Monetary Policy Uncertainty and Bond Risk Premium

Fuwei Jiang* Guoshi Tong†

Current version: Jan. 2017

Abstract

We show that uncertainty of monetary policy (MPU) commands a risk premium in the US Treasury bond market. Using the news based *MPU* measure in Baker, Bloom, and Davis (2016) to capture monetary policy uncertainty, we find that *MPU* forecasts significantly and positively future monthly Treasury bond excess returns. This forecastability remains significant controlling for standard bond risk premium predictors based on yield curve and macroeconomic fundamentals. The predictive power of *MPU* is not driven by uncertainty of economic growth, inflation and general economic condition, and is confirmed in out-of-sample tests.

Keywords: Bond Return Predictability, Monetary Policy Uncertainty, Out-of-sample Forecasting

*School of Finance, Central University of Finance and Economics, Beijing, 100081, China, telephone: +65 90598413; e-mail: jfuwei@gmail.com.

†Hanqing Advanced Institute of Economics and Finance, Renmin University of China, Beijing, 100872, P.R. China , telephone: +86 6251 1138; e-mail: gstong@ruc.edu.cn.

Monetary Policy Uncertainty and Bond Risk Premium

Abstract

We show that uncertainty of monetary policy (MPU) commands a risk premium in the US Treasury bond market. Using the news based *MPU* measure in Baker, Bloom, and Davis (2016) to capture monetary policy uncertainty, we find that *MPU* forecasts significantly and positively future monthly Treasury bond excess returns. This forecastability remains significant controlling for standard bond risk premium predictors based on yield curve and macroeconomic fundamentals. The predictive power of *MPU* is not driven by uncertainty of economic growth, inflation and general economic condition, and is confirmed in out-of-sample tests.

JEL classifications: C22, C53, G11, G12, G17

Keywords: Bond Return Predictability, Monetary Policy Uncertainty, Out-of-sample Forecasting

1. Introduction

The effects of monetary policy actions on Treasury bond prices are of great interest to both bond holders and policy makers. Recent studies such as Kuttner (2001); Gürkaynak, Sack, and Swanson (2005) and Christensen and Krogstrup (2015) have provided evidence that unexpected changes of monetary policies, such as the adjustment of target short rate, the forward guidance and the large scale asset purchase (QE), can exert large influences on the current and expected future interest rates as well as bond prices. Differentiating from these existing works, we focus on the impact of uncertainties around these monetary policy decisions. We argue that bond market participants should be concerned with monetary policy uncertainty, since it directly increases the uncertainties of future evolvement of yields and bond prices. Intuitively, as this policy driven uncertainty is not fully diversifiable, Treasury bond holders should charge a risk premium for bearing this policy risk (Pástor and Veronesi (2013)). However, to our best knowledge, empirical evidence on this bond pricing implication of monetary policy uncertainty remains limited, potentially due to the difficulty in measuring monetary policy uncertainty (Christiano, Eichenbaum, and Evans (1999); Buraschi, Carnelli, and Whelan (2014)).

In this article, we empirically investigate the unique predictive ability of monetary policy uncertainty for expected bond risk premium. To this end, we use a novel news based measure, *MPU*, constructed in Baker, Bloom, and Davis (2016) to quantitatively capture the degree of uncertainty in monetary policy. This *MPU* measure records a scaled frequency count of newspaper articles containing terms related to monetary policy and uncertainty by the US Federal Reserve. It therefore reflects the public's subjective uncertainty and concerns on monetary policy. The underlying identification assumption is that increased newspaper coverage on monetary policy and uncertainty indicates that the public perceives more uncertainty about central bank actions.

[Insert Figure 1 about here]

Figure 1 displays this *MPU* index from January 1985 to December 2014. While there is no evidence of drift over time, the index spikes around the time of Black Monday in 1987, the September 11 attacks in 2001, the March 2003 invasion of Iraq, the announcements of QE I and II in Nov 2008 and 2011, and the Taper Tantrum started in June 2013. In particular, *MPU* displays a sharp increase in the months leading up to the announcement of QE I and II but dissipates quickly after. It also remains elevated for several months during the Taper Tantrum in the summer of 2013.

The appeal to use this news based measure in the study of monetary policy uncertainty and Treasury bond risk premium is twofold. First, it allows for a continuous track of monetary policy risk compared with alternatives. Existing literature linking monetary policy and asset price dynamics frequently use event studies around Federal Open Market Committee (FOMC) meetings to identify release of information (e.g. Kuttner (2001); Bernanke and Kuttner (2005); Gürkaynak, Sack, and Swanson (2005); Fleming and Piazzesi (2005); Mueller, Tahbaz-Salehi, and Vedolin (2016)). However, this discrete event of FOMC meeting only occurs infrequently and just captures short intervals of policy shocks. In contrast, *MPU* is available on an ongoing basis and traces changes in monetary policy uncertainty at a higher frequency.

Secondly, this news based index provides a comprehensive yet model free way to capture monetary policy uncertainty, complementary to existing quantitative measures. For example, Gürkaynak, Sack, and Swanson (2005) argues that change on fed fund future prices, a popular measure of monetary policy surprise, can not fully reflect the richness of monetary policy shock. Market participants also update their expectations on the future path of monetary policy as inferred from the speeches and statements of members of the policy committee. In an effort to address this concern, Buraschi, Carnelli, and Whelan (2014) constructs an empirical proxy for the shocks on expected future path of monetary policy through residuals from Taylor rule regressions, and shows that their estimated path shock is a source of priced risk. The *MPU* index offers an alternative approach, which measures monetary policy uncertainty through textual information. The benefit of this measure is that it directly accounts for the public's subjective perception aspects while abstracting away from any model specification.

We utilize *MPU* to predict the future monthly US Treasury bond risk premium. Our findings suggest that monthly excess returns of Treasury bonds across various maturities are indeed predictable by *MPU*, supporting the existence of monetary policy risk premium. In particular, using Treasury bond data from 1985 till 2014, we show that a one standard deviation increase in *MPU* is associated with a 3 to 13 basis point expected increase in the monthly excess return of a 6-month to 5-year government bond. In addition, the majority of these risk premia are not spanned by the contemporaneous yields, echoing the findings in Duffee (2011) and Joslin, Priebsch, and Singleton (2014) who stress the role of un-spanned factors in driving yield curve dynamics.

We compare the predictive power of *MPU* with that of standard bond risk premium predictors based on the yield curve and macroeconomic fundamentals. Our analysis suggests that this news based *MPU* measure generates as much or higher R^2 than that of the forward rates based CP factor from Cochrane and Piazzesi (2005) and the macro fundamentals based LN factor from Ludvigson and Ng (2009). Besides, we also see sizable improvement of the predictive power on Treasury excess returns when augmenting the CP and LN factors with *MPU*. This indicates that monetary policy uncertainty constitutes an independent source of risk not embedded in the standard factors.

To deal with the potential fragility of in-sample results, we next examine the out-of-sample forecast performance of *MPU*. Following Campbell and Thompson (2008), we calculate the out-of-sample R^2_{OS} statistics for *MPU* driven forecasts against the benchmark forecasts under expectation hypothesis. The results affirm the predictive power of *MPU* in real time for monthly Treasury excess returns across maturities. The estimated out-of-sample R^2_{OS}s range from 8.7% to 1.3% for a 6-month to 5-year bond and are significantly positive at 10% confidence based on the Clark and West (2007) test. In line with the in-sample analysis, we also check the incremental predictive power of *MPU* when augmented with CP and LN factors in real time. To avoid look ahead bias in building LN factor, we follow Ghysels, Horan, and Moench (2014) and Eriksen (2015) to construct a panel of vintage data from Archival Federal Reserve Economic Data (ALFRED). These vintages of data allow us to create a variant of LN factor that are free from data revisions and publication lag, so that it is truly available to investors in real time. Our results suggest that adding *MPU* to the real time predictive models based on CP and LN factors lead to universal improvement in out-of-sample R^2_{OS}s across maturities.

It has been documented in the literature that Treasury bond risk premium predictability can be state dependent. For example, Andreasen, Engsted, Møller, and Sander (2016) finds that the predictive power by term structure variables is concentrated in periods of economic expansion and largely absent in recession. On the other hand, Gargano, Pettenuzzo, and Timmermann (2014), using models that incorporate time-varying parameters and stochastic volatility in the predictive regressions, shows that bond risk premium predictability by LN factor is confined in economic recession rather than expansion. We accordingly check the out-of-sample R^2_{OS}s for *MPU* based forecasts against the benchmark forecasts in periods of NBER expansion and recession separately. We find that although the forecast accuracy of *MPU* deteriorates in economic recession, the point estimates of out-of-sample R^2_{OS}s in periods of recession are still positive. Following Cochrane and Piazzesi (2005), we also calculate the real time trading profits of a strategy that uses return forecasts by *MPU* to judge its economic value at different state of the economy. Our results illustrate that *MPU* contains information value that creates trading profits in both expansion and recession periods.

Since monetary policy decisions typically involve systematic responses to macroeconomic shocks, it is plausible that monetary policy uncertainty is linked to uncertainty on macroeconomic condition. To account for this effect, we re-assess the predictive power of *MPU* controlling for several macroeconomic uncertainty proxies. In particular, we first follow Wright (2011) and Hong, Sraer, and Yu (2016), among others, to compute the inter-quartile range of 1-year ahead inflation and real GDP growth forecasts from Survey of Professional Forecasters (SPF) as proxies for uncertainty on expected inflation and economic growth. We then use the Jurado, Ludvgison, and Ng (2015) macro uncertainty index (MU) as a comprehensive measure of uncertainty in economic fundamentals. Running bivariate predictive regressions, we find that these macroeconomic uncertainty proxies do not impair the predictive power by *MPU*, suggesting that policy uncertainty does contain independent predictive information.

Furthermore, we control for alternative market-based measures for macroeconomic uncertainty that use financial indicators. For example, we include the market based version of Jurado, Ludvgison, and Ng (2015) index (FU) that extracts common uncertainty component from many financial indicators across a broad range of markets and sectors. Another widely-used proxy is the VIX, that summarizes 30-day option implied volatility on S&P500 index. Finally, as we recognize that fiscal policy may also drive Treasury yields[1], we also include a news based fiscal policy uncertainty index from Baker, Bloom, and Davis (2016). Controlling for these uncertainty proxies, our empirical analysis find *MPU* remains significant, hence indicating that monetary policy uncertainty does reflect an independent source of priced risk in Treasury market.

