Predicting interest rates in real time

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Introduction: Motivation

- Macro indicators help predicting interest rates (Ang & Piazzesi, 2003; Monch, 2008; Ludvigson & Ng, 2009; Coroneo, Giannone & Modugno 2016)
  - Evidence based on revised data
  - Important to correctly specify the information set in real-time in macro and finance (Orphanides, 2001; Orphanides & Van Norden, 2002; Croushore & Stark, 2003)

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  - Important to correctly specify the information set in real-time in macro and finance (Orphanides, 2001; Orphanides & Van Norden, 2002; Croushore & Stark, 2003)
- Existing studies on real-time yield curve predictability:
  - Use either selected macro variables (Ghysels et al., 2014) or interest rate surveys (Altavilla et al., 2017);
  - Do not exploit filtering techniques that, as shown by Giannone et al. (2008), allow to efficiently extract real-time information

Introduction: This Paper

We study the predictive ability of real-time macro data for the yield curve

- Mixed frequencies dynamic factor model for Treasury zero-coupon yields, real-time macro variables and interest rate surveys
- Treat macroeconomic factors as unobservable components

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Findings, with U.S. data (1972-2016):

- Real-time macro information helps predict interest rates in normal times, especially short maturities at long horizons
- Data revisions drive the difference in the predictive ability between real-time and revised macro information.
- After 2008, we document a weaker role of macro variables and a helpful role of interest rate surveys.

Model's building blocks: Yields

We model the cross-section of bond yields using the Dynamic Nelson-Siegel framework of Diebold and Li (2006).

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

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- F_t^y identified through restrictions on the loadings:

$$a_y^{NS} = 0; \quad \Gamma_{yy}^{NS}(\tau) = \left[1 \quad \left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) \quad \left(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right)\right]$$

  where τ is the maturity of the bond

Model's building blocks: Real-time Macro Variables

Real-time macro variables are potentially driven by yield curve factors and some macro specific factors:

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

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- $\Gamma_{xx} F_t^x$ measures the information in real-time macro variables that is not spanned by the yield curve (Coroneo et al., 2016)

Model's building blocks: Interest Rate Surveys

We exploit the informational content of surveys:

$$E^s_{t-h}(y^q_{t,\tau}) = a_s + \Gamma_{h,\tau} F^q_t + v^q_{t,h,\tau},\ t = 3, 6, 9, \ldots$$

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- F^q_t quarterly factor measured as quarterly average of the monthly factors

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

can be represented as

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

Joint Model

- Observables

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

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- Joint dynamics for $F_t = [F_t^y, F_t^x]$ and $F_t^q = [F_t^{yq}, F_t^{xq}]$

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

this is a VAR(1) with time varying coefficients.

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- Idiosyncratic components $v_t = [v_t^y \quad v_t^x \quad v_t^s]'$

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

  where B and R are diagonal matrices

Estimation

- State-space form

$$
\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}
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where $F_t^* = \begin{bmatrix} F_t & F_t^q & c_t & v_t \end{bmatrix}'$

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- Restrictions on Γ^* and A_t^*:

$$H_1 \, vec(\Gamma^*) = q_1, \quad H_2 \, vec(A_t^*) = q_2$$

with H_1 and H_2: selection matrices, q_1 and q_2 restrictions

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- This is a **restricted** dynamic factor model with **missing values** and **time-varying coefficients**
- Estimation by QML (Doz, Giannone & Reichlin, 2012) by ERM algorithm
  1. Expectation-step: **time-varying parameter** Kalman smoother
  2. Restricted Maximization-step: update the parameters maximizing the **expected lagrangian** (Coroneo, Giannone & Modugno, 2016)

Data

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- Real-time macro variables

Series N.	Mnemonic	Description	Transf.	Delay (days)
1	AHE	Average Hourly Earnings: Total Private	1	4
2	CPI	Consumer Price Index: All Items	1	15
3	INC	Real Disposable Personal Income	1	28
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	3
8	Manf	PMI Composite Index (NAPM)	0	1
9	Paym	All Employees: Total nonfarm	1	4
10	PCE	Personal Consumption Expenditures	1	28
11	PPIc	Producer Price Index: Crude Materials	1	16
12	PPIf	Producer Price Index: Finished Goods	1	16
13	CU	Capacity Utilization: Total Industry	0	16
14	Unem	Civilian Unemployment Rate	0	14
15	CC	Conf. Board Consumer Confidence	0	-3
16	GBA	Philadelphia Fed Outlook survey	0	-15

Note: Transformation codes: 0 = no transformation, 1 = annual growth rate.

