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Caruso, Alberto and Coroneo, Laura orcid.org/0000-0001-5740-9315 (2023) Does real-time macroeconomic information help to predict interest rates? Journal of Money Credit and Banking. ISSN 0022-2879

https://doi.org/10.1111/jmcb.13021

Does real-time macroeconomic information help to predict interest rates?

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August 18, 2022

Abstract

We analyse the predictive ability of real-time macroeconomic information for the yield curve of interest rates. We specify a mixed-frequency macro-yields model in real-time that incorporates interest rate surveys and treats macroeconomic factors as unobservable components. Results indicate that real-time macroeconomic information is helpful to predict interest rates, and that data revisions drive a superior predictive ability of revised macro data over real-time macro data. We also find that interest rate surveys can have significant predictive power over and above real-time macro variables.

JEL classification codes: C32, C38, C53, E43, E44, G12.
Keywords: Government Bonds; Real-Time Macroeconomics; Forecasting; Survey Data; Factor Models.

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We thank the editor, Pok-sang Lam, and two anonymous reviewers for comments that helped improve the paper. We are also grateful to Carlo Altavilla, Laurent Ferrara, Gergely Gánics, Domenico Giannone, Adam Golinski, Michal Horvath, Elmar Mertens, Ivan Petrella, Lucrezia Reichlin, Dick van Dijk and seminar and conference participants at the International Institute of Forecasters - Macroeconomic Forecasting Seminar, the 2021 Oxford-MMF workshop (University of Oxford), the 2nd conference on Forecasting at Central Banks (Bank of England), the NBP Workshop on Forecasting (Bank of Poland), the Workshop on Big Data and Economic Forecasting (European Commission), the 8th Italian Congress of Econometrics and Empirical Economics (University of Salento), the 12th International Conference on Computational and Financial Econometrics (University of Pisa), the Annual Conference of the International Association for Applied Econometrics (IAAE 2019, Nicosia), the Conference on Real-Time Data Analysis, Methods and Applications (National Bank of Belgium), the University of York and the University of Sheffield for useful comments. The authors acknowledge the support of Now-Casting Economics Ltd. in the early stage of the paper. The views expressed in this paper are those of the authors and do not necessarily reflect those of EY.

1 Introduction

Macroeconomic variables may incorporate important information for forecasting the evolution of the yield curve. This is due to both the behaviour of policy makers, who operate on interest rates to stimulate aggregate demand and control inflation, and market agents, who closely monitor macroeconomic data and react to macroeconomic news (Beechey & Wright 2009, Altavilla, Giannone & Modugno 2017). Indeed, following the seminal work by Ang & Piazzesi (2003), there is a consensus in the literature that macroeconomic indicators are successful at predicting interest rates and excess bond returns.[1] However, Ghysels, Horan & Moench (2017) find limited evidence of predictive ability of real-time macroeconomic variables for excess bond returns: they argue that the result of the previous literature was an artefact coming from the use of revised data, instead of real-time macroeconomic data.[2]

In this paper, we assess the relevance of real-time macroeconomic information to predict the future path of the yield curve of interest rates. Our contribution is to make interest rate predictions based on the information set available to agents at each point in time by taking into account all the characteristics of the real-time macroeconomic data flow.[3] First, most macroeconomic data is released in a non-synchronous way and with different publication lags; therefore the available information at each point in time can be described by a dataset that has a ragged edge, and it is not balanced. Second, macroeconomic data is very often subsequently revised: the revisions might be substantial and affect the estimation and the forecast computed using different vintages of the data. Third, in real-time forecasting, soft information provided by surveys can have an important role as it is timely, not subject to revisions, and can readily incorporate any information available to survey participants, such as information about the current state of the economy or forward-looking information contained in monetary policy announcements. However, one drawback of using survey

[1] See among others Mönch (2008), Ludvigson & Ng (2009), Favero, Niu & Sala (2012) and Coroneo, Giannone & Modugno (2016).

[2] A common denominator of this literature, in fact, is the use of revised macroeconomic data to predict interest rates, which involves using an information set that is different from the one available to market participants when the predictions were made.

[3] Adequately specifying the information set available to agents in real-time is particularly important when evaluating models in macroeconomics and finance, especially when the objective is to forecast asset prices using external information, since according to the efficient market hypothesis asset prices should already incorporate all the available information about their future evolution, see Orphanides (2001), Orphanides & Van Norden (2002) and Croushore & Stark (2003).

expectations is that their projections are only for quarterly averages.

In order to exploit the informational content of real-time macro data for interest rate predictions, we specify a mixed-frequency macro-yields model in real-time that incorporates interest rate surveys and treats macroeconomic factors as unobservable components, which we extract simultaneously with the traditional yield curve factors. Similarly to Coroneo et al. (2016), we identify the factors driving the yield curve by constraining the loadings to follow the smooth pattern proposed by Nelson & Siegel (1987). More specifically, our empirical model is a mixed-frequency dynamic factor model for Treasury zero-coupon yields, a representative set of real-time macroeconomic variables and interest rate surveys with restrictions on the factor loadings.

Our model can be estimated by maximum likelihood – see Doz, Giannone & Reichlin (2012) – using an Expectation-Maximization (EM) algorithm adapted to the presence of restrictions on the factor loadings and to missing data. Using U.S. data from 1972 to 2019, we find that real-time macroeconomic information is helpful to predict interest rates, especially short maturities at mid and long horizons, and that data revisions drive an increase in the predictive power of revised macro information with respect to real-time macro information. Moreover, during a period when a forward guidance policy is implemented, we find that incorporating interest rate surveys in the model significantly improves its predictive ability.

Our finding that data revisions drive the increased predictive ability of revised macro data with respect to real-time macro data is in line with Ghysels et al. (2017). However, while they find that real-time macro information has only a marginal (and often statistically non significant) role in predicting excess bond returns, our results show that real-time macroeconomic information is helpful to predict interest rates, as its predictive power is similar to that of revised macro data. The crucial difference between our approach and the one in Ghysels et al. (2017) lies in how the real-time dataset is specified: we use the latest information available to market participants at the time in which forecasts are made (that includes both new releases of data points and revisions of already observed data), Ghysels et al. (2017) instead use first releases of data. In general, when the objective is to forecast macroeconomic variables, first releases provide accurate predictions (Koenig, Dolmas & Piger 2003). However, to predict financial variables, it is important to use all the latest available information, as financial operators care about the final revised value of a macroeconomic series (Gilbert 2011). Indeed, our results indicate that the latest information available on real-time macro variables has a stronger predictive ability than their first releases, which is in line with the intuition that revisions enhance the quality of macroeconomic information.

Lastly, we find that incorporating interest rate surveys from the Surveys of Professional Forecasters (SPF) can improve the predictive ability of models that use only information embedded in the yield curve and in macroeconomic variables. Surveys, in fact, incorporate soft information about the future path of interest rates – that comes from policy announcements, for example – that cannot be taken into account by standard macroeconomic variables. With this in mind, we test the relevance of the information contained in the SPF survey forecasts for the real-time macro-yields model. Results indicate that they enhance the predictive ability of the model in a period in which the Federal Reserve implemented a forward guidance policy. The resulting improvement in predictive ability is statistically significant. This intuitively appealing result is in line with Altavilla, Giacomini & Ragusa (2017), who use the selected survey forecast value as their forecast for the specific horizon and maturity. However, our results show that in some periods our model produces more accurate forecasts than the survey forecasts. Therefore, we incorporate the surveys into the model itself. In this way, we combine in a single framework the "soft" information embedded in the surveys with the information carried by interest rates and by the real-time macroeconomic data, fully exploiting all the relevant available information in forecasting the whole yield curve.

The paper is organised as follows. Section 2 outlines the mixed-frequency real-time macro-yields model. Section 3 describes the data and Section 4 outlines the estimation procedure and some preliminary results. Section 5 describes the out-of-sample forecasting exercise, and Section 6 the results. Finally, Section 7 concludes. Appendix A contains details about the state-space representation of the model and the estimation procedure.

2 Model

We model the joint behavior of monthly government bond yields, real-time macroeconomic indicators, and quarterly interest rate surveys using a mixed-frequency dynamic factor model. Bond yields at different maturities are driven by the traditional level, slope and curvature factors, while real-time macroeconomic variables load on the yield curve factors as well as on some additional macro factors that capture the information in macroeconomic variables over and above the yield curve factors. Finally, interest rate surveys load on quarterly averages of the monthly yield and macro factors. In what follows, we describe each point in detail.

2.1 Yields

We model the cross-section of bond yields using the Dynamic Nelson-Siegel framework of Diebold & Li (2006). Denoting by y_t the $N_y \times 1$ vector of yields with N_y different maturities at time t, we have

$$y_t \;=\; a_y + \; \Gamma_{yy}\; F_t^y + v_t^y, \tag{1}$$

where F_t^y is a 3×1 vector containing the latent yield-curve factors at time t, Γ_{yy} is a $N_y \times 3$ matrix of factor loadings, and v_t^y is an $N_y \times 1$ vector of idiosyncratic components. The yield curve factors F_t^y are identified by constraining the factor loadings to follow the smooth pattern proposed by Nelson & Siegel (1987)

$$a_y = 0; \quad \Gamma_{yy}^{(\tau)} = \begin{bmatrix} 1 & \dfrac{1-e^{-\lambda\tau}}{\lambda\tau} & \dfrac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau} \end{bmatrix} \equiv \Gamma_{NS}^{(\tau)}, \tag{2}$$

where $\Gamma_{yy}^{(\tau)}$ is the row of the matrix of factor loadings corresponding to the yield with maturity τ months and λ is a decay parameter of the factor loadings. Diebold & Li (2006) show that this functional form of the factor loadings implies that the three yield curve factors can be interpreted as the level, slope, and curvature of the yield curve. The specific shape of the loadings depends on the decay parameter λ, which we calibrate to the value that maximizes the loading on the curvature factor for the yields with maturity 30 months, as in Diebold & Li (2006). Due to its flexibility and parsimony, the Nelson & Siegel

(1987) model accurately fits the yield curve and performs well in out-of-sample forecasting exercises, see Diebold & Li (2006) and Coroneo, Nyholm & Vidova-Koleva (2011).[4]

2.2 Real-time macro variables

We assume that real-time macroeconomic variables are potentially driven by two sources of co-movement: the yield curve factors F_t^y and some macro specific factors F_t^x. Denoting by x_t the $N_x \times 1$ vector of real-time macroeconomic variables at time t, we have

$$x_t \;=\; a_x + \Gamma_{xy}\; F_t^y + \Gamma_{xx}\; F_t^x + v_t^x, \tag{3}$$

where F_t^x is an $r \times 1$ vector of macroeconomic latent factors, Γ_{xy} is a $N_x \times 3$ matrix of factor loadings of the real-time macro variables on the yield curve factors, Γ_{xx} is a $N_x \times r$ matrix of factor loadings of the real-time macro variables on the macro factors, and v_t^x is an $N_x \times 1$ vector of idiosyncratic components.

To accommodate for the features of the real-time macroeconomic information set, we allow x_t to contain missing values due to publication lags. As for data revisions, these can be easily accommodated in an out-of-sample exercise by using the latest vintage of data available at the date in which the forecasts are made.

Allowing Γ_{xy} to be different from zero is crucial to ensure that the macroeconomic factors F_t^x capture only those source of co-movement in the macroeconomic variables that are not already spanned by the yield curve factors. Also, assuming that macroeconomic factors do not provide any information about the contemporaneous shape of the yield curve ($\Gamma_{yx} = 0$ in (1)) restricts the macroeconomic factors F_t^x to be unspanned by the cross-section of yields. This restriction is expected to be immaterial since the yield factors F_t^y are notoriously effective at fitting the entire yield curve. Coroneo et al. (2016) perform a likelihood ratio test for $\Gamma_{yx} = 0$ and do not reject the restriction. They also show that imposing a block-diagonal structure of the factor loadings ($\Gamma_{xy} = 0$ and $\Gamma_{yx} = 0$) implies a duplication of factors and, as a consequence of the loss of parsimony of the model, a deterioration of the forecasting performance. Accordingly, in the remainder of the paper,

[4] We do not impose no-arbitrage restrictions on interest rates, since Coroneo et al. (2011) and Duffee (2011) show that they do not improve the out of sample forecasting performance for interest rates.

we will maintain the restriction $\Gamma_{yx} = 0$ and leave Γ_{xy} unrestricted.

2.3 Interest rate surveys

The information set that forecasters use in real-time to form their expectations about future interest rates includes not only current and past interest rates and real-time macroeconomic information, but also interest rate surveys. However, surveys are usually available at a lower frequency than interest rates, most often on a quarterly basis, and their projections are for quarterly averages of the variables of interest.[5][6]

Surveys might be good predictors of the yield curve, because they can embed "soft" and forward-looking information that is difficult to incorporate into econometric models. For example, they can take into account policy announcements, which are of fundamental importance in periods in which forward guidance is used by central banks, or they can consider the existence of possible non-linearities, for example the presence of a zero lower bound for interest rates.