Our work complements the growing literature that studies the effects of government induced uncertainty on real economy and asset prices. Among them, Baker, Bloom, and Davis (2016) finds that a positive shock to economic policy uncertainty triggers negative responses by industrial production and real investment. Pástor and Veronesi (2013) builds a general equilibrium model of government policy choices and shows that undiversifiable uncertainty on policy making commands a risk premium. Brogaard and Detzel (2015) provides empirical support for the existence of economic policy risk premium in US stock market. Kelly, Pástor, and Veronesi (2016) shows that policy uncertainty is also priced in equity option market. Our study empirically extends these policy risk premium analysis to the Treasury bond market and highlights the role of monetary policy uncertainty in shaping bond excess returns. Our findings on the predictive power of *MPU* also adds to the bond return predictability literature (e.g. Fama and Bliss (1987); Campbell and Shiller (1991); Cochrane and Piazzesi (2005); Ludvigson and Ng (2009); Eriksen (2015)) that has traditionally focused on predictors based on yield curve and macroeconomic fundamentals.

The rest of this article is organized as follows. In section 2, we lay out the econometric framework for assessing the time variation in Treasury bond risk premium. In section 3, we describe and summarize the data on monetary policy uncertainty, Treasury bond prices and return

[1] Specifically, Ulrich (2013) documents through a general equilibrium model that uncertainty about the future path of government spending is a first-order risk factor in the bond market, leading to rising real and nominal interest rates as well as a steeper term spread.

predictors. Section 4 documents our empirical results for in- and out-of-sample predictability tests of Treasury excess returns by monetary policy uncertainty. Finally, Section 5 concludes.

2. Treasury Bond Risk Premium Prediction

Our studies focus on US Treasury bond risk premium. Denote $P_t^{(n)}$ as the nominal price of a Treasury bond at time t with n years left to expiry, no coupon payment and a terminal payoff normalized to 1 dollar. The continuously compounded log yield of this n-year Treasury bond at time t is given by $y_t^{(n)} = -(1/n)ln(P_t^{(n)})$, where we use parentheses to denote the remaining time to maturity. Let h be the forecasting horizon in months, the log forward rate at time t for loans between time $t+n-h/12$ and $t+n$ is defined to be $f_t^{n-h/12,n} = ln(P_t^{(n-h/12)}) - ln(P_t^{(n)})$. And the h-month holding period excess return on a n-year risky Treasury bond, relative to the h-month risk free rate is computed as:

$$rx_{t+h/12}^{(n)} = ln(P_{t+h/12}^{(n-h/12)}) - ln(P_t^{(n)}) - h/12\, y_t^{(h/12)}, \tag{1}$$

where we assume that all the log yields have been annualized and hence $h/12\, y_t^{(h/12)}$ represents the h-months log risk free rate at time t.

The prevailing way to assess the time variation in Treasury bond risk premium in the literature is through a predictive regression generally specified as follows:

$$rx_{t+h/12}^{(n)} = \alpha^{(n)} + \beta^{(n)} Z_t + \varepsilon_{t+h/12}^{(n)}\,, \tag{2}$$

where $rx_{t+h/12}^{(n)}$ is again the h-month excess return of buying a n-year risky Treasury bond and selling it as a $(n-h/12)$-year bond h months later. Z_t is a vector of covariates that are observable at time t and aim to predict bond risk premium ahead. Following Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009), we suppress the maturity dependence in Z_t to reflect the fact that

Treasuries returns tend to co-move and load on the same (maturity independent) factors. Note that when the regression coefficients $\beta^{(n)} = 0$, this specification reduces to the expectation hypothesis, under which Treasury excess returns are unpredictable and bond risk premia are constant over time.

The previous empirical research has uncovered forecastable variation in bond risk premium by a variety of candidates for Z_t, a rejection of the expectation hypothesis. A seminal paper by Cochrane and Piazzesi (2005) shows that a tent shape linear combination of the forward rates forecast Treasury excess returns. More importantly, this tent shaped forward rate factor subsumes the predictive content of forward spread, yield spread and yield factors estimated as principal components of the yield covariance matrix, which were documented to forecast bond excess returns in Fama and Bliss (1987); Campbell and Shiller (1991)) and Litterman and Scheinkman (1991). Although these studies presumes that all information on future interest rate dynamics are reflected in today's yield curve, recent studies have linked bond risk premium to factors not spanned by the current yields. A prominent example is Ludvigson and Ng (2009), who extracts latent factors from a large panel of macroeconomic information. While Ludvigson and Ng (2009) shows that these latent macro factors possess predictive information above and beyond the Cochrane and Piazzesi (2005) forward rate factor, Ghysels, Horan, and Moench (2014) posits that some fraction of the predictability derives from macro data revisions and publication lags which were not available to investors in real time. Accordingly, to conduct real time forecast evaluation, Ghysels, Horan, and Moench (2014) suggests a variant of theses latent factors constructed from a panel of vintages data on macroeconomic variables. Eriksen (2015), using survey forecasts from Survey of Professional Forecasters, extracts proxy for expected business condition and find it consistently affects bond excess returns beyond the current term structure and macroeconomic variables.

In this article, we examine the role of monetary policy uncertainty as a potential incremental source of priced risk for Treasury bond investors. Intuitively, high monetary policy uncertainty may increase bond holders' perceived uncertainty about future bond yields and prices. Baker, Bloom, and Davis (2016) and Pástor and Veronesi (2012, 2013) provide theoretical models arguing that policy uncertainty could have large influences on real economy and asset prices. Pástor and Veronesi (2013), in particular, builds a general equilibrium model of government policy choices and shows that undiversifiable uncertainty on policy making commands a risk premium. Brogaard and Detzel (2015), using the same predictive regression framework articulated above, finds empirical support for a positive risk premium for general economic policy uncertainty in US stock market. In this article, we argue that, given the important role of monetary polices for bond yields and prices, it is of natural interest to extend the analysis to analyze the links between monetary policy uncertainty and bond risk premium. We detail the construction of monetary policy uncertainty index and other standard bond risk premium predictors in the next section.

3. Data and Summary Statistics

Our goal is to relate monetary policy uncertainty with Treasury bond risk premium. To quantitatively capture the degree of monetary policy uncertainty, we use the news-based uncertainty index in Baker, Bloom, and Davis (2016) under the category of monetary policy. This *MPU* index is constructed as a scaled frequency count of news articles that mention uncertainties, economics along with one of monetary policy terms such as federal reserve, open market operation, quantitative easing, discount window, etc. The underlying identification assumption is that increased news article coverage indicates that the public perceives more uncertainty of central bank actions. The *MPU* index we use spans from 1985:m1 to 2014:m12 and is available at monthly frequency in real time.

We obtain monthly Treasury bonds and bills prices for the same period above from the Fama-Bliss dataset available from the Center for Research in Security Prices (CRSP). We focus on US Treasuries with a time to maturity of 6 months and one through five years. We then fit the yield curve with these bond prices at the end of each month through the Nelson and Siegel (1987) function, which would allow us to calculate Treasury excess returns at monthly frequency.[2] As a robustness check, we also reconstruct the yield curve at daily frequency starting from the method developed in Svensson (1994) and relying on the parameters estimated in Gürkaynak, Sack, and Wright (2007). The computed monthly excess returns based on this alternative yield curve is quantitatively similar to those based on the Fama-Bliss datasets.

Our rationale to look at monthly, rather than longer horizon, holding period returns of Treasury bonds is twofold. First, as emphasized in Gargano, Pettenuzzo, and Timmermann (2014), using monthly rather than annual returns provides a sizable increase in the number of (non-overlapping) data points available for predictive regression model estimation, which helps to reduce serial correlation in the regression residuals. Secondly, the *MPU* index we monitor can experience dramatic fluctuations during a short period of time lasting less than a quarter or a year, e.g. at Black Monday of 1987, Sept 11 attack, QE announcement, etc. Hence, looking at longer holding period could easily miss some large swings of the monetary policy risk and Treasury excess returns, especially at the turning point of market condition and economic cycle.

In order to compare the predictive power of *MPU* with prevailing Treasury return predictors, we then detail our construction of the Cochrane and Piazzesi (2005) forward rate based factor (CP) and the Ludvigson and Ng (2009) macroeconomic information based factor (LN). Cochrane and Piazzesi (2005) create their CP factor as the fitted value of a first stage regression of average Treasury excess return on a vector of one- through five- year forward rates. Since the estimated loadings of the CP factor have a tent shape form which peaks at the three year forward rate, one may well approximate the CP factor as the spread between the three-year forward and average of one-year and five-year forward rate. As argued in Ghysels, Horan, and Moench (2014), the benefit of using observable forward rates instead of estimated linear combination is to avoid potential over-fitting and errors-in-variables bias.

[2] Specifically, we estimate the following function form of yield curve, $y_t^{(n)} = \beta_0 + \beta_1 \frac{1-e^{-n/\lambda}}{n/\lambda} + \beta_2 [\frac{1-e^{-n/\lambda}}{n/\lambda} - e^{-n/\lambda}]$ by nonlinear least square. A more parsimonious approach as in Diebold and Li (2006) which fix λ at pre-specified value produces similar fitted curve and excess returns.

Regarding the Ludvigson and Ng (2009) macro factor, we consider a variant of Ludvigson and Ng (2009) that is free from data revision and publication lags. Specifically, we follow Eriksen (2015) and Ghysels, Horan, and Moench (2014) to build a panel of 67 real-time vintage macroeconomic variables from the Archival Federal Reserve Economic Data (ALFRED) database maintained by the Federal Reserve Bank of St. Louis. The data we build broadly covers the same economic categories in Ludvigson and Ng (2009), which include labor market and output variables, money stock and price indexes, income series, and housing indicators. We create monthly panel by picking out the latest vintage data within each month. If there is no recorded vintage during a month, we will use previous months' vintage to avoid look ahead bias. We then estimate the real time LN factor from this panel using the dynamic factor model of Stock and Watson (2010) and select the optimal number of factors based on the information criteria of Bai and Ng (2002).[3]

[Insert Table 1 about here]

Table 1 presents the summary statistics for monthly Treasury excess returns, $rx^{(n)}_{t+1/12}$, across the maturities of $n = 6$ months, 1 year,2 year, 3year, 5 years, along with the lagged predicting characters of CP, LN factor and *MPU* index. Note that we have omitted the four-year bond case as the corresponding results are very close to those of the three-year bond. A glance at panel A reveals that the means and standard deviations of Treasury excess returns increase as the maturity expands. However, the sharp ratios of the Treasury excess returns decrease along the maturity, with 6 month Treasury bond having the highest sharp ratio of around 0.6. While excess returns on short term bonds tend to be positively skewed, those on the 3-year to 5-year bond are slightly negative. In addition, the first order autocorrelations of bond excess returns range from 0.28 to 0.11 and decrease across maturity.

