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Discussion Papers

Deutsches Institut für Wirtschaftsforschung

2026

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IMPRESSUM

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<http://www.diw.de>

ISSN electronic edition 1619-4535

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Nowcasting the Income Distribution *

Nina Maria Brehl[†] Geraldine Dany-Knedlik[‡] Laura Pagenhardt[§]

Date: October 27, 2026

Abstract

This paper proposes a framework for nowcasting the income distribution in real time. Decile means of the annual U.S. household income distribution are combined with a panel of about 80 quarterly macroeconomic indicators in a mixed-frequency dynamic factor model (DFM) and evaluated pseudo-real-time from 1990 to 2024. Relative to an autoregressive benchmark, the DFM reduces decile-level nowcast errors by 16% on average and by up to 25% in the middle of the distribution; improvements are smallest at the two tails, with the volatile bottom decile the hardest to nowcast. The DFM also substantially improves directional accuracy, raising the share of detected turning points from 7% under the benchmark to 45%. The signal is available about eighteen months before the official release, and a news decomposition shows that labor-market releases carry more weight at the bottom of the distribution and price releases at the top. For inequality measures, the DFM does not improve on the benchmark. The framework complements microsimulation and functional approaches by supplying timely, evaluable decile-level signals from standard state-space tools for distributional surveillance and as real-time priors when micro data are delayed.

JEL codes: C32, C38, C53, D31, E27

Keywords: Nowcasting; Mixed-frequency dynamic factor models; Income distribution; Inequality; Turning point detection

*We thank Thomas Blanchet, Britta Gehrke, Raffaella Giacomini, Alexander Kriwoluzky, Robert Lehmann, Isabelle Méjean, Gabriel Pérez-Quirós, Malte Rieth, Frank Schorfheide, Ben Schumann, Elias Wolf and seminar and conference participants at the CEPR Symposium in Paris, the DIW Berlin and SOEP, the International Association for Applied Econometrics, the International Conference on European Economics and Politics, the International Symposium on Forecasting, the Ghent University Workshop on Empirical Macroeconomics, the IWH Workshop on Forecasting in Times of Structural Change and Uncertainty, the Sailing the Macro Workshop, the Society of Economic Measurement and the VGR Kolloquium Berlin for helpful comments and suggestions.

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1 Introduction

Macroeconomic surveillance routinely produces real-time estimates of GDP, employment, and inflation, drawing on a well-established mixed-frequency toolkit. The distributional consequences of macroeconomic fluctuations, by contrast, remain effectively invisible in real time: survey-based measures of the household income distribution are released with delays of at least nine to twelve months, while existing approaches to distributional nowcasting either rely on resource-intensive microsimulation pipelines that require contemporaneous micro inputs, or remain operationally untested at the release calendars relevant for policy use. This asymmetry matters most in periods of rapid economic change or large-scale policy intervention – precisely when distributional information is most valuable, policymakers and analysts must rely on aggregate signals that mask the heterogeneous responses across the income distribution. During the pandemic, for example, real income in the bottom decile of the U.S. household income distribution fell by more than 7% in 2020 and by almost a further 5% in 2021, while the top decile was essentially flat – a divergence that became observable in official statistics only in September of the following year.

This paper asks how the income distribution can be nowcast in real time, and proposes a framework that adapts the standard nowcasting machinery to distributional targets. We discretize the distribution into decile mean household incomes and combine these annual targets with a large panel of quarterly macroeconomic indicators in a mixed-frequency dynamic factor model (DFM), estimated by quasi-maximum likelihood via the expectation-maximization (EM) algorithm and Kalman smoother (Bańbura and Modugno, 2014; Doz et al., 2012). We evaluate nowcasts ($t \mid t$) and one-step-ahead forecasts ($t + 1 \mid t$) in a pseudo-real-time design against a univariate autoregressive benchmark, using root mean squared errors (RMSE) and directional accuracy at income-specific turning points. Beyond decile means, we assess model performance for two classes of inequality measures – percentile ratios and the top-bottom growth spread – constructed from the decile targets. Finally, we trace when during the year the signal becomes available and which data releases carry it, using the nowcasts at four quarterly information cut-offs and a news decomposition of their revisions.

The combination of a mixed-frequency DFM with a discretized distributional target is well suited to this problem on three grounds. First, DFMs have become the workhorse of macroeconomic nowcasting because they accommodate ragged-edge release calendars, mixed frequencies, and sequential news updates within a unified state-space framework, while compressing high-dimensional, noisy predictor panels into a small number of latent common factors (Bańbura and Modugno, 2014; Doz et al., 2011, 2012; Giannone et al., 2008; Stock and Watson, 2002). These properties fit our setting: the targets are annual, the predictor panel is large, and a strong common cyclical component runs through most of the distribution. Second, decile means are stable, interpretable point targets that interface naturally with this machinery. They capture heterogeneous business-cycle sensitivities

across the distribution while remaining robust to the sampling noise that affects narrower percentiles, and they admit standard forecast-evaluation metrics without the auxiliary modeling choices required by other approaches, such as functional time-series and functional MIDAS models (e.g. [Chang et al., 2024](#); [Chernozhukov et al., 2013](#); [Marcellino et al., 2024](#)). Third, the framework is complementary to existing approaches: by delivering updatable, evaluable decile-level signals from off-the-shelf state-space tools, it can be used stand-alone for surveillance and turning-point detection, or serve as a real-time prior in microsimulation pipelines ([Blanchet et al., 2022](#)) when micro data are delayed.

We implement the framework for the United States using annual decile-level total household income from the *Current Population Survey Annual Social and Economic Supplement* (CPS ASEC). Total income captures both labor and non-labor resources before tax, including transfers and retirement income, and therefore provides a more complete measure of household resources than labor income alone, particularly during downturns. We combine these micro-level data with a panel of up to 81 quarterly macroeconomic indicators for the U.S. economy, drawn from 100 candidate series. The income data cover the income years 1967 to 2024, collected in the ASEC waves 1968 to 2025; nowcasts and forecasts are evaluated for the income years 1990 to 2024.

Our findings suggest that incorporating macroeconomic information through a factor model improves nowcasts of the income distribution, above all in the middle of the distribution. A single-decile DFM, which adds the macroeconomic panel to the history of one income series, reduces the RMSE relative to the autoregressive benchmark in nine of ten deciles, by 12% on average and by up to 21% in the middle of the distribution. Estimating all deciles jointly improves the nowcasts further in every decile: the pooled DFM reduces the RMSE by 16% on average and by 21–25% in the upper-middle deciles, where the gains are statistically significant. These improvements are heterogeneous along the distribution in an economically interpretable way. Macroeconomic indicators are most informative for the middle deciles, where labor-market, wage, and consumption dynamics dominate income growth. Relative gains are smallest at the two tails. At the top, this is consistent with top-decile dynamics that are less tied to the business cycle; at the bottom it reflects the pronounced idiosyncratic volatility of low-income households, which also leaves the bottom decile with the largest absolute errors in the distribution. One-step-ahead forecasts improve on the benchmark by 16% on average, significantly in every decile. Directional accuracy improves even more markedly: the benchmark detects almost none of the turning points in decile income growth (7% on average), whereas the pooled DFM identifies 45% of them, and the share of correctly predicted signs rises from 59% to 77%, with significant directional accuracy in every decile. For the inequality measures, whose relative movements largely net out the common cyclical component, the DFM adds little.

The timing of the signal is particularly relevant for policy use. Nowcast accuracy is essentially flat over the year: the nowcasts produced at the end of the first quarter, when the model has observed

only the first quarter of the current year’s macroeconomic data and income data up to two years back, are as accurate as those of October, so that the signal is available about eighteen months before the official release. The release of the previous year’s income data in September does not improve the nowcasts; the predictive content lies in the macroeconomic data. A news decomposition shows which releases carry it: national-accounts measures of wages and personal income account for the largest share of the news throughout the distribution, followed by timely labor-market, housing, and sentiment indicators, and the weights shift systematically along the distribution, with labor-market indicators mattering most at the bottom and price indicators at the top.

Notably, the performance gains come from the factor structure and the joint modeling of the distribution rather than from further elaboration. Shrinking the predictor set via elastic net pre-selection and imposing distribution-structured block loadings do not improve on the performance of a plain unrestricted DFM estimated jointly for all deciles on the full panel, and three common factors suffice. An off-the-shelf specification is sufficient – a result that suggests that the common factors already absorb most of the predictive content in the macroeconomic panel, while also simplifying implementation.

This paper relates to three strands of the literature.

A first strand concerns real-time inequality measurement via microsimulation and reweighting. The microsimulation approach of [Blanchet et al. \(2022\)](#) integrates multiple micro sources with tax-and-benefit rules to reconstruct current distributions and produce policy-relevant decompositions and counterfactuals.¹ These pipelines deliver cross-sectional detail and program-level attribution that no time-series approach can match. Their accuracy is assessed by comparing preliminary with final estimates rather than against forecasting benchmarks over a long evaluation sample, and their reliance on contemporaneous micro inputs limits their applicability when survey data are delayed. We contribute a complementary tool: updatable decile-level signals from standard state-space machinery that can be evaluated with conventional performance metrics and used as real-time priors in microsimulation pipelines.

A second strand concerns the modeling of distributional dynamics. Functional time-series approaches model the entire distribution or its density-valued objects, delivering shape-coherent inference across quantiles ([Chang et al., 2024](#); [Marcellino et al., 2024](#)). Quantile and distribution regression frameworks provide micro-founded heterogeneity and counterfactual interpretation ([Chernozhukov et al., 2013](#); [Koenker, 2004](#)), with recent extensions incorporating latent factor structures to capture common drivers across quantiles ([Chen et al., 2021](#)). These approaches deliver representational richness but require basis, bandwidth, and prior choices to discipline their high-dimensional parameter spaces, and they integrate less naturally with the ragged-edge release calendars that characterize operational nowcasting environments. By targeting decile means within a

¹See [Levy \(2023\)](#) for an international implementation building on this framework.

standard mixed-frequency DFM, we provide a lightweight and operational alternative that captures heterogeneous responses across the distribution while remaining directly compatible with the standard forecast-evaluation toolkit.

A third strand concerns mixed-frequency aggregation for macroeconomic nowcasting. Bridge equations, MIDAS regressions, and dynamic factor models have established the canonical toolkit for synthesizing high-frequency indicators to nowcast low-frequency aggregates such as GDP and industrial production (Bańbura and Modugno, 2014; Giannone et al., 2008; Mariano and Murasawa, 2003).² Mixed-frequency DFMs have become standard at policy institutions because of their scalability, ragged-edge handling, and transparent state-space representation. We extend this canonical machinery to distributional targets, whose publication lags are particularly severe, and show that the magnitude of the resulting gains is comparable to those documented for GDP nowcasting and for annual regional targets (Barbaglia et al., 2026) – evidence that the standard toolkit transfers to survey-based distributional targets without loss of predictive performance.

The remainder of the paper is structured as follows. Section 2 describes the micro- and macro-level variables and dataset construction. Section 3 details the mixed-frequency DFM, the model specification, and the evaluation protocol. Section 4 reports the empirical results. Section 5 concludes.

2 Data

2.1 Micro-level data

We use annual micro-level data from the *Current Population Survey Annual Social and Economic Supplement* (CPS ASEC), jointly administered by the U.S. Census Bureau and the Bureau of Labor Statistics and obtained through IPUMS-CPS (Flood et al., 2025). The ASEC is fielded annually in March and collects the income of all household members for the previous calendar year, together with employment, demographic characteristics, and program participation. We work at the household level, one observation per household and survey year, weighted by the ASEC household weight (ASECWT). The analysis sample comprises about 61,000 households per year and covers income years 1967 to 2024, collected in the ASEC waves 1968 to 2025, so that year-on-year growth rates are available for the income years 1968 to 2024.

Our target is total household income, captured by the CPS variable HHINCOME, which aggregates pre-tax cash income from all household members during the calendar year: wage and salary earnings, self-employment income, pensions, asset income (interest, dividends, rents), and cash transfers

²For accessible overviews, see Bok et al. (2018); the foundations of large-dimensional factor forecasting are discussed in Stock and Watson (2002) and Forni et al. (2000).

(Social Security, SSI, unemployment insurance, and other government benefits). We focus on total household income because it captures the joint distribution of labor, capital, and transfer resources and is of particular policy relevance.³

Throughout the paper, all income series are indexed by the *income year*, that is, the calendar year to which the reported incomes refer, rather than by the survey year in which they were collected. This convention matters for the nowcasting exercise: the ASEC microdata for income year t are released in September of year $t + 1$, so that a nowcast of the income distribution of year t produced at the end of the third quarter of year t precedes the official release by roughly twelve months.

We drop households with special income codes, missing income, or non-positive weights, and in the 2014 wave the subsample that received the redesigned income questionnaire. Nominal incomes are deflated by the Consumer Price Index for All Urban Consumers (CPI-U) of the income year and expressed in constant 1983 dollars. Because of methodological changes in CPS topcoding from income year 1995 onward, we winsorize the top 5% of the weighted within-year distribution, that is, incomes above the weighted 95th percentile of a given year are set to that percentile. Sample construction, the treatment of the upper tail, and survey breaks are documented in Appendix A.1.

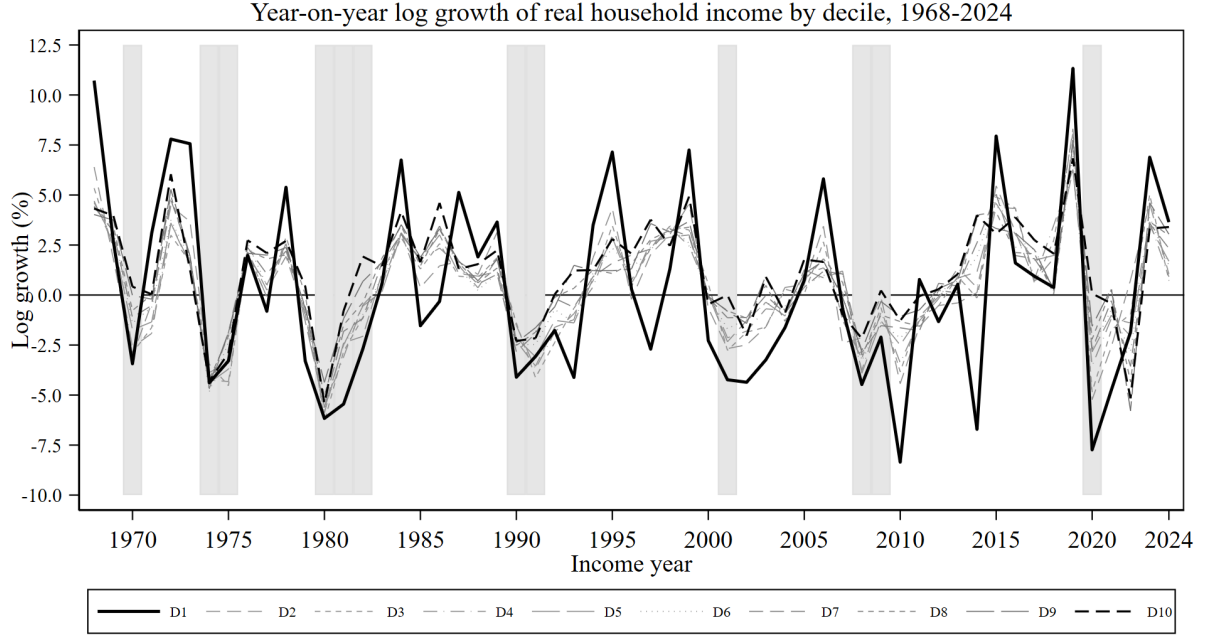
We partition households into deciles of the weighted, winsorized within-year income distribution and compute the weighted mean real income within each decile. To achieve stationarity, we transform the decile means into year-on-year log growth rates, $g_{d,t} = 100 (\ln \bar{y}_{d,t} - \ln \bar{y}_{d,t-1})$, which serve as the nowcasting targets and are consistent with the log-linear temporal aggregation in Section 3.2. Figure 1 displays the growth rates of real decile mean household income for the income years 1968 to 2024. A strong common cyclical component is evident, and the lower half of the distribution contracts in every recession year shaded in the figure. The pandemic period illustrates the heterogeneity that motivates our exercise: in income year 2020, real income in the bottom decile fell by more than 7% while the top decile was flat, and the bottom decile contracted again in 2021 while the upper half of the distribution had already stabilized.⁴ At the same time, the bottom decile displays markedly greater volatility, while average growth is higher in the upper deciles. The summary statistics in Table 1 confirm this impression: average growth rises from the middle of the distribution towards the top, while volatility is highest at the bottom of the distribution and fairly uniform across its upper half.

