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Working Paper Series Nº 2016-31

DEPARTMENT OF ECONOMICS, FEA-USP
WORKING PAPER Nº 2016-31

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Keywords: bonds; factor-augmented VAR; forecasting; term structure; yield curve

JEL Codes: E58; C38; E47

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1. Introduction

Term structure models with macroeconomic factors rarely produce better predictions than the random walk benchmark. In this paper, we propose a term structure model with macroeconomic factors for the US yield curve that consistently outperform the random walk benchmark. Moreover, our model outdoes the main extant models in the literature, improving forecasts at the short and medium horizons for virtually every maturity. The key feature of our model is the use of a comprehensive data set of forward-looking indicators that has not been previously employed by the literature.

We summarize our forecasting strategy as follows. First, we extract the first two principal components from a large data set of macroeconomic and financial variables that include many forward-looking indicators. We then estimate a dynamic Nelson-Siegel model as in Diebold et al. (2006), but augmenting their VAR specification with these principal components. Finally, we forecast the values of the level, slope and curvature factors of the yield curve in order to predict the yields at each maturity. Our forecasting strategy thus hinges on a factor-augmented dynamic Nelson-Siegel (FADNS) specification. The FADNS model outperforms the random walk benchmark for every maturity from 5 to 30 years at the 6- to 12-month forecasting horizons. Moreover, for medium-term maturities (7 and 10 years), the FADNS model also outperforms the random walk benchmark as early as at the 3-month forecasting horizon. This is in stark contrast with previous models in the literature. For instance, Altavilla et al. (2014a,b) – who propose a model based on (few) forward-looking indicators – and de Pooter et al. (2010) – who propose a model with (backward-looking) macroeconomic factors -- can improve with respect to the random walk benchmark only for short-term maturities and only at short-term forecasting horizons.

To provide some figures, for the 10-year yield, the mean absolute forecast error (MAFE) of our FADNS model at the 12-month horizon is 0.363 percentage point (pp), whereas it is 0.524 pp for the random walk, 0.488 pp for the autoregressive model, 0.539 pp for the regression model that captures the interaction between future yield curve changes with historic term structure slope as in Steeley (2014), 0.679 pp for Diebold and Li's (2006) VAR model for the level, slope and curvature factors, 0.496 pp for Altavilla et al.'s (2014b) augmented dynamic Nelson-Siegel model by future Fed funds rate, and 0.435 pp for Diebold et al.'s (2006) dynamic Nelson–Siegel model. In relative terms, the improvements of the FADNS approach range from 20% with respect to Diebold et al.'s (2006) dynamic Nelson–Siegel model to 87% with respect to Diebold and Li's (2006) VAR model.

The only yield for which we do not outclass the random walk at any forecasting horizon is the 1-year interest rate. This is in line with previous results in the literature. Steeley (2014) points out that the implementation of the zero interest rate policy (ZIRP) comes with a deterioration in the forecasting ability of term structure models à la Diebold and Li (2006) relative to simple autoregressive alternatives, which includes the random walk benchmark. This effect is especially strong for short-term yields because their volatility becomes much lower under the ZIRP. On the other hand, de Pooter et al. (2010), Exterkate et al. (2013) and van Dijk et al. (2014) argue that including macroeconomic information is particularly useful in volatile times, such as in recessionary periods.[1] It is thus very reassuring that our FADNS forecasting model performs so well at most maturities within an out-of-sample period characterized by low volatility and stable real activity growth.

Further analysis reveals that the forecasting improvement we obtain with the FADNS model comes mainly from the forward-looking nature of the variables we employ. Our data set of predictor variables contains 169 real-time weekly variables about economic activity, inflation, economic uncertainty, financial markets, fiscal policy, monetary policy and credit conditions.[2] Most of the variables (63%) are forward looking. For instance, our data set contains 6- to 24-month ahead market expectations for a host of series such as quarterly GDP growth, consumer price inflation, core price inflation, government balance sheet, and current account deficits.

The importance of relying on forward-looking variables is also highlighted by Kim and Orphanides (2012) and Altavilla et al. (2014a,b). However, differently from these papers, our forecasting model uses a much larger number of variables instead of restricting attention to only a few variables such as the expected Fed funds rate. To capture the information from this large set of variables in an effective way, we use principal components analysis. This follows a large literature that shows the inclusion of a small number of principal components extract from large data sets leads to significant forecast improvements (Stock and Watson, 2002a,b; Bernanke and Boivin, 2003; Bernanke et al., 2005; de Pooter et al., 2007).To provide further evidence that conditioning on the information of a wide array of forward-looking indicators is crucial, we augment the extant forecasting models with the principal components extract from our data set. The results show a clear improvement on the forecasting performance once we incorporate them, confirming the importance of including forward-looking indicators in the way we do.

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[1] Xiang and Zhu (2013) and Hevia et al. (2015) propose a regime-switching Nelson-Siegel model, allowing some parameters to vary according to the volatility regime. The out-of-sample forecasting improves significantly.
[2] Real-time variables are time-stamped at the time they first become available to investors.

To assess robustness, we entertain a different collection of forward-looking indicators with a longer time span (from 1989 to 2015), but at the quarterly frequency. The qualitative results remain the same. In particular, we find that exploiting market expectations from the Survey of Professional Forecasters (SPF) also equips the FADNS model with better forecasts.

As opposed to Ang and Piazzesi (2003) and Moench (2008), we do not impose no-arbitrage restrictions. Duffee (2002, 2011) argues that no-arbitrage models are not flexible enough to predict the dynamics of the yield curve. In particular, he shows that it is much more important to assume that the level of the term structure is close to a random walk than imposing the absence of arbitrage opportunities. See also Almeida and Vicente (2008), Carriero (2011) and Carriero and Giacomini (2011) for more details on how no-arbitrage restrictions affect the prediction of the term structure of interest rates.

We organize the remainder of this paper as follows. Section 2 presents the FADNS model. Section 3 describes the data set. Section 4 reports both in- and out-of-sample results. Section 5 examines the reasons why our forecasting model outperforms the extant models in the literature. Section 6 presents a robustness exercise for a different data set, with a longer time span and lower frequency. Finally, Section 7 concludes.

2. The FADNS model

We combine two different methods in the literature to come up with a new predicting model for the US yield curve. We forecast the values of the level, slope and curvature factors of the Nelson-Siegel decomposition of the yield curve using a dynamic VAR framework that incorporates the information conveyed by the principal components of a wide array of macroeconomic and financial variables. In doing so, we combine Diebold et al.'s (2006) dynamic Nelson-Siegel model for the level, slope and curvature factors with Stock and Watson's (2002a,b) idea of conditioning on a manageable number of principal components extracted from a large number of variables. We call this the Factor-Augmented Dynamic Nelson-Siegel (FADNS) model.

Diebold and Li (2006) employ a Nelson-Siegel decomposition of the yield curve with time-varying parameters for the level (L_t), slope (S_t) and curvature (C_t) factors of the term structure of interest rates:

(1) $$y_t^{(n)} = L_t + S_t\left(\frac{1-e^{-\lambda n}}{\lambda n}\right) + C_t\left(\frac{1-e^{-\lambda n}}{\lambda n} - e^{-\lambda n}\right)$$

where $y_t^{(n)}$ is the yield at time t of maturity n and λ is a parameter that controls the rate of exponential decay of the yield curve.[3] They assume a fixed λ and a vector autoregressive specification for (L_t, S_t, C_t). In turn, Diebold et al. (2006) recast equation (1) into a dynamic model in which the Nelson-Siegel factors follow a vector autoregressive process of first order that also includes three macroeconomic variables, namely, unemployment rate, capacity utilization, and Fed funds rate.

Rather than conditioning on a few macroeconomic variables, we propose to control for as much information about the economy as possible. To this end, we collect a large number of backward- and forward-looking macroeconomic and financial variables that are likely in the information set of most market participants. Our final data set comprises 169 different variables from which we extract principal components as in Stock and Watson (2002b).[4]

Denote the Nelson-Siegel factors by $Z_t = (\beta_{1t}, \beta_{2t}, \beta_{3t})'$ and the (k×1)-vector of principal components by F_t. Also, let c denote a (k+3)×1 vector of constants, $\Phi(L)$ a (k+3)×(k+3) first-order autoregressive matrix, and ω_t a vector of reduced-form shocks. The FADNS then reads

(2) $$\begin{pmatrix} F_t \\ Z_t \end{pmatrix} = c + \Phi(L) \begin{pmatrix} F_t \\ Z_t \end{pmatrix} + \omega_t.$$

To estimate the FADNS model, we proceed in two steps as in Vieira et al. (2017). We first extract level, slope and curvature from the yield curve as well as the principal components from our large panel of macro-financial indicators. We then estimate by quasi-maximum likelihood the FADNS coefficients in (2). To obtain forecasts, we plug in the coefficient estimates to predict the future values of the Nelson-Siegel factors

(3) $$\hat{\beta}_{i,t} = \hat{c}_i + \sum_{j=1}^{3} \hat{\varphi}_{i,k+j} \hat{\beta}_{j,t-1} + \sum_{j=1}^{k} \hat{\varphi}_{i,j} \mathrm{F}_{j,t-1},$$

and then compute the expected yield curve h-months ahead by means of

(4) $$\hat{y}_{t+h|t}^{(n)} = \hat{\beta}_{1,t+h|t} + \hat{\beta}_{2,t+h|t} \left(\frac{1-e^{-\lambda n}}{\lambda n}\right) + \hat{\beta}_{3,t+h|t} \left(\frac{1-e^{-\lambda n}}{\lambda n} - e^{-\lambda n}\right).$$

3. Data description

Our data set contains 169 weekly variables from December 2007 to December 2015. In order to improve the predictive power of our model, more than half of the variables in our

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[3] Krippner (2015) offers an explicit foundation for the level, slope and curvature factors of the Nelson-Siegel decomposition using a Taylor approximation of a generic Gaussian affine term structure model.

[4] Although the principal component analysis formally requires independent and identically distributed observations, Stock and Watson (2002a) and Doz et al. (2012) show that it performs similarly to full maximum likelihood estimation for a large panel in the context of both static and dynamic factor models, respectively.

data set are forward-looking (63%; 107 out of 169). Indeed, Ang et al. (2007) show that forward-looking variables such as survey-based measures of expected inflation predict better future inflation than many backward-looking macroeconomic variables. The data set begins in December 2007 because this is the earliest date for which we could gather most of the weekly forward-looking variables. In Section 7 we entertain a different collection of forward-looking indicators with a longer time span (from 1989 to 2015), but at the quarterly frequency.

