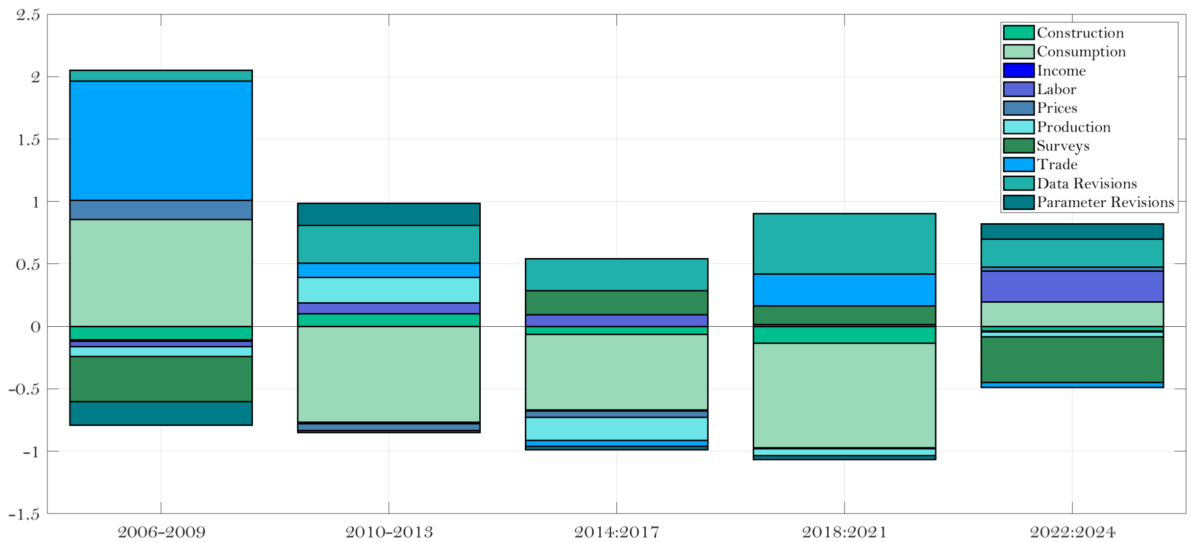


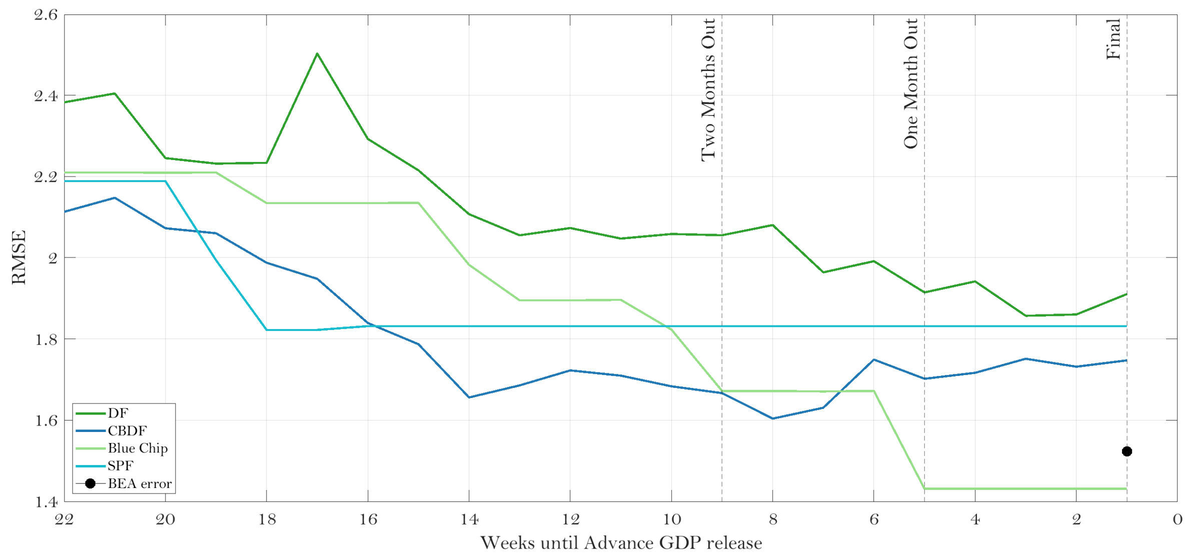
FIGURE 16. Average Impact by Category Across Grouped Years (excluding 2020:Q2 and 2020:Q3)



approach, the impact weights for the GDP nowcast revision depend on the model-implied coefficients for each component $b_{k,j}$ due to data release j, which are then weighted through the nominal shares $w_{k,t-1}$ (and for monthly components, transformed into QoQ quantities). This point is well illustrated in the impact weight analysis of Section 2.1. Similarly, the new component-based GDP nowcast update due to parameter and data revisions is computed as a weighted sum of the components' updates due to parameter and data revisions, respectively.

In Figure 15, we display the component-based impacts for GDP averaged across data categories (for details on variables in each category, refer to Table 1). To see more clearly GDP impact trends over time, we average the impacts into sub-periods in Figure 16. From the figure, there are several conclusions. First, surprises in trade category series lead to sizeable GDP revisions during the financial crisis, but relatively

FIGURE 17. RMSE against Latest GDP



small revisions afterwards. Second, consumption category series lead to positive GDP nowcast revisions for 2006-2009 and negative revisions in subsequent periods. Finally, data and parameter revisions have a small impact for GDP nowcast updates in most periods, but they play an important role during the financial crisis and more recently during the Covid-19 pandemic, both characterised by considerable structural change.