In addition to decile means, we evaluate our framework’s ability to nowcast standard measures of inequality: the percentile ratios P90/P10, P50/P10, P90/P50, and the income growth spread between the top (D10) and bottom (D1) of the distribution. These measures are widely used to

³We do not equalize for household size. Negative incomes, which arise from self-employment and farm losses, are retained and fall into the bottom decile.

⁴The preceding income year 2019 shows the largest common increase in the sample, with growth between 6% and 11% across deciles. This observation is collected in the 2020 ASEC, whose response rates were affected by the pandemic; see Appendix A.1.5.

Figure 1: Year-on-year growth of real household income by decile, 1968–2024



Notes: Year-on-year log growth rates ($\times 100$) of within-year decile means of real household income (CPS ASEC, HHINCOME), one observation per household, weighted by ASECWTH, deflated by the CPI-U of the income year (1983=100). Upper tail winsorized within year at the 95th percentile. Time axis in income years. Gray zones are NBER recession years (calendar years with at least six months of recession).

Table 1: Year-on-year growth of real household income by decile: summary statistics

Decile	Mean	Abs. Mean	Std. Dev.	Min	Max
D1	0.29	3.83	4.71	-8.35	11.33
D2	0.37	2.39	2.98	-5.89	8.31
D3	0.30	2.26	2.85	-6.31	8.10
D4	0.29	2.13	2.60	-5.62	6.28
D5	0.36	2.08	2.48	-5.59	6.23
D6	0.47	2.03	2.47	-5.73	6.97
D7	0.60	2.02	2.47	-5.47	7.55
D8	0.75	2.01	2.44	-5.04	7.52
D9	0.93	2.08	2.48	-5.79	7.75
D10	1.15	2.25	2.57	-5.41	6.84

Notes: Descriptive statistics of year-on-year decile-mean log growth ($\times 100$) of within-year real household income, income years 1968–2024 ($T = 57$). Mean is the average growth rate, Abs. Mean the average absolute growth rate. Data construction as in Figure 1.

summarize the shape of the income distribution and the relative position of households across its segments.

Percentile values are approximated from decile mean incomes as follows. The median is approximated as the average of the fifth and sixth decile means, $P50_t = (D5_t + D6_t)/2$. The

tenth and ninetieth percentiles are approximated by interpolation within the adjacent deciles, $P10_t = 0.8 D1_t + 0.2 D2_t$ and $P90_t = 0.8 D9_t + 0.2 D10_t$. Since these are interpolations of decile means rather than sample percentiles, we refer to the resulting ratios as decile-mean ratios where the distinction matters. The growth spread is defined as the difference between the year-on-year log growth of the top and the bottom decile mean, $\text{Spread}_t = g_{10,t} - g_{1,t}$.

2.2 Macro-level data

The candidate panel consists of 100 quarterly U.S. macroeconomic series. A series enters the estimation of a given vintage once it covers at least two thirds of the estimation sample from 1968Q1, so that the number of predictors rises from 66 in the first vintage to 81 in the last; 19 candidate series never meet this rule within the evaluation period. The predictor panel is grouped for presentation into seven categories: *Output and Growth* (e.g. real GDP, industrial production, total hours worked), *Labor Market* (e.g. wages and unemployment), *Consumption and Income* (e.g. personal income, consumer credit, household liabilities), *Housing and Investment* (e.g. building permits, housing starts, house prices), *Prices and Inflation* (e.g. CPI, PPI, PCE deflators, oil prices), *Financial Conditions* (e.g. federal funds rate, real Treasury yields, equity prices), and *Surveys and Sentiment* (e.g. PMIs and consumer sentiment indices). The complete list of series, including source mnemonics, sample coverage, and transformations is provided in Appendix Table A3.

Monthly, weekly, and daily series are averaged within the quarter. Nominal series are deflated, series without seasonal adjustment at the source are adjusted by STL, the seasonal-trend decomposition based on loess (Cleveland et al., 1990), and each series is then transformed to stationarity by first differences, log differences, or second log differences as documented in Appendix Table A3. All predictors are standardized prior to estimation.

To replicate operational nowcasting conditions, we construct quarterly pseudo-real-time data vintages. A vintage dated on the first day of a quarter contains every observation whose release date falls on or before that day. For series obtained from FRED, we use the first-release dates recorded in the ALFRED archive, so that, for instance, the vintage of April 1 does not yet contain March payroll employment, which is published in the first week of April. ALFRED dates are used only where they refer to an individual observation. Observations that were loaded into the archive in bulk, as is common for the early part of a series, receive an inferred availability date instead. Inferred dates are also used for all Macrobond series and follow a frequency-specific rule: an observation of a monthly, weekly, or daily series is assigned the first day of the quarter following the observation quarter as its release date, so that the quarterly aggregate enters the vintage dated on that day. An observation of a quarterly series is assigned the first day of the second month of the following quarter. The annual income data of year $t - 1$ enter the vintages from October 1 of year t , in line with the September

release of the ASEC. Each vintage therefore reproduces the data that a forecaster could have used on the vintage date, up to revisions of previously published observations, which the vintages do not track.

3 Methodology

To nowcast the discretized household income distribution, we employ a mixed-frequency dynamic factor model (DFM) and compare the results to a univariate autoregressive benchmark. The benchmark provides a parsimonious baseline that uses only the history of the target series, so that the gain from the DFM measures the predictive content of the macroeconomic information. The DFM, in turn, exploits the common variation in a broad panel of quarterly macroeconomic indicators to produce decile-level nowcasts. This section describes both models, the specifications considered, and the out-of-sample evaluation protocol.⁵

3.1 Autoregressive benchmark

Our benchmark is a univariate $AR(p)$ model with constant, estimated separately for each target series, that is, for each decile growth rate and each inequality measure. It allows for fully series-specific dynamics without imposing cross-decile relationships and is a standard baseline in the forecasting literature (Hyndman and Athanasopoulos, 2018). Since the log growth rates are stationary, no differencing is required. The lag order is chosen anew in every vintage by the Bayesian Information Criterion (Schwarz, 1978), using only the income years observed at the vintage date. The candidate orders are $p \in \{0, 1, 2\}$, where $p = 0$ reduces the model to its constant, that is, to the historical mean of the series. The estimation window expands with each vintage and starts in 1968. Because the ASEC for income year $t - 1$ is released in September, the benchmark observes income growth up to $t - 1$ in the vintages of the third and fourth quarter, and only up to $t - 2$ in those of the first and second quarter, so that the nowcast for year t is a one-step-ahead forecast in the former and a two-step-ahead forecast in the latter. For the decile series the BIC selects $p = 2$ in two thirds of the series-vintage combinations and the historical mean in one fifth, with a shift towards $p \leq 1$ after 2020; for the inequality measures it selects the historical mean in all but one case. We refer to this benchmark as AR.

⁵While we describe the framework in terms of the U.S. application, nothing in the setup is specific to it: the same machinery applies to any low-frequency, survey-based distributional target combined with a higher-frequency predictor panel.

3.2 Mixed-frequency dynamic factor model

To nowcast the discretized household income distribution we employ a mixed-frequency DFM estimated with the quasi-maximum likelihood approach of [Bańbura and Modugno \(2014\)](#) in the block implementation of [Bok et al. \(2018\)](#). DFMs are well suited to capturing common cyclical variation across large sets of variables, making them an effective tool for nowcasting deciles throughout the distribution. Their mixed-frequency structure allows quarterly macroeconomic indicators to be combined with annual income data within a unified framework. This section provides a brief overview of the mixed-frequency DFM and the model specifications used throughout the analysis. Full details are provided in Appendix B.

Let y_t denote an n -dimensional vector of stationary macroeconomic indicators and annual income-decile targets. We assume the standard factor representation

$$y_t = \Lambda f_t + e_t + \xi_t, \quad \xi_t \sim \mathcal{N}(0, R), \quad (1)$$

where f_t is a $k \times 1$ vector of latent common factors and Λ is an $n \times k$ loading matrix. The idiosyncratic component e_t is orthogonal to the factors and captures series-specific variation. It is serially correlated and follows a univariate autoregressive process of order one,

$$e_t = \Phi e_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \Sigma),$$

where $\Phi = \text{diag}(\rho_1, \dots, \rho_n)$ and innovations are mutually uncorrelated across series. The term ξ_t is a white-noise measurement error with diagonal covariance matrix $R = \text{diag}(r_1, \dots, r_n)$.

Each factor follows a univariate autoregressive process of order one,

$$f_{j,t} = a_j f_{j,t-1} + u_{j,t}, \quad u_{j,t} \sim \mathcal{N}(0, q_j), \quad j = 1, \dots, k, \quad (2)$$

and the factors are mutually uncorrelated, so that the transition matrix and the innovation covariance of the factor block are diagonal. This is the structure of [Bok et al. \(2018\)](#), which is more parsimonious than an unrestricted factor VAR and pins down the rotation of the factors through their distinct persistence. In the baseline specification every series loads on all k factors; the block specifications in Section 3.3 restrict selected loadings to zero.

The factor f_t in Equation (2) evolves at the higher, quarterly frequency and drives both the quarterly and the annual series. The lower-frequency series are therefore only observed every fourth period. We model the annual series as functions of a latent quarterly process ([Mariano and Murasawa, 2003](#)). Specifically, the annual income growth rate can be expressed as a weighted sum of unobserved quarterly growth rates. Approximating the annual level by the average of the four quarterly levels, $\log Y_t^A \approx \frac{1}{4} \sum_{i=0}^3 \log Y_{t-i}^q$, gives

$$\begin{aligned}
y_t^A &= \Delta \log Y_t^A = \log Y_t^A - \log Y_{t-4}^A \\
&\approx \frac{1}{4} \left(\sum_{\iota=0}^3 \log Y_{t-\iota}^q - \sum_{\iota=4}^7 \log Y_{t-\iota}^q \right) \\
&= \frac{1}{4} (y_t^q + 2y_{t-1}^q + 3y_{t-2}^q + 4y_{t-3}^q + 3y_{t-4}^q + 2y_{t-5}^q + y_{t-6}^q), \tag{3}
\end{aligned}$$

where $y_t^q = \Delta \log Y_t^q$ denotes the unobserved quarter-on-quarter growth rate of the annual income variable. Since all series are standardized before estimation and the loadings are estimated freely, the scale factor $\frac{1}{4}$ is immaterial for the results.

Since the factors are unobserved, model parameters cannot be estimated in closed form. We follow the quasi-maximum likelihood approach of [Bańbura and Modugno \(2014\)](#) and estimate the model via the expectation-maximization algorithm combined with the Kalman smoother ([Dempster et al., 1977](#)). Prior to estimation all series, including the annual targets, are standardized with the mean and standard deviation of the respective vintage. Nowcasts are then transformed back to the original scale. A key advantage of this framework is its ability to handle arbitrary patterns of missing data, mixed frequency, and “ragged edges,” allowing the inclusion of series that begin after the first evaluation vintage, and hence the expansion of the information set as new data become available.

The EM algorithm converges to a local maximum of the likelihood and is sensitive to its starting values on short annual targets. In each vintage we therefore run it twice, once initialized by principal components of the balanced panel and once by the parameter estimates of the preceding vintage (previous-year quarter), and keep the run with the higher likelihood. The iterations stop when the relative change of the log-likelihood falls below 10^{-4} .

3.3 Model specifications

Our baseline specification, DFM-Pooled, models the ten decile growth rates jointly with the full macroeconomic panel and three common factors. Pooling lets the model exploit the strong comovement across deciles documented in Appendix Table [A2](#), while unrestricted loadings allow each decile to respond differently to the common factors. All predictors that satisfy the coverage rule of Section [2.2](#) enter without prior selection, so that the baseline involves no data-driven choice that could introduce forward-looking information. The number of factors is chosen by comparing specifications with one to four factors in the pseudo-real-time evaluation: the third factor improves accuracy significantly over one and two factors across the distribution, whereas a fourth factor yields no further significant gain (Clark-West tests in Appendix [C.3](#)). We therefore use three factors throughout.

We consider four departures from the baseline. First, DFM-Single models each target separately, with the same predictor panel and three factors, and thus allows for fully heterogeneous dynamics at the cost of ignoring cross-decile information. The comparison between the pooled and the single specification isolates the value of pooling. Second, the inequality measures of Section 2.1 can be nowcast in two ways: directly, by using the log growth of a ratio or the growth spread as the target of a single-target DFM, or indirectly, by computing the measure from the pooled decile nowcasts. We report both strategies, since their agreement is informative about whether the discretized representation of the distribution is internally consistent.

Third, following the observation of Boivin and Ng (2006) that a carefully chosen subset of indicators can outperform a very large panel when idiosyncratic components are persistent or cross-correlated, we shrink the predictor set with an elastic net estimated on the expanding window of each vintage (Zou and Hastie, 2005). We consider four selection rules: all indicators with non-zero coefficients at the cross-validated penalty and mixing parameter, and the first 5, 10, and 20 of these in order of entry along the elastic net regularization path (fewer if the elastic net retains fewer). The selection is run separately for each decile, and the union across the ten deciles forms the predictor panel of the pooled DFM. The elastic net, including the cross-validation of its tuning parameters, is re-estimated at each vintage using only data available at that date, so the selection never uses information beyond the vintage date. Fourth, we impose a block structure on the loadings (Bok et al., 2018; Cascaldi-Garcia et al., 2024): a global factor loads on all series, and additional group factors load only on the deciles of a segment of the distribution and on the predictors selected by the elastic net for at least one decile of that segment. We consider three segmentations, (a) deciles 1–6 and 7–10, (b) deciles 1–7 and 8–10, and (c) deciles 1–3, 4–7, and 8–10, where designs (a) and (b) have three factors like the baseline and design (c) has four. Appendix Sections B.2 and B.3 give the details of the selection procedure and of the block designs.

Finally, since the pandemic quarters are extreme relative to the rest of the sample, we re-estimate the baseline with all macroeconomic observations of 2020Q2 to 2020Q4 set to missing in every vintage that contains them. The masked observations thus enter neither the parameter estimation nor the information set from which the nowcasts are computed, so that the nowcast for 2020 relies on the macroeconomic data up to 2020Q1. The income data are not affected, and the vintages up to 2019, which do not contain the pandemic quarters, are identical to the baseline. Results for all alternative specifications are reported in Section 4.5 and Appendix C.2.

3.4 Out-of-sample evaluation

To assess the forecasting performance of the different models, we implement a pseudo-real-time evaluation exercise (e.g. Giannone et al., 2008; Proietti et al., 2021). For each income year t between

1990 and 2024, we reconstruct the information set available on October 1 of year t , the first day of the fourth quarter. We label the four information cut-offs of a year by the quarter in which they fall: Q1 (April 1), Q2 (July 1), Q3 (October 1), and Q4 (January 1 of the following year). The main results use the Q3 cut-off. At that point the most recent ASEC release refers to income year $t - 1$, so that the exercise is a genuine nowcast of the distribution of year t about twelve months ahead of its publication.⁶ The information set accounts for the publication date of every observation, using the first-release dates of the ALFRED archive for FRED series and a frequency-specific publication lag for the remaining series, as described in Section 2.2. We use the most recent data vintage and abstract from historical data revisions, thereby isolating the effect of the information flow rather than revision noise.

Given this pseudo-real-time dataset, each model is re-estimated on an expanding window starting in 1968 and used to produce a nowcast for income year t and a forecast for year $t + 1$. For the October vintages, the nowcast is a one-step-ahead and the forecast a two-step-ahead prediction relative to the last observed income year. Realized log growth rates of the decile means and the inequality measures are then compared with the model predictions to compute root mean squared errors (RMSE). We report RMSE in absolute terms and relative to the AR benchmark of Section 3.1, which is estimated for every target series with the same information set and horizon. Differences in predictive accuracy between non-nested models are tested with the Diebold–Mariano test (Diebold and Mariano, 1995). Given the short evaluation sample of 35 years, we apply the small-sample correction of Harvey et al. (HLN, 1997) throughout. Comparisons between nested factor specifications use the Clark–West test (Clark and West, 2007). Both use a Newey–West variance (Newey and West, 1987) with one lag, and we report significance at the 5% and 10% levels.⁷ Detailed test results by decile are reported in Appendix C.3.

