Flights to Safety and Volatility Pricing

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Abstract

Unexpected shifts in the realized stock market volatility, often associated with financial crises, carry a significantly negative risk premium across stocks and Treasuries, which suggests the existence of a unified pricing model. Investors require a premium for holding the risky assets (stocks), which correlate negatively with volatility surprises, while they are willing to pay a premium for holding the safe assets (Treasury bonds), which correlate positively. This is consistent with investors' "flights to safety", and the corresponding change in sign in the stock-bond correlation, during times of economic uncertainty. Furthermore, because of their positive loadings on volatility, bonds perform well in bad times, which explains their lower expected returns. Interestingly, the joint pricing of stocks and Treasuries leads to economically meaningful and statistically significant risk premia estimates, and to a good performance of asset pricing models. In contrast, both the implied volatility index, VIX, and the tail index, SKEW, are not robustly priced across the two financial markets.

JEL Classification *: G01, G12, C11, C21, C22*

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1 Introduction

Times of market stress are characterized by "flights to safety" (or "flights to quality"), where investors sell their riskier investments to purchase safer assets. As a result, there is an increase in demand for government backed securities, accompanied by a decline in demand for securities issued by private agents during such times. For instance, the 2007-2008 financial market turmoil has spurred investors to flee stocks and seek the safety of the US Treasuries in an attempt to reduce their stock market risk exposure. This phenomenon has led to one of the worst periods for holding stocks to coincide with one of the best periods to hold Treasuries.

Because the U.S. government debt is usually issued in the form of U.S. Treasury securities, these investment vehicles are perceived to be safer assets as they lack significant default risk. Therefore, it is not surprising that investors turn to Treasuries during times of increased uncertainty as a safe haven for their investments: the so called "flight to safety". This type of action leads to a negative stock-bond return correlation, even though this correlation is positive most of the time (see Figure 1). Meanwhile, times of increased economic uncertainty are also characterized by a heightened stock market volatility (see Figure 2). Flights-to-safety episodes point thus to the interconnectedness between the stock and Treasury markets, and to their possible joint sensitivity to stock market volatility risk. Motivated by these observations, I assess the pricing ability of stock market volatility across stocks and Treasuries, while also searching for indicators of flights to safety. From here forth, I refer to stock market volatility simply as volatility.

[Figure 1]

[Figure 2]

I make the following contributions to the literature. First, I capture the flights-to-safety phenomenon using unexpected shifts in realized volatility. I show that stocks correlate negatively with volatility surprises, while Treasuries correlate in a positive fashion. Stocks are thus perceived as being risky investments during turbulent times, while Treasuries are considered to be safe. This leads to investors' flight to the safety of the Treasury market during times of economic uncertainty, when aggregate risk aversion increases. Furthermore, a conditional model specification reveals a significant time variation in these correlations: there is a procyclical variation in the stocks correlations with volatility, accompanied by a countercyclical variation in the bond correlations.

Second, I document that unexpected volatility is priced across stocks and Treasuries, with a negative price of risk. Investors require a premium for holding the risky assets (most stocks), while they are willing to pay a premium for holding the safe assets (Treasury bonds). Moreover, conditional tests document a procyclical variation in the volatility price of risk, which is relatively low (i.e., more negative) during recessions and financial crises, when there is a decline in economic growth, and it is relatively high (i.e., less negative) during expansions, when the economy is growing at a faster pace. Meanwhile, I document a countercyclical variation in the market price of risk.

Third, by relating volatility to bond returns I provide empirical support for the existence of a unified pricing model for the stock and Treasury markets. I also show that asset pricing models tested in the joint markets provide risk premia estimates that are both economically meaningful (i.e., similar to their realized analogs) and statistically significant. Furthermore, I find that asset pricing models, including the Capital Asset Pricing Model (CAPM), have a good explanatory power for the cross-section of returns when tested in the joint markets, which provides further support for the use of a common stochastic discount factor, and points to the fact that the stock market does not represent all the available assets that are priced by models like CAPM.

Fourth, I establish a relation between volatility and future U.S. economic activity and inflation, by documenting that volatility has a significant forecasting power for the business cycle index, up to 12 months in the future.

Finally, I show that the implied volatility index, *VIX*, the tail index, *SKEW*, and the downside risk (as defined in Ang, Chen and Xing (2006)) do not help in capturing flights to safety, and that they are also not robustly priced across the two financial markets.

The literature has focused on flights to safety for some time, starting with the model in Vayanos (2004), where managers become more risk averse during volatile times, when there is a high probability of withdrawals. In Caballero and Krishnamurthy (2008), Knightian uncertainty is an important ingredient in the flights to quality episodes, as it it leads agents to drop risky financial claims in favor of safe claims. As could be expected, the stock-Treasury bond return correlation is informative for the flights-to-safety episodes. This metric is known to be highly unstable: while positive most of the time, it becomes negative during recessions and financial crises, a phenomenon called decoupling. Gulko (2002) finds that decoupling is associated with steep stock market declines, while Baele, Bekaert, and Inghelbrecht (2010) argue that the time variation in the stock-Treasury bond return correlation is driven more by phenomena like flights to quality (or safety) than by changing macroeconomic fundamentals. Furthermore, Connolly, Stivers, and Sun (2005) and Bansal, Connolly and Stivers (2010) document that periods with low stock-bond correlation are characterized by higher stock volatility.

At the same time, the literature has been applying various methodologies for identifying flights to safety based on stock and bond returns (see, e.g., Baur and Lucey (2009), Bekaert, Engstrom, and Xing (2009), and Baele, Bekaert, Inghelbrecht, and Wei (2019)). Realized volatility seems like a good candidate for such an exercise because it is related to financial crises and business cycles (see Figure 2).

Furthermore, because investment decisions are made by allocating funds between stocks and Treasuries, these assets should be priced using discounted future cash flows, discounted by the same stochastic discount factor. Accordingly, the literature has been moving towards developing a unified asset pricing model for the stock and bond markets, which motivates me to assess volatility's pricing ability across these asset classes.

Using monthly returns on 36 portfolios (25 size- and value-sorted portfolios and 11 maturity-sorted Treasury portfolios) over the period January 1952 to December 2014, I estimate significantly negative volatility prices of risk ranging from -45 bp tp -95 bp per month, while controlling for market risk.[1] A parsimonious pricing kernel that includes only the market return and (unexpected) volatility explains up to 74% (71%) of the cross-sectional variation in stock and bond returns in an unconditional (conditional) asset pricing setting. These findings support the existence of a unified pricing model for the two financial markets.

To understand the negative volatility price of risk, it suffices to look at the most turbulent times, when market returns are often highly negative, while volatility rises in response to a series of volatil-

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[1] My sample ends on December 2014 because that is the last available date in WRDS for the legacy Treasury maturity-sorted portfolio returns.

ity surprises. Assets with positive covariances with (unexpected) volatility are desirable because they enhance investors' ability to hedge against a deterioration in the investment opportunities set. As a result, investors are willing to pay a premium for holding such assets.

Furthermore, a detailed analysis of the channels through which volatility gets priced across the two financial markets gives insights into the way market participants react during times of market stress. I find that investors require a premium for holding stocks, which correlate negatively to volatility surprises, while they are willing to pay a premium for holding bonds, which correlate positively. The explanation lies in the fact that stocks and bonds have different risk-return profiles, that make them natural hedges for each other during times of heightened volatility. Furthermore, the opposite signs of these correlations indicate the flights to safety that occur during times of economic uncertainty.

An in-depth analysis of the stocks market shows that, while most stocks experience a drop in returns during times of heightened volatility, with small-cap stocks being affected the most, large-cap stocks seem to be immune to volatility shocks (or even to pay off in some cases). The relatively greater ability of the latter group to weather volatility surprises, such as those often associated with financial crises, partially accounts for their lower expected returns. Across the book-to-market quintiles, large-cap stocks earn between 2.25% and 3.39% lower premia per annum, that are attributable to volatility risk exposure.

Meanwhile, the Treasury market analysis shows significantly positive volatility loadings, that are monotonically increasing with maturity. Results imply that Treasuries pay off in times of heightened volatility, which explains their lower expected returns. My results are in line with the findings in Baker and Wurgler (2012), who show that government bonds comove most strongly with stocks of large, mature firms. They also relate to the results in Ludvigson and Ng (2009), who show that bond returns are forecastable by macroeconomic fundamentals. Furthermore, across Treasuries, I find that a long-term bond (i.e., 61-120 months to maturity) has a 0.94% lower premium per annum compared to a short-term bond, because it provides more insurance against volatility shocks.

Interestingly, asset pricing tests performed in the joint markets lead to economically meaningful risk premia estimates that are similar to their realized analogs, a result that is hard to obtain when tests are performed in the stock market in isolation. Moreover, asset pricing models (including the CAPM) perform well in the joint markets, with the CAPM explaining up to 68% of the cross-sectional variation in returns.

Assessing volatility pricing effects in the Treasury market is a meaningful exercise, since this market is very large and important (it reached almost $13 trillion at the end of my sample period). Furthermore, the role played by volatility across the stock and bond markets is fundamental, because portfolio decisions involve allocating funds between stocks and Treasuries. Therefore, from an investment perspective, it is important to identify the common determinants of the required rates of return across financial markets. Furthermore, because markets are exposed to common macroeconomic shocks, financial assets should be priced using discounted future cash flows, discounted by the same stochastic discount factor.

My findings are robust to the methodology used for estimating volatility surprises. My first approach uses the residual from an *AR(1)* model applied to volatility. My second approach uses the difference between predicted volatility (built using a $GJR\ Asymmetric - GARCH$ model) and realized volatility, and provides additional evidence that volatility surprises, however computed, are important sources of risk across financial markets. Results are further robust when I control for the Fama-French (1993) size and value factors, the Jegadeesh and Titman (1993) momentum factor, and the Amihud (2002) illiquidity factor.

Finally, I assess the ability of three alternative factors in capturing flights-to-safety episodes, while also testing their pricing impact across markets. First, I look at the implied volatility index, *VIX*, which is a proxy for bad times risk and has been shown to price the cross-section of stock returns (see, e.g., Ang, Hodrick, Xing and Zhang (2006)). Also, flights to safety may occur when financial markets experience extrem events. And because there is a large literature on disaster risk that points to tail risk as having a crucial impact on asset returns (see, e.g., Rietz (1988), Barro (2006), Gabaix (2012), Wachter (2013), and Kelly and Jiang (2014)), I consider tail risk as a second factor of interest.[2] Note that I differ from prior authors as I perform my exercise using a traded

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[2] Also, Harvey and Siddique (2000) document the effect of higher moments in the cross-section of stock returns.

factor, the *SKEW* index, which measures the perceived tail risk in the market portfolio. Third, I also consider the downside risk factor of Ang, Chen and Xing (2006). Overall, I find that realized volatility is a more suitable indicator for flights to safety than any of these alternatives, and also that *VIX*, *SKEW* and downside risk are not robustly priced across the two financial markets.

My work is related to two different strands of literature. My paper contributes to the part of the literature that has been working towards developing a unified asset pricing model for the stock and bond markets. Some examples are Ferson and Harvey (1991), Baker and Wurgler (2012), Bekaert, Engstrom, and Xing (2009), Campbell, Sunderam, and Viceira (2017), Lettau and Wachter (2011), and Koijen, Lustig, and Van Nieuwerburgh (2017). My work is distinct from this literature, as I explore the role of volatility in the cross-section of stocks and Treasuries.

A second strand of the literature has been focusing on empirically characterizing flights to safety. Some examples are Baur and Lucey (2009), Bekaert, Engstrom, and Xing (2009), Baele, Bekaert, Inghelbrecht, and Wei (2019), and Adrian, Crump and Vogt (2019). I complement this literature by capturing flights to safety using volatility loadings in the stock and Treasury markets.

The remainder of the paper is structured as follows. Section 2 presents the data. Section 3 details the methodology used for indentifying unexpected volatility, and the asset pricing models used in the paper. Section 4 empirically documents the flights to safety. Section 5 prices volatility across the stock and Treasury markets. Section 6 examines possible alternative indicators for flights to safety. Section 7 links volatility to economic activity. Section 8 concludes. The Appendix presents technical details on the *GJR Assymetric Volatility model* of Glosten, Jagannathan and Runkle (1993), and on the *Griddy-Gibbs sampler* of Geman and Geman (1984) and Gelfand and Smith (1990).

2 Data

I build the monthly realized volatility using daily market return data that I download from CRSP over the period January 1952 to December 2014. Using such a long sample justifies volatility's role as a state variable proxying for bad time risk. The set of test assets consists of 36 portfolios: 25

size-and value-sorted portfolios and 11 maturity-sorted Treasury portfolios. I download the value-weighted returns for the stock market portfolios from Kenneth French's website at Dartmouth, and I download the returns on the Treasury portfolios from CRSP. The first Treasury portfolio has return maturities from one to six months, while the last one has return maturities between 60 and 120 months. Only non-callable, non-flower notes and bonds are included in these portfolios. Treasury portfolio returns are computed as equal-weighted averages of the unadjusted holding period returns of individual bonds.

For asset pricing tests I use classical risk factors such as the size, value and momentum factors. I download the monthly returns for *SMB*, *HML* and *MOM* from Ken French's website at Dartmouth. I also use the *Amihud* illiquidity factor, which I build based on stock level data that I download from CRSP.

For conditioning tests, I construct three state variables based on data that I download from WRDS. The first variable is the default spread, DEF, built as the difference between the yields of a long-term corporate Baa bond and a long-term corporate Aaa bond.[3] The second variable is the term spread, $TERM$, built as the difference between the yields of a thirty-year and a one-year government bond. The third variable is the dividend yield on the S&P500 value-weighted portfolio, DY,which is the sum of dividends over the last 12 months, divided by the level of the index.

Table 1 reports the average excess returns for the test assets. According to the liquidity preference hypothesis, bond returns should increase with maturity, because long-term bonds are more sensitive to interest rate risk. This monotonic pattern can be observed in Panel A of Table 1, with average bond excess returns (in excess of the one-month T-bill rate) increasing with maturity from 4bp to 16bp per month, all statistically significant. Meanwhile, Panel B shows that, with the exception of the corner small-growth portfolio, returns are statistically significant in the stock market. Consistent with the previous literature, stocks sorted based on size and book-to-market display a sizeable dispersion in returns in both dimensions (with the exception of the growth stocks in the size dimension).[4]

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[3] The yields on the corporate bonds come from the Federal Reserve Bank Reports in WRDS.

[4] See Basu (1977), Ball (1978), Banz (1981), Reinganum (1981), and Fama and French (1993, 2008), among others.

[Table 1]

3 Methodology

I now present the methodology used for estimating unexpected volatility, and I describe the asset pricing models used for testing its pricing ability.

