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By

Philippe Mueller
Andrea Vedolin
Yu-Min Yen

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Philippe Mueller is a Lecturer in Finance at the London School of Economics and Political Science. He received his PhD in Finance and Economics from Columbia University in 2008. His research interests include: Asset Pricing, Macro-Finance, Financial Econometrics, Fixed Income, Monetary Policy, Banking. Andrea Vedolin is a lecturer in Finance at the London School of Economics and Political Science. She received her PhD in Economics from the University of Lugano in 2010. Her research interests include: Asset Pricing, Derivatives Pricing and Financial Econometrics. Yu-Min Yen is a PhD candidate in Finance at the London School of Economics. His research interests include: Financial Econometrics, Fixed Income security, Portfolio Choice, Dynamic Asset Pricing Models, Macro-Fnance and Macroeconomics.

Bond Variance Risk Premia*

Philippe Mueller
London School of Economics†

Andrea Vedolin
London School of Economics‡

Yu-Min Yen
London School of Economics§

Abstract

Using data from 1983 to 2010, we propose a new fear measure for Treasury markets, akin to the VIX for equities, labeled TIV. We show that TIV explains one third of the time variation in funding liquidity and that the spread between the VIX and TIV captures flight to quality. We then construct Treasury bond variance risk premia as the difference between the implied variance and an expected variance estimate using autoregressive models. Bond variance risk premia display pronounced spikes during crisis periods. We show that variance risk premia encompass a broad spectrum of macroeconomic uncertainty. Uncertainty about the nominal and the real side of the economy increase variance risk premia but uncertainty about monetary policy has a strongly negative effect. We document that bond variance risk premia predict excess returns on Treasuries, stocks, corporate bonds and mortgage-backed securities, both in-sample and out-of-sample. Furthermore, this predictability is not subsumed by other standard predictors.

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†Dept. of Finance, Houghton Street, London WC2A 2AE, UK, +44 20 7955 7012, p.mueller@lse.ac.uk.

‡Dept. of Finance, Houghton Street, London WC2A 2AE, UK, +44 20 7107 5017, a.vedolin@lse.ac.uk.

§Dept. of Finance, Houghton Street, London WC2A 2AE, UK, y.yen@lse.ac.uk.

During the recent financial crisis one sector generated significant profits for the leading investment banks: Volatility arbitrage trading in forex, fixed income, and commodities. According to a BIS (2010) survey on foreign exchange and derivatives markets activity, the interest rate derivatives market has grown by 24% over the last three years to reach an average daily turnover of USD 2.1 trillion. As a consequence, both market and academic interest in equity-index volatility measures and their associated risk premia has grown rapidly. For instance, the VIX index—also dubbed the "investors' fear index"—is believed to be a good proxy of aggregate uncertainty or risk aversion.[1] The VIX is also shown to be a good predictor for the cross-section of stocks (Ang, Hodrick, Xing, and Zhang, 2006), corporate credit spreads (Collin-Dufresne, Martin, and Goldstein, 2001) and bond excess returns (Baele, Bekaert, and Inghelbrecht, 2010). Furthermore, the associated variance risk premium extracted from equity markets predicts the equity premium (Drechsler and Yaron, 2011), as well as corporate credit spreads (Wang, Zhou, and Zhou, 2010). Given this extensive literature for equity markets, it is rather surprising that no effort has been undertaken to measure these risk premia in fixed income markets. Filling this gap is one goal of this paper.

The importance of understanding interest rate volatility and the risk premia associated with it is manifested in Figure 1, where we plot the Mortgage Bankers Association (MBA) Refinancing index together with the variance risk premium calculated from 30 year Treasury futures. The MBA refinancing index is based on the number of applications for mortgage refinancing. The figure nicely displays that mortgage refinancing is subject to distinct waves such as the peak of the housing boom in May 2003 or the bust during the most recent financial crisis. During these periods, the bond variance risk premium also peaks and it has moved almost in tandem with the MBA index since 2005. The intuition is relatively straightforward. If interest rates drop, the duration of any mortgage-backed security portfolio decreases due to a higher refinancing rate. To hedge the duration, the portfolio manager must either buy Treasury bonds or bond options. This hedging activity not only affects the price of the underlying but also its volatility (Duarte, 2008). Consequently, risk-averse investors demand a premium for the associated risks.

[1] See, e.g., Bollerslev, Gibson, and Zhou (2011), Korteweg and Polson (2010) and Bekaert, Hoerova, and Lo Duca (2011), among others.

[Insert Figure 1 approximately here.]

We contribute to the literature in the following ways. First, we construct a new measure of fear for Treasury markets (akin to the VIX for equities), which we label TIV for *Treasury Implied Volatility*.[2] Second, we construct and describe the term structure of bond variance risk premia for 30 year, 10 year and 5 year Treasury futures and investigate the underlying economic drivers of these risk premia. Finally, we document the strong predictive power of bond variance risk premia for excess returns on Treasury bonds, stocks, corporate bonds and mortgage-backed securities. The predictability is in-sample and out-of-sample and robust to the inclusion of other standard predictors.

To construct the TIV, we follow the recent literature and calculate implied variance measures using a model-free approach (Britten-Jones and Neuberger, 2000).[3] Moreover, we are the first to estimate and study a term structure of variance risk premia for the Treasury market. Even though there is ample evidence of priced variance risk in both the index and single stock equity market, we know surprisingly little about the compensation for variance risk in fixed income markets.

The variance risk premium is defined as the difference between the expected risk-neutral and physical variance. While the risk-neutral expectation can be estimated in a completely model-free fashion using a cross-section of options written on the underlying asset, the calculation of the objective expectation requires some mild auxiliary modeling assumptions. A priori, it is not clear, what the best proxy for this objective expectation should be. Andersen, Bollerslev, and Diebold (2007) show that simple autoregressive type models estimated directly for the realized volatility often perform better than parametric approaches designed to forecast the integrated volatility. In calculating our benchmark bond variance risk pre-

[2] We calculate both equity and bond implied volatilities using newly available high frequency data. The time-series for the TIV starts in 1983. In addition, we calculate our own VIX measure, also with a start date in 1983, thus considerably longer than the Chicago Board of Option Exchange (CBOE) VIX available since 1991.

[3] In addition, we also construct implied variance measures as in Martin (2011), using so called simple variance swaps. Whereas the replication of standard variance swaps relies on the Itô assumption which is violated in case there are jumps, simple variance swaps provide a genuine measure of implied variance under very general assumptions. While this distinction is important from a methodological perspective, the main results are robust to the choice of method.

mium, we thus use the HAR-TCJ model for realized variance proposed by Corsi, Pirino, and Renò (2010). We augment the model by including lagged implied variance as additional regressors.[4]

Using data from 1983 to 2010, we find that the implied volatility measures we derive in both equity and bond markets are remarkably similar, which is manifested in the high unconditional correlation of around 60% on average.[5] Increases in the VIX index are often dubbed as an increase in economic uncertainty. We find a similar pattern for the bond market. Implied volatility in bond markets spikes in crisis times and it therefore offers itself as a gauge of fear for fixed income markets. The construction of the TIV measure has an economic merit which goes beyond that of the VIX itself. First, we show that TIV is strongly related to proxies of funding liquidity. A one standard deviation change in the TIV implies more than half a standard deviation change in a funding liquidity proxy and spikes in the TIV can therefore be interpreted as shocks to funding liquidity. This empirical finding relates to the theoretical work of Brunnermeier and Pedersen (2009), who show that lower liquidity can lead to higher asset volatility. Moreover, the authors demonstrate that in periods of flight to quality, highly liquid assets are characterized by relatively low volatility. Thus, the spread between low and high volatility assets can explain part of the liquidity spread. In our empirical analysis, we find that the volatility spread between the VIX and the TIV provides a useful measure of flight to quality periods: While the spread is most of the time no more than 10%, it almost triples during the October 1987 crash, the LTCM default in August 1998, and the Lehman bankruptcy in September 2008.

While the co-movement between the time-series is high, the TIV and VIX differ in their magnitude. For our sample period, the average model-free implied volatility of the S&P 500 index is 20% with a standard deviation of 8.4, in contrast, the 30 year Treasury implied

[4]Recently, Bollerslev, Sizova, and Tauchen (2012) use a simple heterogenous autoregressive RV model to construct the stock market variance risk premium while Busch, Christensen, and Nielsen (2011) use the augmented HAR-RV model with lagged IV to improve forecasts of realized volatility. In the Online Appendix we show that the HAR-TCJ model with lagged IV performs best in predicting out-of-sample realized variance.

[5]The correlation between the implied volatility measures for 30 year Treasury futures and equities is as high as 69%, whereas the correlation between the implied volatility measures for 5 year Treasury futures and equities is around 53%.

volatility is 10% on average with a standard deviation of merely 2.4. Thus, in the case of the S&P 500 index, volatility risk accounts for a much larger proportion of overall risk than in Treasury markets. Despite the high co-movement, we find that variance risk premia in bond and equity markets can behave differently. While the variance risk premium in the equity market is essentially always positive (i.e., it acts as an insurance premium), the variance risk premium in the Treasury market can switch sign. To grasp a better intuition for this behavior, we study macroeconomic determinants of bond versus equity variance risk premia. Proxies of macroeconomic uncertainty from forecast data explain up to 45% of the time variation in bond and equity variance risk premia. Higher uncertainty usually implies a higher variance risk premium. However, uncertainty about short term yields (which can be interpreted as uncertainty about monetary policy actions) has a significant negative impact on bond variance risk premia. Larger uncertainty about the short end makes investors with negative expectations about future interest rates willing to buy long term bonds, because these provide a hedge against the increased duration due to a drop in short term yields. Hence, investors pay a premium for holding these bonds. Inline with recent findings (Joslin, 2010), we also document that the shape of the term structure significantly affects bond variance risk premia.

If bond variance risk premia encompass general macroeconomic uncertainty, do they contain any useful information about asset returns? A principal components analysis of the bond variance risk premia time series allows us to summarize the information in the term structure of bond variance risk premia in a parsimonious way. We show that the three principal components have economically significant predictive power for excess returns across different assets. The results can be summarized as follows: A one standard deviation change in the third principal component of Treasury bond variance risk premia, a curvature factor, induces a 0.17 standard deviation decrease in bond excess returns, while the same kind of shock has an opposite effect of roughly the same magnitude on stock market excess returns. A one standard deviation change in the second principal component, a slope factor, induces a 0.24 standard deviation increase in stock excess returns and up to half a standard deviation change in corporate bond and mortgage-backed securities excess returns. Finally, a one standard deviation shock to the first principal component, a level factor, has a strong positive effect on corporate bond and mortgage-backed securities excess returns. Bond variance risk premia explain roughly 3% of the time variation in Treasury excess returns, around 9% of stock excess returns and up to 35% of corporate and mortgage-backed securities excess returns.

When we add the equity variance risk premium to the regressions, the significance of the bond variance risk premia remains economically and statistically high, whereas the equity variance risk premium adds very little predictive power. We show that the predictability of bond variance risk premia prevails in-sample and out-of-sample and is robust to the inclusion of other standard predictors in the literature. We conclude that bond variance risk premia broadly capture uncertainty about the macroeconomy and monetary policy, as well as additional information about the term structure that is relevant for all asset classes. Moreover, bond variance risk premia have a great advantage over most of the other predictor variables that rely on either macroeconomic fundamentals or forecast data: They can be obtained on a daily basis (or at even higher frequencies) while the other variables are often only available at the monthly frequency at best.

Our paper is related to two strands of the literature. First, it fits into the large body of research that has focused on the stock market variance risk premium and—to a lesser degree—on variance risk premia of individual stocks or commodities.[6] To the best of our knowledge, our paper is the first to study variance risk premia in the Treasury market.

One reason why variance risk in fixed income markets has been neglected in the past could be that standard dynamic term structure models assume that the fixed income market is complete and therefore, interest rate derivatives are redundant assets. Only recently, there is emerging (albeit sometimes mixed) evidence for the existence of unspanned stochastic volatility, the second body of research that is related to our paper.[7]

[6]For literature on the stock market variance risk premium, see, e.g., Driessen, Maenhout, and Vilkov (2009), Bollerslev, Gibson, and Zhou (2011), Carr and Wu (2009), Cremers, Halling, and Weinbaum (2010) and Todorov (2010), among others. Bakshi and Kapadia (2003) and Vedolin (2010) for example study the variance risk premia of individual stocks and Trolle and Schwartz (2009) investigate variance risk premia in commodity markets.

[7]Joslin (2010) studies the variance risk premium using swap data and proposes a model that under certain restrictions can generate unspanned stochastic volatility. Additionally, see Collin-Dufresne and Goldstein (2002), Heidari and Wu (2003), Casassus, Collin-Dufresne, and Goldstein (2005), Collin-Dufresne, Goldstein,

To summarize, in this paper, we provide new empirical facts about variance risk premia in the fixed income markets. We construct a term structure of Treasury bond variance risk premia and investigate its determinants. In addition, we document the strong predictive power for a wide range of assets. However, we remain agnostic about the form of structural model that could rationalize our findings and leave this for future research.

The rest of the paper is organized as follows. Section I. describes our data set and Section II. describes the econometric methods used to estimate the TIV measure and the variance risk premia. Section III. presents the results of our empirical study and Section IV. concludes. To save space, we defer additional data description, alternative methods to estimate implied and realized variance, and robustness checks to the Online Appendix.[8]

I. Data

In this section, we briefly introduce the data used in our analysis. Firstly, we use futures and options data to construct the bond and equity variance risk premia. Secondly, we calculate excess returns for Treasury, stock, corporate bond and mortgage-backed securities portfolios. Finally, we use a large set of macro and forecast data as controls to explore the determinants and the predictive power of the variance risk premia. The summary statistics for excess returns and additional variables are contained in the Online Appendix.

A. Futures and Options Data

Treasury Futures and Options: To calculate implied and realized variance measures for Treasury bonds, we use futures and options data from the Chicago Mercantile Exchange (CME). We use high-frequency intra-day price data of the 30 year Treasury bond futures, the 10 year and 5 year Treasury notes futures and end-of-day prices of options written on the underlying futures. The data runs from October 1982, May 1985 and May 1990 to June 2010

and Jones (2008), Bibkov and Chernov (2009), Trolle and Schwartz (2009), Andersen and Benzoni (2010) and Almeida, Graveline, and Joslin (2010) among others.

[8]The Online Appendix is available on the authors' webpage.

for the 30 year, 10 year, and 5 year Treasury bond futures and options, respectively. Using a monthly frequency throughout the paper, we have at most 333, 302, and 242 observations available, respectively.

Treasury futures are traded electronically as well as by open outcry. While the quality of electronic trading data is higher, the data only becomes available in August 2000. To maximize our time span, we use data from electronic as well as pit trading sessions. We only consider trades that occur during regular trading hours (07:20–14:00) when the products are traded side-by-side in both markets.[9]

The contract months for the Treasury futures are the first three (30 year Treasury bond futures) or five (10 year and 5 year Treasury notes futures) consecutive contracts in the March, June, September, and December quarterly cycle. This means that at any given point in time, up to five contracts on the same underlying are traded. To get one time series, we roll the futures on the 28^{th} of the month preceding the contract month.