Beyond point forecasts, we evaluate directional accuracy. We define a turning point as a sign change of the year-on-year growth rate of a decile mean between two consecutive years. The hit rate is the share of actual turning points that the model identifies in both timing and direction, and the precision is the share of turning points signaled by the model that actually occurred. We report both, since a model that signals many turning points can achieve a high hit rate at the cost of false alarms. We complement these with the share of years in which the sign of the nowcast is correct and assess its significance with the test of Pesaran and Timmermann (1992), which compares the share of correct signs with the share expected if predicted and realized signs were independent. We deliberately do

⁶Section 4.3 reports results for the Q1, Q2, and Q4 cut-offs, which deliver similar accuracy.

⁷For the two-step-ahead predictions (forecasts of $t + 1$ and nowcasts at the first- and second-quarter cut-offs) one lag corresponds to the usual choice of $h - 1$. For the one-step-ahead nowcasts, optimal forecast errors would be serially uncorrelated and no lag would be required. We nevertheless allow for first-order autocorrelation, since the errors of models re-estimated on overlapping expanding windows need not be uncorrelated in practice, and with 35 observations a single lag is a small cost. With zero lags, the conclusions are unchanged.

not condition on aggregate business-cycle turning points such as those dated by the NBER, since distributional inflection points need not coincide with aggregate recessions and expansions.

4 Results

4.1 Nowcast performance

We assess the nowcasts in two steps. We first ask what macroeconomic information adds to a single income series, comparing the single-decile DFM to the $AR(p)$ benchmark. We then investigate what the remaining deciles add through a pooled DFM. Table 2 reports the RMSE of both DFMs relative to the benchmark. Values below unity indicate an improvement over the benchmark; significance refers to the Diebold–Mariano test with HLN correction of Section 3.4.

Table 2: RMSE relative to the $AR(p)$ benchmark by model and income decile

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Avg
$AR(p)$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DFM-Single	0.97	0.85	0.83	0.88	0.88	0.81*	0.79*	0.83*	0.89	1.00	0.88
DFM-Pooled	0.94	0.84	0.80	0.84	0.83	0.76*	0.75**	0.79*	0.85	0.95	0.84

Notes: Root mean squared errors relative to the $AR(p)$ benchmark at the nowcast horizon ($t | t$), October 1 (Q3) cut-off, income years 1990–2024. Values below unity indicate an improvement over the benchmark. Avg denotes the ratio of cross-decile average RMSE. DFM-Single is a three-factor DFM with a single decile series and the full predictor panel; DFM-Pooled predicts all deciles jointly with the same panel and number of factors. Significance from the Diebold–Mariano test against $AR(p)$ with HLN small-sample correction: ** $p < 0.05$, * $p < 0.10$. Bold: lowest value per column.

The $AR(p)$ benchmark is deliberately simple, and this simplicity is informative. Year-on-year growth of decile-mean income is only weakly autocorrelated, so the history of an income series carries little information about its growth in the following year. The improvement of the single-decile DFM over the benchmark therefore measures the predictive content that the macroeconomic panel adds to what the history of the income series itself can deliver.

The results suggest that incorporating macroeconomic information alone improves the nowcasts in nine of ten deciles: the single-decile DFM reduces the RMSE by 12% on average relative to the benchmark. The gains are concentrated in the middle of the distribution: in D6 to D8 the RMSE falls by 17–21%. Averaged over all deciles, the improvement is not significant at conventional levels, which reflects both the small evaluation sample and the weak gains at the tails, where macroeconomic information adds little: the RMSE falls by 3% for D1 and not at all for D10. At the top, decile-mean growth is as volatile as in the middle of the distribution (Table 1), yet the macroeconomic panel explains little of it: top incomes are less tied to the labor-market and demand variables that dominate the panel, and winsorization at the 95th percentile (Appendix A.1) removes the incomes whose

variation is most closely linked to the cycle from the decile mean. At the bottom, income growth is dominated by idiosyncratic shocks that the macroeconomic panel cannot anticipate. In the middle of the distribution, by contrast, incomes are predominantly driven by labor-market, wage, and consumption dynamics, which the quarterly predictor panel measures well. Section 4.3 shows which indicators drive the nowcasts in the different parts of the distribution.

The gains are qualitatively in line with the mixed-frequency DFM nowcasting literature. [Barbaglia et al. \(2026\)](#) apply a closely related approach to nowcast annual regional gross value added for European NUTS-2 regions with quarterly information, a setting that shares both the frequency mismatch and the cross-sectional structure of our application, and document improvements over univariate benchmarks; analogous evidence exists for quarterly GDP ([Bańbura and Modugno, 2014](#); [Giannone et al., 2008](#)). Our results show that the standard mixed-frequency DFM machinery carries over to low-frequency, survey-based distributional targets, with the largest gains where incomes are most closely tied to the business cycle.

Estimating all deciles jointly improves the nowcasts further. The pooled DFM has a lower RMSE than the single-decile DFM in every decile, by about 4% on average.⁸ Relative to the benchmark, the pooled DFM reduces the RMSE by 16% on average and by 21–25% in D6 to D8. With ten instead of one income series, the model can determine more precisely the part of the common macroeconomic variation that is relevant for household income and how strongly each decile loads on it. Given the strong comovement of decile growth rates (Appendix Table A2), this information is valuable on short annual samples. Further structure, by contrast, does not help: neither pre-selecting predictors nor restricting the factor loadings to segments of the distribution improves on the pooled DFM (Section 4.5 and Appendix C.2). We therefore use the pooled DFM as our main specification.

The relative performance measure masks substantial differences in the nowcastability of incomes along the distribution. Table 3 reports the absolute RMSE of year-on-year decile-mean log differences in percentage points.

Table 3: RMSE by model and income decile

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Avg
AR(p)	4.74	3.14	3.01	2.48	2.33	2.47	2.52	2.55	2.61	2.45	2.83
DFM-Single	4.58	2.67	2.49	2.18	2.06	2.01	1.99	2.12	2.33	2.45	2.49
DFM-Pooled	4.45	2.65	2.42	2.09	1.94	1.88	1.89	2.01	2.23	2.33	2.39

Notes: Absolute root mean squared errors of year-on-year decile-mean log growth rates ($\times 100$, in percentage points) at the nowcast horizon ($t \mid t$), income years 1990–2024. Avg denotes cross-decile average RMSE. Bold: lowest value per column. Model definitions as in Table 2.

In absolute terms, the bottom decile exhibits by far the largest errors. The benchmark delivers

⁸This difference is statistically significant on average and at the decile level for D1, D3, and D4 (5% level) and D5 to D8 (10% level).

an RMSE of 4.74 percentage points for D1, and the pooled DFM reduces this only to 4.45, so the bottom tail remains the most volatile and hardest-to-predict segment of the distribution. This reflects the pronounced volatility of lower-income dynamics documented in Section 2.1: bottom-decile incomes are exposed to idiosyncratic shocks that aggregate macroeconomic indicators do not capture, even when these indicators track the underlying business-cycle component. Across the rest of the distribution, absolute errors are considerably smaller, between about 1.9 and 2.7 percentage points for the pooled DFM. The top decile is a special case: its relative gain is small, but its absolute error is close to that of the neighboring deciles. The benchmark already performs comparatively well at the top, and the DFMs match rather than improve on it.

Finally, we examine the nowcasting performance for the inequality measures: P90/P10, P50/P10, P90/P50, and the growth spread between the top and bottom deciles. Each measure enters a single-target DFM in place of the decile mean, with the full predictor panel and three factors, and the benchmark is estimated directly on each measure.⁹ Table 4 reports the absolute RMSE.

Table 4: Nowcasting inequality measures (absolute RMSE)

	$\frac{P90}{P10}$	$\frac{P50}{P10}$	$\frac{P90}{P50}$	Spread
AR(p)	2.93	2.40	1.13	3.71
DFM-Single	2.82	2.39	1.16	3.64

Notes: Absolute RMSE of year-on-year inequality-measure log growth rates ($\times 100$, in percentage points) at nowcast horizon ($t \mid t$), income years 1990–2024. Both models are estimated directly on each measure. Spread denotes the growth differential between D10 and D1 in percentage points. None of the differences is significant (Diebold–Mariano test with HLN correction, $p > 0.10$). Bold: lowest value per column.

For the inequality measures, the DFM does not improve on the benchmark. The RMSE of the DFM is within 4% of the AR(p) for all four measures. The factors capture the common cyclical component that moves all deciles together, and this component largely cancels in ratios and differences of deciles. What remains are relative movements across the distribution, which the macroeconomic panel predicts no better than the history of the measure itself. This is consistent with the literature on income inequality dynamics, which documents that aggregate inequality measures evolve more gradually than their underlying income components, with persistence and long-run trends dominating business-cycle fluctuations (Atkinson et al., 2011; Piketty, 2003). The value of the framework thus lies in nowcasting the level of income growth across the distribution, and the direction of its changes (Section 4.2), rather than in summary inequality statistics.

⁹Deriving them from the pooled decile nowcasts yields very similar errors (Appendix Table C7).

4.2 Directional accuracy at turning points

Point forecast metrics such as RMSE provide only a partial assessment of nowcast performance. From a policy and monitoring perspective, the ability to identify directional changes in real time is equally important: whether incomes in a given part of the distribution are growing or contracting may matter more than the precise magnitude of the change. We therefore evaluate the ability of the competing models to detect turning points in decile-mean income growth.

Table 5 reports, for $AR(p)$, the single-decile and the pooled DFM, the hit rate at turning points (Panel A), the precision (Panel B), and the share of correctly predicted signs with the Pesaran and Timmermann (1992) test (Panel C), as defined in Section 3.4, together with the number of turning points per decile.

Table 5: Hit rate and sign prediction

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Avg
No. Turning Points	13	9	9	7	7	7	7	11	11	11	–
<i>Panel A: Hit rate (%)</i>											
$AR(p)$	0	0	11	29	14	14	0	0	0	0	7
DFM-Single	15	33	56	43	57	57	57	36	27	9	39
DFM-Pooled	15	33	67	57	57	57	57	55	36	18	45
<i>Panel B: Precision of signaled turning points (%)</i>											
$AR(p)$	0	0	6	11	6	6	0	0	0	0	3
DFM-Single	12	27	38	27	31	27	27	31	21	12	25
DFM-Pooled	12	21	55	27	31	31	31	40	29	17	29
<i>Panel C: Correct sign prediction (%)</i>											
$AR(p)$	49	54	57	66**	66**	54	54	60	66*	63	59
DFM-Single	60*	77**	80**	80**	83**	80**	80**	77**	71**	69*	76
DFM-Pooled	60*	71**	89**	80**	83**	83**	83**	80**	71**	69*	77

Notes: **Panel A:** Hit rate is defined as the share of sign changes in year-on-year decile-mean log growth correctly identified by the model in both timing and direction. **Panel B:** Precision is the share of sign changes signaled by the model that coincide with an actual sign change in the same year and direction. **Panel C:** Share of correctly predicted signs. Significance from the Pesaran–Timmermann test of directional accuracy: ** $p < 0.05$, * $p < 0.10$. Nowcasts at the October 1 (Q3) cut-off, income years 1990–2024. Avg denotes cross-decile average. Bold: highest value per column within each panel. Model definitions as in Table 2.

The $AR(p)$ benchmark detects almost no turning points: it identifies 7% of them on average and none at all in six of the ten deciles (Panel A). This is unsurprising: decile income growth is only weakly autocorrelated, so a univariate model has little to extrapolate from and cannot, by construction, anticipate cyclical inflection points driven by macroeconomic shocks. The few sign changes it does produce are not tied to the cycle: on average only 3% of them coincide with an actual turning point (Panel B).

Macroeconomic information changes this markedly. DFM-Single identifies 39% of the turning points on average and more than half of them in D3 and D5 to D7. Pooling raises the average hit rate further to 45%, with gains concentrated in D3, D4, and D8 to D10. Notably, the improvement is not confined to the segments of the distribution where the RMSE gains are concentrated: in D1, D2, and D10, where the benchmark detects no turning point at all, the DFMs identify between 9% and 33% of them, indicating that the factors carry directional information in the tails of the distribution even where they deliver comparatively little in terms of point-forecast accuracy. The DFMs do produce false alarms: about one in three to four of the turning points they signal is confirmed by the data (precision of 25–29%, against 3% for the benchmark). With seven to thirteen turning points per decile, a single additional hit changes the hit rate by eight to fourteen percentage points, so differences between the two DFM specifications at the decile level should not be over-interpreted.

Beyond turning-point hits, we also evaluate the broader directional accuracy of the nowcasts, defined as the share of correctly predicted signs of year-on-year growth (not restricted to sign changes, Panel C). The pattern reinforces the turning-point evidence. The benchmark predicts the correct sign in 49–66% of the years across deciles, with an average of 59%, and its directional accuracy is significant only for D4, D5, and D9. DFM-Single and DFM-Pooled predict the correct sign in 76% and 77% of the years on average, with the highest rates in the middle of the distribution (up to 89% for D3), and their directional accuracy is significant in every decile, at the 5% level from D2 to D9 and at the 10% level for the two tail deciles. In terms of signs, pooling adds little to the single-decile model: the directional information stems from the macroeconomic panel.

4.3 Information flow and the sources of predictability

The results so far refer to the information set of October 1. Since nowcasts are updated as data arrive, two further questions arise: how early in the year the signal becomes available, and which releases carry it. We address them with the nowcasts produced at the four quarterly cut-offs of each year (Q1 to Q4, Section 3.4) and with a news decomposition of their revisions (Bańbura and Modugno, 2014), which attributes the revision between consecutive cut-offs to the newly released observations, weighted by their Kalman gains, and to the re-estimation of the parameters at the new vintage. Data revisions play no role in our pseudo-real-time setting. Appendix C.4 provides details.

Table 6 reports the RMSE of the pooled DFM at the four cut-offs. In Panel A the model is re-estimated at each cut-off, so that each nowcast reflects both the data and the parameter estimates available at that date. Accuracy is essentially flat over the year: the average RMSE is 2.35 on April 1, when the model has observed the first quarter of the current year for most of the macroeconomic panel (all Macrobond series and the FRED series released before April 1) and the income data up to $t - 2$, and 2.37 on January 1 of the following year, when it has observed all four quarters and the

income data up to $t - 1$. Diebold–Mariano tests between consecutive cut-offs do not reject equal accuracy in any decile ($p > 0.20$). Relative to the $AR(p)$ benchmark estimated on the same income information, the gain is largest at the first two cut-offs, where both models observe income only up to $t - 2$ and the benchmark therefore forecasts two years ahead while the DFM already draws on the macroeconomic data of the current year (19–20% on average, Appendix Table C1). The signal that the DFM extracts from the macroeconomic panel is thus available in the spring of the nowcast year, about eighteen months before the ASEC release.

Panel B separates the contribution of the data from that of the parameters by holding the parameters of the April vintage fixed within the year, so that the nowcasts change only through the arrival of new observations. The July update, which adds the macroeconomic data of the second quarter, improves the nowcast slightly on average (from 2.35 to 2.33) and in eight of ten deciles; the exceptions are D1 and D5, where the RMSE rises marginally. The October update, which adds the third quarter and, above all, the ASEC release for income year $t - 1$, worsens it in every decile, from 2.33 to 2.51 on average; the January update improves it again. The previous year’s income growth is therefore not what the model needs to nowcast the current year. This mirrors the weak autocorrelation of decile growth noted in Section 4.1. The predictive content lies in the macroeconomic data, and the re-estimation at the October vintage, visible as the difference between Panels A and B, absorbs the new income observation without loss of accuracy.