3.1 *Estimating Unexpected Volatility*

For the main tests, I estimate a model-free measure of volatility using daily market return data. Specifically, I follow Anderson et al. (2003) and I sum up the squared daily market returns within a month, and then I take the square root of this quantity to obtain a monthly measure of realized volatility:

$$V_t = \sqrt{\sum_{i=0}^{n} R_{m,t+i}^2}, \tag{1}$$

where n represents the number of trading days within month t. Next, I estimate the unexpected volatility UV_t as in Engle (1982), using the residual from an *AR(1)* model applied to the V_t series:

$$V_t = \mu_V + \phi_1^V V_{t-1} + UV_t. \tag{2}$$

Note that the term UV_t in Eq. (2) represents the difference between volatility at time t and its conditional expectation.

For robustness checks, I build a second (unexpected) volatility factor, based on predicted and realized volatilities. To this end, I first predict volatility using an underlying model that captures the following stylized facts: volatility increases after a drop in stock prices (Black (1976), Nelson (1990, 1991)), and is persistent (Schwert (1989), French, Schwert, and Stambaugh (1987)); there is usually leptokurtosis in returns; negative shocks to returns drive up volatility (Black (1976)); and there is usually a positive autocorrelation of order one in an index' return series (Campbell,

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Lo and MacKinley (1997)). Furthermore, Bollerslev (1986) shows that the generalized autoregressive conditional heteroskedasticity ($GARCH$) model provides a flexible structure for modeling the volatility of financial time series. Therefore, I follow Bauwens and Lubrano (1998) and I use a $GJR\ Asymmetric\ Student - GARCH$ model with an *AR(1)* specification in the mean equation for the monthly market returns, a *Half-Cauchy* prior for the excess kurtosis parameter υ (υ is the degrees of freedom variable for the *Student-t* distribution), and flat priors on finite intervals for all the other parameters in the model below:

$$\begin{aligned}
R_{m,t} &= \mu + \rho R_{m,t-1} + \eta_t \\
\eta_t &= \varepsilon_t \sqrt{h_t}, \\
\varepsilon_t / I_{t-1} &\sim Student\ (\upsilon), \qquad\qquad t = 1, ..., T. \\
h_t &= \alpha + \phi h_{t-1} + \theta^{+} \eta_{t-1}^{2+} + \theta^{-} \eta_{t-1}^{2-}, \\
\eta_t^{2+} &= \eta_t^2 1_{\{\eta_t > 0\}},\ \eta_t^{2-} = \eta_t^2 1_{\{\eta_t < 0\}}
\end{aligned} \tag{3}$$

Above, h_t represents the conditional variance of market returns. The model described by Eq. (3) accommodates the asymmetry in the news impact curve (see Appendix A for details on the model).

I estimate Eq. (3) using the $Griddy - Gibbs\ sampler$, which is a very popular $Markov\ Chain\ Monte\ Carlo$ method (see Appendix B for details on the estimation) and I present the posterior estimates in Table 2.

Next, I build the second unexpected volatility factor as the difference between realized and predicted volatility, using the estimates from Eqs. (2) and (3):

$$PRED\_UV_t = V_t - \sqrt{h_t}. \tag{4}$$

[Table 2]

Figure 1 presents the monthly realized and predicted volatilities. The two series track each other closely, a result that is due to the $GARCH$ predicting equation being a weighted average of past squared returns, with slowly declining weights. Furthermore, and as expected from a recession and financial crisis proxy, the graph documents a heightened volatility during times of economic uncertainty. The shaded areas in Figure 1 represent: the recessions of 1954, 1957-1958, 1960-1961, 1969-1970, 1973-1975, 1980, 1981-1982, 1983, 1990-1991, 2000-2001, the Cuban missile crisis of October 1962, the credit crunch of 1966, the Penn Central commercial paper debacle of May 1970, the oil crisis of November 1973, the stock market crash of October 1987, the Asian crisis of 1997, the Russian debt default and the LTCM crisis from 1998, the burst of the hi-tech bubble in 2000, the 9/11 terrorist attack, the accounting scandals (Enron, WorldCom) and the Gulf War of 2002, the financial crisis of 2007-2008 (the bursting of the US housing bubble, accompanied by high default rates on subprime and other adjustable rate mortgages), the European sovereign-debt crisis of 2010-2012, the U.S. debt downgrade of 2011, and the emerging market crisis of 2014.

3.2 *Estimating Illiquidity*

An important aspect of financial crises is a reduction in market liquidity. Therefore, I need to control for liquidity effects in my asset pricing exercise. To this end, I download stock level data from CRSP for the period January 1952 to December 2014 to build the Amihud illiquidity factor. For each stock i and each month k, I compute $\frac{1}{\#Days}\sum_{t=1}^{\#Days}\frac{|R_{i,t,k}|}{V_{i,t,k}}$, where $R_{i,t,k}$ and $V_{i,t,k}$ represent the return and dollar volume (measured in millions), respectively, of stock i on day t of month k. I collect data on common stocks (share code in 10 and 11) that trade at the beginning of the month at a price ranging from \$5 to \$1,000 on NYSE (NYSE and MKT), and that have valid data for at least 15 trading days in a given month (see Watanabe and Watanabe (2008), for details). An aggregate measure can then be defined by averaging across stocks for each month k:

$$A_k = \frac{1}{N_k}\sum_{i=1}^{N_k}\left(\frac{1}{\#Days}\sum_{t=1}^{\#Days}\frac{|R_{i,t,k}|}{V_{i,t,k}}\right), \tag{5}$$

where N_k represents the number of stocks in month k. Amihud's "illiquidity ratio" looks directly at price impacts. Periods of illiquidity are periods during which small volumes are associated with large price moves.

I re-scale this measure by $\left(\frac{m_{k-1}}{m_1}\right)$ to make it stationary, where m_{k-1} represents the total market capitalization in month *k-1* for the stocks included in the month k sample, and m_1 is the corresponding value for the initial month. This scaling factor controls for the time trend in the A_k series above (see, e.g. Acharya and Pederson (2005)). Finally, I compute the unexpected Amihud factor *($Amih_k$)* as the residual ϵ_k from the following model:

$$\left(\frac{m_{k-1}}{m_1} A_k\right) = \alpha + \beta_1 \left(\frac{m_{k-1}}{m_1} A_{k-1}\right) + \beta_2 \left(\frac{m_{k-1}}{m_1} A_{k-2}\right) + \epsilon_k. \tag{6}$$

I select the lag length in the autoregressive model in Eq. (6) to ensure that the residuals are serially uncorrelated.[5]

3.3 *Unconditional Asset Pricing Models*

My goal is to test the pricing ability of (unexpected) volatility in the cross-section of stocks and Treasuries. To model the relation between unexpected volatility and expected returns, I assume that the pricing kernel m that prices assets across the two financial markers is represented by a linear factor model of the form:

$$m = 1 + b_i' f_i, \quad E(mR_i^e) = 0, \qquad i = 1, 2, ..., n, \tag{7}$$

where b_i are the factor loadings, f_i is a vector of pricing factors that includes the excess market return, *SMB*, *HML*, *MOM*, Amihud and unexpected volatility, while R_i^e is a vector of excess returns. This linear factor representation of the stochastic discount factor is equivalently written as an expected-return beta model of the form (see Cochrane, 2001):

$$E(R_i^e) = \beta_i' \lambda_i, \tag{8}$$

where $E(R_i^e)$ is the vector of expected excess returns, β_i are the exposures to the risk factors f_i, and λ_i are the corresponding prices of risk. The pricing kernel and the expected-return beta model give a testable implication for the asset pricing models. If unexpected volatility is priced, its cross-sectional price of risk in the λ_j vector should be nonzero.

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[5] The *AR(2)* specification is also the one used by the existing literature when computing the innovation in the Amihud illiquidity factor.

I start by expressing the equilibrium expected excess returns as linear combinations of the (conditional) beta of the asset returns with the market return, β_i^m, and the (conditional) betas of the asset returns with the unexpected volatility, β_i^{UV}, namely:

$$E(R_i^e) = \lambda_0 + \lambda_m \widehat{\boldsymbol{\beta}_i^m} + \lambda_{UV} \widehat{\boldsymbol{\beta}_i^{UV}}. \tag{9}$$

As stated above, the regressors in Eq. (9) are the slope coefficients in the return generating process:

$$R_{i,t}^e = \alpha_i + \beta_i^m R_{m,t}^e + \beta_i^{UV} UV_t + \epsilon_{i,t}, \qquad i = 1, 2, ..., n, \tag{10}$$

with R_m^e being the excess returns on the market portfolio. and n being the number of test assets.

To check the robustness of volatility pricing, I extend the model to account for classical risk factors. To this end, I assume the existence of S state variables X_s that affect stock returns:

$$E(R_i^e) = \lambda_0 + \lambda_m \widehat{\boldsymbol{\beta}_i^m} + \sum_{s=1}^{S} \lambda_s \widehat{\boldsymbol{\beta}_i^s}. \tag{11}$$

The regressors in Eq. (11) are the slope coefficients in the return generating process:

$$R_{i,t}^e = \alpha_i + \beta_i^m R_{m,t}^e + \sum_{s=1}^{S} \beta_i^s X_{s,t} + \epsilon_{i,t}, \qquad i = 1, 2, ..., n. \tag{12}$$

The lambdas in Eq. (11) have the usual interpretation: λ_m is the price of market risk, λ_s is the price of risk associated with the generic factor X_s, and λ_0 represents the pricing error. In order to compare my results with the existing asset pricing literature, I assume for now time invariant betas.

I perform the asset pricing tests using a two-step estimation procedure. First, I estimate the factors' loadings (the betas) on each portfolio, according to Eqs. (10) and (12). Given the betas, I then estimate the prices of risk (the lambdas) in a second step by regressing cross-sectionally the portfolios' excess returns on the betas, as implied by Eqs. (9) and (11). Finally, I analyze the distribution of the lambda estimates. I run the tests at the portfolio level, where the beta estimates have been documented to be more precise.

3.4 *Conditional Asset Pricing Models*

Motivated by the previously documented variability in the conditional stock-bond returns correlation, I extend the exercise using a conditional asset pricing model:

$$m_{t+1} = 1 + b'_{i,t}(Z_t)f_{t+1}, \quad E[m_{t+1}R^e_{i,t+1}/Z_t] = 0, \qquad i = 1, 2, ..., n. \tag{13}$$

The specification used in Eq. (13) implies that the stochastic discount factor m_{t+1} is a linear function of the risk factors, where the coefficients depend in a linear fashion on Z_t.

I estimate the conditional loadings at time *t+1* by conditioning on the set of information available at time *t*, Z_t. I follow the literature and assume that the information set is spanned by three macro variables that can affect the two aspects of the stochastic investment opportunity set, the yield curve and the conditional distribution of asset returns: aggregate dividend yield, term spread, and default spread.[6] I denote the vector of instruments by $Z_t = (DIV, TERM, DY)_t$.

I assume a return generating process:

$$R^e_{i,t+1} = \alpha_i + \beta^m_i(Z_t)R^e_{m,t+1} + \beta^{UV}_i(Z_t)UV_{t+1} + \epsilon_{i,t+1}, \qquad i = 1, 2, ..., n, \tag{14}$$

with n being the number of test assets, and $\beta^m_i(Z_t)$ and $\beta^{UV}_i(Z_t)$ being the time t conditional market beta and respectively, the conditional volatility beta for asset i. The factor $R^e_{i,t+1}$ denotes the time *t+1* excess return on asset i, while $R^e_{m,t+1}$ is the time *t+1* excess return on the market portfolio. The two conditional betas have the linear functional forms:

$$\beta^m_i(Z_t) = b^m_{0i} + B^{m'}_i Z_t \tag{15}$$

$$\beta^{UV}_i(Z_t) = b^{UV}_{0i} + B^{UV'}_i Z_t, \tag{16}$$

where $B^{m'}_i$ and $B^{UV'}_i$ are vectors of coefficients.

Substituting Eqs. (15) and (16) into Eq. (14), leads to

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[6] See, e.g., Ferson and Schadt (1996) or Petkova and Zhang (2005).

$$R^e_{i,t+1} = \alpha_i + (b^m_{0i} + B^{m'}_i Z_t)R^e_{m,t+1} + (b^{UV}_{0i} + B^{UV'}_i Z_t)UV_{t+1} + \epsilon_{i,t+1}, \qquad i = 1, 2, ..., n. \tag{17}$$

I estimate the parameters in Eq. (17), and then I use them to construct the fitted betas $\widehat{\beta^m_i(Z_t)}$ and $\widehat{\beta^{UV}_i(Z_t)}$ in Eqs. (15) and (16). Next, the fitted betas enter as regressors in the conditional asset pricing model:

$$E[R^e_{i,t+1}/Z_t] = \lambda_0(Z_t) + \lambda_m(Z_t)\widehat{\beta^m_i(Z_t)} + \lambda_{UV}(Z_t)\widehat{\beta^{UV}_i(Z_t)}, \qquad i = 1, 2, ..., n. \tag{18}$$

In Eq. (18), $\lambda_m(Z_t)$ and $\lambda_{UV}(Z_t)$ represent the conditional prices of systematic risk (or the conditional expected risk premia) for the market return and volatility. The $\lambda_0(Z_t)$ term represents the model pricing error.

Finally, I check the robustness of the volatility pricing effect in the presence of previously established risk factors. To this end, I use a generalized conditional model of the form:

$$E[R^e_{i,t+1}/Z_t] = \lambda_0(Z_t) + \lambda_m(Z_t)\widehat{\beta^m_i(Z_t)} + \sum_{s=1}^{S} \lambda_s(Z_t)\widehat{\beta^s_i(Z_t)}, \qquad i = 1, 2, ..., n. \tag{19}$$

As above, the conditional betas for any generic factor s in Eq. (19) depend in a linear fashion on Z_t.

4 Flights to Safety

As can be observed in Figure 1, volatility has a strong countercyclical pattern, peaking just before or during recessions, and falling sharply late in recessions or early in recovery periods. To have a better understanding of what happens during recessions and financial crises, it is useful to look at the realized correlation between the stock and Treasury markets. First, I compute the unconditional correlation between the monthly returns on the stock market portfolio and the 10-year Treasury bond, which is positive and equal to 0.10. Next, I compute the conditional correlation using 1-year rolling windows, on a monthly basis, over the period January 1952 to December 2014.

I plot the time series of the realized stock-bond return correlations in Figure 2. It is expected to have, in general, a positive correlation between bond and stock returns, because both of them are major asset classes representing long duration assets (see Baele et al., 2010). The graph shows that, while positive most of the time, the correlation becomes negative during recessions or financial crises (the shaded areas in the graph). This result is in line with Gulko (2002), who documents the decoupling phenomenon: the unconditional positive correlation between stocks and bonds switches sign during stock market crashes. My finding also aligns with the results in Connolly et al. (2005), who document a lower correlation between stock and bond returns during times of increased stock market uncertainty. It also supports the previous findings by Campbell, Sunderam, and Viceira (2017) (see Figure 1 in their paper), and by Baele, Bekaert, and Inghelbrecht (2010) (see Figure 1 in their paper).