The forward-looking variables in our data set are from Bloomberg and contain financial variables (such as TED spread, 5-year CDS, and corporate bond spreads) and weekly market expectations for real activity, inflation, external, and fiscal accounts for 6, 12 and 24 months ahead. To ensure that only up-to-date market expectations are considered, we gather forecasts only from institutions that regularly submit predictions. There are between 12 and 31 financial institutions that submit weekly forecasts depending on the forecasted variable. To the best of our knowledge, this is the first paper to explore such a comprehensive data set of market expectations to predict the yield curve of interest rates in the US.

We can separate the variables in our data set into five groups according to the information they convey: Economic Uncertainty, Economic Activity, Inflation, Fiscal, Monetary and Financial. Economic Uncertainty is the largest group, accounting for 29% (49) of all variables. The variables in this group refer to the sample standard deviation, range and skewness of the institutions' predictions. Economic Activity responds for 21% (36) of all variables, including employment, consumer confidence, retail sales, and expected activity indicators. Inflation answers for 21% (36) of the data, including producer and consumer aggregate indices – observed inflation and expected inflation (6, 12 and 24 months ahead) -- and commodity prices (e.g. energy, livestock and crop prices).

The Fiscal group accounts for 9% (15) of the variables, containing annual variation in federal and local government nominal debt, presidential approval rating and expected government budget as a percentage of GDP. The Monetary group is responsible for 7% (11) of the data set, containing credit, bank reserves, monetary aggregate variables and also forward-looking variables such as market expectations about future Fed funds rate and 10-year treasury yield. Finally, the Financial group accounts for 13% of the variables (22), including the S&P 500 index, credit spread (difference between corporate bond and treasury yields), speculative and commercial net contracts outstanding, Bloomberg's financial condition index,[5] and expected changes in the dollar-to-euro exchange rate. We also include in this group international indicators such as the 5-year China, Germany and Eurozone CDS as well as the Emerging Market Bond Index (EMBI).

Before extracting principal components, we must first make sure that all variables are stationary. For any given variable, we take first differences if we find evidence of unit root at the 10% significance level. We then compute the principal components of the resulting set of variables.[6] Table 1 presents the variables with the highest correlation with the first two principal components based on the whole sample. The first principal component explains 24% of the overall variation, loading mostly on variables in the Economic Activity, Economic Uncertainty and Financial groups. The second principal component explains 19% of the total variation in the data and correlates mostly with indicators from the Inflation group.

The Appendix contains the full list of variables in our data set.

[Table 1 about here]

3.1 The level, slope and curvature factors from the US yield curve

We start with the average weekly term structure of interest rates from the daily zero coupon yields released by Bloomberg.[7] We consider the following fixed maturities: 3, 6, 12, 24, 36, 48, 60, 72, 84, 96, 108, 120, 180, 240, and 360 months. We retrieve the level, slope and curvature factors from the US yield curve using a constant λ equal to 0.0609, as in Diebold and Li (2006), and then estimate (2) using a VAR(1) specification.

For the out-of-sample exercise, we assess only maturities higher than 1 year because of the extremely low interest rate volatility after the recent crisis. Steeley (2014) claims that, under the ZIRP, any model without a strong weight in the inertial component will have problems in forecasting the short-term yields. Figure 1 shows the 1-year rolling volatility for 1-, 5-, 10-, and 30-year yields over the period from 2009 to 2015. We observe a sharp reduction in the volatility of the short-term yields, especially at the 1-year yield after 2012 with the quantitative easing. Figure 2 plots the ratio between volatility levels before and after December 2012. Again, we observe that interest rate volatility declines significantly. For instance, the volatility ratios are 70% for the 30-year yields, about 40% for the 5- , 7- and 10-year yields, and 10% for the 1-year yield.

[5] This index tracks the overall level of financial stress in US money, bond, and equity markets to help assess the availability and cost of credit.
[6] For the descriptive analysis, we estimate the principal components using the whole sample. However, in the forecasting exercise, we compute the principal components in real time, that is, we re-estimating the principal components every time we add one more observation to the sample.
[7] For more information, see https://pt.scribd.com/document/36123534/Bloomberg-Interpolation.

[Figures 1 and 2 about here]

4. Implementing FADNS forecasts

This section first shows that the principal components of the wide array of macroeconomic and financial variables indeed convey relevant information about the yield curve by examining a factor-augmented Taylor rule. We then report both in- and out-of-sample forecasting performance of the FADNS model relative to the extant macro-finance term structure models in the literature.

4.1 Factor-augmented Taylor rule

We adapt Bernanke and Boivin's (2003) augmented Taylor rule to the weekly frequency as follows:

(4) $$R_t = \rho R_{t-1} + (1-\ \rho)\left[\beta_1\left(CPI_{12m} - CPI_{target}\right) + \beta_2(g_{12m} - g_{Potential}) + \beta_3\widehat{R_t}\right],$$

where R_t is the Federal Reserve target interest rate (namely, the Fed funds rate), CPI_{12m} is the expected consumer price index inflation excluding food and energy over the next 12 months, CPI_{target} is the inflation target, g_{12m} is the expected GDP growth over the next 12 months, $g_{potential}$ is the potential GDP growth, and $\widehat{R_t} = c + \sum_{i=1}^{2}\widehat{a}_\imath F_{it}$ is the projection of the Fed funds rate onto the first two principal components (F_{1t} , F_{2t}) computed from of entire data set of financial and macroeconomic variables.

Table 2 shows that the principal components indeed affect the Fed funds rate. Projecting R_t onto $(F_{1t,}F_{2t})$ yields a significantly negative coefficient estimate for F_{1t}, reflecting a strong correlation of R_t with higher GDP growth, lower unemployment and economic uncertainty. In turn, the significantly positive coefficient for F_{2t} shows that the Fed funds rate increases with higher expected inflation, commodity prices and exchange rate depreciation.

[Table 2 about here]

To estimate the Taylor rule in equation (4), we measure the inflation gap as the difference between the market's expectation of core inflation over the next 12 months and the long-run inflation target of 2% defined by the Federal Open Market Committee (FOMC). To measure output gap, we take the difference between the market's expectation of GDP growth over the next 12 months and the real potential GDP released by the Congressional Budget

Office (CBO).[8] Table 3 reports the estimation results for two specifications of the Taylor Rule. In the first specification (Column A), we do not include the projection of the Fed funds rate on the principal components. The coefficient estimates are as expected, implying that higher inflation and increasing GDP gap translate into a greater Fed funds rate. In the augmented specification (Column B), the coefficient on the output gap is still significant but it decreases by half, whereas the coefficient on the inflation target becomes insignificant.[9] The coefficient estimate on $\widehat{R_t}$ is significantly positive, suggesting that principal components indeed convey relevant information.

[Table 3 about here]

4.2 Estimating the yield curve

This section discusses the in-sample results from the FADNS estimation. Table 4 reports the sample average and standard deviation of the actual and predicted yields as well as of the corresponding absolute errors. The FADNS model fits well the level, slope, and curvature of the US term structure of interest rates from December 2007 to December 2012.

[Table 4 about here]

As in Diebold and Li (2006), we do not find a clear pattern between the magnitude of the residuals and maturity. This is in contrast with Moench (2008), who finds that the mean absolute error (MAE) increases with maturity. In addition, we find lower MAEs than Moench (2008) for every yield, confirming Steeley's (2014) findings that residuals are smaller and less volatile after the 2007-2009 recessionary period. The FADNS model entails a lower MAE than Diebold and Li's (2006) autoregressive model. The largest estimation errors are of circa 50 basis points (bps) for the 1-year yield in the week of Lehman Brothers' bankruptcy and of 23 bps for the 10-year yield one month later.

Altogether, we find that the FADNS captures very well both the short and long ends of the US term structure of interest rates. In the next section, we examine whether the excellent in-sample performance also translates into superior forecasts out-of-sample.

[8] The CBO releases real potential GDP growth on quarterly basis. We interpolate this series linearly to obtain weekly observations.

[9] Adding the principal components directly into the Taylor rule yields similar results, but with lower standard errors in view that the estimation is now in one step. As a result, the coefficient estimate for inflation becomes significant at the 10% level.

4.3 Forecasting the yield curve

In this section, we assess the forecasting performance of our FADNS model relative to the extant models in the literature. Apart from the usual random walk benchmark (RW), we also contemplate the forecasting performance of the autoregressive model (AR), the slope model (Diebold and Li, 2006; Steeley, 2014), Diebold and Li's (2006) VAR model for the level, slope and curvature factors (DL), Diebold et al.'s (2006) dynamic Nelson–Siegel model (DNS), and Altavilla et al.'s (2014b) augmented dynamic Nelson-Siegel model by the future Fed funds rate (FFF). Despite their simplicity, the AR and RW models are actually quite challenging benchmarks, especially at shorter forecasting horizons (see Joslin et al., 2011).

The DNS model can be framed in transition and measurement equations. The transition equation is:

$$(5)\qquad \begin{pmatrix} L_t & - & \mu_L \\ S_t & - & \mu_S \\ C_t & - & \mu_C \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} L_{t-1} & - & \mu_L \\ S_{t-1} & - & \mu_S \\ C_{t-1} & - & \mu_C \end{pmatrix} + \begin{pmatrix} \eta_t(L) \\ \eta_t(S) \\ \eta_t(C) \end{pmatrix},$$

whereas the measurement equation is given by

$$(6)\qquad \begin{pmatrix} y_t^{(1)} \\ y_t^{(2)} \\ \vdots \\ y_t^{(N)} \end{pmatrix} = \begin{pmatrix} 1 & \left(\frac{1-e^{-\lambda n}}{\lambda n}\right) & \left(\frac{1-e^{-\lambda n}}{\lambda n} - e^{-\lambda n}\right) \\ 1 & \left(\frac{1-e^{-\lambda n}}{\lambda n}\right) & \left(\frac{1-e^{-\lambda n}}{\lambda n} - e^{-\lambda n}\right) \\ \vdots & \vdots & \vdots \\ 1 & \left(\frac{1-e^{-\lambda n}}{\lambda n}\right) & \left(\frac{1-e^{-\lambda n}}{\lambda n} - e^{-\lambda n}\right) \end{pmatrix} \begin{pmatrix} L_t \\ S_t \\ C_t \end{pmatrix} + \begin{pmatrix} \varepsilon_t^{(1)} \\ \varepsilon_t^{(2)} \\ \vdots \\ \varepsilon_t^{(N-1)} \\ \varepsilon_t^{(N)} \end{pmatrix}.$$

We estimate jointly the level, slope, and curvature factors as well as λ in the DNS model. We use the coefficient estimates of a VAR(1) model with λ equal to 0.0609 as initial values.

