Nowcasting the Income Distribution *

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Abstract

This paper proposes a transparent and operational framework to nowcast the income distribution in real time. We combine decile means of the annual household income distribution with a broad panel of quarterly macroeconomic indicators in a mixed-frequency dynamic factor model (DFM) and implement a disciplined pseudo-real-time evaluation from 1990 to 2024. Factor models that exploit high-frequency macro information systematically improve nowcast accuracy relative to univariate ARIMA benchmarks across the distribution, with the largest gains in the middle. Cross-decile dependence is informative but not the dominant source of gains. Combining variable selection and distribution-structured factors delivers additional benefits at the tails, where predictability is intrinsically weaker. The framework is intentionally portable: it relies on off-the-shelf state-space tools, handles ragged edges and mixed frequencies, and produces updatable signals suitable for institutional monitoring. It complements microsimulation and functional approaches by supplying evaluable decile-level priors when microdata are delayed, and it can be embedded in broader pipelines that require timely distributional inputs.

JEL-codes:C38, C53, E27, D31

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1 Introduction

High-frequency information about distributional dynamics is most valuable precisely when economic conditions shift rapidly or policy interventions are implemented at scale. Yet survey-based measures of the income distribution arrive with substantial lags, limiting their usefulness for real-time decision making. By contrast, monthly and quarterly indicators for labor markets, real activity, prices, sentiment, and financial conditions arrive in near real time and plausibly contain signals about within-year changes across the distribution.

This paper develops and evaluates a mixed-frequency nowcasting framework for the income distribution that prioritizes transparency, scalability, and pseudo-real-time performance. We model the distribution in a discretized form – decile mean household incomes – and use a standard state-space dynamic factor model (DFM) to synthesize high-frequency macroeconomic indicators with annual micro targets. DFMs are well suited to mixed-frequency, ragged-edge settings and to sequential news updates (Bańbura and Modugno, 2014; Giannone et al., 2008), while remaining robust in finite samples with Expectation Maximization and Kalman estimation (Doz et al., 2011, 2012).

Our objective is applied and econometric: we ask whether (i) cross-decile information and (ii) high-frequency macro indicators improve short-horizon forecasts of decile-level income growth beyond persistence. The design explicitly targets pseudo-real time evaluation with a disciplined horse race of a suite of DFM specifications against univariate ARIMA and restricted ARIMAX benchmarks. The framework is portable and suitable for institutions that need updatable, evaluable distributional indicators.

To explore potential accuracy gains within a standard DFM, we introduce three additional methodological choices: (i) a joint DFM including all deciles to exploit potential gains from cross-decile dependence, (ii) a real-time variable-selection pipeline to raise the signal-to-noise ratio of the predictor set, and (iii) distribution-structured factors that align latent factors with heterogeneous decile sensitivities to macro shocks.

We implement the framework for the United States by combining annual decile-level total household income from the *Current Population Survey Annual Social and Economic Supplement* with monthly and quarterly macro indicators. Our sample spans the period from 1968 to 2024. Nowcasts ($t \mid t$) are evaluated from 1990 to 2024 using Root Mean Squared Forecast Errors (RMSFE) and standard predictive-accuracy tests. We also report state dependence through directional accuracy around income-specific turning points.

Our main findings are threefold. First, incorporating macroeconomic information through DFMs yields substantial improvements in nowcasting the income distribution relative to univariate and ARIMAX benchmarks. Second, pooling information across deciles provides only modest additional

gains, indicating that cross-decile dynamics contain limited incremental predictive content beyond common macro factors. Third, variable selection and distribution-structured factor identification act primarily as complementary refinements: while they do not materially improve average accuracy, they help stabilize performance at the tails – especially at the top of the distribution – where full-panel models are more prone to miss turning points. Robustness checks across alternative factor structures, selection parameters, and macro panels confirm that the dominant source of predictive improvement stems from exploiting broad macroeconomic information within a factor framework.

Our research complements three active strands of literature. First, we complement microsimulation and reweighting pipelines for real-time inequality. Projects such as Blanchet et al. (2022) and international implementations (e.g. Levy, 2023) integrate multiple micro sources and tax-benefit rules to reconstruct current distributions and produce policy-relevant decompositions and counterfactuals. These pipelines deliver rich cross-sectional detail and program-level attribution but are not primarily designed for real-time forecast evaluation. In contrast, we supply updatable, evaluable decile-level signals built on standard state-space machinery that can (i) be used on their own for surveillance and turning-point detection, or (ii) feed back as real-time priors/constraints into microsimulation workflows when micro data are delayed.

Second, functional time-series approaches model the entire income distribution or its functional objects, yielding shape-coherent inference across quantiles and densities (e.g. Chang et al., 2024; Marcellino et al., 2024). In addition, individual-level and quantile or distribution regression frameworks provide micro-founded heterogeneity and counterfactual interpretation (e.g. Chernozhukov et al., 2013; Koenker, 2004). While functional methods offer representational richness, they require smoothing and basis choices as well as heavier computation. Furthermore, models of this category offer less direct integration with ragged-edge release calendars typical in operational nowcasting. We complement this strand by targeting discretized distributional components (decile means) with a standard mixed-frequency DFM that is easy to align with institutional news accounting and vintage discipline. The distribution structure aligns factors with lower, middle, and upper segments, importing some of the heterogeneity benefits in a lightweight, operational form.

Third, we contribute to the literature on mixed-frequency aggregation for macro indicators. Workhorse bridge, MIDAS and DFM models have established how to synthesize high-frequency indicators for low-frequency macro aggregates such as gross domestic product and industrial production (Bańbura and Modugno, 2014; Giannone et al., 2008; Mariano and Murasawa, 2003). In applied environments, mixed-frequency DFMs have become a workhorse for policy institutions, owing to their scalability and ragged-edge handling (Bańbura and Modugno, 2014).[1] We apply these tools to distributional targets whose publication lags are especially severe. We further investigate two

[1] An accessible overview is given by Bok et al. (2018). Surveys of factor-forecasting foundations are provided by Stock and Watson (2002) and Forni et al. (2000).

additional modeling choices: (i) a real-time variable selection pipeline that disciplines the macro set by decile, and (ii) a distribution-structured identification that concentrates factor loadings on bottom, middle and top segments. These are identification and selection choices within a conventional DFM rather than new estimators. Still, they bridge a gap between aggregate nowcasting practice and distributional monitoring.

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 presents headline results, ablation analysis of gains, and turning point analysis. Section 5 concludes.

2 Data

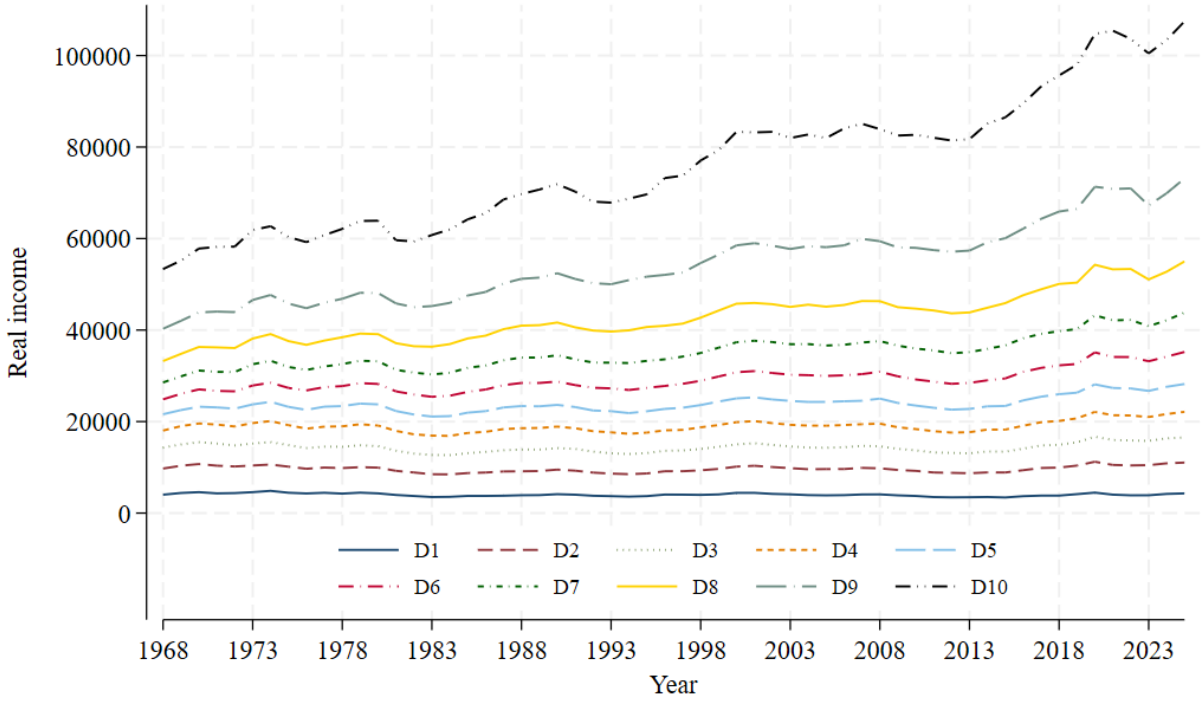
2.1 Micro-level data

Our objective is to nowcast the distribution of total household income. Total income is the relevant concept for economic well-being and distributional policy because it incorporates non-labor income sources that are directly shaped by tax-and-transfer programs. It thus captures the resources available to households that are unemployed, retired, or otherwise out of the labor force in addition to those who are working. During downturns, when labor income declines but transfers expand, total household income provides a more accurate picture of distributional dynamics than labor income on its own.

We therefore use annual micro-level data from the *Current Population Survey* (CPS) *Annual Social and Economic Supplement* (ASEC). The CPS is a nationally representative survey jointly administered by the U.S. Census Bureau and the Bureau of Labor Statistics. The ASEC, fielded annually in March, collects detailed information on household and individual income for the previous calendar year along with employment, demographic characteristics, and program participation. The CPS ASEC covers the civilian non-institutionalized population and contains approximately 75,000 households per year. Person- and household-level survey weights ensure representativeness of all estimates.

Our income concept is all cash income received by household members before taxes and other deductions, captured in the household-level variable `HHINCOME`. It includes wage and salary earnings, self-employment income, private and public pensions, asset income (interest, dividends, rents), and cash transfers such as Social Security, Supplemental Security Income, unemployment insurance, and other government benefits. Because `HHINCOME` covers all household members, it captures income from employed, unemployed, retired, and non-labor-force individuals alike. To ensure representativeness, income is weighted using household weights (`ASECWTH`).

Figure 1: Real household income by decile (levels)



Notes: Annual within-year decile means of CPS ASEC weighted household income (`HHINCOME`), deflated by CPI-U (base year 1983=100). Upper tail treated by within-year winsorization at the 95th percentile.