4.1 ***Results Using Unconditional Models***

To capture the flight to safety phenomenon, I turn my attention to the volatility loadings. To this end, I run the first-pass regression from Eq. (10). Table 3 Panel A) presents results for the Treasury market. I find positive and statistically significant market betas across all Treasury portfolios. Because the stock-Treasury bond correlation is positive most of the time (as can be seen in Figure 2), it is not surprising that the estimated time-invariable market betas for Treasury securities are positive. I also find an increasing pattern in market betas across Treasury bonds, which is in line with the findings in Fama and French (1993). Specifically, short maturity bonds have a market beta close to zero, while long maturity bonds have a market beta of 0.06 (*t-stat* = 4.18). The former result was expected, since short-term Treasuries are considered to be riskless securities.

[Table 3]

However, the important finding is that all of the volatility loadings on Treasuries are positive and statistically significant. This result implies that Treasuries pay off in times of increased economic uncertainty, when volatility rises. Furthermore, there is a strictly increasing pattern in volatility loadings across the different maturity bonds, with short maturity bonds having a volatility beta of 0.01 (*t-stat* = 2.84), while long maturity bonds have a volatility beta of 0.15 (*t-stat* = 4.05). These results imply that long maturity bonds provide a hedge against volatility risk. Therefore, they should be in high demand, and should require lower expected returns when compared to short-maturity bonds. Why do we then observe higher rates of return required by investors on long maturity Treasuries, as outlined in Table 1? The answer is that long term bonds also have a higher market beta, which makes them relatively riskier when compared to short term bonds. In addition, long term bonds are exposed to interest rate risk.

Table 3 Panel B) reports the estimates for the factor loadings in the stock market. All of the market betas are positive and statistically significant, implying that all stocks are affected by market downturn risk. Meanwhile, the majority of volatility betas are significantly negative. The latter result was expected, as stocks usually experience low returns during turbulent times. Interestingly, volatility loadings increase with size in a strictly monotonic fashion. Small cap portfolios have a significantly negative volatility exposure, whereas large cap portfolios are not affected by volatility surprises or even pay off in some cases, holding the market return constant. This result is in line with the findings in Coval and Shumway (2001). Furthermore, there is a sizeable spread in volatility loadings between small-cap and large-cap stocks. For example, among the low book-to-market (growth) firms, the small-cap stocks have a volatility beta of -0.40 (*t-stat* = - 3.51), while the large-cap stocks have a beta of 0.11 (*t-stat* = 3.11). Among the high book-to-market (value) firms, the small-cap stocks have a volatility beta of -0.42 (*t-stat* = - 5.16), while the large-cap stocks have a beta of 0.05 (*t-stat* = 0.63). Therefore, large cap firms act as a safer investment during turbulent times. That is because bonds and bond-like stocks depart from speculative stocks as investors' risk aversion increases. These results are in line with the findings in Baker and Wurgler (2012), who show that government bonds comove most strongly with stocks of large, mature firms.

The size results can be interpreted as a flight to safety into larger, well-known companies, who have better acces to capital markets during volatile times. Meanwhile, value portfolios tend to have slightly more negative volatility betas than growth portfolios, but the results are economically weaker than in the size dimension. The model from Eq. (10) explains between 60% and 89% of the time series variation in portfolio excess returns.

Figure 3 plots the average portfolio excess returns in Panel A, and the volatility loadings in Panel B. The graphs show a nice alignment in the size dimension between portfolio returns and volatility loadings.

[Figure 3]

Note that, because both stocks and bonds have positive exposure to market risk, *CAPM* can not explain by itself the flight-to-safety phenomenon. Instead, it is the opposite exposure to volatility risk that captures this effect.

4.2 ***Robustness Checks***

This section ensures that the above results are not a by-product of the way I measure unexpected volatility. To this end, I use the second measure of unexpected volatility from Eq. (4), *PRED_ UV*. Table 4 repeats the time series regression from Eq. (10). Panel A) presents results for the Treasury market, where I find again positive and statistically significant market betas across all Treasury portfolios. As above, there is an increasing pattern in market betas across Treasury bonds, with short maturity bonds having a market beta close to zero, while long maturity bonds having a market beta of 0.07 (*t-stat* = 4.52). The second measure of unexpected volatility seems to do a better job at fitting the yield curve, with the intercepts being almost all insignificant.

[Table 4]

As before, all of the volatility loadings on Treasuries are positive and statistically significant; there is a strictly increasing pattern in volatility loadings across the different maturity bonds, with short maturity bonds having a volatility beta of 0.01 (*t-stat* = 2.07), while long maturity bonds have a volatility beta of 0.16 (*t-stat* = 4.62).

Table 4 Panel B) reports the estimates for the factor loadings in the stock market. As above, all of the market betas are positive and statistically significant, while the majority of volatility betas are significantly negative. Again, volatility loadings increase with size in a strictly monotonic fashion. Figure 3 plots the volatility loadings for the second measure in Panel C.

4.3 *Results Using Conditional Models*

Motivated by the time variability in the stock-bond correlation, I perform the conditional time series tests from Eq. (17), I use the aggregate dividend yield, the term spread, and the default spread as part of the information set available at time t. The vector of instruments is thus $Z_t = (DIV, TERM, DY)_t$. First I run the regression from Eq. (17) to estimate the parameters needed to build the conditional market and volatility betas in Eqs. (15)-(16). Figure 4 plots the monthly time series of cross-sectional averages and maximum (minimum) of the conditional volatility betas. The important finding here is that the average conditional volatility beta has, most of the time, opposite signs in the two markets. Panel A shows that most of the time, the average conditional volatility beta is positive for Treasuries, while Panel B shows that the average conditional volatility beta is always negative for stocks.

[Figure 4]

5 Pricing Volatility

The above findings motivate me to formally investigate the volatility pricing effects across the two financial markets. Because stocks and Treasuries are interconnected and jointly sensitive to volatility risk, as evidenced by the most recent financial crisis, it is reasonable to formally investigate the volatility effect across these markets. If volatility proxies for common underlying sources of macroeconomic risk, then it should be priced across the two financial markets.[7]

5.1 *Unconditional Asset Pricing Tests*

The first step in the unconditional asset pricing exercise is to estimate the factor loadings in the first-pass regression (10). The second step consists of estimating Eq. (9) using the fitted regressors from Eq. (10). To ensure that the volatility pricing ability, if supported by the data, is robust

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[7] Also, if the test assets in one of the markets have a factor structure (as is the case with the stock market portfolios), and if the variables tested have some correlation with these factors, then one obtains a good model fit (see Lewellen, Nagel and Shanken, 2010). Testing the asset pricing model outside the stock market addresses this issue.

with respect to the inclusion of classical risk factors in the model, I also estimate the asset pricing model from Eqs. (11)-(12). To this end, I consider the following findings.

First, Fama and French (1996) rely on their three-factor model with market return, SMB and HML for explaining stock return anomalies related to firm characteristics.[8] Second, another posible candidate for a state variable is the momentum factor (*MOM*) of Jegadeesh and Titman (1993).[9] Third, an important aspect of financial crises is a reduction in market liquidity, due to an increased risk aversion among market makers. Therefore, I also control for liquidity in the asset pricing model using the Amihud (2002) illiquidity factor.

I document the average returns for the traded risk factors in Table 5 Panel A, and I present the cross-correlation matrix for these factors and volatility in Panel B. There is a significantly negative correlation between UV and market return (equal to –33%), which was expected since rises in volatility tend to correspond to downturns in the market. There is also a significant negative correlation between UV and *SMB,* although not economically large (equal to -26%). This is in line with the results reported in the previous section, which show that returns of small stocks are more (negatively) affected by volatility risk. There is also a significant correlation between volatility and aggregate illiquidity (equal to 41%), which suggests that times of heightened volatility tend to coincide with times of low aggregate liquidity, as was experienced during the recent U.S. financial crisis. Finally, UV has a significant correlation to ΔVIX, although not large from an economic angle (equal only to 41%). The table presents similar correlations for the $PRED\_UV$ factor.

[Table 5]

I now turn to estimating the factors' prices of risk using the Fama-MacBeth (1973) methodology and the second-pass regression from Eq. (9). I use the statistical distribution of the estimated lambdas to assess whether the risk factors included in the asset pricing model are priced in the cross-section of returns. While performing this exercise, it is important to keep in mind the

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[8] HML and SMB are mimicking portfolios for book-to-market equity and size (zero-investment portfolios). HML is the difference between high book-to-market-stocks portfolios and low book-to-market-stocks portfolios, with similar weighted-average size, while SMB is the difference between the returns on small-stocks portfolios and those of big-stocks portfolios, with similar weighted-average book-to-market equity.

[9] MOM is built as the average return on the two high prior (months 2-12) return portfolios minus the average return on the two low prior return portfolios.

following theoretical result. If the factors form a basis for the space of returns, and if the factors are traded in the market place, then their risk prices should be close in value to their means (see Cochrane, 2001).[10]

Table 6 documents the findings. The first set of rows presents the results for the *CAPM* model, which is practically Eq. (9) without the volatility factor. It is reassuring to see that the theoretical result in Cochrane (2001) holds here. The first row of this table together with Table 5 Panel A highlight a novel result: the estimated market risk premium (equal to 58 bp per month, *t-stat* = 3.35) is similar to the realized analog of 59 bp from Table 5. This is a result that the literature has had a hard time obtaining. My finding may be due to the fact that the stock market does not represent all the available assets that are priced by models like CAPM. Adding Treasuries leads to a better performance of asset pricing models, and translates into an estimated market risk premium that makes economic sense. I document another interesting result in the first set of rows: the market return explains by itself a sizeable amount of the cross-sectional variation in returns in the joint markets, with an R^2_{adj} of 68%.

[Table 6]

The second set of rows in Table 6 supports the role of volatility as a risk factor that is priced across financial markets. Controlling for market risk, volatility has an estimated risk premium of -56 bp per month (*t-stat* = - 1.93). Although there is, on average, a significant trade-off between market risk and return over the period January 1952 to December 2014 across the two markets, a non-beta measure of risk like volatility plays an important and apparently systematic role, with a noticeable influence on both stocks and Treasuries expected returns. The negative price of volatility risk suggests that during turbulent times investors are willing to pay a premium for holding the safe assets (Treasury bonds), which correlate positively with volatility, and they require a premium for holding the risky assets (stocks), which correlate in anegative fashion. This is consistent with investors' flight to safety during volatile times. These results are also consistent with Merton's (1973) intertemporal asset-pricing model (ICAPM), where the risk premia are associated with the

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[10] I refer only to traded factors here, thus excluding the non-traded unexpected volatility factor.

conditional covariances between asset returns and innovations in state variables that describe the time variation in the investment opportunity set. According to Campbell (1993, 1996), investors want to hedge against changes in forecasts of future volatilities, so they are concerned about the unexpected component of volatility.

5.2 *The Contribution of Volatility to Expected Returns*

The previous subsection established that volatility is a priced risk factor across the stock and Treasury markets. This subsection shows that the contribution of volatility risk to expected returns is economically substantial, as well. Table 7 describes how much of the expected returns can be explained by exposure to volatility risk.

I find that Treasury bonds have lower premia (as can be seen in Table 1) because they pay off in times of heightened volatility. As an example, a long-term Treasury bond has a 0.96% (= -1.02-(-0.06)) lower premium per annum because of its insurance against volatility shocks (see Table 7 Panel A). In the stock market, results suggest that investors demand large-cap stocks during turbulent times, because small-cap stocks expose them to larger volatility risk (on top of market risk). In accordance to rational asset pricing, this hedging demand drives up the price for such stocks, and leads to lower expected returns for large-cap stocks. Specifically, large-cap stocks have between 2.25% (= -0.11-2.14) and 3.39% (= -0.73-2.66) lower premium per annum when compared to small-cap stocks, across the value quintiles (see Table 7 Panel B).

These findings also imply that in the $ICAPM$ world the market portfolio is not mean-variance efficient with respect to the universe of common stocks, and suggests adding a position that takes into account volatility. Since investors are not fully insured against systematic volatility risk, the premium they pay for assets that covary positively with volatility reflects their attempts to reduce this risk exposure.

[Table 7]

5.3 *Robustness Checks*

In this section I ensure again that my results are not a by-product of the way I measure unexpected volatility, and that they are robust when controlling for previously documented sources of systematic risk.

5.3.1 *Controlling for Other Risk Factors*

A stringent test consists of assessing the empirical performance of volatility in the presence of the Fama-French (1993) factors. Therefore, in the next step I perform cross-sectional tests, where I control for classical risk factors. I present the estimates of the parameters in Eq. (11), for various values of s, in Table 6. I find that volatility has a significant price of risk of -0.95 bp per month (*t-stat* = -2.96) when the *SMB* and *HML* factors are included in the model. Volatility continues to mantain its pricing ability when the *MOM* factor is included in the model (with a price of risk of -97 bp per month, *t-stat*= -3.03). Finally, and in light of recent literature that documents that stock market liquidity prices the cross-section of Treasury bond returns (see Li et al., 2009), the question is whether volatility has a pricing effect in the presence of liquidity risk. Results show that, when controlling for the Amihud factor from Eq. (6), volatility continues to price the cross-section of returns (with a price of risk of -103 bp per month, *t-stat* = -2.98), while illiquidity does not have explanatory power here.

Overall, while the estimated market risk premium continues to be significant and close its realized analog, the volatility pricing ability is robust across different model specifications. As for *SMB,* it has an insignificant price of risk, while *HML* and *MOM* have significant prices of risk. Similarly to the market, the estimated prices of risk for these traded factors are close to the realized analogs (the exception being the *MOM* factor, result probably due to factors not being completely orthogonal to each other).

Finally, I use the R^2_{adj} statistic from the cross-sectional regression of average excess returns on the risk factors' loadings for comparing the relative performance of the different asset pricing models (see Jagannathan and Wang, 1996). When *CAPM* is augmented with volatility, R^2_{adj} goes from 68% to 70%. Volatility also adds to the explanatory power of the Fama-French (1993) and

Carhart (1997) models.

5.3.2 *Using the Second Measure of Unexpected Volatility*

This section ensures that results are robust with respect to the methodology used for building unexpected volatility. To this end, I use the second (unexpected) volatility factor from Eq.(4), $PRED\_UV$. I present the correlation of this new (unexpected) volatility factor with the other risk factors in Table 5 Panel B. Similar to the first volatility measure, it has a negative and significant correlation with the *SMB* factor (-24%) and significant correlations with the ΔVIX and *Amih* factors (44% and 39%, respectively).

I report the results for the asset pricing tests performed using the new volatility measure in Table 8. I estimate a significant price of risk for the second volatility factor, ranging between -56 bp per month (*t-stat* = -1.95) and -95 bp per month (*t-stat* = -2.96) across the various asset pricing model specifications. The volatility effect is robust with respect to the *SMB*, *HML, MOM* and *Amih* factors. Augmenting the classical asset pricing models with volatility leads to a slightly higher explanatory power. As before, results make economic sense and they support the use of a pricing kernel that includes unexpected volatility when pricing the cross-section of stocks and Treasuries.

