Changing Expectations and the Correlation of Stocks and Bonds

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Abstract

The aim of this paper is to empirically examine the economic mechanisms underlying the correlation of stock and bond returns. Using a Campbell-Shiller decomposition we express unexpected stock and bond returns into news components related to macroeconomic fundamentals. The variance and covariance of these news components constitute the variance and covariance of stock and bond returns. We therefore attempt to use time-varying comovement among the innovations to shed light on the economic mechanisms driving the time variation in the realised second moments of stock and bond returns. Using survey forecast data for the macroeconomic components we show that the uncertainty in cash flow and excess stock returns is able to explain the variation in excess stock variance up to an R^2 of 24%. The variation in excess bond variance can be attributed to the uncertainty in real short-term interest rates and excess bond returns up to an R^2 of 16%. As for the covariance between stock and bond returns, it is determined by the interaction between several of the macroeconomic news components and we are able to account for up to 24% of the variation. Our findings highlight the importance of the interaction between cash flow news and inflation news for negative stock-bond correlation.

Key words: stock return volatility, bond return volatility, stock-bond return correlation, survey forecasts, macroeconomic news, dynamic conditional correlation

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1 Introduction

It has been well documented that there is substantial time variation in the correlation between the US stock market and long-term government bond returns, including periods of negative correlation. The mechanisms of this time variation however are far less understood. This is an important question since stock-bond correlation plays a pivotal role in most investors' asset allocation decisions and their portfolio's diversification benefits. It seems that investors are keenly aware of this since Agnew and Balduzzi [2006] empirically document that investors re-balance between stocks and bonds in response to price changes in these markets. In this paper, we aim to explore the economic mechanism that is driving the time variation in stock-bond correlation.

[Figure 1 about here.]

Correlation is a function of the covariance of returns and the respective volatilities. We make this distinction to highlight the importance of the respective components. Figure 1 plots the monthly realised volatility, covariance and correlation of the US stock and 10-year US Treasury bond returns. It is clear from this that for an investor with a portfolio of stocks and bonds any diversification benefits being sought by the investor will depend crucially on both the covariance and the volatility of returns. For instance, in the early 1990's when the covariance remained fairly constant but volatility changes across these markets were highly correlated; as can be seen from figure 1 the correlation was affected. We therefore concentrate our study on explaining the time variation in the covariance and variances of stock and bond returns.

We use the Campbell-Shiller (1988) decomposition as a theoretical framework to express unexpected stock and bond returns as components related to economic fundamentals. The decomposition uses an accounting identity to decompose unexpected stock returns into changing expectations (i.e. unexpected values) of future real cash flow, future real short-term interest rates and the future excess returns on stocks (stock risk premium). Unexpected bond returns are decomposed into changing expectations of future inflation rates (this determines the real value of the nominal bond payments), future real short-term interest rates and future excess returns on long-term bonds (bond risk premium). Since the variance and covariance of these components constitute the variance and covariance of stock and bond returns, we attempt to use time-varying comovement among the fundamental components to shed light on the economic mechanisms driving the time variation in the realised second moments of stock and bond returns.

Campbell and Ammer [1993] use such a framework within a vector autoregressive (VAR) model. They estimate their model implicitly assuming that the stock-bond correlation is time-invariant[1], contrary to Figure 1. Recently, several studies including Chen and Zhao [2009] show that use of a VAR model is extremely sensitive to the choice of state variables and can thus lead to differing conclusions depending on the choice of state variables. Recently, Piazzesi and Schneider [2011] show that investors' actual historical predictions (from survey forecast data) are different from the in-sample statistical predictions obtained from using a VAR model. Thus by using actual historical forecasts rather than statistical forecasts to obtain the expected values of the decomposed components, our method can better help to understand the true nature of asset pricing puzzles such as the time variation in stock-bond correlation.

Our novel approach consists of using survey forecast data from the BlueChip Economic Indicators (BCEI) survey to obtain a time-series of expected values for the fundamental components of the decomposition, namely cash flow, short-term interest rate and excess bond returns. To our knowledge this data has not been used before to study stock-bond correlation. Forecasts for the inflation rate are obtained from a structural model developed at the Federal Reserve Bank of Cleveland by Haubrich and Bianco [2010] and forecasts of excess stock returns are obtained by using a predictive linear model on a range of state variables known in the literature to display some predictability for stock returns. We document the approach in more detail in the subsequent sections. Once we have a time-series of forecasts for the decomposed components together with knowing the realised values, time-series of the unexpected values (news) of these components are easily obtained. We then use the Dynamic Conditional Correlation (DCC) model introduced by Engle [2002] to describe the time-varying comovement among these news components and look at the extent to which these explain the time variation in the second moments of stock and bond returns.

[1]They use a Generalised Method of Moments (GMM) approach correcting for the heteroskedasticity and autocorrelation of the pricing errors but which ultimately assumes a constant variance-covariance matrix of the pricing errors.

Before we report our findings as to the economic mechanisms driving the second moments of stock and bond returns, we examine other variables that have been highlighted in the literature as being related to the stock-bond correlation. The work by Chordia et al. [2005] and Goyenko [2006] conclude that stock-bond comovement is due to time variation in investors' liquidity needs. Since stock and bond markets are highly integrated, the author's argue that liquidity has a cross-market effect which they attribute to trading activity across these markets. More recently, Baele et al. [2010] use a dynamic factor model to find that liquidity plays an important role while macroeconomic factors contribute very little to movements in second moments of stock-bond returns. Viceira [2010] also reports that financial variables such as the yield spread and the short term nominal rate are able to positively forecast the stock-bond covariance. Works by Gulko [2002], Connolly et al. [2005] and Connolly et al. [2007] study the effect of a flight-to-quality in asset markets on stock-bond comovement. Generally they find that rising stock market uncertainty[2] tends to decrease the comovement between stock and bond markets, thus causing a decoupling of these asset classes.

Our empirical investigation uncovers several new results and also confirms several previous findings. We find that uncertainty in real cash flow and uncertainty in future excess returns are able to explain up to 24% in the time variation of stock variance. The dynamics between these two uncertainties also contributes to stock market volatility. Such an observation appears plausible if one considers the large cash flow shocks observed in the recent financial crisis and the corresponding volatility of the stock markets. As for the bond market, uncertainty in future excess returns and the real interest rate are able to contemporaneously explain up to 16% of the variation in bond variance across time. We find that the interaction between the uncertainties also plays a significant role in explaining bond variance. Uncertainty in the inflation rate seems to play minor role in the volatility of bond returns since during our sample period, the inflation rate was relatively low and stable. The real interest rate news on the other hand appears important since unexpected decreases of the real interest rate during the recent financial would have pushed bond prices up which would have been accompanied by an increase in bond market variance.

[2]This is often proxied for by using a market volatility index such as CBOE's VIX Index, which measures the implied volatility of options on the Standard & Poor's 500 stock index. It is often called the "fear index" by market practitioners. For more details on the history and purposed of this index see Whaley [2009].

Regarding the covariance between stock and bond returns, it is the uncertainty of the real cash flow, inflation rate and the real interest rate that can explain up to 22% of the variation in the covariance. Indeed we find that the covariance between real cash flow news and inflation news is a mechanism by which the stock-bond covariance turns negative, a finding consistent with David and Veronesi [2008]. A possible reason for this is that an unexpected increase in the inflation rate is bad news for bond returns, while an unexpected increase in cash flow is good news for stock returns. This causes investors to sell their bonds in favour of stocks, thus driving the correlation to be negative. Our results generally highlight that macroeconomic factors do have the ability to partially explain the time variation in the second moments of stock and bond returns. This allows us to investigate the economic mechanism that drive the (co)variance of stock and bond returns.

Our research is related to three streams of the literature with three resulting contributions. First, similar to Campbell and Ammer [1993] we employ a dynamic accounting framework using the Campbell-Shiller decomposition in order to directly investigate the role of macroeconomic factors in changing stock and bond prices. Campbell and Ammer [1993] use a VAR model and examine the offsetting effects on the variances and covariance of stock and bond returns. They find that while unexpected shocks of the real interest rate drive returns of stocks and bonds in the same direction, expected inflation increases excess stock returns and lowers excess bond returns. However, Campbell and Ammer [1993] focus on the unconditional moments and thus implicitly assume that the stock-bond correlation is time invariant. We contribute to this strand of literature by using analyst forecasts to generate a time-series of forecasts for the decomposed components of stock and bond returns and are thus able to investigate the time variation of the conditional stock-bond correlation. Indeed, we believe we are among the first to demonstrate the informational content of survey forecasts for the variation in stock-bond correlation.

Second, our paper is related to previous theoretical work which has attempted to shed light on the underlying economic linkages that tie fundamentals to stock-bond return volatilities and covariances. For instance, Barsky [1989] was amongst the first to investigate this by proposing a general equilibrium model to show that unconditional stock-bond covariance is state-dependent[3]. Other studies have adopted the approach of using a stock-bond pricing model incorporating various economic mechanisms in order to explain the time variation of the correlation. Bekaert et al. [2010] employ a model where agents who are pricing stocks and bonds have a stochastic risk aversion, David and Veronesi [2008] base their model on investors learning about the expected components of earnings and inflation from other fundamental components, while Campbell et al. [2009b] propose a pricing model with a latent factor to capture the covariance between inflation and the real economy to create a model with the ability to generate time varying stock-bond covariance. Since all these economic models have limited success in fully explaining the time variation of stock and bond (co)variance, our contribution to this strand is to empirically demonstrate the economic mechanisms that drive changes in the volatility and correlation of stock and bons returns over time.

Third, econometric tools have been developed to acknowledge and describe the time variation in correlation. Specifically for stock and bond returns, De Goeij and Marquering [2004] and Cappiello et al. [2006] both develop and estimate dynamic correlation models. We contribute to this strand of literature by adopting Engle [2002] Dynamic Conditional Correlation (DCC) model to explicitly obtain the (co)variance time series of stock and bond return news components, allowing us to investigate the components theoretically motivated significance on explaining stock-bond (co)variance. Such a tool allows us to extend the work done by Viceira [2010] to directly explore the time variation in the covariance of the news components of both stock and bond returns[4], hence directly investigating the role of the interaction of macroeconomic factors on stock-bond correlation.

The rest of the paper is structured as follows. Section 2 presents the theoretical expressions of the second moments of stock and bond returns using the Campbell-Shiller decomposition. Section 3 outlines the raw data sources for our survey forecasts and historical data. Section 4 details the method of construction for the component news time

[3] He found that low productivity growth and high market risk are likely to lower both corporate profits and the real interest rate, which propels stock and bond prices in opposite directions. Note that similarly to Campbell and Ammer [1993], this study also implicitly assumes that the stock-bond correlation is constant over time.

[4] Viceira [2010] use a VAR approach to study the covariance of bond return news components with the short term nominal rate and yield spread. By using excess stock returns as one of the state variables, the role of the short rate and yield spread on stock-bond correlation was also examined. Our paper instead focuses on the interaction of news components to contemporaneously explain the time variation in stock-bond correlation.

series. Discussion of our results and some concluding remarks are made in sections 5 and 6 respectively.

2 Theoretical stock-bond correlation

The decomposition of Campbell and Shiller [1988] and Campbell and Ammer [1993] provide a convenient theoretical framework for our empirical work. Their methodology allows us to express the innovation to a long-term asset return as the sum of revisions in the expected decomposed components. In the next sections we show how the conditional stock-bond correlation can be written as various components on stock and bond return innovations. First we decompose innovations to stock returns into their constituent parts.

2.1 Surprises in stock returns

Stocks have claim to stochastic real cash flows. Appendix A derives the innovation to stock returns as changing expectations of future real dividend growth, future real interest rates and future excess stock returns:

$$e_{t+1}^S - \mathbb{E}_t[e_{t+1}^S] = (\mathbb{E}_{t+1} - \mathbb{E}_t)\left[\sum_{j=1}^{\infty}\rho^j \Delta d_{t+j} - \sum_{j=1}^{\infty}\rho^j r_{t+j} - \sum_{j=2}^{\infty}\rho^j e_{t+j}^S\right] \tag{1}$$

where e_t^S is the log excess stock return at time t, r_t is the log real short term interest rate, ρ is a constant discount factor, d_t is the log real dividend paid at time t and Δ is the one-period backwards difference. This equation for stock returns relates the unexpected stock return at time $t+1$ to changes in rational expectations (otherwise known as surprises, innovations or news) of future dividends, future expected interest rates and future excess returns. Note that $\mathbb{E}_t$ denotes the expectation formed at time t, conditional on an information set that includes the history of stock prices, short term interest rates and dividends up to time t. Equation 1 is an identity which is obtained through imposing internal consistency on expectations to rule out the possibility of a asset pricing bubble. We can write it more simply as:

$$\tilde{e}_{t+1}^S = \tilde{S}_{CF,t+1} - \tilde{S}_{r,t+1} - \tilde{S}_{e,t+1} \tag{2}$$

where the tilde is used to denote a surprise to a component and the subscript is used to denote the respective components and the time at which the surprise occurs. Equation

2 neatly states that if for example the unexpected return to stocks is positive, assuming that the short-term interest rate is deterministic, then either the expected future dividends must be higher or expected future excess returns are lower, or a bit of both. From this simple example, it is clear that the new information used in each time period to update the forecasts of future dividends, short term interest rate and excess returns, is what drives the surprises in stock returns.