A successful attempt to incorporate information from surveys into econometric models in order to forecast the yield curve is in Altavilla, Giacomini & Ragusa (2017). They find that using survey data on the 3-month Treasury Bill can significantly improve the forecasting performance of the Dynamic Nelson-Siegel model. Accordingly, we exploit the informational content of the SPF on the 3-month Treasury Bill.

However, while Altavilla, Giacomini & Ragusa (2017) use exponential tilting, in our case we incorporate survey forecasts into our model. The main difference between our approach and exponential tilting is that the latter involves using the survey forecast value as the forecast for the selected maturity (anchoring) and then adjusting the predictions for all other maturities (tilting). The adjustment is proportional to the deviation of the model predictions of the anchored maturity from the survey value. In our approach, instead, we do not anchor any prediction to the surveys, and therefore all predictions take into account

[5] The Blue Chip Financial Forecasts survey is conducted on a monthly basis but the projections are for quarterly averages. See the Online Appendix for details on how our mixed-frequency approach allows to incorporate Blue Chip Financial Forecasts without requiring any interpolation of the data.

[6] In Section 6.3, we incorporate federal funds futures into our model, as they are available at a higher frequency and there is strong evidence of their predictive ability for the federal funds rate (see Gürkaynak, Sack & Swanson 2007).

all the available information (yields, real-time macro variables and survey expectations).

SPF forecasts are released the middle of the quarter for the current quarter and the following four quarters. Given that the values reported are quarterly averages, we can denote the SPF forecast for the quarterly yield at time t made at time $t-h$ as $E^s_{t-h}(y^q_{t,\tau})$. This forecast is related to the unobservable monthly forecasts as follows

$$E^s_{t-h}(y^q_{t,\tau}) = \frac{1}{3}\left[E^s_{t-h}(y_{t,\tau}) + E^s_{t-h}(y_{t-1,\tau}) + E^s_{t-h}(y_{t-2,\tau})\right], \; t = 3, 6, 9, \ldots \tag{4}$$

We assume that the unobservable monthly forecast is related to the monthly factors as follows

$$E^s_{t-h}(y_{t,\tau}) = a_s + \Gamma_{h,\tau} F_t + \upsilon_{t,h,\tau}$$

where $F_t = [F^y_t, F^x_t]$. Substituting in (4), we get that the survey forecast expectation is given by

$$E^s_{t-h}(y^q_{t,\tau}) = a_s + \Gamma_{h,\tau}\left(\frac{1}{3}F_t + \frac{1}{3}F_{t-1} + \frac{1}{3}F_{t-2}\right) + \upsilon^q_{t,h,\tau} = a_s + \Gamma_{h,\tau} F^q_t + \upsilon^q_{t,h,\tau}, \; t = 3, 6, 9, \ldots \tag{5}$$

where F^q_t are the quarterly factors (measured as quarterly averages of the monthly factors F_t, F_{t-1} and F_{t-2}), and $\upsilon^q_{t,h,\tau}$ follows an AR(1) to allow for persistent forecast errors (see Coibion & Gorodnichenko 2015, Mertens & Nason 2020). This implies that we are using survey expectations for interest rates made at time $t-h$ to filter out the expectation of the quarterly factors at time t, while at the same time allowing for persistent forecast errors that can accommodate persistent deviations of survey values from model-based expectations.

We can write the quarterly factors at a monthly frequency, such that at the end of the quarter they represent the quarterly average, as follows

$$F^q_t = \begin{cases} F_t, & t = 1, 4, 7, 10, \ldots \\ \frac{1}{2}F^q_{t-1} + \frac{1}{2}F_t, & t = 2, 5, 8, 11, \ldots \\ \frac{2}{3}F^q_{t-1} + \frac{1}{3}F_t, & \text{otherwise.} \end{cases}$$

This can be represented as

$$F^q_t - w_t F_t = \iota_t F^q_{t-1} \tag{6}$$

where w_t is equal to $1, 1/2, 1/3$ respectively the first, second and third month of the quarter, and ι_t is equal to $0, 1/2, 2/3$ respectively the first, second and third month of the quarter.

2.4 Joint model

The yield curve and the macroeconomic factors are extracted by estimating (1), (3) and (5) simultaneously as follows:

$$\begin{pmatrix} y_t \\ x_t \\ E^s(y_t^q) \end{pmatrix} = \begin{pmatrix} 0 \\ a_x \\ a_s \end{pmatrix} + \begin{bmatrix} \Gamma_{yy} & \Gamma_{yx} & 0 \\ \Gamma_{xy} & \Gamma_{xx} & 0 \\ 0 & 0 & \Gamma_q \end{bmatrix} \begin{pmatrix} F_t^y \\ F_t^x \\ F_t^q \end{pmatrix} + \begin{pmatrix} v_t^y \\ v_t^x \\ v_t^q \end{pmatrix}, \ \Gamma_{yy} = \Gamma_{NS}, \ \Gamma_{yx} = 0, \tag{7}$$

where the vector of observables at month t includes the vector of yields y_t, the vector of real-time macro variables x_t (which contains missing values due to publication lags), and the vector of interest rate surveys $E^s(y_t^q)$ (which contains missing values in the first two months of each quarter due to their availability only at a quarterly frequency). Also note that the vector of quarterly factors includes both the yield curve and the macro factors, i.e. $F_t^q = [F_t^{yq}, F_t^{xq}]$.

The joint dynamics of the yield curve and the macroeconomic factors follow

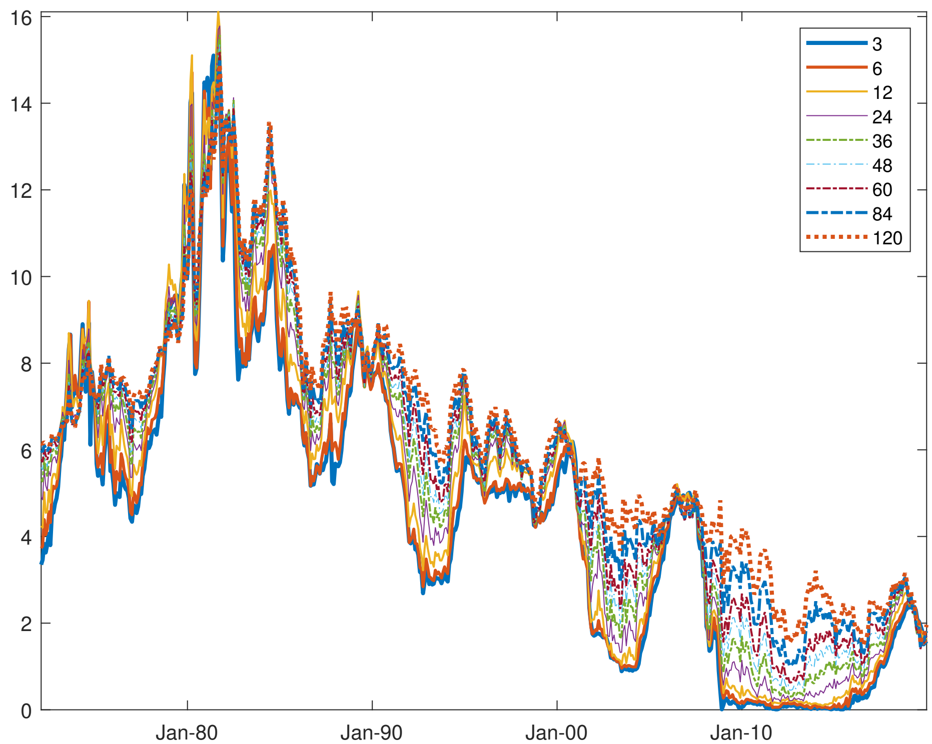
$$\begin{pmatrix} F_t \\ F_t^q \end{pmatrix} = \begin{pmatrix} \mu \\ w_t\mu \end{pmatrix} + \begin{bmatrix} A & 0 \\ w_t A & \iota_t I_r \end{bmatrix} \begin{pmatrix} F_{t-1} \\ F_{t-1}^q \end{pmatrix} + \begin{pmatrix} u_t \\ w_t u_t \end{pmatrix}, u_t \sim N(0, Q), \tag{8}$$

where $F_t = [F_t^y, F_t^x]$. This is a VAR(1) with time-varying coefficients, where w_t is equal to $1, 1/2, 1/3$ respectively the first, second and third month of the quarter, and ι_t is equal to $0, 1/2, 2/3$ respectively the first, second and third month of the quarter, as in (6). The matrix A is unrestricted, and therefore we allow for bi-directional Granger causality between the yield curve and macro factors.

The idiosyncratic components in (7) are modelled to follow independent autoregressive processes. Denoting $v_t = [v_t^y \quad v_t^x \quad v_t^q]'$, we have

$$v_t = Bv_{t-1} + \xi_t, \quad \xi_t \sim N(0, R) \tag{9}$$

Figure 1: Interest rates data



The chart shows the end-of-month zero-coupon yields on 3-month and 6-month Treasury Bills, and on 1, 2, 3, 4, 5, 7 and 10-year Treasury bonds used in our analysis. Source: FRED and Federal Reserve Board data.

where B and R are diagonal matrices, implying that the common factors fully account for the cross-correlation among the observables. The residuals to the idiosyncratic components of the individual variables, ξ_t, and the innovations driving the common factors, u_t, are assumed to be normally distributed and mutually independent. This assumption implies that the common factors are not allowed to react to variable specific shocks.

3 Data

Our dataset for interest rates and macroeconomic variables consists of U.S. observations from January 1972 to December 2019. For interest rates, we use end-of-month zero-coupon yields on 3-month and 6-month Treasury Bills from the FRED dataset, and on 1, 2, 3, 4, 5, 7 and 10-year bonds from the Federal Reserve Board dataset. In Figure 1, we plot the

Table 1: Real-time macroeconomic data

Series N.	Mnemonic	Description	Transf.	Av. Delay (days)
1	AHE	Average Hourly Earnings: Total Private	1	5
2	CPI	Consumer Price Index: All Items	1	18
3	INC	Real Disposable Personal Income	1	21
4	FFR	Effective Federal Funds Rate	0	0
5	HSal	New One Family Houses Sold	1	24
6	IP	Industrial Production Index	1	16
7	M1	M1 Money Stock	1	16
8	Manf	PMI Composite Index (NAPM)	0	3
9	Paym	All Employees: Total nonfarm	1	6
10	PCE	Personal Consumption Expenditures	1	21
11	PPIc	Producer Price Index: Crude Materials	1	13
12	PPIf	Producer Price Index: Finished Goods	1	13
13	CU	Capacity Utilization: Total Industry	0	16
14	Unem	Civilian Unemployment Rate	0	5
15	CC	Conf. Board Consumer Confidence	0	−3
16	GBA	Philadelphia Fed Outlook survey	0	−15

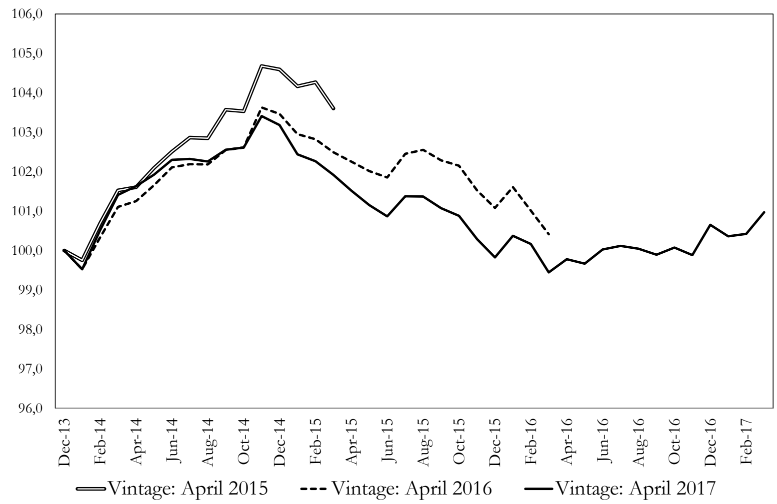
Note: real-time macroeconomic data descriptions, transformations and publication delays (average number of days from the end of the reference month). Transformation codes: 0 = no transformation, 1 = annual growth rate. Sources: Archival Federal Reserve Economic Database (ALFRED), FRED, Datastream.

time series of interest rates in our sample. The figure shows a strong comovement among interest rates. Starting in 2009, short term interest rates stayed close to the zero lower bound for a prolonged period, with a lift off at the end of 2015.