4 Real-Time Historical Nowcast Evaluation

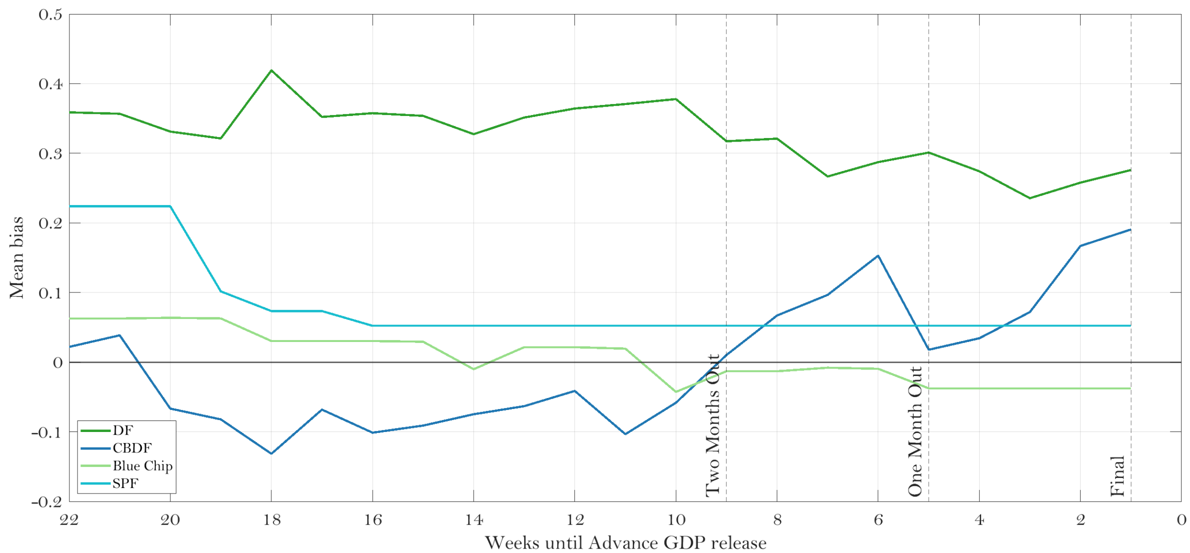
In this section, we study the forecasting performance of our new CBDF model through a large real-time forecast evaluation exercise, comparing it to: the DF model of Almuzara et al. (2023) currently used by the New York Fed, the model of Higgins (2014) currently used by the Atlanta Fed, as well as GDP estimates of professional forecasters such as SPF and Blue Chip. In Appendix A.2, we also compare the performance of our component-based model against a large number of alternative model specifications. We use real-time data[15] from 1985:M1 and compute the CBDF and DF models' nowcasts weekly starting 2006:Q2 through 2024:Q4. We evaluate the different approaches against the latest available GDP values as of 18/04/2025; comparisons against the Advance GDP release can be found in Appendix A.3. We evaluate point and density forecast performance of each approach; point performance is measured in terms of root mean squared error (RMSE) and forecast bias; density performance is evaluated in terms of average log-predictive scores[16].

In Figure 17, we present the point nowcast accuracy of the CBDF model in terms of RMSE for

[15] In order to align the information sets, all series are in real-time weekly vintages, except BoP non-monetary gold due to data availability.

[16] Log scores are computed as the logarithm of the nowcast density evaluated at the realised value and are used to evaluate density forecast performance.

FIGURE 18. Bias against Latest GDP



different weeks throughout the reference quarter (starting 4 weeks before each quarter and finishing when the BEA Advance estimate is released, around 4 weeks after the end of each quarter), averaged over the sample of 75 quarters 2006:Q2-2024Q4[17]. The figure also displays the average performance of the DF model of Almuzara et al. (2023) currently used by the New York Fed, estimated over the same periods, as well as the performance of the SPF and Blue Chip. As is clear from the figure, the point nowcast performance of the new component-based approach is better than that of the standard DF model, uniformly over the quarter, with RMSE improvements of around 15% on average. Moreover, the CBDF model also performs comparably (in terms of point accuracy) to professional forecasters' estimates, widely monitored by market participants and commentators. Impressively, at the end of the quarter, the RMSE of the Blue Chip is actually lower than the RMSE of the BEA (computed as the difference between the Advance GDP release and the final available GDP series).

Figure 18 compares the average forecast bias for each method. It is clear from the figure that the DF model suffers from some positive forecast bias, implying it systematically over-estimates GDP growth; the bias is resolved in the component-based approach. Finally, in Figure 19, we show the log-predictive scores for the DF and CBDF models (log scores cannot be computed for the SPF and Blue Chip since these lack a full probability nowcast density around their GDP estimate). In particular, we find that the new component-based approach can improve the density nowcast performance (in terms of log-predictive score) of the standard DF model with 20% on average.

We also compare our approach against the model of Higgins (2014) currently used by the Atlanta Fed, known as the GDPNow model. Due to availability of GDPNow nowcasts, we can only perform the comparison over a reduced sample of 51 quarters spanning 2011Q3-2024Q4. In Figure 20, we display the RMSE performance of our model relative to GDPNow throughout different points of the quarter[18]. The

[17]Throughout the analysis, outlier quarters 2009:Q1, 2020:Q2 and 2020:Q3 are excluded for all models.

[18]Since GDPNow is not released at equidistant points in time, we fill non-update days in the 90-day forecast window of

FIGURE 19. Log Scores against Latest GDP

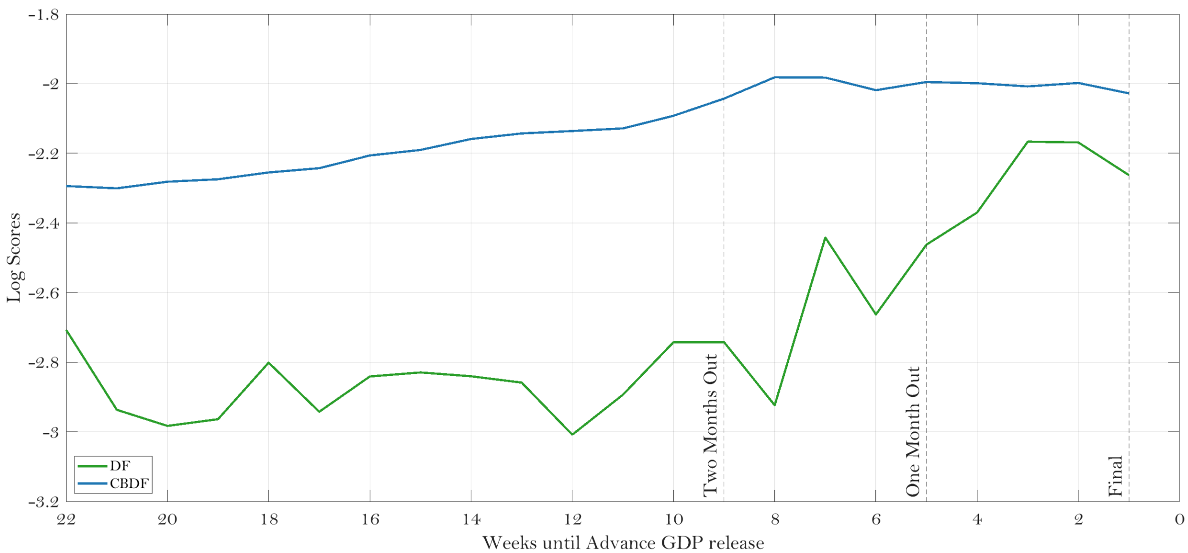
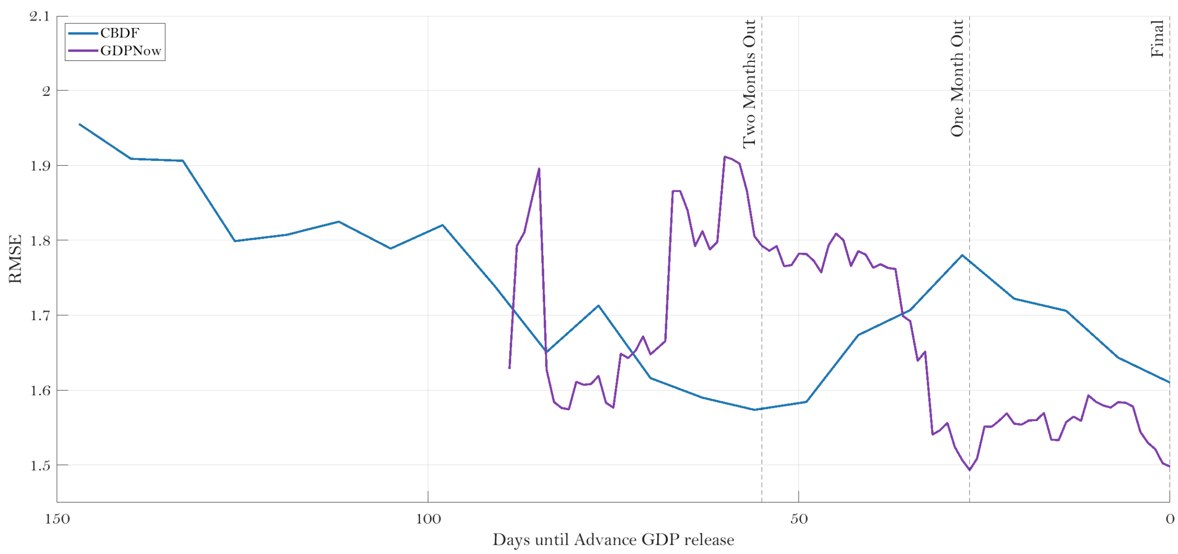