Regarding return predictors, we find CP and LN factors to be more persistent than *MPU*. For

[3]Unlike Ludvigson and Ng (2009), we do not further select among the nonlinear transformations of the factors as some of the series would then have very dramatic spikes.

example, CP has first and second order autocorrelations of 0.94 and 0.84 respectively, which is consistent with Cochrane and Piazzesi (2005) who argue that CP factor fluctuates at business cycle frequency and relate it to the annual Treasury excess returns. In contrast, *MPU* is autocorrelated at around 0.6 at first order and 0.3 at second order, suggesting that it swings at a higher frequency. Panel B indicates that Treasury bond excess returns have high correlations across maturities, which is in line with the intuition that yield curve dynamics follow some factor structure. As expected, Treasury excess returns are correlated with lagged CP factor, re-assuring that the shape of the yield curve contain information on bond risk premium. The LN factor we summarize here is actually the latest vintage of ALFRED data. It also correlates with future bond excess returns at about the same magnitude as that of CP, echoing the findings in Ludvigson and Ng (2009). Finally, *MPU* exhibits correlations with future bond excess returns that are as high as the CP and LN factors.

An immediate question is whether the information content contained in *MPU* is already captured by the cross sectional variation of current yields. To address this concern, we conduct a spanning test in the sense of Joslin, Priebsch, and Singleton (2014). Specifically, we run the following regression:

$$MPU_t = a + \theta \mathscr{Y}_t + \varepsilon_t, \tag{3}$$

where *MPU* is the monetary policy uncertainty index, and $\mathscr{Y}_t$ denotes either the first three or first five principal components of the yields covariance matrix that summarize the term structure.

[Insert Table 2 about here]

If a variable is fully spanned by the current yield curve, then the associated R^2 of this regression should equal to unity. Table 2 demonstrates that the projection of *MPU* on the first three or five principal components give an adjusted R^2 of 9.2% or 12.1% respectively. This result suggests that at least 88% variation of *MPU* is not spanned by the current yield curve, or equivalently in the terminology of Duffee (2011), *MPU* is a "hidden" factor largely irrelevant to the cross section of current yields.

4. Empirical Results

4.1. *In-Sample Predictability of MPU*

In this section, we use the predictive regression framework of (2) articulated above to test the impact of monetary policy uncertainty on Treasury bond risk premium. The main regression of our concern is:

$$rx^{(n)}_{t+1/12} = \alpha + \beta_p MPU_t + \varepsilon_{t+1/12} \ , \tag{4}$$

where $rx^{(n)}_{t+1/12}$ denotes the monthly excess return of an n-year Treasury bond, and MPU is the Baker, Bloom, and Davis (2016) index of monetary policy uncertainty. We set $n =$ 6-month, 1-year, 2-year, 3-year and 5-year and predict bond risk premium for each maturity separately. Note that, for abbreviation purpose, we have omitted the superscript (n) on top of the coefficients. To perform our estimation, we use the full range of observations and report the estimated slope coefficients, β_p, the corresponding White (1980) heteroskedasticity-robust t-statistics, and the associated adjusted R^2s. The null hypothesis we test is no-predictability, i.e. $\beta_p = 0$, and hence regression reduces to expectation hypothesis.

[Insert Table 3 about here]

We report in Table 3 our in-sample estimation results. We find that MPU forecasts positively future monthly Treasury excess returns across the entire maturity spectrum. The magnitude of the estimated slope coefficients increase as the maturity expands and are universally significant at 10% confidence level at least, according to the White (1980) t-statistics. In particular, a one standard deviation increase of MPU is associated with a 3 to 13 basis point increase in expected monthly excess returns for a 6-month to 5-year Treasury. While the associated adjusted R^2 for a 5-year bond is relatively low at about 0.7%, it range from 1.4% to 8.5% for the remainder of the maturity spectrum, with the highest attained for the 6-month Treasury bond.

[Insert Table 4 about here]

We then compare the predictive power of *MPU* against the prevailing Treasury return predictors of CP and LN factor constructed above. In particular, we re-run the univariate regression in model (4) but with *MPU* replaced by CP and LN factors, denoted as X:

$$rx^{(n)}_{t+1/12} = \alpha + \beta X_t + \varepsilon_{t+1/12} \ . \tag{5}$$

We document in Panel A of Table 4 our estimation results of model (5). Begin with the CP factor, we see that while CP performs poorly in the very short and long end of the maturity range, it significantly forecasts monthly excess returns for a 1-year through 3-year Treasury bond. In terms of economic significance, CP is able to explain between 1.27% to 1.52% of the one month ahead variation in risk premium for a 2-year to 3-year Treasury bond. As a comparison, *MPU* explains 1.39% to 1.79% of the excess return variation on a 2-year and 3-year Treasury bond, which is comparable to that of CP. Yet on the remaining of maturity range, especially on the 6-month and 1-year bond, *MPU* exhibits much stronger predictability both statistically and in terms of magnitude. Turning to the LN factor, we see similar pattern of predictability as that of CP across the maturity spectrum. Specifically, LN explains between 1.42% and 1.51% of the one month ahead variation of risk premium on a 2-year and 3-year bond, which is again comparable to that of *MPU*. Whereas, its predictive power for returns on 6-month and 1-year Treasury is significantly inferior to that of *MPU*, which explains 8.45% and 3.69% of the future return variation respectively. Note that, as in the summary section, these in-sample results on LN are obtained using the latest available vintage of the ALFRED data.

We next test whether monetary policy uncertainty contains any incremental information in predicting Treasury excess returns, when controlling for the effect of LN or CP factor. In particular, we run the bivariate forecasting regression of :

$$rx^{(n)}_{t+1/12} = \alpha + \beta X_t + \beta_p EPU_t + \varepsilon_{t+1/12} \ . \tag{6}$$

Panel B of Table 4 reveals that *MPU* remains statistically significant when controlling for CP or LN factor for the majority of the maturity spectrum. While *MPU* turns into border-line significance for the 5-year bond, the estimated slope coefficients stay largely unchanged and the associated adjusted R^2s increase by about 7% to 0.8% for the rest of maturity range. This implies that *MPU* provides independent information relative to the standard predictors . The CP and LN factor also stays statistically significant at a few maturities when augmented with *MPU*, suggesting that these traditional predictors and *MPU* may capture distinct aspects of the potentially multifaceted risks that govern Treasury bond risk premium.

In summary, our in-sample estimation results indicate that monetary policy uncertainty, proxied by the *MPU* index, possesses strong in-sample predictive power on monthly US Treasury excess returns. In terms of both the magnitude and statistical significance, the predictive power of *MPU* is comparable to or stronger than that of the prevailing CP and LN factors across the maturity spectrum. In addition, the predictive information contained in *MPU* is not embedded in CP and LN factors, and thus adding *MPU* as an additional predictor would further improve the forecasting power on Treasury bond risk premium.

4.2. Out-of-sample Predictability of MPU

The extensive literature on return predictability have shown that, although the in-sample analysis provides more efficient parameter estimates and thus more precise forecasts by utilizing all available data, out-of-sample tests seem to be a more relevant standard for assessing genuine predictability in real time. In particular, out-of-sample analysis implicitly examine the stability of the data-generating process and guard against in-sample over-fitting.

In this section, we test the out-of-sample predictive power of MPU on US Treasury bond risk premium. As in the in-sample analysis, we set n = 6-month, 1-year, 2-year, 3-year and 5-year and examine the impact of MPU for each bond maturity separately. Following the framework in Campbell and Thompson (2008) and Ludvigson and Ng (2009), we estimate our predictive regression models recursively, and compare the predictive accuracy of the forecasts generated with MPU against the benchmark forecasts that ignore MPU. We use the historical average model implied by expectation hypothesis (EH) as the benchmark when we evaluate the accuracy of univariate MPU based forecast as in model (4). Whereas, when evaluating the MPU augmented bivariate model of (6), we adopt the CP or LN based forecasts in model (5) as the benchmark. Note that in this out-of-sample analysis, the LN factor is created through real time vintages data and are thus free from data revision and publication lag.

To carry out the out-of-sample tests, we start with an initial training periods from 1985:m1 to 1999:m12 and estimate both the factors and predictive regressions to produce the first out-of-sample forecast for 2000:m1. We then expand the estimation window recursively and repeat the above steps to obtain out-of-sample forecast for the next period and continue in this way until we reach the end of the sample period. The out-of-sample forecast evaluation periods thus span from 2000:m1 to 2014:m12. The length of the initial estimation periods balances the desire for having enough observations for precisely estimating the initial parameters with the desire for a relatively long out-of-sample period for forecast evaluation.

Following Campbell and Thompson (2008), we then calculate the out-of-sample R^2_{OS} statistic as:

$$R^2_{OS} = 1 - \frac{\sum_{t=p}^{T-1/12} (rx^{(n)}_{t+1/12} - \widehat{rx}^{(n)}_{t+1/12})^2}{\sum_{t=p}^{T-1/12} (rx^{(n)}_{t+1/12} - \widetilde{rx}^{(n)}_{t+1/12})^2}\ , \tag{7}$$

where $\widehat{rx}^{(n)}_{t+1/12}$ and $\widetilde{rx}^{(n)}_{t+1/12}$ denote the monthly Treasury excess return forecasts generated by the regression model of interest and the benchmark, respectively, $rx^{(n)}_{t+1/12}$ represents the realized monthly Treasury excess return at time $t+1/12$, p stands for the end of the initial training periods and T is the ending time of the full sample. The R^2_{OS} statistic can be interpreted as the ratio of

MSFE between the candidate forecasting model and the benchmark. Its magnitude lies in the range of $(-\infty, 1]$ and a positive R^2_{OS} would indicate that the candidate forecasts of interest outperform the benchmark in terms of the mean squared forecasting errors (MSFE).