As in Steeley (2014), we obtain the forecasts of the Slope model by regressing each yield on the past realization of the corresponding term spread. This implies

$$(7)\qquad \hat{y}_{t+h|t}^{(n)} = \hat{y}_t^{(n)} + \hat{\lambda}^{(n)} + \hat{\varphi}^{(n)}\left(y_t^{(n)} - y_t^{(3)}\right)$$

as the *h*-step ahead forecast of the yield on maturity *n.*

The DL forecasting strategy is as follows. First, we extract the level, slope and curvature factors from the yield curve for each week using Nelson and Siegel's (1987) decomposition with λ fixed at 0.0609. Then, we forecast the Nelson-Siegel factors using a VAR(1) process to back out the future values of the yields. The *h*-steps ahead forecast of the yield on maturity *n* then is

(8) $$\hat{y}_{t+h|t}^{(n)} = \hat{\beta}_{1,t+h|t} + \hat{\beta}_{2,t+h|t}\left(\frac{1-e^{-\lambda n}}{\lambda n}\right) + \hat{\beta}_{3,t+h|t}\left(\frac{1-e^{-\lambda n}}{\lambda n} - e^{-\lambda n}\right).$$

Altavilla et al. (2014b) augments Diebold and Li's (2006) term structure model by the expectations on the Fed funds rates h-steps ahead. To obtain the forecasts of the FFF model, we first extract the Nelson-Siegel factors from the yield curve. Then, we calculate

(9) $$\hat{\beta}_{i,t+h} = \hat{c}_i + \sum_{j=1}^{3} \hat{\varphi}_{i,k+j}\hat{\beta}_{j,t} + \hat{\varphi}_i \mathrm{X}_t + \eta_{t+h},$$

where X_t denotes the expectations on the Fed funds rates. Altavilla et al.'s (2014b) original model measures expectations on the Fed funds rates by the consensus from the Survey of Professional Forecasters (SPF). Because the SPF survey is at the quarterly frequency, we replace it with the implied future Fed funds rates that is available at the weekly frequency.[10]

To obtain out-of-sample forecasts, we use an expanding estimation window. The initial window runs from the first week of December 2007 to the last week of December 2012, so that our initial forecast is for yields in the first week of January 2013. We then forecast the yields for every subsequent week up to the last week of December 2015 by adding one new weekly observation. To compute *h*-step ahead forecasts, we iterate forward the one-period-ahead forecasts.[11]

Table 5 reports the mean absolute forecast error (MAFE) of each model for yields with maturity ranging from 1 to 30 years. The FADNS model performs very well relative to the RW and AR benchmarks. At the 3-month horizon, it not only entails comparable forecasts for the 5-year yield, but also clearly outclasses them for the 7- and 10-year yields. At longer horizons, the FADNS beats the RW and AR models for any yield with maturity of 5 or more years, with an average reduction of 25% in the MAFE. In particular, the FADNS model entails clear improvements for longer horizons and with much lower MAFE for the 5- to 10-year yields at any horizon from 6 to 12 months ahead. This is quite an achievement given the low volatility that characterizes the out-of-sample period. As expected given Steeley's (2014) findings, the random walk dominates for the 1-year yield at any horizon.

[Table 5 about here]

As for alternative models, FFF is the only to outperform the RW benchmark at longer horizons. Although both FFF and DNS offer some improvement over the AR benchmark, they are clearly inferior to the FADNS model. More specifically, the latter outperforms the second best alternative by about 3.5 bps on average. The DL and slope models perform

[10] In Section 6, we redo the analysis with survey analysts' forecasts at the quarterly frequency as in Altavilla et al. (2014b).

[11] See Marcellino, Stock and Watson (2006) for an excellent discussion about the relative advantages and drawbacks of direct and iterated AR forecasts.

poorly relative to the benchmarks. Altogether, the results in Table 5 suggest that adding the principal components is key to improve the forecasting performance for every yield and horizon.

The FADNS model produces forecast errors with lower mean and variance, especially for longer-term yields. Figure 3 displays box plots for the 3-, 6- and 12-month ahead forecast errors of the 5-, 10- and 30-year yields. The dispersion of the 5-year yield forecast errors of the FADNS model is much lower than the dispersion of almost every competing model for horizons superior than 3-month. The only exception is the FFF model, whose forecast errors also exhibit lower variance. Perhaps not surprisingly, the FFF model also relies on forward-looking variables to forecast the short-end of the yield curve.

[Figure 3 about here]

The principal components of our FADNS model are very useful for forecasting purposes because they have a strong correlation with the medium- and long-term yields. As a result, the FADNS model is able to improve forecasts at longer horizons and maturities. For instance, the MAFE distribution for the 30-year yield in Figure 3 displays the lowest mean and percentiles, stochastically dominating the other models.

It remains to check whether this superior performance is indeed statistically significant. To this end, we run a Model Confidence Set (MCS) analysis as in Hansen et al. (2011). This procedure determines the number of superior models within a collection of alterative specifications given a confidence level. This number obviously depends on how informative the data are. If the data contain useful information, the MCS analysis can select only a few, if not a single, model. The main advantage of the MCS analysis is that it is not about comparing predictive ability against one single benchmark. It treats the performance of every model in a symmetric way, attempting only to identify which models entail a better out-of-sample predictive power.

The stars in Table 5 indicate the superior models according to the MCS analysis. There is no model that delivers superior 1-year yield forecasts relative to the RW benchmark, except for AR at the 12-month horizon. The picture dramatically changes for longer-term yields, though. In particular, the FADNS model not only consistently beats the random walk, but also belongs to the set of superior models at the 10% significance level for virtually every maturity above one year. In fact, it is the only superior model for the 7- and 10-year yields at all horizons. For the 5- and 30-year yields, FADNS is in the collection of superior models for horizons superior to 3 months at 10% significance level, but there are other models in the superior set. The FFF model presents good performance for 5-year yield at 3- to 9-month horizons. For the 30-year yield, RW is the best model at the 3-month horizon, whereas RW, AR and FFF are among the superior models at 25% significance level at the 6-month horizon. Finally, DNS and DL forecasts are a bit disappointing, never achieving superior performance regardless of the maturity and horizon.

5. Where does the superior performance of the FADNS model come from?

Most forecasting models of the term structure of interest rates that rely on macroeconomic and financial variables fail to beat the random walk benchmark at shorter forecasting horizons (Ang and Piazzesi, 2003; Moench, 2008). More recently, de Pooter et al. (2010) and Altavilla et al. (2014a,b) show some promising results, especially at shorter horizons. These recent models do not outclass the random walk either for long-term yields or at longer forecasting horizons, however.

In what follows, we show that the FADNS yields better forecasts because of the forward-looking nature of the financial and macroeconomic variables we employ. To this end, we split the dataset into two groups. The first set contains the 62 macro-finance variables that are backward looking, whereas the second comprises the 107 forward-looking indicators.

Table 6 shows how the forecasting performance of the FADNS changes as we move from principal components based on backward-looking variables to principal components from forward-looking indicators. FADNS-past denotes the model that uses only backward-looking variables, whereas FADNS-fwrd refers to the model that uses only forward-looking. As a benchmark, we employ the FADNS model that uses the full data set.

[Table 6 about here]

The FADNS-past model usually offers the highest MAFE for every maturity, except for the 1- and 30-year yields at the 3-month forecasting horizon. In stark contrast, the FADNS-fwrd model compares well with the FADNS model for virtually all yields. As compared to the FADNS-past, we observe that the FADNS-fwrd forecast errors are on average 4 bps lower in magnitude. This means that entertaining a large number of forward-looking macro-finance indicators is key to the superior performance of the FADNS model.

To statistically compare the performance of the FADNS-past and FADNS-fwrd models, we perform White's (2000) reality check. The null hypothesis is that the FADNS model forecasts are not statistically different from the FADNS-past or FADNS-fwrd forecasts. Table 6 documents that the forecasts of FADNS and FADNS-fwrd are not statistically different for every yield. The same does not apply to FADNS-past, though. We find evidence that it entails inferior performance for some yields at horizons longer than 3 months.

If using forward-looking variables is key to improve forecasting performance, one could argue for incorporating their information in the competing models as well. Table 7 reports the gains in the MAFE sense. As a benchmark, the last column displays how much we gain by moving from DNS to FADNS. Augmenting the DL and FFF models with principal components markedly improve the yield curve forecasting. For maturities above 1-year and at any forecasting horizon, the MAFE reduces on average 18% with respect to the original specification. The Slope model exhibits only some slightly lower forecast errors for yields with maturities longer than 5 years, but the reductions are less important.

[Table 7 about here]

We also assess the statistical significance of these gains by means of White's (2000) reality check. As above, the augmented version of the DNS model is statistically superior to the bare DNS model for virtually every yield and horizon. A similar pattern arises for the DL and FFF models with principal components. For the 7- and 10-year yields, the improvements are uniform across horizons. Adding the principal components to the AR model also bring forth significant gains for the 10- and 30-year yields. The exception is the slope model, whose forecasting performance sees no statistically significant improvement. All in all, the results suggest that forecasting performance typically improves once we incorporate principal components from a large panel of forward-looking indicators into the models. The gains are particularly strong for yields with longer maturities due to their higher volatilities.

6. Robustness using SPF data

In this section, we check whether our results are an artifact due to the short time span of our data set. To consider a longer time span, we resort to quarterly data from the Survey of Professional Forecasters (SPF) available at the website of the Federal Reserve Bank of Philadelphia.[12]

Our panel of macro-finance indicators has 86 variables at the quarterly frequency; of which 55% are forward looking (the detailed list is in Appendix II). Real activity indicators such as GDP, consumption, and employment amount to over 60% of the variables, whereas 20% relate to inflation and fiscal indicators. The remaining are financial, monetary and credit-related variables. To compute principal components, we ensure that every variable is stationary by taking first differences if necessary. We then gather the effective quarterly interest rate from Bloomberg for the same fixed maturities as before. Bloomberg publishes

[12] The Survey of Professional Forecasters is available from 1968 and is oldest quarterly survey of macroeconomic forecasts in the United States. Initially, it was conducted by the American Statistical Association and the National Bureau of Economic Research. Since 1990, it is maintained by The Federal Reserve Bank of Philadelphia.

yield data as from the first quarter of 1989. We initially estimate the models using data from the first quarter of 1989 to the last quarter of 2002, and then assess the forecasting performance using data from 2003 to 2015.