FIGURE 20. RMSE against Latest GDP



main conclusion from the figure is that our model performs comparably well to the Atlanta Fed's model: it is better on average in terms of point forecast accuracy until around 6 weeks before the Advance BEA release, while the Atlanta Fed's model has an advantage in terms of point accuracy closer to the release date. There are two additional advantages of our new component-based approach, as well as the DF model of Almuzara et al. (2023) currently used by the New York Fed: (i) both begin producing GDP nowcasts 8 weeks earlier each quarter, providing useful early quarterly estimates, and (ii) both models provide a full probability density precisely quantifying the uncertainty around their nowcast estimate, which is in contrast to GDPNow as well as other professional judgement-based estimates. In addition,

GDPNow with the previously available nowcast and then average across quarters.

the component-based approach has the added advantage over the DF model of generating the impact decomposition and nowcast density for all six GDP components, providing a transparent interpretation of its output.

5 Conclusion

In this paper, we develop a new component-based nowcast model which effectively combines ideas from dynamic factor models and from 'bottom-up' approaches, bridging the gap between the two. Relative to existing dynamic factor models, the main advantages of our new approach are: (i) it imposes the national accounting identity, incorporating important missing restrictions in standard DF models which link key components to GDP, and (ii) it utilises timely monthly component releases effectively, which delivers improvements in the accuracy of the model's nowcast for GDP. Relative to existing 'bottom-up' approaches and professional forecasts based on expert judgement and heuristics, our new method models all GDP components jointly, through a single dynamic factor model, designed to capture common and component-specific co-movements in the data and deliver a model-consistent GDP probability density. We establish the impact analysis of our new approach demonstrating how nowcast revisions to both GDP and its components can be decomposed into impacts due to incoming data releases and updates, providing a transparent interpretation of the model's output. We also demonstrate that the new approach delivers forecasting improvements over existing methods in a real-time out-of-sample forecasting exercise.

More generally, the conceptual approach taken in this paper is applicable in many diverse settings. The idea behind removing a target variable from the model and imposing instead an accounting identity, or some other theoretical relationship, in order to construct its forecast through model-implied forecasts for its elements, is general and can be applied to different models, variables and countries, and the formal analysis can be further disaggregated to include a larger number of subcomponents.

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A Appendix

A.1 Details of Estimation Approach

The Gibbs algorithm for the Bayesian estimation of DF model is standard; we refer the reader to Almuzara et al. (2023) for precise details on the steps of the algorithm. Below, we provide a detailed description of the priors used for our component-based model.

Let $Y_{m,t}$ be an n_m-vector of monthly series and $Y_{q,t}$ an n_q-vector of quarterly series (imputed to the third month of each quarter). The model relates them to a time-varying trend g_t, unobservable factors f_t and errors e_t via the measurement equation:

$$Y_t = \begin{bmatrix} Y_{m,t} \\ Y_{q,t} \end{bmatrix} = \begin{bmatrix} I_{n_m} & 0_{n_m \times n_q} \\ 0_{n_q \times n_m} & \frac{1}{3}(1 + 2L + 3L^2 + 2L^3 + L^4) I_{n_q} \end{bmatrix} y_t,$$

$$y_t = \mu + \iota g_t + \Lambda f_t + e_t.$$

With $n = n_m + n_q$, y_t is the n-vector of monthly-equivalent series for Y_t. If the i-th entry of Y_t is a monthly series we have $Y_{it} = y_{it}$, while if it is a quarterly series we have

$$Y_{i,t} = \frac{1}{3}\left\{(\bar{y}_{i,t} + \bar{y}_{i,t-1} + \bar{y}_{i,t-2}) - (\bar{y}_{i,t-3} + \bar{y}_{i,t-4} + \bar{y}_{i,t-5})\right\},$$

where $\bar{y}_{i,t}$ is such that $\Delta \bar{y}_{i,t} = y_{i,t}$, as in Mariano and Murasawa (2003). The long-run trend g_t is modelled after Antolín-Díaz, Drechsel, and Petrella (2017) and Antolín-Díaz, Drechsel, and Petrella (2024), with an entry of ι corresponding to government spending set to 1 and 0 otherwise.

The model for latent variables[19] is

$$\begin{aligned} f_t &= \Phi_1 f_{t-1} + \sigma_{f,t} \odot \varepsilon_{f,t}, \\ e_t &= \phi_1 \odot e_{t-1} + \sigma_{e,t} \odot \varepsilon_{e,t}, \\ \varepsilon_{f,t} | \mathcal{F}_{t-1} &\sim \mathcal{N}(0_{n_f \times 1}, I_{n_f}), \quad \varepsilon_{e,t} | \mathcal{F}_{t-1} \sim \mathcal{N}(0_{n_e \times 1}, I_{n_e}), \end{aligned}$$

with time-varying trend and volatilities[20] given by

$$\begin{aligned} g_t &= g_{t-1} + \gamma_g v_{g,t}, \\ \ln \sigma^2_{f,t} &= \ln \sigma^2_{f,t-1} + \gamma_f \odot v_{f,t}, \\ \ln \sigma^2_{e,t} &= \ln \sigma^2_{e,t-1} + \gamma_e \odot v_{e,t}, \\ v_{g,t} | \mathcal{F}_{t-1} &\sim \mathcal{N}(0, 1), \quad v_{f,t} | \mathcal{F}_{t-1} \sim \mathcal{N}(0_{n_f \times 1}, I_{n_f}), \quad v_{e,t} | \mathcal{F}_{t-1} \sim \mathcal{N}(0_{n_e \times 1}, I_{n_e}). \end{aligned}$$

[19]The loadings Λ are subject to certain restrictions for identification, this is achieved by specifying that certain factors (e.g., the consumption, investment and trade factors) only affect a subset of observables.