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- End-of-month zero-coupon yields on 3-month, 6-month and and on 1, 2, 3, 4, 5, 7 and 10-year
- SPF median forecast of the 3-m T-Bill for 3 and 4 quarters ahead

Number of factors

We use a modified version of the Bai and Ng (2002) information criterion, as described in Coroneo et al. (2016):

	1972-2008		1972-2016	
N. of factors	**IC**	**V**	**IC**	**V**
3	-0.05	0.43	-0.06	0.43
4	-0.16	0.30	-0.15	0.30
5	-0.22	0.21	-0.15	0.23
6	-0.19	0.17	-0.10	0.19
7	-0.07	0.15	0.01	0.16
8	0.06	0.13	0.09	0.13

Up to 2008 $\rightarrow$ IC is minimized with 5 factors, as in Coroneo et al. (2016).
Full sample $\rightarrow$ no clear-cut results, we use 4 factors for parsimony.

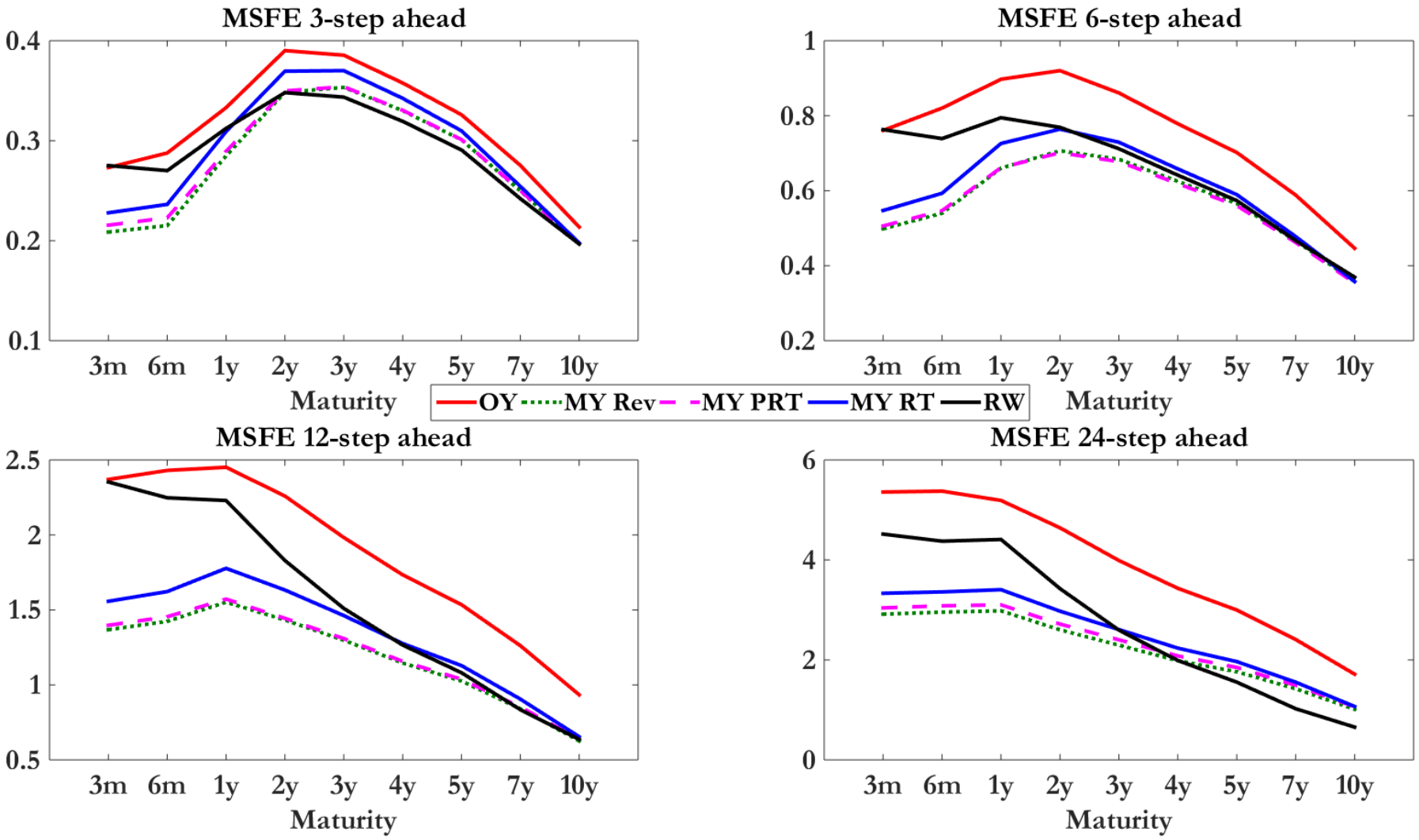
Forecast

- Recursive estimation from Jan-1972
- OOS evaluation in two sub-samples:
  - Normal times: from Jan-1995 to Dec-2008
  - Unconventional times: from Jan-2009 to Dec-2016.
- Reconstruct the information set available to the forecasters at each point in time in which the forecast is computed (end of each month)
- Forecast of the interest rates based on iterative forecasts of the factors

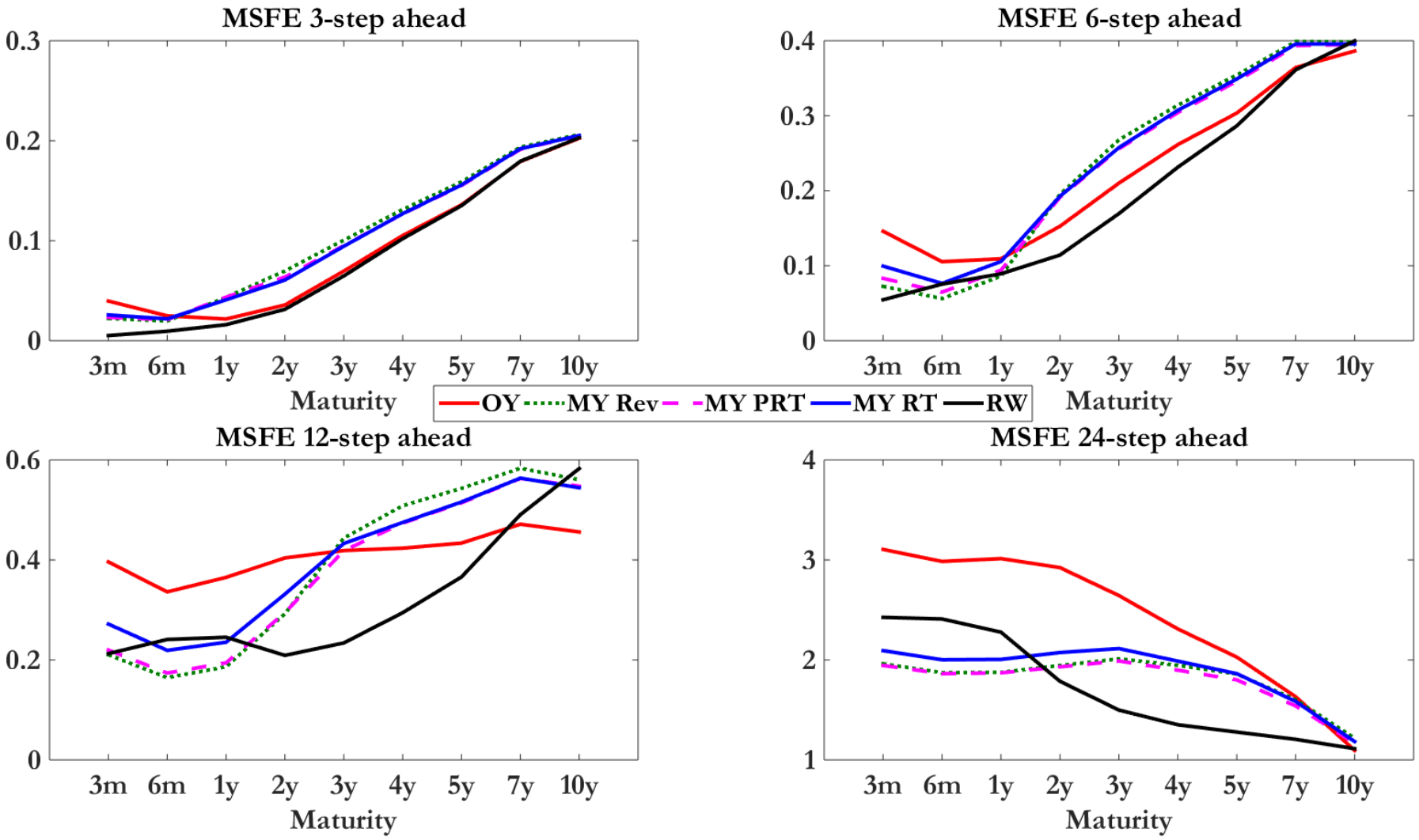
$$E_t(y_{t+h}^{(\tau)}) \equiv \hat{y}_{t+h|t} = \max(\hat{\Gamma}_{|t}^{y*} \hat{F}_{t+h|t}^{*}, 0)$$