For options, the contract months are the first three consecutive months (two serial expirations and one quarterly expiration) plus the next two (30 year futures) or four (10 year and 5 year futures) months in the March, June, September, and December quarterly cycle. Serials exercise into the first nearby quarterly futures contract, quarterlies exercise into futures contracts of the same delivery period. We roll our options data consistent with the procedure applied to the futures.[10]

S&P 500 Index Futures and Options: Inline with our approach for Treasuries, we calculate the implied and realized variance measures for the stock market using futures and options on the S&P 500 index from CME. The sample period is from January 1983 to June 2010.[11]

[9]Liquidity in the after-hours electronic market is significantly smaller than during regular trading hours.

[10]Detailed information about the contract specifications of Treasury futures and options can be found on the CME website, www.cmegroup.com.

[11]We compare our results to the VIX and VXO measures that are calculated using options on the S&P 500 cash index instead of S&P 500 index futures. The VIX is the implied volatility calculated using a model-free approach, whereas the VXO is calculated using the Black and Scholes (1973) implied volatility. The VIX is available starting in January 1990 and the VXO is available since January 1986. Over the common sample period, the VIX and our implied volatility measure from index futures options using the same methodology have a correlation of over 99.4% and the root mean squared error is below 1%.

B. *Excess Returns Data*

Treasury Bonds: We use the Fama-Bliss discount bond database from CRSP to calculate annual Treasury bond excess returns for two to five year bonds. We denote the return on a τ-year bond with log price $p_t^{(\tau)}$ by $r_{t+1}^{(\tau)} = p_{t+1}^{(\tau-1)} - p_t^{(\tau)}$. The annual excess bond return is defined as $rx_{t+1}^{(\tau)} \equiv r_{t+1}^{(\tau)} - y_t^{(1)}$, where $y_t^{(1)}$ is the one year yield.

Stocks: To proxy for the market portfolio, we use the value-weighted index from CRSP. The growth and value portfolio returns are constructed using the six portfolios formed on size and book-to-market from Ken French's data library. The respective returns are the average of the returns of the small and big growth and value portfolio, respectively. The three, six and twelve month excess returns are defined as the cumulative return on the respective portfolio minus the Treasury yield.

Corporate Bonds and CMBS: We use corporate bond and commercial mortgage-backed securities (CMBS) indices from Barclays Capital to calculate three, six and twelve month excess returns. We use AAA, BBB, and CCC indices for long and intermediate corporate bonds and AAA, BBB, and B indices for CMBS. CMBS data is available starting in 1997.

C. *Other Data*

Forecasts: We use forecast data from BlueChip Economic Indicators (BCEI) to calculate proxies of uncertainty about macroeconomic variables. BCEI collects monthly forecasts of twelve key financial and macroeconomic indicators from about fifty professional economists in leading financial and economic advisory firms.[12] The forecasts are made for different time horizons. This data exhibits strong seasonality and thus, we adjust the series using a 12-period ARIMA filter. We use the cross sectional standard deviation of the filtered panel data within each month as the monthly gauge of uncertainty. We calculate the time series of

[12]The twelve series are the real gross domestic product (RGDP), the GDP chained price index (GDPI), the consumer price index (CPI), industrial production (IP), real disposable personal income (DPI), non-residential investment (NRI), the unemployment rate (UNEM), housing starts (HS), corporate profits (CP), total US auto and truck Sales (AS), the three-month secondary market T-bill rate (SR) and the ten year constant maturity Treasury yield (LR).

the cross sectional standard deviation using the forecasts for the current and the subsequent calendar year for each forecast variable i. Thus, for each variable we have two time series reflecting the uncertainty of the forecaster. Our uncertainty proxy $\widehat{U}^i$ is the first principal component extracted from these two time series.[13] In our analysis, we use uncertainty about the real (RGDP) and the nominal (CPI) side of the economy, as well as uncertainty about short and long rates (SR and LR), where $\widehat{U}^{SR}$ can also be interpreted as uncertainty about monetary policy. The forecast data is available until December 2009.

Macroeconomic Factors: We compute the eight static macroeconomic factors $\widehat{F}_j, j = 1\ldots, 8$, from Ludvigson and Ng (2009, 2011) for an updated data set through June 2010.[14] We also estimate volatility proxies for inflation and consumption, σ_π and σ_g. We calculate these by estimating a GARCH process for monthly CPI inflation and consumption (non-durables and services). The data is from Global Insight and the Federal Reserve Economic Data base (FRED).

Additional Variables: Using the Fama-Bliss data, we also construct a tent-shaped factor from forward rates, the Cochrane and Piazzesi (2005) factor, CP. Furthermore, we calculate the slope of the term structure as the difference between the ten year and the one month Treasury yield (SLOPE). In addition, we use the log dividend yield (DY), the log earnings/price ratio (E/P), and the net equity expansion (NTIS) from Goyal and Welch (2008), and REF, the Mortgage Bankers Association refinancing index.

[13]As the principal components are latent, we ensure that the first principal component is positively correlated with the two uncertainty proxies.

[14]The original data set was previously used in Stock and Watson (2002). Some of the macroeconomic variables are no longer available after 2007. Consequently, we use 125 instead of 132 macroeconomic time series. In addition, we exclude all stock market and interest rate time series and work with a set of 104 variables. We also use the full data set with 125 variables and the original factors for shorter sample period ending in 2007 as a robustness check. Our results remain unchanged. A detailed description of the macroeconomic data is provided in the Online Appendix.

II. Estimation of Bond Variance Measures and Variance Risk Premia

In this section, we describe the methods used to estimate the expected risk-neutral and objective variance, $\mathbb{E}_t^{\mathbb{Q}}\left(\int_t^T \sigma_u^2 du\right)$ and $\mathbb{E}_t^{\mathbb{P}}\left(\int_t^T \sigma_u^2 du\right)$, and the variance risk premium, defined as the difference between the two.[15]

Moreover, we define a *Treasury Implied Volatility* or TIV measure in the spirit of the well known VIX index that is calculated by CBOE for the S&P 500 index. Our proposed TIV measure is the 30 year Treasury bond futures implied volatility, i.e. the square root of the implied variance.[16] We calculate a daily TIV measure going back to October 1982.[17]

A. *Implied Variance*

As is commonly done, we use options to back out a proxy for the expected variance under the risk-neutral measure, $\mathbb{E}_t^{\mathbb{Q}}\left(\int_t^T \sigma_u^2 du\right)$.[18] We implement a model-free method as proposed by Britten-Jones and Neuberger (2000) that only requires current option prices to calculate the implied variance (subsequently denoted MIV).

One well-established application of the model-free implied variance is the VIX, which is an index of implied volatility (i.e. the square root of the MIV) calculated using options on the S&P 500. Neuberger (1994) shows that the VIX corresponds to the quadratic variation of the forward price of the S&P 500 index under the risk-neutral measure. One issue with

[15]We present and discuss additional methods to estimate expected variance in the Online Appendix. Overall, our empirical results are robust to using reasonable alternative methods to what is described in this section.

[16]Unlike the 10 year and 5 year instruments, the 30 year Treasury futures and options have the longest available history and they are very liquid even in the 1980s.

[17]The time series for the TIV measure will be made available on the authors' website. As mentioned in Section I., we construct our own VIX measure, which is based on options on S&P 500 index futures rather than on the underlying cash index. This allows us to obtain a longer time series as options data on S&P 500 index futures date back to the 1980s with high trading volumes, whereas the VIX only starts in 1990.

[18]The simplest way to calculate the implied variance would be to invert the standard Black (1976) formula (we denote the implied variance from this method BIV). Black's model is often used to value interest rate options. Busch, Christensen, and Nielsen (2011) for example use this measure to study the forecasting power of implied volatility for realized volatility of Treasury bond futures. However, one of the relevant assumptions underlying the model is constant volatility, which is inconsistent with the application to forecasting changes in volatility. Nevertheless, the empirical results are qualitatively robust to using the BIV measure instead of a model-free approach.

the replication of the variance swap is that it heavily relies on the Itô assumption for the underlying process. In the presence of skewness, Carr and Lee (2009) show that the VIX will be upward biased compared to the true risk-neutral quadratic variation. Martin (2011) introduces the simple variance swap for which the realized leg can be computed from simple returns of the underlying index and the index forward. He shows that—just as the VIX—the SVIX can also be approximated as a portfolio of out-of-the-money options and can be constructed under slightly weaker assumptions and in the presence of jumps.[19]

To implement the methods for calculating the implied variance for options on Treasury futures, we treat the American options as European.[20] Furthermore, we assume that the short risk-free rate is non-stochastic (or at least not too volatile) such that the forward and futures prices coincide.[21]

To calculate the model-free implied variance, MIV, we then follow Demeterfi, Derman, Kamal, and Zhou (1999) and Britten-Jones and Neuberger (2000). They show that if the underlying asset price is continuous, the risk-neutral expectation of total return variance is defined as an integral of option prices over an infinite range of strike prices. Since in practice, the number of traded options for any underlying asset is finite, the available strike price series is a finite sequence. Denote $\mathsf{C}(T, K)$ the spot call price with strike price K expiring at time T. Suppose the available strike prices of the call options belong to $\left[\underline{K}^{\mathsf{C}},\ \overline{K}^{\mathsf{C}}\right]$, where $\overline{K}^{\mathsf{C}} \geq \underline{K}^{\mathsf{C}} \geq 0$. As shown in Jiang and Tian (2005), a truncated version of the integral over

[19]For robustness checks, we also implement this method and denote the resulting implied variance measure SIV. Again, results are robust. Summary statistics are provided in the Online Appendix.

[20]Jorion (1995) shows that early exercise premia are small for short maturity at-the-money options on futures, while Overdahl (1988) demonstrates that early exercise of options on Treasury futures happens about 0.1% of the time and happens both with calls and puts but only with options that are significantly in the money. In the empirical implementation, we use only out-of-the money options and thus assume that the early exercise option will not distort the option price.

[21]Similar to the issue with the Black (1976) implied volatility, this is a slight inconsistency in the approach as interest rates are clearly assumed to be stochastic when it comes to calculating the payoff of the option (which is written on a futures contract that is dependent on an underlying interest rate process). However, the assumption we have to make to implement the method concerns the short risk-free rate and not directly the interest rate underlying the Treasury futures option.

the infinite range of strike prices can be used to evaluate the model-free implied volatility. We use the trapezoidal rule to numerically calculate the integral:

$$2\int_{\underline{K}^{\mathsf{C}}}^{\overline{K}^{\mathsf{C}}} \frac{\mathsf{C}\,(T,K) - \max\,(0,F_t - K)}{K^2} dK \approx \frac{\overline{K}^{\mathsf{C}} - \underline{K}^{\mathsf{C}}}{m} \sum_{i=1}^{m} \left[g_{t,T}\left(K_i^{\mathsf{C}}\right) + g_{t,T}\left(K_{i-1}^{\mathsf{C}}\right)\right],$$

where

$$g_{t,T}\left(K_i^{\mathsf{C}}\right) = \frac{\mathsf{C}\left(T,K_i^{\mathsf{C}}\right) - \max\left(0,F_t - K_i^{\mathsf{C}}\right)}{\left(K_i^{\mathsf{C}}\right)^2}, \tag{1}$$

F_t is the forward price and K_i^{C} is the i^{th} largest strike price for the call option. To implement the trapezoidal rule, we now need the option prices $\mathsf{C}\left(T,K_i^{\mathsf{C}}\right)$, for $i = 1,\ldots,m$. Since some of these prices are not available, we apply a cubic spline interpolation method as proposed in Forsythe, Malcolm, and Moler (1977) to obtain the missing values.[22]

Then,

$$\mathrm{MIV}_{t,\tau} = \frac{\overline{K}^{\mathsf{C}} - \underline{K}^{\mathsf{C}}}{m} \sum_{i=1}^{m} \left[g_{t,T}\left(K_i^{\mathsf{C}}\right) + g_{t,T}\left(K_{i-1}^{\mathsf{C}}\right)\right], \tag{2}$$

where $\tau = T - t$ denotes the time horizon or time to maturity. As mentioned above, we replace F_t in equation (1) by the futures price. Since in-the-money options are less liquid, equation (2) is evaluated for out-of-the money options whose strike prices are no less than $0.94 \times F_t$ (calls) or no bigger than $1.06 \times F_t$ (puts).[23] Finally, we set $m = 100$ and restrict $\mathrm{MIV}_{t,\tau} = 0$ when $t = T$.

We estimate the MIV at the end of each month for a $\tau = 30$ day horizon to get our monthly time series, denoted $\mathrm{MIV}_t^{(i)}$, where $i = \{30y, 10y, 5y, E\}$ stands for either the 30 year, 10 year of 5 year Treasuries or the equity index.[24]

[22] Jiang and Tian (2005) take a different approach: They first calculate the implied volatilities of available options with the Black and Scholes formula, and then use the interpolation method to obtain the Black and Scholes implied volatilities of the unavailable options. Using these implied volatilities, they use the Black and Scholes formula again to obtain a continuum of option prices. They claim that their method can avoid the nonlinearity problem in the option prices. However, we find a direct use of the interpolation method on the option prices to be more robust.

[23] Following Jiang and Tian (2005) we use out-of-the-money puts to get prices for the in-the-money calls.

[24] Note that we drop the subscript τ as we focus on the monthly horizon.

B. Realized Variance

To estimate $\mathbb{E}_t^{\mathbb{P}}\left(\int_t^T \sigma_u^2 du\right)$, the daily expected variance under the physical measure, we first consider the daily realized variance $\mathrm{RV}_{t,1\mathrm{d}}$, which is defined as:

$$\mathrm{RV}_{t,1\mathrm{d}} = \sum_{i=1}^{M} r_{t,i}^2,$$

where $r_{t,i} = \log P(t-1+i/M) - \log P(t-1+(i-1)/M)$ is the intra-daily log return in the i^{th} sub-interval of day t and $P\,(t-1+i/M)$ is the asset price at time $t-1+i/M$. For each day, we take $r_{t,i}$ between 7:25 and 14:00. Inline with Andersen, Bollerslev, and Diebold (2007), we use five minute intervals to calculate $\mathrm{RV}_{t,1\mathrm{d}}$.