De Pooter et al. (2010) and Exterkate et al. (2013) argue that it is very hard to outclass yield curve forecasts from autoregressive models in periods of low market volatility. It is thus interesting to see how the models fare from 2003 to 2007 in view of the relatively low volatility that characterized this period; the implied volatility in the S&P 500 is 40% lower in this period than from 1998 to 2002, and 15% than from 2008 to 2015 during the quantitative easing.

[Table 8 about here]

Indeed, Table 8 shows that most models find it very hard to beat the RW and AR benchmarks in the period running from 2003 to 2015. The FADNS model comes to our rescue again, with lower MAFE for the 7- and 10-year yields at most forecasting horizons. Restricting attention exclusively to the forward-looking indicators from the SPF data set does not seem to affect much the predictive ability of the FADNS (see column FADNS-fwrd). On the contrary, it entails superior forecasting performance also for the 5-year yield. The MCS analysis also reveals that the RW belongs to the set of superior model only for the 1-year and 30-year yields.

Table 9 documents that conditioning on the principal components usually produces lower MAFE, particularly at the 3- and 6-month forecasting horizons. The results also indicate that the gains are particularly strong for dynamic models such as FFF and DNS. As before, White’s reality check confirms the statistical significance of these improvements for almost every maturity at the 3- and 6-month forecasting horizons. We take this as further evidence that using dynamic models with forward-looking macro-finance variables yields more accurate predictions.

[Table 9 about here]

7. Conclusion

We propose forecasting the yield curve using a factor-augmented dynamic Nelson-Siegel model (FADNS). In particular, we predict the future level, slope and curvature factors using a VAR model that also includes principal components from a large panel of forward-looking macroeconomic and financial indicators. Out-of-sample analysis shows that the FADNS model fares very well relative to the extant macro-finance term structure models in the literature.

This paper contributes to the understanding of the ingredients needed to improve yield curve forecasts. First, it does not suffice to consider an arbitrarily large number of predictors as in Ang and Piazzesi (2003) and Moench (2008). It is crucial that their information is of a forward-looking nature. Second, it is not enough to condition on a few forward-looking variables as in de Pooter et al. (2007) and Altavilla et al. (2004a,b). We need a large number of forward-looking variables to best capture the future trajectory of the yield curve.

References

Almeida, C. and Vicente, J. (2008) The role of no-arbitrage on forecasting: Lessons from a parametric term structure model, Journal of Banking and Finance 32, 2695-2705.

Altavilla, C.; Giacomini, R. and Constantini, R. (2014a) Bond returns and market expectations, Journal of Financial Econometrics 12, 708-729.

Altavilla, C.; Giacomini, R. and Ragusa, G. (2014b) Anchoring the yield curve using survey expectations, Working Paper 1632, European Central Bank.

Ang, A. and Piazzesi, M. (2003) A no-arbitrage vector autoregression of term structure dynamics with macroeconomic and latent variables, Journal of Monetary Economics 50, 745-787.

Ang, A.; Bekaert, G. and Wei, M. (2007) Do macro variables, asset markets, or surveys forecast inflation better?, Journal of Monetary Economics 54, 1163-1212.

Bernanke, B. and Boivin, J. (2003) Monetary policy in a data-rich environment, Journal of Monetary Economics 50, 525-546.

Bernanke, B.; Boivin, J. and Eliasz, P. (2005) Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach, Quarterly Journal of Economics 120, 387-422.

Carriero, A. (2011) Forecasting the yield curve using priors from no arbitrage affine term structure models, International Economic Review 52, 425-459.

Carriero, A. and Giacomini, R. (2011) How useful are no-arbitrage restrictions for forecasting the term structure of interest rates?, Journal of Econometrics 164, 21-34.

de Pooter M., Ravazzolo F., van Dijk D. (2007) Predicting the term structure of interest rates: Incorporating parameter uncertainty, model uncertainty and macroeconomic information, Tinbergen Institute Discussion Paper 2007-028/4.

de Pooter M., Ravazzolo F., van Dijk D. (2010) Term structure forecasting using macro factors and forecast combination. Federal Reserve working paper 993.

Diebold, F. and Li, C. (2006) Forecasting the term structure of government bond yields, Journal of Econometrics 130, 337-364.

Diebold, F.; Rudebusch, G. and Aruoba, S. (2006) The macroeconomy and the yield curve: A dynamic latent factor approach, Journal of Econometrics 131, 309–338.

Doz, C.; Giannone, D and Reichlin, L. (2012) A quasi-maximum likelihood approach for large approximate dynamic factor models, Review of Economics and Statistics 94, 1014-1024.

Duffee, G. (2002) Term premia and interest rate forecast in affine models, Journal of Finance 57, 405-443.

Duffee, G. (2011) Forecasting with the term structure: The role of no-arbitrage restrictions, Working Paper, Department of Economics, John Hopkins University.

Exterkate, P., van Dijk, D., Heij, C. and Groenen, P. (2013) Forecasting the yield curve in a data-rich environment using the factor-augmented Nelson–Siegel model, Journal of Forecasting 32, 193–214.

Hansen, P. R.; Lunde, Asger and Nason, J. M. (2011) The model confidence set, Econometrica 79, 453-497.

Hevia, C.; Gonzales-Rozada, M.; Sola, M. and Spagnolo, F. (2015) Estimating and forecasting the yield curve using a Markov switching dynamic Nelson and Siegel model, Journal of Applied Econometrics 30, 987-1009.

Joslin, S.; Singleton, K. and Zhu, H. (2011) A new perspective on Gaussian dynamic term structure models, Review of Financial Studies 24, 926-970.

Kim, D. and Orphanides, A. (2012) Term structure estimation with survey data on interest rate forecast, Journal of Financial and Quantitative Analysis 47, 241-272.

Krippner, L. (2015) A theoretical foundation for the Nelson-Siegel class of yield curve models, Journal of Applied Econometrics 30, 97-118.

Marcellino, M.; Stock, J. and Watson, M. (2006) A comparison of direct and iterated AR methods for forecasting macroeconomic series *h*-steps ahead, Journal of Econometrics 135, 499-526.

Moench, E. (2008) Forecasting the yield curve in a data-rich environment: A no-arbitrage factor-augmented VAR approach, Journal of Econometrics 146, 26-43.

Nelson, C. and Siegel, A. (1987) Parsimonious modeling of yield curves, Journal of Business 60, 473-489.

Steeley, J. (2014) Forecasting the term structure when short-term rates are near zero, Journal of Forecasting, 33, 350-363.

Stock, J. and Watson, M. (2002a) Forecasting using principal components from a large number of predictors, Journal of American Statistical Association 97, 1167-1179.

Stock, J. and Watson, M. (2002b) Macroeconomic forecasting using diffusion indexes, Journal of Business and Economic Statistics 20, 147-162.

van Dijk, D.; Koopman, S.; van der Wel, M. and Wright, J. (2014) Forecasting interest rates with shifting endpoints, Journal of Applied Econometrics 29, 693-712.

Vieira, F.; Fernandes, M. and Chague, F. (2017) Forecasting the Brazilian yield curve using forward-looking variables, International Journal of Forecasting 33, 121-131.

White, H. (2000) A reality check for data snooping, Econometrica 68, 1097-1126.

Xiang, J. and Zhu, X. (2013) A regime-switching Nelson-Siegel term structure model and interest rate forecast, Journal of Financial Econometrics, 1-34.

Table 1

Principal components from the panel of 169 macro-financial indicators, full sample

Principal Components Analysis	Correlation
Factor 1 - 23.7% of total variance	
Standard deviation of GDP growth for the next 12 months	0.926
Financial condition index – Bloomberg	0.885
Standard deviation of CPI inflation for the next 12 months	0.861
Annualized GDP growth expected for the next 12 months – median	-0.854
Unemployment annual change expected for the next 12 months - median	0.848
Financial condition index – Bloomberg	-0.840
Annualized GDP growth expected for the next 6 months – average	-0.837
Unemployment annual change expected for the next 12 months - median	0.834
Initial jobless claims - Net annual change	0.815
Budget result % of GDP expected for the next 6 months –average	-0.810
Factor 2 - 18.9% of total variance	
CRB energy index – YoY	0.902
CRB index – YoY	0.894
Consumer inflation expected for the next 12 months –average	0.893
Natural gas price – YoY	0.835
Terms of trade – USD	0.827
Current account % GDP annual change for the next 6 months – average	-0.695
Euro exchange rate expected for the next 6 months – average	0.766
Rasmussen Presidential approval index – approval	-0.756
US buying climate index	-0.702
Dollar index spot rate (DXY)	-0.677

This table reports the variables with the highest correlation with each of the principal components extracted from the panel of 169 macroeconomic and financial indicators.

Table 2

Policy Rule based on Factors

	PCA
Constant	0.5550
	(0.0251)
First principal component	-0.2243
	(0.0416)
Second principal component	0.1051
	(0.0273)
R-square	0.561

This table documents factor-based rules for the target interest rate of the Federal Reserve. We regress the target interest rate on the first 2 principal components of the macroeconomic and financial variables. We also display robust standard errors in parentheses.

Table 3

Augmented Taylor Rule

	A	B
Smoothing coefficient - ρ	0.813	0.743
	(0.008)	(0.014)
Inflation gap - β_1	0.085	0.001
	(0.051)	(0.038)
Output gap - β_2	0.177	0.081
	(0.030)	(0.026)
Predicted target interest rate using PCA - β_3		0.404
		(0.056)
R-square	0.951	0.955

This table reports the regression results for equation (4). Column A displays the coefficient estimates for the traditional Taylor rule, whereas Column B shows the estimates for augmented Taylor rules that include the target interest rate predicted by the factor models in Table 2. We report robust standard errors in parentheses.