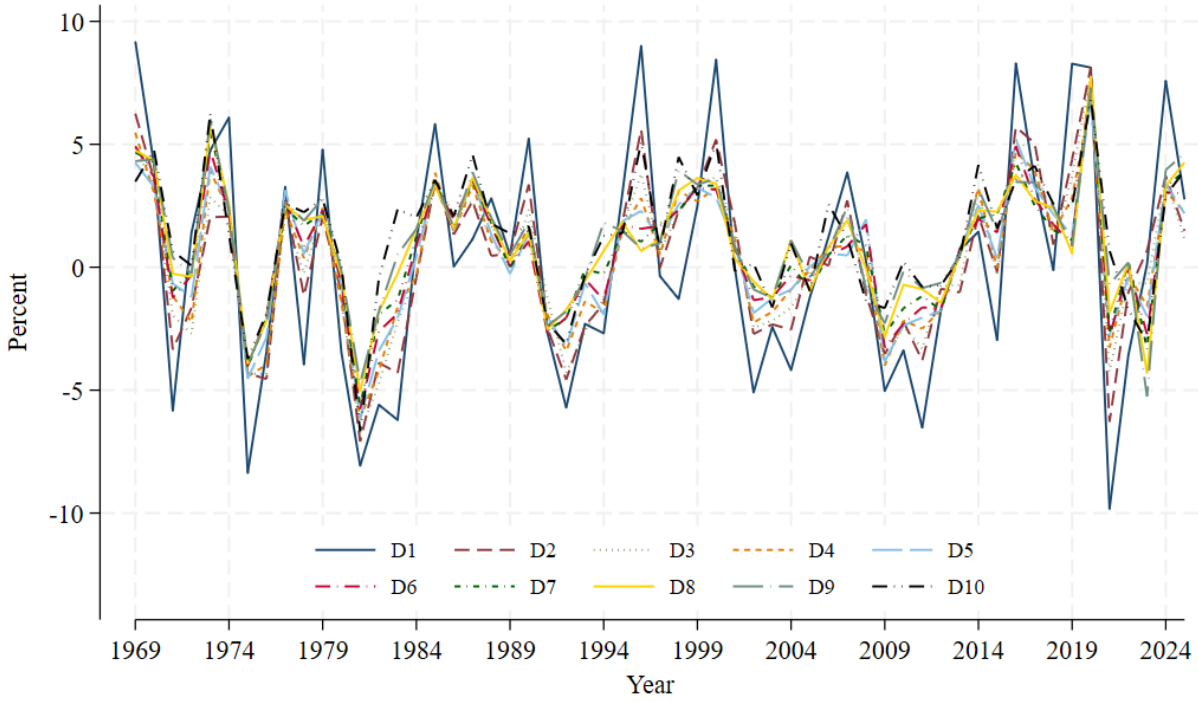
To construct annual distributional targets, we partition households into deciles of the weighted income distribution and compute the mean income within each decile. Decile means balance granularity and robustness: they are more informative than quintiles but remain stable in annual survey data, unlike narrower percentiles that are sensitive to sampling noise. To ensure time-consistent upper tails in the presence of confidentiality protections and processing changes, we winsorize the top 5% of the weighted within-year distribution and compute decile means on the winsorized series.[2] We exclude households with extreme negative income values (CPS special code −9,999,997), households with missing income, and observations with zero or negative weights. As the ASEC is consistently documented and broadly comparable across years from 1968, we drop earlier observations (1962-1967). Nominal incomes are deflated using the Consumer Price Index for All Urban Consumers (CPI-U) and expressed in constant dollars (base year: 1983). The resulting real-income series are shown in Figure 1. Additional information on the sample construction is provided in Appendix A.1.

To achieve stationarity for our nowcasting exercise, we compute year-on-year growth rates in

[2]The CPS income series exhibits a break in the income year 1995 due to the adoption of cell-mean topcoding and concurrent changes in income measurement. These changes mechanically raised reported incomes at the top of the distribution. See Appendix A.1 for details.

decile-mean income. Figure 2 displays the resulting series. Table 1 reports summary statistics.

Figure 2: Year-on-year growth of real household income by decile



Notes: Percent growth of annual within-year decile means from Figure 1. Series are weighted by `ASECWTH` and deflated by CPI-U (base 1983=100). Upper tail treated by within-year winsorization at the 95th percentile.

Table 1: Year-over-year growth of real household income by decile

Decile	Mean	Stand. Dev.	Min	Max
1	0.23	4.85	−9.83	9.19
2	0.27	3.34	−7.09	8.15
3	0.30	3.00	−6.74	7.85
4	0.40	2.77	−6.14	6.81
5	0.50	2.63	−6.14	6.86
6	0.64	2.56	−5.77	7.77
7	0.78	2.51	−5.65	7.56
8	0.92	2.50	−5.04	7.75
9	1.08	2.51	−5.26	7.31
10	1.27	2.62	−6.67	6.83

Notes: Descriptive statistice of growth rate of annual within-year decile means of household income (`HHINCOME`), weighted by `ASECWTH` and deflated by CPI-U (base 1983=100). Upper tail treated by within-year winsorization at the 95th percentile (weighted); growth in percent.

2.2 Macro-level data

The macroeconomic indicator set is built to support short-horizon mixed-frequency nowcasting. It spans real activity, labor markets, prices, finance and credit, sentiment, international trade, housing, and sectoral detail to capture heterogeneous links to income dynamics across the distribution. Complete series-level details (ID, source mnemonic, frequency, transformation, first observation, and publication lag) are documented in Table A3 in Appendix A.2.

Our macro dataset contains 123 quarterly series from the following categories (series counts in parentheses): Expenditure & Income (14, e.g. real gross domestic product and total hours worked), Labor Market (27, e.g. unemployment and job claims), Average Hourly Earnings (11, e.g. sectoral average hourly earnings), Prices (9, e.g. CPI-U and Producer Price Index), Production & Sales (10, e.g. industrial production and new orders), Foreign Trade (4, e.g. real exports and imports), Housing (8, e.g. new home sales and permits), Financial Market, Credit & Debt (14, e.g. S&P 500, consumer credit), Interest Rates (4, e.g. the fed funds rate), Consumer and Business Confidence (16), Regional Business Surveys (3), and Migration (1).

All macroeconomic predictors enter the model at quarterly frequency. When a source series is originally monthly or daily, we form quarterly aggregates aligned with release calendars. We transform each series to achieve stationarity.[3] Pseudo-real-time evaluation relies on series-specific publication lags, which emulate real release calendars. All modeling variables are standardized before estimation.

3 Methodology

We employ the DFM proposed by Bańbura and Modugno (2014), which allows to incorporate data at multiple frequencies and is designed to handle time series with ragged edges and missing observations. DFMs are well suited to capture common trends in variables, making them an ideal tool to forecast deciles along the same distribution.This section provides a brief overview of the mixed-frequency DFM and model specifications used throughout the analysis; full details are provided in Appendix B.

3.1 Model and estimation

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

$$y_t = \Lambda f_t + \epsilon_t, \qquad \epsilon_t \sim \mathcal{N}(0, R), \tag{1}$$

[3]Level variables are averaged (or end-of-period where appropriate), while growth transformations are computed at the quarterly frequency. See Table A3 for details.

where f_t is a $k \times 1$ vector of latent common factors and Λ is an $n \times k$ matrix of factor loadings. The idiosyncratic component ϵ_t is orthogonal to the factors and captures series-specific variation.

The latent factors evolve according to a stationary VAR(p) process,

$$f_t = A_1 f_{t-1} + \cdots + A_p f_{t-p} + u_t, \qquad u_t \sim \mathcal{N}(0, Q), \tag{2}$$

where $A_1, \ldots, A_p$ are autoregressive coefficient matrices. In all specifications, we set $p = 1$ for parsimony, which is standard in the nowcasting literature and sufficient to capture the persistent dynamics of macroeconomic activity.

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). A key advantage of this framework is its ability to handle arbitrary patterns of missing data (ragged-edge structure) and mixed frequencies. To incorporate quarterly macroeconomic series alongside annual income targets, we adopt the aggregation scheme of Mariano and Murasawa (2003), which treats low-frequency observations as partially observed high-frequency latent processes. This ensures internal consistency between the mixed-frequency mapping used in estimation and the aggregation used in the variable-selection step.

3.2 Selection of model specifications

To assess the predictive content of macroeconomic indicators and cross-decile information for nowcasting the income distribution, we estimate a range of benchmark and factor-based models.

Our benchmark model is a univariate ARIMA(p, d, q) model estimated separately for each income decile. This allows for fully decile-specific dynamics without imposing cross-decile relationships. We conduct a grid search over $p, d, q \in \{0, 1, 2\}$ and select the model with the lowest Akaike Selection Criterion (AIC). This procedure yields an ARIMA(0,1,2) specification for all deciles except the bottom decile, which is best described by ARIMA(0,1,1). We refer to this benchmark collectively as `ARIMA`.

To evaluate whether information from other parts of the income distribution improves predictions for a given decile, we estimate parsimonious ARIMAX models that augment the ARIMA specification with lagged values of neighboring or tail deciles. These models maintain a comparable dimension while allowing us to test the predictive relevance of cross-decile spillovers. We refer to these specifications as `ARIMAX`.

We consider two different classes of mixed-frequency DFMs that incorporate macroeconomic information: First, in `DFM-S[ingle]-All` models, we estimate a separate DFM for each income decile, using the full macroeconomic dataset. This isolates the contribution of high-frequency macro indicators without cross-decile pooling. Second, in `DFM-P[ooled]-All` models, all income deciles

and macroeconomic indicators are jointly modeled, allowing the factors to capture cross-sectional co-movement in addition to macroeconomic co-movement.

Each DFM is estimated with one, two, and three factors. We ultimately focus on compact systems, as additional factors beyond three contribute little to the explained variance of the decile-income dynamics and may introduce unnecessary estimation noise. In our baseline results, we focus on three-factor models.[4]

3.3 Variable selection and decile-structured blocks

All 123 quarterly macroeconomic indicators described in Section 2.2 may contain predictive information for the evolution of the income distribution. However, Boivin and Ng (2006) suggest that a carefully chosen subset of indicators may perform better in factor model environments than very large panels, especially when idiosyncratic components of the high-frequency series are persistent or cross-correlated. To enhance the signal-to-noise ratio given the limited time span of the annual target series, we therefore implement a data-driven variable selection procedure. We summarize the procedure here and provide expansive details in Appendix B.2.

We employ an expanding-window Elastic-Net selection with the objective to obtain a parsimonious but economically interpretable set of predictors that consistently explains movements in specific parts of the income distribution. In particular, we construct annual data vintages using an expanding window from 1990 through 2024 and estimate a separate Elastic-Net regression for every income decile, retaining only those predictors that are selected for each vintage. The resulting dataset of 20 macroeconomic indicators is used in a separate DFM, `DFM-P-EN_f3`.

In addition, we implement model specifications that exploit the cross-correlation structure of the income distribution and the variable selection. As shown in Figure A.1 in Appendix A, deciles 1–3, 4–7 and 8–10 exhibit strong co-movement, respectively, with correlations gradually declining across wider distributional segments. Motivated by this structure, and following Bok et al. (2018) and Cascaldi-Garcia et al. (2024), we impose block-wise restrictions on the factor loadings, grouping deciles accordingly and allowing each factor to load only on the set of macro variables selected for a particular segment of the distribution. We denote this model `DFM-P-EN_1|4|8`.

3.4 Out-of-sample evaluation

To assess the forecasting performance of the different models, we follow the standard practice in the nowcasting literature and implement a pseudo-real-time evaluation exercise (e.g. Giannone et al., 2008; Proietti et al., 2021). For each year between 1990 and 2024, we reconstruct the information

[4] As shown in Appendix C.1, Clark-West tests suggest that three-factor models improve performance significantly compared to one- and two-factor models.

set available at the end of the third quarter of that year. This requires accounting for the publication lag of every series and assuming that these lags remain constant over time. In doing so, we use the most recent data vintage and abstract from historical data revisions, thereby isolating the effect of information flow rather than revision noise.

Given this simulated real-time dataset, each model is re-estimated in an expanding-window fashion and used to produce a nowcast of each income decile for year t. Realized decile incomes from the CPS ASEC are then compared with the corresponding model predictions to compute Root Mean Squared Forecast Errors (RMSFEs). This procedure ensures that model comparisons reflect genuine real-time forecasting performance and that improvements are not driven by access to information unavailable to forecasters at the time.

4 Results

4.1 Forecast evaluation: Main results

The main objective of this paper is to assess whether incorporating (i) information from other parts of the income distribution and (ii) macroeconomic indicators improves the prediction of discretized income shares within a simple, off-the-shelf framework. Forecast performance is evaluated in pseudo-real time at the nowcast ($t \mid t$) horizon. Incremental predictive accuracy is assessed using the Diebold-Mariano (DM, non-nested; Diebold and Mariano, 1995) and Clark-West (CW, nested; Clark and West, 2007) tests.[5] Detailed results of both tests by decile are provided in Appendix C.1.

As a first step, we compare two multivariate specifications with an `ARIMA` benchmark: (i) a single-decile DFM with three factors (`DFM-S-All_f3`) and (ii) an ARIMAX model including lagged bottom (D1–D3), middle (D4–D7), and top (D8–D10) income-group aggregates (`ARIMAX_L1`). Table 2 reports average and decile-specific RMSFEs relative to the benchmark. Values below unity indicate an improvement over the `ARIMA` model.

Two main findings emerge. First, augmenting the univariate benchmark with information from other parts of the income distribution yields only modest gains. The relative RMSFEs of `ARIMAX_L1` remain close below or even above unity and are statistically insignificant across most deciles, suggesting limited incremental predictive content from cross-distribution lags in this specification.[6]

Second, incorporating macroeconomic information through the factor model leads to economically and statistically meaningful improvements. The `DFM-S-All_f3` reduces RMSFE by about

[5] We use Newey-West HAC with lag $\ell = \lfloor T^{1/3} \rfloor$ for the DM test; the CW test is implemented for nested comparisons. Two-sided p-values are reported.

[6] Alternative ARIMAX variants, including tail-only specifications, deliver qualitatively similar results.