[20]The volatilities $\sigma_{f,t}$ and $\sigma_{e,t}$ are drawn through a linear non-Gaussian step approximated with a Gaussian mixture as in Kim, Shephard, and Chib (1998) and Omori, Chib, Shephard, and Nakajima (2007).

The parameter vector includes

$$\theta = \left[\mu', \gamma_g', \mathrm{vec}(\Lambda)', \mathrm{vec}(\Phi)', \gamma_f', \phi', \gamma_e', \sigma_{ft}', \sigma_{et}'\right]'.$$

We make use of normal and inverse-gamma priors distributions, just as in Almuzara et al. (2023):[21]

$$\begin{aligned}
&\mu \sim \mathcal{N}(m_\mu, P_\mu^{-1}),\ \gamma_g \sim 1/\sqrt{\Gamma(\nu_g/2, 2/(\nu_g s_g^2))},\\
&\mathrm{vec}\,(\Lambda) \sim \mathcal{N}(m_\Lambda, P_\Lambda^{-1}), \quad \text{(subject to the identifying restrictions)},\ \ \mathrm{vec}\,(\Phi) \sim \mathcal{N}(m_\Phi, P_\Phi^{-1}),\\
&\gamma_f \sim 1/\sqrt{\Gamma_{n_f}(\nu_f/2, 2/(\nu_f s_f^2))},\ \mathrm{vec}\,(\phi) \sim \mathcal{N}(m_\phi, P_\phi^{-1}),\\
&\gamma_e \sim 1/\sqrt{\Gamma_n(\nu_e/2, 2/(\nu_e s_e^2))}\\
&s_{i,f,t} \in \{1.01, ..., 10\} \text{ w.p. } \pi_{i,f,t} \sim \mathcal{B}(\alpha_{i,f,t}, \beta_{i,f,t})\\
&s_{i,e,t} \in \{1.01, ..., 10\} \text{ w.p. } \pi_{i,e,t} \sim \mathcal{B}(\alpha_{i,e,t}, \beta_{i,e,t})
\end{aligned}$$

The choice for the prior parameters is as follows:

$$\begin{aligned}
m_\mu &= 0_{n\times 1},\ P_\mu = 100 \times I_n\\
s_g^2 &= 0.005, \nu_g = 10\\
m_\Lambda &= \hat{m}_\Lambda^{MLE},\ P_\Lambda = (10 - 10^{-1/n}) \times (I_{n_f} \otimes I_n)\\
m_\Phi &= \mathrm{vec}\,(I_{n_f}),\ X_d = [I_{n_f}, 2I_{n_f}]',\ P_\Phi = (\ X_d' X_d \otimes I_{n_f})\\
\alpha_{i,f,t} &= \alpha_{i,e,t} = 19.2,\ \beta_{i,f,t} = \beta_{i,e,t} = 0.83\\
m_\phi &= 0_{n\times 1},\ P_\Phi = 25 \times I_n\\
s_e^2 &= 0.0001,\ \nu_e = 18,\ s_f^2 = 0.001,\ \nu_e = 2
\end{aligned}$$

[21] $\Gamma_K(\alpha, \beta)$ is a vector of K independent $\Gamma(\alpha_k, \beta_k)$-distributed random variables.

A.2 Comparison against Alternative Specifications

FIGURE 21. RMSE against Latest GDP: DF specifications

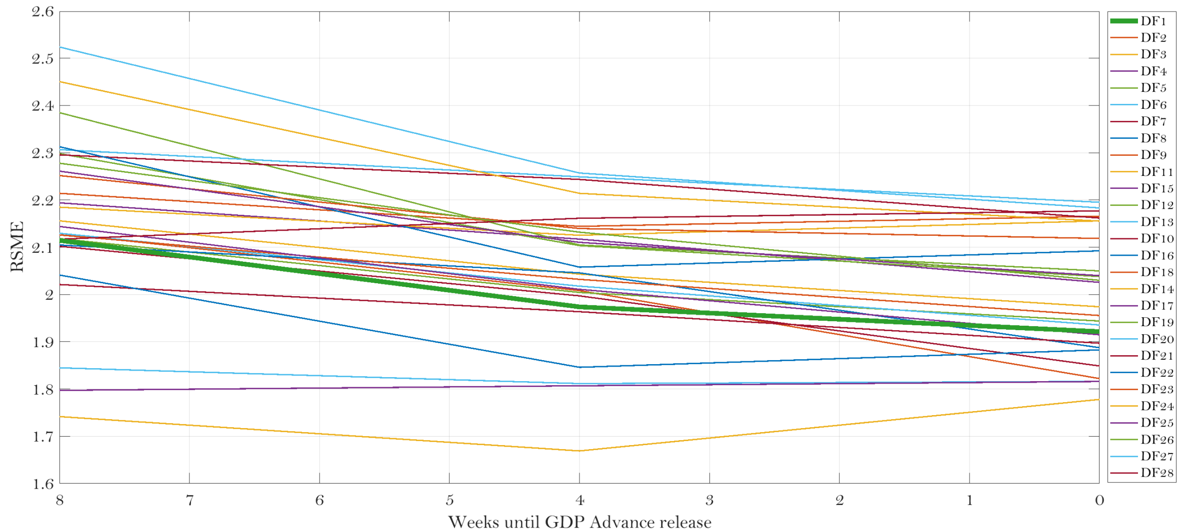
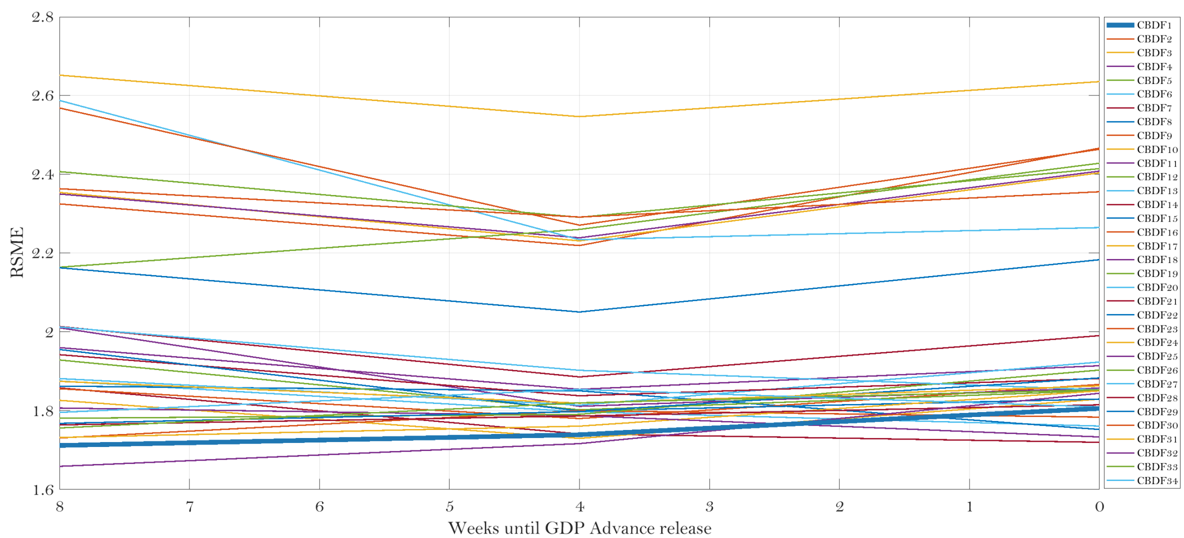