Table 4

Average and standard deviation of the actual and fitted yields

Yield	Mean			Standard Deviation		
	Actual	FADNS	MAE	Actual	FADNS	MAE
1 year	0.47	0.31	0.17	0.64	0.64	0.11
5 years	1.71	1.90	0.19	0.71	0.68	0.11
7 years	2.23	2.44	0.21	0.72	0.69	0.13
10 years	2.73	2.93	0.20	0.72	0.72	0.09
30 years	3.64	3.75	0.16	0.67	0.80	0.11

This table reports sample mean and standard deviation (in percentage points) of the actual and FADNS fitted yields as well as of the corresponding mean absolute errors (MAE) for each maturity.

Table 5

Mean absolute forecast errors across maturities and horizons

	RW	AR	Slope	DL	FFF	DNS	FADNS
				3 months ahead			
1	0.042*	0.062	0.047	0.151	0.139	0.164	0.165
5	0.187	0.170**	0.195	0.210	0.166*	0.207	0.187
7	0.226	0.204	0.230	0.261	0.214	0.238	0.189*
10	0.253	0.245	0.258	0.350	0.291	0.249	0.232*
30	0.317	0.347	0.329	0.409	0.393	0.439	0.380
				6 months ahead			
1	0.066*	0.077	0.071	0.191	0.156	0.220	0.201
5	0.250	0.196	0.262	0.255	0.178*	0.254	0.181*
7	0.323	0.251	0.329	0.374	0.226	0.307	0.197*
10	0.398	0.347	0.401	0.495	0.378	0.367	0.303*
30	0.515**	0.515**	0.524	0.571	0.501**	0.630	0.481*
				9 months ahead			
1	0.086*	0.094	0.089	0.224	0.178	0.252	0.210
5	0.286	0.276	0.301	0.308	0.204**	0.279	0.195*
7	0.371	0.321	0.378	0.457	0.256	0.323	0.219*
10	0.465	0.426	0.472	0.604	0.441	0.401	0.334*
30	0.630	0.652	0.631	0.633	0.538	0.678	0.483*
				12 months ahead			
1	0.108*	0.110*	0.110	0.292	0.205	0.231	0.208
5	0.321	0.364	0.335	0.355	0.240	0.311	0.210*
7	0.416	0.383	0.424	0.527	0.299	0.347	0.247*
10	0.524	0.488	0.539	0.679	0.496	0.435	0.363*
30	0.659	0.764	0.667	0.627	0.572	0.654	0.453*

This table summarizes the mean absolute forecast error (in percentage points) of each model. We estimate every model using data from December 2007 to December 2012 and then produce *h*-month ahead forecasts, with h = 3, 6, 9 and 12, for the period running from January 2013 to December 2015. RW refers to the random walk model, AR refers to the autoregressive model, DL refers to the Diebold and Li' (2006) model, DNS to the dynamic Nelson-Siegel model, Slope to the regression of the term structure on the past yield curve slope, and FFF to Altavilla et al.'s (2014b) model with future contracts of FED funds rates, and FADNS to our factor-augmented dynamic Nelson-Siegel model with the first 2 principal components. We identify the superior models at the 10% and 25% significance levels with * and **, respectively.

Table 6

Forecasting performance with different predictor variables

	FADNS	FADNS – past	FADNS – fwrd
	3 months ahead		
1	0.165	0.149	0.158
5	0.187	0.195	0.186
7	0.189	0.204	0.189
10	0.232	0.228	0.229
30	0.380	0.482**	0.388
	6 months ahead		
1	0.201	0.201	0.186
5	0.181	0.231*	0.189
7	0.197	0.257*	0.202
10	0.303	0.323	0.302
30	0.481	0.591**	0.487
	12 months ahead		
1	0.208	0.261*	0.184
5	0.210	0.246**	0.226
7	0.247	0.291**	0.256
10	0.363	0.374	0.361
30	0.453	0.516**	0.458

This table reports the mean absolute forecast errors (in percentage points) of the FADNS models as well as the analog figures for the FADNS-past and FADNS-fwrd models. The former extracts the principal components only from backward-looking macro-finance variables, whereas the latter computes the principal components using only forward-looking and forecasting uncertainty indicators. Using White's reality check test, * and ** indicate an inferiority of the model regarding to FADNS at 10% and 25% significance level, respectively.

Table 7

Relative mean absolute forecast error for augmented models with principal components

	AR	Slope	DL	FFF	DNS
			3 months ahead		
1	1.659	1.122	1.004	0.915**	1.004
5	1.280	1.001	0.814*	0.973	0.904**
7	1.124	0.995	0.791*	0.890**	0.791*
10	0.915**	0.993	0.740*	0.885**	0.934**
30	0.872*	0.991	0.990*	0.976	0.865*
			6 months ahead		
1	1.031	1.034	0.915**	0.892**	0.915**
5	1.903	1.001	0.681*	0.991	0.714*
7	1.522	0.988	0.667*	0.833*	0.641*
10	0.946**	0.989	0.747*	0.863*	0.825*
30	0.822*	0.985	0.992	0.951	0.764*
			12 months ahead		
1	1.164	1.008	0.818*	0.964	0.897**
5	1.593	0.996	0.673*	0.978	0.677*
7	1.397	0.981	0.669*	0.781*	0.713*
10	0.819*	0.986	0.771*	0.817*	0.835*
30	0.724*	0.989	0.997	0.844*	0.692*

This table compares the mean absolute forecast errors (MAFE) of the extant models in the literature with and without the first two principal components from our large panel of macro-finance indicators. AR refers to the autoregressive model, DL refers to the Diebold and Li' (2006) model, DNS to the dynamic Nelson-Siegel model, Slope to the regression of the term structure on the past yield curve slope, and FFF to Altavilla et al.'s (2014b) model with future contracts of FED funds rates. Ratios below one indicate that adding principal components improves forecasting performance. * and ** indicate statistical significance according to White's reality check at the 10% and 25% significance level, respectively.

Table 8

Mean absolute forecast errors across maturities and horizons at the quarterly frequency

	RW	AR	Slope	DL	FFF	DNS	FADNS	FADNS – fwrd
				3 months ahead				
1	0.191*	0.208	0.382	0.447	0.324	0.347	0.308	0.315
5	0.273**	0.278**	0.422	0.408	0.425	0.391	0.280**	0.266*
7	0.281	0.288	0.423	0.418	0.414	0.392	0.276	0.257*
10	0.275	0.278	0.422	0.424	0.388	0.388	0.250	0.236*
30	0.300*	0.302	0.457	0.514	0.440	0.435	0.431	0.443
				6 months ahead				
1	0.370*	0.444	0.505	0.554	0.489	0.456	0.488	0.477
5	0.422	0.420	0.491	0.483	0.569	0.531	0.434	0.399*
7	0.434	0.430	0.482	0.483	0.565	0.535	0.413	0.372*
10	0.422	0.430	0.475	0.480	0.542	0.530	0.386	0.346*
30	0.455*	0.461	0.517	0.526	0.544	0.547	0.515	0.516
				9 months ahead				
1	0.555*	0.687	0.669	0.704	0.685	0.583	0.620	0.631
5	0.492	0.497	0.589	0.590	0.682	0.580	0.514	0.454*
7	0.495	0.506	0.568	0.575	0.663	0.582	0.477	0.431*
10	0.473	0.500	0.546	0.548	0.617	0.584	0.445	0.394*
30	0.521*	0.534	0.546	0.556	0.579	0.594	0.544	0.546
				12 months ahead				
1	0.747*	0.953	0.850	0.891	0.884	0.782	0.787	0.825
5	0.604*	0.664	0.716	0.710	0.838	0.731	0.659	0.658
7	0.591	0.637	0.679	0.675	0.807	0.713	0.601	0.555*
10	0.546	0.597	0.636	0.636	0.763	0.690	0.535	0.497*
30	0.554*	0.569	0.629	0.614	0.607	0.612	0.598	0.582

This table summarizes the mean absolute forecast error (in percentage points) of each model. We estimate every model using data from first quarter of 1989 to last quarter of 2002 and then produce *h*-month ahead forecasts, with *h* = 3, 6, 9 and 12, for the period running from 2003 to 2015. RW refers to the random walk model, AR refers to the autoregressive model, DL refers to the Diebold and Li' (2006) model, DNS to the dynamic Nelson-Siegel model, Slope to the regression of the term structure on the past yield curve slope, and FFF to Altavilla et al.'s (2014b) model with future contracts of FED funds rates, FADNS to our factor-augmented dynamic Nelson-Siegel model with the first 2 principal components, and FADNS-fwrd to our FADNS using only forward-looking variables. . We identify the superior models at the 10% and 25% significance levels with * and **, respectively.

Table 9

Relative Mean Absolute Forecast Error
for Augmented Models at quarterly frequency

	AR	Slope	DL	FFF	DNS
			3 months ahead		
1	1.145	1.029	1.052	0.721*	0.808*
5	0.990	1.014	1.019	0.749*	0.663*
7	0.981	0.983	0.980	0.750*	0.651*
10	0.995	0.953	0.956	0.711*	0.592*
30	0.989	0.924**	1.003	0.853*	0.943
			6 months ahead		
1	1.063	0.998	1.013	1.020	0.928**
5	1.048	0.995	0.994	0.906**	0.873**
7	1.051	0.979	0.961	0.864**	0.839*
10	1.024	0.953	0.956	0.841*	0.816*
30	0.988	0.917**	1.001	0.907**	0.996
			12 months ahead		
1	1.046	0.989	0.995	1.178	0.926**
5	1.150	1.002	1.003	1.085	0.920**
7	1.167	0.993	0.992	1.051	0.885**
10	1.161	0.980	0.977	1.023	0.840*
30	1.066	0.935	0.970	1.007	0.949

This table reports the mean absolute forecast errors (MAFE) of the competitor models from the extant literature versus the same models plus 2 principal components extracted from our dataset. AR refers to the autoregressive model, DL refers to the Diebold and Li' (2006) model, DNS to the dynamic Nelson-Siegel model, Slope to the regression of the term structure on the past yield curve slope, and FFF to Altavilla et al.'s (2014b) model with future contracts of FED funds rates. The ratio is calculated by MAFE of the models with 2 PC to MAFE of the models in traditional fashion. Using White's reality check test, * and ** indicate a superiority of the 2PC model regarding to the traditional form at 10% and 25% significance level, respectively.

Figure 1

This Figure shows the 1-year rolling volatility for 1-, 5-, 10-, and 30-year yields over the period from 2009 to 2015.