As for macro variables, we use a monthly real-time data set using the vintages available in the Archival Federal Reserve Economic Database (ALFRED) of the Federal Reserve Bank of St. Louis and the accurate publication pattern. Macroeconomic data and the average publication delay of the variables are described in Table 1. We use 16 macroeconomic variables, including real activity indicators, inflation measures, surveys, one money aggregate and the Federal Funds rate.[7] We use annual growth rates for all variables, except for capacity utilization, the federal funds rate, the unemployment and the surveys, that we keep in levels. With the exception of the Conference Board Consumer Confidence survey and the GBA Philadelphia Fed Outlook survey, this is the same macro data set

[7]We use a medium-size data set as it has been proven that such dimension provides the best results in forecasting macroeconomic variables using dynamic factor models (see Boivin & Ng 2006, Banbura, Giannone, Modugno & Reichlin 2013, Bańbura & Modugno 2014).

Figure 2: Example: revisions in Industrial Production



The chart shows an example of data revisions in macroeconomic series, showing data for US Industrial Production as released in April 2015, April 2016, April 2017. To avoid re-basing issues, data are normalized to 100 in December 2013. Source: authors' calculations on ALFRED data.

considered in Coroneo et al. (2016). We add these two surveys because of their timeliness and therefore the possibility to include early information in the forecasts: they are released before the start of the reference period (3 and 15 days before), so being amongst the first macroeconomic signals about economic activity taken into account by a forecaster. All the other macroeconomic indicators, with the exception of the Federal Funds rate, are released only after the end of the reference period, which means that in real-time their value for the current month is not available when forming expectations about future interest rates. Notice also that the Federal Funds rate and the surveys (PMI Composite Index, Conference Board Consumer Confidence survey and the GBA Philadelphia Fed Outlook survey) are the only macro variables not subject to revisions. So we obtain their values along with the publication date from the FRED database and, in the case of the PMI Composite Index, from Datastream.

To illustrate the relevance of revisions in macroeconomic series, in Figure 2 we look at an example. The chart refers to the data for US Industrial Production as released in three different vintages, in April 2015, 2016 and 2017. As shown in the chart, the series is subject to substantial revisions, implying that the information in real-time can be substantially different from the one that we can get using revised data. Therefore, it

Table 2: Average Hourly Earnings - revision triangle and construction of the dataset

	2-Aug-19	6-Sep-19	10-Oct-19	1-Nov-19	...	6-Jun-21
Jul-19	**23.46**	23.48	23.51	23.51	...	**23.54**
Aug-19		**23.59**	23.61	23.60	...	**23.64**
Sep-19			**23.65**	23.66	...	**23.70**
Oct-19				**23.70**	...	**23.76**

		Revised	*Pseudo RT*	*Real-Time*	*First release*
Jul-19		23.54	23.54	23.51	23.46
Aug-19		23.64	23.64	23.61	23.59
Sep-19		23.70	23.70	23.65	23.65
Oct-19		23.76	-	-	-

The top panel reports five vintages of data relative to Average Hourly Earnings. The names of the columns represent the release dates of the vintages, the rows represent the reference period of each data point. The bottom panel reports the different possibilities in constructing the macro series for a forecast conducted on the 31st of October 2019, following the definitions reported in the main text.

is important to use the information available in real-time when evaluating the forecasting performance.[8]

In Table 2, we give an example of the information set relative to Average Hourly Earnings in different points in time, in what is called a "revision triangle". In the top panel, the columns represent the publication date of a vintage of data, and correspond to the information set that a forecaster has until the following release. The rows represent the reference period. If a forecaster needs the data relative to July, she must wait until the 2nd of August, date in which the July data gets released. However, that data point, the "first release" (23.46), is subject to revisions: on the 6th of September, the data is revised to 23.48; then, after other revisions, she reads the final revised data (last column), 23.54. The series of "Revised data", therefore, corresponds to the last column. "First Releases" corresponds to the first available data for each reference period (the bold diagonal). A series in real-time corresponds to any of the first four columns of the table. Keeping this revision process in mind, we consider the following definitions of our macro dataset:

- Revised data: we consider the data as available on 6th of June 2021, incorporating all data revisions, in a balanced dataset.

[8]We recall that, however, if the revisions are weakly cross-correlated, factor extraction is robust to data revisions (Giannone, Reichlin & Small 2008).

- Pseudo Real-Time: we still consider the revised data as available on 6th of June 2021, but using the correct calendar of macroeconomic releases and publication lags, in a "ragged edge" dataset with missing data at the end.

- Real-Time: this is the proper real-time dataset that uses both real-time vintages and the correct publication lag structure, as such it takes into account the exact information set at the vintage date (ragged edge dataset). The last value of a series is the first release of that data point, while the previous data points are reported as revised on that specific vintage date.

- First Releases: we consider only the first release for each data point, taking into account the correct publication lag structure (ragged edge dataset).

The bottom panel of Table 2 reports an example of these definitions for the case of a forecast made on the 31st of October 2019. The table shows that using the Revised dataset, we have one extra data point (Oct-19) that in reality was not available to forecasters at the end of October 2019; taking this point away, we have the Pseudo Real-Time dataset. Both these datasets use finally revised values that can be different from the data available at the end of October 2019. The Real-Time dataset has the values for Average Hourly Earnings as released until the 31st of October 2019. The last value of this series is the first release for September 2019, while the previous data points are reported as revised. Finally, the First Release data collects all the first releases: the data point for July 2019 (released the 2nd of August 2019), the data point for August 2019 (released the 6th of September 2019) and the data point for September 2019 (released on the 10th of October 2019).

Surveys of Professional Forecasters (SPF) data on the 3-month Treasury Bill are provided by the Federal Reserve Bank of Philadelphia at quarterly frequency. Data are quarterly averages of the daily levels of interest rates, available since 1981:Q3, and we use the median forecast of the 3-month Treasury Bill collected for three and four quarters ahead.[9] The surveys were conducted by the American Statistical Association (ASA) and the National Bureau of Economic Research (NBER) until 1990:Q2, and then by the Philadelphia Fed. The deadlines for the answers have been known since 1990: Q3 and are in the middle

[9]The horizon up to one year is the same as in Kim & Orphanides (2012).

Table 3: Model selection

	1972-2008		**1972-2019**	
N. of factors	**IC**	**V**	**IC**	**V**
4	-0.161	0.296	-0.152	0.299
5	-0.215	0.216	-0.146	0.231
6	-0.184	0.171	-0.073	0.191
7	-0.065	0.148	0.035	0.163
8	0.056	0.128	0.139	0.139

Note: the table reports the IC criterion relative to models with different numbers of factors, following the modified version of the Bai & Ng (2002) criterion described in Coroneo et al. (2016). Columns IC report the information criteria, columns V report the average variance of the idiosyncratic components.

of the second month of the quarter. Since the deadlines for the respondents define their information set, we fix the release dates in correspondence to those deadlines on the 15th of the second month of the quarter.

4 Estimation and preliminary results

The mixed-frequency real-time macro-yields model in equations (7)-(9) can be cast in a state-space form by augmenting the state variables to include the intercept and the idiosyncratic components, for details see Appendix A.1. Following Doz et al. (2012), we estimate the model by quasi-maximum likelihood using an Expectation-Maximization (EM) algorithm initialized by Principal Components. The complication of having a ragged edge data set, which also involves missing data at the end of the sample, can be solved by adapting the EM algorithm to the presence of missing data, as in Bańbura & Modugno (2014). Also, the factor loading restrictions that identify the yield curve factors can be imposed by performing a constrained maximization in the EM algorithm, for more details see Appendix A.2.

For comparison, we also estimate an only-yields model, which uses only the information contained in yields. This is a restricted version of the macro-yields model in Equations (7)-(9) with $\Gamma_{xy} = 0$, $A_{yx} = 0$ and $Q_{yx} = 0$, and can hence be estimated using the same procedure.

To select the number of factors, we use the information criterion (IC) of Coroneo et al. (2016), which is a modification of the Bai & Ng (2002) criterion to account for the fact that the estimation is performed by quasi-maximum likelihood. We report in Table 3 the IC and the average variance of the idiosyncratic components when different numbers of factors are estimated. Results refer to both the subsample up to the Great Recession (from 1972 to 2008) and to the full sample (from 1972 to 2019). In the sample up to 2008, we find that the IC is minimized for the model with 5 factors, as in Coroneo et al. (2016). However, in the full sample, the information criterion is minimised in correspondence of 4 factors. This is due to the fact that the decrease in the variance of the idiosyncratic component achieved by adding the fifth factor is lower in the full sample than in the sample up to 2008, indicating a more marginal role of the fifth factor in the last part of the sample. Therefore, after 2008, we select the more parsimonious model, with four factors.[10]

5 Out-of-sample forecast

We design a forecasting exercise in a truly real-time out-of-sample fashion. We perform a recursive estimation using data starting in January 1972 and use the out-of-sample evaluation period from January 1995 to December 2019. We reconstruct the information set available to forecasters at each point in time in which the forecast is computed, that is at the end of each month of the out-of-sample period, using the information available at that time. This entails using the real-time vintages for all the variables in the dataset, and also reconstructing the exact calendar of the releases. Since the macroeconomic data releases are not synchronous, we have to deal with the ragged edge of the dataset: as stated above, the estimation performed within an Expectation-Maximization algorithm conveniently helps us in this respect.

Being aware of the presence of the zero lower bound for interest rates, a serious issue since 2008, we impose non-negativity of the predicted interest rates as follows

$$E_t(y_{t+h}^{(\tau)}) \equiv \hat{y}_{t+h|t} = \max(\hat{\Gamma}_{|t}^{y*} \hat{F}_{t+h|t}^{*}, 0)$$

[10]In Section 6.3 we report results for the macro-yields model in real-time when the model selection is performed recursively selecting the model that achieved the lowest MSFE in the most recent sample.

where $\hat{\Gamma}^{y*}_{|t}$ contains the factor loadings for yields and is estimated using information up to time t and $\hat{F}^*_{t+h|t} \equiv E_t(F^*_{t+h})$ is the out-of-sample iterative forecast of the factors.[11] We take as benchmark the forecast at horizon h for the maturity τ produced by a random walk at time t

$$E_t(y^{(\tau)}_{t+h}) \equiv \hat{y}^{(\tau)}_{t+h|t} = y^{(\tau)}_t.$$

The random walk is the standard benchmark for yield curve forecasting as, due to the high persistence of yields, it is quite difficult to produce more accurate forecasts, see Duffee (2002).

6 Results

Our empirical results are organised into two parts. First, we assess the predictive content of real-time macroeconomic information for interest rates by comparing the out-of-sample performance of a macro-yields model in real-time with one that uses revised macro data. We then add the interest rate surveys into the model, and analyse their role over and above real-time macroeconomic information.

6.1 Real-time macro data: is it useful?

In order to assess the role of the real-time macroeconomic data-flow for interest rate predictions, in this section, we report the out-of-sample evaluation of the macro-yields model using real-time data.

In Table 4, we report the Mean Squared Forecast Error (relative to the random walk) of the only-yields model, the macro-yields model using revised macro data and the macro-yields model using real-time macro data. We test for the significance of their outperformance with respect to the random walk using the Diebold & Mariano (2002) test statistic with fixed-b asymptotics. This approach allows to avoid size distortions due to the small sample size and autocorrelation in the loss differentials, see Coroneo & Iacone (2020). Results indicate that macroeconomic data has a strong predictive ability for interest rates especially at long forecasting horizons and short-mid maturities, while the only-yields model

[11] See Appendix A.2 for the definitions of Γ^* and F^*_t.