Table 2: Results: Relative RMSFE

Model	Avg	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
ARIMA	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ARIMAX_L1	0.98	1.07	1.01	1.0	1.02	0.95	0.92	0.98	0.97	0.94	0.97
DFM-S-All_f3	0.76*	0.87	0.79	0.77	0.76*	0.7*	0.67*	0.68*	0.72*	0.78*	0.9

Notes: Root Mean Squared Forecast Errors relative to the benchmark ARIMA at the nowcast horizon ($t \mid t$); values < 1 indicate improvement. Avg denotes the cross-decile average, Dx the nowcast of the xth decile. DFM-S-All_f3 is a single-decile DFM with all macroeconomic indicators and three factors. ARIMAX_L1 denotes ARIMAX models augmented with lagged exogenous predictors grouped by income bracket (D1–D3, D4–D7, D8–D10). * indicates a significant Diebold-Mariano test relative to the ARIMA benchmark at the $p < 0.1$ level.

24% on average relative to the benchmark, with peak gains of roughly 33% at the decile level. This pattern indicates that macroeconomic indicators contain substantial information about the evolution of income shares across the distribution.

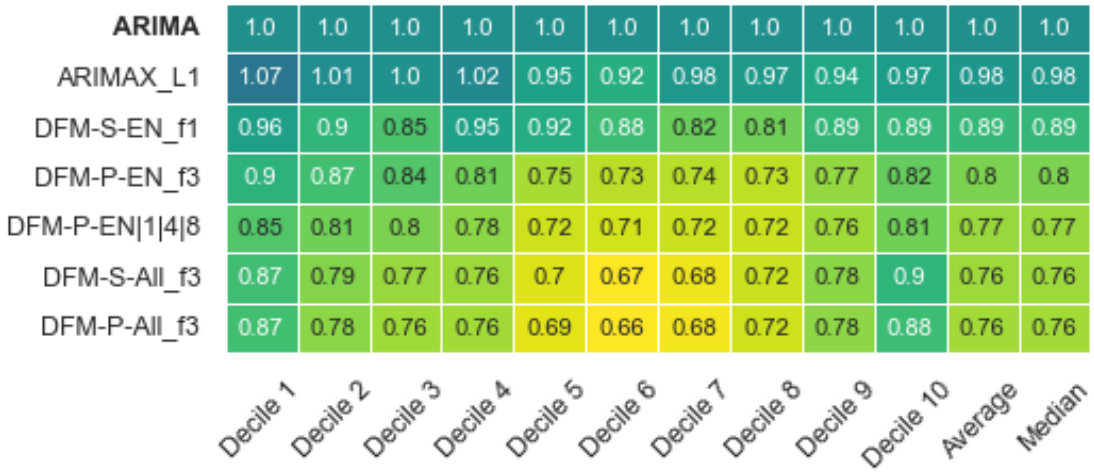
The gains from the factor model are not uniform across the distribution. Improvements are most pronounced in the middle deciles (D5–D7), where several reductions are statistically significant. By contrast, performance gains at the lower and upper tails are smaller and generally not statistically different from the benchmark according to the DM test.

Taken together, these results provide initial evidence that factor-based approaches leveraging mixed-frequency macroeconomic information can meaningfully enhance nowcasts of the income distribution. At the same time, the weaker performance at the tails suggests scope for further refinement, potentially through feature combination, additional model structure, or targeted variable selection to reduce noise. We explore these margins in the next section through an ablation analysis.

4.2 Model refinement and ablation

We investigate three incremental components inside a standard state-space DFM to determine potential forecast gains: Variable selection, pooling across deciles, and factor structure. First, we employ real-time Elastic-Net selection that disciplines the macro panel and aims to reduce noise in the factors and use the remaining per-decile set in a single-decile, single-factor setup (DFM-S-EN_f1). Second, we pool all deciles in one joint non-selected DFM to exploit cross-decile dependence in a factor setting (DFM-P-All_f3). Third, we combine selection and pooling in a three-factor model (DFM-P-EN_f3). Finally, we impose distribution-structured identification on the selected dataset to concentrate factor loadings on lower (D1–D3), middle (D4–D7), and upper (D8–D10) segments and align latent components with heterogeneous decile sensitivities (DFM-P-EN|1|4|8). As before, we evaluate each model in pseudo-real time at the nowcast ($t \mid t$) and one-step-ahead ($t + 1 \mid t$) horizons and test differences between models using DM and CW tests.

Figure 3: Relative RMSFE across the distribution



Notes: Root Mean Squared Forecast Errors relative to the benchmark ARIMA. Values < 1 indicate improvement compared to benchmark. `ARIMAX_L1` is an ARIMAX model with lagged decile groups. `DFM-S-EN_f1` is a single-income, single-factor DFM with Elastic-Net selected predictor panel. `DFM-P-EN_f3` is a pooled three-factor DFM with Elastic Net selected predictor panel. `DFM-P-EN|1|4|8` is a pooled three-factor DFM with Elastic-Net selected predictor panel and low/middle/upper factor structure. `DFM-S-All_f3` is a single-income, three-factor DFM with the full predictor panel. `DFM-P-EN_f3` is a pooled three-factor DFM with the full predictor panel.

Figure 3 summarizes relative RMSFEs (normalized to the `ARIMA` benchmark) across deciles and models. Several insights emerge.

First, factor models deliver the primary gains. Across all specifications, DFMs clearly outperform the univariate `ARIMA` benchmark both on average and across the distribution. This confirms the central result of the previous section: macroeconomic information embedded in factor models contains substantial predictive content for the income distribution. In Appendix C.1, we show that many of these improvements are statistically significant in DM and CW tests.

Second, pooling adds only modest incremental value, relative to single-decile specifications. Although pooled models tend to perform slightly better on average, the magnitude of the gains remains small. This pattern reinforces the earlier finding that cross-decile dynamics contribute relatively little incremental predictive information in this framework.

Third, predictor selection alone can discard useful signal: selection-based trimming does not systematically improve performance relative to the full-panel factor model. In several middle and upper-middle deciles, the full-information specifications deliver lower RMSFEs, indicating that aggressive variable selection may remove macroeconomic variation that supports stable factor extraction.[7]

[7] A useful diagnostic is that Elastic-Net selection alone (without pooling) is dominated by the pooled DFM using the full macro panel. In our setting, DFMs appear well suited to handling large, noisy panels, while selection can inadvertently discard information that matters at particular horizons or vintages.

However, fourth, the combined refinements matter at the tails. While average gains from model refinements are modest, combining selection and pooling improves performance at the upper tail, and adding distribution-structured identification yields further gains, particularly at the extremes of the distribution. This suggests that structural refinements are most valuable where predictability is inherently weaker.

Overall, the evidence indicates that the dominant efficiency gains stem from incorporating macroeconomic predictors within a factor framework. Pooling, variable selection, and distribution-structured identification act primarily as complementary refinements, delivering incremental improvements – most notably at the tails – rather than fundamentally altering average forecast performance.

4.3 Directional accuracy at turning points

Point forecast metrics such as RMSFE provide only a partial assessment of nowcast performance. From a policy and monitoring perspective, the ability to detect turning points in real time is equally important. We therefore evaluate the turning point accuracy of the competing models across the income distribution. We study performance around decile-specific turning points defined as changes in the sign of growth rates of decile-mean incomes.[8]

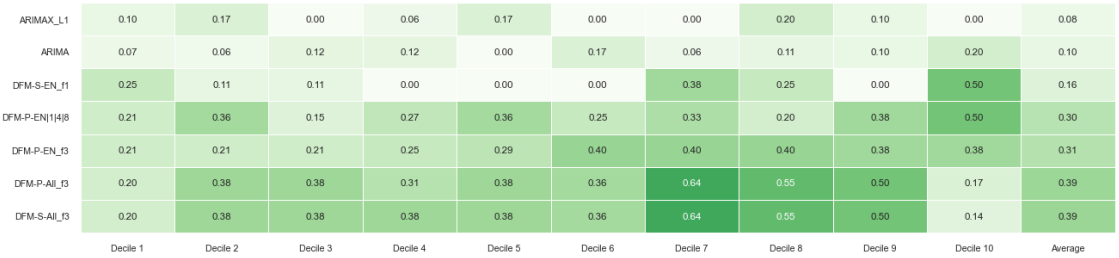
Figure 4 reports model hit rates for decile-specific turning points, defined as correctly predicting both the occurrence and direction of a sign change in income growth. Higher values therefore indicate better real-time detection of distributional inflection points. Several patterns emerge that complement the RMSFE evidence.

First, factor models again dominate the autoregressive benchmarks. Both `ARIMA` and `ARIMAX_L1` display uniformly low hit rates, with average performance around 10% and several deciles close to zero. This confirms that purely autoregressive dynamics alone contain little information about directional shifts in the income distribution. By contrast, all DFM specifications achieve materially higher hit rates, underscoring the importance of macroeconomic information for detecting distributional turning points.

Second, pooling slightly improves average turning-point detection, but the inclusion of the full macro panel remains the key driver of performance. Pooled specifications such as `DFM-P-EN_f3` and `DFM-P-EN|1|4|8` substantially raise the average hit rate relative to the single-decile variable-selection model, indicating that exploiting cross-decile comovement can help identify common directional shifts. However, the strongest overall performance is delivered by the full-information

[8]We deliberately do not rely on aggregate business cycle turning points, such as those dated by the National Bureau of Economic Research (NBER). While such chronologies are appropriate for evaluating macroeconomic forecasts, they are less suitable in the present context as changes in income dynamics need not coincide with aggregate recessions or expansions and different parts of the income distribution often respond with heterogeneous timing and magnitude to macroeconomic conditions. Using NBER turning points would therefore risk understating model performance in detecting distribution-specific inflection points.

Figure 4: Turning point hit rates



Notes: Hit rates of changes in sign of income growth rate per decile and model. We define a "hit" as the correct prediction and direction of a change in sign. Higher values indicate better performance. `ARIMA` is the benchmark univariate model. `ARIMAX_L1` is an ARIMAX model with lagged decile groups. `DFM-S-EN_f1` is a single-income, single-factor DFM with an Elastic-Net selected predictor panel. `DFM-P-EN_f3` is a pooled three-factor DFM with Elastic-Net selected predictor panel. `DFM-P-EN|1|4|8` is a pooled three-factor DFM with an Elastic-Net selected predictor panel and low/middle/upper factor structure. `DFM-S-All_f3` is a single-income, three-factor DFM with the full predictor panel. `DFM-P-EN_f3` is a pooled three-factor DFM with the full predictor panel.

factor models (`DFM-S-All_f3` and `DFM-P-All_f3`), both of which achieve the highest average hit rates (around 39%) and peak values above 60% in the middle deciles. This mirrors the RMSFE results and highlights that retaining the full macroeconomic information set is more important than pooling per se.

Third, variable selection plays a distinct role at the tails – particularly at the top of the distribution. While full-panel models dominate on average, their performance deteriorates in the upper decile, where hit rates fall markedly. In contrast, Elastic-Net based pooled specifications maintain substantially higher accuracy in D10 (around 38 to 50%), indicating that targeted predictor selection helps isolate tail-specific signals that are diluted in large macro panels. In this sense, selection acts as a complementary device that is especially valuable where full-information models struggle.

Finally, consistent with earlier findings, turning points in the middle of the distribution are generally easier to detect than those at the extremes. Nevertheless, the combination of pooling and selection yields the most balanced performance profile across deciles.

Taken together, the turning-point evidence reinforces and refines the RMSFE results. Pooling contributes to improvements in average directional accuracy, but the dominant gains stem from incorporating the full macroeconomic information set. At the same time, Elastic-Net selection becomes particularly valuable at the upper tail, where pooled full-panel models have difficulty detecting income turning points.

4.4 Robustness and diagnostics

In Appendix C.2, we report diagnostics for a number of additional results, examining (i) alternative factor structures based on different income groupings, (ii) variations in the Elastic-Net parameters governing predictor selection, (iii) alternative numbers of latent factors, (iv) modifications to the underlying macroeconomic information set, and (v) an unrestricted Mixed-Frequency Data Sampling (U-MIDAS) model.

5 Conclusion

This paper proposes a transparent and operational framework to nowcast the income distribution in real time by combining annual CPS ASEC decile means with a broad panel of quarterly macroeconomic indicators in a mixed-frequency dynamic factor model (DFM). We emphasize applied forecasting performance and implement a disciplined pseudo-real-time evaluation from 1990 to 2024.