where $\hat{\Gamma}_{|t}^{y*}$ contains the factor loadings for yields and is estimated using information up to time t.

Results: Real-time Macro Variables (Normal Times)



Results: Real-time Macro Variables (Unconv. Times)



Results: relative MSFE (wrt RW), 1995-2008

Only-Yields model

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	0.94	0.97	1.00	1.05	1.05	1.05	1.05	1.05	1.01
3	0.99	1.07	1.07	1.12	1.12	1.12	1.12	1.14	1.09
6	1.00	1.11	1.13	1.20	1.21	1.21	1.22	1.26	1.21
12	1.01	1.08	1.10	1.23	1.31	1.37	1.42	1.51	1.47
24	1.08	1.13	1.08	1.25	1.43	1.62	1.82	2.27	2.56

Macro-Yields model, revised data

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	0.81**	0.80**	0.92	1.00	1.02	1.02	1.02	1.02	1.00
3	0.76*	0.80*	0.91	1.00	1.03	1.03	1.03	1.03	1.00
6	0.65**	0.73*	0.83	0.92	0.96	0.97	0.99	1.00	0.97
12	0.58**	0.63**	0.70**	0.78**	0.86*	0.91	0.95	1.01	0.98
24	0.59**	0.62**	0.62***	0.70**	0.83*	0.94	1.09	1.36	1.54

Macro-Yields model, real-time data

1	0.88	0.87	0.99	1.05	1.06	1.06	1.05	1.04	1.02
3	0.83	0.87	0.99	1.06	1.08	1.07	1.07	1.05	1.01
6	0.72**	0.80*	0.92	0.99	1.02	1.03	1.03	1.02	0.97
12	0.66**	0.72**	0.80*	0.89	0.97	1.01	1.04	1.08	1.03
24	0.67**	0.70**	0.71**	0.80*	0.94	1.06	1.21	1.48	1.62

(*) and (**): significance at the 10% and 5% using the Diebold and Mariano (2002) statistic with fixed-m asymptotics, as in Coroneo and Iacone (2018).