Table 4: Relative MSFE

Only-yields model

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	1.03	1.03	1.02	1.05	1.05	1.04	1.04	1.04	1.02
3	1.06	1.08	1.06	1.11	1.11	1.11	1.10	1.11	1.07
6	1.05	1.10	1.11	1.19	1.20	1.19	1.18	1.19	1.14
12	1.03	1.08	1.10	1.25	1.32	1.34	1.36	1.37	1.26
24	1.08	1.10	1.10	1.28	1.44	1.57	1.67	1.83	1.75

Macro-yields model with revised data

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	0.84*	0.87	0.97	1.03	1.04	1.04	1.03	1.03	1.02
3	0.72*	0.76*	0.92	1.02	1.05	1.05	1.05	1.04	1.02
6	0.63**	0.69**	0.81*	0.95	1.01	1.02	1.03	1.03	1.00
12	0.61**	0.65**	0.72**	0.84*	0.96	1.02	1.05	1.07	1.02
24	0.62**	0.65**	0.67**	0.78*	0.93	1.04	1.15	1.29	1.28

Macro-yields model with real-time data

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	0.89	0.92	1.01	1.05	1.06	1.05	1.04	1.03	1.02
3	0.79*	0.84*	0.99	1.06	1.08	1.07	1.06	1.05	1.02
6	0.71**	0.78*	0.90	1.01	1.05	1.05	1.05	1.04	1.00
12	0.69**	0.74*	0.82*	0.94	1.04	1.08	1.10	1.11	1.03
24	0.69*	0.72*	0.74*	0.87	1.02	1.12	1.22	1.35	1.30

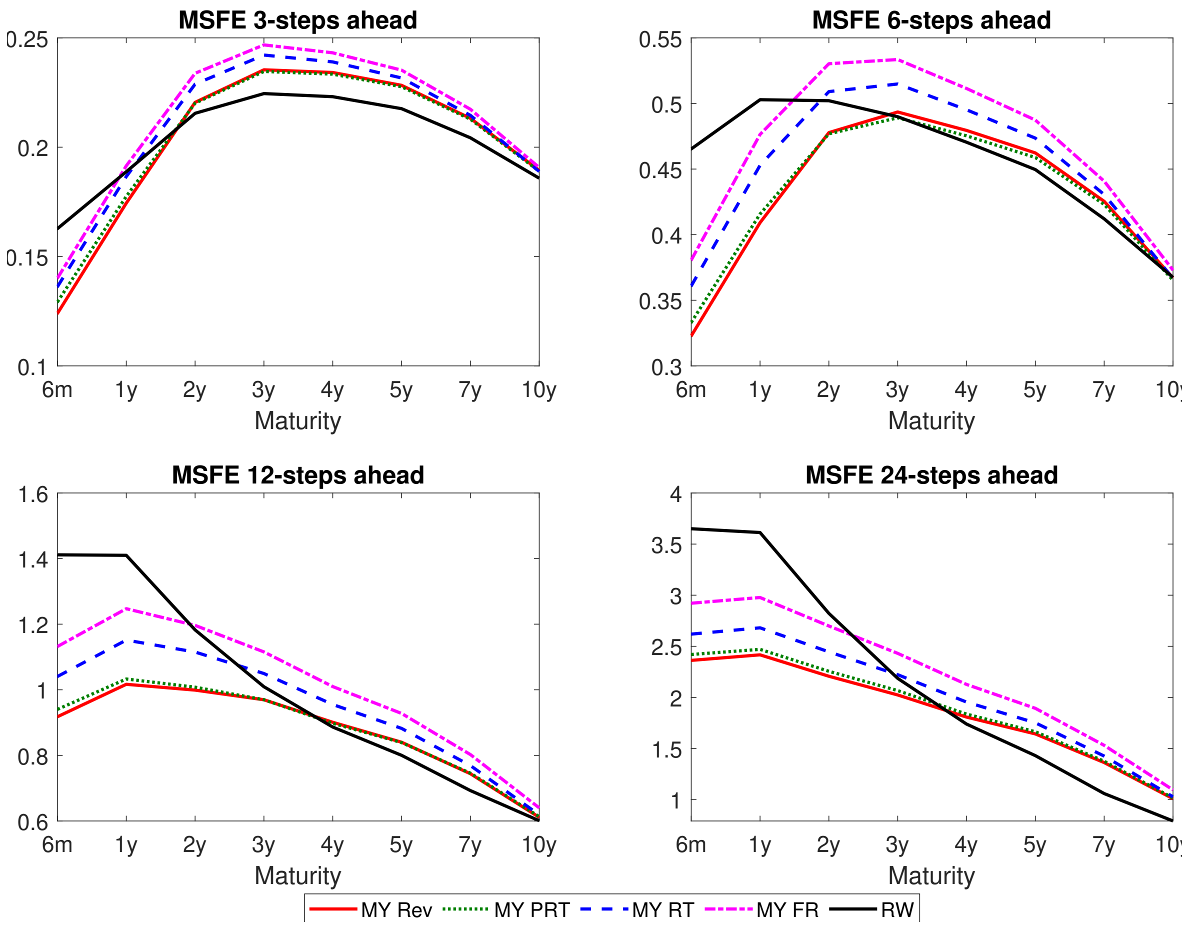
Note: The table reports the relative Mean Squared Forecast Error relative to the random walk of the only-yields model (top panel), the macro-yields model with revised data (middle panel) and the macro-yields model with real-time data (bottom panel), for the evaluation period 1995-2019. A number smaller than one indicates that the model performs better than the random walk. The columns indicate the maturities (from 3 months to 10 years), and the rows denote the forecasting horizons (from 1 to 24 months). (*) and (**) indicate one-side significance at the 10% and 5% level, respectively, using the Diebold & Mariano (2002) test statistic with fixed-b asymptotics, as in Coroneo & Iacone (2020).

never outperforms the random walk.[12] The forecasting ability is stronger using revised data, but robust to the use of real-time macro data: the real-time macro-yields model forecasts significantly better than the random walk at short maturities for mid-long forecasting horizons.

In order to understand the drivers of the difference in the forecasting performance between revised and real-time macroeconomic information, in Figure 3 we plot the Mean

[12] This is consistent with Carriero, Kapetanios & Marcellino (2012) that test the predictive accuracy of a large set of only-yields models and find that, in general, they do not outperform the random walk.

Figure 3: Real-time macroeconomic information



Mean Squared Forecast Error for the macro-yields model with revised data (MY Rev), the macro-yields model with pseudo real-time data (MY PRT), the macro-yields model with real-time data (MY RT), the macro-yields model with first releases (MY FR), and the random walk. Evaluation period 1995-2019.

Squared Forecast Error of the macro-yields model using the four different definitions of the macroeconomic dataset described in Section 3: revised, pseudo real-time, real-time and first releases. Results indicate that the macro-yields model consistently outperforms the random walk at short maturities for all horizons. The real-time macro-yields model is slightly worse than the macro-yields model with revised data and pseudo real-time data, but it still outperforms the random walk at short maturities for all horizons. This indicates that macroeconomic information is useful in predicting interest rates, even when using real-time data. Taking into account only the publication lags plays a lesser role, since the model in pseudo real-time has a forecasting performance very similar to the one with revised data. The model that uses the first releases, instead, performs worse than the others. This is consistent with the intuition that revisions improve the quality of macroeconomic data and, as a consequence, the signal they convey about the future path of interest rates.[13] Therefore, we can conclude that the main drivers of the difference in forecasting performance between the model that uses revised macro data and the one that uses real-time macro data are data revisions.

Our results are different from the general message of Ghysels et al. (2017).[14] In addition to the finding that a "real-time" dataset is significantly less powerful in such a forecasting exercise (our results are milder in this respect), they also find that it performs worse than a dataset with first releases. Their definition of "real-time" differs from ours: their dataset corresponds to our definition of "first releases", lagged by one period (for macro variables with a "standard" publication lag, like Industrial Production) to take into account publication lags; instead, we use the latest information available at the time the forecast is computed, including the revisions occurred up to that point in time, and treat publication lags as missing observations. In this way, the information set closely mimics the data available to the forecaster in real-time, maintaining the contemporaneous relationships between macro variables and interest rates. The filtering techniques widely used in the nowcasting literature (for details see Banbura et al. 2013) conveniently help us in order to efficiently incorporate missing variables and properly treat a ragged edge dataset.

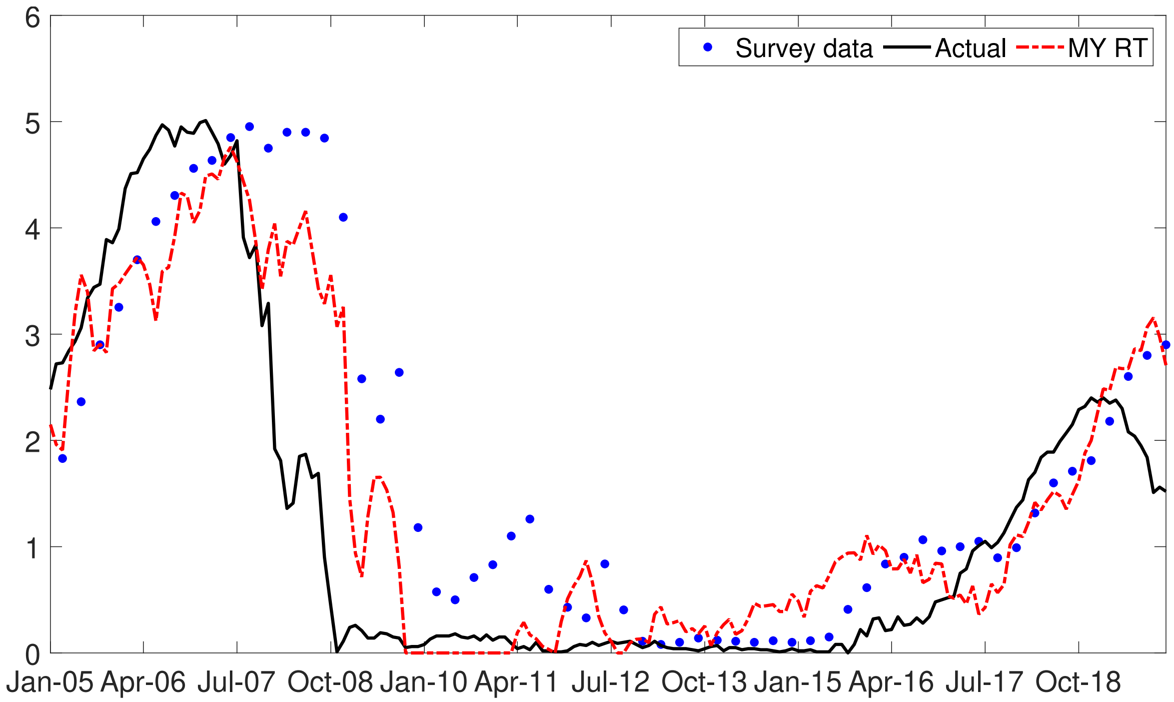
6.2 Interest rate surveys: do they help?

We now add the SPF data on the 3-month Treasury Bill to our real-time dataset, in order to evaluate if they contain additional information to predict the yield curve. We recall that we use the median forecast of the 3-month Treasury Bill collected for three and four quarters ahead. In fact, we assume that at this horizon soft information about monetary policy can play a strong role, especially during periods in which the FOMC uses forward

[13]Factor models are robust to the presence of data revisions, as long as they are weakly cross-correlated (see Giannone et al. 2008, Croushore 2011). Therefore the outperformance of the macro-yields model with revised data indicates that the revisions add new information about the common component.

[14]Note that their analysis refers to excess returns, and is based on a different sample.

Figure 4: Forecasts: real-time macro-yields model vs. interest rate surveys

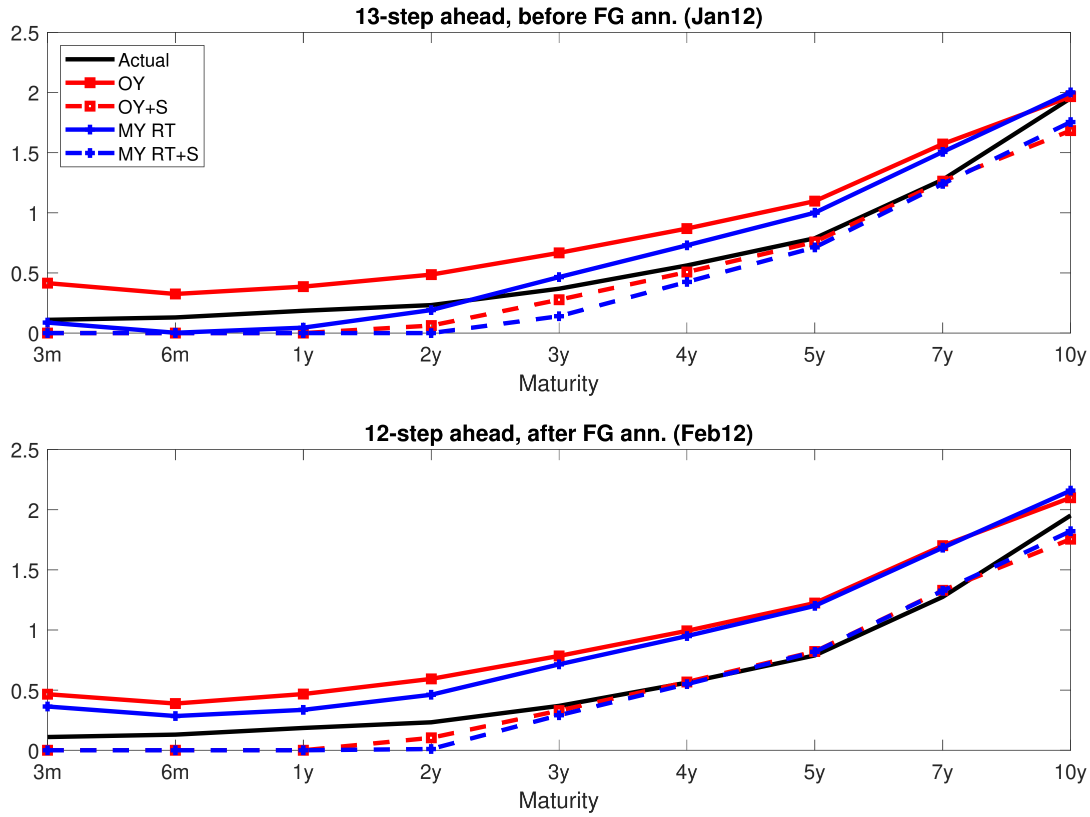


The charts report the 12-month ahead forecast for the 3-month interest rate obtained from the macro-yields model with real-time data (MY RT, dot-dashed red line), the four-quarters ahead SPF forecast for the quarterly average of the 3-month Treasury Bill (Survey data, blue circles), and the realised value (Actual, solid black line).

guidance.