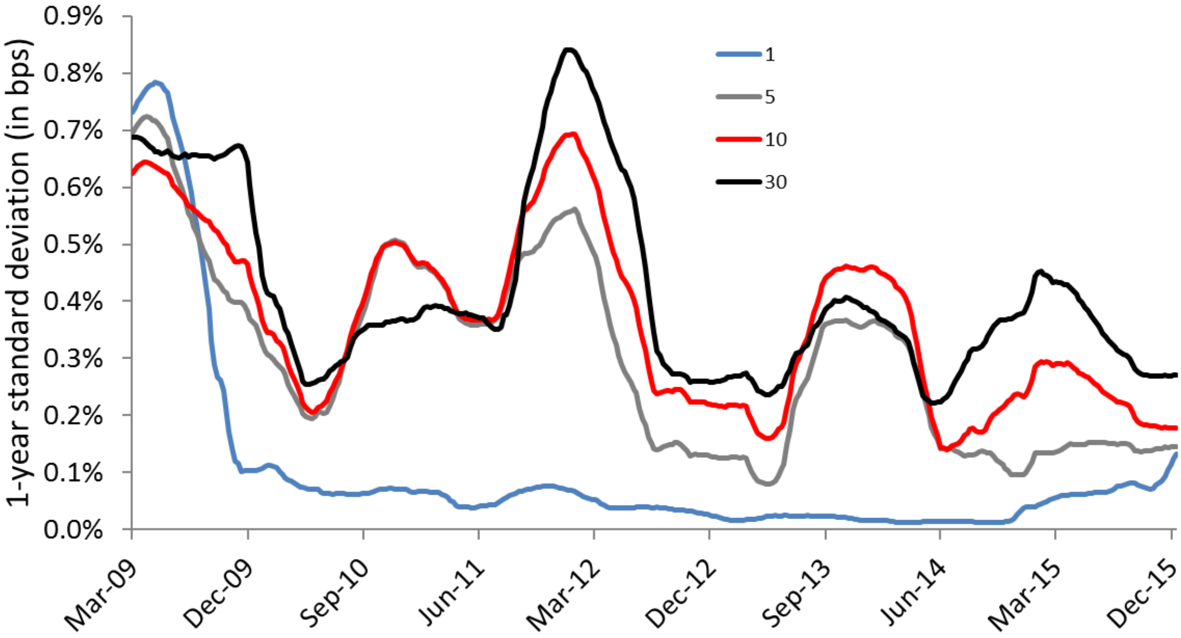


Figure 2

This figure shows the volatility ratio between before and after 2012 for selected yields

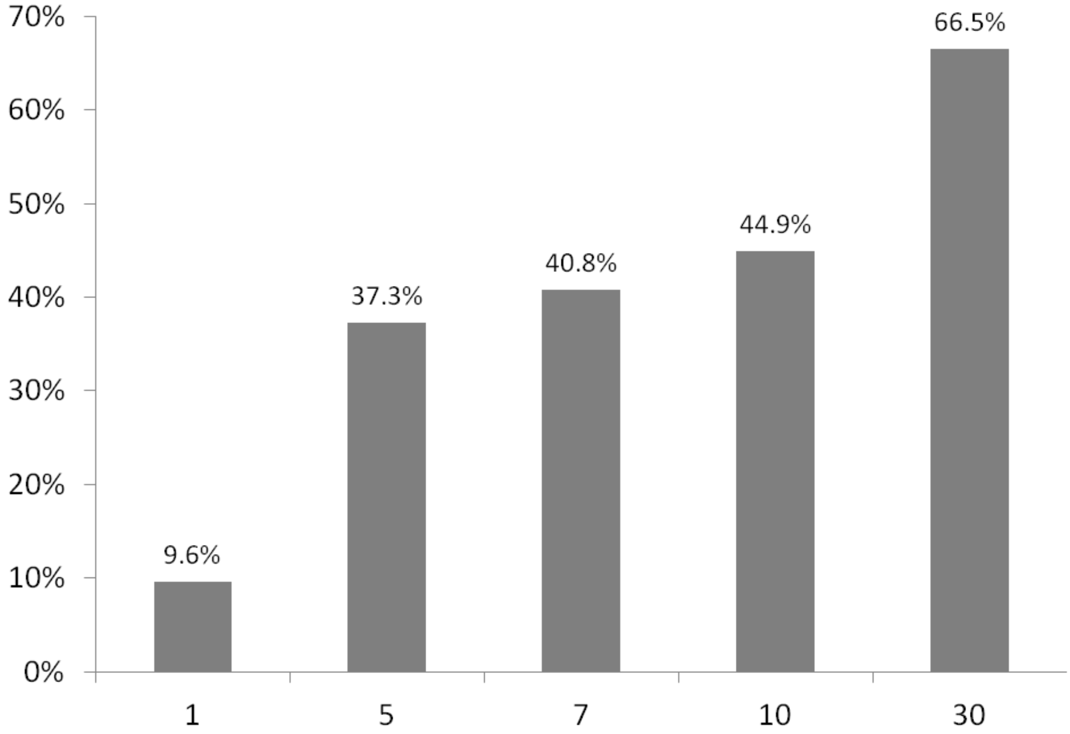
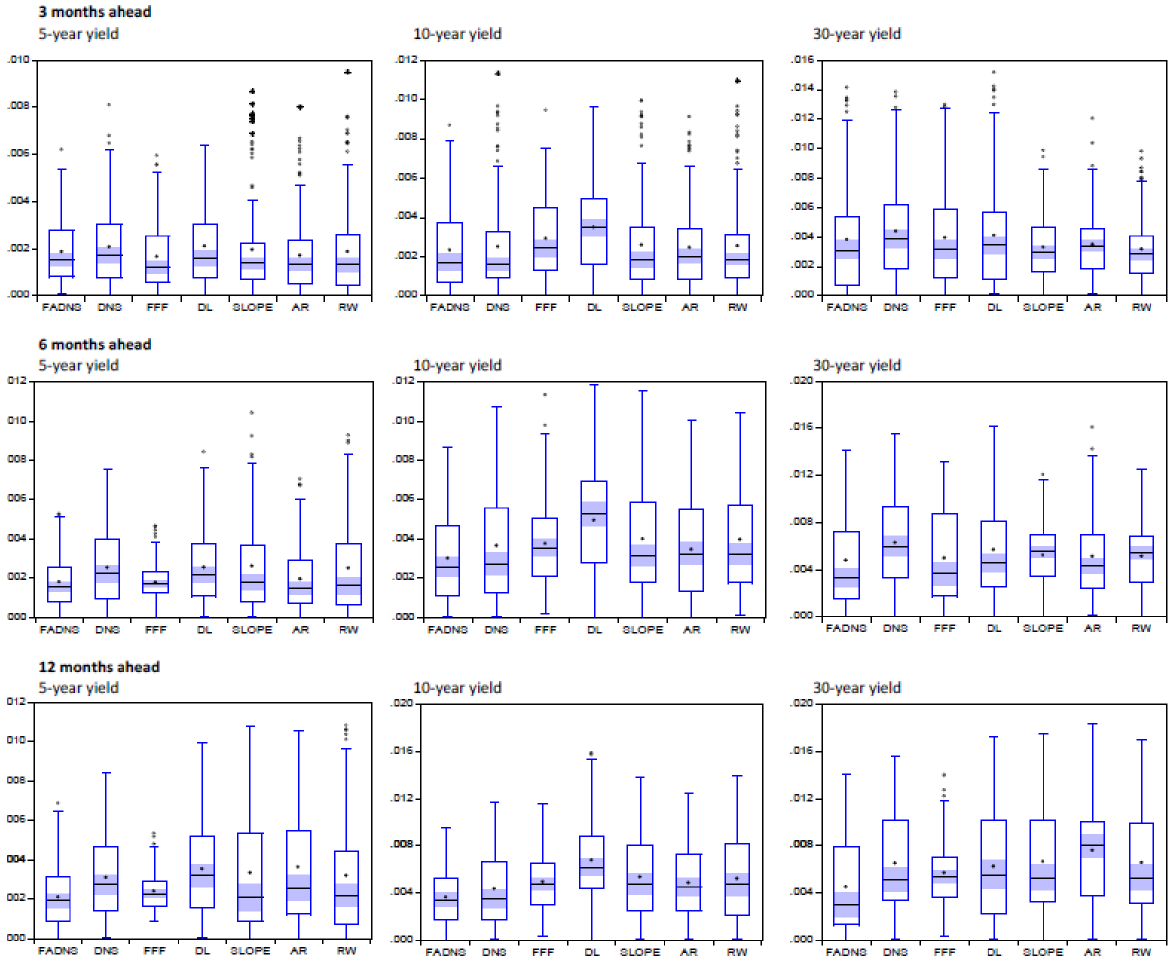


Figure 3

This figure displays box plots for the 3-, 6- and 12-month forecast errors for the 5-, 10- and 30-year yields



Appendix: Data set

i) Weekly Indicators

Name	Transf	Frequency	Release - lag	Source
Financial				
Baltic dry índex	0	daily	real time	Bloomberg
China 5 year CDS	0	daily	real time	Bloomberg
Commercial open interest for S&P 500	0	weekly	Every Friday	Commtiments of Traders
Corporate bonds AAA spread to 10 year treasury	0	daily	0 day	JP Morgan
Corporate bonds BBB spread to 10 year treasury	0	daily	0 day	JP Morgan
Corporate bonds high yield spread to 10 year treasury	0	daily	0 day	JP Morgan
Crack spread	0	daily	real time	Bloomberg Energy
Dollar index spot rate (DXY)	0	daily	real time	ICE
Euro exchange expected rate in 2 years - weighted average	0	daily	1 day	Bloomberg
Euro exchange rate expected for the next 12 months – average	3	daily	1 day	Bloomberg
Euro exchange rate expected for the next 12 months – median	0	daily	1 day	Bloomberg
Euro exchange rate expected for the next 2 years - average	3	daily	1 day	Bloomberg
Euro exchange rate expected for the next 6 months – average	0	daily	1 day	Bloomberg
Euro exchange rate expected for the next 2 years - weighted average	0	daily	1 day	Bloomberg
Euro exchange rate expected for the next 6 months - median	0	daily	1 day	Bloomberg
Euro Zone 5 year CDS - ex Germany	3	daily	real time	Bloomberg
Financial condition index – Bloomberg	0	daily	1 day	Bloomberg
Financial condition index - Goldman Sachs	0	daily	1 day	Goldman Sachs
Germany 5 year CDS	0	daily	real time	Bloomberg
JP Morgan Emerging Market Bond Index (EMBI)	0	daily	1 day	JP Morgan
Speculative open interest for S&P 500	0	weekly	Every Friday	Commtiments of Traders
TED spread - LIBOR minus T-bills (3 months)	0	daily	real time	Bloomberg
Fiscal				
Budget result % of GDP expected for the next 12 months – average	0	daily	1 day	Bloomberg
Budget result % of GDP expected for the next 12 months – median	0	daily	1 day	Bloomberg
Budget result % of GDP expected for the next 2 year – average	0	daily	1 day	Bloomberg
Budget result % of GDP expected for the next 2 year - weighted average	0	daily	1 day	Bloomberg
Budget result % of GDP expected for the next 6 months – average	3	daily	1 day	Bloomberg
Budget result % of GDP expected for the next 6 months – median	3	daily	1 day	Bloomberg
Budget result % of GDP expected in 2 years	0	daily	1 day	Bloomberg
Rasmussen Presidential approval index – approval	0	daily	1 day	Rasmussen
Rasmussen Presidential approval index – disapproval	0	daily	1 day	Rasmussen
Rasmussen Presidential approval index - strong approval	0	daily	1 day	Rasmussen
Rasmussen Presidential approval index - strong disapproval	0	daily	1 day	Rasmussen