To gauge the significance of R^2_{OS}, we use the Clark and West (2007)'s MSFE-adjusted statistic to test the null hypothesis that the MSFE of benchmark model is less than or equal to that of the *MPU* driven forecast ($E(R^2_{OS}) \leq 0$) against the one-sided (upper-tail) alternative hypothesis that the MSFE of benchmark model is larger ($E(R^2_{OS}) > 0$). Clark and West (2007) develop the MSFE-adjusted statistic by modifying the Diebold and Mariano (1995) and West (1996) test statistic. This modified test statistic has a standard normal asymptotic distribution when comparing forecasts with the nested models, and is shown to perform reasonably well in terms of size and power when comparing forecasts from nested linear models for a variety of sample sizes.[4]

[Insert Table 5 about here]

Table 5 presents the out-of-sample forecasting performance of *MPU* on monthly Treasury excess returns over the 2000:m1 to 2014:m12 forecast evaluation period. In comparison with the historical average forecasts, *MPU* generates positive R^2_{OS} ranging from 8.74% to 1.32% for 6-month to 5-year Treasury bond, which are all significantly positive at 10% confidence at least according to the Clark and West (2007) tests. The evidence supports that the predictive power of *MPU* sustains in an out-of-sample forecasting environment.

[Insert Table 6 about here]

As an alternative benchmark, Panel A of Table 6 presents the out-of-sample performance of CP and LN factors as well as their combination for the same evaluation periods. We see that CP

[4]While the Diebold and Mariano (1995) and West (1996) statistic has a standard normal asymptotic distribution when comparing forecasts from non-nested models, Clark and McCracken (2001) and McCracken (2007) show that it has a non-standard distribution when comparing forecasts from nested models. The non-standard distribution can lead the Diebold and Mariano (1995) and West (1996) statistic to be severely undersized when comparing forecasts from nested models, thereby substantially reducing power.

factor delivers a positive and significant R^2_{OS} against the EH benchmark for 2-year Treasury bond excess returns. However, for the rest of the maturity spectrum, the R^2_{OS}s range from -0.98% to -0.08%, signalling an inferior performance relative to the EH benchmark. Regarding macro factor, we see that the real time variant of LN factor consistently generates negative R^2_{OS}s in the range of -0.17% to -2.68%. This stands in line with the findings in Ghysels, Horan, and Moench (2014) that data revision and publication lag drive a significant proportion of bond risk premium predictability. Finally, combining CP and real time LN factors do not raise the R^2_{OS}s into the positive domain.

Panel B of Table 6 demonstrates the incremental predictive power of *MPU* when augmented with CP and real time LN factors in the out-of-sample forecasting environment. Compared with the benchmark of CP, LN or their combination driven forecasts, adding *MPU* results in positive R^2_{OS} ranging from a low of about 1.2% for a 5-year bond to a high of about 8.5% for a 6-month one. And the MSFE-adjusted statistics reveal that the majority of these R^2_{OS} are significantly positive at 10% confidence at least. These evidence indicates that *MPU* contains reliable predictive information which complements that of CP and LN in an out-of-sample environment.

As an additional check on the consistency of the out-of-sample predictability, we follow, among others, Goyal and Welch (2008); Rapach and Zhou (2013) and Eriksen (2015) to compute the differences in cumulative squared prediction errors (DCSPE) between the EH benchmark forecasts and the candidate forecasts driven by CP, LN and *MPU* respectively. The DCSPE are calculated for each bond maturity and return predictor separately as:

$$DCSPE_k = \sum_{t=p}^{k-1/12} (rx^{(n)}_{t+1/12} - \widetilde{rx}^{(n)}_{t+1/12})^2 - \sum_{t=p}^{k-1/12} (rx^{(n)}_{t+1/12} - \widehat{rx}^{(n)}_{t+1/12})^2 \,, \tag{8}$$

where k=p+1/12,...,T is the time index for the evaluation periods and $\widetilde{rx}^{(n)}$ denotes the benchmark forecasts now based on the expectation hypothesis. An increase in DCSPE over time would imply that the candidate forecast has outperformed the benchmark in the last period.

[Insert Figure 2 about here]

We plot the time series of DCSPE in Figure 2 for each bond maturity.[5] We note that the predictive performance of *MPU* tend to increase steadily across the maturity spectrum up until 2010, where it deteriorates a little bit but then pick up since 2013. The CP factor, while doing very well till 2007, sees a sharp decline during the financial crisis that drags the DCSPE curves across maturities below 0. Yet, its predictive performance strikes back since 2010. On the other hand, the real time variant of LN factor has consistently underperform the EH benchmark with large drops of the DCSPE curves around 2004. Overall, these results reveal that the out-of-sample predictive performance of *MPU* is relatively stable among the bond return predictors we consider.

4.3. State-dependent Predictability during NBER expansions and recessions

Recent studies have argued that bond return predictability itself may be state dependent. For example, Andreasen, Engsted, Møller, and Sander (2016) finds that the predictive power by term structure variables, such as CP, is concentrated in periods of economic expansion and largely absent in recession. On the other hand, Gargano, Pettenuzzo, and Timmermann (2014), using models that incorporate time-varying parameters and stochastic volatility in the predictive regressions, shows that bond risk premium predictability by LN factor is confined in economic recession rather than expansion. We accordingly follow the approaches in these literature to assess state-dependent predictability by splitting the out-of-sample forecast errors, ex post, into periods of expansions and recessions using the NBER recession indicator. We re-calculate the R^2_{OS}s for each of the *MPU*, CP and LN factor against the EH benchmark and test its significance for the sub-periods of NBER expansions and recessions separately.

[Insert Table 7 about here]

We present the results in Table 7 for each bond maturity. Starting with CP factor, we see it exhibits strong predictive power in NBER expansions across the maturity spectrum, with signifi-

[5] We have multiplied the returns by 100 (in terms of percentage) to make the graphs easier to diagnose.

cantly positive out-of-sample R^2_{OS}s ranging from 1.28% to 10.48%. In contrast, the R^2_{OS}s in NBER recessions have a negative span of -6.59% to -16.93%, suggesting the absence of predictability in recession that is consistent with Andreasen, Engsted, Møller, and Sander (2016). The real time LN factor yields negative R^2_{OS}s in both NBER expansions and recessions for the majority of the maturity range. However, the R^2_{OS}s are indeed more negative in expansion, indicating a comparatively better predictive performance by real time LN factor in recession periods. Finally, turning to our *MPU* factor, we find it generates lower prediction errors in NBER expansion, with significant R^2_{OS}s spanning from 2.91% for a 3-year bond to 9.73% for a 6-month bond. While the magnitudes of R^2_{OS}s are smaller in NBER recessions, they remain positive across the entire maturity spectrum and are statistically significant for 6-month and 1-year bonds.

4.4. *Trading Rules Profits*

While our in- and out-of-sample analysis so far has uncovered the predictive power of *MPU* on Treasury excess returns, it is of interest to see whether this documented predictability can be used by Treasury investors to guide their trading decisions. In fact, many studies, e.g. Thornton and Valente (2012) and Sarno, Schneider, and Wagner (2016), find it difficult to exploit bond return predictability by yield curve and macroeconomic factors for mean variance investors to improve trading performance. We accordingly examine the trading value of *MPU* in the out-of-sample environment described above.

[Insert Figure 3 about here]

Specifically, we follow Cochrane and Piazzesi (2005) and consider a simple real time trading rule that uses the monthly excess return forecasts, $E_t[rx^{(n)}_{t+1/12}]$, by *MPU* to recommend the size of a position on the n-year Treasury which is then subject to the ex-post excess return of $rx^{(n)}_{t+1/12}$.[6]

[6]Unlike Thornton and Valente (2012) and Sarno, Schneider, and Wagner (2016), we do not use the mean variance optimization framework to exploit bond return predictability. This is due to the fact that, at monthly forecast horizon, the conditional volatility estimates of bond excess returns are relatively low and hence the ex-ante optimal portfolios

The resulting trading rules profit is given by: $E_t[rx^{(n)}_{t+1/12}] \times rx^{(n)}_{t+1/12}$. We cumulate these trading profits and compare it with those generated by CP, real time LN and the EH benchmark forecast.

Figure 3 plots these cumulative performance for each bond maturity separately. Starting from MPU, we observe that the cumulative trading profits across maturities rise sharply in early 2000 when the bond market booms as the interest rates decline. While the MPU profit curves stay relatively flat or deteriorate a little bit since 2004 when the interest rates rise, the cumulative profits jump up again during the financial crisis of 2008 and has since then rise gradually as interest rates keep dropping. As a comparison, the cumulative profits of CP, real time LN and EH benchmark rules exhibit similar pattern but is inferior to that of MPU rule. In particular, the trading profit of CP rule significantly declined during the 2008 crisis especially on the longer end of the maturity spectrum. And the real time LN rule experienced large under-performance during the yield rising episode between 2004 and 2007.

4.5. *Other Uncertainty Measures*

Since a significant part of monetary policy decision involves policy makers' systematic responses to the macroeconomic shocks, it is plausible that the information content of MPU is endogenously linked to the uncertainty of macroeconomic condition. To account for this effect, we construct several proxies for macroeconomic uncertainty, examine their impact on bond risk premium and compare their predictive power with that of MPU. In particular, we first follow Wright (2011) and Hong, Sraer, and Yu (2016) to compute the inter-quartile range of 1-year ahead inflation and real GDP growth forecasts from Survey of Professional Forecasters (SPF). These forecast dispersions serve as our proxies for uncertainty on expected inflation and real growth respectively. We then use a macroeconomic uncertainty index (MU) constructed in Jurado, Ludvgison, and Ng (2015) (JLN)

are highly levered. Yet, when the forecast of excess return deliver a wrong sign to the true one, the ex-post trading performance would fall into a bankruptcy state. While adding leverage constraints as in Campbell and Thompson (2008) could help in principle, it is practically hard to pin down a reasonable leverage constraint for Treasury bond investors.

as a comprehensive measure of uncertainty in economic activities. Furthermore, we also include alternative market-based measures for macroeconomic uncertainty that use financial indicators. For example, we consider the market based version of Jurado, Ludvgison, and Ng (2015) index (FU) that extracts common uncertainty component from many financial indicators across a broad range of markets and sectors. Besides, another market based measure we account for is the VIX index, which summarizes 30-day option implied volatility on S&P500 index.[7] Finally, as we recognize that fiscal policy may also drive Treasury yields (Ulrich (2013)), we take the news based fiscal policy uncertainty index from Baker, Bloom, and Davis (2016) as well.