[Table 8]

5.4 *Conditional Asset Pricing Tests*

Next I perform the conditional asset pricing tests from Eq. (14)-(17). Table 9 documents my findings. The first set of rows presents the results for the conditional *CAPM* model, which is practically Eq. (18) without the volatility factor. The market return has a significant price of risk of 59 bp per month (*t-stat* = 3.41), which is exactly its realized analog. The conditional $CAPM$ model has a good explanatory power in the cross-section of stocks and Treasuries, with an R^2_{adj} of 66%.

The following sets of rows in Table 9 report the results when estimating the models in Eqs. (18) and (19). My findings support the role of volatility as a priced risk factor across markets, when using the conditional asset pricing model specification. Controlling for market risk, volatility has an estimated risk premium of -45 bp per month (*t-stat* = -1.96). When the *SMB* and *HML* factors are included in the model, volatility continues to have a significant price of risk of -0.54 bp per month (*t-stat* = -2.70). Volatility further mantains its pricing ability when the *MOM* factor is also included in the model (with a price of risk of -65 bp per month, *t-stat* = -3.24). Results are similar when controlling for illiquidity.

[Table 9]

Figure 5 plots the time series of the conditional market and volatility prices of risk estimated using the model from Eq. (18). The conditional values are the fitted values from a regression of each price of risk on the conditioning variables. My results indicate that there is a procyclical variation in the volatility risk premia, and a countercyclical variation in the market risk premia. It is not surprising that the two time series are almost mirror images of each other, given the documented flight to safety in the previous sections. During recession or financial crises, the market price of risk increases (i.e., it becomes more positive) and the volatility price of risk decreases (i.e., it becomes more negative). When faced with volatile times, investors require a premium for holding the risky assets (stocks), which correlate negatively to volatility surprises, while they are willing to pay a premium for holding the safe assets (Treasury bonds), which correlate positively. This is consistent with investors' flights to safety during times of economic uncertainty.

[Figure 5]

6 Possible Alternatives for Capturing Flights to Safety

In this section I evaluate the ability of posible alternative factors that may capture flights-to-safety episodes, while also having a pricing impact across markets: *i)* the implied volatility index, *VIX*, which is a measure of perceived market volatility; *ii)* the tail index, SKEW, which measures the perceived tail risk in the market portfolio; and *iii)* the downside risk factor of Ang, Chen and Xing (2006).

6.1 *Results Using the Implied Volatility Index, VIX*

The literature has been extensively using the implied volatility index *VIX* as a proxy for bad times risk. *VIX* is built using the implied volatility of at-the-money options. The question is whether *VIX* captures the flight to safety in a similar fashion to realized volatility. To address it, I perform the time series regression from Eq. (10), while replacing UV with ΔVIX, the monthly changes in implied volatility.[11] Note that this exercise is performed over a much shorter time period, January 1990-December 2014, because *VIX* is not available before 1990.

Table 10 Panel A presents the results for the Treasury portfolios. I find that the ΔVIX betas are statistically insignificant. Panel B presents the results for the stock portfolios. Only a third of the ΔVIX betas are precisely estimated. As a side note, the monotonic pattern previously documented for realized volatility is not present among the ΔVIX betas.

[Table 10]

To make sure that results for ΔVIX are not due to a power issue, given that the *VIX* series is available only starting in 1990, I redo the time series tests for realized volatility over the period January 1990 - December 2014. Table A.1 of the Appendix shows that realized volatility does capture the flight to safety over this recent time period, so the failure of *VIX* in capturing flights to safety is not due to a lack of power in the tests. Perhaps the weaker results obtained when using *VIX* are caused by the *VIX* series being an expectation of volatility. In addition, the (squared) *VIX* includes both the equity variance premium and the conditional variance, which may complicate things when trying to capture the flights to safety phenomenon. Overall, the flights to safety are not evident when using ΔVIX.

I also assess the asset pricing ability of the implied volatility index. Table A.2 Panel A in the Appendix shows that ΔVIX is not robustly priced. ΔVIX loses its explanatory power when used to augment the Carhart (1997) model.

[Figure 5]

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[11] I follow Ang et al. (2006) when building the monthly change in *VIX*.

6.2 *Results Using the Skewness Index, SKEW*

Next I analyze the peformance of the *SKEW* index. *SKEW* measures the perceived tail risk in the S&P 500 based on the implied volatility of out-of-the-money options. I download *SKEW* data from the Chicago Board Option Exchange (CBOE) for the period January 1990 - December 2014. Similarly to the implied volatility index, I build the month-to-month changes in this tail risk index, call it $\Delta SKEW$.

Table 11 shows the results when running the model in Eq. (10) while replacing *UV* with $\Delta SKEW$. I find that the $\Delta SKEW$ betas are mostly statistically insignificant in the Treasury market. As was the case with implied volatility, only a third of the $\Delta SKEW$ betas are precisely estimated in the stock market. Table A.2 of the Appendix performs the asset pricing test from Eq. (9) (again while replacing *UV* with $\Delta SKEW$). It is interesting to see that the tail risk has a positive price of risk in the cross-section of the test assets in models that control for market risk, size and value factors. This means that investors demand a premium for holding assets with positive exposure to $\Delta SKEW$ because such investments expose them to crash risk. However, skewness loses its explanatory power when added to the Carhart (1997) model, as well as when realized volatility is also included in a 3-factor model specification that controls for the market risk. The latter result is probably not surprising, given the infrequent nature of extreme events.

[Table 11]

6.3 *Results Using Downside Risk*

In light of the results in Ang, Chen and Xing (2006), who show that stocks earn compensation for their exposure to downside risk, I perform two additional exercises. First, I analyze whether downside risk plays a role in capturing flights to safety and second, I check if this risk factor has cross-markets pricing effects.

To this end, I follow Ang et al. (2006) and I build downside risk over the period January 1952-December 2014, as:

$$\beta^{-} = \frac{Cov(R_i^e, R_m^e / R_m^e < \mu_m)}{Var(R_m^e / R_m^e < \mu_m)}, \tag{20}$$

where R_i^e and R_m^e are the excess returns on asset i, respectively the market portfolio, while μ_m is the unconditional mean of the market excess return. I also build the upside risk factor, β^{+}, by conditioning on values where the market excess return is above its unconditional mean. Table 12 presents the downside risk loadings in the two markets, using a 2-factor model that also includes upside risk. It shows that downside risk has mostly insignificant loadings in the Treasury market, and so it does not prove helpful in identifying flights to safety. In addition, Table A.2 Panel C of the Appendix shows that downside risk is not priced in the cross-section of stocks and Treasuries.

In summary, it looks like realized volatility is a more suitable indicator for flights to safety, while also being robustly priced across the two financial markets.

[Table 12]

7 Volatility and Economic Activity

Previous literature has related volatility to indicators of economic fundamentals (see, e.g., Schwert (1989), Hamilton and Lin (1996), Chen (2003), Vayanos (2004), and Engle, Ghysels, and Sohn (2006)). Here I document its relation to another business cycle indicator, the Chicago Fed National Activity Index *(CFNAI)*. *CFNAI* is a monthly index designed to gauge overall economic activity and related inflationary pressure. The *CFNAI* is based on 85 existing monthly indicators of national economic activity, drawn from four broad categories of data: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories. The index has an average value of zero and a standard deviation of one, with a positive index reading corresponds to growth above trend and a negative index reading corresponds to growth below trend.[12] Figure 6 plots this series next to the volatility series over the period May 1967-December 2014. The two series exhibit opposite dynamics during times of economic uncertainty

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[12] *CFNAI* is methodologically similar to the index of economic activity developed by Stock and Watson (1999), and it is basically the first principal component of the 85 economic series. It is constructed to have an average value of zero and a standard deviation of one. Data source: http://www.chicagofed.org.

(as previously identified in Figure 1).

[Figure 6]

The next step is to link volatility to the real economy. To this end, I analize the predictive power of volatility for the economic activity index CFNAI using a linear regression model:

$$CFNAI_{t+k} = \alpha + bV_t, \qquad k = 1, 3, 6, 9, 12, 15. \tag{21}$$

Table 13 presents the results. I find that volatility has a significant forecasting power for the business cycle index up to 1 year in the future. Volatility is significantly and negatively associated with future economic activity. An increase in volatility predicts a decrease in economic activity up to 12 months in the future. The economic effect diminishes through time. Specifically, a 1% increase in volatility predicts a 17% growth below trend in economic activity 1-3 months later, a 12% growth below trend 6 months later, an 8% growth below trend 9 months later, and a 5% growth below trend 1 year later (the corresponding R^2_{adj} are 16%, 7%, 3%, and 1%, respectively).

[Table 13]

8 Conclusion

Events historically associated with financial crises attest to the interdependence between stocks and Treasuries, with both asset classes being sensitive to unexpected shifts in volatility. And because volatility changes through time in a stochastic and fairly persistent fashion, the trade-off between volatility risk and asset returns moves in a predictable way over the business cycle. Therefore, volatility seems like a suitable indicator for flights to safety. Furthermore, volatility seems to play a fundamental role in the market, because portfolio decisions involve allocating funds between stocks and Treasuries. Therefore, volatility also seems like a good candidate for entering the joint pricing kernel for stocks and Treasuries.

I show that volatility has cross-markets pricing implications: it exerts a noticeable impact across stocks and Treasuries, carrying a significantly negative price of risk. This implies that, when faced with a downturn in the economy, which results in tighter credit markets, investors are willing to forgo expected returns to get downside protection.

Furthermore, volatility plays a fundamental role in understanding the joint stock-bond price formation. I show that investors are willing to pay a premium for holding the safe assets (Treasury bonds), which correlate positively to volatility surprises and thus, provide insurance against volatility shocks, while they require a premium for holding the risky assets (stocks), which correlate negatively. This is consistent with the change in sign in the stock-bond correlation during times of economic uncertainty, and it signals flights-to-safety episodes in the market. Furthermore, my results highlight the fact that flights to safety enhance the resiliency of financial markets when needed the most, via the stock-bond diversification benefits that increase with stock market uncertainty. Finally, because of their positive loadings on volatility, bonds perform well in bed times, which explains their lower expected returns.

Interestingly, asset pricing tests performed in the joint markets lead to economically sound estimates for factors' risk premia, that are close in value to their realized analogs. Results also show that the cross-markets volatility pricing effect is robust with respect to the inclusion of classical risk factors in the asset pricing model, and that it is not a by-product of the way I estimate volatility shocks. I also find that the size premium has been tied to economic fundamentals, as captured by volatility, and that a volatility premium exists in the Treasury yield curve.

Merton's (1973) model suggests using factors that capture unanticipated changes in the opportunity set as hedging instruments, and volatility is clearly related to such changes. By extending the pricing implications of volatility to Treasuries I have taken one step forward in showing that a unified asset pricing model can be build for the stock and Treasury markets. In light of my results, existing yield curve models could be recast to include the (unexpected) realized volatility factor. Finally, my findings also suggest that volatility is a useful indicator for flights to safety in the market.

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Table 1: Average Excess Returns for the 36 Portfolios

Panel A reports the monthly average excess returns for the 11 Fama maturity-sorted Treasury bond portfolios, and Panel B reports the monthly value-weighted average excess returns for the 25 size- and value-sorted portfolios of Fama and French (1992). I report the results in percentages. Data cover the period January 1952 to December 2014. I report *t-statistics* in parentheses.

Panel A) Average Excess Returns for the Treasury Portfolios

					Maturity					
1-6mo	*7-12mo*	*13-18mo*	*19-24mo*	*25-30mo*	*31-36mo*	*37-42mo*	*43-48mo*	*49-54mo*	*55-60mo*	*61-120mo*
0.04	0.06	0.08	0.09	0.11	0.12	0.13	0.14	0.15	0.12	0.16
(7.55)	*(4.97)*	*(4.34)*	*(3.71)*	*(3.47)*	*(3.39)*	*(3.29)*	*(3.11)*	*(3.12)*	*(2.31)*	*(2.62)*

Panel B) Average Excess Returns for the Stock Portfolios

Book-to-Market Equity (BE/ME) Quintiles

Size Quintiles	*Low*	*2*	*3*	*4*	*High*	Low	*2*	*3*	*4*	*High*
	Average Excess Returns					*t-stats*				
Small	0.30	0.81	0.79	1.04	1.13	*(1.07)*	*(3.36)*	*(3.82)*	*(5.26)*	*(5.37)*
2	0.49	0.78	0.91	0.95	1.06	*(1.97)*	*(3.74)*	*(4.85)*	*(5.19)*	*(5.01)*
3	0.59	0.83	0.79	0.94	1.04	*(2.57)*	*(4.37)*	*(4.53)*	*(5.38)*	*(5.26)*
4	0.65	0.66	0.79	0.88	0.85	*(3.15)*	*(3.70)*	*(4.52)*	*(5.17)*	*(4.25)*
Big	0.55	0.58	0.66	0.57	0.76	*(3.30)*	*(3.74)*	*(4.37)*	*(3.39)*	*(3.96)*

Table 2: Posterior Estimates for the Asymmetric Student-GARCH(1,1) Model

The model used is:

$$\begin{cases} \mathrm{R}_{\mathrm{m,t}} = \mu + \rho \mathrm{R}_{\mathrm{m,t-1}} + \eta_{\mathrm{t}} \\ \eta_{\mathrm{t}} = \varepsilon_{\mathrm{t}} \sqrt{\mathrm{h}_{\mathrm{t}}} \\ \varepsilon_{\mathrm{t}} / \mathrm{I}_{\mathrm{t-1}} \sim \mathrm{Student}(0,1,\upsilon) \\ \mathrm{h}_{\mathrm{t}} = \alpha + \phi \mathrm{h}_{\mathrm{t-1}} + \theta^{+} \eta_{\mathrm{t-1}}^{2+} + \theta^{-} \eta_{\mathrm{t-1}}^{2-} \\ \eta_{\mathrm{t}}^{2+} = \eta_{\mathrm{t}}^{2} 1_{\{\eta_t > 0\}}, \eta_{\mathrm{t}}^{2-} = \eta_{\mathrm{t}}^{2} 1_{\{\eta_t < 0\}} \end{cases} \quad , t=1, \ldots ,T.$$

The R_t represents the monthly time series of returns on the stock market portfolio for the period January 1952 to December 2014. I compute the results using a *Griddy-Gibbs* sampling algorithm, where I keep 5000 draws and I consider the initial 1000 draws as the burn-in sample. I use a *flat prior* on finite intervals for all parameters except for the *prior* on υ, which is *half-Cauchy*. I report *Standard errors* in the parentheses.

	Estimate	*Std Err*
μ	0.21	*(0.02)*
ρ	0.03	*(0.03)*
α	0.10	*(0.04)*
θ^+	0.03	*(0.02)*
ϕ	0.73	*(0.06)*
υ	10.54	*(3.75)*
θ^-	0.21	*(0.06)*

Table 3: Flights to Safety

This table reports the factor loadings from a 2-factor model that includes the market return and unexpected volatility. The test assets are the 11 Fama maturity-sorted Treasury portfolios and the 25 Fama-French (1992) portfolios sorted on size and book-to-market equity. I regress the monthly portfolio excess returns on the excess market return and unexpected volatility using an unconditional model specification. *UV* represents unexpected volatility, and is the residual from an *AR(1)* model applied to the time series of realized stock market volatility. Data cover the period January 1952 to December 2014. I report *t-statistics* in parentheses, and I report R^2_{adj} in percentages.