As a preliminary evidence of the importance of including interest rate surveys in our macro-yields model, in Figure 4, we report the 12-month ahead forecast for the 3-month interest rate obtained from the macro-yields model in real-time, along with the four-quarters ahead survey for the quarterly average of the 3-month Treasury Bill, and the realised value. The figure shows how the macro-yields model is able to provide predictions that are closer to the realised value than the survey forecasts from 2007Q3 up to 2012Q2. After this date, the surveys consistently predict very low values for the 3-month rate, and these predictions are correct. This is due to the fact that on August 9, 2011 the FOMC announced that it would likely keep the federal funds rate at exceptionally low levels "at least through mid-2013". In the figure, we can see the effect of the announcement on the decline of the survey forecast for 2012Q3, which was formed one year ahead, i.e. just after the forward

Figure 5: Example: forecasts made before and after a FG announcement



The charts report the forecasts for the yield curve in February 2013, made in January 2012 (top panel) and in February 2012 (bottom panel), produced by the only-yields model (OY), the only-yields model plus surveys (OY+S), the real-time macro-yields model (MY RT) and the real-time macro-yields model plus surveys (MY RT+S), along with the realized yield curve (Actual) in February 2013.

guidance announcement. The figure also shows that forward guidance announcements have been effective at stabilizing expectations up to mid-2014 when the one-year ahead predictions for mid-2015 indicated a rise in interest rates. On the other hand, the macro-yields model in real-time could not incorporate this type of announcement, and for all this period predicted low interest rates but higher than expected from the survey. Notice also that the time varying relative importance of model-based and survey-based forecasts signals the advantage of efficiently combining the different sources of information.

In Figure 5 we give an intuitive example of the mechanism for which the use of surveys helps to improve the forecasts of the model. In the top panel, we report the 13-month ahead forecasts from the only-yields and the real-time macro-yields model (both with and without the interest rate surveys) made in January 2012, along with the actual realization of the yield curve in February 2013. In the bottom panel, we report the forecasts for February 2013 made one month later, i.e. in February 2012. In between, there have been some macroeconomic releases and revisions, which induced the revisions of the forecasts made using the macro-yields model, but more importantly, there has been an FOMC release with a "forward guidance type" announcement on the 25th of January 2012.[15] In February, the macroeconomic data releases (and the revisions) brought up the forecasts produced by the macro-yields model (solid blue line), but the forecasts obtained using the information in the surveys are lower and closer to the realised values. Notice how, despite including information only on survey forecasts for the 3-month Treasury Bill, the forecasts for all interest rates incorporate this information and, as a consequence, are much lower than in the models that do not use interest rate survey forecasts.

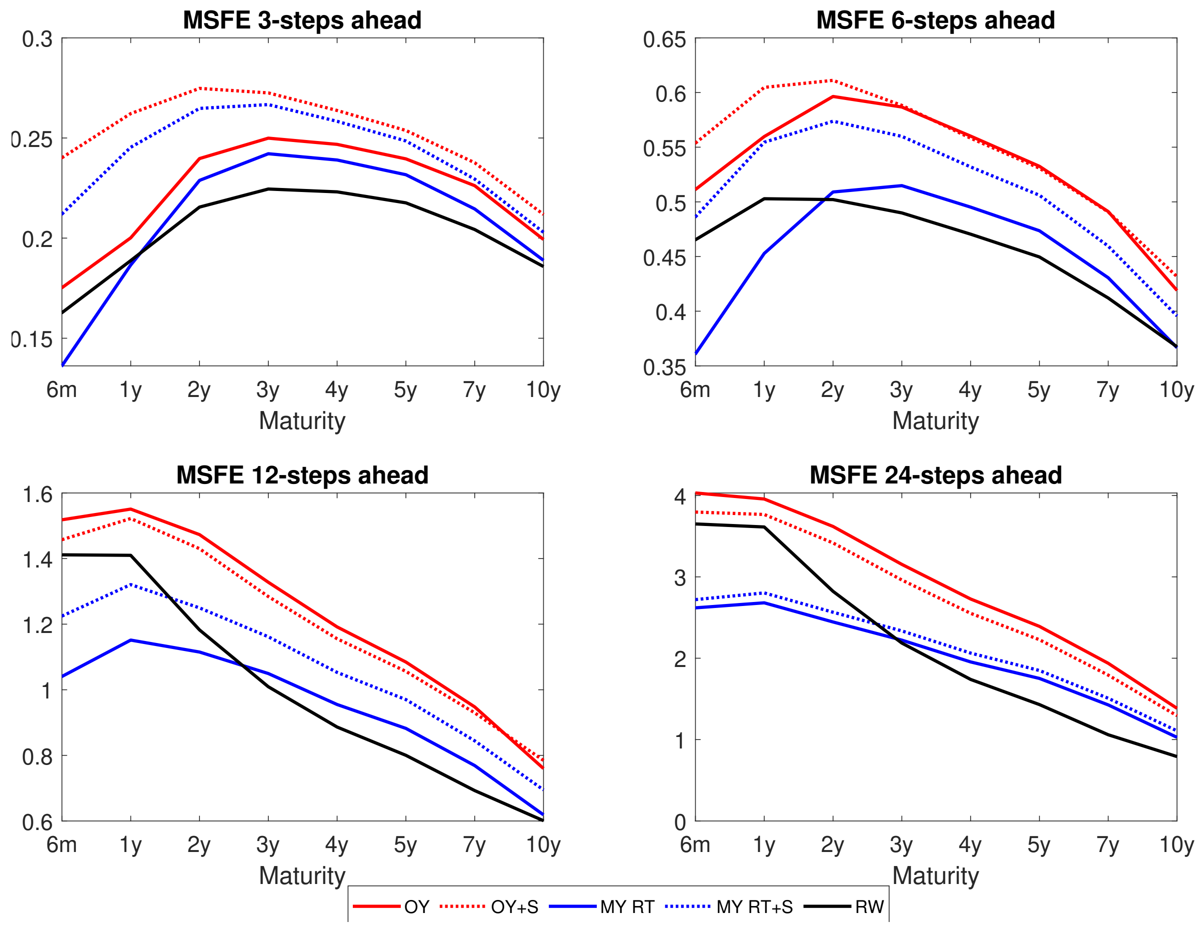
To assess whether interest rate surveys indeed help in predicting interest rates, in Figure 6 we report MSFEs for the macro-yields model in real-time and the only-yields model, both with and without surveys. Results show that in general surveys worsen the results almost on all occasions, and when they bring useful information the impact is marginal.[16] This indicates that, overall, all the relevant information to predict interest rates in real-time can be extracted only from yields and macroeconomic variables. However, as stated above, we expect that there are circumstances in which soft information from surveys can bring additional value to the model, as in the case of forward guidance announcements.

To this aim, we test the relevance of the information contained in the SPF survey forecasts for the real-time macro-yields model using the Giacomini & Rossi (2010) fluctuation test. In Figures 7-8, we report the 50-month rolling relative MSFEs of the real-time macro-yields and the only-yields models, with respect to the MSFE of the corresponding model with the surveys, along with the 90% confidence interval from Giacomini & Rossi (2010). A positive value of the relative MSFEs indicates that the model with the surveys is perform-

[15]The statement reads as follows "(...) the Committee decided today to keep the target range for the federal funds rate at 0 to 1/4 percent and currently anticipates that economic conditions–including low rates of resource utilization and a subdued outlook for inflation over the medium run–are likely to warrant exceptionally low levels for the federal funds rate at least through late 2014." Source: `https://www.federalreserve.gov/newsevents/pressreleases/monetary20120125a.htm`.

[16]This is in line with Coroneo & Iacone (2020) that show that, for the 3-month Treasury Bill, the median SPF forecaster has significantly outperformed the random walk in the sub-sample 1987-1996, but find no evidence of outperformance since then.

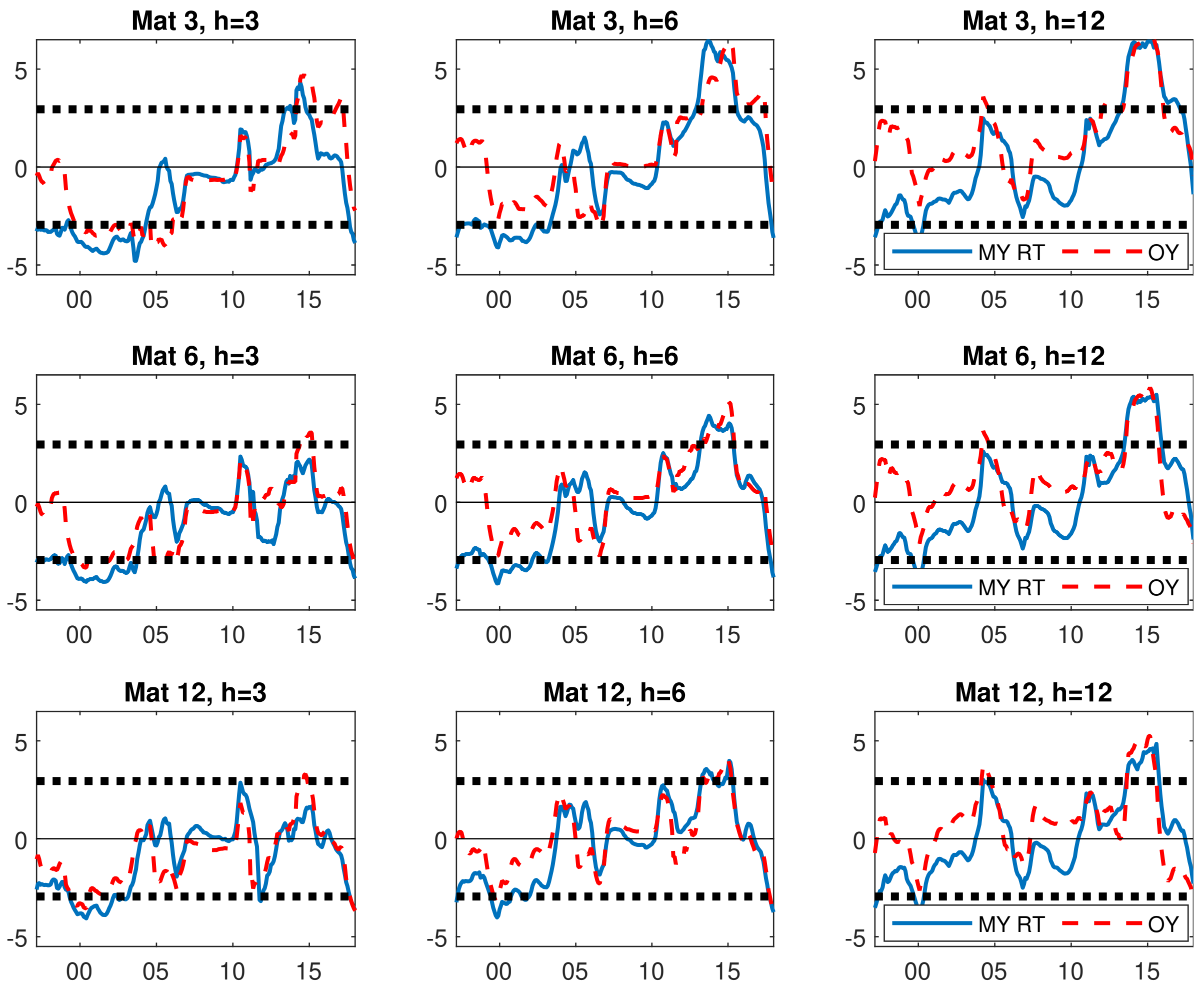
Figure 6: Information from surveys



Mean Squared Forecast Error for the only-yields model without (OY) and with surveys (OY+S), of the real-time macro-yields model without (MY RT) and with surveys (MY RT+S), and the random walk (RW). Evaluation period: 1995-2019.