The normalized monthly realized variation $\mathrm{RV}_{t,1\mathrm{m}}$ is defined by the average of the 21 daily measures.[25] The normalized weekly realized variation $\mathrm{RV}_{t,1\mathrm{w}}$ is correspondingly defined by the average of the five daily measures:

$$\mathrm{RV}_{t,1\mathrm{w}} = \frac{1}{5}\sum_{j=0}^{4} \mathrm{RV}_{t-j,1\mathrm{d}}, \quad \text{and} \quad \mathrm{RV}_{t,1\mathrm{m}} = \frac{1}{21}\sum_{j=0}^{20} \mathrm{RV}_{t-j,1\mathrm{d}}.$$

To better capture the long memory behavior of volatility, Corsi (2009) proposes the heterogenous autoregressive model for realized variance using the daily, weekly and monthly realized variance estimates. Andersen, Bollerslev, and Diebold (2007) extend the standard HAR-RV model to show that the predictability for realized variance over different time intervals almost always comes from the continuous component of the total price variation, rather than the discontinuous jump component. Corsi, Pirino, and Renò (2010) introduce the concept of threshold bipower variation and show that it is well suited for estimating models of volatility dynamics where continuous and jump components are used as explanatory variables. They document that jumps can have a highly significant impact on the estimation of future volatility. Their HAR-TCJ model for forecasting daily realized variance is expressed as:

$$\mathrm{RV}_{t+1,1\mathrm{d}} = \alpha + \beta_D \widehat{TC}_{t,1\mathrm{d}} + \beta_W \widehat{TC}_{t,1\mathrm{w}} + \beta_M \widehat{TC}_{t,1\mathrm{m}} + \beta_J \widehat{TJ}_{t,1\mathrm{d}} + \varepsilon_{t+1},$$

[25] On average, we have 21 trading days per month.

where the threshold bipower variation measure is used to estimate the jump component, $\widehat{TJ}_{t,\mathrm{1d}} = I_{C-Tz>\Psi_\alpha} \times (RV_{t,\mathrm{1d}} - TBPV_t)^+$ and the continuous part $\widehat{TC}_{t,\mathrm{1d}} = \mathrm{RV}_{t,\mathrm{1d}} - \widehat{TJ}_{t,\mathrm{1d}}$.[26]

This simple method avoids some difficulties in long memory time series modeling and the parameters can be consistently estimated by OLS. However, a Newey-West correction is needed to make appropriate statistical inference. Moreover, such a HAR-TCJ type model can be easily modified, for example, by adding extra covariates that contain predictive power.

We aim to obtain the monthly estimates directly, so we replace the daily realized variance $RV_{t+1,\mathrm{1d}}$ by the normalized monthly measure $\mathrm{RV}_{t+21,\mathrm{1m}}$. Moreover, we include lagged estimates of implied variance to further improve the realized variance forecasts. Hence, we run the following OLS regression for the projection:

$$\mathrm{RV}_{t+21,\mathrm{1m}} = \alpha + \beta_D \widehat{TC}_{t,\mathrm{1d}} + \beta_W \widehat{TC}_{t,\mathrm{1w}} + \beta_M \widehat{TC}_{t,\mathrm{1m}} + \beta_J \widehat{TJ}_{t,\mathrm{1d}} + \beta_{IV}' \mathbf{IV}(\mathbf{L})_t + \varepsilon_{t+21,\mathrm{1m}}, \quad (3)$$

where $\mathbf{IV}(\mathbf{L})_t$ contains lagged implied variances up to lag L.[27]

We implement this regression using an expanding window. This allows us to obtain real-time forecasts $\widehat{\mathrm{RV}}_{t+21,\mathrm{1m}}$ for $\mathrm{RV}_{t+21,\mathrm{1m}}$ without any look ahead bias.[28] As the HAR-TCJ predictor for the one month horizon, denoted $\mathrm{RV}_t^{(\mathrm{TCJ})}$, we use:

$$\mathrm{RV}_t^{(\mathrm{TCJ})} = 21 \times \widehat{\mathrm{RV}}_{t+21,\mathrm{1m}},$$

where $\widehat{\mathrm{RV}}_{t+21,\mathrm{1m}}$ is the projected value from regression (3). Furthermore, we denote the simple realized variance estimator obtained from summing $\mathrm{RV}_{t+1,\mathrm{1d}}$ over the past month $\mathrm{RV}_t^{(\mathrm{5m})}$.

The left Panels in Figure 2 show time series plots for the annualized monthly implied volatility measures for the 30 year, 10 year, and 5 year Treasury bond futures, respectively

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[26]The expression for the threshold bipower variation, $TBPV_t$, is given in Corsi, Pirino, and Renò (2010). We use the confidence level $\alpha = 99.9\%$.

[27]We choose the lag length to be four using the Akaike and Bayesian information criteria.

[28]We use daily realized variance estimates from the first 222 trading days as the input for initial estimation: Daily realized variances from day 1 to day 200 are used to construct $\mathrm{RV}_{t,\mathrm{1d}}$, $\mathrm{RV}_{t,\mathrm{1w}}$, and $\mathrm{RV}_{t,\mathrm{1m}}$. Daily realized variances from day 22 to day 222 are used to construct $\mathrm{RV}_{t+21,\mathrm{1m}}$. On day 222, the first out of sample forecast $\widehat{\mathrm{RV}}_{t+21,\mathrm{1m}}$ from the fitted model is constructed by using $\mathrm{RV}_{222,\mathrm{1d}}$, $\mathrm{RV}_{222,\mathrm{1w}}$, and $\mathrm{RV}_{222,\mathrm{1m}}$ as the input data to the initial fitted model. The same method is applied for day $223, 224, \ldots$ with the corresponding parameters.

as well as the S&P 500 index (i.e. we take the square root of the corresponding variance measures to make the magnitudes comparable to the VIX).[29] The right Panels plot the realized volatility measures. The first two Panels in Table 1 present summary statistics of implied and realized volatility measures. Again, all numbers shown are annualized and expressed in percent. The implied volatility measures are on average larger than the realized quantities, both for the Treasury and the equity market, implying a positive variance risk premium. The equity implied and realized volatility is notably higher than the measures for the Treasury markets. The magnitudes of Treasury volatilities are increasing with the maturity of the underlying bonds. Moreover, all measures exhibit positive skewness and excess kurtosis. The autocorrelation coefficients range between roughly 70% and 80%. Finally, as previously mentioned, the summary statistics of the implied volatility measure calculated using options on S&P 500 index futures are almost identical to the summary statistics of the original VIX.

[Insert Figure 2 and Table 1 approximately here.]

Remark: In principle, there exist many different measures of realized variance and a priori, it is not clear what measure we should use. In the Online Appendix, we show that the HAR-TCJ model augmented by lagged implied variance terms performs the best when predicting out-of-sample future variance. The results are robust to the different loss functions we use to evaluate the performance.

C. Variance Risk Premia

We define the variance risk premium for horizon τ as follows:

$$\mathrm{VRP}_{t,\tau} \equiv \mathbb{E}_t^{\mathbb{Q}}\left(\int_t^T \sigma_u^2 du\right) - \mathbb{E}_t^{\mathbb{P}}\left(\int_t^T \sigma_u^2 du\right),$$

where $\tau = T - t$ denotes the time horizon.[30] Economic theory suggests that the variance risk premium should be positive in order to compensate investors who bear risks from expected

[29] As mentioned before, we use options on S&P 500 index futures to be consistent with our calculations for the Treasury implied variance measure.

[30] For notational simplicity, we subsequently drop the subscript τ as we always consider the one month horizon.

price fluctuations. The general positiveness of the variance risk premia can be confirmed empirically from comparing the means of the different volatility measures in Table 1.

In Figure 3 we plot the annualized variance risk premia (expressed in percent), defined as the difference between the model-free implied variance $\mathrm{MIV}^{(i)}$ and the realized variance estimate $\mathrm{RV}^{(\mathrm{TCJ},i)}$ for the 30 year, 10 year and 5 year Treasury futures ($\mathrm{VRP}^{(30y)}$, $\mathrm{VRP}^{(10y)}$ and $\mathrm{VRP}^{(5y)}$, respectively), and the S&P 500 index futures ($\mathrm{VRP}^{(E)}$). As we can see, the three Treasury time series share a lot of co-movement: The unconditional correlations between the 5 year, 10 year and 30 year bond variance risk premia is between 57% and 75%. We also note that $\mathrm{VRP}^{(30y)}$ displays the largest volatility, especially during crisis periods indicated by the shaded areas. The bond variance risk premia are positive on average but they change sign. In contrast, the equity variance risk premium $\mathrm{VRP}^{(E)}$ is essentially always positive and on average significantly higher in magnitude. The correlations between the bond and the equity variance risk premia range between 44% ($\mathrm{VRP}^{(5y)}$) and 66% ($\mathrm{VRP}^{(30y)}$). The summary statistics of the annualized variance risk premia expressed in percent are reported in Table 1, Panel C.

[Insert Figure 3 approximately here.]

D. Treasury Implied Volatility (TIV)

In this section, we introduce a measure for Treasury Implied Volatility in the spirit of the VIX. The TIV measure is the square root of the one month implied variance for futures on 30 year Treasuries, $\mathrm{MIV}^{(30y)}$. The top Panel in Figure 4 plots the annualized TIV measure and our VIX measure (backed out from options on futures) for the common sample period 1983 to 2010. The unconditional correlation between the two monthly time series is 46%. The unconditional correlation between the TIV measure and the original VIX for the period 1990 to 2010 is 62%.[31]

[31] The correlation between the TIV and our VIX measure for the same time period is exactly the same, which is not surprising given the near perfect correlation between the original VIX calculated using options on the cash index and our measure calculated using options on futures. We also calculate the implied volatilities using simple returns, STIV and SVIX. The correlation for the full sample period is 49% and the correlation since 1990 is 64%.

[Insert Figure 4 approximately here.]

The construction of the TIV measure has an economic merit, which goes beyond that of the VIX measure alone. First, the TIV measure can be related to funding liquidity in Treasury markets and second, the spread between the VIX and the TIV can be interpreted as a proxy for flight to quality.

Theoretical work by Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) predicts that higher volatility leads to a tightening of funding constraints for market makers. Moreover, Fontaine and Garcia (2011) establish a robust link between market uncertainty (measured by the VIX) and funding liquidity. In their paper, funding liquidity is estimated through price differentials of Treasuries of different age. Empirically, our TIV measure is strongly related to funding liquidity. When regressing the funding liquidity proxy on the TIV measure, we find a highly significant slope coefficient with a t-statistic larger than five and an R^2 of 30%.[32] The relationship is also economically significant: A one standard deviation change in the TIV implies more than half a standard deviation change in the funding liquidity proxy. Thus, spikes in the TIV can be interpreted as funding shocks, which lead to an increase in the funding liquidity premium.

Brunnermeier and Pedersen (2009) also show that in periods of flight to quality, highly liquid assets are characterized by relatively low volatility. As a consequence, the volatility spread between low and high volatility assets explains part of the liquidity spread. We plot the volatility spread between the VIX and the TIV in Figure 4 (middle Panel). Most of the time, the spread is no larger than 10% but sometimes experiences sudden extreme spikes. For example during the October 1987 crash, the LTCM default in August 1998 or the Lehman default in September 2008, the spread tripled within a month. These are periods usually associated with flight to quality (see, e.g. Caballero and Krishnamurthy, 2008).

Apart from the TIV measure, there is a Treasury option volatility measure available in the market, the Merrill Lynch Option Volatility Estimate (MOVE) index. The MOVE is a yield curve weighted index of the normalized implied volatility on one month Treasury

[32]We thank René Garcia for sharing the data.

options, which are weighted on the 2, 5, 10, and 30 year contracts. This index is available since 1988. The bottom Panel of Figure 4 plots our TIV measure along with the MOVE index. The correlation for the common time period is 81%. Two main differences between the MOVE and the TIV make the latter a more appealing proxy for volatility risk in the Treasury market. First, the MOVE is calculated using Treasury options while we use options on Treasury futures. Treasury options are options on benchmark Treasury securities, which are not exchange traded and hence are significantly less liquid. In practice, they are thus marked at some fixed spread to swaptions. Second, there is no transparent market for out-of-the money Treasury options, so the MOVE index is calculated using the Black (1976) model to compute implied volatility of at-the-money options.[33]

In the next section, we study the determinants of the variance risk premia and document the strong predictive power of the bond variance risk premia for excess returns on Treasury, stock, corporate bond and CMBS portfolios.

III. Empirical Evidence

In this section, we first investigate the economic determinants of bond and equity variance risk premia. Inline with intuition, we find that the variance risk premia are largely driven by uncertainty about real and nominal variables. Secondly, we study the predictive power of the Treasury bond variance risk premia for Treasury, stock, corporate bond and mortgage-backed security excess returns. We do this univariate and multivariate, i.e. we run regressions using only information from the bond variance risk premia measures as regressors before including additional explanatory variables. Due to multicollinearity concerns with regards to the bond variance risk premia, we perform a principal components analysis and use the three principal components as regressors instead of the individual Treasury variance risk premia. We find that estimated coefficients of bond variance risk premia are both

[33]Moreover, the MOVE would not suitable to calculate bond variance risk premia as this would require high frequency data on benchmark Treasury securities.

economically and statistically significant, in- and out-of-sample, even if we include standard predictors suggested in the literature.

We calculate the variance risk premia using the methods described in the previous section. In our main specification, the variance risk premium is the difference between the model-free implied variance and the augmented HAR-TCJ projection. However, the results in this section are also robust to using other IV or RV measures.[34]

To study the determinants and predictability of bond variance risk premia, we choose July 1991 to June 2010 as the sample period. Starting in mid 1990, we have data for all variance risk premia and we can calculate the principal components. However, since we calculate the variance risk premia using an expanding window to remove any look-ahead bias, we allow for a burn-in period of one year.

A. *What Drives Bond Variance Risk Premia?*

It is natural to assume that variance risk premia are associated with higher uncertainty. Options provide investors with a hedge against high variance in the underlying returns and high variance usually occurs when unexpected shocks affect macroeconomic variables. The premium that investors are willing to pay or receive to hedge against such events is related to their uncertainty. Equilibrium models that study variance risk premia focus on the equity market only. Drechsler and Yaron (2011) link the variance risk premium of the stock market index to uncertainty about fundamentals. In particular, time variation in economic uncertainty and a preference for early resolution of uncertainty are required to generate a positive variance premium that is time varying and predicts excess stock market returns. Drechsler (2010) reports a high correlation between the variance risk premium and the dispersion in the forecasts of next quarter's real GDP growth from the Survey of Professional Forecasters.

To examine whether uncertainty affects bond variance risk premia as well, we regress the monthly variance risk premia measures on uncertainty factors constructed from BlueChip

[34] We also implement implied variance measures based on simple variance swaps (as in Martin, 2011) and by inverting the Black (1976) formula for ATM options. As for the realized variance measures, the results are for example robust to using the standard HAR-RV projection proposed by Corsi (2009).