[Insert Table 8 about here]

To examine their impact on bond risk premium, we run univariate predictive regressions of each macroeconomic uncertainty proxy upon the cross maturities average of the monthly Treasury excess returns. We then augment the predictive models with MPU to check the marginal predictive power of both macro uncertainty proxy and MPU. As shown in panel A of Table 8, among the proxies we consider, uncertainty on expected inflation raises bond risk premium, which complies with the model implications in Bansal and Shaliastovich (2013). Whereas, uncertainty on real growth does not seem to significantly affect average Treasury excess returns.[8] The more comprehensive JLN macro uncertainty index (MU) relates positively to future bond excess returns. While the t-statistics associated with MU is around the border line of 10% significance, the financial indicators based JLN index (FU) as well as the VIX index display significant predictive power on future bond excess returns. Panel B of Table 8 documents the results on bivariate predictive regressions that augment the macro uncertainty proxies with MPU. We observe that, although the slope coefficients and the significance level deteriorate on several macro uncertainty proxies, the predictive power of MPU remains significant across any of the specification. These evidence reveal to us that monetary policy uncertainty does contain independent predictive information not captured by macroeconomic uncertainty.

[7]We also test a related VXO index on S&P100, which delivers similar results.

[8]Based on the calibrated long run risk model of Bansal and Shaliastovich (2013), uncertainty on real growth should decrease bond risk premium.

4.6. GSW Data and Quarterly Forecast Horizon

In this section, we check whether our main results on bond return predictability by *MPU* is robust to the way we construct the yield curve. Specifically, while we have been fitting the yield curve with Nelson and Siegel (1987) function using the Fama-Bliss dataset, this section re-constructs the yield curve through an alternative interpolation scheme that follows Gürkaynak, Sack, and Wright (2007) (GSW). In particular, we rebuild the yield curve at daily frequency starting from the method developed in Svensson (1994) and relying on the parameters estimated in Gürkaynak, Sack, and Wright (2007). The time t log yield of an n-year zero coupon Treasury bond, $y_{t,GSW}^{(n)}$, is then given by:

$$y_{t,GSW}^{(n)} = \beta_0 + \beta_1 \frac{1-e^{-n/\kappa_1}}{n/\kappa_1} + \beta_2 [\frac{1-e^{-n/\kappa_1}}{n/\kappa_1} - e^{-n/\kappa_1}] + \beta_3 [\frac{1-e^{-n/\kappa_2}}{n/\kappa_2} - e^{-n/\kappa_2}], \tag{9}$$

where the parameters $(\beta_0, \beta_1, \beta_2, \beta_3, \kappa_1, \kappa_2)$ are estimated by Gürkaynak, Sack, and Wright (2007) at daily frequency with a large spectrum of outstanding Treasury securities.[9] This alternative approach provides a relatively more smooth yield curve that spans a long maturity spectrum. To keep results comparable, we sample this GSW dataset at the last trading day of each month to convert yields into monthly frequency and focus on bonds with the same maturities as above. The monthly bond excess returns are then computed analogously to Section 2. as the monthly holding period excess returns of buying an n-year bond and selling it a month later as an $(n-1/12)$-year one. As an supplementary analysis, we also calculate quarterly holding period returns where we hold an n-year bond for a quarter and sell it as an $(n-3/12)$-year one later.

[Insert Table 9 about here]

Table 9 presents the full sample estimation results from regressing these monthly and quarterly Treasury excess returns upon *MPU*. We observe that at monthly forecasting horizon, the results using GSW data quantitatively mirror those in Table 3. In fact, the *MPU* index forecasts

[9] This GSW dataset is available at http://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html.

significantly future monthly Treasury excess returns across the entire maturity spectrum, and is able to explain between 0.35% to 5.20% of variation in one month ahead bond risk premium. The highest associated R^2s of 5.20% is attained at the very short end of the maturity spectrum, which is consistent with our main results based on the Fama-Bliss dataset. However, at quarterly forecast horizon, *MPU* is not significant in predicting future Treasury excess returns at any maturity. This is possibly due to the short memory of *MPU* so that the corresponding monetary policy risk premium dissipates within a quarter.

5. Concluding Remarks

This paper has examined the predictive ability of monetary policy uncertainty on future Treasury bond excess returns. Using the news based *MPU* measure in Baker, Bloom, and Davis (2016) as a proxy, we show that monetary policy uncertainty commands a positive risk premium in US Treasury bond market. This finding provides an empirical support to the policy risk premium model in Pástor and Veronesi (2013) and echoes Brogaard and Detzel (2015) who illustrates that higher economic policy uncertainty raises risk premium in equity market. Moreover, our results reveal that, the information content of *MPU* is not spanned by the cross section of current yield and hence is "hidden" from the term structure. Besides, we also find that *MPU* predictability on monthly Treasury excess returns is comparable but independent to that of standard bond return predictors such as Cochrane and Piazzesi (2005) (CP) and Ludvigson and Ng (2009) (LN) factors. An out-of-sample analysis further confirms the predictive power of *MPU* in real time and exhibits that this predictability is relatively stable across NBER expansions and recessions. Finally, we show that monetary policy risk premium is not driven by uncertainties of macroeconomic conditions and that, compared to uncertainty on fiscal policy and other economic polices, monetary policy uncertainty does play a dominant role in affecting Treasury market.

References

Andreasen, M. M., Engsted, T., Møller, S. V., Sander, M., 2016. Bond market asymmetries across recessions and expansions: New evidence on risk premia, Working Paper.

Bai, J., Ng, S., 2002. Determining the number of factors in approximate factor models. Econometrica 70 (1), 135–172.

Baker, S., Bloom, N., Davis, S., 2016. Measuring economic policy uncertainty. Quarterly Journal of Economics.

Bansal, R., Shaliastovich, I., 2013. A long-run risks explanation of predictability puzzles in bond and currency markets. The Review of Financial Studies 26 (1), 1–33.

Bernanke, B. S., Kuttner, K. N., 2005. What explains the stock market's reaction to federal reserve policy? The Journal of Finance 60 (3), 1221–1257.

Brogaard, J., Detzel, A., 2015. The asset pricing implications of government economic policy uncertainty. Management Science 61, 3–18.

Buraschi, A., Carnelli, A., Whelan, P., 2014. Monetary policy and treasury risk premia. Available at SSRN 2411782.

Campbell, J. Y., Shiller, R. J., 1991. Yield spreads and interest rate movements: A bird's eye view. The Review of Economic Studies 58 (3), 495–514.

Campbell, J. Y., Thompson, S. B., 2008. Predicting excess stock returns out of sample: Can anything beat the historical average? The Review of Financial Studies 21 (4), 1509–1531.

Christensen, J. H., Krogstrup, S., 2015. Transmission of asset purchases: the role of reserves. FRBSF Economic Letter 2015, 20.

Christiano, L. J., Eichenbaum, M., Evans, C. L., 1999. Monetary policy shocks: What have we learned and to what end? Handbook of Macroeconomics 1, 65–148.

Clark, T. E., McCracken, M. W., 2001. Tests of equal forecast accuracy and encompassing for nested models. Journal of Econometrics 105 (1), 85–110.

Clark, T. E., West, K. D., 2007. Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics 138, 291–311.

Cochrane, J. H., Piazzesi, M., 2005. Bond risk premia. American Economic Review 95 (1), 138–160.

Diebold, F. X., Li, C., 2006. Forecasting the term structure of government bond yields. Journal of Econometrics 130 (2), 337–364.

Diebold, F. X., Mariano, R. S., 1995. Comparing predictive accuracy. Journal of Business and Economic Statistics 13, 253–265.

Duffee, G. R., 2011. Information in (and not in) the term structure. The Review of Financial Studies 24 (9), 2895–2934.

Eriksen, J. N., 2015. Expected business conditions and bond risk premia. Journal of Financial and Quantitative Analysis.

Fama, E. F., Bliss, R. R., 1987. The information in long-maturity forward rates. The American Economic Review 77 (4), 680–692.

Fleming, M. J., Piazzesi, M., 2005. Monetary policy tick-by-tick, working paper.

Gargano, A., Pettenuzzo, D., Timmermann, A., 2014. Bond return predictability: Economic value and links to the macroeconomy, Working Paper.

Ghysels, E., Horan, C., Moench, E., 2014. Forecasting through the rear-view mirror: Data revisions and bond return predictability, Federal Reserve Bank of New York Staff Reports No. 581.

Goyal, A., Welch, I., 2008. A comprehensive look at the empirical performance of equity premium prediction. The Review of Financial Studies 21 (4), 1455–1508.

Gürkaynak, R. S., Sack, B., Swanson, E. T., 2005. Do actions speak louder than words? the response of asset prices to monetary policy actions and statements. International Journal of Central Banking.

Gürkaynak, R. S., Sack, B., Wright, J. H., 2007. The U.S. treasury yield curve: 1961 to the present. Journal of Monetary Economics 54 (8), 2291–2304.

Hong, H. G., Sraer, D. A., Yu, J., 2016. Inflation bets on the long bond. The Review of Financial Studies.

Joslin, S., Priebsch, M., Singleton, K. J., 2014. Risk premiums in dynamic term structure models with unspanned macro risks. The Journal of Finance 69 (3), 1197–1233.

Jurado, K., Ludvgison, S. C., Ng, S., 2015. Measuring uncertainty. American Economic Review 105 (3), 1177–1216.

Kelly, B., Pástor, L., Veronesi, P., 2016. The price of political uncertainty: Theory and evidence from the option market. The Journal of Finance.

Kuttner, K. N., 2001. Monetary policy surprises and interest rates: Evidence from the fed funds futures market. Journal of Monetary Economics 47 (3), 523–544.

Litterman, R., Scheinkman, J., 1991. Common factors affecting bond returns. Journal of Fixed Income 1 (1), 54–61.

Ludvigson, S. C., Ng, S., 2009. Macro factors in bond risk premia. The Review of Financial Studies 22, 5027–5067.

McCracken, M. W., 2007. Asymptotics for out of sample tests of granger causality. Journal of Econometrics 140 (2), 719–752.

Mueller, P., Tahbaz-Salehi, A., Vedolin, A., 2016. Exchange rates and monetary policy uncertainty. The Journal of Finance.

Nelson, C. R., Siegel, A. F., 1987. Parsimonious modeling of yield curves. Journal of Business 60 (4), 473–489.