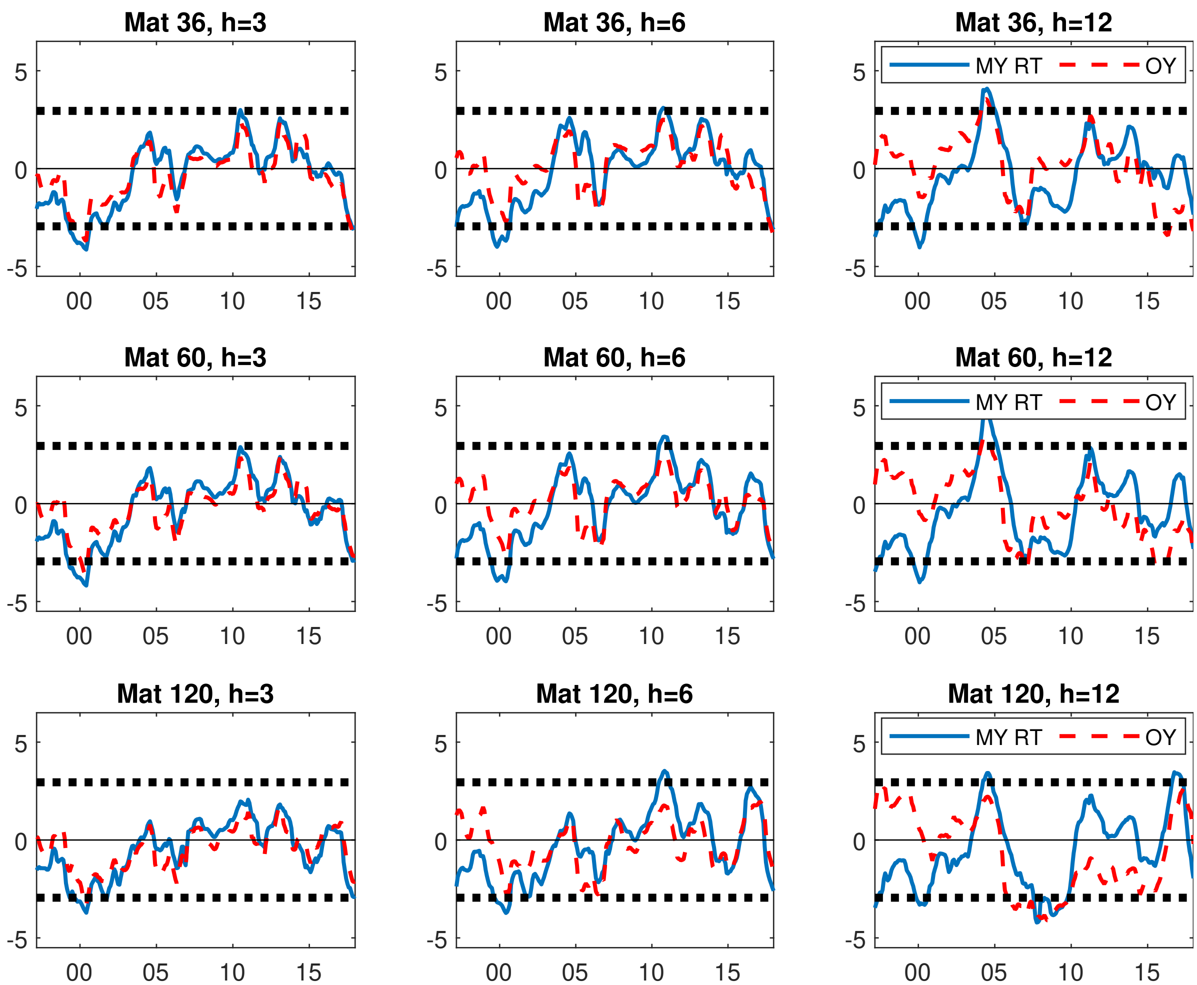
ing better. Results show that the real-time macro-yields model significantly outperforms its counterpart with surveys at the beginning of the sample, this happens for all maturities and all forecasting horizons. After 2003, the relative performance of the real-time macro-yields models with and without surveys are within the 90% confidence interval. In the last part of the sample, for short maturities both the real-time macro-yields and the only-yields models with surveys significantly outperform the corresponding models without surveys. This is the period in which the Federal Reserve adopted forward guidance and, therefore, the use of SPF forecasts, in a mixed-frequency model, improves the predictive

Figure 7: Time-varying value of information from surveys for maturities 3, 6 and 12 months



Giacomini & Rossi (2010) fluctuation tests for the real-time macro-yields model (blue line) and the only-yields model (dashed red line) with respect to the corresponding model with SPF surveys. Results are reported for maturities 3 month (top plots), 6 months (middle plots) and 12 months (bottom plots), and forecasting horizons 3 months (left plots), 6 months (middle plots) and 12 months (right plots). The dates refer to the midpoints of the 50 observations rolling windows. The dotted black lines denote the 10% critical values.

Figure 8: Time-varying value of information from surveys for maturities 36, 60 and 120 months



Giacomini & Rossi (2010) fluctuation tests for the real-time macro-yields model (blue line) and the only-yields model (dashed red line) with respect to the corresponding model with surveys. Results are reported for maturities 36 month (top plots), 60 months (middle plots) and 120 months (bottom plots), and forecasting horizons 3 months (left plots), 6 months (middle plots) and 12 months (right plots). The dates refer to the midpoints of the 50 observations rolling windows. The dotted black lines denote the 10% critical values.

Table 5: Real-time macro-yields model with real-time model selection

Macro-yields model with real-time data and model selection									
	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	0.90	0.94	1.05	1.07	1.07	1.06	1.05	1.03	1.02
3	0.79*	0.83*	0.99	1.08	1.09	1.08	1.07	1.05	1.02
6	0.68**	0.75*	0.87	1.01	1.05	1.05	1.05	1.04	1.00
12	0.63**	0.68**	0.76*	0.89	0.99	1.02	1.05	1.06	0.99
24	0.62**	0.65*	0.68**	0.80	0.94	1.04	1.14	1.27	1.23

Note: The table reports the relative Mean Squared Forecast Error relative to the random walk of the real-time macro-yields model when the model selection is based on the 5-year rolling average Mean Squared Forecast Error across all maturities at 1, 3 and 6 month ahead. The evaluation period is 1995-2019. A number smaller than one indicates that the model performs better than the random walk. The columns indicate the maturities (from 3 months to 10 years), and the rows denote the forecasting horizons (from 1 to 24 months). (*) and (**) indicate one-side significance at the 10% and 5%, respectively, using the Diebold & Mariano (2002) test statistic with fixed-b asymptotics, as in Coroneo & Iacone (2020).

power of both the only-yields model and the real-time macro-yields model. The improvement is statistically significant for mid-long horizons and short maturities, which are the cases in which a forward guidance announcement is hoped to be effective. Note that the results show that adding the SPF is more beneficial to the only-yields model than to the macro-yields one, as surveys may carry some information about the state of the economy that is already embedded in "standard" real-time macroeconomic variables.

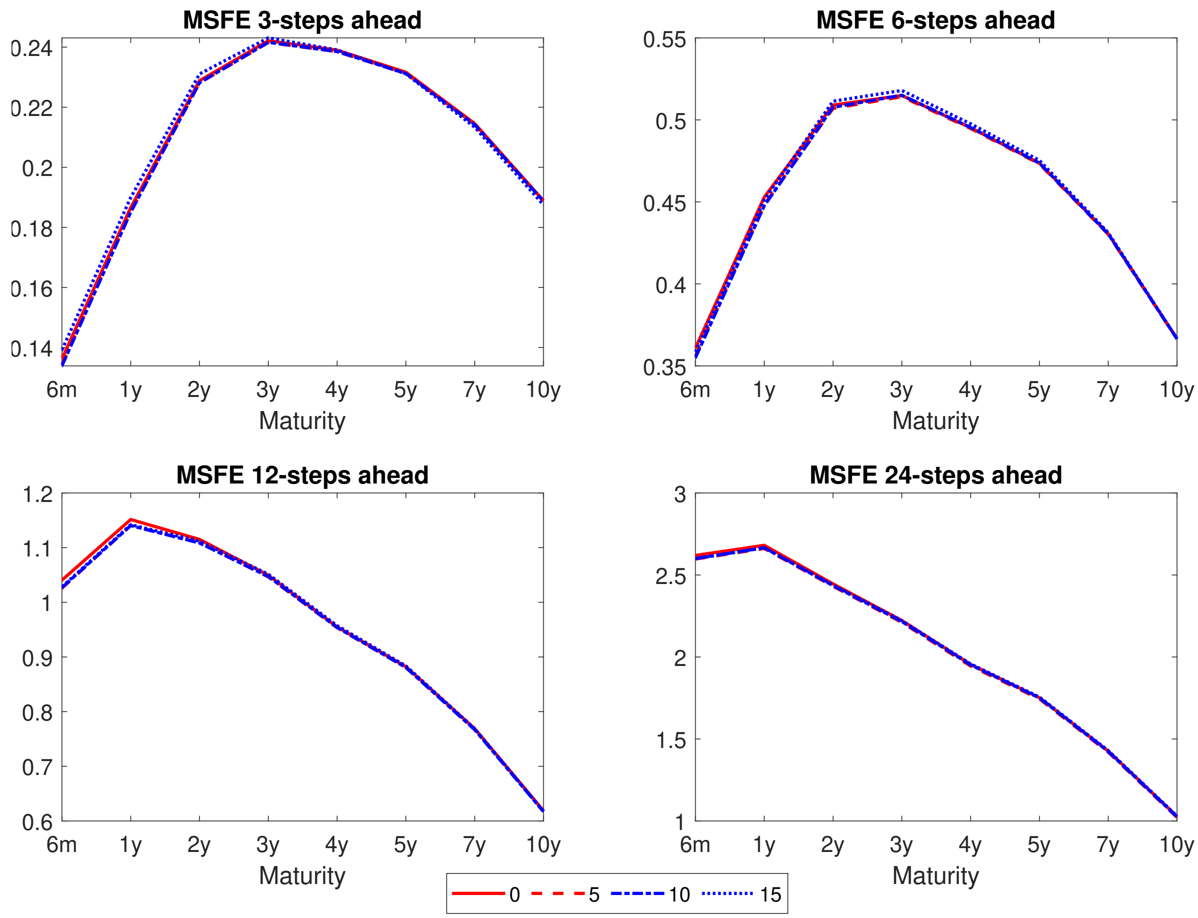
6.3 Additional experiments

In order to assess the robustness of the results presented in Sections 6.1 and 6.2, and to further understand their drivers, in this section we report the results of some additional experiments.[17]

We start by performing model selection in real-time by recursively selecting the number of factors every year, according to the most recent performance of the real-time macro-yields model. The MSFEs (relative to the random walk) of the real-time macro-yields model when model selection is incorporated into the forecasting exercise, reported in Table 5, are comparable to the ones presented in the bottom panel of Table 4.

[17]More details are available in the Online Appendix.

Figure 9: Additional data releases

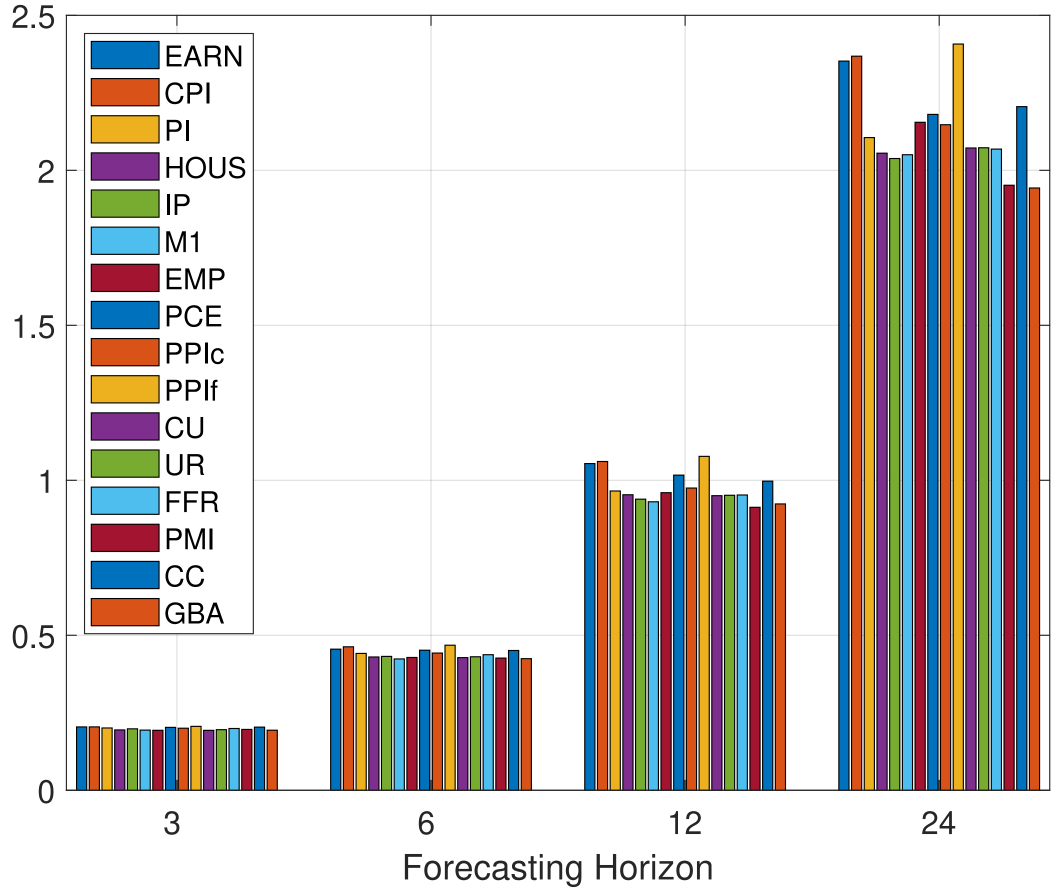


Mean Squared Forecast Error of the real-time macro-yields model estimated at the end of the month (0), and 5, 10, 15 days after the end of the month. Evaluation period: 1995-2019.