Panel A) Volatility Loadings in the Treasury Market

Bond Maturity										
1-6mo	*7-12mo*	*13-18mo*	*19-24mo*	*25-30mo*	*31-36mo*	*37-42mo*	*43-48mo*	*49-54mo*	*55-60mo*	*61-120mo*
					$\hat{\alpha}_i$					
0.03	0.05	0.07	0.07	0.09	0.10	0.11	0.11	0.12	0.09	0.12
(7.01)	*(4.28)*	*(3.69)*	*(3.07)*	*(2.86)*	*(2.78)*	*(2.69)*	*(2.51)*	*(2.54)*	*(1.73)*	*(2.02)*
					$\hat{\beta}_i^m$					
0.00	0.01	0.02	0.03	0.03	0.04	0.04	0.04	0.04	0.05	0.06
(3.58)	*(4.99)*	*(4.51)*	*(4.56)*	*(4.25)*	*(4.15)*	*(4.06)*	*(3.70)*	*(3.49)*	*(3.81)*	*(4.18)*
					$\hat{\beta}_i^{UV}$					
0.01	0.03	0.04	0.06	0.08	0.10	0.11	0.12	0.12	0.14	0.15
(2.84)	*(3.93)*	*(3.82)*	*(4.23)*	*(4.31)*	*(4.60)*	*(4.62)*	*(4.32)*	*(4.14)*	*(4.36)*	*(4.05)*
					R^2_{adj}					
1.81	3.66	3.14	3.47	3.30	3.48	3.47	2.97	2.68	3.07	3.01

Table 3 – *Continued*

Panel B) Volatility Loadings in the Stock Market

Size Quintiles	*Book-to-Market Equity (BE/ME) Quintiles*									
	Low	*2*	*3*	*4*	*High*	*Low*	*2*	*3*	*4*	*High*
	$\hat{\alpha}_i$					*t-stats for* $\hat{\alpha}_i$				
Small	-0.49	0.12	0.19	0.47	0.54	*(-2.70)*	*(0.84)*	*(1.52)*	*(3.96)*	*(4.18)*
2	-0.29	0.12	0.33	0.38	0.43	*(-2.28)*	*(1.21)*	*(3.45)*	*(4.06)*	*(3.62)*
3	-0.16	0.20	0.22	0.38	0.43	*(-1.48)*	*(2.49)*	*(2.81)*	*(4.46)*	*(3.97)*
4	-0.06	0.04	0.21	0.33	0.23	*(-0.69)*	*(0.68)*	*(2.83)*	*(4.02)*	*(2.08)*
Big	-0.05	0.02	0.16	0.02	0.18	*(-0.89)*	*(0.44)*	*(2.17)*	*(0.28)*	*(1.52)*
	$\hat{\beta}_i^m$					*t-stats for* $\hat{\beta}_i^m$				
Small	1.33	1.16	1.03	0.97	1.00	*(30.40)*	*(32.12)*	*(34.59)*	*(33.31)*	*(31.92)*
2	1.32	1.10	0.99	0.97	1.07	*(42.26)*	*(44.10)*	*(43.07)*	*(42.57)*	*(37.34)*
3	1.26	1.06	0.97	0.94	1.02	*(48.74)*	*(54.46)*	*(51.55)*	*(45.22)*	*(38.28)*
4	1.19	1.04	0.98	0.95	1.07	*(60.65)*	*(65.68)*	*(54.53)*	*(48.18)*	*(40.26)*
Big	1.01	0.95	0.85	0.92	0.98	*(74.04)*	*(72.37)*	*(47.49)*	*(42.36)*	*(34.61)*
	$\hat{\beta}_i^{UV}$					*t-stats for* $\hat{\beta}_i^{UV}$				
Small	-0.40	-0.38	-0.32	-0.32	-0.42	*(-3.51)*	*(-4.11)*	*(-4.16)*	*(-4.22)*	*(-5.16)*
2	-0.25	-0.33	-0.32	-0.26	-0.35	*(-3.14)*	*(-5.18)*	*(-5.39)*	*(-4.49)*	*(-4.72)*
3	-0.23	-0.23	-0.21	-0.21	-0.22	*(-3.47)*	*(-4.57)*	*(-4.23)*	*(-3.84)*	*(-3.18)*
4	-0.13	-0.14	-0.20	-0.13	-0.14	*(-2.59)*	*(-3.44)*	*(-4.35)*	*(-2.48)*	*(-2.12)*
Big	0.11	0.07	0.02	0.08	0.05	*(3.11)*	*(2.18)*	*(0.36)*	*(1.39)*	*(0.63)*

Size Quintiles	*Book-to-Market Equity (BE/ME) Quintiles*				
	Low	*2*	*3*	*4*	*High*
	R_{adj}^2				
Small	59.97	62.82	66.07	64.48	63.20
2	73.71	75.96	75.21	74.46	69.53
3	78.81	82.43	80.76	76.39	69.83
4	84.94	86.95	82.42	78.17	71.45
Big	88.82	88.44	76.95	72.33	63.77

Table 4: Flights to Safety - Robustness Checks

This table reports the factor loadings from a 2-factor model that includes the market return and unexpected volatility. The test assets are the 11 Fama maturity-sorted Treasury portfolios and the 25 Fama-French (1992) portfolios sorted on size and book-to-market equity. I regress the monthly portfolio excess returns on the excess market return and unexpected volatility using an unconditional model specification. *PRED_UV* is the second unexpected volatility measure, and is constructed as the difference between predicted and realized volatility (see Eqs. (1) - (4) in the text). Data cover the period January 1952 to December 2014. I report *t-statistics* in parentheses, and I report R^2_{adj} in percentages.

Panel A) Volatility Loadings in the Treasury Market for the 2nd Volatility Measure

Bond Maturity										
1-6mo	*7-12mo*	*13-18mo*	*19-24mo*	*25-30mo*	*31-36mo*	*37-42mo*	*43-48mo*	*49-54mo*	*55-60mo*	*61-120mo*
$\hat{\alpha}_i$										
0.03	0.02	0.02	-0.01	-0.02	-0.04	-0.05	-0.06	-0.06	-0.11	-0.11
(3.96)	*(1.06)*	*(0.61)*	*(-0.18)*	*(-0.49)*	*(-0.74)*	*(-0.91)*	*(-1.06)*	*(-0.88)*	*(-1.58)*	*(-1.39)*
$\hat{\beta}_i^m$										
0.00	0.01	0.02	0.03	0.03	0.04	0.04	0.04	0.04	0.05	0.07
(3.36)	*(4.90)*	*(4.47)*	*(4.57)*	*(4.33)*	*(4.27)*	*(4.22)*	*(3.98)*	*(3.74)*	*(4.04)*	*(4.52)*
$\hat{\beta}_i^{PRED\_UV}$										
0.01	0.02	0.04	0.06	0.07	0.09	0.11	0.12	0.12	0.14	0.16
(2.07)	*(3.43)*	*(3.45)*	*(3.96)*	*(4.20)*	*(4.50)*	*(4.65)*	*(4.61)*	*(4.40)*	*(4.62)*	*(4.62)*
R^2_{adj}										
1.32	3.20	2.80	3.19	3.18	3.37	3.50	3.31	2.97	3.36	3.62

Table 4 – *Continued*

Panel B) Volatility Loadings in the Stock Market for the 2nd Volatility Measure

	Book-to-Market Equity (BE/ME) Quintiles									
Size Quintiles	*Low*	*2*	*3*	*4*	*High*	*Low*	*2*	*3*	*4*	*High*
			$\hat{\alpha}_i$					*t-stats for* $\hat{\alpha}_i$		
Small	-0.11	0.51	0.54	0.84	1.09	*(-0.44)*	*(2.56)*	*(3.28)*	*(5.27)*	*(6.32)*
2	-0.04	0.52	0.69	0.71	0.88	*(-0.23)*	*(3.74)*	*(5.44)*	*(5.69)*	*(5.58)*
3	0.05	0.44	0.44	0.60	0.64	*(0.35)*	*(4.07)*	*(4.25)*	*(5.28)*	*(4.39)*
4	0.01	0.20	0.50	0.49	0.45	*(0.06)*	*(2.33)*	*(5.10)*	*(4.50)*	*(3.07)*
Big	-0.21	-0.09	0.16	0.06	0.20	*(-2.77)*	*(-1.26)*	*(1.65)*	*(0.48)*	*(1.27)*
			$\hat{\beta}_i^m$					*t-stats for* $\hat{\beta}_i^m$		
Small	1.34	1.17	1.03	0.97	0.99	*(30.00)*	*(31.64)*	*(33.99)*	*(32.69)*	*(31.19)*
2	1.33	1.10	0.99	0.97	1.07	*(41.62)*	*(43.22)*	*(42.22)*	*(41.72)*	*(36.56)*
3	1.27	1.07	0.98	0.94	1.02	*(48.01)*	*(53.47)*	*(50.63)*	*(44.44)*	*(37.73)*
4	1.20	1.04	0.97	0.95	1.06	*(59.94)*	*(64.53)*	*(53.46)*	*(47.33)*	*(39.46)*
Big	1.01	0.95	0.85	0.90	0.97	*(73.16)*	*(71.53)*	*(46.61)*	*(41.06)*	*(33.79)*
			$\hat{\beta}_i^{PRED\_UV}$					*t-stats for* $\hat{\beta}_i^{PRED\_UV}$		
Small	-0.27	-0.27	-0.25	-0.26	-0.38	*(-2.56)*	*(-3.15)*	*(-3.47)*	*(-3.72)*	*(-5.11)*
2	-0.18	-0.27	-0.25	-0.23	-0.31	*(-2.40)*	*(-4.58)*	*(-4.63)*	*(-4.27)*	*(-4.60)*
3	-0.15	-0.17	-0.16	-0.16	-0.15	*(-2.39)*	*(-3.60)*	*(-3.49)*	*(-3.15)*	*(-2.33)*
4	-0.05	-0.11	-0.20	-0.11	-0.15	*(-1.01)*	*(-2.94)*	*(-4.72)*	*(-2.38)*	*(-2.40)*
Big	0.11	0.08	0.00	-0.02	-0.01	*(3.34)*	*(2.52)*	*(-0.02)*	*(-0.33)*	*(-0.17)*

	Book-to-Market Equity (BE/ME) Quintiles				
Size Quintiles	*Low*	*2*	*3*	*4*	*High*
			R_{adj}^2		
Small	59.66	62.48	65.83	64.30	63.17
2	73.57	75.78	74.96	74.39	69.48
3	78.64	82.25	80.61	76.24	69.64
4	84.83	86.89	82.50	78.16	71.49
Big	88.85	88.46	76.95	72.26	63.75

Table 5: Average Returns and Cross-Correlations of Asset Pricing Factors

The R^e_m is the excess market return. The *MOM* is the momentum factor of Jegadeesh and Titman (1993). The *HML* and *SMB* are mimicking portfolios for book-to-market equity and size (zero-investment portfolios). *UV* represents unexpected volatility, and is the residual from an *AR(1)* model applied to the time series of realized stock market volatility. *PRED_UV* is the second unexpected volatility measure, built as the difference between predicted and realized volatility. Δ*VIX* represents month-to-month innovations in implied volatility index, and Δ*SKEW* represents month-to-month innovations in the *SKEW* index, and captures tail risk. *Amih* represents the Amihud residual. Data cover the period January 1952 to December 2014 (the exception is the *VIX* and *SKEW* series, which is available only from January 1990). I report the results in percentages, on a monthly basis. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. I report *t-statistics* in parentheses.

Panel A) Average Returns for the Traded Factors

	R^e_m	*SMB*	*HML*	*MOM*
Average	0.59	0.17	0.36	0.73
t-stat	*(3.77)*	*(1.60)*	*(3.68)*	*(5.07)*

Panel B) Cross-Correlations for all Factors

	R^e_m	*UV*	*PRED_UV*	*SMB*	*HML*	*MOM*	Δ*VIX*	Δ*SKEW*	*Amih*
R^e_m	1.00								
UV	-0.33***	1.00							
PRED_UV	-0.37***	0.84***	1.00						
SMB	0.26***	-0.26***	-0.24***	1.00					
HML	-0.24***	0.06	0.03	-0.20***	1.00				
MOM	-0.12***	-0.04	-0.04	-0.02	-0.19***	1.00			
Δ*VIX*	-0.70***	0.46***	0.44***	-0.18***	0.11**	0.21***	1.00		
Δ*SKEW*	0.20***	0.04	0.01	-0.09	0.02	-0.07	-0.07	1.00	
Amih	-0.36***	0.41***	0.39***	-0.31***	0.12***	0.02	0.22***	0.03	1.00

Table 6: Unconditional Risk Premia

I estimate the factors' risk premia using the Fama-MacBeth (1973) procedure for the following asset pricing model:

$$E\left(R_{i,t+1}^{e}\right)=\lambda_0+\lambda_m\beta_i^m+\sum_{s=1}^{S}\lambda_s\beta_i^s\ ,$$

where λ_m is the market price of risk and λ_s is the price of risk associated with the generic factor *s*. The left-hand side variable is a vector of monthly excess returns for the 11 maturity-sorted Treasury portfolios and the 25 size- and value-sorted portfolios, and the betas represent factors' loadings estimated in the corresponding time series models. *UV* represents unexpected volatility, and is the residual from an *AR(1)* model applied to the time series of realized stock market volatility. *MOM* is the momentum factor of Jegadeesh and Titman (1993). *HML* and *SMB* are mimicking portfolios for book-to-market equity and size (zero-investment portfolios). *Amih* is the Amihud residual. I report results in percentages, on a monthly basis. Data cover the period January 1952 to December 2014. I report the Fama-MacBeth *t-statistics* in parentheses. I report the root MSE for each model and the R_{adj}^2 in percentages.

Model	$\hat{\lambda}_0$	$\hat{\lambda}_m$	$\hat{\lambda}_{UV}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	$\hat{\lambda}_{Amih}$	*Avg MSE*	R^2_{adj}
CAPM	0.14	0.58						3.85	67.61
	(3.81)	*(3.35)*							
CAPM & UV	0.19	0.43	-0.56					3.02	70.42
	(4.99)	*(2.67)*	*(-1.93)*						
FF-3	0.11	0.46		0.14	0.40			1.81	88.77
	(3.29)	*(2.82)*		*(1.31)*	*(4.03)*				
FF-3 and UV	0.18	0.38	-0.95	0.17	0.38			1.70	89.94
	(4.81)	*(2.34)*	*(-2.96)*	*(1.60)*	*(3.82)*				
Carhart	0.05	0.62		0.14	0.41	3.39		1.72	95.20
	(1.60)	*(3.86)*		*(1.28)*	*(4.13)*	*(6.58)*			
Carhart and UV	0.11	0.55	-0.97	0.16	0.39	3.49		1.61	96.03
	(3.35)	*(3.46)*	*(-3.03)*	*(1.53)*	*(3.95)*	*(6.57)*			
Carhart, UV and Amih	0.12	0.55	-1.03	0.17	0.39	3.48	-0.17	1.54	96.07
	(3.45)	*(3.45)*	*(-2.98)*	*(1.56)*	*(3.93)*	*(6.56)*	*(-0.79)*		

Table 7: Volatility Contribution to Assets' Risk Premia

This table reports the contribution of market volatility to the assets' risk premia. For each portfolio, I compute the risk premium as the product between the volatility price of risk and the volatility loading on the portfolio's return. I estimate the loadings using a 2-factor model specification that controls for market risk. I report the results in percentage, on a yearly basis. Panel A reports results for bond portfolios, and Panel B reports results for stock portfolios. Data cover the period January 1952-December 2014.