Table 6: Nowcast RMSE by information cut-off

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Avg
<i>Panel A: parameters re-estimated at each cut-off</i>											
April 1	4.29	2.70	2.47	2.05	1.85	1.81	1.88	2.01	2.22	2.25	2.35
July 1	4.41	2.69	2.44	2.03	1.84	1.79	1.84	1.93	2.09	2.16	2.32
October 1	4.45	2.65	2.42	2.09	1.94	1.88	1.89	2.01	2.23	2.33	2.39
January 1	4.50	2.65	2.43	2.07	1.90	1.86	1.88	1.99	2.21	2.24	2.37
<i>Panel B: parameters of the April vintage held fixed</i>											
July 1	4.43	2.69	2.44	2.04	1.86	1.80	1.85	1.94	2.10	2.18	2.33
October 1	4.55	2.71	2.53	2.25	2.11	2.02	2.00	2.12	2.33	2.47	2.51
January 1	4.46	2.65	2.45	2.10	1.93	1.89	1.91	2.02	2.25	2.28	2.39

Notes: Absolute RMSE of year-on-year decile-mean log growth rates ($\times 100$, in percentage points), DFM–Pooled, income years 1990–2024. Cut-offs: April 1 (Q1), July 1 (Q2), and October 1 (Q3) of the nowcast year and January 1 (Q4) of the following year; the ASEC data for income year $t - 1$ enter on October 1. **Panel A:** nowcasts as published at each cut-off, with the model re-estimated on each vintage (the October 1 row is the main specification of Table 3). **Panel B:** nowcasts obtained by updating the April 1 model with the data of the later cut-offs without re-estimating its parameters; the April 1 row is identical to Panel A. Differences between cut-offs in Panel A are not significant (Diebold–Mariano test, $p > 0.20$ in all deciles). Relative RMSE against the benchmark with the same information set in Appendix Table C1.

Figure 2 shows which releases move the nowcasts. For each decile it reports the share of the absolute news impact over all within-year updates accounted for by the twelve indicators with the

largest average share, pooled over the income years 1990 to 2024. Two features stand out. First, the two most important releases are the national-accounts measures closest to the target itself, private wage and salary disbursements and real personal income less transfers, which together account for 12–14% of the news in every decile. They are followed by a small set of timely weekly and monthly indicators, initial jobless claims, the Case–Shiller house price index, nonfarm payroll employment, and the Conference Board consumer confidence index. The six together account for roughly a third of the news in the bottom deciles and somewhat more than a quarter at the top.¹⁰ Second, the weights shift systematically along the distribution. Labor-market indicators matter most at the bottom. For example, initial claims account for 7.1% of the news in D1 against 4.2% in D10. In contrast, price indicators matter most at the top. For instance, the ISM Manufacturing Prices Index accounts for 2.0% of the news in D1, compared with up to 3.7% in the upper half of the distribution.

Figure 2: Share of news impact by indicator and income decile, 1990–2024

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Private wage and salary disbursements	8.6	8.4	8.6	8.3	7.9	7.2	7.0	7.1	7.1	7.4
Real personal income less transfers	5.2	5.3	5.5	5.6	5.6	5.4	5.3	5.4	5.4	5.6
Initial jobless claims	7.1	6.3	6.0	5.4	4.8	4.4	4.4	4.5	4.2	4.2
S&P/Case-Shiller house price index	4.8	4.7	4.8	4.8	4.6	4.4	4.3	4.4	4.4	4.4
Nonfarm payroll employment	5.5	4.6	4.8	4.3	3.8	3.1	2.8	2.8	2.8	3.0
Conference Board consumer confidence	3.5	3.6	3.2	3.1	3.1	3.2	3.3	3.3	3.2	3.1
PCE price index	2.3	2.7	2.7	3.1	3.3	3.6	3.6	3.5	3.6	3.6
ISM manufacturing prices index	2.0	2.3	2.3	2.6	3.0	3.6	3.7	3.6	3.7	3.6
Michigan current economic conditions	2.7	2.8	2.5	2.5	2.5	2.6	2.7	2.8	2.6	2.5
Consumer price index	1.8	2.2	2.2	2.5	2.7	2.9	3.0	2.9	3.0	3.0
Core PCE price index	1.7	2.0	2.0	2.3	2.5	2.7	2.7	2.7	2.8	2.8
Real disposable personal income	1.9	2.2	2.2	2.3	2.5	2.6	2.7	2.7	2.7	2.6

Notes: Share of the absolute news impact on the nowcast of each decile (columns) accounted for by each indicator (rows), in percent, summed over the within-year updates from April to January and pooled over the income years 1990–2024. Twelve indicators with the largest average share across deciles, out of 66 to 81 in the panel; DFM-Pooled. The decomposition is model-based and attributes revisions to releases; it does not identify causal effects.

¹⁰The composition shifts over time. In the first half of the evaluation period the two income aggregates account for close to a fifth of the news, whereas since 2010 the house price index, jobless claims, and the survey indicators lead the ranking (Appendix Figure C2). The pattern across the distribution described in the text is the same in both periods.

A large news impact is not the same as a useful one, however. The income aggregates and payroll employment move the nowcast towards the realized value in 60 to 75% of the cases, whereas initial claims and the house price index, which rank among the largest sources of news, do so in only 35 to 56% (Appendix Table C4); part of the model’s reaction to these timely but volatile releases is noise, consistent with the false alarms among the turning-point signals in Section 4.2.

The within-year revisions of the nowcasts are driven by the data, not by the re-estimation of the model: news accounts for 97% of the revision between April and July, 86% between July and October, and 73% between October and January, when the new income observation enters the sample (Appendix Table C6). The exception is 2020, where the re-estimation at the October vintage shifts the nowcasts of all deciles by two to three percentage points, so that the pandemic quarters change the parameters and not only the data; we return to this in Section 4.5.

4.4 Forecast performance

We repeat the exercise from Section 4.1 for the one-step-ahead forecast horizon. Table 7 reports the absolute RMSE of our main specifications (Panel A) and the RMSE relative to the $AR(p)$ benchmark (Panel B). Statistical significance is again assessed using the Diebold–Mariano test. Results for the inequality measures are reported in Appendix C.6.

Table 7: One-step-ahead RMSE by model and income decile

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Avg
<i>Panel A: Absolute RMSE</i>											
$AR(p)$	4.90	3.15	3.14	2.78	2.47	2.41	2.48	2.50	2.61	2.42	2.89
DFM-Single	4.29	2.64	2.55	2.19	2.05	2.03	2.06	2.12	2.25	2.11	2.43
DFM-Pooled	4.30	2.65	2.54	2.18	2.04	2.01	2.04	2.11	2.23	2.10	2.42
<i>Panel B: RMSE relative to $AR(p)$</i>											
$AR(p)$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DFM-Single	0.88**	0.84**	0.81**	0.79**	0.83**	0.84**	0.83**	0.85**	0.86**	0.87**	0.84**
DFM-Pooled	0.88**	0.84**	0.81**	0.78**	0.82**	0.84**	0.82**	0.84**	0.86**	0.87**	0.84**

Notes: Absolute RMSE of one-step-ahead forecasts ($t + 1 \mid t$) at the October 1 (Q3) cut-off of the years 1990–2023, income years 1991–2024. **Panel A:** absolute RMSE of year-on-year decile-mean log growth rates ($\times 100$, in percentage points). **Panel B:** RMSE relative to the $AR(p)$ benchmark. Avg denotes the cross-decile average RMSE (Panel A) and its ratio (Panel B). Significance from the Diebold–Mariano test against $AR(p)$ with HLN small-sample correction ($h = 2$): ** $p < 0.05$, * $p < 0.10$. Bold: lowest value per column within each panel. Model definitions as in Table 2.

Overall, the forecast performance of the DFM specifications deteriorates marginally at the one-step-ahead horizon relative to the nowcast. This is intuitive given the additional uncertainty associated with forecasting further ahead with less contemporaneous information available. The DFMs’ forecast errors are marginally larger than at the nowcast horizon across most deciles, with the exception of the two tail deciles, D1 and D10, where accuracy improves slightly compared to

the nowcast. The improvement against the $AR(p)$ benchmark amounts to 16% on average, ranges from 12% to 22% across deciles, and is statistically significant at the 5% level for all deciles and on average. The gains are thus more evenly spread across the distribution than at the nowcast horizon, where they are concentrated in the middle deciles. At this horizon, the two DFM specifications perform almost identically; the advantage of pooling observed for the nowcasts does not carry over to the forecasts.

4.5 Additional results, model extensions, and robustness

First, we examine the number of factors (Table C2). Pooled models with one or two factors perform worse than the three-factor model, and the Clark-West test confirms that the third factor adds predictive content (Appendix C.3). A fourth factor does not improve accuracy on the full sample: the RMSE is practically unchanged, and the Clark-West test does not reject equal predictive accuracy. Only when the NBER recession years are excluded does the fourth factor deliver a significant gain. We therefore retain three factors as the more parsimonious specification.

As described in Section 3.3, we consider two natural extensions of the main DFM specification. First, we implement a pre-selection procedure (elastic net) that shrinks the predictor set to a smaller number of relevant variables, with the goal of improving the signal-to-noise ratio (see Appendix B.2 for further details). Second, we restrict the factor loadings in line with the selected variable set, allowing factors to load only on macroeconomic indicators relevant to specific segments of the income distribution (Appendix B.3). Neither extension improves nowcasting performance, suggesting that an unrestricted model that is free to exploit the full set of macroeconomic information provides the best representation of the latent factors. Taken together, the dominant source of predictive gains is the incorporation of macroeconomic information through a factor model, complemented by the joint estimation of all deciles. This mirrors evidence in other domains that a small number of global factors can absorb most of the common variation even when the underlying panel has clear block or sectoral structure (Delle Chiaie et al., 2022) and that the benefits of targeted pre-selection can be highly conditional on the information environment (Ferrara and Simoni, 2023).

Downturns are the periods in which timely distributional information matters most, and also the periods in which the DFM advantage is largest. Restricted to the six NBER recession years in the evaluation sample (1990, 1991, 2001, 2008, 2009, 2020), the pooled DFM reduces the RMSE by 29% on average against 16% in the full sample (Appendix C.7). The evidence rests on few and heterogeneous episodes, however: the DFMs beat the benchmark in five of the six years, most clearly in 2020, but miss by more than five percentage points in 2009.

Conversely, the main results do not hinge on the recession years (Appendix C.8). Excluding the NBER recession years from the evaluation sample, the pooled DFM still reduces the RMSE

by 11% on average relative to the benchmark. Excluding only the pandemic years 2020 and 2021, the average improvement shrinks to 8%. Part of the DFM’s average advantage thus stems from the pandemic period, in which the macroeconomic panel signaled the income losses at the bottom of the distribution, while its advantage in the middle of the distribution is robust to excluding these years.

The pandemic also raises the question whether the extreme observations of 2020 distort the parameter estimates in later years. We therefore re-estimate the pooled DFM with all macroeconomic indicators set to missing in the second to fourth quarter of 2020 (Appendix C.9). Nowcasts up to 2019 are unaffected by construction, and for 2021 to 2024 the two specifications are practically identical. The only notable difference arises for 2020 itself, for which the masked model has no information on the pandemic shock. The pandemic quarters thus do not distort the estimates for the subsequent years.

5 Conclusion

This paper proposes a framework for nowcasting the income distribution in real time. By discretizing the distribution into decile means and combining annual CPS ASEC microdata with a broad panel of quarterly U.S. macroeconomic indicators within a mixed-frequency dynamic factor model, we adapt the standard nowcasting toolkit to a class of targets that has so far been the domain of microsimulation and functional time-series approaches. A pseudo-real-time evaluation over 1990–2024 against a univariate autoregressive benchmark, at four information cut-offs per year, allows us to assess predictive performance under operationally realistic conditions.

The empirical results show that mixed-frequency factor models improve on univariate benchmarks for distributional targets. Since decile income growth is only weakly autocorrelated, these gains measure the predictive content of the macroeconomic panel. The pooled DFM reduces the average RMSE by 16% relative to the autoregressive benchmark, with gains of 21–25% in the upper-middle deciles, and similar gains for the one-step-ahead forecasts. These gains are heterogeneous along the distribution in an economically interpretable way: macroeconomic indicators are most informative for the middle deciles, where labor-market and demand-side dynamics dominate. They are less informative at the bottom, where idiosyncratic volatility dominates, and at the top, where income dynamics are less tied to the business cycle and winsorization of the upper tail removes the most cyclical incomes from the decile mean. Beyond point forecasts, the model substantially improves directional accuracy: the average hit rate at turning points rises from 7% under the benchmark to 45%, and the share of correctly predicted signs from 59% to 77%, with significant directional accuracy in every decile. For the inequality measures, in which the common cyclical component largely cancels, the DFM does not improve on the benchmark. The predictive gains in decile means stem from the factor structure and from estimating all deciles jointly, rather than from further elaboration; predictor

selection and block-structured loadings do not improve on a plain unrestricted pooled DFM estimated on the full panel.

The signal is available early. Nowcast accuracy is essentially flat over the year, so that nowcasts produced in April, about eighteen months before the official release, are as accurate as those produced after the release of the previous year's income data. A news decomposition attributes the within-year revisions to individual data releases: national-accounts measures of wages and personal income carry the largest share of the news throughout the distribution, labor-market indicators matter most at the bottom and price indicators at the top. Not all of this news is useful, however; timely but volatile indicators such as initial jobless claims and house prices move the nowcasts towards the realized value in only about half of the cases or fewer, which is consistent with the false alarms among the signaled turning points.

Our analysis is subject to several limitations. The annual frequency of CPS ASEC targets implies a small effective evaluation sample, which constrains the statistical power of forecast accuracy tests despite the small-sample corrections employed; individual years, such as the pandemic year 2020 or the recession year 2009, noticeably affect the comparisons. The pseudo-real-time design abstracts from data revisions in the macroeconomic panel and therefore cannot fully replicate the information environment of a genuine real-time setting. The news decomposition is model-based and attributes revisions to releases without identifying causal effects. Finally, the U.S. application reflects a specific institutional release calendar; transferring the framework to other survey-based distributional targets will require recalibration of publication lags and predictor sets.

Several extensions appear natural. A first direction concerns the joint modeling of the full distributional shape: functional mixed-frequency factor models that estimate smooth loadings across the income support in a single state-space step would relax the discretization assumed here and allow inequality measures to be derived from a coherent density rather than from interpolated decile means. A second direction involves moving from pseudo-real-time to genuine real-time evaluation by exploiting historical data vintages, which would discipline the comparison against benchmarks in the presence of revisions and ragged-edge information flow. A third direction is the cross-country extension: most national statistical systems publish annual income survey microdata with comparable lags, and the framework developed here transfers naturally to European household income surveys (EU-SILC, SOEP) and other settings where timely distributional monitoring is of immediate policy relevance. Pursuing these directions would deepen the integration of distributional information into the standard macroeconomic nowcasting toolkit, and ultimately reduce the asymmetry with which aggregate and distributional signals enter real-time economic surveillance.

Data availability statement

The CPS ASEC microdata are publicly available from IPUMS-CPS (Flood et al., 2025); the replication package contains the extract specification and the Stata code to construct the decile means and inequality measures. Of the macroeconomic predictors, the FRED series and their ALFRED first-release dates are publicly available; they are included in the package together with the code that constructs the pseudo-real-time vintages. The Macrobond series are proprietary and cannot be redistributed; the package lists their Macrobond mnemonics (Appendix Table A3) and provides the retrieval script, so that users with a Macrobond license can rebuild the panel. The MATLAB and Python code for estimation, evaluation, and the news decomposition will be made publicly available in a permanent online repository upon publication.

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Appendix

A Data

A.1 Micro data

This appendix provides additional details on the micro-data construction summarized in Section 2.1.

A.1.1 Sample construction

The CPS ASEC microdata are obtained from the IPUMS-CPS portal.¹¹ We restrict the sample to observations from 1968 onward because the ASEC public-use microfiles are not consistently documented for earlier years; pre-1968 vintages also have universe limitations (e.g. the exclusion of children under 14) that undermine cross-time comparability. From 1968 onward, the ASEC provides large, stable annual samples that support reliable distributional statistics, with continuous technical documentation maintained by the Census Bureau.

The IPUMS extract is organized at the person level. Since HHINCOME and ASECWTH are household-level variables, we retain one record per household and survey year, identified by the IPUMS household identifier SERIAL. Before this step we drop records with special income codes (HHINCOME equal to 99,999,999 or -9,999,997), missing income, and non-positive household weights. In the 2014 wave we additionally drop the households that received the redesigned income questionnaire; see Appendix A.1.5. Table A1 summarizes the resulting sample sizes. The final sample comprises 3,526,002 household-year observations, between roughly 47,000 (1968) and 76,000 (2005) households per survey year. Level series are available from income year 1967 onward; the growth-rate sample used throughout the paper covers the income years 1968 to 2024.

A.1.2 Upper-tail treatment

The CPS income series exhibits a structural break in income year 1995, when the Census Bureau adopted cell-mean topcoding alongside concurrent changes to income measurement. These changes mechanically raised reported incomes at the top of the distribution and introduced a discontinuity that biases any time-series analysis of the upper tail. To restore time-consistency, we winsorize the top 5% of the weighted within-year household-income distribution, that is, we replace incomes above the weighted 95th percentile of a given survey year by that percentile, and compute all decile-level statistics on the winsorized series.