We then analyze how additional data releases affect interest rate predictions by forecasting interest rates a few days after the reference period, when some additional macro data points for the latest month are released. MSFEs reported in Figure 9 indicate that waiting a few days to make the interest rate predictions does not allow to get more accurate interest rate forecasts, further corroborating the evidence that publication lags play only a minor role.

To assess the contribution of each macroeconomic variable to the accuracy of interest rate forecasts, we re-estimate the real-time macro-yields model removing one macroeconomic variable at once. MSFEs, reported in Figure 10, indicate that excluding the Producer

Figure 10: Individual contribution of macroeconomic variables

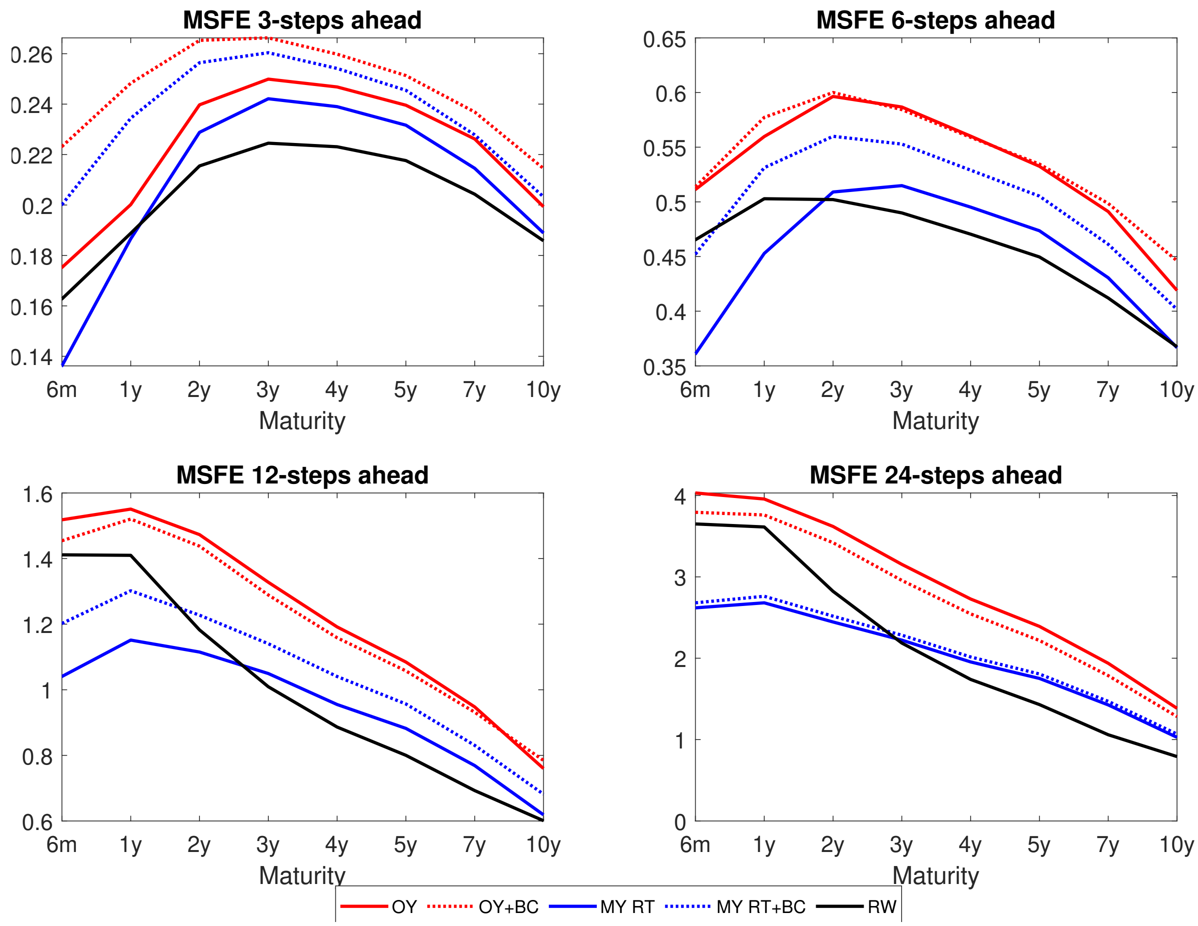


Mean Squared Forecast Error of the real-time macro-yields model estimated excluding one macro variable at a time. The legend refers to the mnemonics for macro variables as listed in Table 1. The forecasting horizons are in months. Evaluation period: 1995-2019.

Price Index for finished goods deteriorates the forecast accuracy the most, followed by the Consumer Price Index, Average Hourly Earnings, and the Conference Board Consumer Confidence.

We also use an alternative dataset for interest rates surveys, the Blue Chip Financial Forecasts (BCFF) that is available at a monthly frequency, as opposed to the SPF that is available only quarterly. As for our baseline analysis, we use 3 and 4 quarter-ahead predictions for the 3-month Treasury Bill. MSFEs in Figure 11 are similar to the ones presented in Figure 6 that instead use the SPF, in line with the finding in Reifschneider & Tulip (2019) that SPF and BCFF have similar accuracy for the 3-month Treasury bill

Figure 11: Information from BCFF

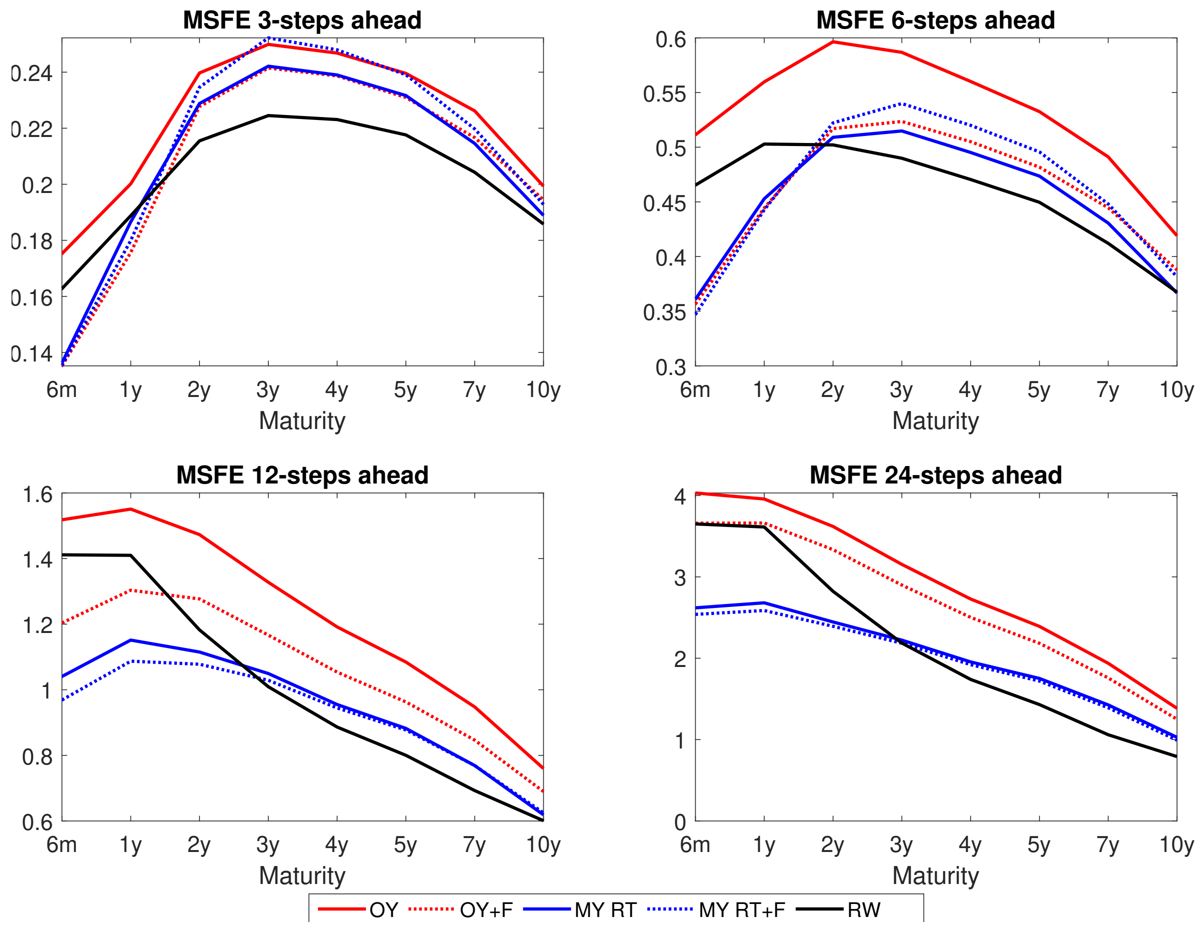


Mean Squared Forecast Error for the only-yields model without (OY) and with BCFF (OY+BC), of the macro-yields model without (MY RT) and with BCFF (MY RT+BC), and the random walk (RW). Evaluation period: 1995-2019.

rate.

We now incorporate federal funds futures into the real-time macro-yields model. We use end of month CBOT implied rates from October 1988 for contracts expiring in the following 1, 3 and 6 months. MSFEs in Figure 12 indicate a large improvement in the performance of the only-yields model when information from federal funds futures is included. On the contrary, the contribution of federal funds futures for the real-time macro-yields model is only marginal and including macroeconomic variables is still crucial to achieve more accurate interest rate predictions at longer horizons.