It has been suggested that earnings rather than dividends should be used as the appropriate measure of cash flow, as earnings are more stable than dividends, less affected by financial policy or share repurchases and that Modigliani-Miller's propositions on the irrelevance of dividend policy gives no theoretical reason to expect managers to pursue any particular dividend policy. We therefore choose to adapt the cash flow component in equation 1 according to:

$$\tilde{S}_{CF,t+1} = (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=1}^{\infty} \rho^j \Delta d_{t+j} = (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=1}^{\infty} \rho^j \Delta e_{t+j} \tag{3}$$

where Δe_{t+j} is the growth in (log) real earnings at time $t+j$, which we can express more simply as:

$$\Delta e_{t+j} = log \left(1 + \frac{E_{t+j}}{E_{t+j-1}} \right) \tag{4}$$

where E_t is defined as the real earnings at time t. Equation 4 therefore implies that innovations to real dividend growth and real earnings growth over an infinite horizon contain the same information. Using this alternative expression we can therefore use forward-looking earnings forecasts to proxy for the news of the cash flow component. More details on the construction of all the news components are outlined later.

2.2 Surprises in bond returns

Government bonds are subject to fixed nominal cash flows. We can thus derive an expression for bonds which holds exactly[5]:

$$e_{t+1}^{B,(N)} - \mathbb{E}_t[e_{t+1}^{B,(N)}] = (\mathbb{E}_{t+1} - \mathbb{E}_t) \left[-\sum_{j=1}^{N} \pi_{t+j} - \sum_{j=1}^{N} r_{t+j} - \sum_{j=2}^{N} e_{t+j}^{B} \right] \tag{5}$$

[5]See Appendix A for details of the decomposition.

where e_t^B is the log excess bond return at time t (similarly defined as the log holding period return in excess of the short term interest rate) and π_t is the inflation rate at time t. Changes in expected inflation alter the real value of the fixed nominal payoff on the bond, so can cause capital gains or losses even if the expected future return on the bond is constant[6]. Similarly to above, we can write equation 5 more simply as:

$$\tilde{e}_{t+1}^B = -\tilde{B}_{\pi,t+1} - \tilde{B}_{r,t+1} - \tilde{B}_{e,t+1} \tag{6}$$

If we were to assume $\tilde{B}_{e,t+1} = 0$, i.e. that the bond risk premium is constant, we could recover the expectations hypothesis of the term structure. However, we leave Equation 6 free from restrictive assumptions and obtain a time series for all of the news components.

2.3 Stock-bond correlation

Using Equations 2 and 6 the conditional variance of excess stock and bond returns can be decomposed as:

$$\begin{aligned} var_t(\tilde{e}_{t+1}^S) = {} & var_t(\tilde{S}_{CF,t+1}) + var_t(\tilde{S}_{r,t+1}) + var_t(\tilde{S}_{e,t+1}) - 2cov_t(\tilde{S}_{CF,t+1}, \tilde{S}_{r,t+1}) \\ & - 2cov_t(\tilde{S}_{CF,t+1}, \tilde{S}_{e,t+1}) + 2cov_t(\tilde{S}_{r,t+1}, \tilde{S}_{e,t+1}) \end{aligned} \tag{7}$$

$$\begin{aligned} var_t(\tilde{e}_{t+1}^B) = {} & var_t(\tilde{B}_{\pi,t+1}) + var_t(\tilde{B}_{r,t+1}) + var_t(\tilde{B}_{e,t+1}) + 2cov_t(\tilde{B}_{\pi,t+1}, \tilde{B}_{r,t+1}) \\ & + 2cov_t(\tilde{B}_{\pi,t+1}, \tilde{B}_{e,t+1}) + 2cov_t(, \tilde{B}_{r,t+1}, \tilde{B}_{e,t+1}) \end{aligned} \tag{8}$$

The conditional covariance between excess stock and bond returns can therefore be written as:

$$\begin{aligned} cov_t(\tilde{e}_{t+1}^S, \tilde{e}_{t+1}^B) = & - cov_t(\tilde{S}_{CF,t+1}, \tilde{B}_{\pi,t+1}) - cov_t(\tilde{S}_{CF,t+1}, \tilde{B}_{r,t+1}) - cov_t(\tilde{S}_{CF,t+1}, \tilde{B}_{e,t+1}) \\ & + cov_t(\tilde{S}_{r,t+1}, \tilde{B}_{\pi,t+1}) + cov_t(\tilde{S}_{r,t+1}, \tilde{B}_{r,t+1}) + cov_t(\tilde{S}_{r,t+1}, \tilde{B}_{e,t+1}) \\ & + cov_t(\tilde{S}_{e,t+1}, \tilde{B}_{\pi,t+1}) + cov_t(\tilde{S}_{e,t+1}, \tilde{B}_{r,t+1}) + cov_t(\tilde{S}_{e,t+1}, \tilde{B}_{e,t+1}) \end{aligned} \tag{9}$$

[6] Note that in this case the maturity of the bond decreases as time passes, so the relevant expectations are taken over the maturity length. The summation is from 1 to N which represents the maturity of the bond.

The conditional correlation between returns thus being a function of Equations 7, 8 and 9 through:

$$corr_t(\tilde{e}^S_{t+1}, \tilde{e}^B_{t+1}) = \frac{cov_t(\tilde{e}^S_{t+1}, \tilde{e}^B_{t+1})}{\sqrt{var_t(\tilde{e}^S_{t+1}) var_t(\tilde{e}^B_{t+1})}} \tag{10}$$

2.4 Component expectations

Our aim is to explore the economic mechanisms that drive the time variation in second moments of stock and bond returns through examining the time variation in the variance and covariance of the decomposed news components, namely cash flow news, real interest rate news, inflation news and excess stock and bond return news. In order to obtain a time-series of news components, we need a method to obtain a time-series of expected values for these components. There are three potential methods to obtain such expectations as we outline below.

Model-implied: A common method is to build a predictive model for the variable of interest (either structural or reduced form) using state variables known to exhibit some predictability. After estimating the model using actual data, the model can then be used to generate expected values of the variable N periods ahead. For example, one commonly used model is the VAR system as used by Campbell and Ammer [1993] for the Campbell-Shiller style decompositions of Equations 2 and 6 above. For this particular method however, Welch and Goyal [2008] and Chen and Zhao [2009] find that VAR models are sensitive to the sample period and the choice of state variables. The model's conclusions can change as a result of the choice of sample period and state variables. The VAR model's results and the model-implied approach are thus dependent on the validity of the model's assumptions, construction and conclusions.

Market-implied: By using market data it may be possible to back out the "market's expectation" of the variable. For example, a popular market measure of expected inflation is the break-even inflation rate defined as the difference between equivalent-maturity yields on nominal Treasury bonds and Treasury inflation protected securities (TIPS). The problem with such an approach is that it is often influenced by other factors such as liquidity and risk. For the case of the breakeven rate, Campbell et al. [2009a] show that liquidity differences between nominal and TIPS bonds, and an inflation risk premium bias the level of the expected inflation rate obtained from TIPS. Such a method to generate the expected value of the variable may therefore not provide a precise expectation value for that variable.

Survey data: A recent trend within the literature is to use professional forecast data as a direct measure of the expectation of the variable of interest. Ang et al. [2007] find that professional forecasts significantly outperform time series, Philips curve and term structure models for predicting inflation out of sample. Piazzesi and Schneider [2011] also note that investors' actual historical predictions are different from the in-sample predictions found by statistical models such as the VAR model. They comment quite validly that investors ex-ante may not recognise the same patterns that we observe today with the benefit of hindsight (ex-post). Professional forecast data therefore seems like a promising method to generate direct expectations of the decomposed components of Equations 2 and 6 above.

In our work, we use mainly professional survey forecasts but also model implied forecasts. Expectations of cash flow, the short term interest rate and long-term bond returns are obtained from forecasts made by a panel of economists from the BlueChip Economic Indicators (BCEI) survey database on corporate profits, 3-month T-Bills and 10-year Treasury bonds. Expectations of the inflation rate are obtained from a structural model developed at the Federal Reserve Bank of Cleveland by Haubrich and Bianco [2010] which provides monthly forecasts of the inflation rate over the next 10 years. Lastly, expectations of excess stock returns are obtained from the well-adopted method of using a predictive regression on a battery of state variables known in the literature to have some predictive power (Fama and Schwert [1977], Fama and French [1988], Campbell and Shiller [1988], Cochrane and Piazzesi [2005]). We outline our data sources in more detail in the next section.

After backing-out the news time-series from the forecasts and actual (realised) values of the components, we employ the Dynamic Conditional Correlation (DCC) model of Engle [2002] to describe the conditional variance and covariance of these news components[7]. We then look to the explanatory power of these conditional second moments of the decomposed news components to explain the time variation in the second moments of stock and bond returns.

[7] As a robustness check we use a Exponentially Weighted Moving Average(EWMA) model to describe the conditional variance and covariance of the news components. Our findings remain qualitatively unchanged.

3 Data

Our study uses monthly data on U.S. stock market returns, U.S. 10-year Treasury bond returns, survey forecasts of corporate profits, the 3-month Treasury bill yield, the 10-year Treasury bond yield and model-implied forecasts of inflation rates and stock returns. We also obtain the actual (realised) time-series of all the forecasted variables above. Our data series go from July 1984 to December 2009, a total of 306 observations. We proxy for the U.S. stock market by using the aggregate value-weighted return index of the stocks traded in the NYSE, AMEX and Nasdaq markets from the Centre for Research in Security Prices (CRSP). We proxy for the U.S. bond market by the 10-year Treasury bond, since monetary policy has less of an impact on long-term government bonds than on short-term bonds. The nominal zero-coupon yield for the 10-year bond is obtained from the daily off-the-run Treasury yield curves constructed by Gurkaynak et al. [2007][8]. We also require the nominal 3-month yield which is obtained from the Federal Reserve System's H.15 Release[9]. The monthly Treasury yields are observed as of the last trading day of each month.

Survey forecasts for the future level of corporate profits, 3-month nominal yield and the 10-year T-Bond yield come from the BlueChip Economic Indicators (BCEI) database which surveys approximately 50 economists employed by financial institutions, non-financial corporations and research organisations. At the beginning of each month participants forecast future values of various variables for the current calendar year and for the next calendar year. From this we back-out the one-year ahead forecast for our variables[10]. Each month we obtain the 'consensus' forecast which is the mean of the participants' forecast as the 1-year ahead expected value of the level of corporate profits, the 3-month T-Bill yield and the 10-year T-Bond yield.

We note that forecasts of corporate profits from BCEI are forecasts of the level of corporate earnings before-tax with inventory valuation and capital consumption adjustment for the National Income and Product Accounts (NIPA) at the Bureau of Economic Analysis (BEA). This represents an aggregate measure of cash flow to US firms from current production. Although this is based on all US firms that are required to file Federal corporate

[8]Their daily Treasury yield curves are available from 1961 to the present at http://www.federalreserve.gov/econresdata/researchdata.htm.

[9]Available from http://www.federalreserve.gov/releases/h15/data.htm

[10]For more details on the procedure see Appendix B.

tax returns and so includes both public and private firms, we use this variable as the proxy for aggregate cash flow to compare its validity with the more traditional sources of earnings forecasts from IBES.

Since this survey is not anonymous, the career concerns of the respondents may influence their official stated forecast. We address this concern by comparing the BCEI data to the Survey of Professional Forecasters (SPF) data[11]. We find that the mean and median forecasts from SPF are similar to those from the BCEI. This robustness check is reassuring since Ang et al. [2007] find that forecasts from SPF significantly outperform a variety of other methods for predicting inflation. Since the participants in the BCEI survey have qualifications similar to those of the SPF participants, it is likely that the BCEI forecasts also exhibit these attractive features for corporate profits and interest rate forecasts.

Forecasts of the inflation rate are directly from the Federal Reserve Bank of Cleveland (Cleveland FED) who generate the expected values of the inflation rate through estimating a structural model on the real and nominal term structures. The work by Haubrich and Ritchken [2011] at the Cleveland FED estimate their model using nominal Treasury yields, SPF survey forecasts of inflation and inflation swap rates[12]. We are therefore confident that the expected inflation rate implied by this model is the best of the survey and market-implied measures of future inflation rates. For this reason we therefore use the model-implied data for our expected inflation measure[13].

To obtain a model-implied forecast of stock returns, we use a predictive linear model based on state variables known in the literature to display some predictability. These variables include the dividend yield, term spread, default spread and the Cochrane and Piazzesi [2005] factor. The data to construct these variables was obtained from both CRSP and DataStream. For further details on the data sources and construction, see Appendix B.

[11]SPF forecasts are quarterly and cover a range of forecast horizons that overlap with those obtain from BCEI. The data is obtained directly from the Philadelphia FED.

[12]These are obtained from derivative securities known as zero coupon inflation swaps. They are the most liquid inflation derivative contracts and trade in the over-the-counter market.

[13]The data is available directly from http://www.clevelandfed.org/research/index.cfm

4 Empirical proxies of news components

We now outline in detail the method for constructing each of the news components. We note that as we are considering a 10-year Treasury bond, the summations in Equation 5 pertain to a 10-year horizon ($N = 10$), with the revisions calculated over monthly intervals. Henceforth, to prevent confusion in the notation, t refers to the month in which we are taking the expectation, whilst j refers to the yearly horizon of the forecast value (expected value) that we require. Using the inflation rate as an example, with $j = 2$, π_{t+12j} denotes the 2-year forecast of the annual inflation rate at month t. We therefore express the expectation at month t of the total future inflation rate over the next 10-years as: $\mathbb{E}_t\left(\sum_{j=1}^{10} \pi_{t+12j}\right)$. This analogy applies similarly to the other expected components that we consider.