Rasmussen Presidential approval index – total	0	daily	1 day	Rasmussen
US public debt held by the public – YoY	0	daily	1 week	US Treasury
US public debt intragovernmental holdings outstanding – YoY	0	daily	1 week	US Treasury
US total public debt outstandind – YoY	3	daily	1 week	US Treasury
Inflation				
Breakeven inflation - 1 year	0	daily	real time	Bloomberg
Breakeven inflation - 10 year	0	daily	real time	Bloomberg
Breakeven inflation - 2 year	3	daily	real time	Bloomberg
Breakeven inflation - 30 year	0	daily	real time	Bloomberg
Breakeven inflation - 5 year	0	daily	real time	Bloomberg
Butter price – YoY	0	weekly	10 days	USDA
Cattle live slaughtered steer price – YoY	0	daily	3 days	USDA
Consumer inflation expected for the next 12 months – average	0	daily	1 day	Bloomberg
Consumer inflation expected for the next 12 months – median	0	daily	1 day	Bloomberg
Consumer inflation expected for the next 2 years –average	0	daily	1 day	Bloomberg
Consumer inflation expected for the next 2 years -weighted average	0	daily	1 day	Bloomberg
Consumer inflation expected for the next 6 months -average	0	daily	1 day	Bloomberg
Consumer inflation expected for the next 6 months -median	0	daily	1 day	Bloomberg
Consumer inflation expected in 2 years	0	daily	1 day	Bloomberg
Core consumer inflation expected for the next 6 months - average	0	daily	1 day	Bloomberg
Core consumer inflation expected for the next 12 months - average	0	daily	1 day	Bloomberg
Core consumer inflation expected for the next 12 months - median	0	daily	1 day	Bloomberg
Core consumer inflation expected for the next 2 years - average	0	daily	1 day	Bloomberg
Core consumer inflation expected for the next 2 years - weighted average	0	daily	1 day	Bloomberg
Core consumer inflation expected for the next 6 months - median	0	daily	1 day	Bloomberg
Core consumer inflation expected in 2 years	0	daily	1 day	Bloomberg
Corn future price - YoY	0	daily	real time	Chicago Board of Trade
CRB agricultural index - YoY	0	daily	real time	Thomson Reuters
CRB energy index - YoY	0	daily	real time	Thomson Reuters
CRB index - YoY	0	daily	real time	Thomson Reuters
CRB industrial metal index - YoY	0	daily	real time	Thomson Reuters
CRB livestock index - YoY	0	daily	real time	Thomson Reuters
CRB precious metal index - YoY	0	daily	real time	Thomson Reuters
Dairy prices nonfat dry milk - YoY	0	weekly	10 days	USDA
Dry whey protein price - YoY	0	daily	real time	CME
Feedstuff fish meal wholesale price - YoY	3	weekly	10 days	USDA
Heating oil residential price - YoY	3	weekly	10 days	US EIA
Natural gas price - YoY	0	daily	real time	NY Mercantile

				Exch
Pork meat and bone meal price - YoY	0	weekly	10 days	USDA
Retail on-highway diesel price - YoY	0	weekly	10 days	US EIA
Terms of trade - USD	0	daily	1 day	Citi Bank
Real activity				
Annualized GDP growth expected for the next 12 months - average	0	daily	1 day	Bloomberg
Annualized GDP growth expected for the next 12 months - median	0	daily	1 day	Bloomberg
Annualized GDP growth expected for the next 2 years - average	0	daily	1 day	Bloomberg
Annualized GDP growth expected for the next 2 years - weighted average	0	daily	1 day	Bloomberg
Annualized GDP growth expected for the next 6 months - average	0	daily	1 day	Bloomberg
Annualized GDP growth expected for the next 6 months - median	0	daily	1 day	Bloomberg
Annualized GDP growth expected in 2 years	0	daily	1 day	Bloomberg
Continuing jobless claims - Net annual change	0	weekly	2 weeks	Dep. of Labor
Current account % GDP annual change expected for the next 12 months - average	0	daily	1 day	Bloomberg
Current account % GDP annual change expected for the next 12 months - average	0	daily	1 day	Bloomberg
Current account % GDP annual change expected for the next 12 months - median	0	daily	1 day	Bloomberg
Current account % GDP annual change expected for the next 2 years - average	3	daily	1 day	Bloomberg
Current account % GDP annual change expected for the next 2 years - weighted average	0	daily	1 day	Bloomberg
Current account % GDP annual change expected for the next 6 months - average	0	daily	1 day	Bloomberg
Current account % GDP annual change expected for the next 6 months - median	0	daily	1 day	Bloomberg
Current account % GDP annual change expected in 2 years	3	daily	1 day	Bloomberg
Forecast revision index - Global	0	weekly	Every Friday	JP Morgan
Forecast revision index - US	0	weekly	Every Friday	JP Morgan
Initial jobless claims - Net annual change	3	weekly	1 week	Dep. of Labor
Johnson Redbook index same store sales - YoY	0	weekly	10 days	Redbook Research
Personal finance index	0	weekly	1 week	Bloomberg
Retail Economist-Goldman Sachs US chain sotre sales YoY - ex Walmart	0	weekly	10 days	ICSC - Goldman Sachs
Unemployment annual change expected for the next 12 months - average	0	daily	1 day	Bloomberg
Unemployment annual change expected for the next 12 months - average	0	daily	1 day	Bloomberg
Unemployment annual change expected for the next 12 months - median	0	daily	1 day	Bloomberg
Unemployment annual change expected for the next 2 years - average	3	daily	1 day	Bloomberg
Unemployment annual change expected for the next 2 years - weighted average	3	daily	1 day	Bloomberg
Unemployment annual change expected for the next 6 months - average	0	daily	1 day	Bloomberg
Unemployment annual change expected for the next 6 months - median	0	daily	1 day	Bloomberg
Unemployment annual change expected in 2 years	3	daily	1 day	Bloomberg

US buying climate index	0	weekly	1 week	Bloomberg
US consumer comfort index	0	weekly	1 week	Bloomberg
US consumer comfort index for those part-time employed	0	weekly	1 week	Bloomberg
US economic surprise	0	daily	1 day	Citi Bank
US national economy expectation diffusion index	0	weekly	1 week	Bloomberg
Working natural gas change in estimated storage data	0	weekly	1 week	US EIA
Forecast Uncertainty				
Assimetry for 10 year Treasury yield for the next 12 months	0	daily	1 day	Bloomberg
Assimetry for budget result % of GDP for the next 12 months	0	daily	1 day	Bloomberg
Assimetry for core inflation for the next 12 months	0	daily	1 day	Bloomberg
Assimetry for core inflation forecasting for the next 6 months	0	daily	1 day	Bloomberg
Assimetry for CPI inflation for the next 12 months	0	daily	1 day	Bloomberg
Assimetry for CPI inflation forecasting for the next 6 months	0	daily	1 day	Bloomberg
Assimetry for current account % GDP annual change for the next 12 months	0	daily	1 day	Bloomberg
Assimetry for current account % GDP annual change forecasting for the next 6 months	0	daily	1 day	Bloomberg
Assimetry for Euro for the next 12 months	0	daily	1 day	Bloomberg
Assimetry for GDP forecasting for the next 6 months	0	daily	1 day	Bloomberg
Assimetry for GDP growth for the next 12 months	0	daily	1 day	Bloomberg
Assimetry for unemployment annual change for the next 12 months	0	daily	1 day	Bloomberg
Assimetry for unemployment annual change forecasting for the next 6 months	0	daily	1 day	Bloomberg
Difference between maximum and minimun value (DMMV) for GDP growth for the next 6 months	0	daily	1 day	Bloomberg
Difference between volatility implied in Euro options and its historical price volatility	0	daily	1 day	Bloomberg
Difference between volatility implied in S&P options and its historical price volatility	0	daily	1 day	Bloomberg
Difference between volatility implied in TIPs Bonds options and its historical price volatility	0	daily	1 day	Bloomberg
Difference between volatility implied in US Treasury Bonds options and its historical price volatility	0	daily	1 day	Bloomberg
DMMV for 10 year Treasury yield for the next 12 months	0	daily	1 day	Bloomberg
DMMV for budget result % of GDP for the next 12 months	0	daily	1 day	Bloomberg
DMMV for budget result % of GDP for the next 6 months	0	daily	1 day	Bloomberg
DMMV for core inflation for the next 12 months	0	daily	1 day	Bloomberg
DMMV for core inflation for the next 6 months	0	daily	1 day	Bloomberg
DMMV for CPI inflation for the next 12 months	0	daily	1 day	Bloomberg
DMMV for CPI inflation for the next 6 months	0	daily	1 day	Bloomberg
DMMV for current account % GDP annual change for the next 12 months	0	daily	1 day	Bloomberg
DMMV for current account % GDP annual change for the next 6 months	0	daily	1 day	Bloomberg
DMMV for Euro for the next 12 months	0	daily	1 day	Bloomberg
DMMV for Euro for the next 6 months	0	daily	1 day	Bloomberg
DMMV for Fed Funds forecast for the next 6 months	0	daily	1 day	Bloomberg
DMMV for GDP growth for the next 12 months	0	daily	1 day	Bloomberg
DMMV for unemployment annual change for the next 12 months	0	daily	1 day	Bloomberg