¹¹Documentation is available at <https://cps.ipums.org/cps/>.

Table A1: Sample construction for CPS ASEC household income

Step	N
Raw person records (all years)	10,130,204
Keep survey year ≥ 1968	9,714,805
Drop NIU, missing, and special income codes	9,711,972
Drop zero or negative household weights	9,711,707
Keep one record per household and year	3,548,674
Drop 2014 redesign subsample (HFLAG= 1)	3,526,002
of which capped by winsorization at P95 (not removed)	174,212
Final analysis sample (household-years)	3,526,002

Notes: Counts refer to person records up to the deduplication step and to household-year observations thereafter. Winsorization caps incomes above the weighted within-year 95th percentile at that percentile and does not remove observations (4.9% of household-years are affected).

The 5% threshold is chosen to bracket the share of households affected by the 1995 topcoding change, and the cap is applied uniformly across all years.

A.1.3 Decile construction

For each survey year, we rank households by their winsorized HHINCOME and assign them to deciles based on equal-population cut-offs of the cumulative household weight distribution, so that each decile contains 10% of the weighted household population. We then compute the weighted mean of real income within each decile, $\bar{y}_{d,t} = \sum_{i \in d} w_i y_i / \sum_{i \in d} w_i$, and express the decile means as year-on-year log growth rates, $g_{d,t} = 100 (\ln \bar{y}_{d,t} - \ln \bar{y}_{d,t-1})$, which serve as the nowcasting targets.

A.1.4 Deflation and time index

HHINCOME in the ASEC of survey year s refers to the calendar year $s - 1$. All series are indexed by this income year $t = s - 1$. Nominal incomes are deflated by the annual average CPI-U of the income year, rebased to 1983 = 100. Since the deflator is constant within a year, deflating before or after the within-year winsorization and decile assignment yields identical decile means.

A.1.5 Survey breaks

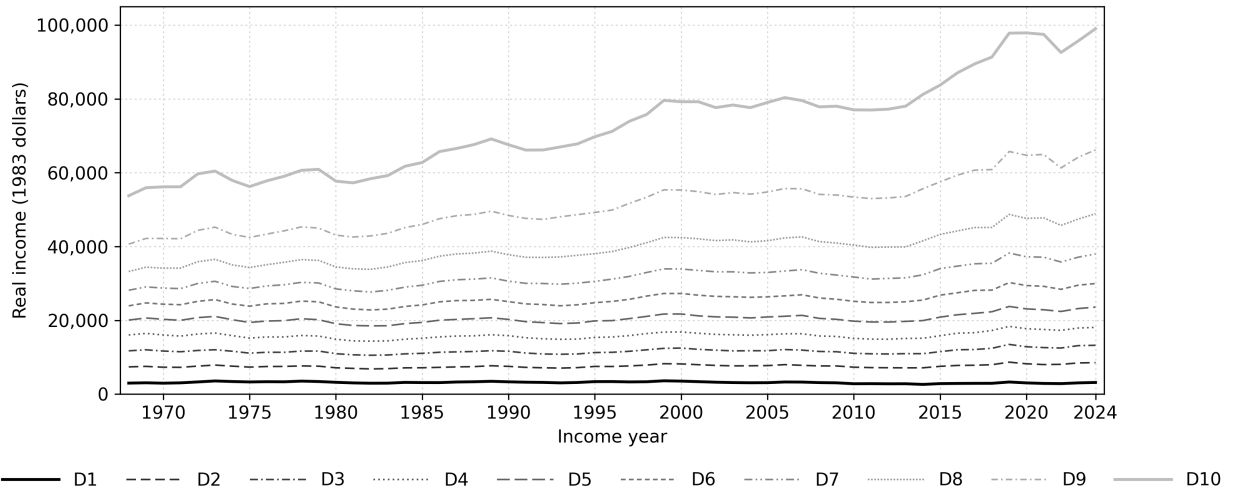
Besides the change in topcoding from income year 1995 onward, which is addressed by the winsorization described above, three changes in the survey instrument or its processing affect the comparability of the ASEC income data over time. First, the 2014 ASEC (income year 2013) was fielded as a randomized split-sample experiment in which three eighths of the sample received a redesigned income questionnaire that has been used for all subsequent waves (Semega and Welniak, 2015). We keep only the traditional subsample of this wave (HFLAG= 0), so that the series

is measured with the traditional instrument through income year 2013 and with the redesigned instrument from income year 2014 onward; the instrument change thus enters the growth rate of income year 2014. Second, with the 2019 ASEC (income year 2018) the Census Bureau introduced a new data processing system that changed the imputation of missing income and the treatment of topcoded values (Rothbaum, 2019). Third, response rates of the 2020 ASEC (income year 2019) dropped sharply during the first weeks of the pandemic, and nonrespondents were disproportionately lower-income households (Rothbaum and Bee, 2021); the corrected research weights are not part of the public-use extract. We do not adjust the series for these breaks, which affect three of the 57 growth observations per decile. Since all three fall into the evaluation period, the nowcast errors for the income years 2014, 2018, and 2019 include the effect of the respective break.

A.1.6 Descriptive statistics

Figure A1 shows the level series of real decile mean household incomes. Table A2 displays pairwise Pearson correlations of decile growth rates, providing a reference for the cross-decile dependence structure that motivates the pooled and block-structured DFM specifications discussed in Section 3.3.

Figure A1: Real household income by decile (levels)



Notes: Weighted within-year decile means of real household income in 1983 dollars, income years 1967–2024. Data construction as in Figure 1.

A.2 Macro data

Table A3 gives the full set of macro variables included in the DFM framework and variable selection process, along with their frequency, observed sample and unit. A series enters the estimation once it covers two thirds of the training sample.

Table A2: Correlations across income decile growth rates

Decile	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
D1	.	0.90	0.83	0.80	0.80	0.79	0.76	0.72	0.69	0.66
D2	0.90	.	0.96	0.92	0.90	0.89	0.86	0.83	0.79	0.78
D3	0.83	0.96	.	0.98	0.95	0.92	0.88	0.85	0.83	0.82
D4	0.80	0.92	0.98	.	0.98	0.94	0.91	0.88	0.86	0.86
D5	0.80	0.90	0.95	0.98	.	0.98	0.95	0.93	0.90	0.90
D6	0.79	0.89	0.92	0.94	0.98	.	0.99	0.96	0.93	0.90
D7	0.76	0.86	0.88	0.91	0.95	0.99	.	0.99	0.95	0.91
D8	0.72	0.83	0.85	0.88	0.93	0.96	0.99	.	0.98	0.94
D9	0.69	0.79	0.83	0.86	0.90	0.93	0.95	0.98	.	0.96
D10	0.66	0.78	0.82	0.86	0.90	0.90	0.91	0.94	0.96	.

Notes: Pairwise Pearson correlation coefficients of year-on-year log growth rates ($\times 100$) of real decile means, income years 1968–2024 ($T = 57$). Data construction as in Figure A1.

Table A3: Macroeconomic dataset

No.	Series	Source	Source Code	Freq.	Unit	Transf.	First Obs.	Used from
<i>Output & Growth</i>								
1	Export Price Index (End Use): All Commodities	FRED	IQ	M	Index (2000=100), SA applied	2nd log diff.	1984-Q1	2016
2	Federal Government: Current Expenditures	FRED	FGEXPND	Q	Billions of US\$	Log diff.	1968-Q1	all
3	Federal Government: Receipts	FRED	FGRECPT	Q	Billions of US\$, deflated by PCE price index	Log diff.	1968-Q1	all
4	GDP Share: Gross Private Domestic Investment, Change in Private Inventories	FRED	A014RE1Q156NBEA	Q	Percent, SA applied	Level	1968-Q1	all
5	GDP: Terms of Trade Index, Goods	FRED	W370RG3Q020SBEA	Q	Index (2017=100)	Log diff.	1968-Q1	all
6	Import Price Index: All Commodities	FRED	IR	M	Index (2000=100), SA applied	2nd log diff.	1983-Q1	2013
7	Industrial Production Index	FRED	INDPRO	M	Index (2017=100)	Log diff.	1968-Q1	all
8	Light Weight Vehicle Sales	FRED	ALTSALES	M	Millions of Units	Log diff.	1976-Q2	1992
9	Manufacturers' New Orders: Durable Goods	FRED	DGORDER	M	Millions of US\$, deflated by PPI manufacturing	Log diff.	1985-Q1	2019
10	Nonfarm Business Sector: Hours of All Persons	FRED	HOANBS	Q	Index (2017=100)	Log diff.	1968-Q1	all
11	Real Exports of Goods & Services	FRED	EXPGSC1	Q	Billions of Chained 2017 US\$	Log diff.	1968-Q1	all
12	Real Gross Domestic Income	FRED	A261RX1Q020SBEA	Q	Billions of Chained 2017 US\$	Log diff.	1968-Q1	all
13	Real Gross Domestic Product	FRED	GDPC1	Q	Billions of Chained 2017 US\$	Log diff.	1968-Q1	all
14	Real Imports of Goods & Services	FRED	IMPGSC1	Q	Billions of Chained 2017 US\$	Log diff.	1968-Q1	all

Continued. . .

Table A3 – continued

No.	Series	Source	Source Code	Freq.	Unit	Transf.	First Obs.	Used from
15	Total Business Inventories	FRED	BUSINV	M	Millions of US\$, deflated by PPI manufacturing	Log diff.	1985-Q1	2019
<i>Labor Market</i>								
16	All Employees: Construction	FRED	USCONS	M	Thousands of Persons	Log diff.	1968-Q1	all
17	All Employees: Education & Health Services	FRED	USEHS	M	Thousands of Persons	Log diff.	1968-Q1	all
18	All Employees: Financial Activities	FRED	USFIRE	M	Thousands of Persons	Log diff.	1968-Q1	all
19	All Employees: Government	FRED	USGOVT	M	Thousands of Persons	Log diff.	1968-Q1	all
20	All Employees: Information Services	FRED	USINFO	M	Thousands of Persons	Log diff.	1968-Q1	all
21	All Employees: Leisure & Hospitality	FRED	USLAH	M	Thousands of Persons	Log diff.	1968-Q1	all
22	All Employees: Manufacturing	FRED	MANEMP	M	Thousands of Persons	Log diff.	1968-Q1	all
23	All Employees: Mining and Logging	FRED	USMINE	M	Thousands of Persons	Log diff.	1968-Q1	all
24	All Employees: Other Services	FRED	USSERV	M	Thousands of Persons	Log diff.	1968-Q1	all
25	All Employees: Professional & Business Services	FRED	USPBS	M	Thousands of Persons	Log diff.	1968-Q1	all
26	All Employees: Total Nonfarm	FRED	PAYEMS	M	Thousands of Persons	Log diff.	1968-Q1	all
27	All Employees: Trade, Transportation & Utilities	FRED	USTPU	M	Thousands of Persons	Log diff.	1968-Q1	all
28	Mean Duration of Unemployment	FRED	UEMPMEAN	M	Weeks	Diff.	1968-Q1	all
29	Avg Weekly Hours: Prod & Nonsupervisory, Manufacturing	FRED	AWHMAN	M	Hours	Level	1968-Q1	all
30	Avg Weekly Hours: Prod & Nonsupervisory, Total Private	FRED	AWHNONAG	M	Hours	Diff.	1968-Q1	all
31	Civilian Employment	FRED	CE160V	M	Thousands of Persons	Log diff.	1968-Q1	all
32	Civilian Unemployment Rate	FRED	UNRATE	M	Percent	Diff.	1968-Q1	all

Continued. . .

Table A3 – continued

No.	Series	Source	Source Code	Freq.	Unit	Transf.	First Obs.	Used from
33	Compensation of Employees, Received: Wage and Salary Disbursements: Government	FRED	B202RC1	M	Billions of US\$, deflated by PCE price index	Log diff.	1968-Q1	all
34	Compensation of Employees, Received: Wage and Salary Disbursements: Private Industries	FRED	A132RC1	M	Billions of US\$, deflated by PCE price index	Log diff.	1968-Q1	all
35	Initial Claims for Unempl. Insurance	FRED	ICSA	W	Number	Log diff.	1968-Q1	all
36	Median Duration of Unemployment	FRED	UEMPMED	M	Weeks	Diff.	1968-Q1	all
37	Nonfarm Business Sector: Unit Labor Cost	FRED	ULCNFB	Q	Index (2017=100)	Log diff.	1968-Q1	all
38	Avg Hourly Earnings of Production and Nonsupervisory Employees: Construction	FRED	CES2000000008	M	US\$ per Hour, deflated by PCE price index	Log diff.	1968-Q1	all
39	Avg Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing	FRED	CES3000000008	M	US\$ per Hour, deflated by PCE price index	Log diff.	1968-Q1	all
<i>Consumption & Income</i>								
40	Conference Board, Ratio Corporate Domestic Profits After Tax to Net Value Added	MB	uslead0375	Q	Percent	Diff.	1968-Q1	all
41	Net Expenditures Abroad by U.S. Residents, Less: Personal Remittances in Kind to Nonresidents	MB	usnaac34251	M	US\$	Log diff.	1968-Q1	all
42	Personal Savings Rate	FRED	PSAVERT	M	Percent	Diff.	1968-Q1	all
43	Real Disposable Personal Income	FRED	DPIC96	Q	Billions of Chained 2017 US\$	Log diff.	1968-Q1	all
44	Real Personal Consumption Expenditures	FRED	PCECC96	Q	Billions of Chained 2017 US\$	Log diff.	1968-Q1	all

Continued. . .

Table A3 – continued

No.	Series	Source	Source Code	Freq.	Unit	Transf.	First Obs.	Used from
45	Real Personal Income less Transfers	FRED	W875RX1	M	Billions of Chained 2017 US\$	Log diff.	1968-Q1	all
46	Total Consumer Credit	MB	usbank0100	M	Billions of US\$	Log diff.	1968-Q1	all
47	Total Liabilities of Households & Nonprofit Organizations	FRED	TLBSHNO	Q	Millions of US\$, deflated by PCE price index	Log diff.	1968-Q1	all
<i>Housing & Investment</i>								
48	Housing Starts: Total New Privately Owned Housing Units	FRED	H0UST	M	Thousands of Units	Log diff.	1968-Q1	all
49	Monthly Supply of New Houses in the United States	FRED	MSACSR	M	Months' Supply	Log diff.	1968-Q1	all
50	New Private Housing Units Authorized by Building Permits	FRED	PERMIT	M	Thousands of Units	Log diff.	1968-Q1	all
51	S&P/Case-Shiller Home Price Index	MB	uscons11613	M	Index	Log diff.	1968-Q1	all
<i>Prices & Inflation</i>								
52	1-Year Expected Inflation	FRED	EXPINF1YR	M	Percent	Diff.	1982-Q2	2010
53	Consumer Price Index: All Urban Consumers, All Items	FRED	CPIAUCSL	M	Index (1982-84=100)	2nd log diff.	1968-Q1	all
54	CPI: All Items less Food & Energy	FRED	CPILFESL	M	Index (1982-84=100)	2nd log diff.	1968-Q1	all
55	CPI: Owners' Equivalent Rent of Residences	FRED	CUSR0000SEHC	M	Index (1982-84=100)	2nd log diff.	1983-Q3	2014
56	ISM Manufacturing PMI: Prices Index	MB	ussurv1062	M	Index	Diff.	1968-Q1	all
57	PCE Excluding Food and Energy: Chain-Type Price Index	FRED	PCEPILFE	M	Index (2017=100)	2nd log diff.	1968-Q1	all
58	PCE: Chain-type Price Index	FRED	PCECTPI	Q	Index (2017=100)	2nd log diff.	1968-Q1	all
59	PPI: Manufacturing	FRED	PCUOMFGOMFG	M	Index (Dec 1984=100)	2nd log diff.	1986-Q3	2023

Continued. . .