Three main findings emerge. First, factor models that exploit high-frequency macro information systematically improve nowcast accuracy relative to univariate ARIMA benchmarks across most of the distribution, with the largest gains in the middle deciles. Second, pooling deciles in a single DFM yields only modest average improvements over single-decile DFMs, indicating that cross-decile dependence is informative but not the dominant source of gains. Third, while aggressive predictor trimming can discard useful macro signal, the combination of Elastic-Net selection and distribution-structured factors delivers incremental benefits at the tails, where predictability is intrinsically weaker. A turning-point analysis further shows that the factor-based specifications attain substantially higher directional accuracy than autoregressive alternatives, improving the real-time detection of distributional inflection points.

The framework is intentionally portable: it relies on off-the-shelf state-space tools, handles ragged edges and mixed frequencies, and produces updatable signals suitable for institutional monitoring. It complements microsimulation and functional approaches by supplying evaluable decile-level priors when microeconomic data are delayed, and it can be embedded in broader pipelines that require timely distributional inputs.

Overall, the evidence indicates that standard mixed-frequency DFMs – augmented by a simple selection step and distribution-aware identification – offer a scalable and empirically robust tool for real-time monitoring of income inequality. They close a practical gap between fast-moving macroeconomic indicators and slow-moving survey releases, while remaining sufficiently lightweight to be maintained and evaluated in production environments.

References

Bańbura, Marta and Michele Modugno, "Maximum likelihood estimation of factor models on datasets with arbitrary pattern of missing data," *Journal of Applied Econometrics*, 2014, *29* (1), 133–160.

Blanchet, Thomas, Emmanuel Saez, and Gabriel Zucman, "Real-time inequality," *NBER Working Paper*, 2022, *30229*.

Boivin, Jean and Serena Ng, "Are more data always better for factor analysis?," *Journal of Econometrics*, 2006, *132* (1), 169–194.

Bok, Brandyn, Daniele Caratelli, Domenico Giannone, Argia M Sbordone, and Andrea Tambalotti, "Macroeconomic nowcasting and forecasting with big data," *Annual Review of Economics*, 2018, *10*, 615–643.

Cascaldi-Garcia, Danilo, Thiago RT Ferreira, Domenico Giannone, and Michele Modugno, "Back to the present: Learning about the euro area through a now-casting model," *International Journal of Forecasting*, 2024, *40* (2), 661–686.

Chang, Minsu, Xiaohong Chen, and Frank Schorfheide, "Heterogeneity and aggregate fluctuations," *Journal of Political Economy*, 2024, *132* (12), 4021–4067.

Chernozhukov, Victor, Iván Fernández-Val, and Blaise Melly, "Inference on counterfactual distributions," *Econometrica*, 2013, *81* (6), 2205–2268.

Clark, Todd E and Kenneth D West, "Approximately normal tests for equal predictive accuracy in nested models," *Journal of econometrics*, 2007, *138* (1), 291–311.

Dempster, Arthur P, Nan M Laird, and Donald B Rubin, "Maximum likelihood from incomplete data via the EM algorithm," *Journal of the Royal Statistical Society: Series B (methodological)*, 1977, *39* (1), 1–22.

Diebold, Francis X and Roberto S Mariano, "Comparing predictive accuracy," *Journal of Business and Economic Statistics*, 1995, *13* (3), 253–263.

Doz, Catherine, Domenico Giannone, and Lucrezia Reichlin, "A two-step estimator for large approximate dynamic factor models based on Kalman filtering," *Journal of Econometrics*, 2011, *164* (1), 188–205.

_ , _ , and _ , "A quasi-maximum likelihood approach for large, approximate dynamic factor models," *Review of Economics and Statistics*, 2012, *94* (4), 1014–1024.

Forni, Mario, Marc Hallin, Marco Lippi, and Lucrezia Reichlin, "The generalized dynamic factor model: Identification and estimation," *The Review of Economics and Statistics*, 2000, *82* (4), 540–554.

Giannone, Domenico, Lucrezia Reichlin, and David Small, "Nowcasting: The real-time informational content of macroeconomic data," *Journal of Monetary Economics*, 2008, *55* (4), 665–676.

Koenker, Roger, "Quantile regression for longitudinal data," *Journal of multivariate analysis*, 2004, *91* (1), 74–89.

Levy, H., "Nowcasting and provisional estimates of income inequality using microsimulation techniques," Technical Report 12, OECD Publishing 2023.

Marcellino, Massimiliano, Andrea Renzetti, and Tommaso Tornese, "Nowcasting distributions: A functional MIDAS model," 2024. arXiv:2411.05629v1.

Mariano, Roberto S and Yasutomo Murasawa, "A new coincident index of business cycles based on monthly and quarterly series," *Journal of Applied Econometrics*, 2003, *18* (4), 427–443.

Proietti, Tommaso, Alessandro Giovannelli, Ottavio Ricchi, Ambra Citton, Christían Tegami, and Cristina Tinti, "Nowcasting GDP and its components in a data-rich environment: The merits of the indirect approach," *International Journal of Forecasting*, 2021, *37* (4), 1376–1398.

Stock, James H. and Mark W. Watson, "Macroeconomic forecasting using diffusion indexes," *Journal of Business & Economic Statistics*, 2002, *20* (2), 147–162.

Appendix

A Data

A.1 Micro data

Universe and source. We use the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) microdata for the civilian non-institutionalized population. We begin in 1968, the first year for which ASEC public-use microfiles are consistently documented and broadly comparable; earlier files (1962-1967) have universe and documentation limitations and were not released as standard public-use products. Annual file sizes from 1968 onward provide stable household/person counts suitable for distributional statistics. See documentation on ASEC sample and documentation on ASEC sample size. All ASEC files and technical documentation are obtained from the Census Bureau/ASEC portal and IPUMS-CPS.

Income definition and targets for nowcasting. Our household income concept is `HHINCOME`, the CPS total pre-tax *money* income received by all household members during the previous calendar year, aggregating earnings, self-employment income, pensions, asset income, and cash transfers (e.g., Social Security, SSI, UI). Users must adjust nominal amounts for inflation.[9] The ASEC data and CPI documentation are publicly available via Census/BLS portals; we follow the Census/ASEC documentation conventions and deflate nominal incomes are using the CPI-U (base year: 1983). Table A1 reports unconditional summary statistics of price-adjusted within-year decile means. For each year, we rank households by weighted real income and assign them to deciles (D1-D10). Our targets are year-on-year growth rates of decile means of real household income. Figure A.1 shows the cross-correlation structure of income growth rates between deciles.

Sample construction. Before 1968, the ASEC is incompletely documented, was not officially released as public-use files, and has universe limitations (e.g., exclusion of children under 14), undermining cross-time comparability. In addition, from 1968 onward, the ASEC provides large, stable annual samples that support reliable distributional statistics such as decile means, and the Census Bureau maintains continuous technical documentation and releases for these ASEC files, facilitating reproducible historical analysis. We therefore drop pre-1968 observations. In addition, we exclude NIU/special income codes and missing income (e.g., `HHINCOME`=99999999 or special negatives per IPUMS coding) and households with zero or negative household weights `ASECWTH`.

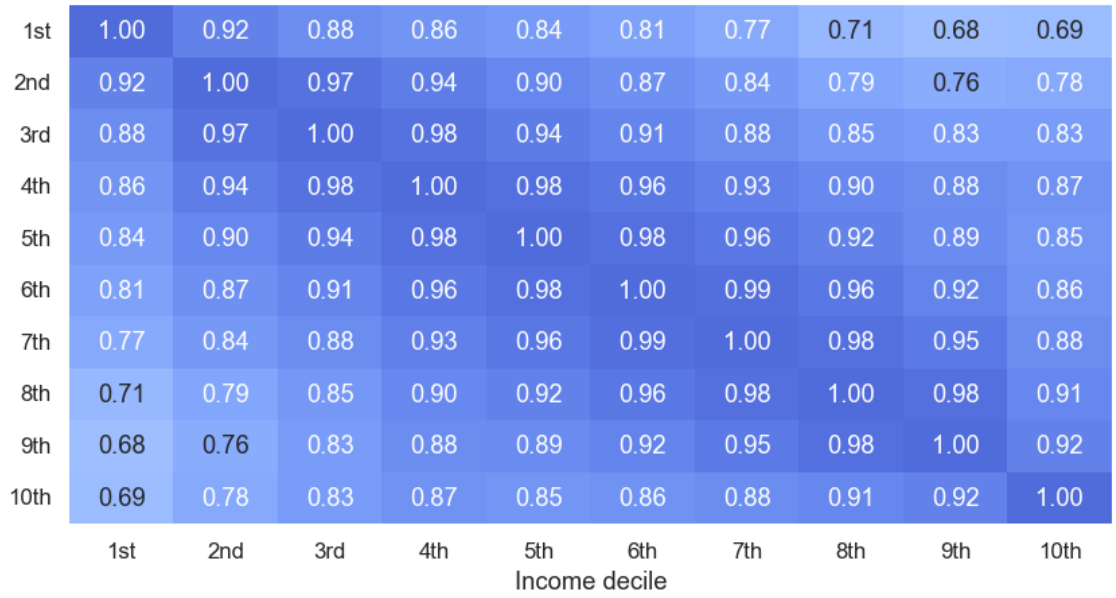
[9] See documentation of of HHINCOME on CPS Ipumps website.

Table A1: Real household income by decile (summary statistics)

Decile	Mean	Stand. Dev.	Min	Max
1	6,291	3,723	−17,282	11,402
2	15,422	2,256	11,404	19,263
3	23,068	2,187	19,264	26,813
4	30,756	2,278	26,814	34,711
5	38,980	2,476	34,713	43,282
6	48,025	2,792	43,284	52,938
7	58,582	3,381	52,940	64,673
8	72,217	4,632	64,676	80,813
9	93,215	8,099	80,818	109,381
10	132,503	11,315	109,394	141,755

Notes: Statistics computed across all sample years on within-year decile means constructed from CPS ASEC household income (`HHINCOME`); weights `ASECWTH`. Real values deflated by CPI-U (base 1983=100). Upper tail treated by within-year winsorization at the 95th percentile (weighted).

Figure A.1: Correlations between income growth rates across deciles



Notes: Pairwise Pearson correlation coefficients of income growth rates between deciles.

All descriptive and target statistics use `ASECWTH`.[10]

Upper-tail treatment. To ensure time-consistent upper tails given confidentiality edits and mid-1990s processing changes, we winsorize the top 5% of the weighted within-year household-income distribution and compute decile means on the winsorized series. The 5% cutoff is chosen via a data-driven rule: we select the smallest winsorization percentile that places the year-over-year

[10] See documentation on ASEC sample notes on CPS Ipumps website.

growth of the D10 mean in 1996 within one standard deviation of the 1986-2006 growth distribution (excluding 1996), and then apply this single cutoff uniformly in all years. For background on ASEC redesigns and processing changes that motivate upper-tail harmonization, see Census redesign and methodology notes.[11] The steps taken in the sample construction and resulting sample size are summarized in Table A2.

Table A2: Sample construction for CPS ASEC household income

Step	N
Raw (all years)	10,130,204
Keep year ≥ 1968	9,714,805
Drop NIU/missing/special	9,711,972
Drop zero/negative weights	9,711,707
Winzorized at 95%	476,316
Final analysis sample	9,235,391

Notes: Sample figures of CPS ASEC microdata with household weights `ASECWTH`. *Winzorized at 95%* removes the top 5% of the *weighted* within-year household-income distribution applied uniformly across years.

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, publication lag and unit.

[11] Additional information is contained in the design note for income poverty on the CPS Ipumps website.