Note also that the summations of the components for the innovation of excess stock returns in Equation 1 have an infinite horizon. For the purposes of this study, we set the horizon of the summations for Equation 1 to be the same as those in Equation 5 of $N = 10$. This implicitly assumes that near term revisions carry more weight than long-term revisions, which we believe is not an unreasonable assumption in order to obtain the news time series of each component.

4.1 Cash flow news

We construct the cash flow news proxy using the BCEI forecast of corporate profits. Denoting the 1-year forecast of real earnings at month t as:

$$E_{t+12|t} = \frac{CP1_t}{(1 + Inf1_t)} \tag{11}$$

where $CP1_t$ is the month t 1-year forecast of annualised corporate profits (earnings) from the BCEI survey and $Inf1_t$ is the month t 1-year forecast of the annualised inflation rate from the Cleveland FED model. Subsequently, we express the 1-year forecast for real earnings growth in month t as:

$$\Delta e_{t+12|t} = \log\left(1 + \frac{E_{t+12|t}}{E_t}\right) \tag{12}$$

where E_t is the actual value of real annualised corporate earnings at month t defined as $\frac{CP0_t}{1+Inf0_t}$, with $Inf0_t$ being the realised annualised inflation rate and $CP0_t$ being the realised annualised corporate profits, both at month t. From Equation 3 it is clear that we require further forecasts of real earnings growth at longer horizons. Since this data is not available from the BCEI database, we therefore need a method to generate forecasts of the annualised growth in corporate profits over the following 9 years. Using a similar methodology to Pástor et al. [2008] we assume that the annualised growth in earnings linearly mean-reverts to a steady state over the following 9 years in which the forecasts are being extended. We believe that by using such a method we do not bias the subsequent forecasts in any direction and so by assuming a mean-reverting process for the subsequent forecasts, we conservatively extended the forecast horizons. The steady state of earnings growth $g^{\Delta e}$ is computed as the rolling average of the growth in real (annualised) corporate profits starting from 1948 to the prior month in which we require the expected value of the level of corporate profits. The subsequent forecasts can thus be expressed as:

$$\Delta e_{t+12j|t} = \Delta e_{t+12j-12|t} + \frac{g_t^{\Delta e} - \Delta e_{t+12|t}}{9} \quad where \quad j = 2, ..., 10. \tag{13}$$

We can then express the total forecast of the growth in corporate profits over the next 10 years at month t as:

$$\mathbb{E}_t \left(\sum_{j=1}^{10} \rho^j \Delta e_{t+12j} \right) = \sum_{j=1}^{10} \rho^j \Delta e_{t+12j|t} \tag{14}$$

We assume that $\rho = 0.96$ in line with the literature [14]. In order to obtain the unexpected value (news) to cash flow, we obtain the total forecast of the growth in corporate profits over the next 10 years from month t, taking the expectations from month $t+1$, i.e. knowing the actual (realised) corporate profits growth between month t and $t+1$:

$$\Delta e_{t+12|t+1} = \log \left(1 + \frac{E_{t+1}}{E_t} \right) \tag{15}$$

$$\Delta e_{t+24|t+1} = \log \left(1 + \frac{E_{t+12|t+1}}{E_{t+1}} \right) \tag{16}$$

$$\Delta e_{t+12j|t+1} = \Delta e_{t+12j-12|t+1} + \frac{g_{t+1}^{\Delta e} - \Delta e_{t+24|t+1}}{8} \quad where \quad j = 3, ..., 10. \tag{17}$$

[14] We note that as a robustness check if we instead assume that $\rho = 1$, we obtain very similar results.

We therefore obtain the cash flow news time series through:

$$\tilde{S}_{CF,t+1} = \sum_{j=1}^{10} \rho^j \Delta e_{t+12j|t+1} - \sum_{j=1}^{10} \rho^j \Delta e_{t+12j|t} \tag{18}$$

It is clear that the approach above is limited by the nature of the survey forecast data which provides at each month t only a forecast of earnings at a 1-year horizon. This method necessarily imposes some assumptions and structure on the expected real growth in corporate profits at longer horizons which we believe compliments the 1-year rolling forecast.

4.2 Real interest rate news

Survey data from BCEI gives us the 1-year forecast of the annual average nominal rate of returns on 3-month Treasury bills. Similarly to the approach adopted to extend the horizon of the earnings growth forecasts, we generate forecasts of the annual average rate on these bills over the following 9 years by assuming that the forecasts mean-revert to a steady state over the following periods. For the case of the 3-month T-Bills, we denote $TBill0_t$ as the actual (realised) annual nominal rate of return on the T-Bills at month t and $TBill1_t$ as the 1-year forecast of the nominal return on the 3-month T-Bills. Note that that the forecast for the real return on 3-month T-bills are defined as the forecast for the nominal return on 3-month T-Bills less the corresponding inflation rate forecast obtained from the Cleveland FED model, which is shown clearly below. The steady state value g^{TBill} is computed as the rolling average of the real 3-month T-bill rate starting from 1925 to the prior month in which we require the expected value of the T-bill rate. Mathematically:

$$r_{t+12|t} = TBill1_t - Inf1_t \tag{19}$$

$$r_{t+12j|t} = r_{t+12j-12|t} + \frac{g_t^{TBill} - r_{t+12|t}}{9} \quad where \quad j = 2, ..., 10. \tag{20}$$

where $Inf1_t$ is the month t 1-year forecast of the annualised inflation rate. The total forecast of the future T-bill rate over the next 10 years at month t can therefore be expressed as:

$$\mathbb{E}_t\left(\sum_{j=1}^{10} r_{t+12j}\right) = \sum_{j=1}^{10} r_{t+12j|t} \tag{21}$$

Taking expectations from the following month, $t+1$, when the information from month t to $t+1$ becomes available, we write:

$$r_{t+12|t+1} = TBill0_{t+1} - Inf0_{t+1} \tag{22}$$

$$r_{t+24|t+1} = TBill1_{t+1} - Inf1_{t+1} \tag{23}$$

$$r_{t+12j|t+1} = r_{t+12j-12|t+1} + \frac{g_{t+1}^{TBill} - r_{t+24|t+1}}{8} \quad where \quad j = 3, ..., 10. \tag{24}$$

where $Inf0_{t+1}$ is the realised annualised inflation rate at month $t+1$. Therefore, obtaining the expectation from month $t+1$ of the total future T-bill rate over the next 10 years from month t:

$$\mathbb{E}_{t+1}\left(\sum_{j=1}^{10} r_{t+12j}\right) = \sum_{j=1}^{10} r_{t+12j|t+1} \tag{25}$$

The real interest rate news for both stocks and bonds can be constructed as:

$$\tilde{S}_{r,t+1} = \tilde{B}_{r,t+1} = \sum_{j=1}^{10} r_{t+12j|t+1} - \sum_{j=1}^{10} r_{t+12j|t} \tag{26}$$

We note that we set the real interest rate news for stocks and bond to be the same due to the earlier assumption of the horizon for the summations of Equation 1 being the same as that for equation 5, of $N = 10$. Indeed if we include ρ in the calculation of real interest rate news for stocks, the correlation between this measure and that above is 0.99. We therefore choose to have the one time series to represent our news to the real interest rate for both stocks and bonds.

4.3 Excess stock return news

Using Equation 1 we can back out the excess future stock return news from knowing the unexpected stock returns, cash flow and real interest rate news. We obtain unexpected stock returns by using a predictive linear regression to model at a monthly frequency the 1-year expected excess return. We use the usual battery of predictive variables known to the literature such as the dividend yield, term spread, default spread, lagged returns and nominal return on the 3-month Treasury bills. Cochrane and Piazzesi [2005] also suggest a factor (CP factor henceforth) constructed from a linear combination of forward rates which seems to have significant predictive power for both future bond and stock returns. Interestingly, the significance of the CP factor as a forecasting variable for stock returns has changed since the work by Cochrane and Piazzesi [2005]. Note that we use the well-adopted parsimonious modeling approach as opposed to simply data mining within our sample period to produce a model with the highest possible fit, so that in our work we use a flexible general model that has been widely used and accepted by other authors and in different sample periods to ours.

Table 1 evaluates the forecast of excess stock returns. We only include those variables from the list above that show reasonable significance in the regressions. We run the predictive regression of the 1-year ahead annualised excess stock returns on the dividend yield d/p, term spread $y^{(5)} - y^{(1)}$ and the CP-factor $\gamma^T f$. Dividend yield is defined as the log dividend payments over the past year minus the log price level; the term spread is defined as the difference in yields between the 5 year and 1-year zero coupon bond; and the CP factor is a single tent-shaped linear combination of forward rates. We perform the regression:

$$e^S_{t+12} = \alpha + \beta_1 dp_t + \beta_2 \left(y^{(5)} - y^{(1)}\right)_t + \beta_3 \left(\gamma^T f\right)_t + \epsilon_{t+12} \tag{27}$$

where $t + 12$ monthly observations ahead implies the 1-year ahead excess stock return[15].

[Table 1 about here.]

Regressions 1, 2 and 4 from Table 1 display the well-known result of the dividend yield and term spread forecasting different components of returns, since the coefficients are relatively unchanged in multiple regressions and with the R^2 increasing. We also notice from regression 5 that the term spread is driven out by the CP-factor, which makes sense since the information content of the CP-factor subsumes that of the term spread, since both are from zero-coupon bond yields. However, it seems as if the recent financial crisis has restored the forecastability of the dividend yield since in regressions 6 and 7, it drives out the CP-factor. We use the coefficients from regression 4 to produce a model-implied expectation for excess stock returns 1 year from now. Knowing the actual (realised) excess stock returns, we are able to work out the unexpected excess stock returns series via:

$$\tilde{e}^S_{t+1} = \frac{1}{12} e^S_{t+1} - \frac{11}{12} \mathbb{E}_t \left(e^S_{t+12}\right) \tag{28}$$

[15] We note that the (restricted) CP-factor was constructed using the Fama-Bliss zero coupon bond yields obtained from CRSP from January 1964 to November 2009 to recover the well-known tent-shape for the coefficients on the respective combination of forward rates. Only using data from June 1984 to November 2009 would not produce the tent shaped structure.

where e^S_{t+1} is the realised annual excess returns to stocks in month $t+1$[16].

[Figure 2 about here.]

Panel A of Figure 2 plots the forecasted excess returns on stocks versus the actual returns. Unexpected stock returns is essentially the vertical distance between the realised and forecasted curves. From this returns to stocks are somewhat hard to predict at a monthly frequency using the state variables that we have stated above.

4.4 Inflation news

Model-implied data from the Cleveland FED gives us forecasts of the annual rate of inflation for the next 10 years at a monthly frequency. Denoting $Inf1_t$ as the 1-year forecast of the annual inflation rate at month t, with the number changing depending on the horizon of the forecast. Writing an expression for the average forecasted (expected) future inflation rate over the next 10 years at month t as:

$$\begin{aligned} InfTotal10_t = \frac{1}{10}(&Inf1_t + Inf2_t + Inf3_t + Inf4_t + Inf5_t + Inf6_t \\ &+ Inf7_t + Inf8_t + Inf9_t + Inf10_t) \end{aligned} \tag{29}$$

Naturally we can write:

$$\mathbb{E}_t\left(\sum_{j=1}^{10}\pi_{t+12j}\right) = 10InfTotal10_t \tag{30}$$

From Equation 5, we also need the total inflation rate over the next 10 years from month t but taking expectations from month $t+1$: $\mathbb{E}_{t+1}\left(\sum_{j=1}^{10}\pi_{t+12j}\right)$. This implies that we have one month of realised information available to us, so that we know the realised inflation rate from month t to month $t+1$, which we denote as $Inf0_{t+1}$[17]. Therefore, taking expectations from month $t+1$ of the total future inflation rate over the next 10 years from month t:

$$\mathbb{E}_{t+1}\left(\sum_{j=1}^{10}\pi_{t+12j}\right) = 10\left(\frac{1}{12}Inf0_{t+1} + \frac{11}{12}InfTotal10_{t+1}\right) \tag{31}$$

[16] Annual excess returns means that this is the excess returns over the past 12 months

[17] This is an annual rate and is constructed as the year-on-year percentage change in the CPI level.

We therefore express the news to the inflation rate as[18]:

$$\tilde{B}_{\pi,t+1} = \mathbb{E}_{t+1}\left(\sum_{j=1}^{10} \pi_{t+12j}\right) - \mathbb{E}_{t}\left(\sum_{j=1}^{10} \pi_{t+12j}\right) \tag{33}$$

4.5 Excess bond return news

Similarly to obtaining excess future stock return news above, we can use Equation 5 to back out the excess future bond return news from unexpected bond returns, inflation and real interest rate news. Instead of obtaining unexpected bond returns through assuming a model for expected excess bond returns as we did for excess stock returns above, we utilise the 1-year forecast of the 10-year T-bond yield from the BCEI forecast survey database. Note that the forecast for the 10-year T-Bond is from a survey question that asks for a constant-maturity Treasury yield expectation. As we proxy for the long-term bond using the 10-year nominal zero coupon bond, to obtain the yield expectation implied by the surveys for this bond, we first compute the expected change in the 10-year Treasury bond yield and then add the expected change to the current 10-year zero coupon bond yield, which we denote as $TBond1_t$, that is the 1-year forecast of the nominal return on the 10-year zero-coupon T-Bond at month t. We can then express the expected excess bond returns in one year as:

$$\mathbb{E}_t\left(e^B_{t+12}\right) = TBond1_t - TBill1_t \tag{34}$$

where similarly to above $TBill1_t$ represents the 1-year forecast of the nominal return on the 3-month T-Bills. Knowing the actual (realised) excess bond returns, we are able to naturally back out the unexpected returns to the 10-year T-Bond through:

$$\tilde{e}^B_{t+1} = \frac{1}{12}e^B_{t+1} - \frac{11}{12}\mathbb{E}_t\left(e^B_{t+12}\right) \tag{35}$$

where e^B_{t+1} is the realised annual excess returns to the 10-year T-Bond in month $t+1$[19]. Panel B of Figure 2 plots the forecast of excess bond returns versus the actual returns in that month. The vertical distance between the forecast and the realised values makes up

[18] We also consider an alternative way to construct inflation rate news as:

$$\tilde{B}_{\pi,t+1} = Inf0_{t+1} + \frac{9}{10}InfTotal10_{t+1} - Inf1_t - \frac{9}{10}InfTotal10_t \tag{32}$$

The correlation between these two measures is 0.995. We therefore don't consider this measure going forward.