FIGURE 22. RMSE against Latest GDP: CBDF specifications



We present a comprehensive comparison of the performance of the final specification of our component-based model against a number of alternative model specifications: 29 different DF and 36 component-based DF specifications. A brief description of the features of the different models can be found in Table A.2. All models are estimated on real-time data on samples from 1985:M1; we compute the GDP nowcast of all specifications at three points in each quarter (two months, one months and one day before the BEA Advance Release) over 75 quarters 2006:Q2-2024:Q4. We evaluate the point nowcast (in terms of RMSE) of all specifications, including the main CBDF model, against the latest available GDP values as of 18/04/2025 in Figures 21 and 22 and against the Advance GDP release in Figure 23 and 24.

TABLE 2. List of Specifications

Spec.	Details
■ DF 1*	Priors and lag structure: Baseline DF model, priors as in Almuzara et al. (2023)
■ DF 2	Priors and lag structure: $p_f = 1$
■ DF 3	Priors and lag structure: loose trend priors $\nu_g = 10$, $\sigma_g^2 = 0.1$
■ DF 4	Priors and lag structure: loose trend priors $\nu_g = 5$, $\sigma_g^2 = 0.5$
■ DF 5	Priors and lag structure: loose trend priors $\nu_g = 10$, $\sigma_g^2 = 0.005$
■ DF 6	Priors and lag structure: Minnesota prior centred on zero w priors from DF 5
■ DF 7	Priors and lag structure: spec DF5, $\eta_f = 1$, overall shrinkage = 1
■ DF 8	Priors and lag structure: spec DF5, $\eta_f = 1$, overall shrinkage = 2
■ DF 9	Priors and lag structure: outlier space 1.0001-10
■ DF 10	Priors and lag structure: spec combination DF7 and spec DF9
■ DF 11	Factor Structure: 1 global factor
■ DF 12	Factor Structure: 2 global factors
■ DF 13	Factor Structure: 3 global factors
■ DF 14	Factor Structure: 4 global factors
■ DF 15	Factor Structure: No Covid factor
■ DF 16	Factor Structure: 3 global factors with DF10 changes
■ DF 17	Factor Structure: 4 global factors with DF10 changes
■ DF 18	Factor Structure: 1 global factor with $p_f = 1$
■ DF 19	Additional Vars: Stock return, corporate bond spread, 10y-2y yield spread and 30y fixed mortgage rates
■ DF 20	Additional Vars: Stock return and corporate bond spread
■ DF 21	Additional Vars: Large financial block with expanding window
■ DF 22	Additional Vars: Small financial block with expanding window
■ DF 23	Additional Vars: DF22 + DF10
■ DF 24	Additional Vars: Added quarterly components to DF1
■ DF 25	Additional Vars: DF25 + DF10
■ DF 26	Additional Vars: DF 25 without monthly inventory series
■ DF 27	Additional Vars: DF 25 without monthly trade and trade price indices
■ DF 28	Additional Vars: Vehicle sales, initial and continuing claims, consumer sentiment and nonfarm hours
■ CBDF 1*	Final Components-Based Specification
■ CBDF 2	Added 9 components (including disaggregated financial comps)
■ CBDF 3	Replaced smaller investment components with real private fixed investment
■ CBDF 4	Added back small investment components
■ CBDF 5	Created investment block with CBFN3
■ CBDF 6	Created consumption block with CBFN3
■ CBDF 7	Replaced inventory component with direct contribution to gdp
■ CBDF 8	Moved trend to inventories
■ CBDF 9	New component-based block structure
■ CBDF 10	Deflated monthly nominal trade with price index
■ CBDF 11	CBDF9 + CBDF7 + DF10
■ CBDF 12	Constructed inventories contribution in place of direct contributions + CBDF9
■ CBDF 13	Added financial data to investment block, $n_f = 2$ + loose priors from DF5
■ CBDF 14	Dropped core prices, added consumer sentiment, loaded labour vars on C block, $p_f = 2$ + DF10
■ CBDF 15	CBDF11 + DF9 $p_f = 2$
■ CBDF 16	CBDF11 + DF9 $p_f = 1$, all series load on G and Cv blocks
■ CBDF 17	CBDF16 + 2 spread vars loaded on I, G, Cv blocks
■ CBDF 18	CBDF16 + consumer sentiment, dropped core prices, labour series only on G, Cv blocks
■ CBDF 19	CBDF17 spreads only load on I block
■ CBDF 20	CBDF16 remove core prices
■ CBDF 21	CBDF16 + labour vars on C, govt. trend, consumer sentiment on G&C, spreads on G&I, select vars on Cv
■ CBDF 22	CBDF16 with added trade variables
■ CBDF 23	CBDF22 removed petroleum series and load new trade vars on T block
■ CBDF 24	CBDF23 + CBDF14
■ CBDF 25	CBDF23 + CBDF14 + 2 spread variables on I&G blocks
■ CBDF 26	CBDF25 with only corporate bond spread
■ CBDF 27	CBDF23 with exchange rate and commodity index on I
■ CBDF 28	CBDF24 $p_f = 1$
■ CBDF 29	CBDF26 $p_f = 1$
■ CBDF 30	CBDF29 with inventories modelled as growth rate in place of contribution
■ CBDF 31	CBDF30 add inventories to T block
■ CBDF 32	CBDF32 with $p_e = 2$
■ CBDF 33	CBDF32 with loosened priors on γ_e, γ_f: $\nu_e = \nu_f = 10$; $\sigma_e^2 = \sigma_f^2 = 0.005$
■ CBDF 34	CBDF32 with loosened priors γ_e, γ_f: $\nu_e = \nu_f = 2$; $\sigma_e^2 = \sigma_f^2 = 0.001$

A.3 Additional Results

Below, we provide all forecast results of the paper evaluated against the first release of GDP published by the BEA, known as the Advance Estimate.