DMMV for unemployment annual change for the next 6 months	0	daily	1 day	Bloomberg
Standard deviation of 10 year Treasury yield for the next 12 months	0	daily	1 day	Bloomberg
Standard deviation of budget result % of GDP for the next 12 months	0	daily	1 day	Bloomberg
Standard deviation of budget result % of GDP for the next 6 months	0	daily	1 day	Bloomberg
Standard deviation of core inflation for the next 12 months	0	daily	1 day	Bloomberg
Standard deviation of core inflation for the next 6 months	0	daily	1 day	Bloomberg
Standard deviation of CPI inflation for the next 12 months	0	daily	1 day	Bloomberg
Standard deviation of CPI inflation for the next 6 months	0	daily	1 day	Bloomberg
Standard deviation of current account % GDP annual change for the next 12 months	0	daily	1 day	Bloomberg
Standard deviation of current account % GDP annual change for the next 6 months	0	daily	1 day	Bloomberg
Standard deviation of Euro for the next 12 months	0	daily	1 day	Bloomberg
Standard deviation of Euro for the next 6 months	0	daily	1 day	Bloomberg
Standard deviation of Fed Funds forecast for the next 6 months	0	daily	1 day	Bloomberg
Standard deviation of GDP growth for the next 12 months	0	daily	1 day	Bloomberg
Standard deviation of GDP growth for the next 6 months	0	daily	1 day	Bloomberg
Standard deviation of unemployment annual change for the next 12 months	0	daily	1 day	Bloomberg
Standard deviation of unemployment annual change for the next 6 months	0	daily	1 day	Bloomberg
Monetary and credit				
Federal funds target expected rate for the next 6 months - median	0	daily	1 day	Bloomberg
Federal funds target rate expected for the next 6 months - average	0	daily	1 day	Bloomberg
Federal reserve deposits level	2	weekly	20 days	FED
Federal reserve notes held by FR banks net	0	weekly	20 days	FED
Monetary base - M1	0	weekly	20 days	FED
Monetary base - M1	0	weekly	20 days	FED
Mortgage market applications index – YoY	0	weekly	10 days	MBA
Mortgage market refinancing index - % total	0	weekly	10 days	MBA
Mortgage market refinancing index – YoY	0	weekly	10 days	MBA
US 10 year treasury yield expected for the next 12 months - average	3	daily	1 day	Bloomberg
US 10 year treasury yield expected for the next 12 months - median	3	daily	1 day	Bloomberg

This table reports all series collected for principal components analysis. We present the description, transformation code, periodicity, release and source. The transformation code are: 0 – stationary with no intercept, 1 – stationary with intercept, 2 – stationary with trend and intercept, 3 – first difference.

ii) Quarterly indicators

Name	**Transf**	**Source**
Financial		
S&P 500 equity index (QoQ)	1	FED of Philadelphia
Real Effective Exchange Rate - USD (QoQ)	1	Barclays
Nominal Effective Exchange Rate - USD (QoQ)	1	Barclays
U.S. Dollar Index - DXY (QoQ)	1	Bloomberg
Financial Condition Index	2	Goldman Sachs
National Financial Conditions Index	2	FED of Chicago
10-year Treasury Rate - current quarter	3	Survey Prof. Forecasters
10-year Treasury Rate - current 4-quarter ahead	3	Survey Prof. Forecasters
10-year Treasury Rate - current 2-quarter ahead	3	Survey Prof. Forecasters
10-year Treasury Rate - current next quarter	3	Survey Prof. Forecasters
3-month Treasury Bill Rate - current quarter	3	Survey Prof. Forecasters
3-month Treasury Bill Rate - next quarter	3	Survey Prof. Forecasters
3-month Treasury Bill Rate - 2-quarter ahead	3	Survey Prof. Forecasters
3-month Treasury Bill Rate - 4-quarter ahead	3	Survey Prof. Forecasters
Inflation		
GNP/GDP Price Index (QoQ, sa)	1	FED of Philadelphia
Consumer Price Index Monthly (QoQ, sa)	1	FED of Philadelphia
Core Consumer Price Index (QoQ, sa)	1	FED of Philadelphia
Producer Price Index, Finished Goods (QoQ, sa)	1	FED of Philadelphia
Core Producer Price Index, Finished Goods (QoQ, sa)	1	FED of Philadelphia
ISM manufacturing prices (level, sa)	4	FED of Philadelphia
Michigan Consumer Confidence - 1 year ahead inflation (level, sa)	2	FED of Philadelphia
10-year CPI Inflation Rate	2	Survey Prof. Forecasters
CPI Inflation Rate next year (annual rate)	2	Survey Prof. Forecasters
CPI Inflation Rate current year (annual rate)	2	Survey Prof. Forecasters
CPI Inflation Rate 4-quarter ahead (QoQ, sa)	2	Survey Prof. Forecasters
CPI Inflation Rate next quarter (QoQ, sa)	2	Survey Prof. Forecasters
CPI Inflation Rate current quarter (QoQ, sa)	2	Survey Prof. Forecasters
CPI Inflation Rate 2-quarter ahead (QoQ, sa)	2	Survey Prof. Forecasters
CPI Inflation Rate 3-quarter ahead (QoQ, sa)	2	Survey Prof. Forecasters
GDP Price Index - current quarter (QoQ,sa)	2	Survey Prof. Forecasters
GDP Price Index - next quarter (QoQ,sa)	2	Survey Prof. Forecasters
Activity		
Real GNP/GDP (QoQ, sa)	1	FED of Philadelphia
Real Personal Consumption Expenditure (QoQ, sa)	1	FED of Philadelphia
Nonresidential Domestic Investment (QoQ, sa)	1	FED of Philadelphia
Residential Domestic Investment (QoQ, sa)	1	FED of Philadelphia
Change in Inventories to GDP (p.p., sa)	1	FED of Philadelphia
Real Exports of Goods and Services (QoQ, sa)	1	FED of Philadelphia
Real Imports of Goods and Services (QoQ, sa)	1	FED of Philadelphia
Real Government Cons. Expenditures & Gross Invest. (QoQ, sa)	1	FED of Philadelphia
Nominal GNP/GDP (bn, QoQ, sa)	1	FED of Philadelphia
Nominal Personal Consumption Expenditures (bn, QoQ, sa)	1	FED of Philadelphia

Wage and Salary Disbursements (bn, QoQ, sa)	1	FED of Philadelphia
Other Labor Income / Supplements to Wages and Sal. (bn, QoQ, sa)	1	FED of Philadelphia
Nominal Personal Saving (bn, QoQ, sa)	1	FED of Philadelphia
Personal Saving Rate to Disposable Personal Income (p.p., sa)	1	FED of Philadelphia
Output Per Hour of All Persons: Business Sector (QoQ, sa)	1	FED of Philadelphia
Civilian Rate of Unemployment (p.p., quarterly average)	2	FED of Philadelphia
Civilian Labor Force, 16+ (QoQ, sa)	1	FED of Philadelphia
Civilian Labor Force Participation Rate to Nonistutional Pop (p.p., sa)	4	FED of Philadelphia
Change Nonfarm Payroll (quarterly average, sa)	2	FED of Philadelphia
Total Aggregate Weekly Hours (QoQ, sa)	1	FED of Philadelphia
Industrial Production Index (QoQ, sa)	1	FED of Philadelphia
Manufacturing Capacity Utilization Rate (p.p., sa)	4	FED of Philadelphia
Housing Starts (QoQ, sa)	1	FED of Philadelphia
ISM Manufacturing (level, sa)	4	Bloomberg
Initial Jobless Claims (level, thousands)	4	Bloomberg
Small Business Optimism (level, sa)	2	Bloomberg
Michigan Consumer Confidence (level, sa)	2	Bloomberg
Anxious index - 4-quarter ahead	2	Survey Prof. Forecasters
Anxious index - 1-quarter ahead	2	Survey Prof. Forecasters
Anxious index - current quarter	2	Survey Prof. Forecasters
Anxious index - 3-quarter ahead	2	Survey Prof. Forecasters
Real GDP growth - 4-quarter ahead (QoQ, sa)	2	Survey Prof. Forecasters
Unemployment rate - 4-quarter ahead (p.p., sa)	4	Survey Prof. Forecasters
Nominal GDP growth - current quarter (QoQ, sa)	2	Survey Prof. Forecasters
Unemployment rate - 3-quarter ahead (p.p., sa)	4	Survey Prof. Forecasters
Nominal GDP growth - average of current year (Annual rate, sa)	3	Survey Prof. Forecasters
Unemployment rate - current quarter (p.p., sa)	2	Survey Prof. Forecasters
Real GDP growth - current quarter (QoQ, sa)	2	Survey Prof. Forecasters
Real GDP growth - average of next year (Annual rate, sa)	2	Survey Prof. Forecasters
Housing Starts - 2-quarter ahead (QoQ, sa)	1	Survey Prof. Forecasters
Nominal GDP growth - 4-quarter ahead (QoQ, sa)	2	Survey Prof. Forecasters
Nominal GDP growth - average of next year (Annual rate, sa)	2	Survey Prof. Forecasters
Unemployment rate - last quarter (p.p., sa)	2	Survey Prof. Forecasters
Nominal GDP growth - 2-quarter ahead (QoQ, sa)	2	Survey Prof. Forecasters
Housing Starts - current quarter (QoQ, sa)	1	Survey Prof. Forecasters
Housing Starts - next quarter (QoQ, sa)	2	Survey Prof. Forecasters
Nominal GDP growth - 3-quarter ahead (QoQ, sa)	3	Survey Prof. Forecasters
Nominal GDP growth - 4-quarter ahead (QoQ, sa)	1	Survey Prof. Forecasters
Industrial Production - current quarter (QoQ, sa)	1	Survey Prof. Forecasters
Industrial Production - next quarter (QoQ, sa)	2	Survey Prof. Forecasters
Industrial production - 2-quarter ahead (QoQ, sa)	2	Survey Prof. Forecasters
Industrial production - 3-quarter ahead (QoQ, sa)	2	Survey Prof. Forecasters
Industrial production - 4-quarter ahead (QoQ, sa)	2	Survey Prof. Forecasters
Monetary and credit		
M1 Measure of the Money Stock (YoY)	2	FED of Philadelphia

p.p. - percentage points; sa - seasonal adjusted; QoQ - quater over quater changes; YoY - year over year changes

1 - no chages; 2 - less average; 3 - less trend; 4 - first difference