Results: relative MSFE (wrt RW), 2009-2016

Only-Yields model

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	4.66	2.92	1.48	1.07	1.03	1.01	1.00	1.01	1.03
3	7.70	2.63	1.35	1.14	1.08	1.03	1.01	1.00	1.00
6	2.67	1.40	1.22	1.34	1.24	1.13	1.06	1.01	0.97
12	1.86	1.40	1.49	1.93	1.79	1.44	1.19	0.96	0.78
24	1.28	1.24	1.32	1.64	1.76	1.71	1.59	1.35	0.98

Macro-Yields model, revised data

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	3.75	4.08	2.05	1.32	1.15	1.08	1.05	1.03	1.01
3	4.31	2.09	2.71	2.22	1.55	1.29	1.18	1.08	1.02
6	1.33	0.74	0.97	1.71	1.58	1.36	1.24	1.11	1.00
12	0.99	0.68	0.76	1.40	1.89	1.73	1.48	1.19	0.96
24	0.81	0.78	0.82	1.09	1.34	1.44	1.45	1.33	1.09

Macro-Yields model, real-time data

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	3.83	3.74	1.77	1.24	1.12	1.06	1.04	1.02	1.01
3	4.95	2.29	2.55	1.94	1.46	1.25	1.15	1.07	1.01
6	1.81	1.01	1.19	1.69	1.52	1.33	1.22	1.10	0.99
12	1.28	0.91	0.96	1.59	1.85	1.61	1.41	1.15	0.93
24	0.86	0.83	0.88	1.16	1.41	1.47	1.46	1.32	1.06

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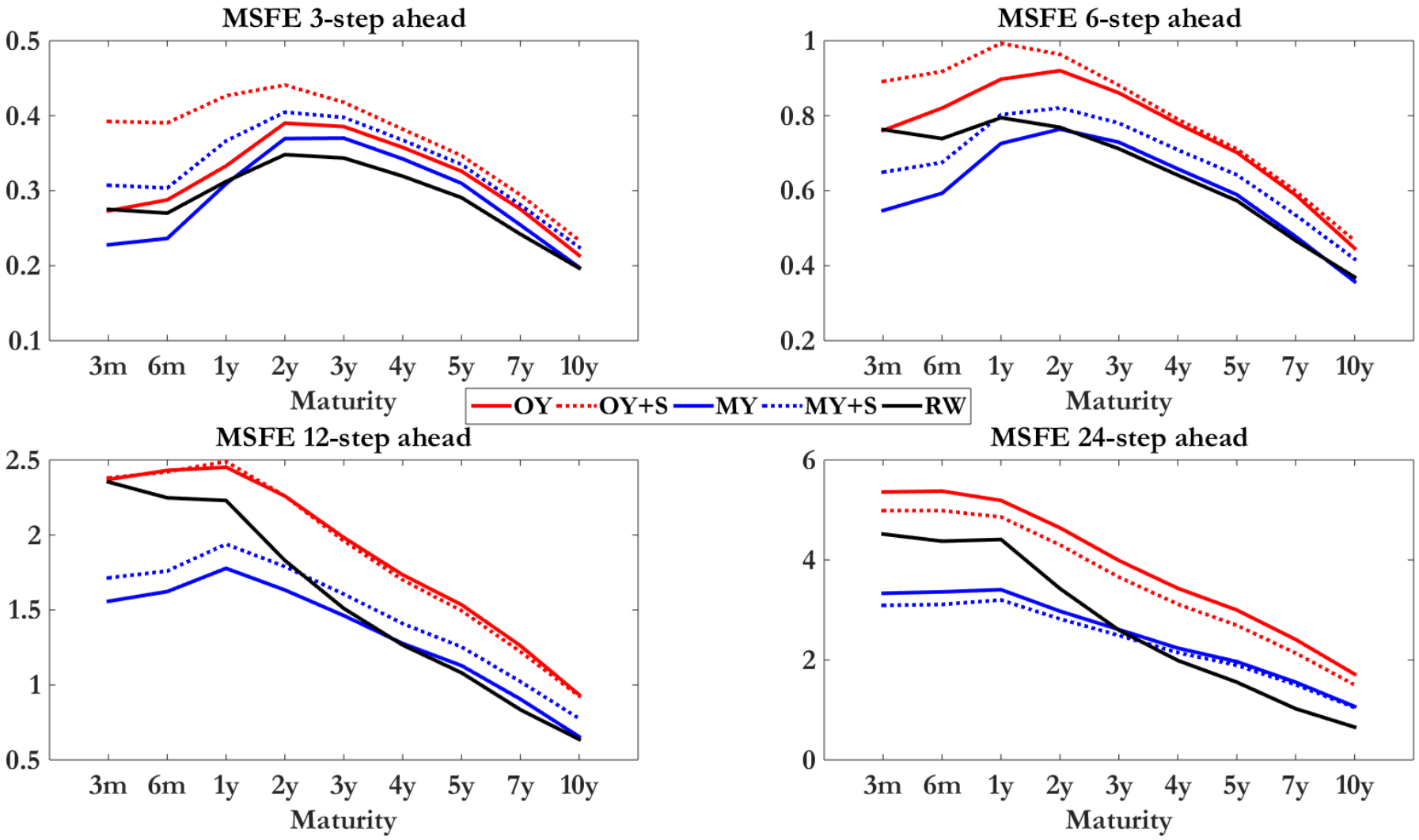