Economic Indicator forecast data. We proxy for uncertainty about the real and nominal side of the economy by the cross sectional standard deviation of the forecasts of CPI ($\widehat{U}^{CPI}$) and real GDP ($\widehat{U}^{RGDP}$) for the current and the next calendar year, respectively. We also construct uncertainty proxies for the three month Treasury bill rate (which can be interpreted as uncertainty about monetary policy) and the ten year Treasury note yield ($\widehat{U}^{SR}$ and $\widehat{U}^{LR}$, respectively).[35] In addition to the uncertainty measures, we include two variables that measure the time-varying volatility of inflation and consumption (σ_π and σ_g, respectively) and two macro factors that can be interpreted as a real ($\widehat{F}_1$) and a nominal (or inflation) factor ($\widehat{F}_2$) in the regression. The macro volatilities are calculated by estimating a GARCH(1,1) process using monthly CPI and per capita consumption (non-durables and services). The macro factors are constructed using the first two principal components of a large set of macro variables as in Ludvigson and Ng (2009, 2011).[36] Finally, we add the slope of the term structure (SLOPE) and the refinancing index from the Mortgage Bankers Association (REF) as additional regressors. Hence, we run the following regression:

$$\text{VRP}_t^{(i)} = \beta'^U \widehat{\mathbf{U}}_t + \beta'^F \widehat{\mathbf{F}}_t + \beta'^S \widehat{\mathbf{S}}_t + \epsilon_t^{(i)},$$

where $\text{VRP}_t^{(i)}$ is the bond or equity variance risk premium ($i = \{30y, 10y, 5y, E\}$) at time t, $\widehat{\mathbf{U}}_t$ is a vector of the uncertainty measures, $\widehat{\mathbf{F}}_t$ contains the real and nominal macro factors, and $\widehat{\mathbf{S}}_t$ contains the macro volatilities, the slope of the term structure and the refinancing index. $\epsilon_t^{(i)}$ is the error term. All coefficients are estimated with ordinary-least squares and standardized to allow for a straightforward assessment of the economic significance. We report t-statistics that are calculated using Newey and West (1987) standard errors. The sample spans the period from July 1991 to December 2009.[37]

In order to avoid multicollinearity concerns in this regression, we consider the cross-correlations of the potential determinants presented in Table 2. The uncertainty proxies for the short and the long end of the yield curve are positively correlated, but the coef-

[35]See Section I. for details.

[36]Given that the factors are principal components, the economic interpretation is not straightforward. We calculate the marginal correlations of the individual time series with the respective factors for our data set. As in Ludvigson and Ng (2009), it is reasonable to interpret the first factor as a real factor. The second factor can be interpreted as a nominal or inflation factor. See the Online Appendix for additional information.

[37]We only have the BlueChip data available until the end of 2009.

ficient is merely 42%. Both uncertainty measures also exhibit a positive correlation with uncertainty about real GDP. Apart from this, only $\widehat{F}_1$ and σ_π exhibit sizable correlations with other determinants: the correlation for the two time series is -0.61. Moreover, $\widehat{F}_1$ and σ_π are correlated with $\widehat{U}^{CPI}$ (-0.74 and 0.57, respectively). Overall, correlations are fairly moderate and give no reason for concern.

[Insert Tables 2 and 3 approximately here.]

The determinant regression results are presented in Table 3. In summary, the results confirm that uncertainty variables have relevant explanatory power for variance risk premia but there are distinct differences between the Treasury maturities and also between Treasury and equity variance risk premia.

The four uncertainty factors alone explain around 45% of the variation in 30 year bond and equity variance risk premia. For 10 year and 5 year bond variance risk premia, this number drops to 21% and 12%, respectively. In general, higher uncertainty is associated with an increase in bond and equity variance risk premia. However, uncertainty about the short rate is a notable exception, as 30 year Treasury and equity variance risk premia significantly decrease given an increase in uncertainty about monetary policy. Intuitively, we can explain this as follows: Larger uncertainty about the short end makes investors with negative expectations more willing to buy long term bonds, because these provide a hedge against an increased duration due to a drop in the short term yields. Hence, investors pay a premium for holding these bonds. It should be noted, however, that interpreting signs with proxies of uncertainty can be difficult. First, the impact of uncertainty on risk premia in equilibrium models usually depends on the amount of pessimists versus optimists, where pessimists are those agents who have a lower than the consensus forecast (see, e.g., Jouini and Napp, 2007, for equity markets, and Xiong and Yan, 2010, for bond markets). Uncertainty only implies a positive impact on risk premia if wealth-weighted beliefs are dominated by pessimists. Second, it is not mandatory that higher uncertainty is always associated with worsening economic conditions (see, e.g., Patton and Timmermann, 2010).

Uncertainty about inflation has the largest economic impact on the variance risk premia: A one standard deviation change in inflation uncertainty implies on average almost half a standard deviation change in the variance risk premia. Inline with intuition, uncertainty about the long rate predominantly affects 30 year bond variance risk premia and uncertainty about real GDP is only significant for equity variance risk premia. The shape of the term structure, i.e. the slope, affects both bond and equity variance risk premia. A one standard deviation move in the slope moves bond variance risk premia by between 0.2 and 0.35 standard deviations.

These results are robust to adding levels and volatilities of macro variables to the regression. The macro volatilities are at most marginally significant, while the real factor has a negative effect on both bond and equity variance risk premia with an increasing statistical significance in the maturity of the underlying. For bond variance risk premia, the coefficient is around -0.14 and the effect almost doubles for equity variance risk premia. In addition, the price factor has a significantly positive effect on equity variance risk premia. At the same time, adding $\widehat{F}_1$ and $\widehat{F}_2$ to the bond variance risk premia regressions only marginally improves the adjusted R^2, further supporting the notion that variance risk premia are driven predominantly by uncertainty and not by actual macro fundamentals.[38]

As shown in Figure 1, the MBA refinancing index is highly correlated with Treasury variance risk premia. In a regression of the individual variance risk premia on the refinancing index, the coefficients are positive and strongly significant. A one standard deviation move in the refinancing index is associated with 0.3 to 0.45 standard deviation moves in the variance risk premia. In the multivariate regressions, however, the effect is muted. The strong statistical significance only remains for the equity variance risk premia, while the uncertainty proxies largely drive out the refinancing index for bond variance risk premia.

[38]Adding even more macro factors does not further improve the fit of the regression.

B. Principal Components

Next we want to assess the predictive power of bond variance risk premia for different assets. To this end, we regress excess returns on bond variance risk premia. Since the average pairwise correlation between the individual bond variance risk premia is very high, we calculate the principal components of the bond variance risk premia to circumvent the issue of multicollinearity.[39] The principal components analysis allows us to summarize in a parsimonious way the information in the term structure of bond variance risk premia.

We denote by $\text{VRP}^{(PC1)}$, $\text{VRP}^{(PC2)}$ and $\text{VRP}^{(PC3)}$, the first, second, and third principal component, respectively. The first principal component explains roughly 77% of the variation in the Treasury variance risk premia, while the second and third principal components explain the remaining 15% and 8%, respectively. Table 4 reports the factor loadings for the three bond variance risk premia. It seems appropriate to interpret the three principal components in analogy to the term structure literature as level, slope and curvature (see, e.g., Litterman and Scheinkman, 1991).

[Insert Table 4 approximately here.]

In interpreting the loadings, one has to keep in mind our setup, where the horizon for the variance risk premia is constant while the underlying bond maturity is changing. To calculate a term structure in the usual sense, we would need longer maturity options for each futures. Due to a lack of liquidity and availability of longer maturity options, this is not possible.[40]

Adding the equity variance risk premium to the principal components analysis does not significantly alter the pattern. The first principal component still explains almost 70% of the total variation and can be interpreted as a level factor for the Treasury variance risk

[39] The pairwise correlations between the bond variance risk premia range between 57% and 75% for our sample.

[40] Feunou, Fontaine, Taamouti, and Tédongap (2011) estimate a term structure of uncertainty using equity options. They use multiple horizons for the same underlying and then perform a principal components analysis. They find that the first three principal components can also be interpreted as level, slope and curvature.

premia (the correlation with $\text{VRP}^{(PC1)}$ is 98%). The second factor explains 15% and can be interpreted as a slope factor for bond variance risk premia. Moreover, the equity variance risk premium strongly loads on this factor. The correlation with $\text{VRP}^{(PC2)}$ is 53%. The third factor explains 10% and is again a slope factor, exhibiting a correlation with $\text{VRP}^{(PC2)}$ of almost 85%. Finally, the last factor is a curvature factor. It explains the remaining 5% of the variation and its correlation with $\text{VRP}^{(PC3)}$ is 84%.

In the next section, we use the three principal components instead of the individual variance risk premia to examine the predictive ability of the bond variance risk premia. However, we include the regression results using the original variance risk premia in the Online Appendix. The principal components analysis allows to better understand some of the regression results using the actual variance risk premia. It turns out for example that the third PC, the curvature factor, has significant predictive power for Treasury bond excess returns. As shown in Table 4, the loadings of the 30 year and the 10 year Treasury variance risk premia on this factor are exactly opposite. Hence, it is not too surprising that the sign of the coefficients for these two variance risk premia is exactly opposite as well.

C. In-Sample Predictability

Using the principal components for the Treasury variance risk premia, we study the in-sample predictive power of bond variance risk premia for fixed income and equity excess returns. To do this, we run the following type of regression:

$$rx_{t+h}^{(i)} = \beta_h'^{(i)} \mathbf{VRP}_t + \gamma_h'^{(i)} \mathbf{M}_t + \epsilon_{t+h}^{(i)},$$

where $rx_{t+h}^{(i)}$ denotes the h-period excess returns for asset i. $\mathbf{VRP}_t$ is a vector containing the principal components of the bond variance risk premia, $\text{VRP}^{(PC1)}$, $\text{VRP}^{(PC2)}$ and $\text{VRP}^{(PC3)}$. $\mathbf{M}_t$ denotes a vector of additional predictor variables and $\epsilon_{t+h}^{(i)}$ is the error term.

We calculate excess returns for two to five year Treasury bonds, the stock market, a growth and value portfolio, corporate bond indices for AAA, BBB and CCC rated securities, and commercial mortgage-backed securities indices for AAA, BBB and B rated securities. For

Treasuries, we only calculate annual excess returns, whereas for all other assets we calculate three, six and twelve month excess returns as the difference between the respective portfolio returns and the corresponding Treasury rate.

Note that we always report standardized regression results, meaning that, for all regressors and regressands, we de-mean and divide by the standard deviation. This makes coefficients comparable across different predictors and allows to directly interpret not only the statistical but also the economic significance. We report t-statistics that are calculated using Newey and West (1987) standard errors. The sample period is always from July 1991 to June 2010, except for CMBS excess returns, which are only available starting in January 1997.

For the fixed income excess return regressions (Treasuries, corporates, CMBS), $\mathbf{M}_t$ includes the equity variance risk premium, the Cochrane and Piazzesi (2005) factor, CP, and the eight macro factors from Ludvigson and Ng (2009, 2011), $\widehat{F}_j, j = 1\ldots,8$. For the stock portfolio excess return regressions, we include the log dividend yield, DY, the log earnings to price ratio, E/P, and NTIS, the net equity expansion as additional regressors as in Goyal and Welch (2008).[41]

[Insert Tables 5 and 6 approximately here.]

In Tables 5 and 6 we present the regression results excluding the additional control variables.[42] Panel A in Table 5 contains the results for Treasury bond excess returns. The coefficients for the third PC are significant and negative for all maturities, implying that spikes in this PC lead to lower excess returns. A one standard deviation positive shock roughly results in a 0.18 standard deviation reduction in bond excess returns for all maturities. The third PC is the curvature factor, meaning that an increase in the curvature of bond variance risk premia predicts lower Treasury bond excess returns. The average adjusted R^2 is roughly 3%.

[41]We exclude some of the additional regressors from Goyal and Welch (2008) as the updated data is not available. We also exclude the book-to-market ratio as it exhibits a correlation of almost 80% with DY over the sample period. Moreover, it is not significant.

[42]Slightly abusing the language, we refer to these results as the univariate regression results.

Univariate regression results for stock excess returns are reported in Panel B of Table 5. We find predictability in the second and third principal components for the market, growth and value portfolio excess returns for horizons between six and twelve months. The statistical and economic significance for the second PC, the slope factor, is particularly high. A one standard deviation move in the slope factor results in 0.2 to 0.3 standard deviation larger excess returns for longer horizons. The third PC is significant for the market and growth portfolios. However, unlike for Treasury bond excess returns, the coefficient for stock excess returns is now positive and is estimated at 0.17 for six month excess returns. Adjusted R^2 range between 7% and 9% for the market and growth portfolio and reach 11% for the value portfolio.

Table 6 presents the regression results for long and intermediate corporate bond excess returns (Panels A and B), and commercial mortgage-backed securities excess returns (Panel C). Overall, the predictability is strong with adjusted R^2 ranging between 5% for three month excess returns on intermediate AAA rated bonds and reaching 38% for twelve month BBB rated CMBS. The predictive power increases with the horizon and is strongest for intermediate rating categories, i.e. BBB rated securities. Predictability for intermediate maturity bonds is slightly higher than for long maturity bonds. Unlike for Treasuries and stocks, the curvature factor does not contain any predictive power. However, the first PC, the level factor, is very strongly significant, both statistically and empirically. For twelve month corporate bond excess returns, the coefficients range between 0.35 for intermediate AAA bonds and 0.52 for intermediate BBB bonds. For CMBS, the first PC is strongly significant for AAA and BBB rated securities and six to twelve month excess returns. The second PC is also almost uniformly strongly significant at all horizons. However, it works less well for high yield corporate bonds and CMBS. As with the first PC, the coefficients almost reach 0.5 for six and twelve month excess returns.

To summarize the univariate regressions, bond variance risk premia have significant predictive power for a wide range of assets at various horizons. It is also worth noting that the predictability is not concentrated in one specific latent factor. Relevant information is contained in the whole "term structure" of bond variance risk premia. In a separate analysis, we also run truly univariate regressions, i.e. using only one variance risk premium at a time. The main results hold, meaning that we do find predictability. However, as the predictability for Treasury excess returns for example is mainly contained in the third PC, it is not always straightforward to pick it up. In addition, the variance risk premia may load with different signs on principal components with predictive power, further complicating the detection and interpretation of the predictability when using only one bond variance risk premium time series at a time.

To check the robustness of our univariate results, we next add different established predictors of bond and equity excess returns to the regression. The results are reported in Tables 7 to 10.

[Insert Tables 7 to 10 approximately here.]

To summarize, the results from the multivariate regressions with respect to the principal components of Treasury variance risk premia are remarkably robust to the inclusion of a host of control variables. Moreover, Treasury variance risk premia truly seem to pick up information that is relevant for a wide range of asset classes and that goes beyond what is contained in standard macroeconomic variables and the term structure of interest rates. In particular, the predictive power of Treasury variance risk premia is much more general than the documented predictability of the equity market variance risk premium, which predominantly works for stock excess returns.

The coefficients for Treasury bond excess returns presented in Table 7 are still significantly negative and economically relevant. Now, all three PCs are significant with the same sign. The coefficients range between -0.14 and -0.27. Thus, an increase in the level, slope or curvature of the term structure of bond variance risk premia results in lower Treasury excess returns. Including the CP factor and the macro factors increases the adjusted R^2 to almost 30% across all maturities for the Treasury bond excess return regressions. As in Ludvigson and Ng (2009), the macro factors explain a significant fraction of the variation in bond excess returns over the sample period, and the CP factor is highly significant as well. Unlike the bond variance risk premia, the equity variance risk premium does not seem to contain any relevant information for forecasting bond excess returns at an annual horizon.[43]

Table 8 presents the results for the stock excess return regressions including as additional control variables the equity market variance risk premium, the dividend yield (DY), the earnings to price ratio (E/P) and net equity expansion (NTIS). The equity variance risk premium has significant predictive power for the market and growth portfolios, a result which is inline with the findings in Bollerslev, Tauchen, and Zhou (2010). NTIS is strongly significant for six and twelve month excess returns, while DY only has predictive power for twelve month excess returns on the market and growth portfolios. As in the univariate regressions, the second and third PCs are statistically significant for six to twelve month excess returns while the economic significance remains largely unchanged. Overall, the adjusted R^2 raise to between 30% and 40% for twelve month excess returns.