Table A3 – continued

No.	Series	Source	Source Code	Freq.	Unit	Transf.	First Obs.	Used from
60	Spot Oil Price: West Texas Intermediate	FRED	DCOILWTICO	D	US\$ per Barrel	2nd log diff.	1986-Q3	2023
<i>Financial Conditions</i>								
61	10-Year Real Interest Rate	FRED	REAINTRATREARAT10Y	M	Percent	Diff.	1982-Q2	2010
62	10-Year Treasury Constant Maturity Rate	FRED	GS10	M	Percent	Diff.	1968-Q1	all
63	Effective Federal Funds Rate	FRED	FEDFUNDS	M	Percent	Diff.	1968-Q1	all
64	Dow Jones Industrial Average, Close	MB	useqin0032	M	Index	Log diff.	1968-Q1	all
65	Household Debt as a Percent of GDP	MB	usflob_015451	Q	Percent	Diff.	1968-Q1	all
66	Federal Reserve Real Broad Dollar Index	MB	usexri0005	M	Index	Log diff.	1973-Q2	all
67	Households & Nonprofit Organizations, Directly & Indirectly Held Debt Securities as a Percentage of Disposable Personal Income	MB	usflob_039566	Q	Percent	Diff.	1968-Q1	all
68	Rest of the World; Foreign Direct Investment in U.S.; Asset (Current Cost), Transactions	FRED	ROWFDIQ027S	Q	Millions of US\$	Log diff.	1968-Q1	all
69	S&P 500	MB	sp500_500	M	Index	Log diff.	1968-Q1	all
<i>Surveys & Sentiment</i>								
70	Philadelphia Fed Manufacturing Business Outlook Survey: Current General Activity	MB	ussurv1102	M	Index	Diff.	1968-Q3	all
71	ISM Manufacturing PMI	MB	ussurv1055	M	Index	Diff.	1968-Q1	all
72	Conference Board: Current Condition Economy	MB	ussurv0791	Q	Index	Diff.	1976-Q3	1993
73	Conference Board: Current Condition Own Business	MB	ussurv0794	Q	Index	Diff.	1978-Q4	2000
74	Conference Board: Expectation Own Business	MB	ussurv0793	Q	Index	Diff.	1976-Q3	1993

Continued. . .

Table A3 – continued

No.	Series	Source	Source Code	Freq.	Unit	Transf.	First Obs.	Used from
75	Conference Board: Expectations Economy	MB	ussurv0792	Q	Index	Diff.	1976-Q3	1993
76	Conference Board: Consumer Confidence Index	MB	ussurv1459	M	Index (1985=100)	Diff.	1968-Q1	all
77	Conference Board: Measure of CEO Confidence	MB	ussurv1462	Q	Index	Diff.	1976-Q3	1993
78	ISM Manufacturing PMI: Employment Index	MB	ussurv1058	M	Index	Diff.	1968-Q1	all
79	U. of Michigan: Consumer Expectations	MB	ussurv0356	M	Index (1966:Q1=100)	Diff.	1968-Q1	all
80	U. of Michigan: Current Economic Conditions	MB	ussurv0355	M	Index (1966:Q1=100)	Diff.	1968-Q1	all
81	U. of Michigan: Consumer Sentiment	FRED	UMCSENT	M	Index (1966:Q1=100), SA applied	Level	1968-Q1	all

Notes: Macroeconomic variables in the candidate set of the pooled DFM. The seven groups serve presentation only and play no role in the estimation. National-accounts components are grouped with the table they originate from, so that the corporate profit share and net expenditures abroad (both NIPA income and outlay accounts) appear under Consumption & Income. FRED denotes the Federal Reserve Economic Data database of the Federal Reserve Bank of St. Louis, MB denotes Macrobond; **Source Code** is the database identifier. **Freq.** is the native frequency (M monthly, Q quarterly, W weekly, D daily); monthly, weekly, and daily series are averaged within the quarter. **Unit** is the native unit of the raw series; nominal series marked as deflated are divided by the PCE price index (PCECTPI) or the manufacturing PPI (PCUOMFGOMFG) before transformation, and series marked SA are seasonally adjusted by STL prior to estimation, all other series are seasonally adjusted at the source. **Transf.** is the stationarity transformation of the quarterly series: Level, first difference (Diff.), 100 times the first difference of the log (Log diff.), or 100 times the second difference of the log (2nd log diff.). **First Obs.** is the first quarter with a transformed observation in the vintage data. **Used from** gives the first third-quarter vintage (1990 to 2024) in which the series satisfies the two-thirds coverage rule of Section 2.2; *all* means the series enters every vintage. A further 19 candidate series never satisfy the rule within the evaluation period and are therefore not part of any estimation: ATCGNO, AMDMVS, UTCGTI, AMDMTI, AMTMUO, WHLSLRIMSA, RRSFS, uscons6235, uscons6236, uscons6237, TLRESCONS, DRCLT100N, DRCLACBS, usrate2241, DTWEXAFEGS, usrate1940, ussurv08198, ussurv1066, ussurv1044.

B Details on the methodology

This section gives some details on the method and estimation of the Dynamic Factor Model (DFM) described in Section 3.2. We refer the inclined reader to [Bańbura and Modugno \(2014\)](#) and the associated appendix for a more comprehensive exposition of the method. The implementation follows the block structure of [Bok et al. \(2018\)](#), with one factor per block, a factor lag order of one, and univariate AR(1) idiosyncratic components.

B.1 Details on the DFM estimation

State space representation. Let N_q and N_a denote the number of quarterly and annual series ($n = N_q + N_a$) and k the number of factors. Because the annual series are related to the current and six lagged values of the quarterly latent processes, each factor $f_{j,t}$ enters the state vector together with its six lags, $F_{j,t} = (f_{j,t}, \dots, f_{j,t-6})'$. The state vector is

$$\alpha_t = \begin{bmatrix} F_{1,t} \\ \vdots \\ F_{k,t} \\ e_t^q \\ s_{1,t} \\ \vdots \\ s_{N_a,t} \end{bmatrix},$$

where $e_t^q = (e_{1,t}, \dots, e_{N_q,t})'$ collects the N_q idiosyncratic components of the quarterly series and $s_{l,t} = (e_{l,t}, \dots, e_{l,t-6})'$ the idiosyncratic component of annual series l together with its six lags.

The quarterly idiosyncratic components enter only contemporaneously: their AR(1) dynamics run through the transition equation, which links $e_{i,t}$ to $e_{i,t-1}$, the same state one period earlier. The model in state space form is

$$y_t = H\alpha_t + \xi_t, \quad \xi_t \sim \mathcal{N}(0, R), \quad (4)$$

$$\alpha_t = \Gamma\alpha_{t-1} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, Q). \quad (5)$$

With the aggregation weights $w = (1, 2, 3, 4, 3, 2, 1)'$ of Equation (3), the observation matrix H

in Equation (4) has the structure

$$H = \begin{bmatrix} \Lambda_{1,q} \bar{e}_1' & \dots & \Lambda_{k,q} \bar{e}_1' & I_{N_q} & 0 \\ \Lambda_{1,a} w' & \dots & \Lambda_{k,a} w' & 0 & I_{N_a} \otimes w' \end{bmatrix},$$

where $\Lambda_{j,q}$ ($N_q \times 1$) are the loadings of the quarterly series on factor j , which enter only through the contemporaneous factor ($\bar{e}_1$ is the first unit vector of length seven), and $\Lambda_{j,a}$ ($N_a \times 1$) are the loadings of the annual series, which are spread over the current and six lagged factor values with the weights w . Each annual series thus has one free loading per factor, and the same weights aggregate its idiosyncratic states. In the block specifications of Section 3.3, selected entries of $\Lambda_{j,q}$ and $\Lambda_{j,a}$ are restricted to zero.

The transition matrix is block diagonal,

$$\Gamma = \text{diag}(A_1, \dots, A_k, B_q, B_{a,1}, \dots, B_{a,N_a}),$$

where A_j is the 7×7 companion matrix of the AR(1) process of factor j with coefficient a_j , $B_q = \text{diag}(\rho_1, \dots, \rho_{N_q})$ is the diagonal matrix of the AR(1) coefficients of the quarterly idiosyncratic components, and $B_{a,l}$ is the 7×7 companion matrix of the AR(1) idiosyncratic component of annual series l with coefficient ρ_l . In each companion matrix only the first row contains a free coefficient. The remaining rows shift the lags and carry no innovation. Accordingly, the innovation covariance Q is diagonal, with the variances q_j and σ_i^2 at the positions of the contemporaneous states and zeros at the positions of the lagged states.

Missing observations and nowcasts. Missing observations, including the ragged edge of each vintage and the quarters in which the annual series are not observed, are handled in the Kalman filter by a selection matrix W_t that removes the rows of the observation equation for which y_t is missing (Bańbura and Modugno, 2014). After estimation, the Kalman smoother is run with the estimated parameters on the data matrix extended by empty quarters up to the fourth quarter of year $t + 1$. The nowcast for year t is the smoothed value of the target series in the fourth quarter of year t , and the forecast for year $t + 1$ is the smoothed value in the fourth quarter of year $t + 1$.

Setting initial conditions. The EM algorithm converges to a local maximum of the likelihood, and the parameter estimates can therefore depend on the initial conditions. To reduce this dependence, we estimate the model in each vintage from two sets of initial conditions and retain the estimate with the higher likelihood. The first set follows Bańbura and Modugno (2014): the observation matrix H_0 , the transition matrix Γ_0 , and the innovation covariance matrix Q_0 are derived by performing a

principal component analysis on the higher-frequency variables and regressing the lower-frequency data on the projected higher-frequency data, while respecting the aggregation scheme. The second set consists of the final parameter estimates selected in the previous vintage, where newly available series enter with zero factor loadings and the idiosyncratic starting values of the principal-component initialization.

Expectation maximization (EM) algorithm. The EM algorithm developed by [Bańbura and Modugno \(2014\)](#) follows two alternating steps until it converges at a local maximum of the likelihood. Let $\theta^{(m)} = \{H^{(m)}, \Gamma^{(m)}, Q^{(m)}, R^{(m)}\}$ denote the parameters in iteration m , and let Ω_T denote the available data.

1. **E-Step** In the first iteration we start with the initial conditions α_0 , an initial guess for the state vector and P_0 , which indicates the uncertainty in the current guess. By applying the Kalman filter and Kalman smoother we update the state vector based on the current iteration's model parameters $\theta^{(m)}$. This can be interpreted as “filling in” the unobserved data. We compute the conditional moments of the states given the data, $\alpha_{t|T} = \mathbb{E}_{\theta^{(m)}}[\alpha_t | \Omega_T]$, $P_{t|T} = \text{Var}_{\theta^{(m)}}(\alpha_t | \Omega_T)$ and $P_{t,t-1|T} = \text{Cov}_{\theta^{(m)}}(\alpha_t, \alpha_{t-1} | \Omega_T)$. These moments give the expected value of the complete-data log-likelihood, that is, the joint likelihood of the data and the unobserved states, conditional on the observed data ([Bańbura and Modugno, 2014](#), eq. 3). Second moments are computed as $\mathbb{E}_{\theta^{(m)}}[\alpha_t \alpha_t' | \Omega_T] = \alpha_{t|T} \alpha_{t|T}' + P_{t|T}$, and analogously for the cross moments. As in [Bańbura and Modugno \(2014\)](#), eqs. 14–15), the AR(1) idiosyncratic components are part of the state vector, so their conditional moments are obtained from the same smoother pass.
2. **M-Step** In the Maximization Step, we re-estimate the model parameters H , Γ , Q , and R by maximizing the expected complete-data log-likelihood computed during the E-Step. This maximization yields updated parameter estimates for iteration $m + 1$. We then use these updated parameters in the next E-Step to update the state vector and covariance. The initial state α_0 is updated to its smoothed estimate $\alpha_{0|T}$, and P_0 is kept at its initial value.

The loadings in H are updated with the missing-data estimator of [Bańbura and Modugno \(2014\)](#), eq. 11), extended for the AR(1) idiosyncratic states. For the annual series, they are updated with the restricted estimator of [Bańbura and Modugno \(2014\)](#), eq. 13), which imposes the aggregation

weights w . Following [Bańbura and Modugno \(2014, eqs. 6 and 8\)](#), for each factor j ,

$$a_j^{(m+1)} = \left(\sum_{t=1}^T \mathbb{E}[f_{j,t} f_{j,t-1}] \right) \left(\sum_{t=1}^T \mathbb{E}[f_{j,t-1}^2] \right)^{-1}, \quad (6)$$

$$q_j^{(m+1)} = \frac{1}{T} \left(\sum_{t=1}^T \mathbb{E}[f_{j,t}^2] - a_j^{(m+1)} \sum_{t=1}^T \mathbb{E}[f_{j,t} f_{j,t-1}] \right), \quad (7)$$

and the AR(1) coefficients ρ_i and innovation variances σ_i^2 of the quarterly idiosyncratic components $e_{i,t}$, as well as those of the annual idiosyncratic components $e_{l,t}$, are updated in the same way. The updated coefficients enter the first rows of the companion blocks of $\Gamma^{(m+1)}$, and the updated variances enter the corresponding diagonal elements of $Q^{(m+1)}$.

Following [Bańbura and Modugno \(2014, eq. 12\)](#), the covariance of the measurement errors is

$$R^{(m+1)} = \text{diag} \left(\frac{1}{T} \sum_{t=1}^T \left[(W_t y_t - W_t H^{(m+1)} \alpha_{t|T}) (W_t y_t - W_t H^{(m+1)} \alpha_{t|T})' \right. \right. \\ \left. \left. + W_t H^{(m+1)} P_{t|T} H^{(m+1)'} W_t + (I - W_t) R^{(m)} (I - W_t) \right] \right), \quad (8)$$

where W_t is a selection matrix that selects only the available data. The diagonal elements for the quarterly series are bounded below by 10^{-4} , and those for the annual series are fixed at 10^{-4} . The algorithm stops when the relative change in the log-likelihood between two iterations falls below 10^{-4} , or after at most 5,000 iterations.

B.2 Variable selection

All 100 candidate indicators described in Section 2.2 may contain predictive information for the income distribution. However, a smaller set of targeted predictors can improve the accuracy of factor models when idiosyncratic components are persistent or cross-correlated ([Boivin and Ng, 2006](#)). We therefore implement a data-driven pre-selection with an elastic net, estimated vintage by vintage on an expanding window. For notational convenience, some symbols are reused throughout this section, with their specific meanings determined by the context.

The selection requires predictors at the annual frequency of the targets. To be consistent with the mixed-frequency DFM, we aggregate each transformed quarterly series with the weights (1, 2, 3, 4, 3, 2, 1) of Equation (3) and take the fourth-quarter value as the annual observation. The selection also requires a balanced panel, so that in each vintage only indicators observed without gaps from 1970 onward are admissible; this excludes series with a late start. For each vintage $t_0 = 1990, \dots, 2024$ and each decile we estimate an elastic net on the income years 1970 to $t_0 - 1$,

the last year for which the target is published, which yields 350 regressions. The elastic net solves

$$\hat{\beta} = \arg \min_{\beta} \left\{ \frac{1}{2T} \sum_{t=1}^T (y_t - X_t' \beta)^2 + \lambda \left(\alpha \|\beta\|_1 + \frac{1-\alpha}{2} \|\beta\|_2^2 \right) \right\},$$

with standardized predictors and an intercept, where $\alpha \in [0, 1]$ governs the mix of Lasso and Ridge penalties and λ the penalty strength. We choose (α, λ) on a grid of 10 values of α between 0.05 and 0.95 and 30 values of λ between 10^{-2} and 10 by time-series cross-validation with five expanding-window splits. Predictors with a non-zero coefficient at the selected penalty are ranked by the order in which they enter the regularization path from the largest penalty downwards (Bai and Ng, 2008), and we keep the first r predictors per decile, with $r \in \{5, 10, 20\}$ or no cap. The union of the predictors selected across the ten deciles then enters a pooled three-factor DFM. Without a cap the union comprises 52 to 61 indicators depending on the vintage, with $r = 20$ between 30 and 50, with $r = 10$ between 16 and 31, and with $r = 5$ between 8 and 18. The smaller sets with $r \leq 10$ are thus substantially more parsimonious than the baseline panel, whereas the uncapped selection differs from it mainly through the exclusion of late-starting series. Results are reported in Appendix C.2.

B.3 DFMs with block structure

In the nowcasting literature, an established approach to improve the robustness of factor estimation and to reflect economic comovement is to impose a block structure on the loading matrix (Bok et al., 2018; Cascaldi-Garcia et al., 2024). We implement specifications that exploit the correlation structure of the income distribution in Table A2, where adjacent deciles comove strongly and correlations decline with the distance between deciles, together with the decile-specific selection of the previous section.