[19] Similarly to that above, annual excess returns means the excess returns over the previous 12 months.

the news. It is clear that the survey forecasts for bond returns is a much better predictor than the model-implied forecasts for stock returns in our sample period. This should theoretically imply that the risk premium to bonds should be somewhat lower that the risk premium to stocks. Our particular interest is to study the role of the news of the risk premiums in explaining the time variation of stock-bond volatility and covariance, as we shall see in the next section.

5 Results

5.1 Realised second moments

Figure 1 plots the monthly realised second moments of stock and bond returns. Following the approach of Schwert [1989] we construct these based on daily returns within a month. If we denote $r^S_{i,t}$ and $r^B_{i,t}$ as the daily stock and bond returns on day i in month t respectively, the realised variance of stock and bond returns are computed as the sum of squared daily returns[20]:

$$\sigma^2_{S,t} = \sum_{i=1}^{N_t} (r^S_{i,t})^2, \quad \sigma^2_{B,t} = \sum_{i=1}^{N_t} (r^B_{i,t})^2$$

where N_t is the number of daily returns in month t. The monthly realised covariance between stock and bond returns is obtained from:

$$cov_t(S,B) = \sum_{i=1}^{N_t} r^S_{i,t} r^B_{i,t}$$

We note the inherent noise in the estimate of monthly variance from just 22 daily observations. Ideally we would employ a method similar to Bollerslev and Zhou [2006] which uses higher-frequency intra-day data to estimate the variance. However intra-day data over the time period that we require for both stocks and bonds is difficult to obtain. We therefore continue to use daily returns to construct our variance and covariance measures.

Panel A of Figure 1 shows that the stock market was very volatile during the stock market crash of 1987, during the Asian financial crisis, the Russian government's debt default and the collapse of the hedge fund Long-Term Capital Management (LTCM) during 1997-1998, the bursting of the internet bubble in 2001 and during the more recent financial

[20] We do not subtract the sample mean from each daily return to compute monthly second moments as this is a very minor adjustment.

crisis in 2007-2009. In contrast looking at panel B the bond market has been relatively more stable. The notable exceptions being the volatility around the stock market crash of 1987, between 1997-2001 and during the recent financial crisis.

Panel C of Figure 1 shows that the stock-bond covariance is large in magnitude around increased stock and bond market volatility. Interestingly, before 1998 during periods of increased volatility the covariance remained positive. It is only from 1998 until the end of the sample period that we observe the covariance between stocks and bond becomes negative when financial turmoil occurs. Naturally the same pattern is observable from Panel D for the correlation. It is clear that there is substantial time variation, with most of the movement occurring around the periods of increased stock market volatility. This could imply that before 1998, long-term bonds did not necessarily provide the diversification that investors sought when shifting from stocks to bonds, but after 1998 the role of bonds changed.

5.2 Descriptive statistics of news components

Figure 3 displays the time series of the news components constructed in section 4 and highlights that the forecasting errors fall in a small range around zero. This is confirmed by the mean values of the forecasting errors as shown by the descriptive statistics in Table 2, implying the use of well performing forecasts for the components.

[Figure 3 about here.]

Table 2 reports the correlation matrix of the return components estimated from the news time series over the full sample. Several observations are apparent. First, shocks to excess stock returns and to excess bond returns have a positive correlation of 0.43. The convention that long-term assets tend to move together holds here, however we note that Campbell and Ammer [1993] find this particular correlation to be above 0.80 in all of their subsamples. They attribute this to the notion that similar variables are able to forecast both stock and bond returns as shown by Fama and French [1993]. The lower correlation in our sample period is possibly because the role and risk profile of bonds has changed to those of hedging instruments for stock market risk as highlighted by Connolly et al. [2005] and Campbell et al. [2009b] among others.

[Table 2 about here.]

Second, we notice that future excess stock return news has a slight positive correlation of 0.10 with the news to long-horizon forecasts of the inflation rate. This means that when investors learn that the long run-inflation will be higher than expected, they also tend to learn that the stock risk premium (future excess stock returns) will be higher than expected. Assuming that inflation risk is priced in the stock market (Chen et al. [1986]), this increase in the stock risk premium could imply compensation for an investor who is willing to bear inflation risk when holding stocks for the long-run. This observation is in line with that by Campbell and Ammer [1993].

On the other hand, excess bond return news and inflation news are negatively correlated, thus when investors learn that the long-run inflation will be higher than expected, they learn that excess bond returns will be lower than expected. Since zero-coupon bonds have fixed nominal payoffs, the capital loss from higher expected inflation will be offset by the capital gains from the lower bond risk premium (expected excess bond returns). This does not necessarily imply that bonds are contemporaneously able to hedge inflation shocks since it depends on the magnitudes of these capital losses and gains [21].

Third, we also note that innovations to future excess stock and bond returns are strongly negatively correlated to real short-term interest rate news. Lastly, similar to what Vuolteenaho [2002] finds at a firm-level, we find that at the aggregate-level the correlation between cash flow news and excess stock return news is positively correlated at 0.37. Such a result will be useful when looking at which components drive aggregate-level stock returns.

We note that all the news time series appear to be stationary in our sample period. Dickey-Fuller tests and augmented Dickey-Fuller tests with 5 lags reject the unit root hypothesis at the 5% level or better. This suggests that stationary asymptotic distributions are likely to approximate well the finite sample distributions of the coefficients and test statistics for the regressions that we perform later.

Given the short sample period that we use for our study, we choose not to do a sub-period analysis since we have no natural break point and do not wish to data mine our

[21] Indeed we find the contemporaneous correlation between the one-period inflation news and unexpected (one-period) bond returns in our data is -0.10, indicating that bonds are not able to contemporaneously hedge inflation shocks.

results. Instead, we compare our findings with those who have performed similar studies in different sample periods (Campbell and Ammer [1993]) and at different data frequencies (Lan and Balduzzi [2011]).

5.3 Unconditional variance decompositions

Table 3 reports the (unconditional) variance decomposition for excess stock returns, excess bond returns and the (unconditional) covariance decomposition between excess stock and bond returns based on the unconditional expressions of Equations 7, 8 and 9. The table reports the (co)variances of the different news components that make up the (co)variance equations of excess stock and bond returns. These numbers are normalised by the (co)variance of the return innovation itself, so that the numbers sum to one for each decomposition. We also present the comparative results from Campbell and Ammer [1993] and Lan and Balduzzi [2011] in the table.

[Table 3 about here.]

5.3.1 Variance decomposition for excess stock returns

Panel A reports that the variance of stock returns is mainly attributable to the variance of future excess stock return news followed by the variance of future real cash flow news. We also find that changing expected real interest rates contributes 23% to the variance of stock returns in our sample period. Our results in a relative sense are similar to both those of Campbell and Ammer [1993] and Lan and Balduzzi [2011] in that uncertainty of excess stock returns followed by uncertainty of real cash flow account for a majority of the total stock variance. The slight difference in magnitude of the coefficients is due to the method in which we obtain excess stock return news. Since we back-out this news proxy from the unexpected (one-period) stock returns less the real cash flow news and real short term interest rate news, this may exaggerate the effect of excess stock return news in explaining the stock market variance, as we can see from our coefficient of 1.44.

Campbell and Ammer [1993] state that the real interest rate news plays a relatively minor role in explaining the variance of stock returns as even though there is time variation in the ex-ante real short-term interest rate, any changes are largely transitory and thus do not cumulate over time. Therefore in their sample period the expected real interest rate is precisely measured with the variance of the real interest rate news being small. This is surprising given the inflationary environment during their sample period being high and uncertain. Unless the uncertainty of the long-run expected nominal interest rate was offset by the uncertainty of the long-run expected inflation rate in their sample period, we find their result somewhat puzzling. Such a result could be due to the use of a VAR model to generate their expectations.

Although we can also claim that the real interest rate news plays a relatively small role, examining Panel B of Figure 3 we see that the variation in real interest rate news is somewhat large. This is especially true at the beginning of our sample period when the Federal Reserve changed their operating procedures within the money markets leading to increased uncertainty about nominal interest rates and the inflation rate, the latter of which can be seen from Panel D of Figure 3.

We note that the variance terms of the decomposition sum to greater than 1, this is accommodated by the negative covariance terms of the decomposition. Intuitively, this indicates to us that the covariance terms, which are often overlooked, do have a role to play in explaining the variance of stock returns. We investigate this further when we perform the conditional variance decompositions.

5.3.2 Variance decomposition for excess bond returns

The variance decomposition of bond returns in Panel B of Table 3 highlights the importance of changing future excess bond returns on the variance of bond returns, accounting for 94%. Changing future real interest rates attribute 29% while the variance of inflation news has a lesser role to play with it accounting for 12% of the variance in bond returns. The large role that the real interest rate news seems to have does not increase the overall variance of bond returns because the real interest rate news is negatively correlated to both excess bond return news and inflation news, the covariance terms of which thus reduce the variance of bond returns. Also as we saw above, the correlation between excess bond return news and inflation news is negative, the covariance between these components thus also having the effect of reducing the bond return variance because the capital loss from higher expected inflation is partly offset by a capital gain from lower expected excess bond returns.

These results are similar to those of Lan and Balduzzi [2011] but differ with respect to the role of inflation news and real interest rate news when comparing with Campbell and Ammer [1993]. The former difference is because our sample period is from 1984 to 2009 when the inflation rate is relatively stable whereas Campbell and Ammer [1993] study a period between 1952 and 1987 when inflation was known to be high and uncertain. This would have naturally magnified the role of inflation news on the variance of bond returns in their results. As for the real interest rate news, its increased importance in our sample period could be due to the expected long-run real interest rate having a persistent effect on changes to bond returns and thus on the volatility of bond returns.

5.3.3 Covariance decomposition for excess stock and bond returns

From Panel C of Table 3 we report the covariance of unexpected stock returns with each of the decomposed components of unexpected bond returns and vice versa. We find that the covariance between stock and bond returns is determined by the interaction between several offsetting forces. Looking first at how unexpected stock returns and the components of unexpected bond returns affect the stock-bond covariance, we find that the covariation between unexpected stock returns and inflation news mildly drives stock and bond returns in opposite directions, contrary to the results of Campbell and Ammer [1993]. We again note however the difference of the inflationary environments in the sample periods that our studies are performed over. This mildly negative effect is offset by a dominant positive covariance between unexpected stock returns and changing future excess bond returns, driving stocks and bonds in the same direction. As for the covariance between unexpected stock returns and real interest rate news, this reduces the covariance of stock and bond returns.

As for how unexpected bond returns and the components of unexpected stock returns affect the stock-bond covariance, we find that the coefficients are are similar in magnitude but of an opposite sign to those of Campbell and Ammer [1993]. This naturally implies to us that the role of bonds have changed since the period of 1952 to 1987. Such a finding supports the notion of the changing risks of nominal bonds as investigated by Campbell et al. [2009b].

Panel D from Table 3 reports the role of covariances between respective stock and bond news components on stock-bond covariance. Such a decomposition is more revealing since we can directly examine the contemporaneous effect of the covariance between the news components on stock-bond covariance. Interestingly, Campbell et al. [2009b] motivate in their work that the covariance between real and inflation rate shocks is the cause of the negative correlation between stock and bond returns. Our results support this statement with both the covariance of future real cash flow shocks and future real interest rate innovations with inflation shocks being negative and significant, implying that the dynamics between these shocks push stocks and bonds in the opposite direction. We also find that the covariance between real interest rate shocks and excess future stock and bond return shocks play a similar role. We note that Barsky [1989] highlighted the importance of the real short-term interest rate for stock-bond correlation. Contrary to Campbell and Ammer [1993] we find that real interest rate changes are important for the co-movement of stock and bond prices.

The negative covariance causing forces are offset by three large positive forces causing stocks and bonds to move in the same direction: the covariance between real interest rate shocks on stocks and bonds, the covariance between excess stock return news and inflation news and lastly the covariance between shocks on excess stock and bonds. Although there are fewer of these positive forces, they are generally larger in magnitude and thus cause stocks and bond to move in the same direction with more force than those forces that work to decouple the stock and bond markets.

5.4 Conditional (co)variance regressions

In order to get a sense of the contemporaneous role that the news components have in explaining the time variation of the second moments of stock and bond returns according to Equations 7, 8 and 9, we use the Dynamic Conditional Correlation (DCC) model of Engle [2002] to compute the conditional (co)variances of the news components. It is estimated in two-stages: The first to estimate the variance of the residual for each news component using a univariate GARCH specification. The second to estimate the parameters of the time-varying correlation matrix[22]. We now look to the explanatory power of these conditional second moments of the decomposed news components in explaining the time variation of

[22] For more details on the estimation, refer to Appendix C.

realised stock and bond return variance and covariance respectively.