Table A3: Dataset

Block	Macrobond code	Series name	Freq	Transf.	First obs.	Lag	Units	SeriesID
Expenditure and Income	gdp	Real GDP	q	pch	1947-04	-3	USD, TN	emp_pbs
Expenditure and Income	gdi	Real GDI	q	pch	1947-04	-3	USD, TN	emp_ehs
Labor Market	hw_tot	Total Hours Worked	q	pch	1948-04	-3	Hours	emp_leis_hosp
Labor Market	unit_lab_cost	Nonfarm Business Sector: Unit Labor Cost	q	pch	1947-04	-3	Index	emp_othserv
Expenditure and Income	pinc_less_trans	Real Personal Income less Transfers	q	pch	1959-02	-1	USD, TN	emp_gov
Expenditure and Income	disp_pinc	Real Disposable Personal Income	q	pch	1959-02	-1	USD, TN	incphw_tot
Expenditure and Income	r_pce	Real Personal Consumption Expenditures	q	pch	1959-02	-1	USD, TN	incphw_min_log
Prices	cpi-u_all	CPI-U: All Items	q	pch	1947-02	0	Index	incphw_constr
Prices	cpi-u_less_fe	CPI-U: All Items less Food and Energy	q	pch	1957-02	0	Index	incphw_manuf
Prices	ppi_manif	PPI: Manifacturing	q	pch	1985-01	-1	Index	incphw_ttu
Prices	pce	PCE: Chain Price Index	q	pch	1959-02	-1	Index	incphw_info
Prices	pce_less_fe	PCE less Food and Energy: Chain Price Index	q	pch	1959-02	-1	Index	incphw_finact
Prices	oil	Spot Oil Price: West Texas Intermediate	q	pch	1986-03	0	USD/Barrel	incphw_pbs
Prices	sp_500	S&P Composite 500	q	pch	1928-03	0	Index	incphw_ehs
Production & Sales	ind_prod	Industrial Production	q	pch	1919-05	-1	Index	incphw_leis_hosp
Production & Sales	manuf_neword_capg	Manufacturers' New Orders: Capital Goods	q	pch	1992-03	-1	USD, Billion	incphw_othserv
Production & Sales	manuf_neword_durg	Manufacturers' New Orders: Durable Goods	q	pch	1992-03	-1	USD, Billion	jolts
Production & Sales	manuf_ship_durg	Manufacturers' Shipments: Durable Goods	q	pch	1992-02	-1	USD, Billion	awhw_manuf
Production & Sales	manuf_unf_ord	Manufacturers' Unfilled Orders: All Industries	q	pch	1992-02	-2	USD, Billion	markit

Block	Macrobond	Series name	Freq	Transf.	First obs.	Lag	Units	SeriesID
Production & Sales	manuf_inv_durg	Manufacturers' Inventories: Durable Goods	q	pch	1992-02	-1	USD, Billion	ism_manuf
Production & Sales	tot_busi_inv	Total Business Inventories	q	pch	1992-02	-2	USD, Billion	awhw_priv
Production & Sales	merch_wholes_inv_tot	Merchant Wholesalers: Inventories: Total	q	pch	1992-02	-1	USD, Billion	inc_gov
Production & Sales	retsales_foodserv	Real Retail Sales & Food Services	q	pch	1992-02	-1	USD, Billion	inc_priv
Production & Sales	vehic_sale	Light Weight Vehicle Sales	q	pch	1976-02	0	USD, Billion	inc_tot
Foreign Trade	r_exp	Real Exports of Goods	q	pch	1992-02	-2	USD, Billion	ism_nonmanuf
Foreign Trade	r_imp	Real Imports of Goods	q	pch	1992-02	-2	USD, Billion	ism_prind
Foreign Trade	exp_ind	Export Price Index	q	pch	1983-10	-1	Index	ism_empind
Foreign Trade	imp_ind	Import Price Index	q	pch	1982-10	-1	Index	nfib_sbo
Housing	permits	Building Permits	q	pch	1946-02	-1	Units	uom_exp
Housing	house_st	Housing Starts	q	pch	1959-02	-1	Units	uom_sent
Housing	home_sales	New Home Sales	q	pch	1963-02	-1	Units	uom_cec
Housing	const_value	Value of Construction Put into Place	q	pch	1993-02	-2	USD, TN	conf_board
Labor Market	civ_emp	Civilian Empl. (Household Survey)	q	pch	1948-02	-1	Number of Persons	esms
Labor Market	u	Unemployment	q	pch	1948-02	-1	Number of Persons	rfms
Labor Market	urate	Civilian Unemployment Rate	q	chg	1948-02	-1	Percent	c_pmi
Labor Market	duration_u	Median Duration of Unemployment	q	pch	1967-08	-1	Weeks	bls_lnu01373395m
Labor Market	u_ins_claims	Initial Claims for Unempl. Insurance	q	pch	1967-02	-1	Number of Persons	ussurv0791
Labor Market	emp_tot	All Employees: Total Nonfarm	q	pch	1939-02	-1	Number of Persons	ussurv0794

Block	Macrobond	Series name	Freq	Transf.	First obs.	Lag	Units	SeriesID
Labor Market	emp_min_log	All Employees: Mining & Logging	q	pch	1939-02	-1	Number of Persons	ussurv0792
Labor Market	emp_constr	All Employees: Construction	q	pch	1939-02	-1	Number of Persons	ussurv0793
Labor Market	emp_manuf	All Employees: Manufacturing	q	pch	1939-02	-1	Number of Persons	ussurv1462
Labor Market	emp_ttu	All Employees: Trade, Transportation & Utilities	q	pch	1939-02	-1	Number of Persons	uspric1134
Labor Market	emp_info	All Employees: Information	q	pch	1939-02	-1	Number of Persons	usbank0269
Labor Market	emp_finact	All Employees: Financial Activities	q	pch	1939-02	-1	Number of Persons	usbank0251
Labor Market	emp_pbs	All Employees: Professional & Business Services	q	pch	1939-02	-1	Number of Persons	usbank1508
Labor Market	emp_ehs	All Employees: Education & Health Services	q	pch	1939-02	-1	Number of Persons	usbank1504
Labor Market	emp_leis_hosp	All Employees: Leisure & Hospitality	q	pch	1939-02	-1	Number of Persons	usbank1505
Labor Market	emp_othserv	All Employees: Other Services	q	pch	1939-02	-1	Number of Persons	usbank1503
Labor Market	emp_gov	All Employees: Government	q	pch	1939-02	-1	Number of Persons	usbank1502
Average Hourly Earnings	incphw_tot	Average Hourly Earnings: Total Private	q	pch	2006-04	-1	USD	bea016_46w369rg_q
Average Hourly Earnings	incphw_min_log	Average Hourly Earnings: Mining & Logging	q	pch	2006-04	-1	USD	usrate1929
Average Hourly Earnings	incphw_constr	Average Hourly Earnings: Construction	q	pch	2006-04	-1	USD	usrate2241
Average Hourly Earnings	incphw_manuf	Average Hourly Earnings: Manufacturing	q	pch	2006-04	-1	USD	usrate1940

Block	Macrobond	Series name	Freq	Transf.	First obs.	Lag	Units	SeriesID
Average Hourly Earnings	incphw_ttu	Average Hourly Earnings: Trade, Transportation & Utilities	q	pch	2006-04	-1	USD	ussurv1102
Average Hourly Earnings	incphw_info	Average Hourly Earnings: Information	q	pch	2006-04	-1	USD	usnaac1340
Average Hourly Earnings	incphw_finact	Average Hourly Earnings: Financial Activities	q	pch	2006-04	-1	USD	usnaac1283
Average Hourly Earnings	incphw_pbs	Average Hourly Earnings: Professional & Business Services	q	pch	2006-04	-1	USD	usnaac1338
Average Hourly Earnings	incphw_ehs	Average Hourly Earnings: Education & Health Services	q	pch	2006-04	-1	USD	usnaac1296
Average Hourly Earnings	incphw_leis_hosp	Average Hourly Earnings: Leisure & Hospitality	q	pch	2006-04	-1	USD	usnaac0642
Average Hourly Earnings	incphw_othserv	Average Hourly Earnings: Other Services	q	pch	2006-04	-1	USD	usexri0005
Labor Market	jolts	JOLTS: Total Job Openings	q	pch	2001-01	-1	Number of Persons	usbank1507
Labor Market	inc_tot	Wage and Salary Disbursments: Total	q	pch	1959-02	-1	USD, TN	usbank0100
Labor Market	inc_priv	Wage and Salary Disbursments: Private Industries	q	pch	1959-02	-1	USD, TN	useqin0032
Labor Market	inc_gov	Wage and Salary Disbursments: Government	q	pch	1959-02	-1	USD, TN	sp400_opearnps
Labor Market	awhw_priv	Average Weekly Hours: Prod & Nonsupervisory: Private Industries	q	pch	1964-02	-1	Hours	usnaac34251
Labor Market	awhw_manuf	Average Weekly Hours: Prod & Nonsupervisory: Manifacturing	q	pch	1939-02	-1	Hours	usflof_017024
Business Confidence	markit	Markit Manufacturing PMI	q	chg	2022-05	-1	Index	usflof_015451
Business Confidence	ism_manuf	ISM Manufacturing PMI	q	chg	1948-02	0	Index	usflof_039566

Block	Macrobond	Series name	Freq	Transf.	First obs.	Lag	Units	SeriesID
Business Confidence	ism_nonmanuf	ISM Non-manufacturing PMI	q	chg	1948-02	0	Index	uslead0105
Business Confidence	ism_prind	ISM Manufacturing PMI: Prices Index	q	chg	1948-02	0	Index	us10yecbgov_m
Business Confidence	ism_empind	ISM Manufacturing PMI: Employment Index	q	chg	1997-08	0	Index	usnaac0662
Business Confidence	nfib_sbo	NFIB Small Business Optimism Index	q	chg	1974-11	0	Index	uslead0375
Consumer Confidence	uom_sent	U. of Michigan: Consumer Sentiment	q	chg	1952-12	0	Index	usrate1948
Consumer Confidence	uom_exp	U. of Michigan: Consumer Expectations	q	chg	1952-12	0	Index	uscons6235
Consumer Confidence	uom_cec	U. of Michigan: Current Economic Conditions	q	chg	1951-03	0	Index	uscons6236
Consumer Confidence	conf_board	Conf. Board: Consumer Confidence	q	chg	1967-03	0	Index	uscons6237
Business (Regional)	esms	Empire State Manufacturing Survey	q	chg	2001-08	0	Index	uscons11613
Business (Regional)	rfms	Richmond Fed Mfg Survey	q	chg	1993-12	0	Index	usbopa2564
Business (Regional)	c_pmi	Chicago PMI	q	chg	1967-03	0	Index	usfofi7962
Inequality		Mean income 1rst decile	a	pch	1968-12	-8	USD	mean_1
Inequality		Mean income 2nd decile	a	pch	1968-12	-8	USD	mean_2
Inequality		Mean income 3rd decile	a	pch	1968-12	-8	USD	mean_3
Inequality		Mean income 4th decile	a	pch	1968-12	-8	USD	mean_4
Inequality		Mean income 5th decile	a	pch	1968-12	-8	USD	mean_5
Inequality		Mean income 6th decile	a	pch	1968-12	-8	USD	mean_6
Inequality		Mean income 7th decile	a	pch	1968-12	-8	USD	mean_7
Inequality		Mean income 8th decile	a	pch	1968-12	-8	USD	mean_8
Inequality		Mean income 9th decile	a	pch	1968-12	-8	USD	mean_9
Inequality		Mean income top 10 percent	a	pch	1968-12	-8	USD	mean_10
Migration	bls_lnu01373395m	Labor Force Participation Rate - Foreign Born	q	chg	2007-01	-1	Percent	hw_tot

Block	Macrobond	Series name	Freq	Transf.	First obs.	Lag	Units	SeriesID
Business Confidence	ussurv0791	Conference Board Current Condition Economy	q	pch	1976-04	0	Index	retsales_foodserv
Business Confidence	ussurv0794	Conference Board Current Condition Own Business	q	pch	1978-07	0	Index	vehic_sale
Business Confidence	ussurv0792	Conference Board Expectations Economc	q	pch	1976-04	0	Index	merch_wholes_inv_tot
Business Confidence	ussurv0793	Conference Board Expectation Own Business	q	pch	1976-04	0	Index	tot_busi_inv
Business Confidence	ussurv1462	Measure of CEO Confidence	q	pch	1976-04	0	Index	manuf_inv_durg
Prices	uspric1134	Shelter, Rent of Primary Residence	q	pch	1914-12	0	Index	r_pce
Credit and Debt	usbank0269	Deliquancy Rates, Consumer Loans, 100 Largest Banks, All, SA	q	chg	1987-01	-3	Percent	pce_less_fe
Credit and Debt	usbank0251	Deliquancy Rates, Consumer Loans, All Banks, All, SA	q	chg	1987-01	-3	Percent	pce
Credit and Debt	usbank1508	Deliquancy, Consumer Credit, 90 Days or More Late, All	q	chg	1999-01	-3	Percent	manuf_neword_durg
Credit and Debt	usbank1504	Deliquancy, Consumer Credit, 90 Days or More Late, Auto	q	chg	1999-01	-3	Percent	manuf_ship_durg
Credit and Debt	usbank1505	Deliquancy, Consumer Credit, 90 Days or More Late, Credit Card	q	chg	1999-01	-3	Percent	oil
Credit and Debt	usbank1503	Deliquancy, 90 Days or More Late, Home Equity Line of Credit	q	chg	1999-01	-3	Percent	manuf_neword_capg
Credit	usbank1502	Deliquancy, Consumer Credit, 90 Days or More Late, Mortgage	q	chg	1999-01	-3	Percent	sp_500
Credit and Debt	usbank1507	Deliquancy, Consumer Credit, 90 Days or More Late, Other	q	chg	1999-01	-3	Percent	ind_prod