Panel A) Market Volatility Contributions to the Treasury Portfolios' Premia

Bond Maturity										
1- 6 mo	*7- 12 mo*	*13- 18 mo*	*19- 24 mo*	*25- 30 mo*	*31- 36 mo*	*37- 42 mo*	*43- 48 mo*	*49- 54 mo*	*55- 60 mo*	*61- 120 mo*
-0.06	-0.20	-0.30	-0.43	-0.55	-0.68	-0.76	-0.80	-0.83	-0.94	-1.02

Panel B) Market Volatility Contributions to the Stock Portfolios' Premia

	Book-to-Market Equity (BE/ME) Quintiles				
Size Quintiles	*Low*	*2*	*3*	*4*	*High*
Small	2.66	2.57	2.14	2.12	2.80
2	1.70	2.24	2.14	1.77	2.35
3	1.55	1.54	1.38	1.38	1.46
4	0.88	0.94	1.35	0.84	0.97
Big	-0.73	-0.49	-0.11	-0.52	-0.31

Table 8: Unconditional Risk Premia – Robustness Tests

I estimate the factors' risk premia using the Fama-MacBeth (1973) procedure for the following asset pricing model:

$$E\left(R_{i,t+1}^{e}\right)=\lambda_0+\lambda_m\beta_i^m+\sum_{s=1}^{S}\lambda_s\beta_i^s ,$$

where λ_m is the market price of risk and λ_s is the price of risk associated with the generic factor s. The left-hand side variable is a vector of monthly excess returns for the 11 maturity-sorted Treasury portfolios and the 25 size- and value-sorted portfolios, and the betas represent factors' loadings estimated in the corresponding time series models. *PRED_UV* represents the second measure of unexpected volatility, and is constructed as the difference between realized and predicted volatility (see Eqs. (5) and (1) in the text). *MOM* is the momentum factor of Jegadeesh and Titman (1993). *HML* and *SMB* are mimicking portfolios for book-to-market equity and size (zero-investment portfolios). *Amih* is the Amihud residual. I report results in percentages, on a monthly basis. Data cover the period January 1952 to December 2014. I report the Fama-MacBeth *t-statistics* in parentheses. I report the root MSE for each model and the R_{adj}^2 in percentages.

Model	$\hat{\lambda}_0$	$\hat{\lambda}_m$	$\hat{\lambda}_{PRED\_UV}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	$\hat{\lambda}_{Amih}$	*Avg MSE*	R^2_{adj}
CAPM	0.14	0.58						3.85	67.61
	(3.81)	*(3.35)*							
CAPM & PRED_UV	0.22	0.37	-0.95					3.18	73.55
	(5.67)	*(2.29)*	*(-2.96)*						
FF-3	0.11	0.46		0.14	0.40			1.81	88.77
	(3.29)	*(2.82)*		*(1.31)*	*(4.03)*				
FF-3 and PRED_UV	0.14	0.42	-0.56	0.15	0.40			1.74	89.06
	(4.45)	*(2.62)*	*(-1.95)*	*(1.43)*	*(4.00)*				
Carhart	0.05	0.62		0.14	0.41	3.39		1.72	95.20
	(1.60)	*(3.86)*		*(1.28)*	*(4.13)*	*(6.58)*			
Carhart and PRED_UV	0.09	0.58	-0.88	0.15	0.41	3.59		1.64	95.63
	(3.19)	*(3.66)*	*(-2.88)*	*(1.42)*	*(4.10)*	*(6.39)*			
Carhart, PRED_UV and Amih	0.09	0.58	-0.86	0.15	0.41	3.59	-0.26	1.59	95.63
	(3.26)	*(3.66)*	*(-2.77)*	*(1.41)*	*(4.10)*	*(6.38)*	*(-1.18)*		

Table 9: Conditional Risk Premia

I estimate the factors' risk premia using the Fama-MacBeth (1973) procedure for the following asset pricing model:

$$E\left(R^{e}_{it+1}/Z_t\right)=\lambda_0(Z_t)+\lambda_m(Z_t)\beta_i^m(Z_t)+\sum_{s=1}^{S}\lambda_s(Z_t)\beta_i^s(Z_t),$$

where λ_m is the market price of risk and λ_s is the price of risk associated with the generic factor *s*. The left-hand side variable is a vector of monthly excess returns for the 11 maturity-sorted Treasury portfolios and the 25 size- and value-sorted portfolios, and the betas represent factors' loadings estimated in the corresponding time series models. *UV* represents unexpected volatility, and is the residual from an *AR(1)* model applied to the time series of realized stock market volatility. *MOM* is the momentum factor of Jegadeesh and Titman (1993). *HML* and *SMB* are mimicking portfolios for book-to-market equity and size (zero-investment portfolios). *Amih* is the Amihud residual. Z_t represents the vector of conditioning variables that enter the information set at time *t*: the default spread, *DEF* (computed as the difference between the yields of a long-term corporate Baa bond and a long-term corporate Aaa bond), the term spread, *TERM* (computed as the difference between the yields of a thirty-year and a one-year government bond), and the dividend yield on the S&P500 value-weighted portfolio*, DY* (computed as the sum of dividends over the last 12 months, divided by the level of the index). I report the results in percentages, on a monthly basis. Data cover the period January 1952 to December 2014. I report the Fama-MacBeth *t-statistics* in parentheses. I report the root MSE for each model and the R^2_{adj} in percentages.

Model	$\hat{\lambda}_0$	$\hat{\lambda}_m$	$\hat{\lambda}_{UV}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	$\hat{\lambda}_{Amih}$	*Avg MSE*	R^2_{adj}
CAPM	0.12	0.59						3.79	65.57
	(3.51)	*(3.41)*							
CAPM & UV	0.15	0.47	-0.45					2.96	70.73
	(4.18)	*(2.87)*	*(-1.96)*						
FF-3	0.10	0.42		0.18	0.38			1.77	90.48
	(3.03)	*(2.54)*		*(1.67)*	*(4.27)*				
FF-3 and UV	0.08	0.48	-0.54	0.19	0.37			1.59	88.75
	(2.53)	*(2.96)*	*(-2.70)*	*(1.79)*	*(3.65)*				
Carhart	0.08	0.54		0.15	0.37	1.28		1.65	87.86
	(2.59)	*(3.33)*		*(1.38)*	*(3.72)*	*(3.34)*			
Carhart and UV	0.07	0.54	-0.65	0.19	0.37	1.56		1.52	90.12
	(2.36)	*(3.36)*	*(-3.24)*	*(1.77)*	*(3.67)*	*(4.05)*			
Carhart, UV and Amih	0.06	0.56	-0.60	0.20	0.36	1.70	0.00	1.45	90.10
	(1.92)	*(3.48)*	*(-3.02)*	*(1.91)*	*(3.57)*	*(4.45)*	*(0.01)*		

Table 10: VIX Loadings

This table reports the ΔVIX loadings from an asset pricing model that also includes the market return. The test assets are the 11 Fama maturity-sorted Treasury portfolios and the 25 Fama-French (1992) portfolios sorted on size and book-to-market equity. I regress the monthly portfolio excess returns on the excess market return and changes in *VIX* using an unconditional model specification. Data cover the period January 1952 to December 2014. I report *t-statistics* in parentheses, and I report R^2_{adj}in percentages.

Panel A) VIX Loadings in the Treasury Market

Bond Maturity										
1-6mo	*7-12mo*	*13-18mo*	*19-24mo*	*25-30mo*	*31-36mo*	*37-42mo*	*43-48mo*	*49-54mo*	*55-60mo*	*61-120mo*
					$\hat{\beta}_i^{\Delta VIX}$					
0.00	0.00	0.00	0.01	0.02	0.02	0.02	0.03	0.02	0.02	0.01
(1.06)	*(0.82)*	*(0.87)*	*(1.46)*	*(1.72)*	*(1.50)*	*(1.55)*	*(1.51)*	*(1.16)*	*(0.94)*	*(0.41)*
					R^2_{adj}					
-0.00	0.00	0.01	2.56	3.02	2.26	2.34	2.16	1.91	1.81	0.27

Panel B) VIX Loadings in the Stock Market

	Book-to-Market Equity (BE/ME) Quintiles										
Size Quintiles	*Low*	*2*	*3*	*4*	*High*		*Low*	*2*	*3*	*4*	*High*
	$\hat{\beta}_i^{\Delta VIX}$						*t-stats for* $\hat{\beta}_i^{\Delta VIX}$				
Small	0.05	-0.06	-0.06	-0.02	0.00		*(0.46)*	*(-0.62)*	*(-0.81)*	*(-0.35)*	*(-0.02)*
2	-0.01	-0.07	-0.12	-0.12	-0.05		*(-0.09)*	*(-1.13)*	*(-2.07)*	*(-2.22)*	*(-0.72)*
3	-0.02	-0.03	-0.10	-0.09	-0.15		*(-0.35)*	*(-0.61)*	*(-2.16)*	*(-1.71)*	*(-2.32)*
4	-0.01	-0.14	-0.15	-0.08	0.00		*(-0.19)*	*(-3.59)*	*(-3.07)*	*(-1.71)*	*(-0.01)*
Big	0.04	-0.05	-0.08	-0.02	-0.04		*(1.34)*	*(-1.41)*	*(-1.88)*	*(-0.34)*	*(-0.49)*

	Book-to-Market Equity (BE/ME) Quintiles				
Size Quintiles	*Low*	*2*	*3*	*4*	*High*
			R^2_{adj}		
Small	56.79	54.54	62.69	56.90	58.94
2	69.43	71.09	69.18	69.35	63.62
3	72.39	79.30	76.82	69.54	66.21
4	79.83	82.85	75.54	74.33	67.67
Big	88.27	84.33	70.04	64.88	61.06

Table 11: SKEW Loadings

This table reports the SKEW loadings from an asset pricing model that also includes the market return. The test assets are the 11 Fama maturity-sorted Treasury portfolios and the 25 Fama-French (1992) portfolios sorted on size and book-to-market equity. I regress the monthly portfolio excess returns on the excess market return and changes in *SKEW* using an unconditional model specification. Data cover the period January 1952 to December 2014. I report *t-statistics* in parentheses, and I report R^2_{adj}in percentages.

Panel A) SKEW Loadings in the Treasury Market

Bond Maturity										
1-6mo	*7-12mo*	*13-18mo*	*19-24mo*	*25-30mo*	*31-36mo*	*37-42mo*	*43-48mo*	*49-54mo*	*55-60mo*	*61-120mo*
					$\hat{\beta}_i^{\Delta SKEW}$					
-0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.01
(-0.34)	*(0.93)*	*(1.45)*	*(1.74)*	*(1.76)*	*(1.73)*	*(1.71)*	*(1.60)*	*(1.39)*	*(1.24)*	*(0.33)*
					R^2_{adj}					
-0.00	0.00	0.02	0.03	0.03	0.03	0.03	0.02	0.02	0.00	-0.00

Panel B) SKEW Loadings in the Stock Market

	Book-to-Market Equity (BE/ME) Quintiles									
Size Quintiles	*Low*	*2*	*3*	*4*	*High*	*Low*	*2*	*3*	*4*	*High*
	$\hat{\beta}_i^{\Delta SKEW}$					*t-stats for* $\hat{\beta}_i^{\Delta SKEW}$				
Small	-0.17	-0.11	-0.10	-0.07	-0.10	*(-2.59)*	*(-2.01)*	*(-2.36)*	*(-1.51)*	*(-2.30)*
2	-0.11	-0.08	-0.04	-0.02	-0.06	*(-2.36)*	*(-2.09)*	*(-1.17)*	*(-0.70)*	*(-1.36)*
3	-0.09	-0.02	0.01	-0.01	-0.03	*(-2.23)*	*(-0.52)*	*(0.43)*	*(-0.33)*	*(-0.75)*
4	-0.04	0.02	0.02	-0.01	0.04	*(-1.18)*	*(0.88)*	*(0.50)*	*(-0.29)*	*(1.13)*
Big	0.01	0.03	0.02	0.04	0.06	*(0.34)*	*(1.29)*	*(0.83)*	*(0.99)*	*(1.36)*

	Book-to-Market Equity (BE/ME) Quintiles				
Size Quintiles	*Low*	*2*	*3*	*4*	*High*
			R^2_{adj}		
Small	57.72	55.09	63.30	57.21	59.66
2	70.00	71.39	68.87	68.89	63.79
3	72.83	79.29	76.47	69.24	65.66
4	79.92	82.15	74.78	74.08	67.81
Big	88.21	84.32	69.75	64.98	61.27

Table 12: Downside Risk Loadings

This table reports the downside risk loadings from an asset pricing model that also includes the upside risk. The test assets are the 11 Fama maturity-sorted Treasury portfolios and the 25 Fama-French (1992) portfolios sorted on size and book-to-market equity. I regress the monthly portfolio excess returns on the downside and upside risks using an unconditional model specification. Data cover the period January 1952 to December 2014. I report *t-statistics* in parentheses, and I report R^2_{adj} in percentages.