5.4.1 Variance of excess stock returns

We regress realised stock market variance on the conditional stock variance news components as specified by Equation 7. Theoretically the coefficients on these components should all be 1. To compare the importance of the uncertainty in real cash flow, real interest rates and excess stock returns on stock market variance, we run univariate regressions on each of the conditional variance components as well as multivariate regressions with all the components from Equation 7. Table 4 reports that uncertainty in real cash flow explains up to 10% of the time variation in stock market volatility, with a 1% increase in the volatility of real cash flow news leading to an approximate increase of 1.5% in stock market volatility. The coefficient is significant at the 5% level. We also find that the uncertainty in future excess returns is able to explain up to 4% in stock market variance. The increase in stock volatility from a 1% increase in the volatility of future excess returns is approximately 0.8%, with the coefficient again highly significant. In both cases the coefficients are different from the theoretical value of 1. Lastly, uncertainty of the real interest rate seems not to have any explanatory power in a univariate context.

[Table 4 about here.]

As for the multivariate regressions, we find that the significance of uncertainty in future excess stock returns is driven out by the uncertainty in real cash flow. The variability of the real interest rate news seems to again have not much of an economic or statistical significance. Regressions 8 and 9 report the estimated coefficients of the regressions of realised stock variance on all the 6 (co)variance components. Since some of these 6 components are highly correlated and may cause collinearity problems when used as regressands. In regression 9 we thus use as regressands the 3 conditional variance components and orthogonalized conditional covariance components. Specifically, we project the 3 conditional covariance components on the 3 conditional variance components and use the residuals as orthogonalized conditional covariance components to run in the regressions.

Uncertainty of real cash flow remains consistently significant in all the regressions, with the coefficients always being positive and greater than the theoretical value of 1. This highlights the role, both economically and statistically that uncertainty in real cash flow has on stock market variance. This comes at no surprise given the cash flow surprises that we observed during the 2007-2009 financial crisis and the increased stock market volatility during this period. David and Veronesi [2008] among others have established the important of real cash flow news in explaining and forecasting the variance of stock returns and thus its importance within stock pricing models. Indeed, the work by Bansal et al. [2006] and Hansen et al. [2008] has shown that in the long-run cash flow news entirely explains changes in stock prices[23]. Our empirical results are in line with these conclusions.

From regression 9 we notice that the covariance between cash flow news and future excess stock return news plays a significant economic and statistical role in explaining the variation in stock market variance. Indeed the R^2 increases by 14% between regression 7 and 9 when we add the covariance terms to the multivariate regressions. Baele et al. [2010] find that non-macroeconomic factors play a much more significant role than macroeconomic factors when explaining the variation in stock variance. Comparing the results from Tables **??** and 4 we see that this is not necessarily the case. We show that real cash flow news, future excess stock return news and the covariance between the two play an important role in explaining stock market variance. An innovation of our work is highlighting the significance of the covariance terms. We believe that future asset pricing models should therefore include the dynamics of these covariance terms in order to capture the empirical observation of time varying stock volatility.

5.4.2 Variance of excess bond returns

Table 5 reports the results of the regressions of realised bond variance on the conditional (co)variance of the news components in Equation 8. Theoretically the coefficients on these components should all be 1. We immediately notice from regressions 1 and 3 that uncertainty in the long-run inflation rate and future excess bond returns effect the variance of bond returns both economically and statistically, although the latter seems to explain more of the time variation than the former with a difference in R^2 of 6%. As for their coefficients, for the variance of inflation news it is greater than the theoretical value of 1, implying that a small fluctuation of inflation news has the ability to explain large variation in bond variance. The opposite is observed for excess bond return news, its coefficient

[23] Also, the importance of cash flow news for stock returns at both the firm and aggregate level has been well established in the literature (Vuolteenaho [2002] and Chen and Zhao [2009]).

being 0.53. Similarly for stock variance, uncertainty of the long-run real interest rate is not significant in a univariate context.

[Table 5 about here.]

The multivariate regressions 4 to 7 show that uncertainty of future excess bond returns and long-run inflation news continue to have significant explanatory power. We note the increased significance of real interest rate news in the multivariate context which is to be expected given the modest negative correlation of real interest news with both inflation and excess return news. In regressions 8 we include all the covariance terms of Equation 8. Due to the issue of collinearity all the coefficients are large and significant. In regression 9 we therefore correct for the collinearity of the last 3 regressands by projecting the 3 conditional covariance components on 3 conditional variance components to obtain the residuals and use these as the orthogonalized conditional covariance components.

Regression 9 reports some interesting results. The variance of inflation news is no longer statistically significant, its economic influence also being reduced. The regression brings out the importance of the uncertainty of the real interest rate for the variation in bond variance. A 1% increase in the volatility of the real interest rate news seems to decrease the volatility of bond returns by 0.9%. The importance of excess bond return news remains significant in all of the regressions. Comparing regressions 8 and 9 we can see reducing the collinearity helps to identify the true economic scale of the news component on explaining the magnitude of the variance of bond returns. Also adding the covariance terms to the regression increases the R^2 to a relatively large 16%, highlighting the important role that these terms play theoretically in explaining the time variation in bond variance. Indeed, Campbell et al. [2009b] find that the covariance between real and inflation shocks is important in explaining the change in risk premia of nominal bonds. From regression 9 we empirically find that this component is significant both economically and statistically.

Lastly, both David and Veronesi [2008] and Baele et al. [2010] find that economic factor models have a harder time explaining bond volatility than stock volatility, our results show that this is indeed the case. We are able to explain up to 21% of the time variation in stock variance but only 16% of the variation in bond variance.

5.4.3 Covariance of excess stock and bond returns

Table 6 reports the results of the regressions of realised stock-bond covariance on the conditional covariance of the news components from Equation 9. Theoretically the coefficients on these components should be equal to 1. From the univariate regressions 4 covariance components display both economic and statistical significance: The covariance between real cash flow news and inflation news; the covariance between real cash flow news and excess bond return news; the covariance between excess stock return news and inflation news; and the covariance between excess stock and bond return news. These results are in line with the findings from the covariance decompositions above, with the exception of the role of the covariance components that involve the real interest rate news. Besides this, the covariance components involving real cash flow news, inflation news and risk premium news all seem to play a significant role contemporaneously for the variation in stock-bond covariance.

[Table 6 about here.]

For the multivariate case, regression 7 shows that only three of the covariance components remain significant for the variation in stock-bond covariance. The first being the covariance between real cash flow news and inflation news. This component has consistently been significant within the unconditional decompositions and now the conditional regressions. Its coefficient is close to its theoretical value of 1. David and Veronesi [2008] find that a positive correlation between earnings and inflation is able to explain negative stock-bond correlation. Our results confirm this since we find a positive correlation between earnings and inflation news from Table 2. The coefficient of 1.19 on the covariance between real earnings and inflation news implies that the component contemporaneously plays an important role in decreasing the stock-bond correlation[24], thus driving stocks and bond in the opposite direction.

The second component, which becomes significant in the multivariate regressions after displaying little explanatory power in the univariate regressions is the covariance between real interest rate news and inflation news. This component must capture some variation in the stock-bond covariance that the others do not. The coefficient is 5.46 implying that

[24] This is because we use the term $-cov(\tilde{S}_{CF}, \tilde{B}_{\pi})$ in the regressions. Thus a coefficient of 1.19 implies $-1.19cov(\tilde{S}_{CF}, \tilde{B}_{\pi})$ which naturally means it reduces the value of the dependent variable $cov_t(S, B)$ when the covariance between the real cash flow news and inflation news is positive.

a small covariation between the news components is able to explain a large variation in the stock-bond covariance. The last component that remains significant is the covariance between excess stock return news and inflation news. Unconditionally these news components have a positive correlation and its covariance seems to increase the correlation between stock and bond returns. The coefficient is again larger than the theoretically value of 1. These three components are able to explain up to 22% of the monthly variation stock-bond covariance.

As previously mentioned, Campbell et al. [2009b] find that the covariance between real and inflation shocks are able to explain the negative correlation between stock and bond returns. The conditional regressions reported in Table 6 have shown that the covariance components important for explaining the time variation in stock-bond covariance involve those between real and inflation variables. However, the only covariance term that demonstrates that it is able to cause the stock-bond covariance to become negative is the covariance between real cash flow news and the long-run inflation news. Theoretically from Equation 9 this what it should do and we empirically demonstrate that this is indeed the case. This leaves some scope for the role of "flight-to-safety" and "flight-to-liquidity" when trying to explain the occurrence of negative covariance. Comparing Tables **??** and 6 we find contrary to Baele et al. [2010] that uncertainty of our macroeconomic factors are able to explain more of the time variation in stock-bond covariance than the non-macroeconomic factors that we use.

5.4.4 Robustness check

We use the Dynamic Conditional Correlation (DCC) model of Engle [2002] to compute the conditional variance and covariance of the news components for use within the regressions to investigate the role of these news components in explaining the time variation in the second moments of stock and bond returns. We found significant results that we were able to link to both theoretical and empirical papers on stock-bond correlation. In order to check that these results were not simply an artifact of the DCC model we were using, here we compute the conditional variance and covariance of the news components using the Exponentially Weighted Moving Average (EWMA) (co)variance model[25]. In a similar fashion to that above, we then regress the realised second moments of stock and bond

[25]For further details of the model and our estimation methodology, see Appendix C.

returns on the conditional variances and covariances of the news components. We report the results for the stock-bond covariance regression in Table 7 below.

[Table 7 about here.]

Comparing the significance of the coefficients, both the economic and statistic, with those in Table 6 where we use the DCC model, we see that the results are fairly similar. Although the R^2 are slightly larger, we are encouraged that the same coefficients that were significant when using the DCC model are also significant when using another conditional covariance model. This robustness check supports are results of the role of macroeconomic components being able to explain the time variation in the second moments of stock and bond returns.

6 Conclusion

In this paper we conduct an empirical investigation into the time variation of the second moments of stock and bond returns. Using a Campbell and Shiller [1988] decomposition we are naturally able to identify and investigate the economic mechanisms on the variation of stock-bond correlation. Our first innovation to the literature is the use of survey forecast data on these economic components to back out a time series of unexpected values (news) for these components. Our second innovation is the use of conditional volatility models to generate (co)variance time series for the news of the economic components. This allows us to perform regressions of realised second moments on the (co)variances of the decomposed economic news components in order to investigate the role of the economic components in explaining the time variation in the volatility and correlation of stock and bond returns, this being our third innovation.

Conducting an unconditional variance decomposition, we find somewhat similar results to those of Campbell and Ammer [1993] and Lan and Balduzzi [2011]. A large part of the variance of excess stock returns is attributed to changing expectations of future excess stock returns following by changing expectations of future real cash flow. As for the variance of excess bond returns, it seems that changing future excess bond returns dominate the other components. An important finding that is different from the current literature is the role of the covariance terms in the decompositions. For both excess stock and bond returns, certain covariance components are important contributors for the volatility of returns. As for the covariance, the decomposition reveals that it is determined by the interaction between several offsetting forces. Importantly, our findings agree with the observation by Campbell et al. [2009b] in that the covariance between real and inflation shocks lead to decreases in the stock-bond covariance.

Complementary to the unconditional decompositions we find that uncertainty of real cash flow, uncertainty of excess stock returns and the covariance between real cash flow news and excess stock return news are all significant for explaining the time variation of stock return variance. Our findings add to the literature that cash flow news obtained from survey forecasts are informative for stock pricing(Pástor et al. [2008]). Variation in bond returns can be explained by uncertainty of the future excess bond returns and the future real short-term interest rate. Another important finding is that the covariance terms also have a significant role in explaining the variation in bond returns. As for the variation in stock-bond covariance, we report that the covariance of cash flow news and inflation news is important for contributing to the occurrence of a negative correlation between stocks and bonds. We also empirically document Campbell et al. [2009b] findings of the importance of real and inflation shocks for stock-bond covariance. We note that we are among the first to demonstrate the informational content of survey forecasts for stock-bond correlation.

The caveats of our work are two fold. The first being the lack of longer range forecasts for the economic components. Since the decompositions of the long-term assets require expected values of the components over a number of horizons, we therefore have to impose a model in order to generate the longer-horizon forecasts. Although every effort was taken to ensure the model would only complement the forecast data that we did have from the surveys, the possibility of measurement error from using such a model therefore exists[26]. The second being the use of a conditional volatility model to generate the time varying (co)variances of the news components. Since higher frequency (i.e. daily) forecasts and actual values for the economic components do not exist, we are unable to generate realised news time series from which we can construct realised monthly (co)variances of the news

[26] We attempt to address this concern by regressing the realised second moments of stock and bond returns on (co)variances of the one-period news time series, i.e. generated from the realised value less the forecasted value without use of a model to extend the forecast horizon. We still find that the (co)variances of the news time series are able to explain a portion of the variation in stock-bond second moment. These results are available from the author on request.

components. Thus, use of a conditional volatility model to generate the (co)variance time series is as good as we can achieve[27].

Contrary to Baele et al. [2010] we show that macroeconomic factors are able to explain time variation in the second moments of stock and bond returns. We note that economic models are only as good as the factors that are used in the models. Our factors are theoretically motivated and seem to do well at explaining some portion of the time variation in the second moments of stock and bond returns, although not all of it. Indeed we believe the phenomena of flight-to-quality and flight-to-liquidity in our sample period would have hampered the effectiveness of our news components in explaining changing stock and bond prices. One way to extend the research in order to proxy for this dynamic would be a time series measure of the cross-sectional dispersion of the analysts' forecasts for the economic components. The additional explanatory power that such a measure would have in the regressions we have performed would be very interesting, especially for the periods of negative correlation. Also, given the inherent noise in our estimation of the realised volatility and correlation of stock and bond returns, we suggest the use of intra-day data in order to obtain a more accurate monthly estimate of the second moments. We leave all this as a suggestion for future work.