Block	Macrobond	Series name	Freq	Transf.	First obs.	Lag	Units	SeriesID
Credit and Debt	usbank0100	Total Consumer Credit, SA, AR	q	chg	1943-02	-1	Percent	house_st
Financial Market	useqin0032	Equity Indices, Dow Jones, Averages, Industrial Index, Price Return, Close	q	pch	1896-05	0	Index, USD	home_sales
Financial Market	sp400_opearnps	S&P MidCap 400, Operating EPS	q	pch	2008-01	-3	Index, USD	r_exp
Expenditure	usnaac34251	Other, Net Expenditures Abroad by U.S. Residents, Less: Personal Remittances in Kind to Nonresidents	q	pch	1959-01	-1	USD	gdi
Credit and Debt	usflof_017024	Households & Nonprofit Organizations, Total Liabilities	q	pch	1945-10	-3	USD	unit_lab_cost
Credit and Debt	usflof_015451	Financial Soundness Indicator, Households, Debt as A Percent of Gross Domestic Product	q	chg	1946-10	-3	Percent	exp_ind
Credit and Debt	usflof_039566	Households & Nonprofit Organizations, Directly & Indirectly Held Debt Securities as A Percentage of Disposable Personal Income, Assets	q	chg	1945-10	-3	Percent	imp_ind
Interest Rate	us10yecbgov_m	Government Benchmarks Reak 10Year Yield Avrg	q	chg	1914-01	-6	Percent	pinc_less_trans
Expenditure	usnaac0662	Personal Saving Rate	q	chg	1947-01	-3	Percent	gdp
Labor Market	uslead0105	Business Cycle Indicators, Labor Force, Employment, & Unemployment, Average Weekly Initial Claims Unemployment Insurance	q	pch	1945-01	-1	number	r_imp

Block	Macrobond	Series name	Freq	Transf.	First obs.	Lag	Units	SeriesID
Labor Market	uslead0375	Business Cycle Indicators, Profits & Cash Flow, Ratio Corporate Domestic Profits After Tax Net Value Added	q	chg	1947-01	-3	Percent	manuf_unf_ord
Interest Rate	usrate1948	Federal Funds Effective Rate	q	chg	1954-07	0	Percent	permits
Housing	uscons6235	Renal Vacancy Rate, Monthly Rent, 500 USD to 599 USD	q	chg	1993-10	-3	Percent	cpi-u_all
Housing	uscons6236	Renal Vacancy Rate, Monthly Rent, 600 USD to 699 USD	q	chg	1993-10	-3	Percent	cpi-u_less_fe
Housing	uscons6237	Renal Vacancy Rate, Monthly Rent, 700 USD to 799 USD	q	chg	1993-10	-3	Percent	ppi_manif
Housing	uscons11613	Shiller Index	q	chg	1890-01	-2	Percent	disp_pinc
Expenditure and Income	usbopa2564	Income on Foreign Direct Investment, Inward Investment	q	pch	1994-01	-3	USD	const_value
Expenditure and Income	usfofi7962	Transactions for Foreign Direct Investment, Inward Investmen	q	pch	1994-01	-3	USD	civ_emp
Expenditure and Income	bea016_46w369rg_q	Terms of Trade Index	q	pch	1947-01	-3	Index	u
Interest Rate	usrate1929	Expected Real Short Rate, 10 Year	q	chg	1983-03	0	Percent	urate
Interest Rate	usrate2241	Expected Real Short Rate, 5-10 Year	q	chg	1983-03	0	percent	duration_u
Prices	usrate1940	Expected Inflation, 10 Year	q	chg	1983-03	0	percent	u_ins_claims
Business Confidence	ussurv1102	Business Surveys, Federal Reserve Bank of Philadelphia, Business Outlook Survey, Manufacturing, Current General Activity	q	pch	1968-05	0	Index	emp_tot
Expenditure and Income	usnaac1340	Private Fixed Investment, Non-Residential, Intellectual Property Products,	q	pch	2007-01	-2	USD	emp_min_log

Block	Macrobond	Series name	Freq	Transf.	First obs.	Lag	Units	SeriesID
Expenditure and Income	usnaac1283	Private Fixed Investment, Non-Residential, Structures	q	pch	2007-01	-2	USD	emp_constr
Expenditure and Income	usnaac1338	Private Fixed Investment, Non-Residential, Equipment	q	pch	2007-01	-2	USD	emp_manuf
Expenditure and Income	usnaac1296	Private Fixed Investment, Residential, Total	q	pch	2007-01	-2	USD	emp_ttu
Expenditure and Income	usnaac0642	GDP Contributions, Gross Private Domestic Investment, Change in Private Inventories	q	chg	1947-04	-2	percent	emp_info
Expenditure and Income	usexri0005	FX Indices, Federal Reserve, Real Broad Index	q	pch	1973-03	0	Index	emp_finact

Notes: All indicators are seasonally adjusted unless otherwise stated. `pch` = percent change. `chg` = first differences.

B Details on the methodology

This section gives some details on the method and estimation of the Dynamic Factor Model (DFM) described in Section 3.1. We refer the inclined reader to Bańbura and Modugno (2014) and the associated appendix for a more comprehensive exposition of the method.

B.1 Modeling the mixed frequency problem.

In our application, we combine quarterly macroeconomic variables with annually observed income data from the CPS ASEC. Note that the factor f_t in Equation 2 evolves at the higher, quarterly frequency and drives both, the quarterly and the annual series. Hence, the lower frequency series are only observed every fourth period and are modeled as functions of a latent quarterly process (Mariano and Murasawa, 2003). Specifically, the annual difference of the observed series can be expressed as a weighted sum of unobserved quarterly growth rates:

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

where y_t^q denotes the unobserved quarter-on-quarter growth rate of the annual income variable.

State Space representation. Given we have N_q quarterly variables and N_a annual variables ($N = N_q + N_a$), and the model factors are grouped into m blocks. The model can be written in state-space representation, with state vector:

$$\alpha_t = \begin{bmatrix} F_t \\ r_t \\ q_t \end{bmatrix}$$

where: F_t are the common latent factors, r_t are the quarterly idiosyncratic residuals, and q_t are the annual aggregation states. The transition equation can be written as:

$$\alpha_t = \Gamma \alpha_{t-1} + \eta_t$$

where η_t is the process noise, $\eta_t \sim \mathcal{N}(0, Q)$. The observation matrix Λ in Equation 1 has the

structure:

$$\Lambda = \begin{bmatrix} \Lambda_{1,Q} & \dots & \Lambda_{m,Q} & I_{N_q} & 0 \\ \Lambda_{1,A} & \dots & \Lambda_{m,A} & 0 & S_{N_a \times 24} \end{bmatrix}$$

where: $\Lambda_{i,Q}$ are the loadings of the i-th block factors onto quarterly variables, $\Lambda_{i,A}$ are the loadings of the i-th block factors onto annual variables, I_{N_q} is the identity matrix relating the quarterly idiosyncratic residuals, $S_{N_a \times 24}$ is the aggregation matrix mapping quarterly latent states into annual observations. Each Λ_i stacks the factor loadings:

$$\Lambda_i = \begin{bmatrix} \Lambda_{i,Q} \\ \Lambda_{i,A} \end{bmatrix}$$

The transition matrix A has block-diagonal form:

$$A = \begin{bmatrix} A_1 & 0 & 0 & 0 & 0 \\ 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & A_m & 0 & 0 \\ 0 & 0 & 0 & BQ & 0 \\ 0 & 0 & 0 & 0 & BA \end{bmatrix}$$

where each A_i governs the dynamics of the i-th block's factors (AR(p) processes), BQ contains the AR(1) coefficients for the quarterly idiosyncratic residuals, BA governs the dynamics of the annual aggregation states. Thus, the full transition equation can be written:

$$\begin{bmatrix} F_{1,t} \\ \vdots \\ F_{m,t} \\ r_t \\ q_t \end{bmatrix} = \text{diag}(A_1, \dots, A_m, BQ, BA) \begin{bmatrix} F_{1,t-1} \\ \vdots \\ F_{m,t-1} \\ r_{t-1} \\ q_{t-1} \end{bmatrix} + \eta_t$$

Setting Initial Conditions. The initial conditions, that is, the observation matrix Λ_0, the transition matrix A_0, and the residual 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 higher frequency projected data whilst respecting the aggregation scheme.

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.

1. **E-Step** In the first iteration we start with the initial conditions Z_0, an initial guess for the state vector and V_0, which indicates the uncertainty in the current guess of the state vector. By applying the Kalman Filter and Kalman Smoother we update the state vector based on the current iteration's model parameters Λ, A, R and Q. This can be interpreted as simulating the unobserved data. We then calculate the expected value of the log-likelihood conditional on the data, that is the likelihood of observing this data given the model parameters.
2. **M-Step** In the Maximization Step, we re-estimate the model parameters Λ, A, R and Q by maximizing the expected complete-data log-likelihood computed during the E-Step. This maximization yields updated parameter estimates for iteration $j+1$. We then use these updated parameters in the next E-Step to update the state vector and covariance.

This delivers the updated parameters :

$$\text{vec}(\Lambda(j+1)) = \left(\sum_{t=1}^{T} \mathbb{E}_{\theta(j)}\left[y_t f_t' \,\middle|\, \Omega_T\right] \otimes W_t\right)^{-1} \left(\sum_{t=1}^{T} W_t \mathbb{E}_{\theta(j)}\left[f_t' \,\middle|\, \Omega_T\right]\right) \tag{4}$$

$$A(j+1) = \left(\sum_{t=1}^{T} \mathbb{E}_{\theta(j)}\left[f_t f_{t-1}' \,\middle|\, \Omega_T\right]\right)\left(\sum_{t=1}^{T} \mathbb{E}_{\theta(j)}\left[f_{t-1} f_{t-1}' \,\middle|\, \Omega_T\right]\right)^{-1} \tag{5}$$

$$\begin{aligned} R(j+1) = \text{diag}\Bigg(\frac{1}{T}\sum_{t=1}^{T}\Big(& W_t y_t y_t' W_t' - W_t y_t \mathbb{E}_{\theta(j)}\left[f_t' \,\middle|\, \Omega_T\right]\Lambda(j+1)' W_t \\ & - W_t \Lambda(j+1)\mathbb{E}_{\theta(j)}\left[f_t \,|\, \Omega_T\right] y_t' W_t \\ & + W_t \Lambda(j+1)\mathbb{E}_{\theta(j)}\left[f_t f_t' \,\middle|\, \Omega_T\right]\Lambda(j+1)' W_t \\ & + (I - W_t) R(j) (I - W_t)\Big)\Bigg) \end{aligned} \tag{6}$$

$$Q(j+1) = \frac{1}{T}\Big(\sum_{t=1}^{T} \mathbb{E}_{\theta(j)}\left[f_t f_t' \,\middle|\, \Omega_T\right] - A(j+1)\sum_{t=1}^{T} \mathbb{E}_{\theta(j)}\left[f_{t-1} f_t' \,\middle|\, \Omega_T\right]\Big), \tag{7}$$

where W_t is a selection matrix that selects only the available data. Note that $\theta(j)$ is a tuple of the j-th iteration model parameters.

B.2 Variable selection procedure

Boivin and Ng (2006) suggest that a carefully chosen subset of indicators may perform better in factor model environments than very large panels, especially when idiosyncratic components of the high-frequency series are persistent or cross-correlated. To enhance the signal-to-noise ratio given the limited time span of the annual target series, we therefore implement a data-driven variable

selection procedure.

We employ an expanding-window Elastic-Net selection with the objective to obtain a parsimonious but economically interpretable set of predictors that consistently explains movements in specific parts of the income distribution. The selection procedure requires that all predictors be expressed at the same frequency as the annual target variables. To ensure consistency with the mixed-frequency DFM and the Kalman aggregation used in estimation, we adopt the Mariano and Murasawa (2003) triangular distributed-lag representation (see Equation (3)). We apply this aggregation to each transformed macroeconomic series to construct annual growth rates suitable for pre-selection.

We employ an expanding-window Elastic-Net selection. In particular, we construct annual-data vintages using an expanding window from 1990 through 2024. For each vintage, we estimate a separate Elastic-Net regression for every income decile, yielding a total of 340 regressions. Decile-specific models allow the selection procedure to reflect heterogeneous sensitivities to macroeconomic fluctuations across the income distribution, which subsequently enables a block-structured factor specification.