FIGURE 23. RMSE against Advance GDP: DF specifications

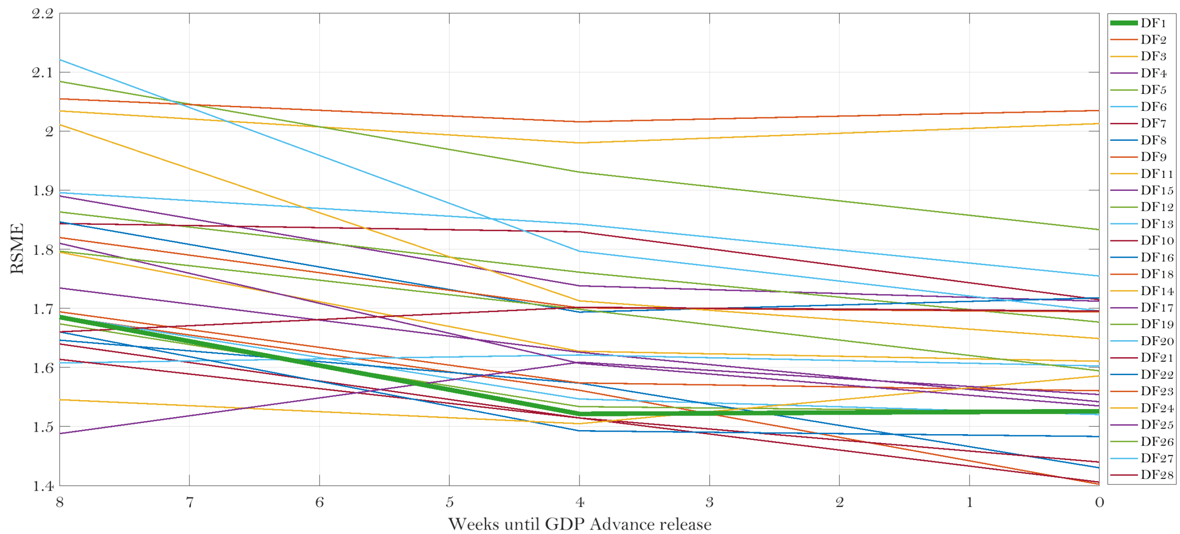


FIGURE 24. RMSE against Advance GDP: CBDF specifications

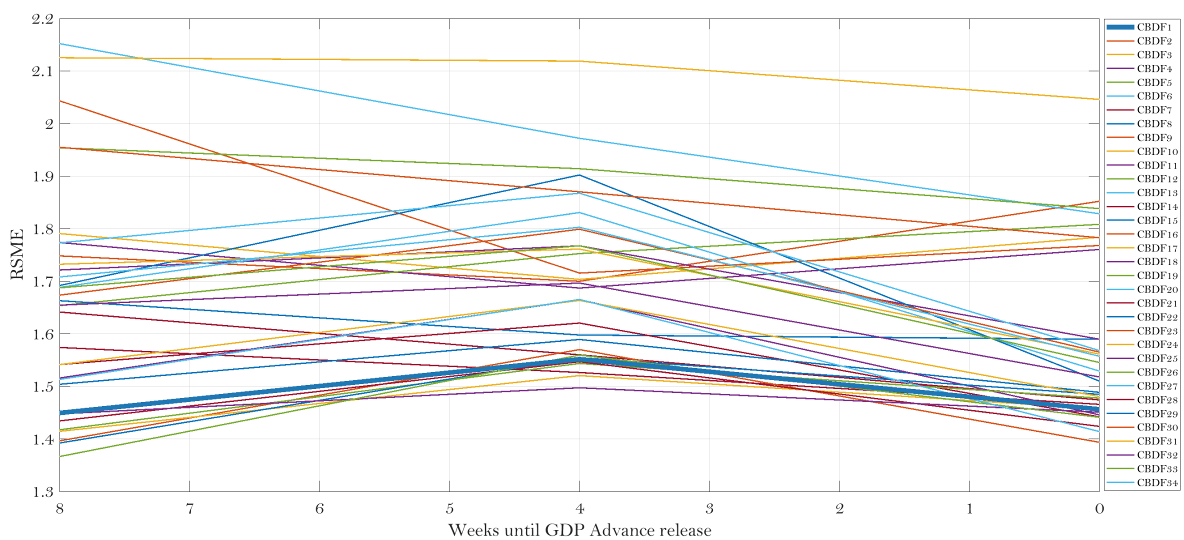


FIGURE 25. RMSE against Advance GDP

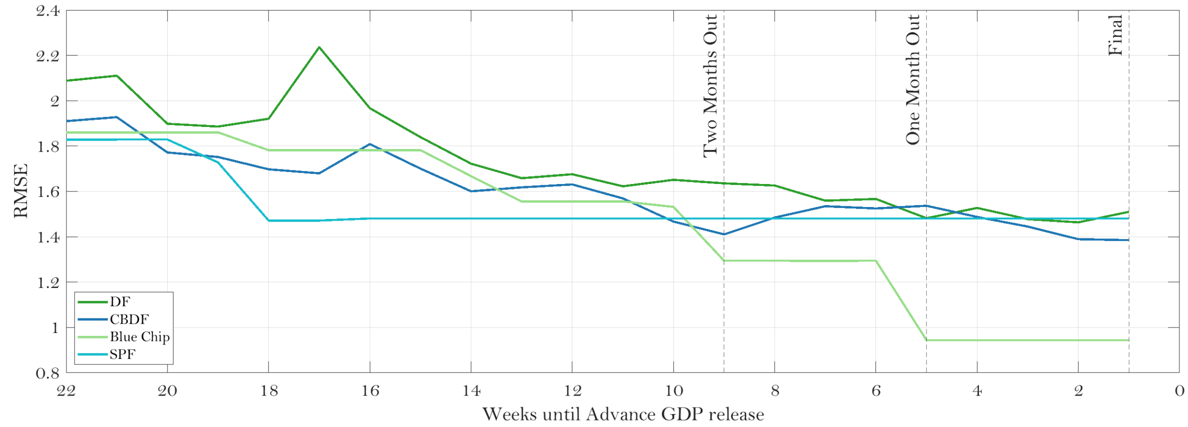


FIGURE 26. Bias against Advance GDP

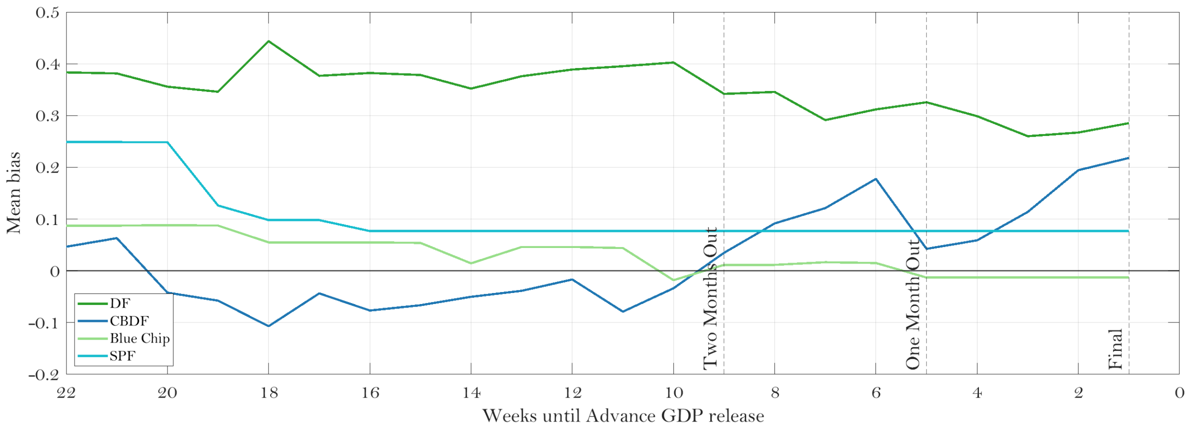