[27] Again, we attempted to address this concern by performing robustness checks of using a different form of conditional volatility model. We found that our results were still present in this case.

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7 Appendix A: Theoretical return expressions

Surprises in stock returns

Using the well-known identity expression of stock returns:

$$R^S_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t}$$

where R^S_{t+1} is the holding period return for stocks from period t to $t+1$, P_{t+1} is the price and D_{t+1} is the dividend paid, all at time $t+1$. Rearranging the equation above, taking logs and then log-linearizing we can approximately write the continuously compounded returns as:

$$\begin{aligned} r^S_{t+1} &\approx k + \rho\,(p_{t+1} - d_{t+1}) + (d_{t+1} - d_t) - (p_t - d_t) \\ &\approx k + \rho\,(p_{t+1} - d_{t+1}) + \Delta d_{t+1} - (p_t - d_t) \end{aligned}$$

where lowercase letters refer to logs, k is a constant of linearization, ρ is a discount factor which is slightly below 1 and Δ represents a one-period backward difference. Log-linearization is a type of series expansion where the log of the sum is approximately a weighted average of the log of the components of the sum. The approximation is good if we assume that the log dividend-price ratio does not follow an explosive process so that we can impose the terminal condition $\lim_{j\to\infty} \rho^j\,(p_{t+j} - d_{t+j}) = 0$. Rearranging the equation in terms of $(p_t - d_t)$ to solve the equation forward and taking expectations at time t we obtain:

$$p_t - d_t \approx \frac{k}{1-\rho} + \mathbb{E}_t \sum_{j=1}^{\infty} \rho^{j-1} \left(\Delta d_{t+j} - r^S_{t+j}\right)$$

Note that $\mathbb{E}_t$ denotes the expectation formed at the end of period t conditional on the information set that includes the history of stock prices and dividends up to period t. We get returns from price changes or dividends. Using equation 7 we can therefore relate changes in returns to changes in rational expectations of future dividend growth and future stock returns. Ignoring the constant, thus treating the variables as deviations from the mean, we can define in general the unexpected return as:

$$r_{t+1} - \mathbb{E}_t[r_{t+1}] = \mathbb{E}_{t+1}[p_{t+1}] - \mathbb{E}_t[p_{t+1}]$$

This is simply just taking expectations with respect to the information set in the previous period so as to obtain the one-step ahead predictor of prices. Plugging in equation 7 into equation 7 we obtain:

$$r_{t+1}^{S} - \mathbb{E}_t[r_{t+1}^{S}] = (\mathbb{E}_{t+1} - \mathbb{E}_t)\left[\sum_{j=1}^{\infty}\rho^{j-1}\Delta d_{t+j} - \sum_{j=2}^{\infty}\rho^{j-1}r_{t+j}^{S}\right]$$

Decomposing stock returns into excess stock returns and the short-term interest rate we can write:

$$r_{t+1}^{S} = e_{t+1}^{S} + r_{t+1}$$

where e_{t+1}^{S} is the log real excess stock returns and r_{t+1} is the log real short term interest rate. Combining with equation 7 leads to:

$$e_{t+1}^{S} - \mathbb{E}_t[e_{t+1}^{S}] = (\mathbb{E}_{t+1} - \mathbb{E}_t)\left[\sum_{j=1}^{\infty}\rho^{j-1}\Delta d_{t+j} - \sum_{j=1}^{\infty}\rho^{j-1}r_{t+j} - \sum_{j=2}^{\infty}\rho^{j-1}e_{t+j}^{S}\right]$$

Surprises in Bond Returns

Defining the log price of an nominal N-period zero-coupon bond at time t as $p_t^{(N)}$, in a similar spirit to that above, the log holding period return on such a bond, which is held from t to $t+1$ can be written as:

$$r_{t+1}^{(N)} = p_{t+1}^{(N-1)} - p_t^{(N)}$$

This can be thought as a difference equation in the log bond price. Solving this equation forward to the maturity date of the bond, where at maturity the bond price is at par (which we set equal to 1 so that the log of the price is zero, i.e. $p_{t+N}^{(0)} = 0$), we obtain:

$$\begin{aligned} p_t^{(N)} &= -\left[r_{t+1}^{(N)} + r_{t+2}^{(N-1)} + \cdots + r_{t+N}^{(1)}\right] \\ &= -\sum_{j=1}^{N} r_{t+j}^{(N+1-j)} \end{aligned}$$

This equation holds ex-post but can also hold ex-ante. Taking expectations at time t:

$$p_t^{(N)} = -\mathbb{E}_t\sum_{j=1}^{N} r_{t+j}^{(N+1-j)}$$

where we obtain an expression that states that the log price of an N-period zero-coupon bond at time t is a sum of the expected future returns. Substituting this into equation 7 we can write:

$$r_{t+1}^{(N)} - \mathbb{E}_t[r_{t+1}^{(N)}] = -\sum_{j=2}^{N}(\mathbb{E}_{t+1} - \mathbb{E}_t)r_{t+j}^{(N+1-j)}$$

This equation states that as the nominal returns to a zero-coupon bond are known over the life of the bond, any unexpected nominal return gains that we see today must be offset by decreases in expected future nominal returns, and vice versa. As we shall be comparing the returns on stocks to those on bonds, we need to work with real returns. As above, we further decompose bond returns into excess bond returns and a short-term interest rate since it will be more useful for our purposes. We therefore write:

$$e_{t+1}^{B} = r_{t+1}^{(N)} - \pi_{t+1} - r_{t+1}$$

where π_{t+1} is the inflation rate at time $t+1$ and as above, r_{t+1} is the log real short term interest rate. Substituting this into equation 7 we obtain:

$$e_{t+1}^{B} - \mathbb{E}_t[e_{t+1}^{B}] = (\mathbb{E}_{t+1} - \mathbb{E}_t)\left[-\sum_{j=1}^{N}\pi_{t+j} - \sum_{j=1}^{N}r_{t+j} - \sum_{j=2}^{N}e_{t+j}^{B}\right]$$

8 Appendix B: Data construction

Our data runs from July 1984 to December 2009 since this is the period in which we have forecast data from the BlueChip Economic Indicators (BCEI) database. As one of the innovations to the literature, we use a monthly frequency in the paper, whilst most other empirical work studying stock-bond correlation use quarterly data.

Stock data

Stock market index: We use the CRSP value-weighted market index comprising of the stocks traded in the NYSE, AMEX and NASDAQ as the market portfolio. Excess returns are defined as returns over the past 12 months less the rolling 3-month Treasury Bill yield over the same holding period.

Earnings: These are from the National Income and Product Account (NIPA) tables (Table 1.12, line 13). We use corporate earnings before-tax with IVA and CCadj. This data is quarterly so to construct monthly earnings data we use a linear interpolation scheme.

Bond data

Bond market index: We use the monthly 10-year zero-coupon bond yield from the daily off-the-run Treasury yield curves constructed by Gurkaynak et al. [2007] which is available from the Fed webpage. If we let $e_{t+1}^{(n)}$ denote the continuously compounded log excess return on an n year discount bond in period $t+1$. Bond excess returns are then defined as $e_{t+1}^{(n)} \equiv r_{t+1}^{(n)} - y_t^{(1)}$, where $r_{t+1}^{(n)}$ is the log holding period return from buying an n year bond at time t and selling it at $t+1$ as an $n-1$ year bond. $y_t^{(1)}$ is the log yield on a rolling 3-month Treasury bill held for one year.

Cochrane and Piazzesi [2005] factor: Following their procedure, we construct 1 through 5 year forward rates from the nominal bond yields, as well as 2 through 5 year excess returns. We then regress the average of the 2 through 5 year excess return on a constant, on the one year yield and the 2 through 5 year forward rates. The CP factor is then the fitted value of this regression.

Empirical proxies for decomposed components

The BlueChip Economic Indicators (BCEI) database provides survey forecasts on an individual level of various macroeconomic variables. Two kinds of monthly forecasts are obtained from participants, one for the current calendar year and one for the next calendar year. For instance, in January 2009, participants provide a 12-month forecast for the value of the macro-variable at the end of the current year 2009, and a 24-month forecast for the variable at the end of the next calendar year 2010. Thus, for February 2009, the forecast horizon for 2009 is now only 11 months while for 2010 it is 23 months, and so on. In order to obtain a constant and consistent time-series of expected values, the forecast for the current year and the next year are weighted together to create a rolling constant horizon 12-month forecast:

$$\mathbb{E}_{t \to t+12} = \frac{m}{12}\mathbb{E}_{t,C} + \frac{12-m}{12}\mathbb{E}_{t,N}$$

where $\mathbb{E}_{t \to t+12}$ denotes the 12-month forecast/expectation of the variable at time t, $\mathbb{E}_{t,C}$ and $\mathbb{E}_{t,N}$ are the respective expectations of the variable for the current and next year at time t and m is the number of remaining months during the current year. For each year being forecasted, 24 forecasts with horizons varying from 1 month to 24 months are made. The constant horizon forecast that we extract from the data therefore displays seasonality. To mitigate this problem of seasonality, we adjust the series with a X-12 ARIMA filter[28].

9 Appendix C: Conditional (co)variance models

Dynamic Conditional Correlation (DCC) model

The Dynamic Conditional Correlation (DCC) model proposed by Engle [2002] is a generalisation of the Constant Conditional Correlation (CCC) model by Bollerslev [1990]. It is thus a simplified multivariate Generalised AutoRegressive Conditional Heteroskedasticity (GARCH) model which has the flexibility of a univariate GARCH model together with a parsimonious correlation specification without having the traditional computational difficulties associated with multivariate GARCH models.

Assuming a random variable x_t as an n-dimensional multivariate normal process with zero mean and variance-covariance matrix H_t, we write:

$$x_t \mid \mathbb{F}_{t-1} \sim \mathcal{N}(0, H_t)$$

We can also write this in terms of a "mean equation":

$$x_t \equiv \sqrt{H_t}\epsilon_t$$

where $\epsilon_t \sim \mathcal{N}(0,1)$ which are the standardised normal distributed disturbances. We express the variance-covariance matrix as:

$$H_t = \mathbb{E}_{t-1}(x_t x_t^{'}) = D_t R_t D_t$$

[28]See http://www.census.gov/srd/www/x12a/ for more details.

where $D_t = diag(\sqrt{H_t})$ whose diagonal elements are the time-varying standard deviation of the residuals of the mean equation for each of the n processes which we assume all respectively follow a GARCH(1,1) model:

$$H_{t,ii} = \mathbb{E}_{t-1}(x_t^2) = \omega_i + \alpha_i x_{i,t-1}^2 + \beta_i H_{t-1,ii}$$

After estimating this model to obtain the conditional variance for each process, the standardised residuals are then defined by:

$$\epsilon_t = D_t^{-1} y_t$$

In contrast to the CCC model the correlation matrix $R_t = \mathbb{E}_{t-1}(\epsilon_t \epsilon_t^{'})$ is now allowed to be time-dependent. Thus a quasi-correlation matrix for the standardised residuals is proposed as a stochastic process for a matrix Q that is an approximation to the correlation matrix. We use a mean-reverting model for the correlation process analogous to the GARCH(1,1) process:

$$Q_t = \bar{R} + \alpha(\epsilon_{t-1}\epsilon_{t-1}^{'} - \bar{R}) + \beta(Q_{t-1} - \bar{R})$$

where $\bar{R} \equiv \frac{1}{T}\Sigma_{t=1}^{T} \epsilon_t \epsilon_t^{'}$ is the unconditional correlation of the standardised residuals. Thus, the conditional correlation depends on the common GARCH parameters α and β and on the unconditional correlation between the standardised residuals. The matrix Q is guaranteed to be positive definite if α, β and $(1 - \alpha - \beta)$ are all positive and if the initial value, Q_1 is positive definite. This is because each subsequent value of Q is a weighted average of positive semi-definite and positive-definite matrices, and thus it is positive-definite. This produces a process for the matrix Q that delivers a positive-definite quasi-correlation matrix for each time period. It does not ensure however that this is a conventional correlation matrix. Thus to convert these Q processes into correlations, it is rescaled according to:

$$R_t = \sqrt{diag(Q_t)} Q_t \sqrt{diag(Q_t)}$$

In order to estimate the variance and correlation parameters, a Maximum Likelihood Estimation (MLE) method can be employed. Such a technique uses trial and error to determine the optimal parameter value that maximises the likelihood of the data to occur for the particular model. We can write the log-likelihood for the data set $\{x_1...x_T\}$ as:

$$
\begin{aligned}
L &= -\frac{1}{2}\sum_{t=1}^{T}\Big(n\log(2\pi) + \log|D_tR_tD_t| + x_t^{'}D_t^{-1}R_t^{-1}D_t^{-1}x_t\Big) \\
&= -\frac{1}{2}\sum_{t=1}^{T}\Big(n\log(2\pi) + 2\log|D_t| + \log|R_t| + \epsilon_t^{'}R_t^{-1}\epsilon_t\Big) \\
&= -\frac{1}{2}\sum_{t=1}^{T}\Big(n\log(2\pi) + 2\log|D_t| + x_t^{'}D_t^{2}x_t^{'} - \epsilon_t^{'}\epsilon_t + \log|R_t| + \epsilon_t^{'}R_t^{-1}\epsilon_t\Big)
\end{aligned}
$$

As outlined in Engle [2009], the log-likelihood can simply be maximised with respect to all the parameters in the model. However the log-likelihood can also be decomposed into two parts. The first containing the variance parameters and the data; the second containing the correlation parameters and the standardised residuals:

$$
\begin{aligned}
L &= L_{vol} + L_{corr} \\
L_{vol} &= -\frac{1}{2}\sum_{t=1}^{T}\Big(n\log(2\pi) + 2\log|D_t| + x_t^{'}D_t^{-2}x_t\Big) \\
L_{corr} &= -\frac{1}{2}\sum_{t=1}^{T}\Big(\log|R_t| + \epsilon_t^{'}R_t^{-1}\epsilon_x - \epsilon_t^{'}\epsilon_r\Big)
\end{aligned}
$$

This can then be estimated using a two-step procedure. The first-step is to maximise the variance part of the likelihood function, L_{vol}, by computing the univariate GARCH models for each of the series and taking the sum of these likelihood functions. The second-step is to then take the standardised residuals from the first-step and maximise the correlation log-likelihood function, L_{corr}, with respect to the correlation parameters. The term $\epsilon_t^{'}\epsilon_t$ can be ignored as it does not depend on the parameters being optimised.