The Elastic Net solves

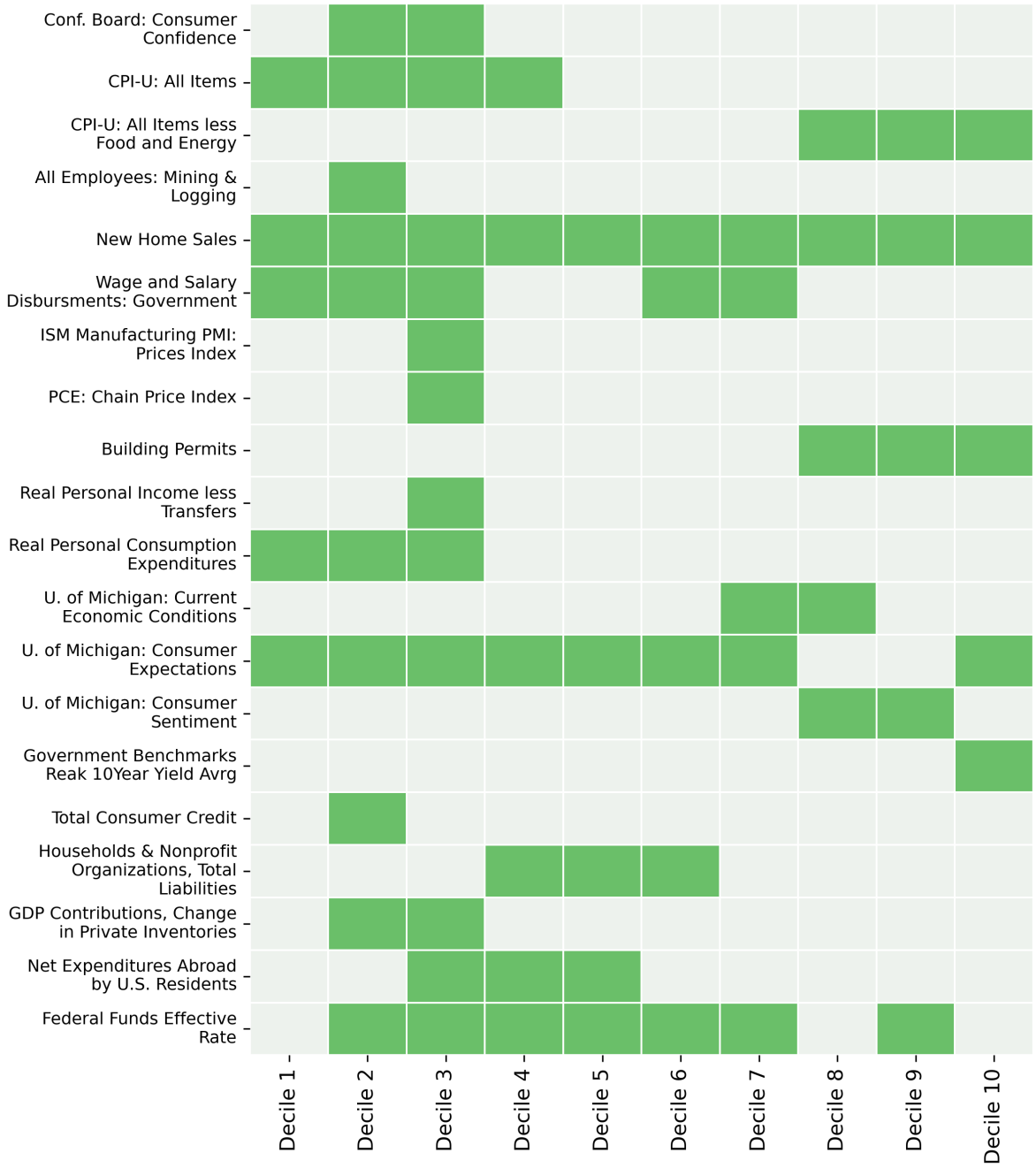
$$\widehat{\beta} = \arg\min_{\beta} \left\{ \frac{1}{T} \sum_{t=1}^{T} (y_t - X_t'\beta)^2 + \lambda \left(\alpha \|\beta\|_1 + \frac{1-\alpha}{2} \|\beta\|_2^2 \right) \right\},$$

where $\alpha \in [0, 1]$ controls the trade-off between Lasso and Ridge penalization, and λ governs penalty strength. We perform a grid search over (α, λ) using expanding-window time-series cross-validation. The pair minimizing the prediction error is used to estimate coefficients for the given vintage. Variables with non-zero coefficients are recorded as selected predictors for that vintage and decile.

To construct a stable predictor set, we compute the selection frequency of each indicator across vintages for each decile. The baseline rule retains all predictors that are selected in every vintage for a given decile. If this yields fewer than five indicators, we add the next most frequently selected variables until the decile-specific set reaches a minimum of five. Combining predictors across deciles results in a final set of 20 indicators, reflecting that several variables carry predictive power for multiple segments of the distribution. Figure B.1 displays the resulting indicator set.

The set of indicators exhibits a clear and economically intuitive structure. First, variables related to labor market conditions – such as wage and salary disbursements or government payroll expenditures – are selected most frequently for the lower and middle income deciles. This aligns with the fact that incomes in the bottom half of the distribution derive predominantly from labor earnings and therefore respond most strongly to employment and wage dynamics. Second, several household demand and consumption indicators, including real personal consumption expenditures, new home sales, and building permits, appear consistently for the middle of the distribution. These

Figure B.1: Variable Selection



Notes: Top 5 variables selected per decile.

households typically adjust spending more sensitively to changes in income and financing conditions, making consumption-based indicators particularly informative for their annual income movements. Third, price and sentiment indicators are selected primarily for the middle and upper-middle deciles. These variables capture households' real purchasing power, expectations about future economic conditions, and prospective wage adjustments, and thus help explain income growth in segments

where expectations and inflation dynamics matter more strongly. Finally, financial market and balance-sheet indicators – such as household liabilities and total consumer credit – are selected predominantly for the upper income deciles. High-income households are more exposed to asset valuations, interest-rate dynamics, and portfolio income; consequently, predictors that reflect credit conditions, financial wealth, or borrowing costs contain greater explanatory power for income movements at the top of the distribution.

Our selection approach introduces several trade-offs. First, using expanding windows necessarily leverages information revealed later in the sample. By focusing on variables selected consistently across vintages, we mitigate this hindsight advantage. Second, the requirement of a balanced predictor set (due to the selection-based specifications) forces exclusion of macroeconomic indicators with later start dates, even if they may be highly informative in real time. In operational forecasting environments, one might instead re-estimate the selection step on a rolling basis using all available data at each point in time. Third, because selection operates in decile-specific regressions, indicators with predictive value concentrated in specific episodes may be excluded if they are not selected consistently enough. In robustness checks, we therefore expand the indicator set beyond the baseline 20 variables.

B.3 DFMs with block structure

In the nowcasting literature, an established approach to improve robustness of factor model estimation and reflect economic comovement is to impose a block structure on the loading matrix (Bok et al., 2018; Cascaldi-Garcia et al., 2024). To investigate the usefulness of this approach in our context, we implement model specifications that exploit the cross-correlation structure of the income distribution, as well as the variable selection. As shown in Figure A.1, lower, middle and upper deciles exhibit strong co-movement, respectively, with correlations gradually declining across wider distributional segments. We therefore employ DFMs that group deciles accordingly and allowing each factor to load only on the set of macro variables selected for a particular segment of the distribution.

We consider three block structures, (i) two blocks, grouping deciles 1–6 and 7–10, (ii) two blocks, grouping deciles 1–7 and 8–10, and (iii) three blocks, grouping deciles 1–3, 4–7 and 8–10 (included in the main results). Each structured model also includes a global factor that loads on all macro indicators to capture broad aggregate dynamics. A macroeconomic predictor is permitted to load on a given block if it was selected by the Elastic Net for at least one decile within that group. We denote these models as `DFM-P-EN[X]`, where $X \in \{a, b, c\}$ denotes the block design.

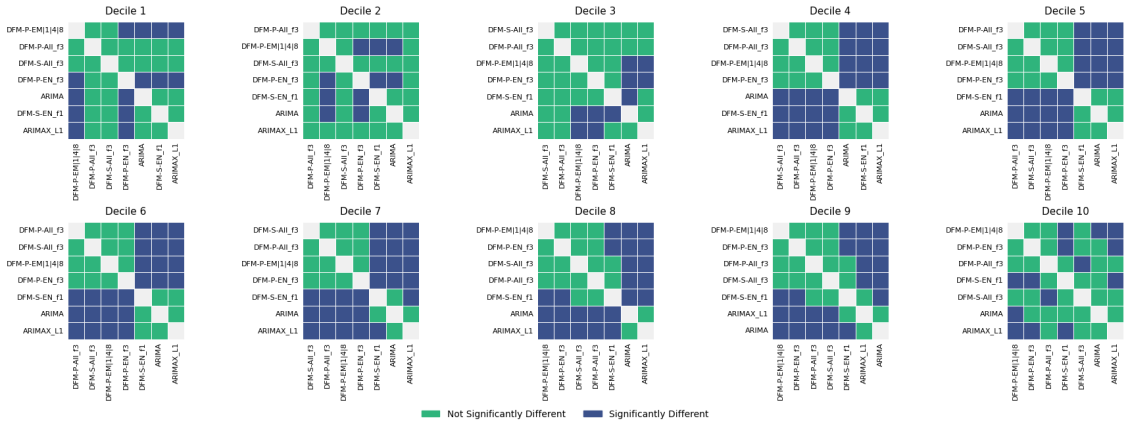
C Additional results and robustness

In Section 4, we present the results of a forecast evaluation horse race of different model specifications. Here, we first present Diebold-Mariano (DM) and Clark-West (CW) statistics of the main model specifications. We then investigate whether our results hinge on the model specifications in an extended horse race.

C.1 Diebold-Mariano and Clark-West statistics

Figure C.1 reports pairwise Diebold-Mariano (DM) tests of equal predictive accuracy for the nowcast horizon by decile. Each panel shows the full comparison matrix across models, where light green indicates that the null of equal predictive accuracy cannot be rejected, and dark blue indicates statistically significant differences.

Figure C.1: Diebold-Mariano matrix per decile



Notes: Pair-wise comparison of model performance via Diebold-Mariano test statistics. Significance level $p < .1$.

Overall, the DM evidence broadly corroborates the ranking suggested by the relative RMSFE results in the main text. In particular, the autoregressive benchmarks (ARIMA and `ARIMAX_L1`) are frequently significantly outperformed by the factor-based specifications, especially in the middle deciles. This reinforces the central conclusion that incorporating macroeconomic information through DFMs delivers the primary forecasting gains.

Within the class of factor models, however, statistically significant differences are comparatively sparse. Many pairwise comparisons among DFM variants appear in light green, indicating that improvements from pooling, variable selection, or factor structuring which are small in RMSFE terms, are also often not statistically distinguishable at conventional levels. This pattern is especially pronounced in the center of the distribution.

At the tails, the matrices reveal somewhat more differentiation. In the upper decile in particular,

EN-based structured specifications show significant improvements where full-panel models don't, consistent with the main-text finding that predictor selection helps stabilize tail performance where full-panel models weaken.

Because the our DFM setup contains nested models, DM comparison may be biased toward the more parsimonious specification. To address this issue, we also report the Clark-West (CW) statistic, which provides a corrected test of equal predictive accuracy for nested forecasting models (Clark and West, 2007). The CW procedure adjusts the usual squared forecast error differential by adding a term that accounts for the expected mean squared forecast error inflation in the larger model under the null of no predictive improvement. Under the null hypothesis that the augmented model does not outperform the benchmark, the adjusted loss differential has mean zero, and the resulting test statistic is asymptotically standard normal and evaluated using a one-sided alternative. This correction yields a more appropriate assessment of forecast gains when the competing models are nested.

Figure C.2 displays the results, comparing models with different factor counts in four model specifications.