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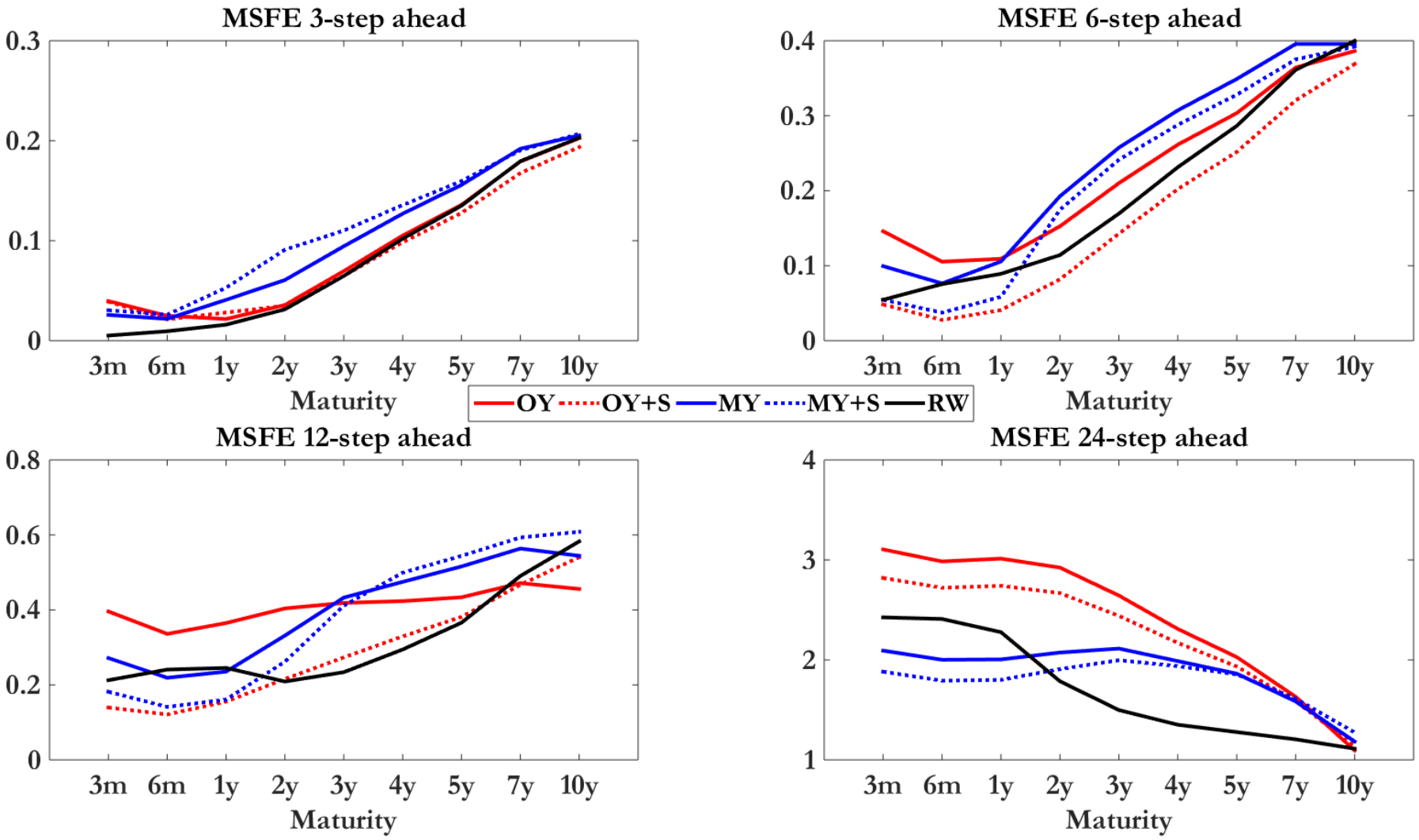