Exponentially Weighted Moving Average (EWMA) model

An Exponentially Weighted Moving Average (EWMA) model can also be used for the conditional variance-covariance matrix. Assuming the same distribution as above for the random variable $x \sim \mathcal{N}(0, H_t)$, we define the EWMA variance-covariance model as:

$$H_t = \lambda H_{t-1} + (1-\lambda) x_{t-1} x_{t-1}^{'}$$
$$\lambda > 0$$

where λ is the weight assigned to the lagged variance-covariance matrix; it is also known as a decay rate since the weight assigned to the x^2 terms decline exponentially as one moves back through time. Note that the same value of λ should be used for both the variance and covariance series in order to ensure consistency of the combined variance-covariance matrix. We similarly estimate λ using the MLE technique. The log-likelihood can thus similarly be written as:

$$L = -\frac{1}{2} \sum_{t=1}^{T} \left(n \log(2\pi) + \log|H_t| + x_t^{'} H_t^{-1} x_t \right)$$

In the usual fashion as above, we determine the value of λ using an iterative procedure to maximize this log-likelihood.

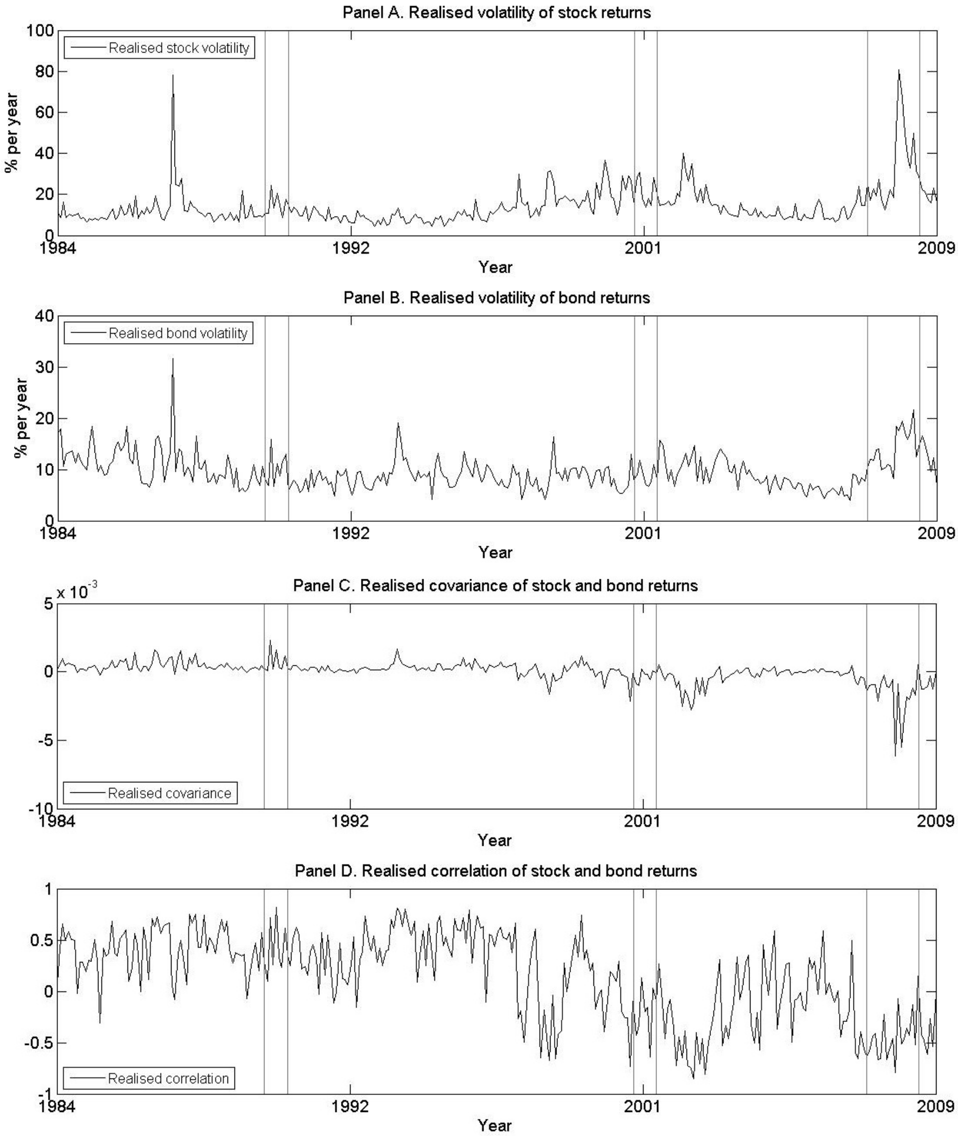

Figure 1: Panel A plots the monthly time series of realised volatility of stock and bond returns, computed as the annualised standard deviation of daily returns within the month. Panels B and C plot the realised covariance and correlation between stock and bond returns, also computed from daily data within the month. All plots are overlaid with NBER recession bands. Stock returns are based on the value-weighted return index of stocks traded in the NYSE, AMEX and Nasdaq markets from the Centre for Research in Security Prices (CRSP). Bond returns are based on the US 10-year Treasury bond yields obtained from daily off-the-run Treasury yield curves constructed by Gurkaynak et al. [2007].

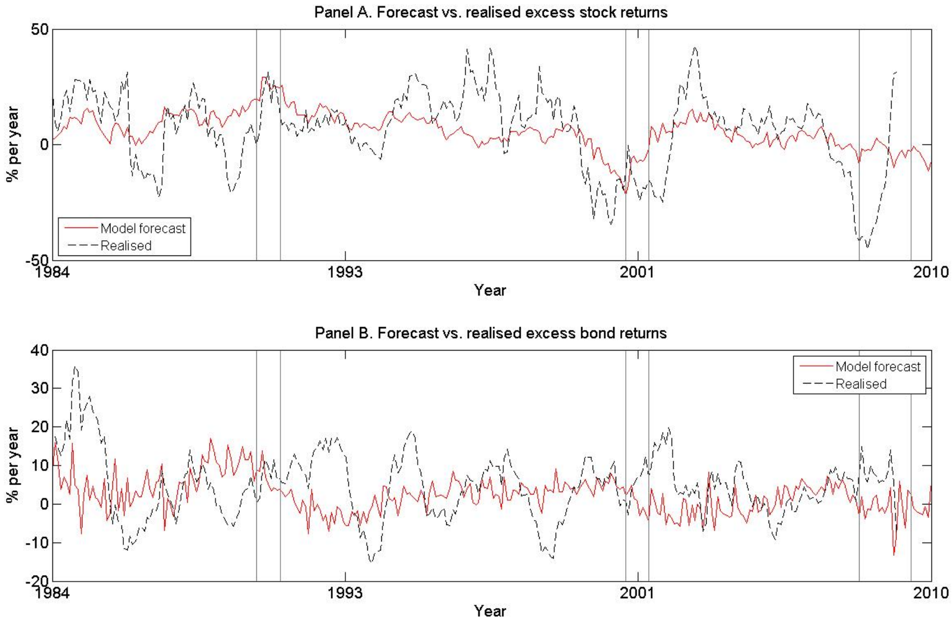

Figure 2: Plots of the forecasted versus the realised excess stock and bond returns

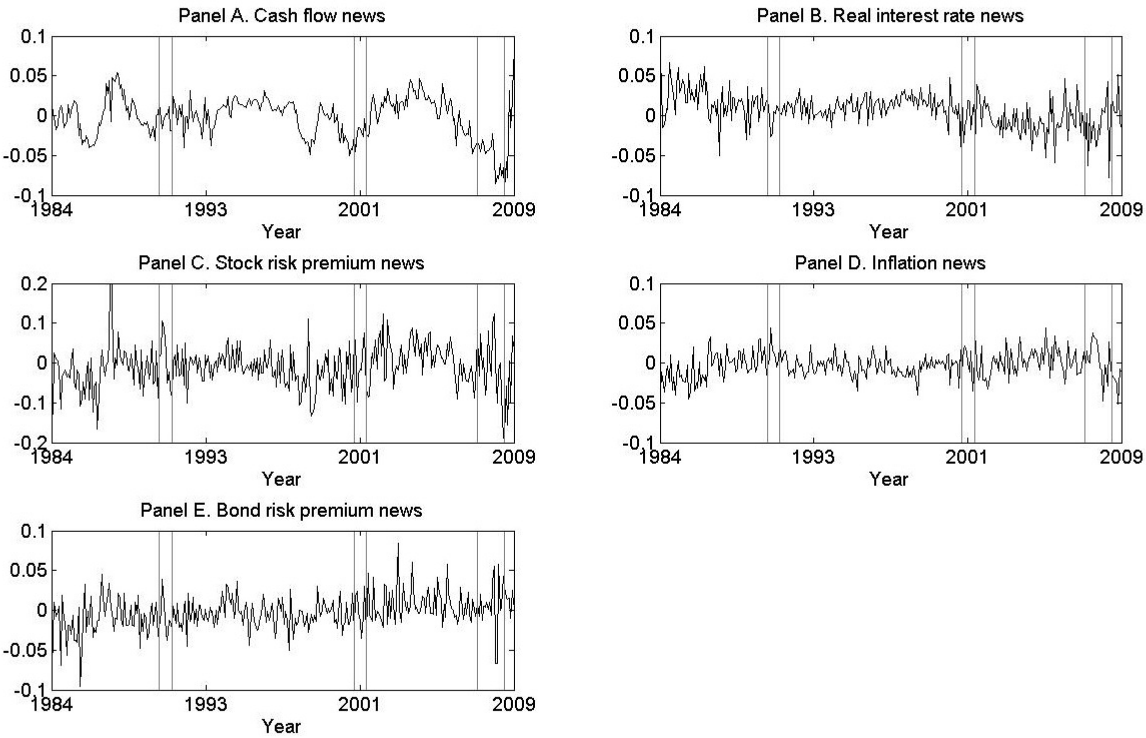

Figure 3: Time series plots of the news components from the Campbell-Shiller decomposition.

Table 1: Forecasts of excess stock returns

All variables are in percentage points and the coefficients are estimated using OLS based on data from June 1984 to November 2009 (306 observations). We do not present the estimated regression intercept α. Returns are based on overlapping monthly observations of annual returns. The dividend price ratio, d/p, is based on the return with and without dividends for the preceding year. Term spread, $y^{(5)} - y^{(1)}$, is the yield on the 5-year zero-coupon bond above the yield on the 1-year zero-coupon bond. The CP-factor, $\gamma^T f$, is constructed from from a linear combination of forward rates. Note that the standard errors are corrected for overlapping observations and heteroskedasticity by GMM. The critical value of the t-statistic at which we reject the null hypothesis of $\beta = 0$ at significance level of 5% is $|t| > 1.96$.

Regression	d/p	(t-stat)	$y^{(5)} - y^{(1)}$	(t-stat)	$\gamma^T f$	(t-stat)	R^2
1	4.88	(1.81)					0.07
2			3.20	(1.04)			0.02
3					2.16	(1.63)	0.05
4	4.56	(1.73)	2.24	(0.76)			0.08
5			-0.44	(-0.11)	2.30	(1.30)	0.05
6	3.78	(1.16)			1.14	(0.74)	0.07
7	4.02	(1.17)	1.21	(0.27)	0.72	(0.31)	0.08

Table 2: Descriptive statistics of the news components

Descriptive statistics of the news time series based on the Campbell-Shiller decomposition. Panel A shows the sample mean and standard deviation of each of the news series respectively. Panel B gives the correlation between the news series and panel C presents the first 5 lags in the autocorrelation of the news time series.

	$\tilde{S}_{CF}$	$\tilde{S}_r$ & $\tilde{B}_r$	$\tilde{S}_e$	$\tilde{B}_\pi$	$\tilde{B}_e$
Panel A: Mean & Std Dev					
Mean	-0.002	0.007	-0.010	-0.003	-0.007
Std Dev	0.026	0.022	0.062	0.017	0.019
Panel B: Correlation					
$\tilde{S}_{CF}$	1.000	0.046	0.374	0.061	0.055
$\tilde{S}_r$ & $\tilde{B}_r$		1.000	-0.396	-0.548	-0.627
$\tilde{S}_e$			1.000	0.104	0.430
$\tilde{B}_\pi$				1.000	-0.212
$\tilde{B}_e$					1.000
Panel C: Autocorrelation					
Lags					
1	0.784	0.255	0.245	0.307	0.266
2	0.731	0.292	0.121	0.190	0.223
3	0.648	0.295	0.098	0.217	0.239
4	0.578	0.250	0.107	0.184	0.168
5	0.547	0.317	0.074	0.088	0.187

Table 3: Unconditional (co)variance decomposition

This table reports the unconditional second moments of stock and bond returns that can be attributed to the unconditional second moments of the news components based on the Campbell-Shiller decomposition. The table reports the variances and covariances of these components, divided by the (co)variance of unexpected stock and bond returns so that the numbers reported add up to one. Panel A and panel B report the ratios of the stock and bond variance components respectively. Panels C and D report the amount of unconditional stock-bond covariance that can be attributed to the unconditional covariance of the decomposed news components. For comparison, we also present the results from Campbell and Ammer [1993] which is based on the 1952 to 1987 sample period and Lan and Balduzzi [2011] which is conducted over 1984 to 2009.