Not very surprisingly at this stage, the univariate results for corporate bonds and CMBS largely carry over to the multivariate regressions.[44] The second PC, i.e. the slope factor emerges as the strongest and most robust predictor while the first PC seems to be driven out at short horizons by the additional controls, the CP factor in particular.

In summary, we find that excess returns on Treasuries, stocks, corporate bonds and CMBS are predictable using bond variance risk premia. Overall, the reported in-sample predictability is strong, both statistically and economically.

D. Out-of-Sample Predictability

There is ample evidence in the literature for the fact that in-sample predictability does not necessarily imply out-of-sample predictability. For instance, Goyal and Welch (2008) show that a large number of predictors have very little out-of-sample predictive power for

[43]These findings echo the results in Mueller, Vedolin, and Zhou (2011) who find that the equity variance risk premium heavily loads on short-term bond risk premia but does not predict excess returns at the annual horizon.

[44]We report the regression results for intermediate corporate bond and CMBS excess returns in Tables 9 and 10. The results for long-term corporate bonds are qualitatively similar but in the interest of space they are deferred to the Online Appendix.

stock market excess returns and they attribute the inconsistent out-of-sample performance of individual predictive regression models to structural instability. In this section, we report results on the out-of-sample forecasting performance of the regression models studied in the previous section. We run out-of-sample regressions using the bond variance risk premia directly instead of the principal components, since these are estimated using an expanding window. We therefore use data only through time t for forecasting excess returns at time $t+1$.

We run the out-of-sample test for the Treasury, long corporate bond, and the stock excess returns but not the mortgage-backed securities, as the available sample period for these is too short. We obtain the initial estimates based on the period from July 1991 to July 1999 and study the out-of-sample predictability for the period starting in July 2000 and ending in June 2010.

For the corporate bond and stock excess returns, we compare the out-of-sample forecasting performance of the bond variance risk premia to a constant expected returns benchmark. For the Treasury excess returns, we have two different model specifications. First, we compare the out-of-sample forecasting performance of the bond variance risk premia to a constant expected returns benchmark where, apart from an MA(12) error term, excess returns are unforecastable as in the expectations hypothesis. Second, since the expectations hypothesis is violated in the data, we compare the out-of-sample forecasting performance of a specification that includes bond variance risk premia plus the CP factor to a benchmark model that only includes CP factor and a constant.

To check whether the bond variance premia have out-of-sample predictive power, we consider two different metrics for the evaluation. The first one is the out-of-sample R^2 statistic, denoted by R^2_{OOS} (Campbell and Thompson, 2008). The R^2_{OOS} measures the proportional reduction in the mean squared error for a competing model relative to the benchmark forecast. It is akin to the in-sample R^2 and has the following form:

$$R^2_{\text{OOS}} = 1 - \frac{\frac{1}{T}\sum_{t=1}^{T}\left(y_t - \hat{y}_t^i\right)^2}{\frac{1}{T}\sum_{t=1}^{T}\left(y_t - \hat{y}_t^j\right)^2},$$

where $\hat{y}_t^i$ is the forecast of the variable y_t from the competing model i and $\hat{y}_t^j$ is the forecast of variable y_t from the benchmark model j. Note that both $\hat{y}_t^i$ and $\hat{y}_t^j$ are obtained based on the data up to period $t-1$. If the R^2_{OOS} is positive, the competing predictive regression has a lower average out-of-sample mean-squared prediction error than the benchmark.

The second metric we employ is the ENC-NEW test statistic of Clark and McCracken (2001). The null hypothesis of the ENC-NEW test is that the model with additional variables does not have better predictive power for excess returns than the benchmark or restricted model. The alternative is that these additional variables have additional information and they could be used to obtain a better forecast.[45]

[**Insert Table 11 approximately here.**]

We report the results in Table 11. The R^2_{OOS} are positive for all assets, which indicates that a model which includes the bond variance risk premia improves both over the constant expected returns benchmark and a model that includes the CP factor. We draw the same conclusion from the reported ENC-NEW statistics. The test statistics reveal that the improvement in forecasting power is strongly statistically significant.

IV. Conclusion

In this paper, we construct daily measures of implied and realized variance in fixed income markets. To calculate the implied variance, we use daily options on 30 year, 10 year and 5 year Treasury futures. We use high frequency futures data to calculate the realized variance. Using thirty years of options data, we propose a new measure of fear for Treasury markets, the TIV, calculated as the square root of the implied variance for 30 year Treasury futures. The TIV measure has two interesting properties: First, it is strongly related to a proxy of funding liquidity and second, the spread between the VIX and TIV can be interpreted as a

[45]The limiting distribution of ENC-NEW is non-standard. Following Ludvigson and Ng (2009), we base our inference on comparing the calculated test statistics with the corresponding 95th percentile of the asymptotic distribution of the ENC-NEW test statistic. Critical values can be found in Clark and McCracken (2001).

measure of flight to quality. The behavior of the TIV resembles in many ways the one of the VIX, however, while the unconditional correlation is high, the two series differ in their magnitudes. Not very surprisingly, we find that the compensation for variance risk in fixed income markets is considerably smaller than in the equity market.

The bond variance risk premia we derive are akin to the variance risk premium for the S&P 500 index. However, while the variance risk premium for the equity index is essentially always positive, i.e. it acts like an insurance premium, the variance risk premia in Treasury markets can turn negative. To grasp a better intuition of this behavior, we explore the economic determinants of both equity and bond variance risk premia in more detail. We find that both are strongly driven by proxies of macroeconomic uncertainty, however, a proxy of uncertainty about monetary policy strongly reduces the variance risk premia in bond markets, especially for longer maturities. We also find that the shape of the term structure of Treasury yields significantly affects bond variance risk premia. These findings corroborate the intuition that bond variance risk premia encompass general macroeconomic uncertainty together with information from the term structure of yields.

We then study whether bond variance risk premia contain any predictive power for excess returns on Treasury bonds, stocks, corporate bonds and commercial mortgage-backed securities. We find that bond variance risk premia explain a significant proportion of the variation in excess returns both in-sample and out-of-sample. Moreover, the predictive power is very robust to the horizon and in particular the inclusion of standard predictors found in the literature.

We are primarily interested in documenting the facts. Is there a compensation for volatility risk in fixed income markets? If yes, how large is it? How does it compare to equity markets? However, ultimately, our paper remains agnostic about the theoretical underpinnings of the empirical results but instead raises new research questions. First, many papers have argued that in times of uncertainty, there is a so-called flight to quality, i.e. investors move from relatively more risky stocks to relatively less risky bonds. Comparing the two implied volatility measures for equity and bond markets, we find that during certain periods, there is a decoupling of the two time series while during other time periods, the time series almost move in lock step. A next step would be to study the lead and lag relationships and the feedback effects between the equity and bond markets in greater detail using the implied volatility measures we introduce for Treasuries.

Secondly, if bond variance risk premia have predictive power across different asset classes, we would expect that these risk premia pick up more than just information contained in the term structure of interest rates. Since we do not find a similar result for the equity variance risk premium, we conclude that bond variance risk premia capture macroeconomic uncertainty which goes beyond that contained in equity variance risk. Moreover, there is also information contained in the term structure of bond variance risk premia that is orthogonal to what can be learned from standard macroeconomic variables. In particular, our results hint that the term structure of uncertainty, i.e. how uncertainty evolves at any given point in time for different horizons, could have opposing effects on variance risk premia. Exploring the effects of different uncertainty horizons on risk compensation is another interesting topic for future research.

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Table 1
Summary Statistics

Panels A and B report summary statistics for the implied and realized volatility measures. MIV denotes the model-free implied variance for a one month horizon. $RV^{(5m)}$ denotes monthly realized variance sampled at the five minute frequency, and $RV^{(TCJ)}$ denotes the HAR-TCJ realized variance estimator augmented with lagged implied variance terms. The VIX is obtained from CBOE. All quantities are annualized and expressed in percent. Note that we report the summary statistics for the implied and realized volatilities, which are obtained as the square root of the respective variance measures. Panel C presents summary statistics for bond and equity variance risk premia. The variance risk premia are annualized and expressed in percent. They are calculated as the difference of the model-free implied variance and the projected value from the HAR-TCJ realized variance estimator augmented with lagged implied variance terms. All data is monthly and the sample spans the period from July 1991 to June 2010.

Panel A: Implied Volatility

	30y Treasury	10y Treasury	5y Treasury	S&P500	
	MIV	MIV	MIV	MIV	VIX
Mean	10.00	6.86	4.43	20.11	20.22
StDev	2.38	1.65	1.22	8.39	8.13
Min	6.03	3.70	1.95	9.97	10.42
Max	21.96	13.26	9.53	58.46	59.89
Skewness	1.95	0.68	0.78	1.55	1.61
Kurtosis	8.92	3.97	4.15	6.53	6.80
AC(1)	0.83	0.72	0.72	0.86	0.86

Panel B: Realized Volatility

	30y Treasury		10y Treasury		5y Treasury		S&P500	
	$RV^{(TCJ)}$	$RV^{(5m)}$	$RV^{(TCJ)}$	$RV^{(5m)}$	$RV^{(TCJ)}$	$RV^{(5m)}$	$RV^{(TCJ)}$	$RV^{(5m)}$
Mean	8.43	8.38	5.57	5.52	3.77	3.72	14.65	14.22
StDev	1.42	2.03	0.80	1.45	0.57	1.04	6.10	7.97
Min	6.25	4.77	4.07	2.87	2.72	1.86	7.37	5.04
Max	15.95	18.46	9.24	10.79	6.71	7.55	51.80	73.79
Skewness	1.99	1.22	1.48	0.83	1.50	0.84	2.18	3.13
Kurtosis	8.76	5.79	6.59	3.89	7.69	3.63	11.20	19.45
AC(1)	0.84	0.71	0.78	0.67	0.76	0.62	0.83	0.77

Panel C: Variance Risk Premia

	30y Treasury	10y Treasury	5y Treasury	S&P500
	VRP	VRP	VRP	VRP
Mean	0.33	0.18	0.07	2.23
StDev	0.35	0.17	0.08	2.19
Min	-0.07	-0.16	-0.04	-0.01
Max	2.44	1.05	0.50	13.22
Skewness	3.14	1.30	1.88	2.38
Kurtosis	16.21	6.18	8.96	9.82
AC(1)	0.68	0.50	0.57	0.77

Table 2
Correlations of Determinants

The table reports correlations between determinants of variance risk premia. The uncertainty variables are defined as the cross sectional standard deviation of the forecasts of the short and long end of the term structure ($\widehat{U}^{(SR)}$ and $\widehat{U}^{(LR)}$), real GDP ($\widehat{U}^{(RGDP)}$), and CPI ($\widehat{U}^{(CPI)}$). SLOPE is the slope of the term structure calculated as the difference between the ten year and the one month Treasury yield. The macro volatilities σ_π and σ_g are estimated using a GARCH(1,1) process for inflation and per capita consumption (non durables and services). The macro variables $\widehat{F}_j, j = 1,2$ are estimated as the first two principal components from a data set of 104 macroeconomic variables. They can be interpreted as a real and a nominal or inflation factor, respectively. REF is the refinancing index published by the Mortgage Bankers Association. All data is monthly and the sample spans the period from July 1991 to December 2009.

	$\widehat{U}^{LR}$	$\widehat{U}^{RGDP}$	$\widehat{U}^{CPI}$	SLOPE	σ_π	σ_g	$\widehat{F}_1$	$\widehat{F}_2$	REF
$\widehat{U}^{SR}$	0.42	0.42	0.00	-0.04	-0.28	0.47	-0.06	0.03	-0.24
$\widehat{U}^{LR}$		0.27	-0.03	0.04	-0.34	0.29	0.07	-0.08	-0.12
$\widehat{U}^{RGDP}$			0.33	0.18	-0.07	0.32	-0.37	0.01	-0.06
$\widehat{U}^{CPI}$				0.12	0.57	-0.23	-0.74	0.07	0.26
SLOPE					0.04	-0.01	-0.18	-0.10	0.09
σ_π						-0.46	-0.61	0.05	0.35
σ_g							0.16	-0.02	-0.20
$\widehat{F}_1$								0.01	-0.40
$\widehat{F}_2$									-0.09

Table 3
Economic Drivers of Bond Variance Risk Premia

The table reports the results from regressing the respective variance risk premia on uncertainty measures $\widehat{\mathbf{U}}_t$ and additional variables $\widehat{\mathbf{F}}_t$ and $\widehat{\mathbf{S}}_t$: $\text{VRP}_t^{(i)} = \beta'^{U}\widehat{\mathbf{U}}_t + \beta'^{F}\widehat{\mathbf{F}}_t + \beta'^{S}\widehat{\mathbf{S}}_t + \epsilon_t^{(i)}$. The uncertainty variables are defined as the cross sectional standard deviation of the forecasts of the short and long end of the term structure ($\widehat{U}^{(SR)}$ and $\widehat{U}^{(LR)}$), real GDP ($\widehat{U}^{(RGDP)}$), and CPI ($\widehat{U}^{(CPI)}$). $\widehat{\mathbf{S}}_t$ includes SLOPE, the slope of the term structure calculated as the difference between the ten year and the one month Treasury yield, the macro volatilities σ_π and σ_g estimated using a GARCH(1,1) process for inflation and per capita consumption (non durables and services) and REF, the MBA refinancing index. The macro variables $\widehat{F}_j, j = 1, 2$ are estimated as the first two principal components from a data set of 104 macroeconomic variables. They can be interpreted as a real and a nominal or inflation factor, respectively. Regressions are standardized, meaning all variables are de-meaned and divided by their standard deviation. Coefficients are estimated with ordinary-least squares, t-statistics are in parentheses and are calculated using Newey and West (1987) standard errors. Data is monthly and the sample spans the period from July 1991 to December 2009.