Pástor, L., Veronesi, P., 2012. Uncertainty about government policy and stock prices. The Journal of Finance 67 (4), 1219–1264.

Pástor, L., Veronesi, P., 2013. Political uncertainty and risk premia. Journal of Financical Economics 110(3), 520–545.

Rapach, D., Zhou, G., 2013. Forecasting stock returns. In: Elliott, G., Timmermann, A. (Eds.), Handbook of Economic Forecasting. Vol. 2, Part A of Handbook of Economic Forecasting. Elsevier, Ch. 6, pp. 328–383.

Sarno, L., Schneider, P., Wagner, C., 2016. The economic value of predicting bond risk premia. Journal of Empirical Finance 37, 247–267.

Stock, J. H., Watson, M. W., 2010. Dynamic factor models. In: Clements, M. P., Hendry, D. (Eds.), Oxford Handbook of Economic Forecasting. Oxford University Press, Ch. 2, pp. 35–59.

Svensson, L. E. O., 1994. Estimating and interpreting forward interest rates: Sweden 1992-1994, NBER Working Paper No. 4871.

Thornton, D. L., Valente, G., 2012. Out-of-sample predictions of bond excess returns and forward rates: An asset allocation perspective. The Review of Financial Studies 25 (10), 3141–3168.

Ulrich, M., 2013. How does the bond market perceive government interventions? Columbia Business School Research Paper.

West, K. D., 1996. Asymptotic inference about predictive ability. Econometrica, 1067–1084.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica: Journal of the Econometric Society, 817–838.

Wright, J. H., 2011. Term premia and inflation uncertainty: Empirical evidence from an international panel dataset. American Economic Review 101, 1514–1534.

Figure 1: **Time series dynamics of the MPU_t factor.**
This figure displays the evolvement of MPU_t over the period of January 1985 till Dec 2014, along with the times of Black Monday, the September 11 attacks, the March 2003 invasion of Iraq, the lead-up to the global financial crisis and announcements of QE I and II, and the Taper Tantrum.

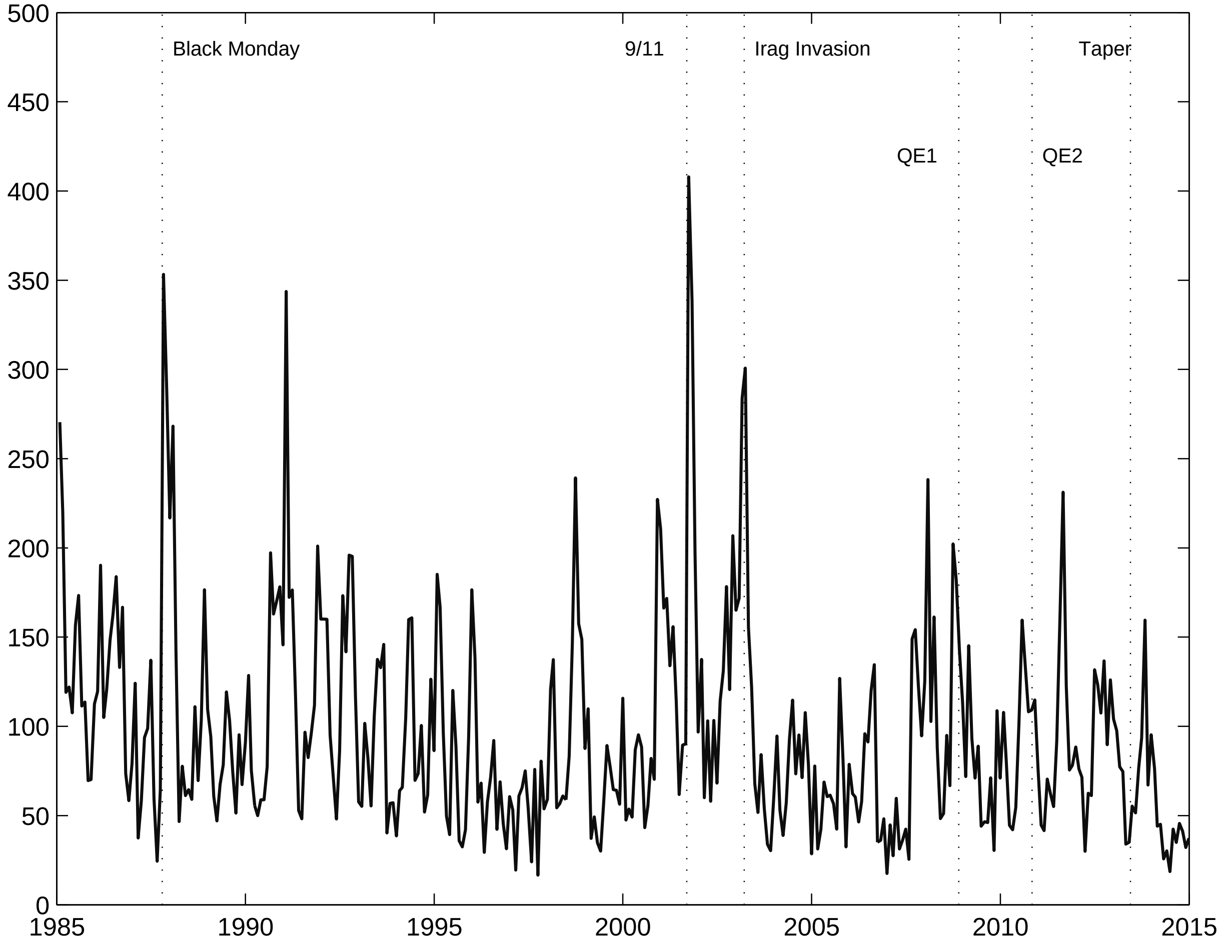

Figure 2: **Differences in cumulative squared prediction errors.**
This figure illustrates the relative forecasting performance on monthly returns of Treasury Bills and Bonds by plotting the difference in cumulative squared prediction errors between the candidate forecasting model and the expectations hypothesis (EH) model over the out-of-sample evaluation period, which covers the period from 2000:m1 to 2014:m12. National Bureau of Economic Research (NBER) recession periods are marked in gray shading.

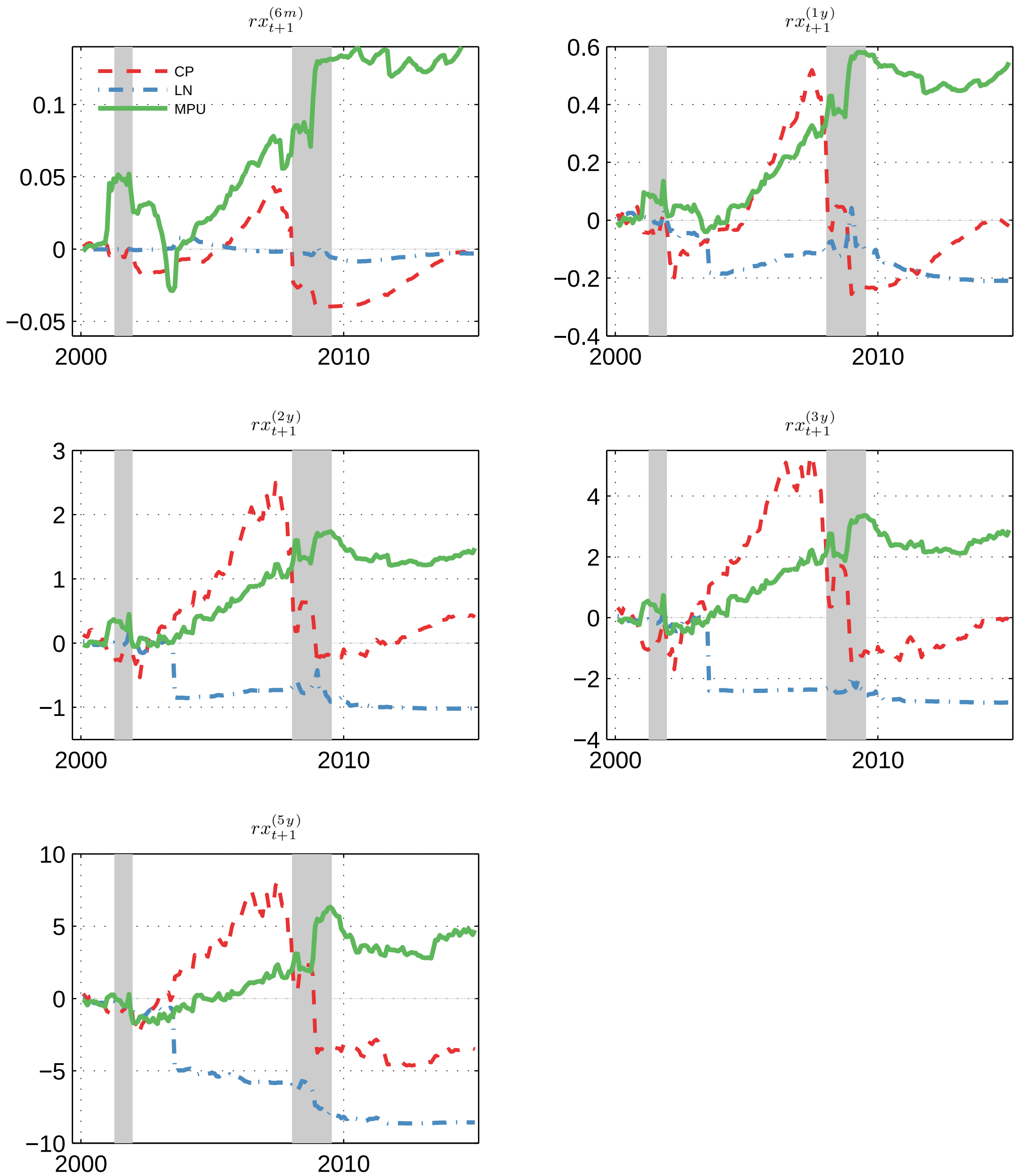

Figure 3: **Cumulative trading rules profits.**
This figure illustrates the cumulative profits of a simple real time trading rule which adopts a forecast $E_t[rx]_{t+1}^{(n)}$ as the size of a position that is subject to the ex-post return $rx_{t+1}^{(n)}$. Each line plots the trading profit of a strategy that uses forecasts based on either expectation hypothesis, EH_t; the forward rate-based factor from Cochrane and Piazzesi (2005), CP_t, the macro-based factor from Ludvigson and Ng (2009), LN_t or the monetary policy uncertainty index as described in Baker, Bloom, and Davis (2016), MPU_t. Trading period ranges from 2000:m1 to 2014:m12. National Bureau of Economic Research (NBER) recession periods are marked in gray shading.