Each block model contains a global factor that loads on all series, deciles, and indicators alike, and one factor per segment of the distribution that loads on the deciles of that segment and on the indicators selected by the uncapped elastic net for at least one decile of the segment. We consider three segmentations: (a) deciles 1–6 and 7–10, (b) deciles 1–7 and 8–10, and (c) deciles 1–3, 4–7, and 8–10. Designs (a) and (b) therefore have three factors like the baseline, design (c) has four. The loading restrictions are imposed in the initialization and preserved in every EM step. Results are reported in Appendix C.2.

C Additional results and robustness

C.1 Nowcast performance at alternative information cut-offs

In the main results discussed in Section 4, the nowcasts use the Q3 cut-off, that is, the data available on October 1 of the nowcast year. The vintages are constructed as described in Section 2.2; at the Q1 and Q2 cut-offs the latest available income observation refers to year $t - 2$, at the Q3 and Q4 cut-offs to year $t - 1$. We compare each cut-off with the benchmark estimated on the same income information, that is, with a two-step forecast for the first two cut-offs and a one-step forecast for the last two. Table C1 shows the RMSEs relative to the benchmark.

Table C1: RMSE relative to the AR(p) benchmark, alternative information cut-offs

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Avg
April 1 (Q1)	0.87*	0.86	0.80*	0.75**	0.75**	0.75**	0.75**	0.80**	0.85**	0.91	0.81**
July 1 (Q2)	0.90*	0.86	0.79**	0.74**	0.75**	0.74**	0.73**	0.77**	0.79**	0.88*	0.80**
October 1 (Q3)	0.94	0.84	0.80	0.84	0.83	0.76*	0.75**	0.79*	0.85	0.95	0.84
January 1 (Q4)	0.95	0.85	0.81	0.84	0.81	0.75*	0.75**	0.78**	0.85*	0.92	0.84

Notes: RMSE relative to the AR(p) benchmark with the same information set: two-step forecast at the Q1 and Q2 cut-offs (latest income observation $t - 2$), one-step forecast at the Q3 and Q4 cut-offs (latest income observation $t - 1$). Pooled DFM with three factors (main specification); cut-offs as defined in Section 3.4. Income years 1990–2024. Avg denotes the ratio of the cross-decile average RMSE. Significance from the Diebold–Mariano test with HLN small-sample correction ($h = 2$ for Q1/Q2, $h = 1$ for Q3/Q4): ** $p < 0.05$, * $p < 0.10$. Bold: lowest value per column.

Nowcast accuracy is essentially flat across the information cut-offs. In absolute terms, the second-quarter nowcasts are the most accurate in most deciles, but the differences between cut-offs are small. Relative to the benchmark with the same information set, the gains are largest at the first two cut-offs (19–20% on average, significant at the 5% level), because the benchmark then has to forecast two steps ahead while the DFM already draws on the macroeconomic data of the current year.

C.2 Alternative model specifications

In Section 4, we present the results of a forecast evaluation horse race of different model specifications. Here, we investigate whether our results hinge on the model specifications in an extended horse race.

Table C2 collects their RMSE relative to the AR(p) benchmark at the nowcast horizon. Panel A reproduces the two main specifications, the single-decile and pooled DFMs estimated on the full predictor panel with unrestricted factor loadings. Panel B varies the number of latent factors of the pooled DFM. Reducing the number of factors costs accuracy across the entire distribution: the

one- and two-factor specifications lose more than half of the improvement over the benchmark. A fourth factor lowers the errors slightly in the bottom deciles but raises them in every decile from D4 upward, leaving the average practically unchanged. Panel C applies the expanding-window elastic net pre-selection described in Appendix B.2, either retaining all selected predictors or restricting the model to at most the top 5, 10, or 20 indicators per decile. Retaining all selected predictors performs on par with the pooled DFM. Restricting the predictor set further does not help: the restricted variants achieve the lowest errors in individual upper deciles, but at the cost of higher errors in the lower half of the distribution, where the top-10 specification barely improves on the benchmark. Panel D introduces block-structured loadings described in Appendix B.3, allowing factors to load only on specific segments of the distribution. None of the three block designs improves prediction performance relative to the main results; in the bottom decile, they do not improve on the benchmark.

Table C2: RMSE relative to the $AR(p)$ benchmark: all model specifications

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Avg
<i>Panel A: Main</i>											
$AR(p)$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DFM-Single	0.97	0.85	0.83	0.88	0.88	0.81*	0.79*	0.83*	0.89	1.00	0.88
DFM-Pooled	0.94	0.84	0.80	0.84	0.83	0.76*	0.75**	0.79*	0.85	0.95	0.84
<i>Panel B: Alternative factor counts</i>											
DFM-Pooled- f_1	1.00	0.89	0.87	0.92	0.94	0.90	0.89	0.91	0.96	1.03	0.93
DFM-Pooled- f_2	1.00	0.90	0.88	0.94	0.95	0.91	0.90	0.93	0.97	1.05	0.95
DFM-Pooled- f_4	0.92	0.81	0.79	0.86	0.86	0.79**	0.77**	0.82*	0.90	1.01	0.85
<i>Panel C: Elastic Net variable selection</i>											
DFM-P-EN	0.94	0.85	0.80	0.86	0.85	0.78*	0.75**	0.80*	0.87	1.00	0.86
DFM-P-EN5	0.97	0.93	0.89	0.88	0.83*	0.77**	0.79**	0.82*	0.87	0.95	0.88
DFM-P-EN10	1.02	1.01	0.97	0.97	0.96	0.89	0.85**	0.83*	0.87	0.91	0.94
DFM-P-EN20	0.98	0.96	0.87	0.92	0.91	0.83	0.80*	0.79*	0.83	0.94	0.89
<i>Panel D: Elastic Net selection and block structure</i>											
DFM-P-EN[a]	1.00	0.89	0.86	0.94	0.96	0.91	0.84	0.87	0.93	1.00	0.92
DFM-P-EN[b]	1.00	0.90	0.87	0.95	0.97	0.92	0.90	0.85	0.90	0.98	0.93
DFM-P-EN[c]	1.01	0.91	0.88	0.86	0.87	0.81	0.81	0.88	0.89	0.96	0.90

Notes: RMSE relative to the $AR(p)$ benchmark at nowcast horizon ($t | t$), October 1 (Q3) cut-off, income years 1990–2024. **Panel A:** Three-factor DFMs, equivalent to Table 2. **Panel B:** Pooled DFM, f_x indicates the number of factors. **Panel C:** Pooled DFM with rolling elastic net pre-selection (DFM-P-EN: all selected predictors), restricted such that at most the top 5, 10, or 20 indicators from the selection per decile are included; the number of indicators retained may vary across vintages. **Panel D:** Pooled DFM with elastic net selection and block structure: a global factor plus one factor per block of deciles, D1–D6 and D7–D10 ([a]), D1–D7 and D8–D10 ([b]), D1–D3, D4–D7, and D8–D10 ([c]); see Appendix B.3. Avg denotes the ratio of cross-decile average RMSE. Significance from the Diebold–Mariano test against $AR(p)$ with HLN small-sample correction, $h = 1$: ** $p < 0.05$, * $p < 0.10$. Bold: Lowest value per column.

C.3 Clark-West statistics

Table C3 summarizes the results of Clark-West (CW, [Clark and West, 2007](#)) tests for nested model comparison. Comparing one factor against two factors, the test does not reject the null of equal predictive accuracy, indicating that the second factor does not yield a statistically significant improvement in forecast accuracy. Moving from two to three factors, however, the CW statistic is significant at the 5% level for all deciles. The third factor thus delivers a substantial and broad-based gain in predictive accuracy. The comparison of three against four factors is less clear-cut. On the full sample (Panel A), the null hypothesis is rejected only for D1 and D2, and only at the 10% level, and not for the cross-decile average. Excluding the NBER recession years (Panel B), the fourth factor delivers significant gains in most deciles and on average. Since the gain from a fourth factor depends on the evaluation sample, we adopt three factors as the more parsimonious preferred specification. We do not extend the factor space further, as the gains from additional factors would have to be weighed against the small effective sample available for estimating them.

Table C3: Clark-West test: pairwise comparison of factor models

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Avg
<i>Panel A: Full sample, 1990–2024</i>											
1f vs 2f	0.37	0.47	0.62	0.64	0.54	0.50	0.43	0.42	0.42	0.65	0.49
1f vs 3f	0.02**	0.04**	0.01**	0.01**	0.01**	0.01**	0.01**	0.02**	0.05*	0.07*	0.02**
1f vs 4f	0.03**	0.04**	0.03**	0.03**	0.02**	0.02**	0.01**	0.03**	0.06*	0.10	0.03**
2f vs 3f	0.03**	0.03**	0.02**	0.01**	0.01**	0.01**	0.01**	0.02**	0.04**	0.05**	0.02**
2f vs 4f	0.04**	0.03**	0.03**	0.02**	0.02**	0.02**	0.01**	0.02**	0.04**	0.06*	0.02**
3f vs 4f	0.09*	0.05*	0.11	0.23	0.28	0.27	0.20	0.33	0.40	0.57	0.14
<i>Panel B: Without NBER recession years</i>											
1f vs 2f	0.75	0.93	0.91	0.97	0.95	0.96	0.96	0.97	0.97	0.97	0.96
1f vs 3f	0.05*	0.07*	0.03**	0.03**	0.03**	0.03**	0.03**	0.05**	0.08*	0.10*	0.04**
1f vs 4f	0.06*	0.06*	0.03**	0.03**	0.03**	0.03**	0.02**	0.04**	0.05*	0.06*	0.04**
2f vs 3f	0.03**	0.02**	0.02**	0.01**	0.01**	0.01**	0.01**	0.02**	0.04**	0.04**	0.02**
2f vs 4f	0.05**	0.03**	0.02**	0.01**	0.02**	0.01**	0.01**	0.02**	0.02**	0.03**	0.02**
3f vs 4f	0.15	0.06*	0.05**	0.02**	0.03**	0.04**	0.03**	0.03**	0.05*	0.01**	0.04**

Notes: Cell entries are one-sided p -values from the Clark-West test for nested model comparison ([Clark and West, 2007](#)), pooled DFMs with two EM starts, October 1 (Q3) cut-off; ** $p < 0.05$ and * $p < 0.10$. Rejection of the null hypothesis indicates that the additional factor(s) carry predictive content. Avg: test on the cross-decile average of the adjusted loss differential. Panel B excludes the NBER recession years 1990, 1991, 2001, 2008, 2009, and 2020 ($T = 29$).

C.4 News decomposition

Let $\hat{y}_{t|v}$ denote the nowcast of a target for income year t produced at vintage v , and let $v' > v$ be the next quarterly vintage of the same year. Following [Bańbura and Modugno \(2014\)](#), the revision $\hat{y}_{t|v'} - \hat{y}_{t|v}$ is written as the sum of three parts. The news component is the contribution of the observations released between v and v' . For each newly released observation $x_{j,s}$ of indicator j in quarter s , the model forecast $\mathbb{E}[x_{j,s} \mid \Omega_v]$ given the information at v is computed with the Kalman smoother, and the impact on the nowcast is the product of the innovation $x_{j,s} - \mathbb{E}[x_{j,s} \mid \Omega_v]$, measured in the standardized units of the series, and the corresponding element of the Kalman gain, which depends on the loadings and on the covariance of the state at v . When several observations are released at once, the impacts are obtained jointly from the linear system that maps the vector of innovations into the revision, so that they add up exactly to the revision induced by the new observations under the parameters of vintage v' . The revision component is the effect of changes in previously published observations and is zero in our pseudo-real-time data. The parameter component is the remainder, the difference between the nowcast at v' and the nowcast that the new data would have produced under the parameters of v ; it captures the re-estimation of the model at the new vintage. We compute the decomposition for the transitions April to July, July to October, and October to January of every income year 1990 to 2024, using the parameters of the newer vintage as in the original formulation. The fixed-parameter nowcasts of Panel B in Table 6 are obtained by running the Kalman smoother with the parameters of the April vintage on the data of the later vintages.

Indicators are ranked by their share of the total absolute news impact on a decile, summed over transitions and years. The signal accuracy of an indicator is the share of its absolute news impact that moved the nowcast towards the realized value, that is, the impact-weighted frequency with which the sign of the impact equals the sign of the gap between the realized value and the nowcast before the update. We use a separate term to distinguish this release-level measure from the hit rate at turning points in Section 4.2. Table C4 reports both measures for the five indicators with the largest news share in each segment of the distribution. Table C5 reports the direction and size of the response of the nowcast to a unit surprise in the leading indicators. Surprises in employment, income, and house prices raise the nowcast in every decile, and surprises in jobless claims and in the consumer and PCE price indices lower it; the ISM prices index has a negligible impact in the bottom decile. The response to price surprises is largest at the top of the distribution and the response to employment surprises largest at the bottom.

The parameter component is also a diagnostic for the stability of the EM estimation across vintages. Table C6 reports the mean absolute revision by transition and the shares of its two non-zero components. With a single EM start from principal components, the parameter component accounts for 60% of the October-to-January revision and its mean absolute size is 0.23 percentage points;

Table C4: Leading sources of news by segment of the distribution, 1990–2024

Segment	Indicator	Share (%)	Signal accuracy
D1–D3	Private wage and salary disbursements	8.6	0.62
	Initial jobless claims	6.5	0.35
	Real personal income less transfers	5.4	0.60
	Nonfarm payroll employment	5.0	0.75
	S&P/Case-Shiller house price index	4.8	0.38
D4–D7	Private wage and salary disbursements	7.6	0.66
	Real personal income less transfers	5.5	0.60
	Initial jobless claims	4.8	0.41
	S&P/Case-Shiller house price index	4.5	0.46
	Nonfarm payroll employment	3.5	0.73
D8–D10	Private wage and salary disbursements	7.2	0.70
	Real personal income less transfers	5.4	0.64
	S&P/Case-Shiller house price index	4.4	0.49
	Initial jobless claims	4.3	0.56
	ISM manufacturing prices index	3.7	0.36

Notes: Share: share of the absolute news impact on the nowcast, averaged over the deciles of the segment. Signal accuracy: share of the indicator's absolute news impact that moved the nowcast towards the realized value, 0.5 corresponds to an uninformative release. DFM–Pooled, within-year updates from April to January, income years 1990–2024.

Table C5: Response of the nowcast to a unit surprise in the leading indicators

Indicator	D1	D5	D10
Private wage and salary disbursements	0.102	0.080	0.083
Real personal income less transfers	0.091	0.080	0.088
Initial jobless claims	–0.015	–0.007	–0.007
S&P/Case-Shiller house price index	0.030	0.028	0.029
Nonfarm payroll employment	0.223	0.146	0.117
Conference Board consumer confidence	0.005	0.004	0.004
PCE price index	–0.132	–0.173	–0.198
ISM manufacturing prices index	0.000	–0.003	–0.005
Michigan current economic conditions	0.007	0.004	0.005
Consumer price index	–0.080	–0.105	–0.120

Notes: Median over all releases 1990–2024 of the impact on the nowcast (percentage points of log growth) per unit of innovation in the indicator, where the innovation is the difference between the released value and the model forecast in standardized units. Indicators ordered by their average news share.

with the two-start procedure of Section 3.2 it falls to 36% and 0.10 percentage points, while the news component is unchanged. The remaining parameter effect is concentrated in 2020. Figure C1 traces the revisions of the bottom and top decile through the pandemic and the following years, and Figure C2 shows the news shares for the period since 2010, in which the timely monthly and weekly releases lead the ranking.

Table C6: Decomposition of nowcast revisions by transition

Transition	Mean absolute revision (pp)	News (%)	Parameters (%)	Parameters, single EM start (%)
April to July	0.70	97	7	7
July to October	0.65	86	21	21
October to January	0.27	73	36	60

Notes: Revision of the DFM-Pooled nowcasts between consecutive cut-offs, with the model re-estimated at each cut-off, averaged over the ten deciles and the income years 1990–2024. News and Parameters: share of the summed absolute revision accounted for by the news and the parameter component; data revisions are zero. The shares do not add to 100 because the components partly offset each other. Last column: parameter share obtained with a single EM start from principal components instead of the two-start procedure of Section 3.2.

C.5 Derived nowcasts of inequality measures

In Section 4.1, we show that nowcasting inequality measures within a DFM framework yields results very similar to the $AR(p)$ benchmark. Table C7 shows that the results are quantitatively similar for the DFMs when the inequality measures are instead derived from the decile nowcasts, for both the single-decile and the pooled specification. For the benchmark, deriving the measures from its decile nowcasts increases the errors for the three percentile ratios, in particular for P90/P50, and slightly reduces them for the spread.