Results: RMSFE (wrt RW) with SPF, 2009-2016

Only-yields model:

Only-Yields

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6	0.88	0.37	0.46	0.72	0.84	0.87	0.88	0.89	0.92
12	0.66	0.50	0.63	1.03	1.17	1.12	1.04	0.95	0.93
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Macro-Yields model, real time data with SPF

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	5.43	5.45	4.55	1.97	1.39	1.21	1.13	1.08	1.07
3	5.92	2.75	3.31	2.90	1.70	1.33	1.18	1.06	1.02
6	1.00	0.49	0.66	1.53	1.42	1.24	1.15	1.04	0.98
12	0.86	0.59	0.66	1.25	1.76	1.70	1.49	1.21	1.04
24	0.78	0.74	0.79	1.07	1.33	1.43	1.45	1.34	1.15

(*), (**) and (***): significance at the 10%, 5% and 1% using the Diebold and Mariano (2002) statistic with fixed-m asymptotics, as in Coroneo and Iacone (2018).

Results: RMSFE (wrt RW) with SPF, 2009-2016

Macro-yields model:

Macro-Yields model, real-time data

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	3.83	3.74	1.77	1.24	1.12	1.06	1.04	1.02	1.01
3	4.95	2.29	2.55	1.94	1.46	1.25	1.15	1.07	1.01
6	1.81	1.01	1.19	1.69	1.52	1.33	1.22	1.10	0.99
12	1.28	0.91	0.96	1.59	1.85	1.61	1.41	1.15	0.93
24	0.86	0.83	0.88	1.16	1.41	1.47	1.46	1.32	1.06