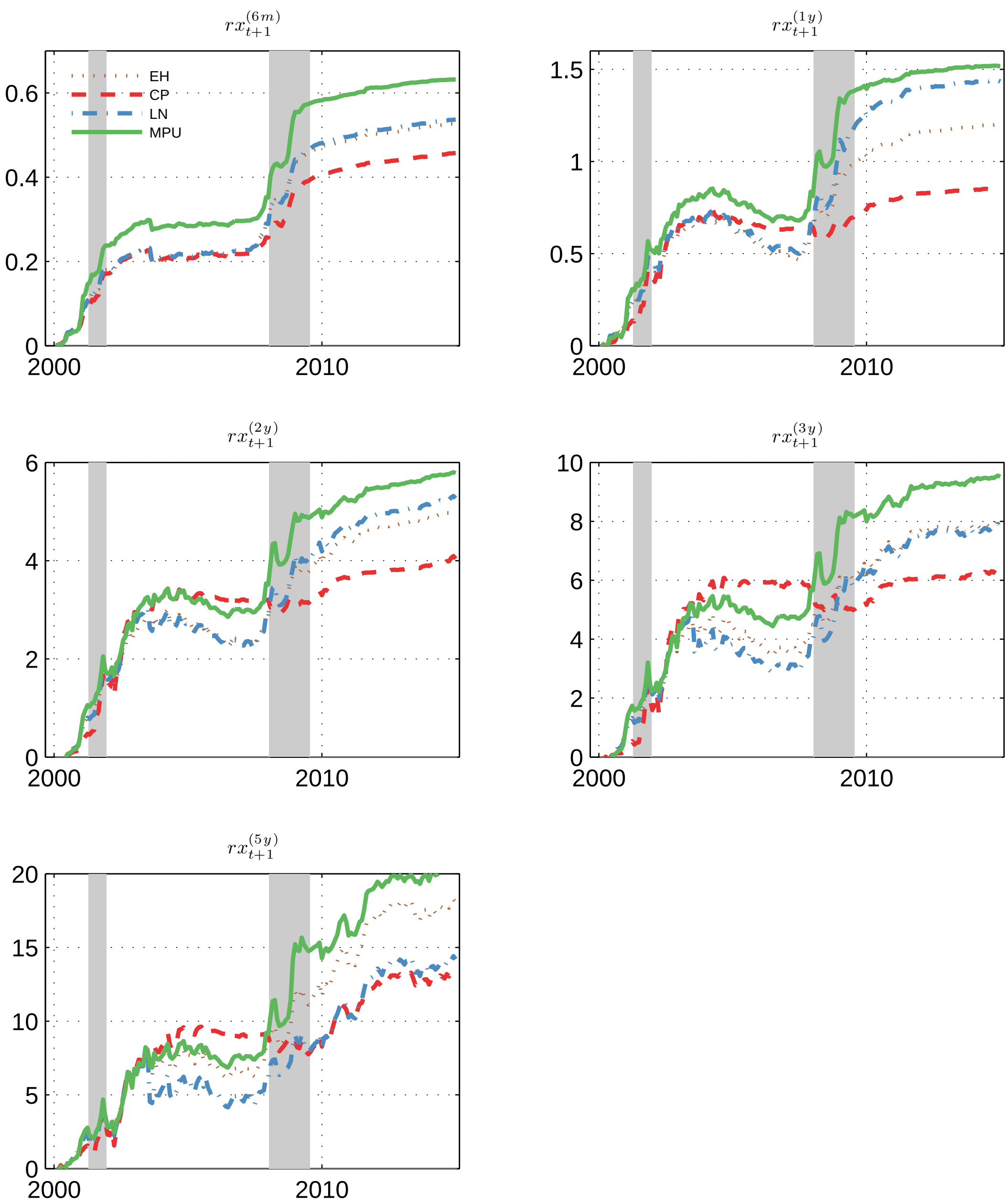

Table 1. Descriptive statistics: Bond risk premium and forecasting factors.

This table reports descriptive statistics for monthly Treasury excess returns $rx^{(n)}_{t+1/12}$, $n = 6$ month and $1, 2, 3$ and 5 years and predictor variables used in the empirical analyses (Panel A) and their contemporaneous correlations (Panel B). CP_t is the forward rate-based factor from Cochrane and Piazzesi (2005), LN_t is the macro-based factor from Ludvigson and Ng (2009), and MPU_t represents the monetary policy uncertainty index. For each variable, we report means, standard deviations, skewness, and kurtosis as well as first- and second-order autocorrelations. In addition, we report Sharpe ratios (SR) for each of the Treasury bonds. Note that predictors are standardized and the sample covers the period from 1985:m1 to 2014:m12.

	$rx^{(6m)}_{t+1}$	$rx^{(1y)}_{t+1}$	$rx^{(2y)}_{t+1}$	$rx^{(3y)}_{t+1}$	$rx^{(5y)}_{t+1}$	CP_t	LN_t	MPU_t
	Panel A: Descriptive statistics							
Mean	0.06	0.09	0.17	0.21	0.31	0.00	0.00	-0.03
Std	0.10	0.25	0.56	0.89	1.54	1.00	1.00	0.88
Skewness	1.19	0.85	0.22	-0.01	-0.03	0.55	1.89	0.99
Kurtosis	8.35	5.41	3.85	3.34	3.33	3.84	8.71	3.36
AC(1)	0.28	0.16	0.19	0.17	0.11	0.87	0.86	0.62
AC(2)	0.15	0.05	-0.03	-0.02	-0.07	0.78	0.85	0.36
SR	0.58	0.36	0.30	0.23	0.20	-	-	-
	Panel B: Correlation matrix							
$rx^{(6m)}_{t+1}$	1.00							
$rx^{(1y)}_{t+1}$	0.78	1.00						
$rx^{(2y)}_{t+1}$	0.70	0.90	1.00					
$rx^{(3y)}_{t+1}$	0.65	0.85	0.98	1.00				
$rx^{(5y)}_{t+1}$	0.57	0.78	0.92	0.96	1.00			
CP_t	0.10	0.15	0.13	0.12	0.05	1.00		
LN_t	0.13	0.15	0.13	0.13	0.10	-0.17	1.00	
MPU_t	0.30	0.20	0.14	0.13	0.10	0.15	0.19	1.00

Table 2. Spanning condition for monetary policy uncertainty MPU.

This table reports slope estimates from the spanning tests of MPU upon the principal components of the yield covariance matrix. The first three principal components are denoted as level_t, slope_t and curv_t factors, and the fourth and fifth component are recorded as $\mathscr{Y}_{4,t}$, and $\mathscr{Y}_{5,t}$ factors. Entries here include the estimated regression coefficients, the White (1980) t-statistics, and the adjusted R^2 values. Although not reported, all regressions contain an intercept. The sample period starts in 1985:m1 and ends in 2014:m12.

	level_t	slope_t	curv_t	$\mathscr{Y}_{4,t}$	$\mathscr{Y}_{5,t}$	R^2 (%)
(a)	0.10	0.14	-0.22			9.15
	(2.17)	(3.08)	(-4.95)			
(b)	0.10	0.14	-0.21	0.15	0.06	12.07
	(2.12)	(3.24)	(-4.99)	(3.20)	(1.26)	

Table 3. In-sample predictive power of MPU.

This table presents the in-sample predictive regressions results for monthly Treasury excess returns $rx^{(n)}_{t+1/12}$, $n = 6$ month and $1, 2, 3$ and 5 years, upon the monetary policy uncertainty index, MPU_t. Entries here are the estimated slope coefficients (β_p), the White (1980) t-statistics (t-stat), and the adjusted R^2 value. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively for standard two sided tests. Sample spans over the period of 1985:m1 through 2014:m12.

	$rx^{(n)}_{t+1/12} = \alpha + \beta_p MPU_t + \varepsilon_{t+1/12}$		
Maturity (n)	β_p	**t-stat**	R^2 **(%)**
6-month	3.47^{***}	(5.12)	8.45
1-year	5.71^{***}	(3.48)	3.69
2-year	9.12^{***}	(2.67)	1.79
3-year	13.09^{**}	(2.30)	1.39
5-year	17.33^{*}	(1.78)	0.70

Table 4. In-sample comparison with CP and LN factors.

This table compares the in-sample predictive power of monetary policy uncertainty index, MPU_t, with that of the Cochrane and Piazzesi (2005) (CP_t) and Ludvigson and Ng (2009) (LN_t) factors. Panel A presents the univariate predictive regression results for monthly Treasury bond excess returns $rx_{t+1/12}^{(n)}$, $n = 6$ month and $1, 2, 3$ and 5 years, upon CP_t or LN_t factors. Panel B reports the bivariate predictive regressions results that incorporate the MPU_t index. Entries here are the estimated slope coefficients on CP_t or LN_t, (β), and on MPU_t, (β_p), along with the White (1980) t-statistics ($t-stat$), and the adjusted R^2 values. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively for standard two sided tests. Sample spans over the period of 1985:m1 through 2014:m12.

	A: CP or LN factors $rx_{t+1/12}^{(n)} = \alpha + \beta X_t + \varepsilon_{t+1/12}$			B: With MPU $rx_{t+1/12}^{(n)} = \alpha + \beta X_t + \beta_p MPU_t + \varepsilon_{t+1/12}$				
X	β	**t-stat**	R^2**(%)**	β	**t-stat**	β_p	**t-stat**	R^2**(%)**
				n: 6-month				
CP	1.00	(1.45)	0.65	0.56	(0.82)	3.38***	(4.87)	8.49
LN	1.32**	(2.25)	1.35	0.76	(1.37)	3.30***	(4.72)	8.72
				n: 1-year				
CP	3.74**	(2.22)	1.91	3.07*	(1.81)	5.20***	(3.07)	4.87
LN	3.68***	(2.58)	1.84	2.81**	(2.01)	5.10***	(3.04)	4.61
				n: 2-year				
CP	7.48**	(2.26)	1.52	6.44*	(1.92)	8.05**	(2.28)	2.82
LN	7.28**	(2.36)	1.42	5.95*	(1.95)	7.82**	(2.24)	2.62
				n: 3-year				
CP	11.11**	(2.15)	1.27	9.63*	(1.86)	11.48**	(1.97)	2.25
LN	11.94**	(2.51)	1.51	10.09**	(2.14)	10.87*	(1.88)	2.34
				n: 5-year				
CP	7.37	(0.81)	-0.05	5.24	(0.57)	16.46*	(1.66)	0.54
LN	15.06*	(1.68)	0.68	12.58	(1.41)	14.57	(1.47)	1.07

Table 5. Out-of-sample predictive power of MPU.