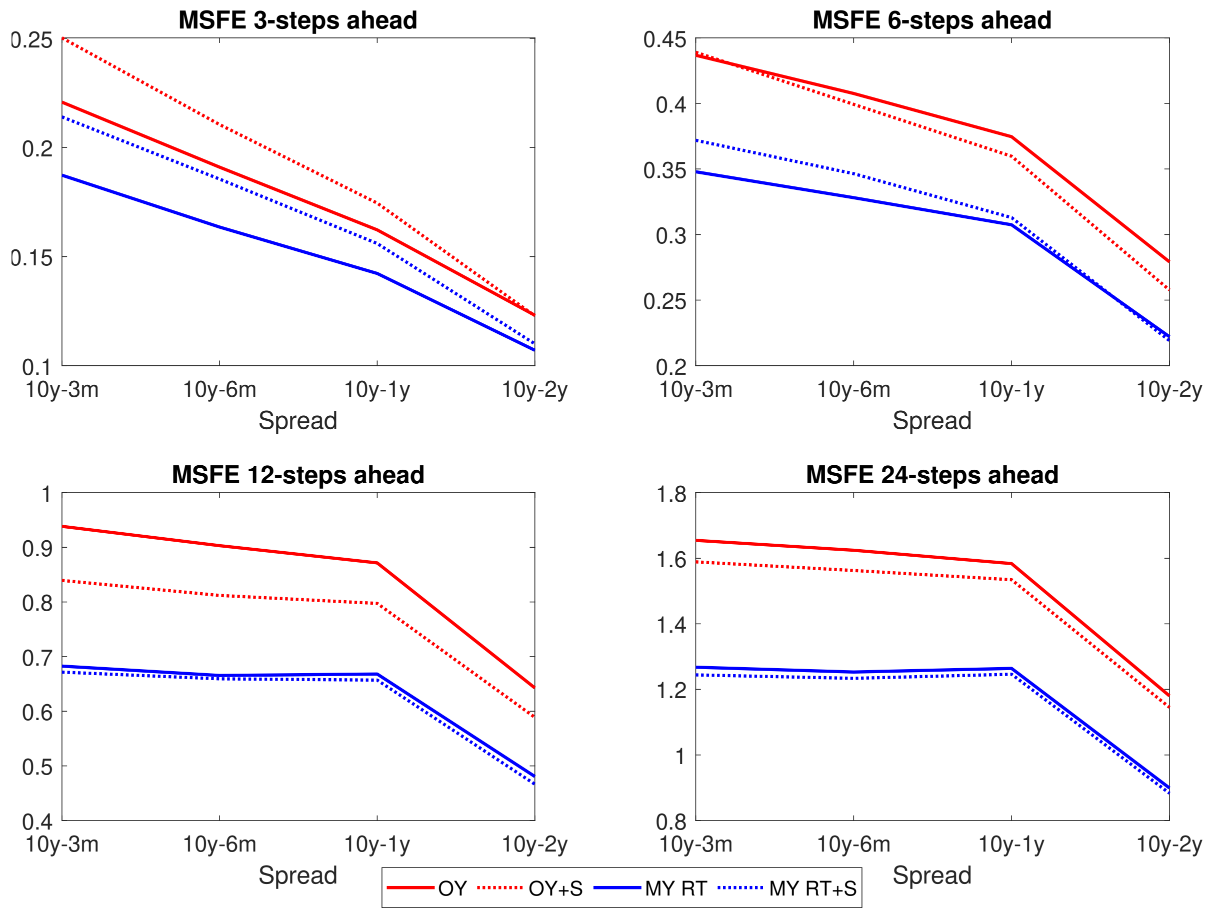
Figure 12: Information from federal funds futures



Mean Squared Forecast Error for the only-yields model without (OY) and with federal funds futures (OY+F), of the macro-yields model without (MY RT) and with federal funds futures (MY RT+F), and the random walk (RW). Evaluation period: 1995-2019.

Finally, we look at the performance of the real-time macro-yields model for interest rate spreads between the 10-year rate and the 3, 6, 12 and 24-month rates. MSFEs in Figure 13 indicate that real-time macro information allows to achieve more accurate forecasts also for interest rate spreads.

Figure 13: Predicting interest rate spreads



Mean Squared Forecast Error for interest rate spreads between the 10 year rate and the 3, 6, 12 and 24 month rate of the only-yields model without (OY) and with surveys (OY+S), of the real-time macro-yields model without (MY RT) and with surveys (MY RT+S). Evaluation period: 1995-2019.

7 Conclusions

In this paper, we assess the predictive ability of real-time macroeconomic information and interest rates surveys for the yield curve of interest rates. We propose a mixed-frequency dynamic factor model with restrictions on the factor loadings which includes Treasury yields, a set of real-time macroeconomic variables and interest rate survey expectations. Through the lens of a real-time out-of-sample exercise, we document the following findings.

First, we show the importance of macroeconomic information in predicting interest rates in a fully real-time out-of-sample exercise in which, in order to reconstruct the information set available to market participants at each point in time, we use the real-time vintages and the exact calendar of data releases.

Second, we document that survey expectations can play an important role in improving interest rate forecasts at mid-long horizons for short maturities. An interpretation of this finding is that surveys incorporate soft information which might be neglected in "standard" data. For example, they can consider forward-looking information coming from policy announcements (e.g. forward guidance). In fact, we prove that properly adding surveys to our model in a forward guidance period significantly enhances its predictive power especially for short maturities.

In future research, we plan to extend our empirical specification to explicitly incorporate long-run trends, this will allow us to account for the recent decline in interest rates. The macro-yields model presented in this paper cannot identify trends as it is estimated on real-time macroeconomic variables transformed to achieve stationarity; however, our model can be easily extended to deal with trends along the lines of Del Negro, Giannone, Giannoni & Tambalotti (2017), and to incorporate long-run inflation expectations as in Van Dijk, Koopman, Van der Wel & Wright (2014). We also plan to analyse the contribution of specific subsets of SPF forecasts by including individual survey predictions (instead of median survey forecasts) into the real-time macro-yields model. This is feasible using our factor model approach and the EM algorithm, which conveniently helps to deal with the entry and exit of experts from the panel of forecasters, see Capistrán & Timmermann (2009).

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A Estimation procedure

A.1 State-space representation

The mixed-frequency macro-yields model with real-time macro information in equations (7)-(9) can be cast in a state-space form by augmenting the state variables to include the intercept and the idiosyncratic components. In particular, the measurement equation can be written as

$$\begin{pmatrix} y_t \\ x_t \\ E^s(y_t^q) \end{pmatrix} = \begin{bmatrix} \Gamma_{yy}^{NS} & 0 & 0 & 0 & I_n & 0 & 0 \\ \Gamma_{xy} & \Gamma_{yy} & 0 & a_x & 0 & I_m & 0 \\ 0 & 0 & \Gamma_q & a_s & 0 & 0 & I_s \end{bmatrix} \begin{pmatrix} F_t^y \\ F_t^x \\ F_t^q \\ c_t \\ v_t^y \\ v_t^x \\ v_t^s \end{pmatrix} + \begin{pmatrix} \eta_t^y \\ \eta_t^x \\ \eta_t^s \end{pmatrix} \tag{10}$$

where $(\eta_t^y, \eta_t^x, \eta_t^s)' \sim N(0, \epsilon I_{n+m+s})$ with ε a very small fixed coefficient. Γ_{yy}^{NS} is the matrix whose rows correspond to the smooth patterns proposed by Nelson & Siegel (1987) and shown in equation (2). Also notice that, since we are using real-time macro data, x_t contains missing values.

If we denote by $F_t = [F_t^y, F_t^x]$ and $v_t = [v_t^y, v_t^x]$, then we can write the state equation as

$$\begin{pmatrix} F_t \\ F_t^q \\ c_t \\ v_t \\ v_t^s \end{pmatrix} = \begin{bmatrix} A & 0 & \mu & 0 & 0 \\ w_t A & \iota_t I_r & w_t \mu & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & B & 0 \\ 0 & 0 & 0 & 0 & B_s \end{bmatrix} \begin{pmatrix} F_{t-1} \\ F_{t-1}^q \\ c_{t-1} \\ v_{t-1} \\ v_{t-1}^s \end{pmatrix} + \begin{pmatrix} u_t \\ u_t^s \\ \nu_t \\ \xi_t \\ \xi_t^s \end{pmatrix} \tag{11}$$

with $(u_t, u_t^s, \nu_t, \xi_t, \xi_t^s)' \sim N(0, blkdiag(Q, w_t' Q w_t, \epsilon, R, R_s))$ and where the coefficients w_t and ι_t are known (w_t is equal to $1, 1/2, 1/3$ and ι_t is equal to $0, 1/2, 2/3$ respectively the first, second and third month of the quarter). In this state-space form, c_t an additional state variable restricted to one at every time t.

A.2 Estimation

The state-space model in (10)-(11) can be written compactly as

$$
\begin{aligned}
z_t &= \Gamma^* F_t^* + v_t^*, \quad v_t^* \sim N(0, R^*) \\
F_t^* &= A_t^* F_{t-1}^* + u_t^*, \quad u_t^* \sim N(0, Q_t^*)
\end{aligned}
$$

where $z_t = \begin{bmatrix} y_t \\ x_t \\ E^s(y_t^q) \end{bmatrix}$, $F_t^* = \begin{bmatrix} F_t \\ F_t^q \\ c_t \\ v_t \\ v_t^s \end{bmatrix}$, $v_t^* = \begin{bmatrix} \eta_t^y \\ \eta_t^x \\ \eta_t^s \end{bmatrix}$ and $u_t^* = \begin{bmatrix} u_t \\ u_t^s \\ \epsilon_t \\ \xi_t \\ \xi_t^s \end{bmatrix}$.

The restrictions on the factor loadings Γ^* and on the transition matrix A_t^* can be written as

$$
H_1 \ \mathrm{vec}(\Gamma^*) = q_1, \qquad H_2 \ \mathrm{vec}(A_t^*) = q_{2t},
$$

where H_1 and H_2 are selection matrices, and q_1 and q_{2t} contain the restrictions.

We assume that $F_1^* \sim N(\pi_1, V_1)$, and define $z = [z_1, \ldots, z_T]$ and $F^* = [F_1^*, \ldots, F_T^*]$. Then denoting the parameters by $\theta_t = \{\Gamma^*, A_t^*, Q_t^*, \pi_1, V_1\}$, we can write the joint loglikelihood of z_t and F_t, for $t = 1, \ldots, T$, as

$$
\begin{aligned}
L(z, F^*; \theta) = & -\sum_{t=1}^{T} \left(\frac{1}{2} \left[z_t - \Gamma^* F_t^*\right]' (R^*)^{-1} \left[z_t - \Gamma^* F_t^*\right] \right) + \\
& -\frac{T}{2} \log |R^*| - \sum_{t=2}^{T} \left(\frac{1}{2} [F_t^* - A_t^* F_{t-1}^*]' (Q_t^*)^{-1} [F_t^* - A_t^* F_{t-1}^*] \right) + \\
& -\frac{T-1}{2} \log |Q_t^*| + \frac{1}{2} [F_1^* - \pi_1]' V_1^{-1} [F_1^* - \pi_1] + \\
& -\frac{1}{2} \log |V_1| - \frac{T(p+k)}{2} \log 2\pi + \lambda_1' \left(H_1 \mathrm{vec}(\Gamma^*) - q_1\right) + \lambda_2' \left(H_2 \mathrm{vec}(A_t^*) - q_2\right)
\end{aligned}
$$

where λ_1 contains the lagrangian multipliers associate with the constraints on the factor loadings Γ^* and λ_2 contains the lagrangian multipliers associated with the constraints on the transition matrix A_t^*.

The computation of the Maximum Likelihood estimates is performed using the EM algorithm. Broadly speaking, the algorithm consists in a sequence of simple steps, each of which uses the time-varying parameter Kalman smoother to extract the common factors for a given set of parameters and closed form solutions to estimate the parameters given the factors. In practice, we use the restricted version of the EM algorithm, the Expectation Restricted Maximization, since we need to impose the smooth pattern on the factor loadings of the yields on the Nelson-Siegel factors. The ERM algorithm alternates Kalman filter extraction of the factors to the restricted maximization of the likelihood. At the j-th iteration the ERM algorithm performs two steps:

1. In the Expectation-step, we compute the expected log-likelihood conditional on the data and the estimates from the previous iteration, i.e.

$$\mathcal{L}(\theta) = E[L(z, F^*; \theta^{(j-1)})|z]$$

which depends on three expectations

$$\begin{aligned} \hat{F}_t^* &\equiv E[F_t^*; \theta^{(j-1)}|z] \\ P_t &\equiv E[F_t^*(F_t^*)'; \theta^{(j-1)}|z] \\ P_{t,t-1} &\equiv E[F_t^*(F_{t-1}^*)'; \theta^{(j-1)}|z] \end{aligned}$$

Given that our observables contain missing values, these expectations can be computed, for given parameters of the model, using the time-varying parameters Kalman smoother. This entails pre-multiplying the measurement equation by a selection matrix S_t of dimension $(n - \#missing) \times n$, as follows

$$S_t z_t = S_t \Gamma^* F_t^* + S_t v_t^*, \quad S_t v_t^* \sim N(0, S_t R^* S_t)$$

and apply the Kalman filter to a time-varying measurement equation with parameters $S_t \Gamma^*$ and $S_t R^* S_t$, and observables $S_t z_t$.

2. In the Restricted Maximization-step, we update the parameters maximizing the ex-

pected the expected lagrangian with missing values with respect to θ:

$$\theta^{(j)} = \arg\max_{\theta} \mathcal{L}(\theta)$$

This can be implemented taking the corresponding partial derivative of the expected log likelihood, setting to zero, and solving. In particular, the measurement equation parameters are estimated by using a selection matrix W_t with diagonal element equal to 1 if non-missing, and 0 otherwise, so that only the available data are used in the calculations.

Following Coroneo et al. (2016), we initialize the yield curve factors with the Nelson-Siegel factors using the two-steps ordinary least squares (OLS) procedure introduced by Diebold & Li (2006). We then project the balanced panel of macroeconomic variables on the Nelson-Siegel factors and use the principal components of the residuals of this regression to initialize the unspanned macroeconomic factors. The quarterly factors are then computed by time aggregating the monthly yield curve and macro factors. All the parameters are initialised with the OLS estimates obtained using the initial guesses of yield and macro factors described above. The initial values for the factor loadings of surveys are obtained by projecting the linearly interpolated quarterly surveys on the quarterly factors observed at a monthly frequency.