	$\text{VRP}^{(30y)}$			$\text{VRP}^{(10y)}$			$\text{VRP}^{(5y)}$			$\text{VRP}^{(E)}$		
$\widehat{U}^{SR}$	-0.213	-0.160	-0.145	-0.062	-0.048	-0.034	-0.011	0.033	0.053	-0.319	-0.282	-0.252
	(-2.45)	(-2.05)	(-1.87)	(-0.51)	(-0.41)	(-0.29)	(-0.09)	(0.29)	(0.47)	(-4.40)	(-3.81)	(-4.89)
$\widehat{U}^{LR}$	0.225	0.215	0.214	0.160	0.109	0.105	0.070	0.007	0.015	0.123	0.158	0.172
	(3.98)	(3.62)	(4.00)	(1.76)	(1.25)	(1.12)	(0.68)	(0.06)	(0.15)	(1.39)	(1.98)	(2.94)
$\widehat{U}^{RGDP}$	0.025	0.007	-0.013	0.129	0.051	0.028	0.107	0.072	0.052	0.182	0.246	0.214
	(0.25)	(0.09)	(-0.17)	(1.32)	(0.57)	(0.31)	(0.97)	(0.60)	(0.44)	(2.13)	(2.73)	(2.10)
$\widehat{U}^{CPI}$	0.630	0.441	0.370	0.381	0.251	0.182	0.308	0.285	0.188	0.553	0.536	0.376
	(3.76)	(2.94)	(2.28)	(3.00)	(1.77)	(1.18)	(1.99)	(1.37)	(0.92)	(4.13)	(4.54)	(3.89)
SLOPE		0.284	0.256		0.370	0.347		0.239	0.194		-0.125	-0.199
		(3.57)	(3.28)		(4.42)	(4.19)		(2.61)	(2.18)		(-1.30)	(-2.57)
σ_π		0.168	0.090		0.096	0.019		-0.125	-0.228		0.009	-0.158
		(1.61)	(0.88)		(1.02)	(0.20)		(-0.86)	(-1.60)		(0.08)	(-1.86)
σ_g		-0.156	-0.155		-0.079	-0.079		-0.225	-0.221		-0.085	-0.078
		(-1.59)	(-1.60)		(-0.75)	(-0.78)		(-1.89)	(-1.95)		(-1.05)	(-1.07)
$\widehat{F}_1$			-0.137			-0.142			-0.169			-0.273
			(-1.68)			-1.45)			(-1.39)			(-2.61)
$\widehat{F}_2$			-0.035			-0.061			0.037			0.075
			(-0.61)			(-1.02)			(0.84)			(2.20)
REF			0.114			0.099			0.182			0.294
			(1.58)			(1.09)			(1.68)			(2.79)
AdjR^2	0.45	0.53	0.55	0.21	0.31	0.32	0.12	0.17	0.20	0.44	0.45	0.57

Table 4
Principal Components of Treasury Variance Risk Premia

The table reports the loadings for the three principal components of the bond variance risk premia, $\mathrm{VRP}^{(PC1)}$, $\mathrm{VRP}^{(PC2)}$ and $\mathrm{VRP}^{(PC3)}$, respectively. We also report the the percentage of the explained variation. Data is monthly and the sample spans the period from July 1991 to June 2010.

	$\mathrm{VRP}^{(PC1)}$	$\mathrm{VRP}^{(PC2)}$	$\mathrm{VRP}^{(PC3)}$
$\mathrm{VRP}^{(30y)}$	0.58	0.57	0.59
$\mathrm{VRP}^{(10y)}$	0.60	0.19	-0.77
$\mathrm{VRP}^{(5y)}$	0.55	-0.80	0.23
Percent explained	77.33	14.93	7.74
Cum. percent explained	77.33	92.26	100.00

Table 5
Excess Bond and Stock Returns

We run the following regression: $rx^{(i)}_{t+h} = \beta'^{(i)}(h)\mathbf{VRP}_t + \epsilon^{(i)}_{t+h}$. For bonds (Panel A), $rx^{(i)}_{t+h}$ is the one year ($h = 12$ months) excess return for $i = \{24, 36, 48, 60\}$ month Treasury bonds. For stocks (Panel B), $rx^{(i)}_{t+h}$ is the three, six, or twelve month excess return on the market (value-weighted CRSP index), value and growth portfolio (from Ken French's Data Library), respectively. $\mathbf{VRP}_t$ is a vector containing the principal components of the bond variance risk premia, $\text{VRP}^{(PC1)}$, $\text{VRP}^{(PC2)}$ and $\text{VRP}^{(PC3)}$. Regressions are standardized, meaning all variables are de-meaned and divided by their standard deviation. Coefficients are estimated with ordinary-least squares, t-statistics are in parentheses and are calculated using Newey and West (1987) standard errors. Data is monthly and the sample spans the period from July 1991 to June 2010.

Panel A: Fama Bliss Treasury Bonds

	2y	3y	4y	5y
$\text{VRP}^{(PC1)}$	0.014	0.037	0.032	0.066
	(0.15)	(0.41)	(0.37)	(0.81)
$\text{VRP}^{(PC2)}$	-0.080	-0.060	-0.057	-0.045
	(-0.99)	(-0.73)	(-0.68)	(-0.53)
$\text{VRP}^{(PC3)}$	-0.166	-0.173	-0.191	-0.189
	(-2.15)	(-2.15)	(-2.42)	(-2.39)
AdjR^2	0.03	0.03	0.03	0.03

Panel B: Stocks

	Market			Growth			Value		
	3m	6m	12m	3m	6m	12m	3m	6m	12m
$\text{VRP}^{(PC1)}$	0.028	0.091	0.150	0.079	0.123	0.188	-0.051	0.053	0.162
	(0.19)	(0.91)	(1.42)	(0.67)	(1.42)	(1.94)	(-0.28)	(0.41)	(1.33)
$\text{VRP}^{(PC2)}$	0.118	0.241	0.212	0.058	0.193	0.177	0.138	0.276	0.304
	(1.11)	(2.34)	(1.86)	(0.58)	(2.10)	(1.90)	(1.20)	(2.49)	(2.38)
$\text{VRP}^{(PC3)}$	0.120	0.176	0.137	0.090	0.162	0.140	0.069	0.122	0.038
	(1.83)	(2.59)	(1.58)	(1.40)	(2.38)	(1.65)	(0.96)	(1.65)	(0.43)
AdjR^2	0.02	0.09	0.08	0.01	0.07	0.08	0.02	0.09	0.11

Table 6
Excess Corporate Bond and Commercial Mortgage-Backed Securities Returns

We run the following regression: $rx^{(i)}_{t+h} = \beta'^{(i)}(h)\mathbf{VRP}_t + \epsilon^{(i)}_{t+h}$, where $rx^{(i)}_{t+h}$ is the three, six, or twelve month excess return on long and intermediate maturity corporate bond (Panels A and B) or commercial mortgage-backed securities indices (Panel C), respectively. We use AAA, BBB and CCC indices for corporate bonds and AAA, BBB, and B indices for CMBS. $\mathbf{VRP}_t$ is a vector containing the principal components of the bond variance risk premia, $\text{VRP}^{(PC1)}$, $\text{VRP}^{(PC2)}$ and $\text{VRP}^{(PC3)}$. Regressions are standardized, meaning all variables are de-meaned and divided by their standard deviation. Coefficients are estimated with ordinary-least squares, t-statistics are in parentheses and are calculated using Newey and West (1987) standard errors. Data is monthly and the sample spans the period from July 1991 to June 2010. CMBS data start in January 1997.

Panel A: Long Corporate Bonds

	AAA			BBB			CCC		
	3m	6m	12m	3m	6m	12m	3m	6m	12m
$\text{VRP}^{(PC1)}$	0.163	0.257	0.423	0.209	0.346	0.508	0.158	0.254	0.397
	(2.04)	(2.81)	(5.32)	(2.05)	(3.67)	(5.48)	(2.00)	(2.84)	(4.21)
$\text{VRP}^{(PC2)}$	0.270	0.245	0.166	0.190	0.285	0.183	0.089	0.115	0.087
	(3.24)	(3.10)	(2.03)	(2.48)	(3.35)	(2.19)	(1.36)	(1.27)	(0.94)
$\text{VRP}^{(PC3)}$	-0.046	-0.025	-0.105	0.074	0.093	0.000	0.016	0.074	0.043
	(-0.65)	(-0.30)	(-1.35)	(1.05)	(1.16)	(0.00)	(0.24)	(0.97)	(0.53)
AdjR^2	0.09	0.12	0.21	0.08	0.20	0.29	0.02	0.08	0.16

Panel B: Intermediate Corporate Bonds

	AAA			BBB			CCC		
	3m	6m	12m	3m	6m	12m	3m	6m	12m
$\text{VRP}^{(PC1)}$	0.130	0.185	0.352	0.237	0.400	0.517	0.238	0.363	0.452
	(1.90)	(2.33)	(3.99)	(2.30)	(4.18)	(4.79)	(1.98)	(3.77)	(3.74)
$\text{VRP}^{(PC2)}$	0.201	0.216	0.195	0.277	0.340	0.238	0.211	0.261	0.132
	(2.94)	(2.70)	(2.32)	(3.63)	(3.97)	(2.66)	(2.11)	(2.96)	(1.33)
$\text{VRP}^{(PC3)}$	-0.073	-0.060	-0.057	0.120	0.132	0.046	0.216	0.195	0.070
	(-1.29)	(-0.86)	(-0.79)	(1.48)	(1.65)	(0.57)	(2.58)	(2.20)	(0.80)
AdjR^2	0.05	0.08	0.16	0.14	0.29	0.32	0.14	0.23	0.22

Panel C: Commercial Mortgage-Backed Securities

	AAA			BBB			B		
	3m	6m	12m	3m	6m	12m	3m	6m	12m
$\text{VRP}^{(PC1)}$	0.161	0.245	0.361	0.051	0.127	0.321	-0.206	-0.133	-0.048
	(1.55)	(2.61)	(2.75)	(0.31)	(0.86)	(2.75)	(-1.28)	(-0.92)	(-0.33)
$\text{VRP}^{(PC2)}$	0.287	0.363	0.416	0.351	0.469	0.488	0.197	0.211	0.353
	(3.35)	(3.34)	(2.99)	(2.73)	(3.29)	(3.46)	(1.59)	(1.29)	(2.01)
$\text{VRP}^{(PC3)}$	0.172	0.196	0.057	0.032	0.095	0.062	-0.041	-0.014	-0.106
	(1.56)	(1.68)	(0.45)	(0.41)	(1.34)	(0.66)	(-0.48)	(-0.17)	(-0.96)
AdjR^2	0.16	0.27	0.34	0.12	0.27	0.38	0.06	0.04	0.11

Table 7
Treasury Bonds Excess Return Predictability

We run the following regression: $rx_{t+h}^{(i)} = \beta'^{(i)}(h)\mathbf{VRP}_t + \gamma'^{(i)}(h)\mathbf{M}_t + \epsilon_{t+h}^{(i)}$, where $rx_{t+h}^{(i)}$ is the one year excess return for $i = \{24, 36, 48, 60\}$ month Treasury bonds. $\mathbf{VRP}_t$ is a vector containing the principal components of the bond variance risk premia, $\text{VRP}^{(PC1)}$, $\text{VRP}^{(PC2)}$ and $\text{VRP}^{(PC3)}$. $\mathbf{M}_t$ includes the equity market variance risk premium ($\text{VRP}_t^{(E)}$), the Cochrane and Piazzesi (2005) factor (CP) and the macro factors $\widehat{F}_j, j = 1\ldots,8$ from Ludvigson and Ng (2009). Regressions are standardized, meaning all variables are demeaned and divided by their standard deviation. Coefficients are estimated with ordinary-least squares, t-statistics are in parentheses and are calculated using Newey and West (1987) standard errors. Data is monthly and the sample spans the period from July 1991 to June 2010.

	2y	3y	4y	5y
$\text{VRP}^{(PC1)}$	-0.265	-0.237	-0.209	-0.142
	(-2.56)	(-2.33)	(-2.22)	(-1.54)
$\text{VRP}^{(PC2)}$	-0.169	-0.162	-0.162	-0.149
	(-2.30)	(-2.16)	(-2.14)	(-1.92)
$\text{VRP}^{(PC3)}$	-0.174	-0.175	-0.174	-0.158
	(-2.80)	(-2.74)	(-2.72)	(-2.44)
$\text{VRP}^{(E)}$	0.102	0.133	0.113	0.104
	(0.73)	(0.93)	(0.78)	(0.70)
CP	0.357	0.359	0.376	0.374
	(3.78)	(3.96)	(4.26)	(4.36)
$\widehat{F}_1$	-0.433	-0.380	-0.331	-0.276
	(-4.30)	(-3.63)	(-3.16)	(-2.58)
$\widehat{F}_2$	0.025	0.024	0.023	0.030
	(0.65)	(0.65)	(0.64)	(0.94)
$\widehat{F}_3$	0.145	0.175	0.226	0.250
	(2.03)	(2.68)	(3.76)	(4.10)
$\widehat{F}_4$	0.028	0.055	0.089	0.123
	(0.43)	(0.79)	(1.25)	(1.68)
$\widehat{F}_5$	0.027	0.042	0.057	0.073
	(0.47)	(0.74)	(1.04)	(1.33)
$\widehat{F}_6$	-0.012	0.040	0.078	0.093
	(-0.15)	(0.49)	(0.94)	(1.13)
$\widehat{F}_7$	0.146	0.192	0.217	0.254
	(1.74)	(2.23)	(2.53)	(2.95)
$\widehat{F}_8$	0.044	0.095	0.126	0.150
	(0.63)	(1.33)	(1.76)	(2.14)
AdjR^2	0.28	0.28	0.30	0.31

Table 8
Stock Excess Returns Predictability

We run the following regression: $rx^{(i)}_{t+h} = \beta'^{(i)}(h)\mathbf{VRP}_t + \gamma'^{(i)}(h)\mathbf{M}_t + \epsilon^{(i)}_{t+h}$, where $rx^{(i)}_{t+h}$ is the three, six, or twelve month excess return on the market (value-weighted CRSP index), value and growth portfolio (from Ken French's Data Library), respectively. $\mathbf{VRP}_t$ is a vector containing the principal components of the bond variance risk premia, $\text{VRP}^{(PC1)}$, $\text{VRP}^{(PC2)}$ and $\text{VRP}^{(PC3)}$. $\mathbf{M}_t$ includes the equity market variance risk premium ($\text{VRP}^{(E)}_t$), the log dividend yield (DY), the log earnings to price ratio (E/P), and the net equity expansion (NTIS) from Goyal and Welch (2008). Regressions are standardized, meaning all variables are de-meaned and divided by their standard deviation. Coefficients are estimated with ordinary-least squares, t-statistics are in parentheses and are calculated using Newey and West (1987) standard errors. Data is monthly and the sample spans the period from July 1991 to June 2010.