Panel A) Downside Risk Loadings in the Treasury Market

Bond Maturity										
1-6mo	*7-12mo*	*13-18mo*	*19-24mo*	*25-30mo*	*31-36mo*	*37-42mo*	*43-48mo*	*49-54mo*	*55-60mo*	*61-120mo*
					$\hat{\beta}_i^{down}$					
-0.00	-0.00	-0.01	-0.01	-0.02	-0.03	-0.03	-0.03	-0.03	-0.02	-0.02
(-1.30)	*(-0.93)*	*(-1.13)*	*(-1.30)*	*(-1.39)*	*(-1.81)*	*(-1.60)*	*(-1.74)*	*(-1.39)*	*(-0.93)*	*(-0.63)*
					R^2_{adj}					
2.26	3.42	2.95	2.99	2.62	2.82	2.47	2.26	1.72	1.58	1.87

Panel B) Downside Risk Loadings in the Stock Market

	Book-to-Market Equity (BE/ME) Quintiles									
Size Quintiles	*Low*	*2*	*3*	*4*	*High*	*Low*	*2*	*3*	*4*	*High*
	$\hat{\beta}_i^{down}$					*t-stats for* $\hat{\beta}_i^{down}$				
Small	1.53	1.33	1.18	1.10	1.19	*(20.34)*	*(21.26)*	*(22.94)*	*(21.90)*	*(21.96)*
2	1.42	1.22	1.12	1.07	1.22	*(26.37)*	*(27.94)*	*(28.01)*	*(27.01)*	*(24.46)*
3	1.35	1.15	1.06	0.96	1.08	*(30.20)*	*(33.96)*	*(32.39)*	*(26.65)*	*(23.59)*
4	1.19	1.07	1.03	0.94	1.09	*(35.39)*	*(39.25)*	*(33.20)*	*(27.67)*	*(23.91)*
Big	0.94	0.92	0.82	0.89	0.97	*(40.04)*	*(40.72)*	*(26.57)*	*(23.87)*	*(20.07)*

	Book-to-Market Equity (BE/ME) Quintiles				
Size Quintiles	*Low*	*2*	*3*	*4*	*High*
			R^2_{adj}		
Small	59.62	62.24	65.58	63.87	62.37
2	73.44	75.23	74.49	73.90	68.87
3	78.54	82.04	80.42	75.93	69.46
4	84.81	86.75	82.01	78.02	71.28
Big	88.81	88.38	77.00	72.27	63.75

Table 13: Predicting Economic Activity using Volatility

I predict economic activity, proxied by *CFNAI*, with volatility using a linear regression model. *CFNAI* is a statistical measure of coincident economic activity, whose movements are meant to closely track periods of economic expansion and contraction, as well as periods of increasing and decreasing inflationary pressure. It is methodologically similar to the index of economic activity developed by Stock and Watson (1999), and it represents a weighted average of 85 monthly indicators of national economic activity. *CFNAI* is the first principal component of the 85 economic series. I download the monthly data for this index for the period March 1967-December 2014 from http://www.chicagofed.org. I report *t-statistics* in parentheses.

	$CFNAI_{t+1}$	$CFNAI_{t+3}$	$CFNAI_{t+6}$	$CFNAI_{t+9}$	$CFNAI_{t+12}$	$CFNAI_{t+15}$
Intercept	0.72	0.71	0.49	0.33	0.22	0.12
(t-stat)	*(9.15)*	*(9.04)*	*(5.95)*	*(3.96)*	*(2.63)*	*(1.44)*
Volatility	*-0.17*	*-0.17*	*-0.12*	*-0.08*	*-0.05*	*-0.03*
(t-stat)	*(-10.46)*	*(-10.32)*	*(-6.77)*	*(-4.47)*	*(-2.94)*	*(-1.58)*
R^2_{adj}	*15.90*	*15.55*	*7.25*	*3.20*	*1.31*	*0.26*

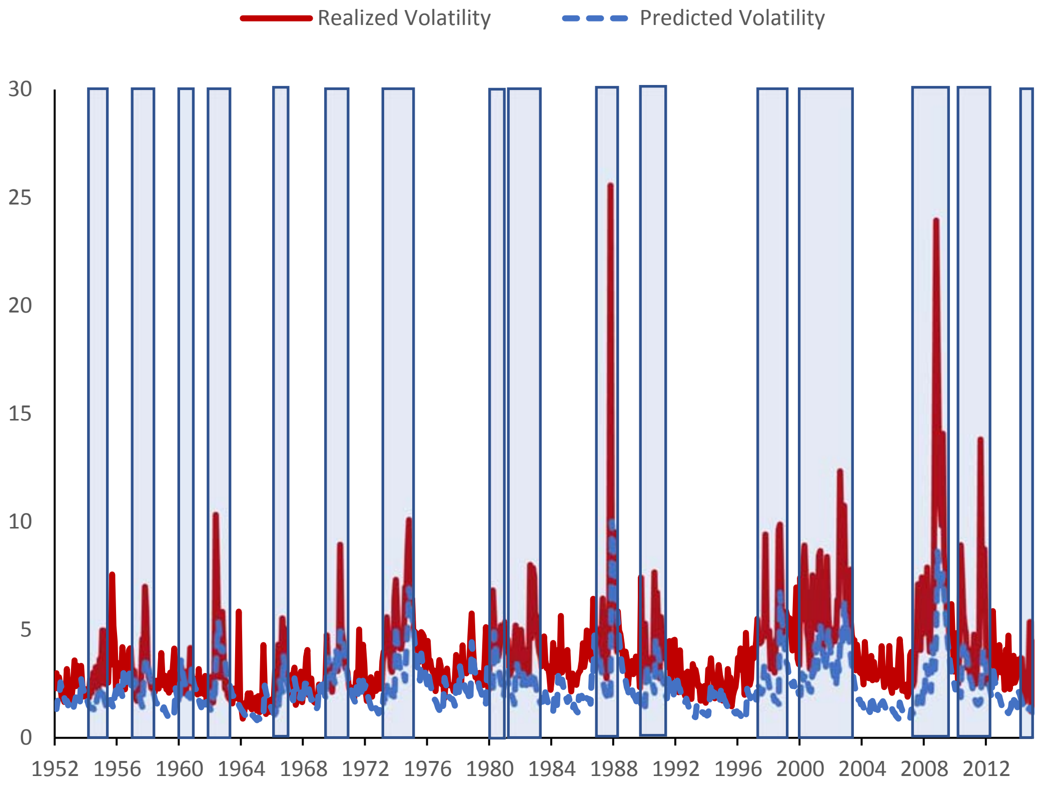


Figure 1. Realized and Predicted Stock Market Volatilities. I build realized volatility on a monthly basis for the period January 1952 to December 2014, using daily market return data from NYSE, AMEX, and NASDAQ maintained by CRSP as follows:

$$v_t = \sqrt{\sum_{i=0}^{\Delta} R_{m,t+i}^2}$$

where $R_{m,t}$ denotes the daily return on the stock market portfolio, and Δ represents the number of trading days in a given month. I predict market volatility based on the estimates of an *Asymmetric-Student GARCH (1,1)* model applied to the monthly stock market return data (see Eq. (3) in the text). I report both series in percentages, at a monthly level. Realized volatility is slightly larger than the predicted volatility. For each year, the tick marks correspond to the month of January. The shaded areas represent NBER recessions or financial crises (see text for details).

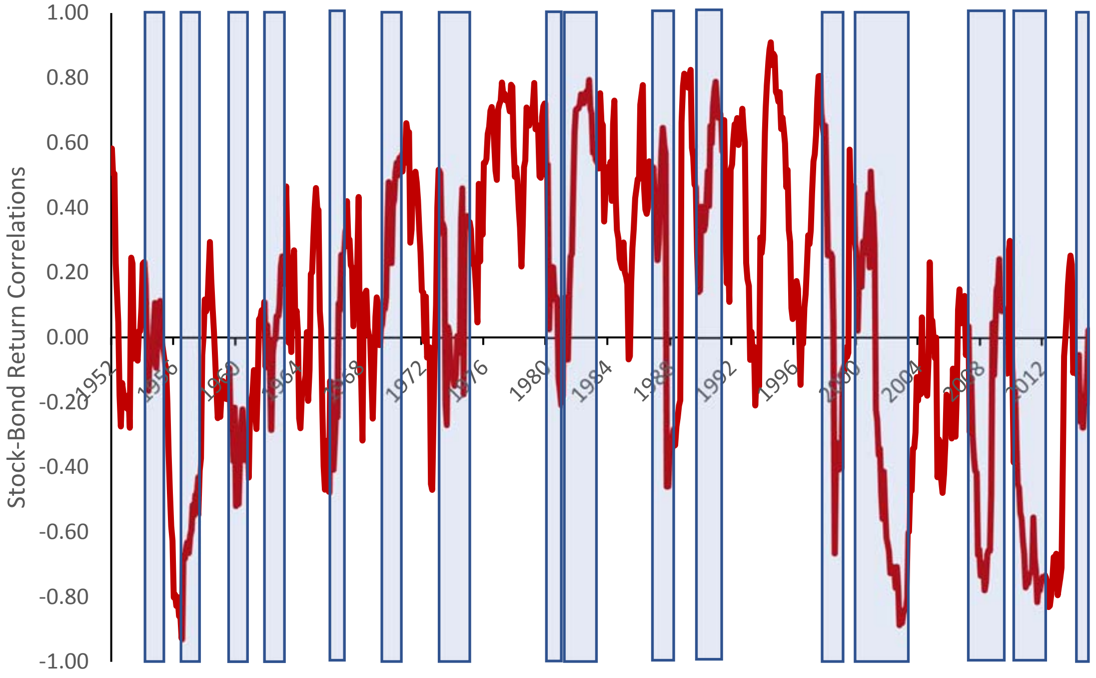
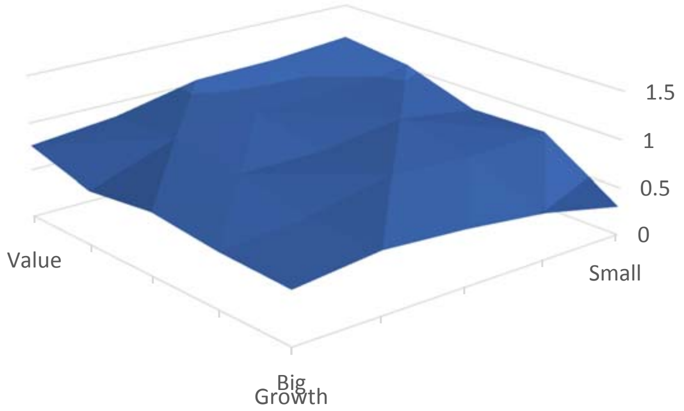
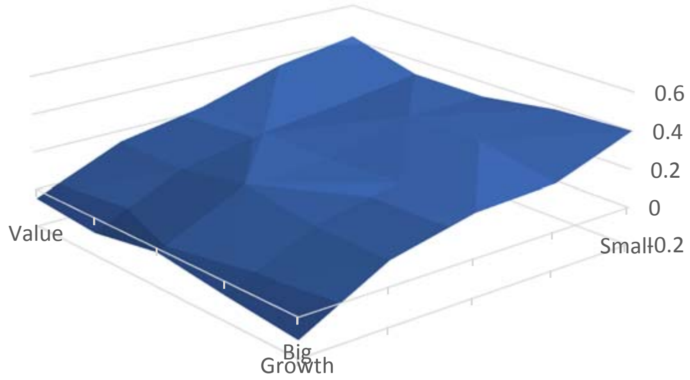


Figure 2. Realized Stock-Bond Return Correlations. I build the rolling 1-year realized correlations between the stock market return and the 10-year Treasury bond return on a monthly basis, for the period January 1952 to December 2014. For each year, the tick marks correspond to the month of January. The shaded areas represent NBER recessions or financial crises (see text for details).

Panel A) Average Excess Returns



Panel B) (–Volatility) Loadings $\hat{\beta}_i^{UV}$ *for the 1st Volatility Measure*



Panel C) (–Volatility) Loadings $\hat{\beta}_i^{PRED\_UV}$ *for the 2nd Volatility Measure*

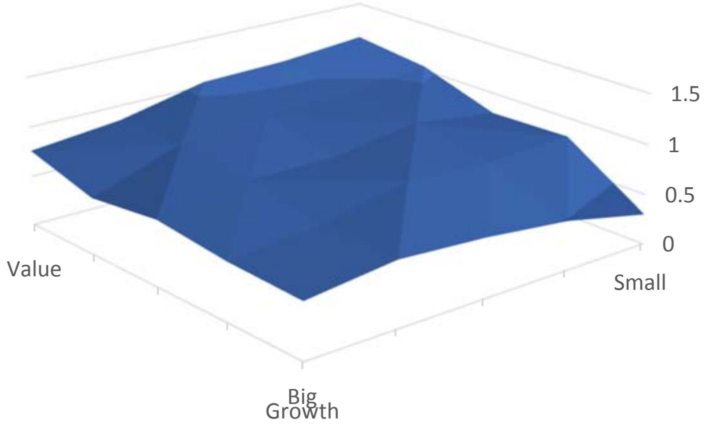
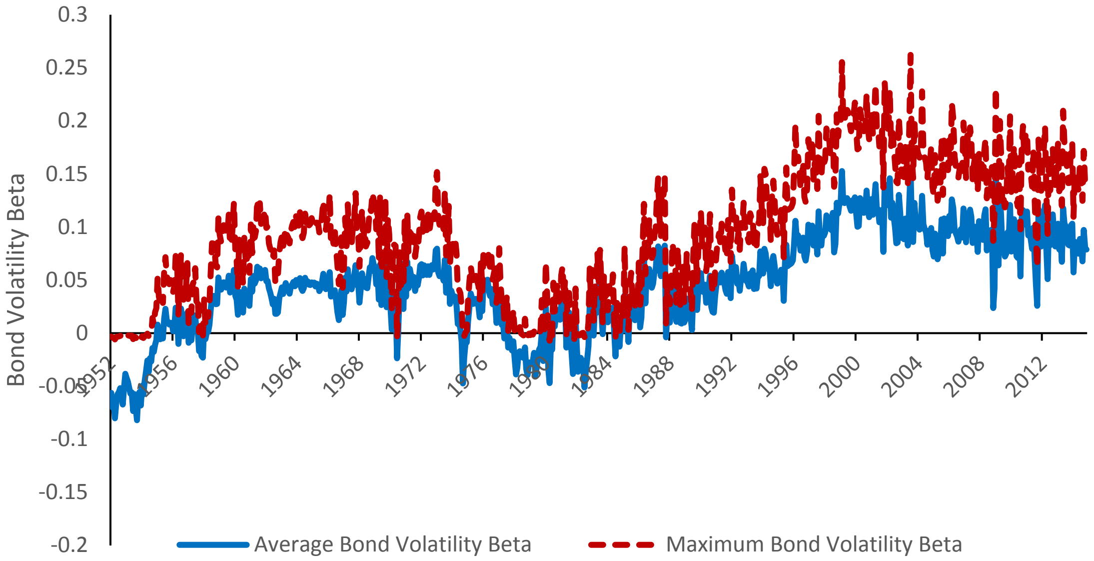


Figure 3. Average Excess Returns and Unexpected Volatility Loadings on Stocks. I obtain the monthly value-weighted portfolio return data for the period January 1952 to December 2014 for the 25 Fama-French (1992) portfolios sorted on size and book-to-market equity from Kenneth French's Web site at Dartmouth. I estimate volatility loadings using Eq. (6) in the text for both measures of (unexpected) volatility. Since most volatility loadings are negative, the plots present (–) loadings for better visualization.