Macro-Yields model, real time data with SPF

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	5.43	5.45	4.55	1.97	1.39	1.21	1.13	1.08	1.07
3	5.92	2.75	3.31	2.90	1.70	1.33	1.18	1.06	1.02
6	1.00	0.49	0.66	1.53	1.42	1.24	1.15	1.04	0.98
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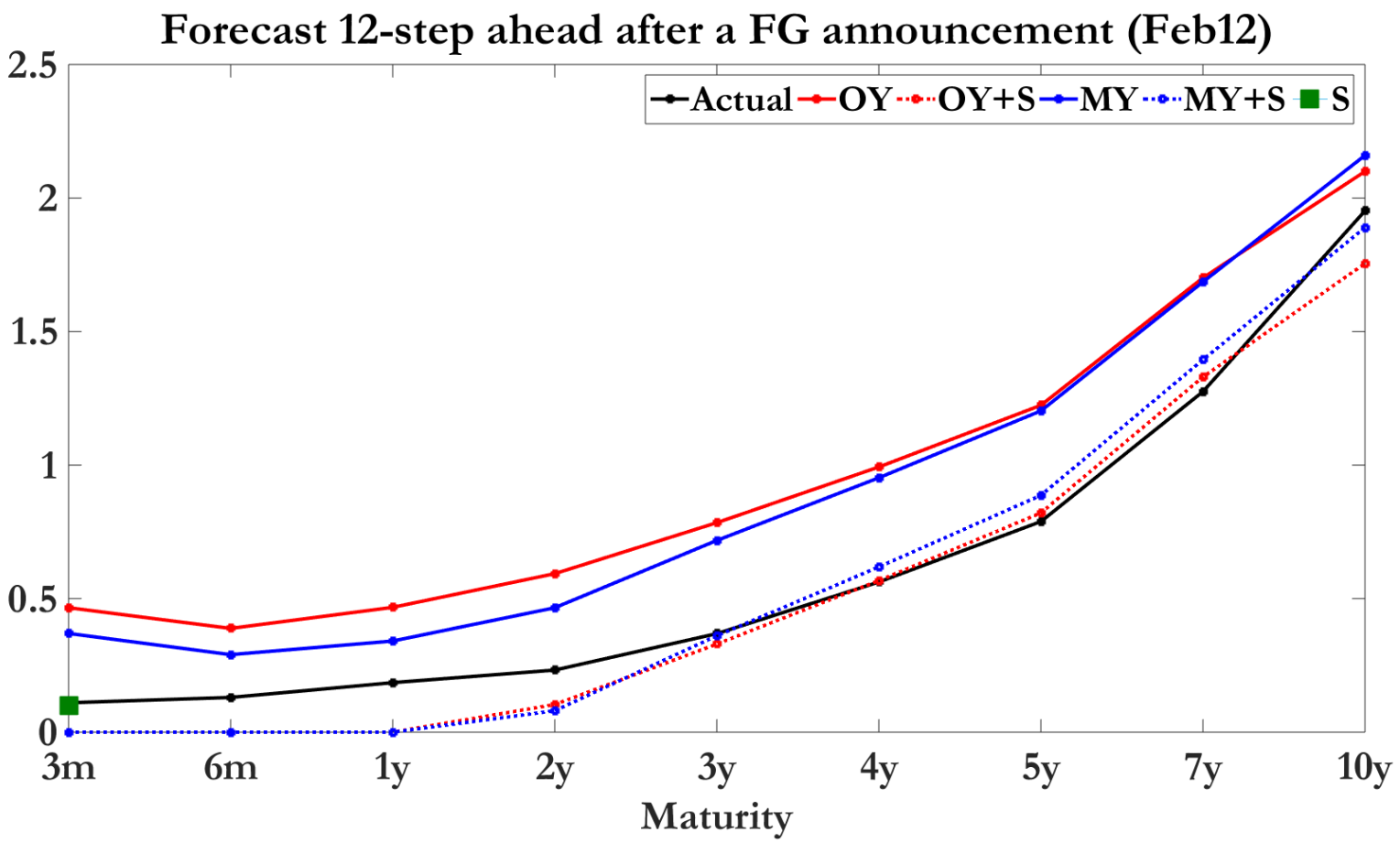
24	0.78	0.74	0.79	1.07	1.33	1.43	1.45	1.34	1.15

(*), (**) and (***): significance at the 10%, 5% and 1% using the Diebold and Mariano (2002) statistic with fixed-m asymptotics, as in Coroneo and Iacone (2018).

Results: example of a forward guidance announcement



Conclusions

- We assess the predictive ability of real-time macro information for the yield curve
- We develop a mixed frequencies dynamic factor model for Treasury zero-coupon yields, a representative set of real-time macroeconomic variables and interest rate surveys
- Findings:
  1. Real-time macroeconomic information has predictive ability for interest rates, in normal times
  2. After 2008, the importance of macro variables is reduced and survey expectations play an important role for interest rate forecasting
- Future research: explicitly incorporate long-run trends along the lines of Del Negro, Giannone, Giannoni & Tambalotti (2017)

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