	Market			Growth			Value		
	3m	6m	12m	3m	6m	12m	3m	6m	12m
$\text{VRP}^{(PC1)}$	-0.029	0.043	0.084	-0.024	0.013	0.054	-0.056	0.064	0.173
	(-0.24)	(0.43)	(0.80)	(-0.23)	(0.14)	(0.57)	(-0.43)	(0.55)	(1.43)
$\text{VRP}^{(PC2)}$	0.090	0.219	0.197	0.026	0.162	0.144	0.105	0.251	0.292
	(1.00)	(2.71)	(2.55)	(0.28)	(2.12)	(2.03)	(1.12)	(2.75)	(3.29)
$\text{VRP}^{(PC3)}$	0.129	0.203	0.162	0.069	0.153	0.128	0.098	0.173	0.102
	(1.51)	(2.07)	(2.56)	(0.87)	(1.71)	(1.87)	(1.21)	(1.50)	(1.58)
$\text{VRP}^{(E)}$	0.207	0.298	0.333	0.267	0.383	0.412	-0.006	0.085	0.190
	(1.70)	(3.42)	(3.99)	(2.47)	(4.16)	(4.71)	(-0.04)	(0.78)	(1.57)
DY	0.146	0.169	0.282	0.149	0.174	0.275	0.085	0.082	0.136
	(1.25)	(1.35)	(2.37)	(1.29)	(1.35)	(2.10)	(0.74)	(0.63)	(1.20)
E/P	0.073	0.153	0.200	0.093	0.172	0.180	-0.091	-0.012	0.083
	(0.43)	(0.89)	(1.38)	(0.64)	(1.06)	(1.24)	(-0.57)	(-0.08)	(0.55)
NTIS	0.285	0.429	0.470	0.213	0.363	0.409	0.193	0.346	0.487
	(1.62)	(2.13)	(2.75)	(1.41)	(2.12)	(2.83)	(1.16)	(1.64)	(2.67)
AdjR^2	0.11	0.30	0.39	0.07	0.25	0.33	0.05	0.19	0.34

Table 9
Excess Intermediate Corporate Bond Returns Predictability

We run the following regression: $rx^{(i)}_{t+h} = \beta'^{(i)}(h)\mathbf{VRP}_t + \gamma'^{(i)}(h)\mathbf{M}_t + \epsilon^{(i)}_{t+h}$, where $rx^{(i)}_{t+h}$ is the three, six, or twelve month excess return on a intermediate-term corporate bond portfolio for rating classes AAA, BBB and CCC, respectively. $\mathbf{VRP}_t$ is a vector containing the principal components of the bond variance risk premia, $\text{VRP}^{(PC1)}$, $\text{VRP}^{(PC2)}$ and $\text{VRP}^{(PC3)}$. $\mathbf{M}_t$ includes the equity market variance risk premium ($\text{VRP}^{(E)}_t$), the Cochrane and Piazzesi (2005) factor (CP) and the macro factors $\widehat{F}_j, j = 1\ldots, 8$ from Ludvigson and Ng (2009). Regressions are standardized, meaning all variables are de-meaned and divided by their standard deviation. Coefficients are estimated with ordinary-least squares, t-statistics are in parentheses and are calculated using Newey and West (1987) standard errors. Data is monthly and the sample spans the period from July 1991 to June 2010.

	AAA			BBB			CCC		
	3m	6m	12m	3m	6m	12m	3m	6m	12m
$\text{VRP}^{(PC1)}$	-0.043	0.014	0.143	0.021	0.181	0.238	0.114	0.214	0.216
	(-0.52)	(0.15)	(1.56)	(0.31)	(2.40)	(2.61)	(1.19)	(2.27)	(2.18)
$\text{VRP}^{(PC2)}$	0.135	0.150	0.083	0.200	0.274	0.145	0.179	0.249	0.093
	(1.50)	(2.02)	(1.39)	(3.02)	(2.89)	(1.61)	(2.45)	(2.61)	(0.93)
$\text{VRP}^{(PC3)}$	-0.084	-0.053	-0.065	0.069	0.098	-0.002	0.198	0.188	0.051
	(-1.24)	(-0.77)	(-1.09)	(0.95)	(1.42)	(-0.04)	(3.06)	(2.48)	(1.00)
$\text{VRP}^{(E)}$	0.174	0.056	0.055	0.220	0.173	0.170	0.149	0.169	0.127
	(1.69)	(0.46)	(0.37)	(1.85)	(1.42)	(1.46)	(0.98)	(1.19)	(1.26)
CP	0.203	0.229	0.202	0.170	0.197	0.185	0.140	0.202	0.205
	(2.34)	(2.41)	(2.34)	(2.26)	(2.25)	(2.56)	(2.05)	(2.33)	(2.50)
$\widehat{F}_1$	-0.121	-0.257	-0.324	-0.128	-0.208	-0.339	-0.044	-0.094	-0.324
	(-1.29)	(-2.66)	(-3.40)	(-0.86)	(-1.39)	(-3.62)	(-0.30)	(-0.62)	(-3.85)
$\widehat{F}_2$	0.003	0.075	0.107	-0.001	0.039	0.092	-0.095	0.004	0.059
	(0.09)	(1.87)	(3.16)	(-0.01)	(1.08)	(2.17)	(-1.27)	(0.10)	(1.65)
$\widehat{F}_3$	0.193	0.192	0.244	0.172	0.111	0.115	0.017	-0.077	-0.107
	(2.04)	(2.01)	(2.99)	(3.01)	(1.71)	(2.18)	(0.28)	(-1.02)	(-1.13)
$\widehat{F}_4$	0.094	0.080	0.106	-0.139	-0.096	-0.027	-0.302	-0.277	-0.243
	(1.16)	(0.93)	(1.50)	(-1.12)	(-0.90)	(-0.32)	(-2.55)	(-2.70)	(-2.55)
$\widehat{F}_5$	-0.012	-0.035	-0.011	-0.012	-0.029	-0.061	-0.025	-0.042	-0.099
	(-0.13)	(-0.40)	(-0.20)	(-0.18)	(-0.40)	(-1.14)	(-0.43)	(-0.84)	(-1.78)
$\widehat{F}_6$	-0.010	0.021	0.132	0.159	0.113	0.100	0.204	0.174	0.188
	(-0.16)	(0.33)	(1.97)	(2.36)	(1.65)	(1.43)	(2.96)	(2.86)	(2.84)
$\widehat{F}_7$	0.133	0.235	0.281	0.088	0.118	0.202	0.016	0.047	0.140
	(2.11)	(3.69)	(3.80)	(1.48)	(1.96)	(3.97)	(0.35)	(0.88)	(2.73)
$\widehat{F}_8$	0.079	0.087	0.189	-0.021	0.009	0.115	-0.013	-0.008	0.077
	(0.99)	(1.41)	(3.82)	(-0.36)	(0.16)	(2.55)	(-0.22)	(-0.13)	(1.79)
AdjR^2	0.13	0.23	0.43	0.27	0.40	0.52	0.29	0.38	0.46

Table 10
Excess Commercial Mortgage-Backed Securities Returns Predictability

We run the following regression: $rx^{(i)}_{t+h} = \beta'^{(i)}(h)\mathbf{VRP}_t + \gamma'^{(i)}(h)\mathbf{M}_t + \epsilon^{(i)}_{t+h}$, where $rx^{(i)}_{t+h}$ is the three, six, or twelve month excess return on a commercial mortgage-backed securities portfolio for rating classes AAA, BBB and B, respectively. $\mathbf{VRP}_t$ is a vector containing the principal components of the bond variance risk premia, $\text{VRP}^{(PC1)}$, $\text{VRP}^{(PC2)}$ and $\text{VRP}^{(PC3)}$. $\mathbf{M}_t$ includes the equity market variance risk premium ($\text{VRP}^{(E)}_t$), the Cochrane and Piazzesi (2005) factor (CP) and the macro factors $\widehat{F}_j, j = 1 \ldots, 8$ from Ludvigson and Ng (2009). Regressions are standardized, meaning all variables are de-meaned and divided by their standard deviation. Coefficients are estimated with ordinary-least squares, t-statistics are in parentheses and are calculated using Newey and West (1987) standard errors. Data is monthly and the sample spans the period from July 1991 to June 2010.

	AAA			BBB			B		
	3m	6m	12m	3m	6m	12m	3m	6m	12m
$\text{VRP}^{(PC1)}$	0.081	0.140	0.095	0.119	0.067	0.098	0.087	0.178	0.053
	(1.09)	(1.58)	(0.61)	(1.49)	(0.92)	(0.74)	(0.69)	(1.44)	(0.36)
$\text{VRP}^{(PC2)}$	0.241	0.336	0.391	0.257	0.412	0.456	0.212	0.260	0.392
	(3.73)	(2.86)	(2.70)	(3.19)	(3.62)	(3.12)	(2.83)	(2.08)	(2.80)
$\text{VRP}^{(PC3)}$	0.201	0.215	0.056	0.044	0.105	0.047	0.080	0.138	0.040
	(1.70)	(1.95)	(0.75)	(0.52)	(1.32)	(0.70)	(0.95)	(1.24)	(0.42)
$\text{VRP}^{(E)}$	-0.041	-0.073	-0.025	-0.260	-0.120	0.033	-0.318	-0.285	-0.138
	(-0.76)	(-0.84)	(-0.28)	(-2.14)	(-1.52)	(0.35)	(-1.71)	(-2.16)	(-1.27)
CP	0.125	0.135	0.139	0.028	0.079	0.099	0.170	0.162	0.184
	(2.16)	(1.63)	(1.68)	(0.42)	(1.19)	(1.15)	(2.47)	(2.13)	(2.34)
$\widehat{F}_1$	-0.066	-0.166	-0.402	-0.058	-0.128	-0.269	0.266	0.309	0.120
	(-0.40)	(-0.94)	(-5.02)	(-0.37)	(-0.71)	(-2.53)	(1.61)	(1.62)	(0.81)
$\widehat{F}_2$	-0.141	0.010	0.115	-0.125	-0.005	0.057	-0.154	-0.089	-0.055
	(-1.21)	(0.23)	(2.15)	(-1.65)	(-0.13)	(1.17)	(-1.43)	(-1.52)	(-1.48)
$\widehat{F}_3$	0.245	0.197	0.145	0.360	0.263	0.142	0.259	0.051	-0.017
	(4.53)	(2.83)	(1.75)	(2.98)	(2.88)	(1.36)	(2.58)	(0.34)	(-0.09)
$\widehat{F}_4$	-0.220	-0.217	-0.159	-0.283	-0.255	-0.191	-0.187	-0.292	-0.365
	(-1.59)	(-1.81)	(-1.80)	(-2.26)	(-2.72)	(-2.17)	(-1.22)	(-2.03)	(-2.70)
$\widehat{F}_5$	-0.027	-0.064	-0.123	0.012	-0.074	-0.119	0.028	-0.036	-0.118
	(-0.40)	(-0.93)	(-1.96)	(0.19)	(-1.62)	(-1.91)	(0.37)	(-0.61)	(-1.62)
$\widehat{F}_6$	0.169	0.088	0.021	0.226	0.210	0.073	0.102	0.179	0.233
	(1.74)	(1.09)	(0.31)	(2.66)	(2.49)	(1.14)	(1.11)	(1.95)	(2.66)
$\widehat{F}_7$	0.033	-0.009	0.062	-0.102	-0.127	-0.034	0.019	-0.047	0.001
	(0.64)	(-0.12)	(1.17)	(-1.59)	(-2.06)	(-0.71)	(0.28)	(-0.60)	(0.01)
$\widehat{F}_8$	-0.170	-0.127	-0.041	-0.181	-0.158	-0.084	-0.156	-0.162	-0.107
	(-1.65)	(-1.48)	(-0.72)	(-2.17)	(-1.84)	(-1.50)	(-1.86)	(-1.56)	(-1.23)
AdjR^2	0.33	0.38	0.49	0.42	0.48	0.50	0.34	0.34	0.37

Table 11
Out-of-Sample Predictability

This table reports the results of the out-of-sample forecast evaluation for one year excess returns for Treasury bonds, the market, growth and value portfolio, and long corporate bonds. $\mathbf{VRP}_t$ is a vector containing the individual bond variance risk premia, $\mathrm{VRP}^{(30y)}$, $\mathrm{VRP}^{(10y)}$ and $\mathrm{VRP}^{(5y)}$. '$\mathbf{VRP}_t$ vs const' reports forecast comparisons of an unrestricted model with bond variance risk premia versus a restricted constant expected return benchmark model. '$\mathbf{VRP}_t$+CP vs const+CP' reports forecast comparisons of an unrestricted model with bond variance risk premia and the CP factor versus a restricted benchmark model including a constant and the CP factor. R^2_{OOS} denotes the out-of-sample R^2 of Campbell and Thompson (2008). A positive number indicates that the unrestricted model has a lower forecast error than the restricted benchmark model. ENC-NEW denotes the test statistic of Clark and McCracken (2001) for the null hypothesis that the benchmark model encompasses the unrestricted model with additional predictors. The alternative is that the unrestricted model contains information that could be used to improve the benchmark model's forecast. * indicates significance for the ENC-NEW test statistic at minimally the 95% level. We obtain the initial estimates based on the period from July 1991 to July 1999 and study the out-of-sample predictability for the period starting in July 2000 and ending in June 2010.

Panel A: Fama Bliss Treasury Bonds		
$\mathbf{VRP}_t$ vs const	R^2_{OOS}	ENC-NEW
2y Treasury Bonds	0.06	7.74*
3y Treasury Bonds	0.06	7.63*
4y Treasury Bonds	0.07	8.57*
5y Treasury Bonds	0.07	8.31*
$\mathbf{VRP}_t$+CP vs const+CP	R^2_{OOS}	ENC-NEW
2y Treasury Bonds	0.13	16.72*
3y Treasury Bonds	0.14	16.97*
4y Treasury Bonds	0.17	20.02*
5y Treasury Bonds	0.18	20.30*
Panel B: Stocks		
$\mathbf{VRP}_t$ vs const	R^2_{OOS}	ENC-NEW
Market	0.12	17.10*
Growth	0.13	18.04*
Value	0.17	23.78*
Panel C: Long Corporate Bonds		
$\mathbf{VRP}_t$ vs const	R^2_{OOS}	ENC-NEW
AAA	0.32	38.36*
BBB	0.38	52.72*
CCC	0.24	35.93*