FIGURE 27. Log Scores against Advance GDP

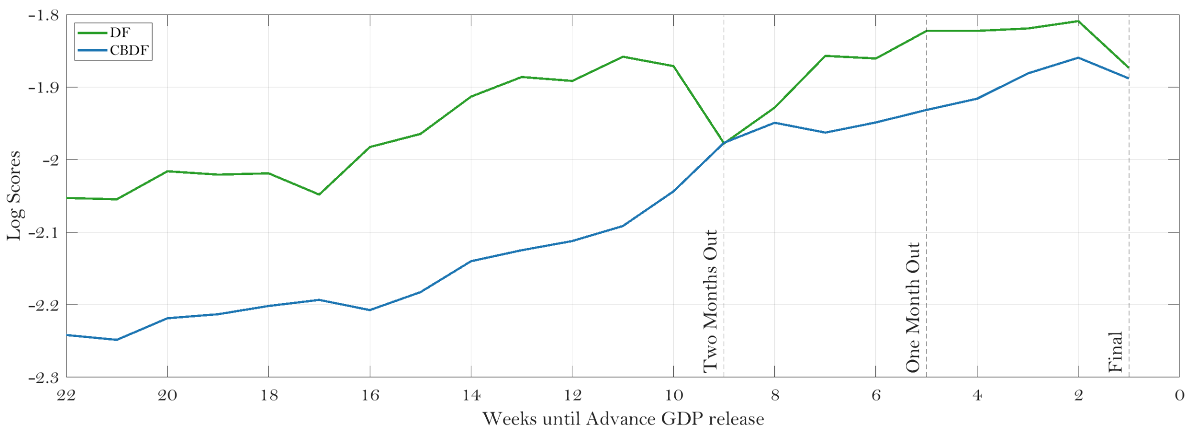


FIGURE 28. RMSE against Advance GDP

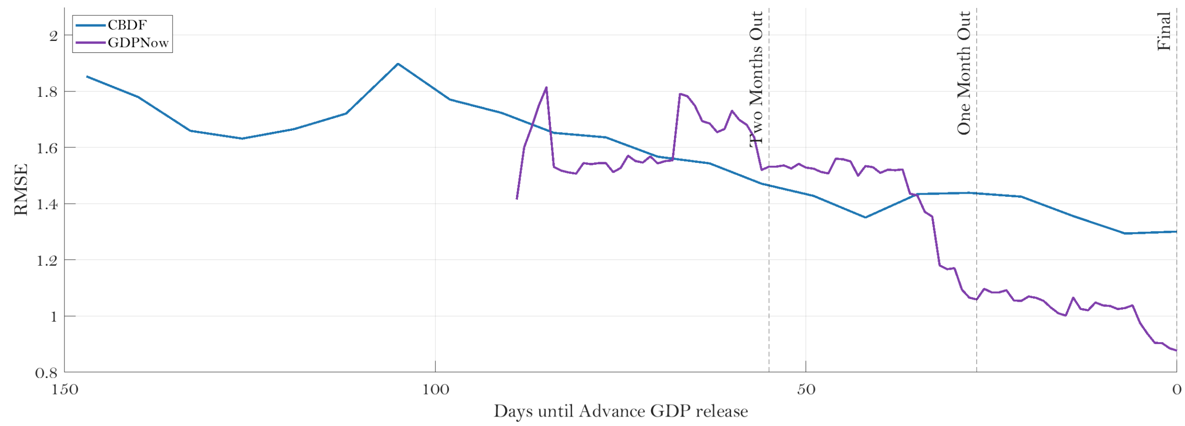


FIGURE 29. Component error decomposition against Advance GDP

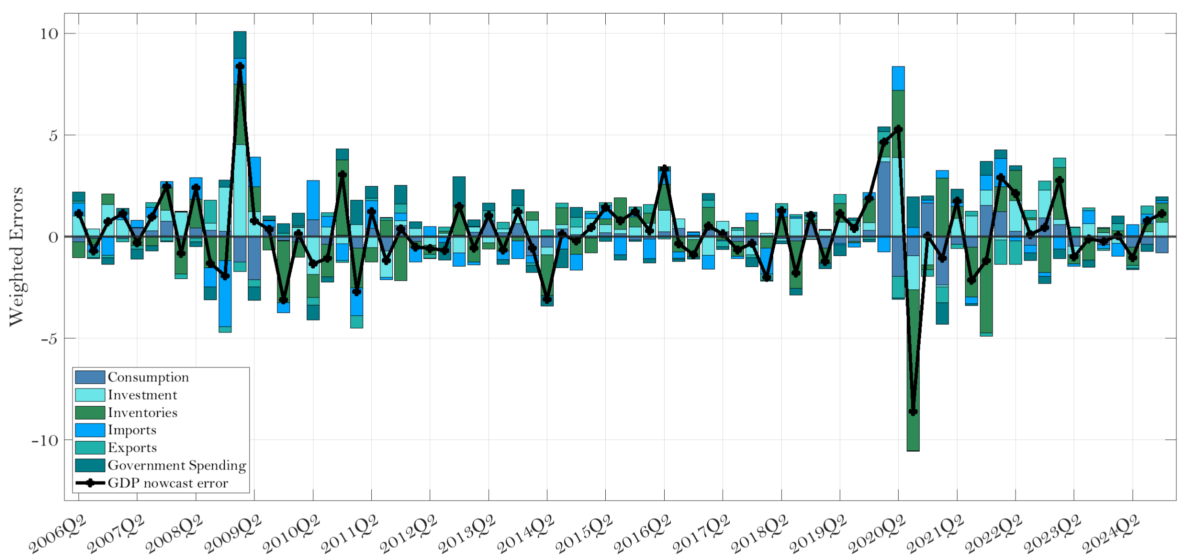


FIGURE 30. Consumption against Advance GDP

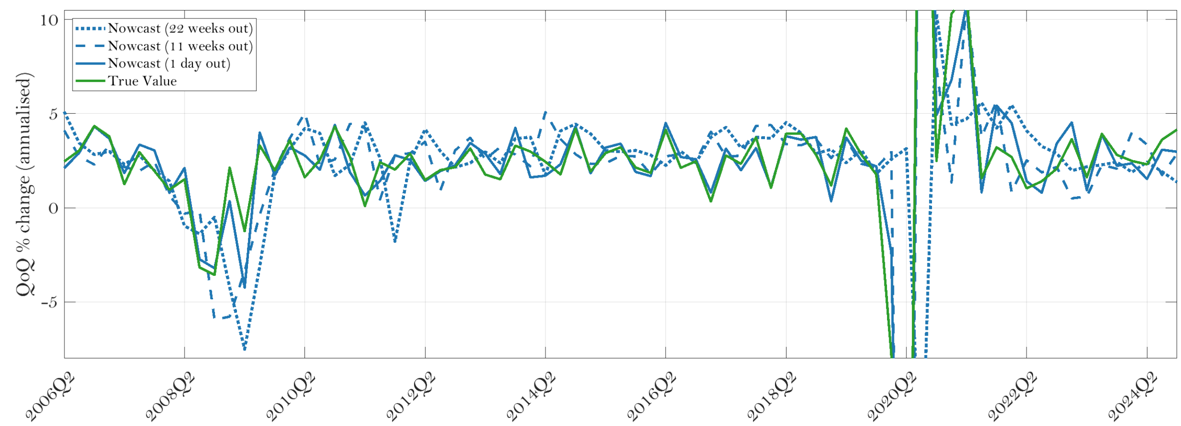