Panel A: $var(\tilde{e}^S)$						
	$var(\tilde{S}_{CF})$	$var(\tilde{S}_r)$	$var(\tilde{S}_e)$	$-2cov(\tilde{S}_{CF}, \tilde{S}_r)$	$-2cov(\tilde{S}_{CF}, \tilde{S}_e)$	$2cov(\tilde{S}_r, \tilde{S}_e)$
	0.25	0.10	1.44	−0.02	−0.45	−0.32
Campbell and Ammer [1993]	0.14	0.01	0.71	−0.02	0.10	−0.14
Lan and Balduzzi [2011]	0.15	0.12	1.05	−0.12	−0.01	−0.18
Panel B: $var(\tilde{e}^B)$						
	$var(\tilde{B}_\pi)$	$var(\tilde{B}_r)$	$var(\tilde{B}_e)$	$2cov(\tilde{B}_\pi, \tilde{B}_r)$	$2cov(\tilde{B}_\pi, \tilde{B}_e)$	$2cov(\tilde{B}_r, \tilde{B}_e)$
	0.12	0.29	0.94	−0.03	−0.12	−0.20
Campbell and Ammer [1993]	1.08	0.02	0.96	−0.12	−1.11	0.15
Lan and Balduzzi [2011]	0.07	0.24	0.93	−0.01	−0.10	−0.13
Panel C: $cov(\tilde{e}^S, \tilde{e}^B)$						
	$cov(\tilde{e}^S, \tilde{B}_\pi)$	$cov(\tilde{e}^S, \tilde{B}_r)$	$cov(\tilde{e}^S, \tilde{B}_e)$	$cov(\tilde{e}^B, \tilde{S}_{CF})$	$cov(\tilde{e}^B, \tilde{S}_r)$	$cov(\tilde{e}^B, \tilde{S}_e)$
	−0.26	−1.29	2.55	1.73	0.59	2.14
Campbell and Ammer [1993]	6.69	−0.84	−8.16	−0.11	−0.32	−2.10
Lan and Balduzzi [2011]	1.23	−1.69	1.46	−3.16	4.53	−0.37
Panel D: $cov(\tilde{e}^S, \tilde{e}^B)$						
	$-cov(\tilde{S}_{CF}, \tilde{B}_\pi)$	$-cov(\tilde{S}_{CF}, \tilde{B}_r)$	$-cov(\tilde{S}_{CF}, \tilde{B}_e)$	$cov(\tilde{S}_r, \tilde{B}_\pi)$	$cov(\tilde{S}_r, \tilde{B}_r)$	$cov(\tilde{S}_r, \tilde{B}_e)$
	−0.68	−0.67	−0.38	−5.04	11.94	−6.31
	$cov(\tilde{S}_e, \tilde{B}_\pi)$	$cov(\tilde{S}_e, \tilde{B}_r)$	$cov(\tilde{S}_e, \tilde{B}_e)$			
	5.31	−12.55	9.23			

Table 4: Regression of realised stock variance

Coefficients from univariate and multivariate regressions of realised stock variance on the conditional stock variance components:

$$\sigma^2_{S,t} = \alpha + \beta_1 var_t(\tilde{S}_{CF,t+1}) + \beta_2 var_t(\tilde{S}_{r,t+1}) + \beta_3 var_t(\tilde{S}_{e,t+1}) \\ - 2\beta_4 cov_t(\tilde{S}_{CF,t+1}, \tilde{S}_{r,t+1}) - 2\beta_5 cov_t(\tilde{S}_{CF,t+1}, \tilde{S}_{e,t+1}) + 2\beta_6 cov_t(\tilde{S}_{r,t+1}, \tilde{S}_{e,t+1}) + \epsilon_t$$

The coefficients are estimated using OLS based on data from July 1984 to November 2009 (305 observations). t-statistics are reported in brackets. The critical value of the t-statistic at which we reject the null hypothesis of $\beta = 0$ at significance level of 5% is $|t| > 1.96$. The last 3 regressands in regression 9 are residuals after projecting the covariance terms on the individual variance components to reduce the affect of collinearity.

Regression	α	$var(\tilde{S}_{CF})$	$var(\tilde{S}_r)$	$var(\tilde{S}_e)$	$-2cov(\tilde{S}_{CF}, \tilde{S}_r)$	$-2cov(\tilde{S}_{CF}, \tilde{S}_e)$	$2cov_t(\tilde{S}_r, \tilde{S}_e)$	R2	AdjR2
1	0.00	2.17						0.10	0.10
	(2.85)	(5.90)							
2	0.00		0.07					0.00	0.00
	(2.51)		(0.04)						
3	0.00			0.61				0.04	0.04
	(0.04)			(3.71)					
4	0.00	2.20	−1.17					0.10	0.10
	(1.76)	(5.93)	(−0.68)						
5	0.00		−0.78	0.62				0.04	0.04
	(0.36)		(−0.44)	(3.73)					
6	0.00	2.04		0.10				0.10	0.10
	(1.05)	(4.51)		(0.49)					
7	0.00	2.06	−1.24	0.11				0.11	0.10
	(1.23)	(4.54)	(−0.71)	(0.54)					
8	0.00	3.66	−1.32	0.92	0.13	2.77	0.78	0.25	0.24
	(0.58)	(7.39)	(−0.69)	(3.00)	(0.13)	(7.26)	(1.35)		
9	0.00	1.90	−2.64	0.16	0.13	2.77	0.78	0.25	0.24
	(1.93)	(4.36)	(−1.64)	(0.87)	(0.13)	(7.26)	(1.35)		

Table 5: Regression of realised bond variance

Coefficients from the univariate and multivariate regressions of realised bond variance on conditional bond variance components:

$$\sigma^2_{B,t} = \alpha + \beta_1 var_t(\tilde{B}_{\pi,t+1}) + \beta_2 var_t(\tilde{B}_{r,t+1}) + \beta_3 var_t(\tilde{B}_{e,t+1}) \\ + 2\beta_4 cov_t(\tilde{B}_{\pi,t+1}, \tilde{B}_{r,t+1}) + 2\beta_5 cov_t(\tilde{B}_{\pi,t+1}, \tilde{B}_{e,t+1}) + 2\beta_6 cov_t(, \tilde{B}_{r,t+1}, \tilde{B}_{e,t+1}) + \epsilon_t$$

The coefficients are estimated using OLS based on data from July 1984 to November 2009 (305 observations). t-statistics are reported in brackets. The critical value of the t-statistic at which we reject the null hypothesis of $\beta = 0$ at significance level of 5% is $|t| > 1.96$. The last 3 regressands in regression 9 are the residuals after projecting the covariance terms on the individual variance components to reduce the affect of collinearity.

Regression	α	$var(\tilde{B}_\pi)$	$var(\tilde{B}_r)$	$var(\tilde{B}_e)$	$2cov(\tilde{B}_\pi, \tilde{B}_r)$	$2cov(\tilde{B}_\pi, \tilde{B}_e)$	$2cov(\tilde{B}_r, \tilde{B}_e)$	R^2	$Adj R^2$
1	0.00	1.79						0.04	0.04
	(2.44)	(3.59)							
2	0.00		0.21					0.00	0.00
	(5.56)		(0.82)						
3	0.00			0.53				0.11	0.10
	(3.55)			(6.02)					
4	0.00	1.87	−0.12					0.04	0.04
	(2.34)	(3.52)	(−0.45)						
5	0.00		−0.13	0.54				0.11	0.10
	(2.77)		(−0.52)	(5.97)					
6	0.00	1.33		0.49				0.13	0.12
	(0.02)	(2.77)		(5.52)					
7	0.00	1.59	−0.38	0.51				0.14	0.13
	(0.63)	(3.12)	(−1.52)	(5.72)					
8	0.00	5.56	1.69	1.08	3.38	1.86	1.37	0.18	0.16
	(0.35)	(4.47)	(2.92)	(5.53)	(3.88)	(3.21)	(3.64)		
9	0.00	0.42	−0.73	0.38	3.38	1.86	1.37	0.18	0.16
	(3.17)	(0.69)	(−2.48)	(4.03)	(3.88)	(3.21)	(3.64)		

Table 6: Regression of realised stock-bond covariance

Coefficients from the univariate and multivariate regressions of realised stock-bond covariance on conditional stock and bond covariance components:

$$\begin{aligned} cov_t(S,B) = \alpha &- \beta_1 cov_t(\tilde{S}_{CF,t+1}, \tilde{B}_{\pi,t+1}) - \beta_2 cov_t(\tilde{S}_{CF,t+1}, \tilde{B}_{r,t+1}) - \beta_3 cov_t(\tilde{S}_{CF,t+1}, \tilde{B}_{e,t+1}) \\ &+ \beta_4 cov_t(\tilde{S}_{r,t+1}, \tilde{B}_{\pi,t+1}) + \beta_5 cov_t(\tilde{S}_{r,t+1}, \tilde{B}_{r,t+1}) + \beta_6 cov_t(\tilde{S}_{r,t+1}, \tilde{B}_{e,t+1}) \\ &+ \beta_7 cov_t(\tilde{S}_{e,t+1}, \tilde{B}_{\pi,t+1}) + \beta_8 cov_t(\tilde{S}_{e,t+1}, \tilde{B}_{r,t+1}) + \beta_9 cov_t(\tilde{S}_{e,t+1}, \tilde{B}_{e,t+1}) + \epsilon_t \end{aligned}$$

The coefficients are estimated using OLS based on data from July 1984 to November 2009 (305 observations). t-statistics are reported in brackets. The critical value of the t-statistic at which we reject the null hypothesis of $\beta = 0$ at significance level of 5% is $|t| > 1.96$. Note that the regressions are performed for all the components listed in the equation above, however only those that displayed any substantial significance, either economic or statistical, in both the univariate and multivariate regressions are displayed in the table.

Regression	α	$-cov(\tilde{S}_{CF}, \tilde{B}_{\pi})$	$-cov(\tilde{S}_{CF}, \tilde{B}_{e})$	$cov(\tilde{S}_{r}, \tilde{B}_{\pi})$	$cov(\tilde{S}_{r}, \tilde{B}_{e})$	$cov(\tilde{S}_{e}, \tilde{B}_{\pi})$	$cov(\tilde{S}_{e}, \tilde{B}_{e})$	R^2	$Adj R^2$
1	0.00	1.05						0.02	0.01
	(0.09)	(2.72)							
2	−0.00		−0.82					0.02	0.01
	(−1.35)		(−2.32)						
3	0.00			0.86				0.01	0.00
	(1.25)			(1.40)					
4	−0.00				−0.16			0.00	0.00
	(−0.48)				(−0.46)				
5	−0.00					1.54		0.08	0.08
	(−3.01)					(5.20)			
6	0.00						−0.47	0.08	0.08
	(4.38)						−(5.11)		
7	0.00	1.19	−0.72	5.46	0.41	2.69	−0.21	0.24	0.22
	(2.93)	(2.37)	(−1.66)	(4.47)	(0.72)	(5.68)	(−1.49)		

Table 7: Robustness regression of realised stock-bond covariance

Coefficients from the univariate and multivariate regressions of realised stock-bond covariance on Exponentially Weighted Moving Average (EWMA) conditional stock and bond covariance components as a robustness check. The coefficients are estimated using OLS based on data from July 1984 to November 2009 (305 observations). t-statistics are reported in brackets. The critical value of the t-statistic at which we reject the null hypothesis of $\beta = 0$ at significance level of 5% is $|t| > 1.96$. Note that the regressions are performed for all the components listed in the equation above, however only those that displayed any substantial significance, either economic or statistical, in both the univariate and multivariate regressions are displayed in the table.

Regression	α	$-cov(\tilde{S}_{CF}, \tilde{B}_{\pi})$	$-cov(\tilde{S}_{CF}, \tilde{B}_e)$	$cov(\tilde{S}_r, \tilde{B}_{\pi})$	$cov(\tilde{S}_r, \tilde{B}_e)$	$cov(\tilde{S}_e, \tilde{B}_{\pi})$	$cov(\tilde{S}_e, \tilde{B}_e)$	R^2	$AdjR^2$
1	−0.00	2.19						0.07	0.06
	(−1.30)	(4.66)							
2	−0.00		−0.45					0.01	0.00
	(−0.89)		(−1.28)						
3	0.00			0.75				0.01	0.01
	(1.67)			(2.14)					
4	−0.00				−1.07			0.05	0.05
	(−3.34)				(−1.03)				
5	−0.00					1.18		0.16	0.16
	−3.02					(7.66)			
6	0.00						−0.24	0.03	0.02
	(2.36)						(−2.94)		
7	0.00	1.71	0.57	7.14	1.90	3.61	0.59	0.42	0.40
	(3.60)	(2.20)	(1.18)	(8.45)	(1.76)	(7.72)	(1.00)		