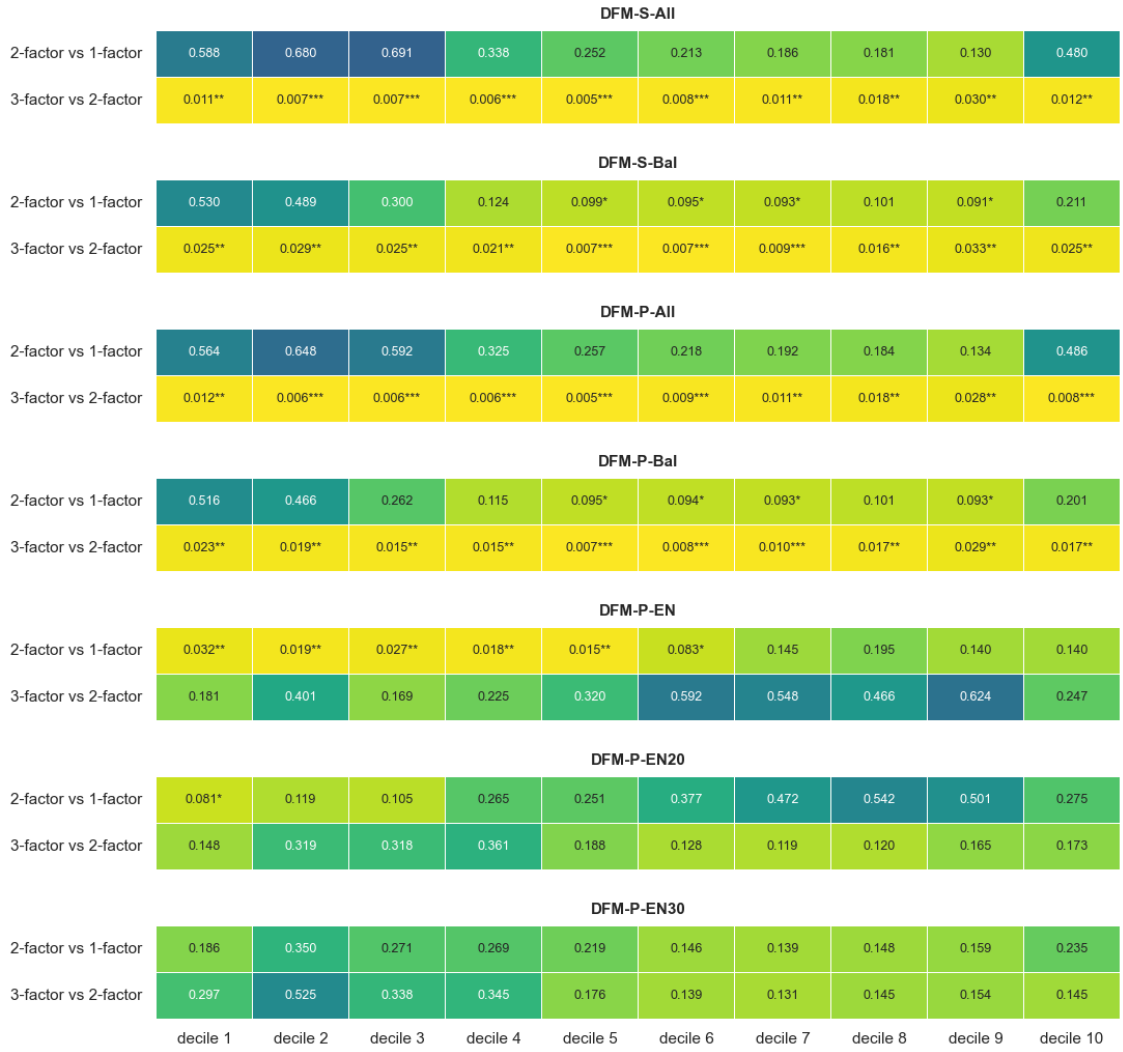
In balanced sets, as well as models with the full macro panel, a third factor leads to a significant improvement in model performance compared to smaller models. The opposite is true in models with an Elastic-Net selected set. In smaller variable sets, too many factors appear to introduce too much noise, leading to worse model performance compared to smaller models.

C.2 Additional model specifications

To assess the robustness of the baseline results, we estimate a range of alternative model specifications that vary along several dimensions of the factor-model design. Specifically, we examine (i) alternative factor structures based on different income groupings (see Section B.3), (ii) variations in the Elastic-Net parameters governing predictor selection (see Section B.2), (iii) alternative numbers of latent factors, and (iv) modifications to the underlying macroeconomic information set, including balanced-panel restrictions. The goal of this exercise is to verify that the main findings are not driven by a particular parametrization or data treatment.

As a simpler model alternative to DFMs, we estimate an unrestricted MIDAS model (`U-MIDAS`) to assess whether macroeconomic indicators provide incremental predictive content for nowcasting income deciles. `U-MIDAS` models regress the annual decile variable on one lag of itself and on quarterly macroeconomic indicators observed within the nowcast year. The choice of macroeconomic variables is made at the income-group level: for each subgroup, we retain only those variables that are selected for all deciles within the group. Specifically, we group deciles 1–3, yielding three macroeconomic predictors, and deciles 4–7 and 8–10, each of which is associated with two macroeconomic predictors.

Figure C.2: Clark-West test statistics

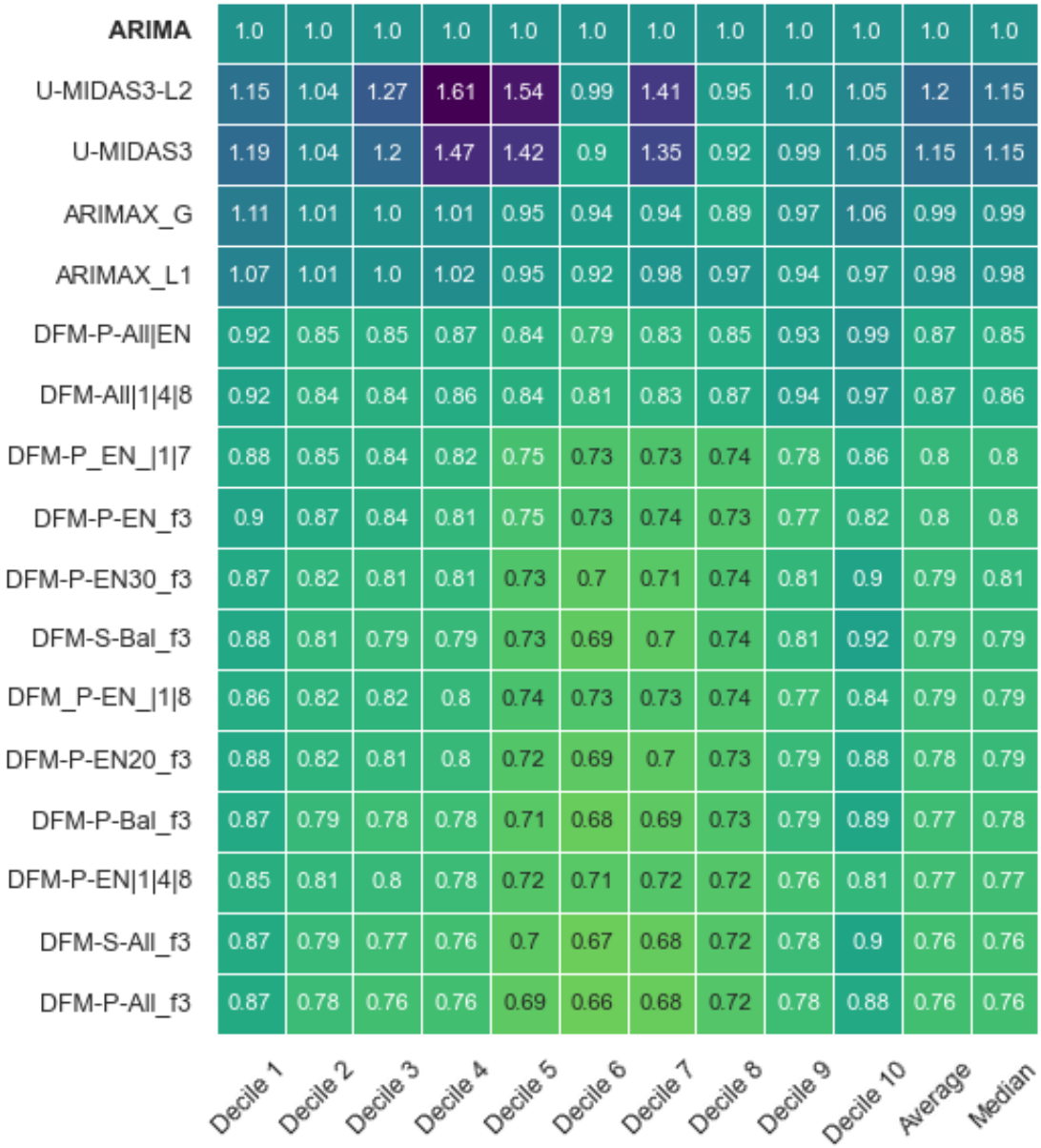


Notes: Pair-wise comparison of model performance via Clark-West test statistics. `DFM-P-All` are pooled DFMs with the full macro panel. `DFM-S-Bal` and `DFM-P-Bal` are single-income and pooled models with a balanced macro set. `DFM-P-EN` are pooled DFM models with Elastic-Net selected macro predictors. Significance levels $^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

Figure C.3 displays the RMSFEs of these additional model specifications together with our baseline results described in Sections 4.1 and 4.2. The main results hold.

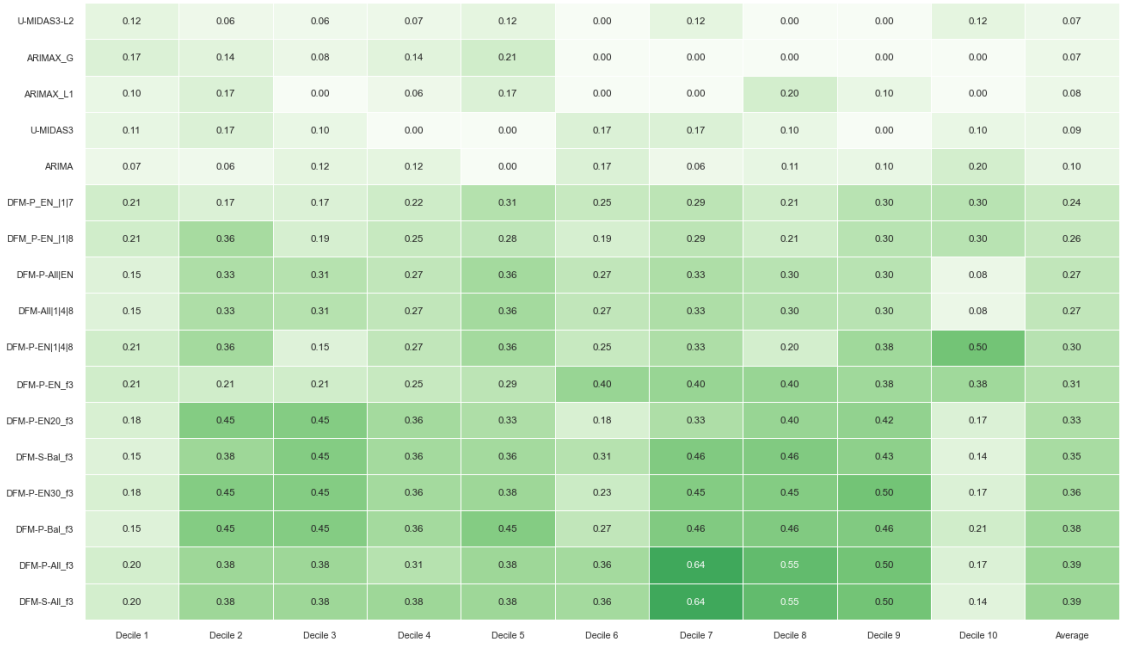
Figure C.4 show the hit rates of the alternative models in a turning point analysis (see Section 4.3). The main results hold.

Figure C.3: Forecast evaluation: Root Mean Squared Forecast Errors



Notes: Root Mean Squared Forecast Errors relative to the benchmark `ARIMA`. Values < 1 indicate improvement compared to benchmark. `ARIMAX_L1` and `ARIMAX_G` are ARIMAX models with lagged decile groups. `DFM-S` and `DFM-P` are single-income and pooled DFMs, respectively, with full macro panel (`All`), Elastic-Net selection (with limit y, where applicable) (`EN(y)`), or balanced set (`Bal`). `a|b(|c)` signals the block structure in place, where applicable. `fx` denotes the number (x) of factors.

Figure C.4: Turning point analysis: Hit rates



Notes: Hit rates of changes in sign of income growth rate per decile and model. We define a "hit" as the correct prediction and direction of a change in sign. Higher values indicate better performance. `ARIMA` is the benchmark univariate model. `ARIMAX_L1` and `ARIMAX_G` are ARIMAX models with lagged decile groups. `DFM-S` and `DFM-P` are single-income and pooled DFMs, respectively, with full macro panel (`All`), Elastic-Net selection (with limit y, where applicable) (`EN(y)`), or balanced set (`Bal`). `a|b(|c)` signals the block structure in place, where applicable. `fx` denotes the number (x) of factors.