FIGURE 31. Investment against Advance GDP

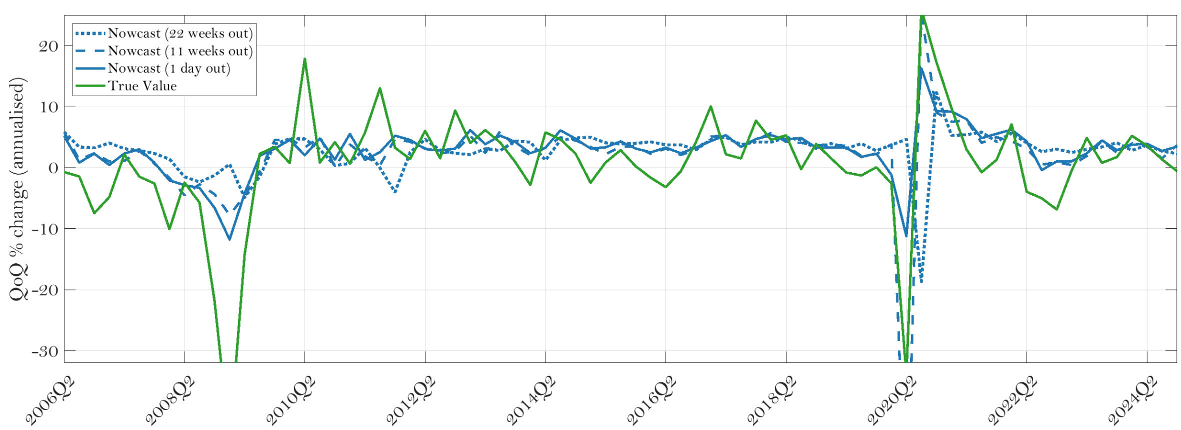


FIGURE 32. Imports against Advance GDP

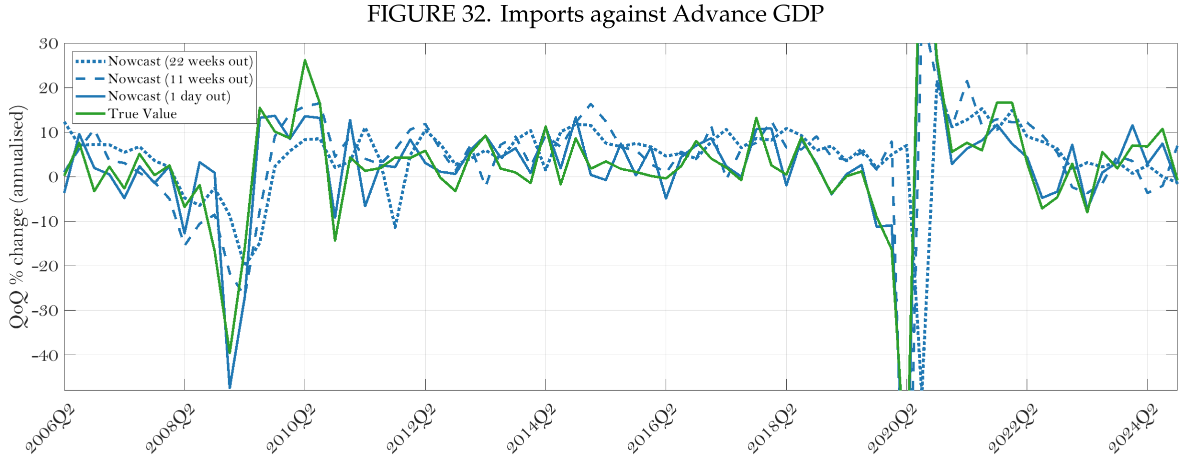


FIGURE 33. Exports against Advance GDP

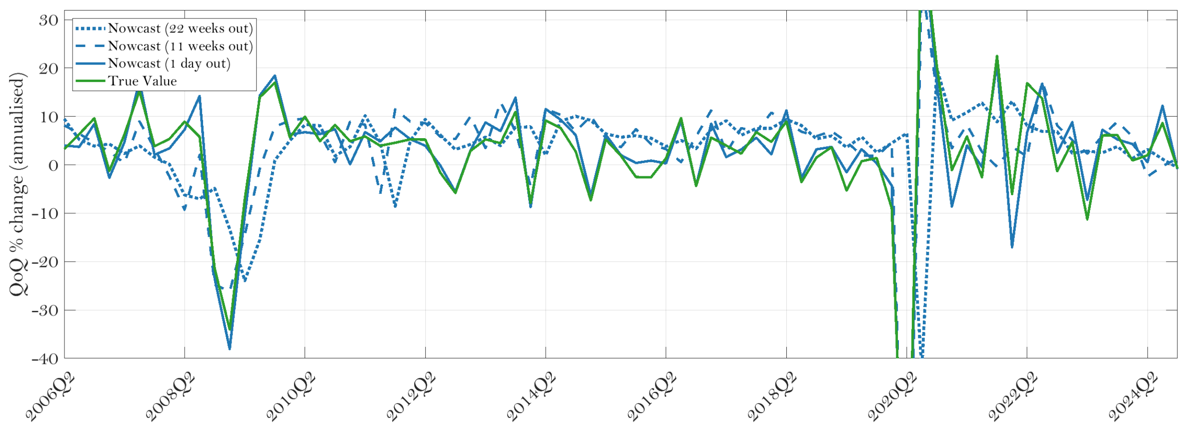


FIGURE 34. Inventories against Advance GDP

FIGURE 35. Government Expenditures against Advance GDP