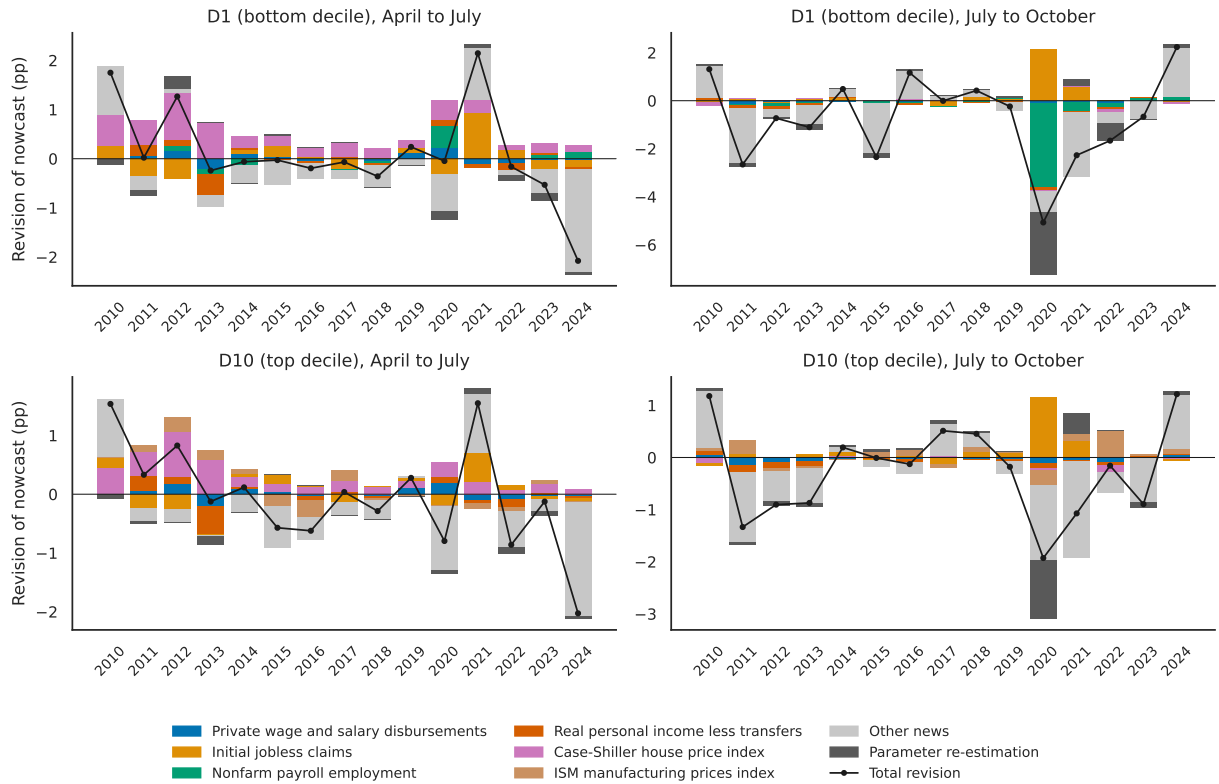
C.6 Forecasts of inequality measures

Table C8 shows the one-step-ahead forecast errors for the inequality measures. As at the nowcast horizon, the DFM improves only slightly on the benchmark: its RMSE is lower for all four measures, by 1–5%, but the difference is significant only for the P90/P10 ratio, and only at the 10% level.

C.7 Nowcast performance during recessions

A key motivation for nowcasting the income distribution in real time is that distributional dynamics are particularly heterogeneous during cyclical downturns, when policymakers most need timely information. To assess whether the DFM advantage persists or strengthens in such periods,

Figure C1: Nowcast revisions and their sources, bottom and top decile, 2010–2024



Notes: Revision of the DFM-Pooled nowcast between the April and July cut-offs (left) and the July and October cut-offs (right), in percentage points, and its decomposition into the news of the five indicators with the largest share for the respective decile over 1990–2024, the news of all other releases, and the re-estimation of the parameters. Data revisions are zero.

Table C7: Inequality measure nowcasts: direct versus derived strategies (absolute RMSE)

	$\frac{P_{90}}{P_{10}}$	$\frac{P_{50}}{P_{10}}$	$\frac{P_{90}}{P_{50}}$	Spread
<i>Direct strategy</i>				
AR(p)	2.93	2.40	1.13	3.71
DFM-Single	2.82	2.39	1.16	3.64
<i>Derived strategy</i>				
AR(p)	2.95	2.57	1.42	3.61
DFM-Single	2.83	2.39	1.18	3.65
DFM-Pooled	2.86	2.41	1.16	3.65

Notes: Absolute RMSE of year-on-year inequality-measure log growth rates ($\times 100$, in percentage points) at the nowcast horizon ($t | t$), income years 1990–2024. Under the *direct* strategy, inequality measures enter the model as annual targets. Under the *derived* strategy, inequality measures are computed from the nowcast decile means. Spread denotes the growth differential between D10 and D1 in percentage points. None of the DFM rows differs significantly from the direct AR(p) (Diebold–Mariano test with HLN correction, $p > 0.10$). Bold: lowest value per column within each panel.

Figure C2: Share of news impact by indicator and income decile, 2010–2024

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Initial jobless claims	9.9	8.6	8.6	7.9	7.4	6.6	6.4	6.5	6.3	6.5
S&P/Case-Shiller house price index	7.4	7.0	7.1	7.0	6.8	6.4	6.3	6.3	6.4	6.6
Nonfarm payroll employment	7.2	5.6	5.8	5.2	4.6	3.7	3.5	3.4	3.4	3.6
ISM manufacturing prices index	2.6	3.6	3.6	4.2	4.6	5.3	5.5	5.4	5.5	5.4
Conference Board consumer confidence	4.5	4.6	4.5	4.4	4.4	4.4	4.5	4.5	4.5	4.5
Michigan current economic conditions	3.9	4.0	3.8	3.8	3.8	3.9	3.9	4.0	3.9	3.8
Real personal income less transfers	3.0	3.2	3.2	3.4	3.5	3.6	3.6	3.6	3.6	3.7
Private wage and salary disbursements	3.1	3.3	3.3	3.3	3.4	3.4	3.5	3.5	3.5	3.5
1-year expected inflation (Cleveland Fed)	1.4	2.5	2.3	2.7	3.1	3.7	3.8	3.8	3.8	3.8
Michigan consumer sentiment	2.1	2.7	2.5	2.7	2.9	3.2	3.3	3.4	3.4	3.2
Total consumer credit	3.3	3.1	3.1	2.9	2.8	2.7	2.7	2.7	2.6	2.5
PCE price index	2.0	2.4	2.4	2.6	2.7	2.9	3.0	3.0	3.0	3.0

Notes: As Figure 2, for the income years 2010–2024.

Table C8: One-step-ahead RMSE for inequality measures

	$\frac{P90}{P10}$	$\frac{P50}{P10}$	$\frac{P90}{P50}$	Spread
AR(p)	2.96	2.42	1.12	3.75
DFM-Single	2.82*	2.32	1.11	3.62

Notes: Absolute RMSE of one-step-ahead forecasts ($t + 1 | t$) of the year-on-year inequality-measure log growth rates ($\times 100$, in percentage points), income years 1991–2024. Both models are estimated directly on each measure. Spread denotes the growth differential between D10 and D1 in percentage points. Significance from the Diebold–Mariano test against AR(p) with HLN small-sample correction ($h = 2$): ** $p < 0.05$, * $p < 0.10$. Bold: lowest value per column.

we restrict attention to NBER recession years (1990, 1991, 2001, 2008, 2009, and 2020). Table C9 reports the RMSE on this recession subsample.

Table C9: RMSE during recession years

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Avg
<i>Absolute RMSE in percentage points</i>											
AR(p)	4.89	4.02	4.22	3.49	3.43	3.51	3.51	3.16	2.96	2.83	3.60
DFM-Single	3.52	2.89	2.79	2.76	2.58	2.20	1.91	2.08	2.30	3.09	2.61
DFM-Pooled	3.48	3.00	2.81	2.70	2.47	2.10	1.90	2.00	2.19	2.88	2.55
<i>RMSE relative to AR(p)</i>											
AR(p)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DFM-Single	0.72	0.72	0.66	0.79	0.75	0.63	0.54	0.66	0.78	1.09	0.73
DFM-Pooled	0.71	0.75	0.67	0.77	0.72	0.60	0.54	0.63	0.74	1.02	0.71

Notes: Absolute RMSE restricted to NBER recession years (1990, 1991, 2001, 2008, 2009, 2020), October 1 (Q3) cut-off. Year-on-year log growth rates ($\times 100$, in percentage points). Avg denotes the cross-decile average. Diebold–Mariano tests are not marked in the table because, with six paired observations, they do not reject equal accuracy for any decile; see the text. Bold: Lowest value per column within each panel.

In recession years, the DFMs reduce the RMSE by 27–29% on average relative to the benchmark, with the largest gains in the middle of the distribution; only the top decile does not benefit. While these gains are larger than in the full sample, they cannot be established statistically: with six paired observations the Diebold–Mariano test does not reject equal accuracy in any decile, which reflects the lack of power rather than evidence of equal accuracy.

The nowcast errors for each recession year are displayed in Table C10. The DFMs outperform the benchmark in five of the six recession years, most strongly in 2020, when the benchmark misses the pandemic contraction by 6.6 percentage points on average across deciles. The exception is 2009: the DFMs nowcast a much sharper decline in household income than was realized, with errors of more than five percentage points on average, while the benchmark is close to the outcome. The recession evidence therefore rests on few and heterogeneous episodes.

Table C10: Nowcast errors by model, year, and income decile (recession years)

Year	Model	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Abs. Avg
1990	AR(p)	-5.28	-3.58	-1.65	-2.35	-2.58	-3.33	-3.71	-3.72	-3.92	-3.64	3.38
	DFM-Single	-3.93	-2.23	-0.82	-0.89	-1.45	-1.95	-2.42	-2.35	-2.49	-2.54	2.11
	DFM-Pooled	-4.04	-2.82	-0.82	-0.96	-1.60	-2.03	-2.51	-2.47	-2.67	-2.77	2.27
1991	AR(p)	-4.01	-1.40	-4.31	-2.29	-1.71	-2.87	-2.49	-0.74	-0.64	-3.34	2.38
	DFM-Single	1.08	-0.51	-1.13	-0.74	-0.01	0.42	0.76	0.45	0.50	0.04	0.57
	DFM-Pooled	1.08	-0.31	-0.85	-0.38	0.25	0.53	0.86	0.61	0.67	0.32	0.59
2001	AR(p)	-5.06	-0.88	-2.13	-1.47	-1.50	-1.16	-0.53	0.01	-0.16	-1.31	1.42
	DFM-Single	-0.40	0.13	-0.17	0.39	0.04	0.48	0.83	0.94	0.63	1.54	0.55
	DFM-Pooled	-0.43	0.16	-0.18	0.38	-0.02	0.42	0.85	0.99	0.69	1.61	0.57
2008	AR(p)	-2.51	0.07	-1.69	-3.39	-4.48	-3.85	-3.45	-3.23	-2.83	-3.25	2.87
	DFM-Single	0.38	2.15	0.83	-0.34	-0.94	-0.36	-0.13	-0.34	-0.09	0.83	0.64
	DFM-Pooled	0.06	1.90	0.52	-0.57	-1.08	-0.53	-0.27	-0.54	-0.41	0.45	0.63
2009	AR(p)	-1.13	-0.42	0.42	1.28	1.14	0.58	0.00	0.37	0.37	-0.78	0.65
	DFM-Single	7.34	6.32	6.59	6.13	5.26	4.35	3.48	3.77	4.30	5.16	5.27
	DFM-Pooled	7.41	6.50	6.74	6.25	5.31	4.40	3.57	3.88	4.35	5.23	5.36
2020	AR(p)	-8.13	-9.02	-8.83	-6.86	-6.13	-6.18	-6.46	-5.92	-5.35	-3.26	6.61
	DFM-Single	1.89	0.37	0.82	2.55	3.05	2.39	1.61	2.26	2.52	4.60	2.21
	DFM-Pooled	0.35	-0.05	0.62	1.81	2.15	1.48	0.99	1.16	1.31	3.45	1.34

Notes: Nowcast errors (actual minus predicted log growth rate ($\times 100$)) by income decile during the NBER recession years, October 1 (Q3) cut-off. Abs. Avg denotes the average absolute error across deciles for each year.

C.8 Sub-samples

Table C11 repeats the comparison with the benchmark on two sub-samples. Excluding the NBER recession years (Panel A), the pooled DFM reduces the RMSE by 11% on average, and the improvement is statistically significant on average and in six of the ten deciles. Excluding the pandemic years 2020 and 2021 (Panel B), the average improvement shrinks to 8% and remains significant only in the middle of the distribution (D6 to D8). The advantage in the middle of the distribution is thus robust across sub-samples, while part of the average advantage stems from the pandemic period.

Table C11: RMSE relative to the AR(p) benchmark, sub-samples

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Avg
<i>Panel A: Without NBER recession years (1990, 1991, 2001, 2008, 2009, 2020)</i>											
AR(p)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DFM-Single	1.01	0.90*	0.90*	0.92	0.95	0.89	0.88**	0.88**	0.92*	0.97	0.93
DFM-Pooled	0.98	0.88**	0.86**	0.88	0.89	0.84**	0.83**	0.84**	0.88**	0.93	0.89**
<i>Panel B: Without the pandemic years 2020 and 2021</i>											
AR(p)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DFM-Single	1.00	0.97	0.95	0.96	0.94	0.87	0.86**	0.88*	0.93	0.96	0.94
DFM-Pooled	0.98	0.97	0.92	0.94	0.91	0.83*	0.83**	0.85*	0.91	0.94	0.92

Notes: Relative RMSE at nowcast horizon ($t | t$), October 1 (Q3) cut-off. **Panel A:** income years 1990–2024 without the NBER recession years ($T = 29$). **Panel B:** income years 1990–2024 without 2020 and 2021 ($T = 33$). Avg denotes the ratio of cross-decile average RMSE. Significance from the Diebold–Mariano test against AR(p) with HLN small-sample correction: ** $p < 0.05$, * $p < 0.10$. Bold: Lowest value per column within each panel.

C.9 COVID robustness

To assess whether the extreme observations of the pandemic distort the parameter estimates in later years, we re-estimate the pooled DFM with all macroeconomic indicators set to missing in the second to fourth quarter of 2020 in every vintage. Table C12 compares this specification with the main specification. Nowcasts up to 2019 are identical by construction. Over the full sample, the masked model is less accurate because it has no information on the pandemic shock when nowcasting 2020. Excluding 2020, and for the years 2021 to 2024, the two specifications are practically identical on average. The pandemic quarters therefore do not distort the estimates for the subsequent years.

Table C12: COVID robustness: absolute RMSE

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Avg
<i>Income years 1990–2024</i>											
DFM-Pooled	4.45	2.65	2.42	2.09	1.94	1.88	1.89	2.01	2.23	2.33	2.39
DFM-Pooled, COVID masked	4.65	2.82	2.60	2.17	2.00	1.98	2.01	2.12	2.30	2.25	2.49
<i>Without 2020</i>											
DFM-Pooled	4.52	2.68	2.45	2.09	1.94	1.89	1.91	2.03	2.25	2.29	2.41
DFM-Pooled, COVID masked	4.47	2.65	2.45	2.10	1.95	1.92	1.94	2.07	2.27	2.27	2.41
<i>Income years 2021–2024</i>											
DFM-Pooled	4.38	2.32	2.37	1.70	1.67	1.80	1.97	2.44	3.39	2.95	2.50
DFM-Pooled, COVID masked	3.93	2.02	2.39	1.74	1.76	2.03	2.22*	2.68*	3.51	2.81	2.51

Notes: Absolute RMSE of year-on-year decile-mean log growth rates ($\times 100$, in percentage points), October 1 (Q3) cut-off. DFM-Pooled: main specification. DFM-Pooled, COVID masked: same model with all macroeconomic indicators set to missing in 2020Q2–2020Q4 in every vintage (estimation, filter, and nowcast); vintages up to 2019 are identical. Avg denotes the cross-decile average RMSE. Significance from the Diebold–Mariano test against DFM-Pooled with HLN small-sample correction: ** $p < 0.05$, * $p < 0.10$. With $T = 4$ in 2021–2024 the test has hardly any power. Bold: Lower value per column within each panel.