This Table presents the out-of-sample predictive regressions results for monthly Treasury bond excess returns $rx^{(n)}_{t+1/12}$, $n = 6$ month and $1, 2, 3$ and 5 years, upon the monetary policy uncertainty index, MPU_t. Entries here are the out-of-sample R^2_{OS} against the historical average benchmark, the Clark and West (2007)'s MSFE-adjusted statistic, and the p-values on whether the R^2_{OS} is significantly positive. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Prediction relies on a recursive scheme and the out-of-sample periods span over 2000:m1 through 2014:m12.

	$rx^{(n)}_{t+1/12} = \alpha + \beta_p MPU_t + \varepsilon_{t+1/12}$		
Maturity (n)	R^2_{OS}**(%)**	**MSFE-adj**	**P-value**
6-month	8.74^{***}	3.39	0.00
1-year	6.96^{***}	3.22	0.00
2-year	3.59^{***}	2.59	0.00
3-year	2.52^{**}	2.16	0.02
5-year	1.32^{*}	1.48	0.07

Table 6. Out-of-Sample comparison with CP and LN factors.

This table compares the out-of-sample predictive power of monetary policy uncertainty index, MPU_t, with that of the Cochrane and Piazzesi (2005) (CP_t) and Ludvigson and Ng (2009) (LN_t) factors for monthly Treasury excess return. Panel A presents the predictive regression results for monthly Treasury excess returns $rx_{t+1/12}^{(n)}$, $n = 6$ month and $1, 2, 3$ and 5 years, upon CP_t, LN_t or their combination. Panel B reports the results for predictive regressions that incorporate the MPU_t index. Entries here are the out-of-sample R^2_{OS} against the historical average benchmark (Panel A) or the CP_t and LN_t based forecasts (Panel B), the Clark and West (2007)'s MSFE-adjusted statistic, and the p-values on whether the R^2_{OS} is significantly positive. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Prediction relies on a recursive scheme and the out-of-sample periods span over 2000:m1 through 2014:m12.

	A: CP or LN factors $rx_{t+1/12}^{(n)} = \alpha + \beta X_t + \varepsilon_{t+1/12}$			B: With MPU $rx_{t+1}^{(n)} = \alpha + \beta X_t + \beta_p MPU_t + \varepsilon_{t+1}$		
X	R^2_{OS}**(%)**	**MSFE-adj**	**P-value**	R^2_{OS}**(%)**	**MSFE-adj**	**P-value**
			n: 6-month			
CP	-0.30	0.40	0.34	8.48^{***}	2.65	0.00
LN	-0.17	0.02	0.49	9.37^{***}	3.89	0.00
CP+LN	-0.71	0.33	0.37	9.05^{***}	3.09	0.00
			n: 1-year			
CP	-0.26	1.03	0.15	6.59^{***}	2.27	0.01
LN	-2.68	-0.21	0.58	7.62^{***}	4.14	0.00
CP+LN	-1.59	1.01	0.16	6.55^{***}	2.88	0.00
			n: 2-year			
CP	0.98^{*}	1.30	0.10	3.06^{**}	1.79	0.04
LN	-2.48	-0.78	0.78	4.08^{***}	2.98	0.00
CP+LN	-0.83	0.96	0.17	3.15^{*}	2.15	0.02
			n: 3-year			
CP	-0.08	1.07	0.14	2.15^{*}	1.55	0.06
LN	-2.44	-0.97	0.83	2.89^{***}	2.51	0.01
CP+LN	-1.88	0.68	0.25	2.19^{**}	1.85	0.03
			n: 5-year			
CP	-0.98	0.12	0.45	1.22	1.17	0.12
LN	-2.39	-1.82	0.97	1.59^{**}	1.74	0.04
CP+LN	-3.28	-0.63	0.74	1.45^{*}	1.40	0.08

Table 7. Out-of-Sample predictability in NBER expansion and recession.

This table presents sub-sample analysis on the out-of-sample predictive power of monetary policy uncertainty index, MPU_t, Cochrane and Piazzesi (2005) (CP_t) factor and Ludvigson and Ng (2009) (LN_t) factor for monthly Treasury excess returns. Entries here are the out-of-sample R^2_{OS} against the historical average benchmark, the Clark and West (2007)'s MSFE-adjusted statistic, and the p-values on whether the R^2_{OS} is significantly positive. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Prediction relies on a recursive scheme and the out-of-sample periods span over 2000:m1 through 2014:m12.

	A: NBER Expansion			B: NBER Recession		
X	R^2_{OS}**(%)**	**MSFE-adj**	**P-value**	R^2_{OS}**(%)**	**MSFE-adj**	**P-value**
			n: 6-month			
MPU	9.73^{***}	2.98	0.00	7.43^{**}	1.94	0.03
CP	4.46^{**}	2.01	0.02	-6.59	-1.36	0.91
LN	0.04	0.18	0.43	-0.45	-0.30	0.62
			n: 1-year			
MPU	7.07^{***}	3.38	0.00	6.80^{*}	1.59	0.06
CP	10.48^{***}	3.10	0.00	-16.93	-1.28	0.90
LN	-4.75	-1.24	0.89	0.54	0.76	0.22
			n: 2-year			
MPU	4.34^{***}	2.93	0.00	2.03	1.01	0.16
CP	6.12^{***}	2.76	0.00	-9.71	-0.80	0.79
LN	-3.16	-0.87	0.81	-1.05	0.00	0.50
			n: 3-year			
MPU	2.91^{***}	2.59	0.00	1.58	0.72	0.24
CP	4.00^{***}	2.43	0.01	-9.93	-0.79	0.79
LN	-3.28	-1.04	0.85	-0.41	0.13	0.45
			n: 5-year			
MPU	0.62	1.19	0.12	3.36	1.09	0.14
CP	1.28^{*}	1.42	0.08	-7.62	-1.09	0.86
LN	-2.50	-1.52	0.94	-2.04	-1.11	0.87

Table 8. Predicting monthly Treasury excess returns with other uncertainty measures.

This table compares the in-sample predictive power of monetary policy uncertainty, MPU, with that of other uncertainty measures. The dependent variable is the average monthly excess returns of bonds with maturities $n = 6$ month and $1, 2, 3$ and 5 years, $\overline{rx_{t+1/12}}$. Panel A presents the estimation results in the univariate predictor case and that for the bivariate case which incorporates MPU is documented in Panel B. The macroeconomic uncertainty measures considered include the inter-quartile range of 1-year ahead inflation and real growth forecasts from Survey of Professional Forecasters (SPF), the macroeconomic uncertainty index in Jurado, Ludvgison, and Ng (2015), and the fiscal policy uncertainty indices, also constructed in Baker, Bloom, and Davis (2016). The financial market based uncertainty measures considered include the financial uncertainty index in Jurado, Ludvgison, and Ng (2015) and the VIX index obtained from CBOE. Entries here are the estimated slope coefficients on other uncertainty measures, (β), and on MPU_t, (β_p), along with the White (1980) t-statistics ($t - stat$), and the adjusted R^2 values. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively for standard two sided tests. Sample spans over the period of 1985:m1 through 2014:m12.

	A: Uncertainty factors $\overline{rx_{t+1/12}} = \alpha + \beta X_t + \varepsilon_{t+1/12}$			B: With MPU $\overline{rx_{t+1/12}} = \alpha + \beta X_t + \beta_p MPU_t + \varepsilon_{t+1/12}$				
Uncertainty	β	**t-stat**	R^2**(%)**	β	**t-stat**	β_p	**t-stat**	R^2**(%)**
	Macro Uncertainty							
CPI disagreement	6.34^{*}	(1.87)	0.68	5.43	(1.63)	9.04^{**}	(2.22)	1.91
GDP disagreement	1.94	(0.52)	-0.19	-0.91	(-0.24)	10.07^{**}	(2.36)	1.23
JLN Macro Uncertainty	6.33	(1.62)	0.44	4.81	(1.27)	8.95^{**}	(2.21)	1.62
JLN Finance Uncertainty	8.59^{**}	(2.40)	1.29	6.59^{*}	(1.75)	7.82^{*}	(1.83)	2.07
VIX	7.70^{*}	(1.86)	0.74	4.12	(0.91)	7.73^{*}	(1.82)	1.41
Fiscal Policy	3.40	(0.99)	-0.03	-3.84	(-1.00)	12.34^{***}	(2.64)	1.40

Table 9. Treasury bonds returns with GSW data and predictive power of *MPU* at different horizons.

This table presents the in-sample predictive regressions results for monthly and quarterly Treasury excess returns $rx^{(n)}_{t+h/12}$, $n = 6$ month and $1, 2, 3$ and 5 years, upon the monetary policy uncertainty index, MPU_t, using GSW data. Panel A and B document predictability of MPU_t at monthly (h=1) and quarterly (h=3) forecast horizons, respectively. Entries here are the estimated slope coefficients (β_p), the White (1980) t-statistics (t-stat), and the adjusted R^2 value. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively for standard two sided tests. Sample spans over the period of 1985:m1 through 2014:m12.

	A: Monthly Forecast Horizon $rx^{(n)}_{t+1/12} = \alpha + \beta_p MPU_t + \varepsilon_{t+1/12}$			B: Quarterly Forecast Horizon $rx^{(n)}_{t+3/12} = \alpha + \beta_p MPU_t + \varepsilon_{t+3/12}$		
Maturity (n)	β_p	**t-stat**	R^2**(%)**	β_p	**t-stat**	R^2**(%)**
6-month	5.75^{***}	(3.93)	4.25	1.71	(1.41)	0.37
1-year	9.75^{***}	(2.83)	2.08	1.64	(0.52)	-0.20
2-year	12.26^{**}	(2.23)	1.19	0.25	(0.05)	-0.28
3-year	14.22^{*}	(1.90)	0.79	-1.18	(-0.16)	-0.27
5-year	15.96^{*}	(1.69)	0.58	-2.37	(-0.25)	-0.26