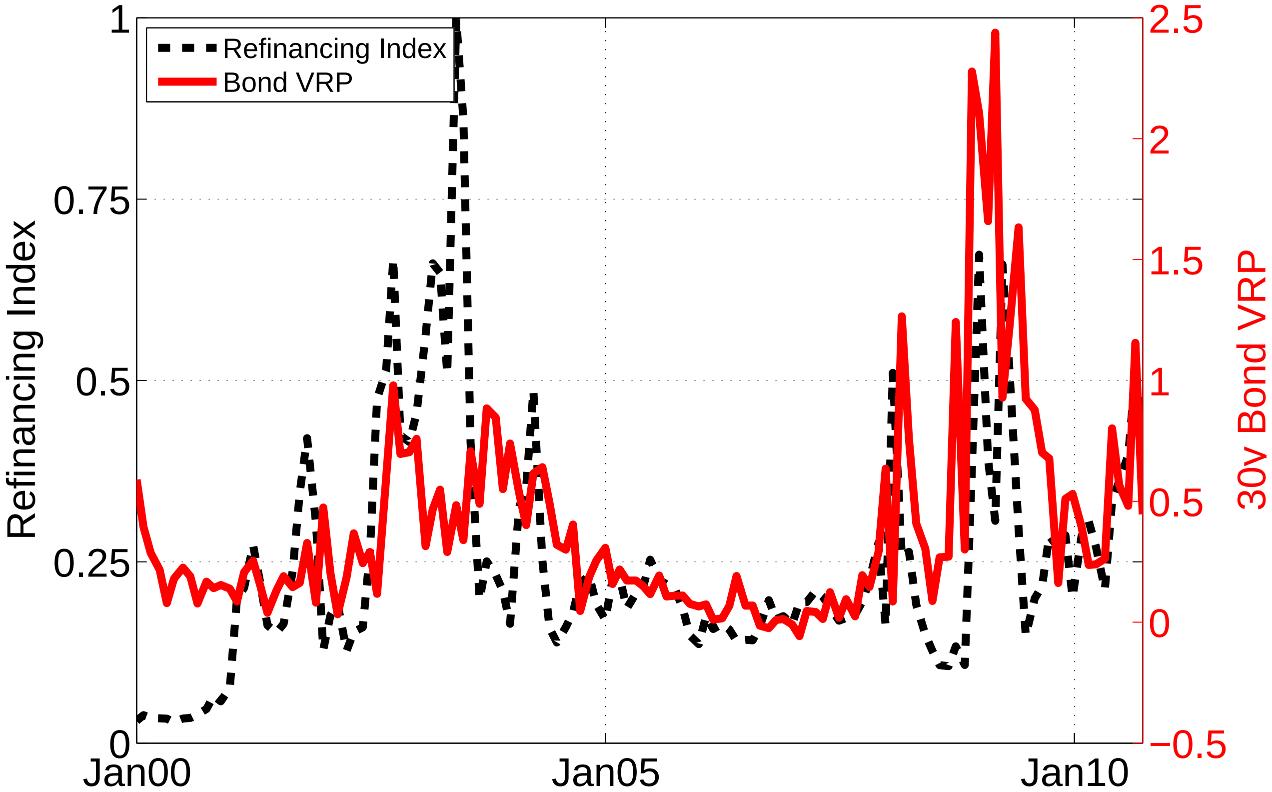

Figure 1. MBA Refinancing Index and 30 Year Bond Variance Risk Premium

This figure plots the time-series of the Mortgage Bankers Association (MBA) refinancing index (dashed line) and the bond variance risk premium for 30 year Treasury futures (solid line). The 30 year Treasury variance risk premium is calculated as the difference between the model-free implied variance (MIV) and the expected realized variance using a HAR-TCJ realized variance estimator augmented with lagged implied variance terms ($RV^{(TCJ)}$). The MBA refinancing index reflects the number of applications for mortgage refinancing and covers about three quarters of all new residential mortgage loans made. The index is seasonally adjusted and divided by a factor of 1,000. Data is monthly and the sample spans the period from January 2000 to June 2010.

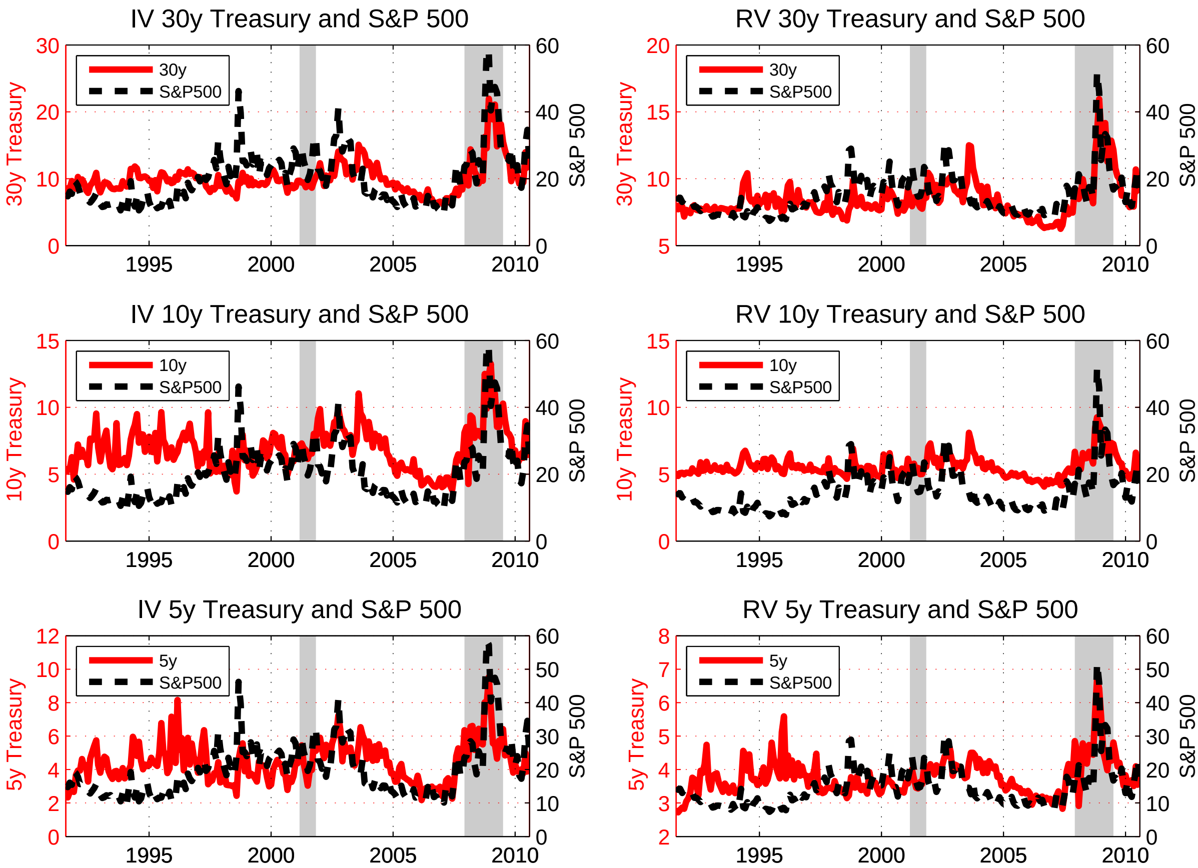

Figure 2. Realized and Implied Volatilities of Treasury and equities

In the left Panels we plot implied volatility measures (IV) for the 30 year, 10 year and 5 year Treasury futures (solid lines) together with the implied volatility of the S&P 500 index (dashed lines), all for a one month horizon. The implied volatilities are the square root of the model-free implied variance (MIV) calculated using options on the respective underlying futures. In the right Panels we plot the realized volatility measures (RV), which are the square root of the HAR-TCJ realized variance estimator augmented with lagged implied variance terms ($RV^{(TCJ)}$). All numbers are annualized and in percent. Shaded areas correspond to recessions as defined by the NBER. Data is monthly and the sample spans the period from July 1991 to June 2010.

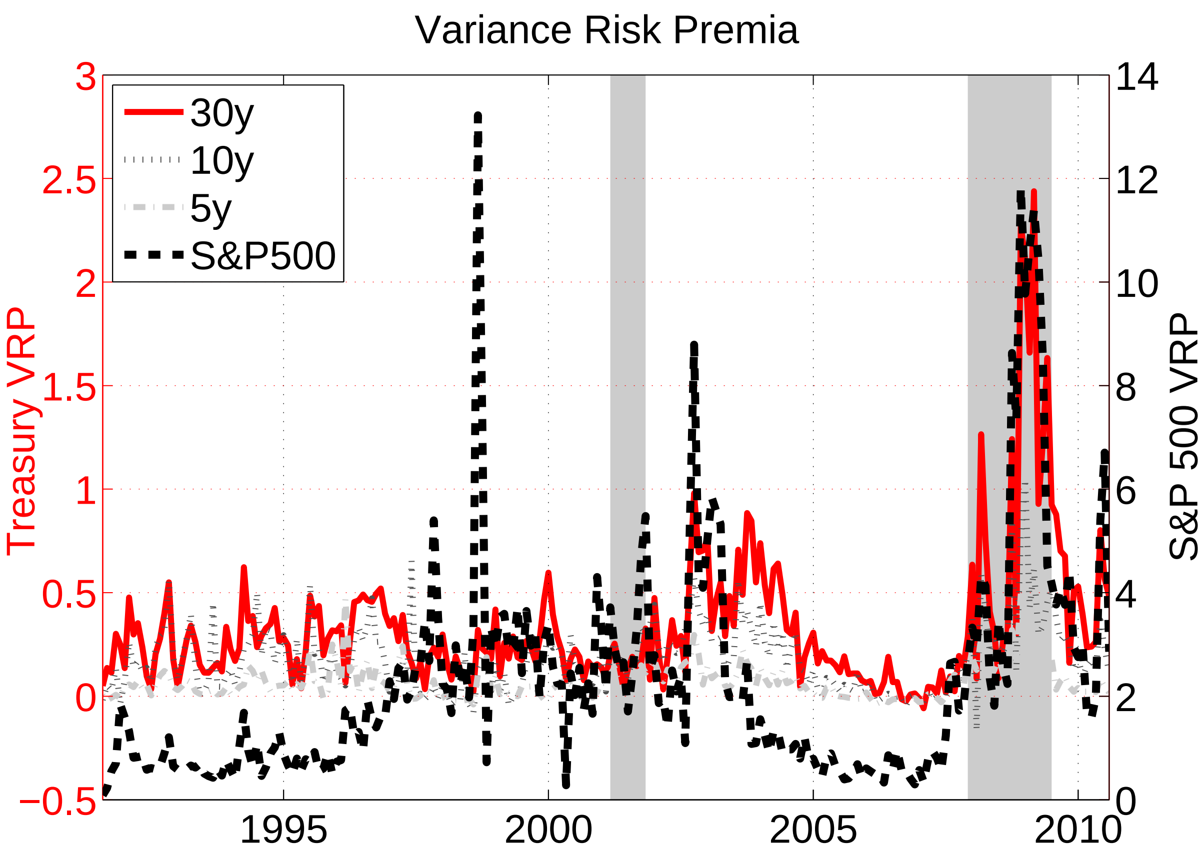

Figure 3. Treasury Bond and Equity Variance Risk Premia

This figure plots annualized variance risk premia for the 30 year, 10 year and 5 year Treasury bonds (left axis, solid, dotted and dashed-dotted lines) and the S&P500 index (right axis, bold dashed line). The variance risk premia are calculated as the difference between the model-free implied variance (MIV) and the expected realized variance using a HAR-TCJ realized variance estimator augmented with lagged implied variance terms ($RV^{(TCJ)}$). Shaded areas correspond to recessions as defined by the NBER. Data is monthly and the sample spans the period from July 1991 to June 2010.

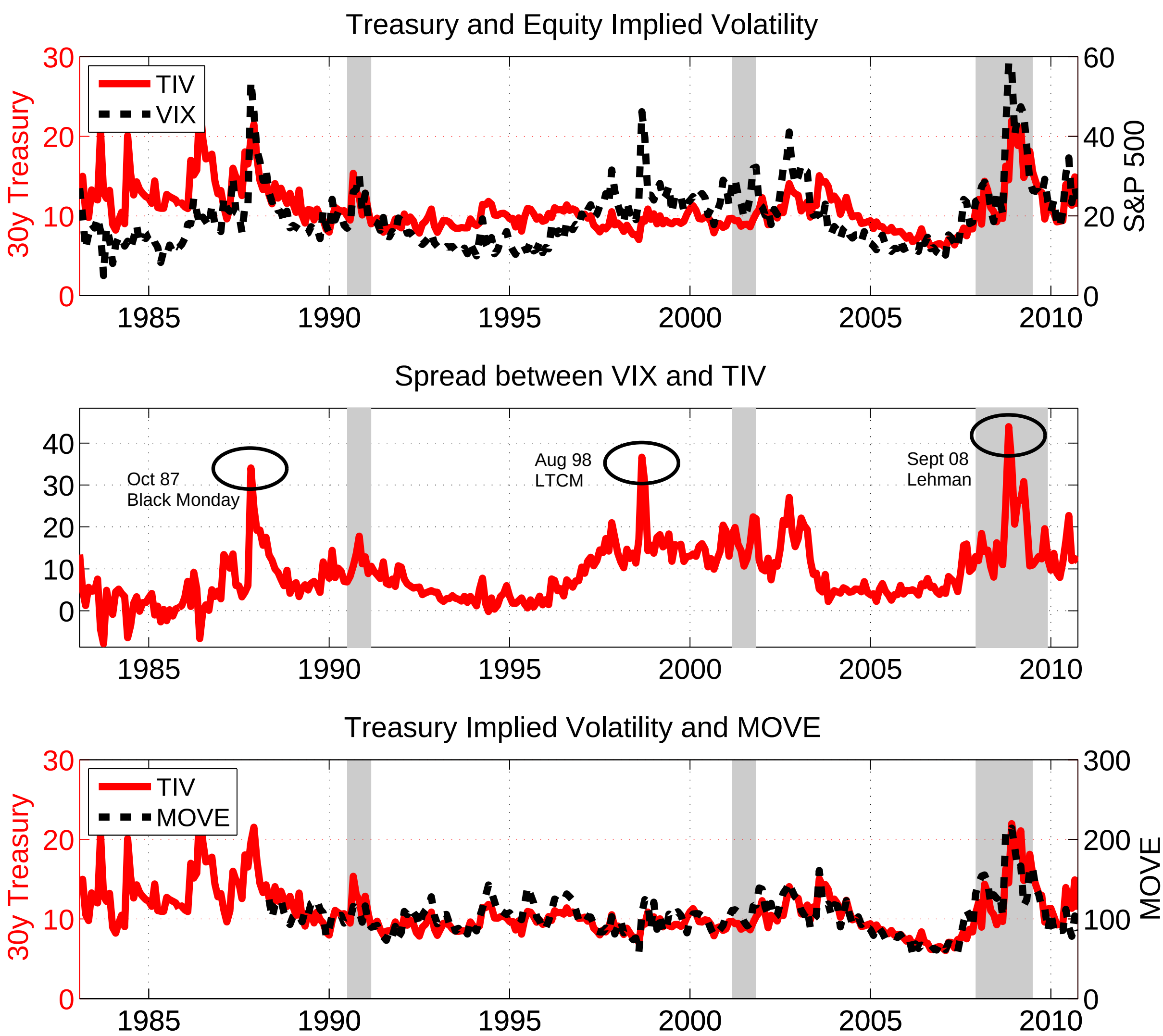

Figure 4. Treasury and Equity Implied Volatility

The top Panel plots the Treasury (solid line) and equity (dashed line) implied volatility measures TIV and VIX, respectively. The measures are calculated using options on the 30 year Treasury bond and the S&P 500 index futures, respectively, as the square root of the model-free implied variance MIV. The unconditional correlation between the TIV and the VIX is 46% over the whole sample period and 63% since 1990, the start date of the CBOE VIX. The middle Panel plots the spread between the VIX and the TIV. The bottom Panel plots the TIV (solid line) together with the Merrill Option Volatility Estimate (MOVE) index (dashed line). The MOVE index is a yield curve weighted index of normalized implied volatility on one month Treasury options for 2, 5, 10 and 30 year Treasuries. Shaded areas correspond to recessions as defined by the NBER. Data is monthly and the sample spans the period from January 1983 to June 2010.