Panel A) Conditional Bond Volatility Beta



Panel B) Conditional Stock Volatility Beta

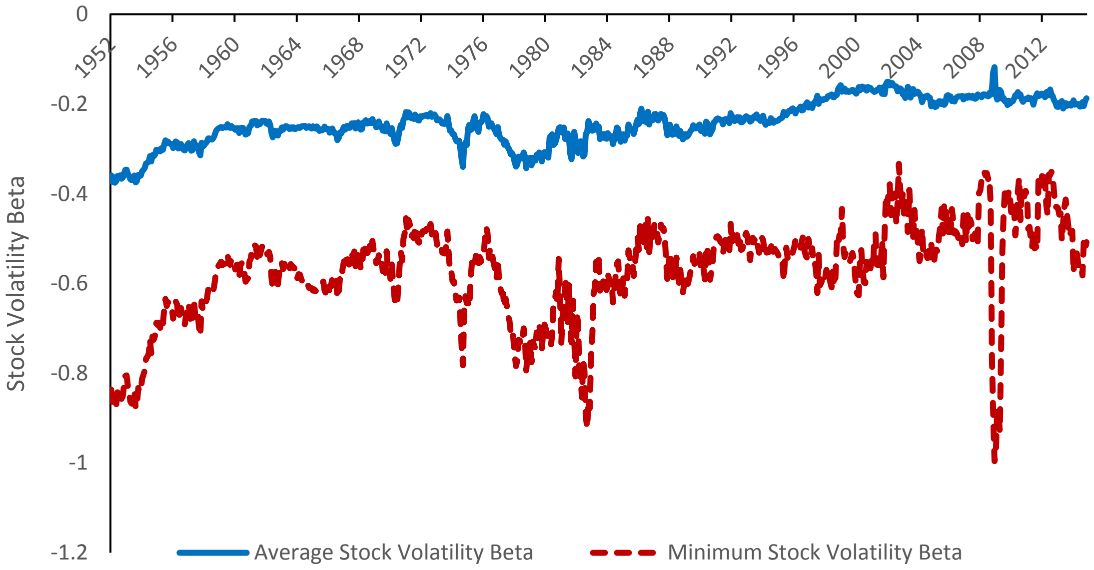


Figure 4. Conditional Volatility Loadings. This figure plots the monthly cross-sectional average and maximum/minimum of the conditional factor loadings. I estimate the conditional betas at a monthly frequency using a two-factor model with market return and unexpected volatility as risk factors (see text for details). I report the results for the period January 1952 to December 2014. For each year, the tick marks correspond to the month of January.

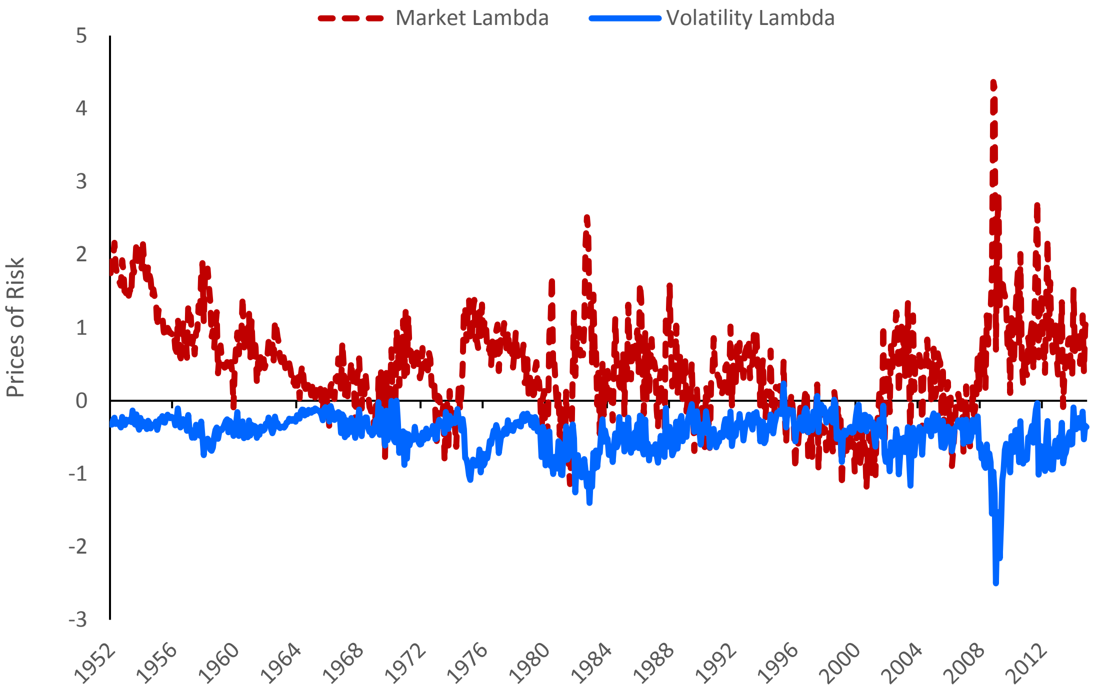


Figure 5. Conditional Risk Premia. This figure plots the conditional monthly market and volatility risk premia. I estimate the conditional lambdas on a monthly frequency using a two-factor model with market return and unexpected volatility as risk factors (see text for details). I report the results for the period January 1952 to December 2014. For each year, the tick marks correspond to the month of January.

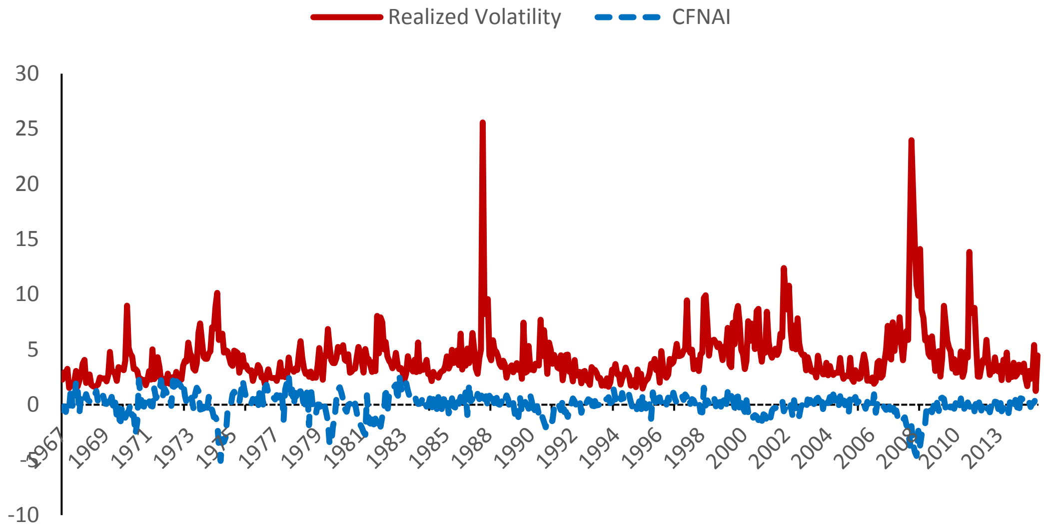


Figure 6. Realized Stock Market Volatility and Economic Activity. The continuous line represents the monthly stock market volatility series and the dashed line represents the monthly *CFNAI* index, a measure of economic activity. Data cover the period May 1967 to December 2014. For each year, the tick marks correspond to the month of January.

Online Appendix

1 The Assymetric Volatility Model

The model used in this study is the *GJR model* of Glosten, Jagannathan and Runkle (1993), which is designed to introduce asymmetry into the model:

$$\begin{aligned} R_{m,t} &= \mu + \rho R_{m,t-1} + \eta_t \\ \eta_t &= \varepsilon_t \sqrt{h_t}, \\ \varepsilon_t / I_{t-1} &\sim \textit{Student}\ (\upsilon), \qquad\qquad t = 1, ..., T. \\ h_t &= \alpha + \phi h_{t-1} + \theta^+ \eta_{t-1}^{2+} + \theta^- \eta_{t-1}^{2-}, \\ \eta_t^{2+} &= \eta_t^2 1_{\{\eta_t > 0\}},\ \eta_t^{2-} = \eta_t^2 1_{\{\eta_t < 0\}} \end{aligned} \tag{A1}$$

The distribution of $R_{m,t}$ is *Student* with mean zero and variance $h_t^{1/2}\upsilon/(\upsilon - 2)$ given past information I_{t-1} and assuming $\upsilon > 2$. The ε_t sequence is independent and the initial variance is a known constant. Let γ denote the parameter vector in this model, with $\gamma = (\mu, \rho, \alpha, \theta^+, \theta^-, \phi, \upsilon)$. The posterior density for a sample of T observations is given by

$$\varphi(\gamma / R) \propto \varphi(\gamma) l(\gamma / R), \tag{A2}$$

with the likelihood function given by

$$l(\gamma / R) \propto \prod_{t=1}^{T} \frac{\Gamma(\frac{\upsilon+1}{2})}{\Gamma(\frac{\upsilon}{2})} (\upsilon h_t^{1/2})^{-1/2} \left[1 + \frac{R_t^2}{\upsilon h_t^{1/2}} \right]^{-\frac{\upsilon+1}{\upsilon}}, \tag{A3}$$

where the prior density, $\varphi(\gamma)$, needs to respect the positivity restrictions on the parameters and the condition $\phi < 1$. Integrability of the posterior density depends in part on the integrability of the prior density. Given an integrable (or proper) prior and a non-pathological likelihood, the posterior will also be integrable. Examining the likelihood function (A3) it can be seen that, if $h_t^{1/2}$ is strictly positive, since the *Student* density is finite and positive, no pathology appears. However, the posterior density of υ is not integrable if one were to use a flat prior (see Bauwens and Lubrano (1998)). For the posterior density of υ to be integrable, the prior information must be such that the posterior is forced to go to zero quickly enough in the tail. The prior at the right tail should be at least $O(\upsilon^{1+d})$, with d being small and positive, e.g. $1/\upsilon^2$ (improper prior obtained by being flat on $1/\upsilon$). This prior must be truncated to the interval (m, ∞), with m being small and positive, to avoid causing problems at the left tail. This approach avoids the problem of $l(\gamma/R)/\upsilon^2$ approaching infinity as υ approaches zero. Therefore, for a proper prior for υ, I use a $half - right\ Cauchy$ centered at 0:

$$\varphi(\upsilon) \propto (1+\upsilon^2)^{-1} \quad (\upsilon > 0). \tag{A4}$$

For the rest of the parameters in the model I use a uniform prior.

2 The Griddy-Gibbs Sampler

The *Gibbs sampler* of Geman and Geman (1984) and Gelfand and Smith (1990) is a very popular $MCMC$ method. Let $\theta_1,\ \theta_2,\ ...\theta_n$ be a set of parameters that need to be estimated, X the available data, and M the model entertained. Suppose that the conditional distributions of each parameter given the others, $f_i(\theta_i/\theta_{j\neq i}, X, M)$ are known, but the likelihood function of the model is hard to obtain. What I do is to draw a random number from each of these conditional distributions. For instance, if $n = 3$, let's consider $\theta_{2,0}$ and $\theta_{3,0}$ two arbitrary starting values of θ_2 and θ_3. Then

1. I draw a random sample $f_1(\theta_1/\theta_{2,0}, \theta_{3,0}, X, M)$, call it $\theta_{1,1}$;
2. I draw a random sample $f_2(\theta_2/\theta_{3,0}, \theta_{1,1}, X, M)$, call it $\theta_{2,1}$;
3. I draw a random sample $f_3(\theta_3/\theta_{2,1}, \theta_{1,1}, X, M)$, call it $\theta_{3,1}$.

This is a *Gibbs iteration.* The iteration can be repeated for n times, with n sufficiently large such that $m < n$ initial random draws can be discarded. I get the *Gibbs sample* this way, $(\theta_{1,m+1}, \theta_{2,m+1}, \theta_{3,m+1}), ...(\theta_{1,n}, \theta_{2,n}, \theta_{3,n})$, which can be used to obtain the point estimates and the variances of the three parameters.

In the case when the conditional posterior distributions of the parameters don't have closed-form expressions, the *Gibbs sampler* implementation can become complicated. But Ritter and Tanner (1992) have a method to obtain draws in this case. It is called the $Griddy - Gibbs\ sampler$:

1. I choose a grid of points from a properly selected interval of θ_i, say $\theta_{i1} \leq \theta_{i2} \leq ... \leq \theta_{im}$. I

evaluate the conditional posterior density function to obtain $w_j = f(\theta_{ij}/\theta_{lk\neq ij}, X, M)$ for $j = 1, ...m$;

2. I use $w_1, ..., w_m$ to obtain an approximation to the inverse cumulative distribution function of $f(\theta_{ij}/\theta_{lk\neq ij}, X, M)$;

3. I draw a $Uniform(0,1)$ random variate and I transform the observation via the approximate inverse CDF to obtain a random draw for θ_i.

The usual *Gibbs sampler* cannot be applied to the $GARCH$ model even if the error term is (conditionally) normal. It requires analytical knowledge of the full conditional posterior densities. Regression models with $GARCH$ errors do not contain this knowledge. To handle this, I apply a unidimensional deterministic integration rule to each coordinate of the posterior density in combination with the *Gibbs sampler*, as described by Bauwens and Lubrano (1998). The random draws of the joint posterior are then obtained by evaluating and inverting the full conditional densities.

I keep 5000 draws in the $Griddy - Gibbs\ sampler$ and I consider the 1000 initial draws as the burn-in sample. The grid I do the search over is similar to the one used by Bauwens and Lubrano (1998): $\mu \times \rho \times \alpha \times \phi \times \theta^+ \times \theta^- \times \upsilon \in (-0.60, 0.94) \times (0.00, 0.40) \times (0.01, 0.90) \times (0.35, 0.95) \times (0.00001, 0.50) \times (0.01, 0.70) \times (0.01, 30)$. I report the posterior estimates in Table B1. The extent to which a volatility shock today feeds through into the next period$'$s volatility is equal to 0.75. The leverage hypothesis of Black (1976) is also supported by the results, with only the coefficient for the negative shocks to returns being precisely estimated.

Table A.1: Volatility Loadings for the Subperiod with VIX (and SKEW) Data

This table reports the factor loadings from a 2-factor model that includes the market return and unexpected volatility. The test assets are the 11 Fama maturity-sorted Treasury portfolios and the 25 Fama-French (1992) portfolios sorted on size and book-to-market equity. I regress the monthly portfolio excess returns on the excess market return and unexpected volatility using an unconditional model specification. *UV* represents unexpected volatility, and is the residual from an *AR(1)* model applied to the time series of realized stock market volatility. Data cover the period January 1990 to December 2014. I report *t-statistics* in parentheses, and I report R^2_{adj} in percentages.

Panel A) Volatility Loadings in the Treasury Market (January 1990-December 2014)

Bond Maturity										
1-6mo	*7-12mo*	*13-18mo*	*19-24mo*	*25-30mo*	*31-36mo*	*37-42mo*	*43-48mo*	*49-54mo*	*55-60mo*	*61-120mo*
					$\hat{\alpha}_i$					
0.03	0.06	0.09	0.12	0.15	0.17	0.20	0.22	0.24	0.24	0.29
(8.15)	*(6.51)*	*(5.38)*	*(4.76)*	*(4.49)*	*(4.23)*	*(4.14)*	*(3.86)*	*(3.75)*	*(3.52)*	*(3.40)*
					$\hat{\beta}_i^m$					
0.00	0.00	-0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.01
(0.83)	*(0.35)*	*(-0.61)*	*(-1.08)*	*(-1.08)*	*(-0.85)*	*(-0.97)*	*(-0.96)*	*(-1.09)*	*(-1.22)*	*(-0.58)*
					$\hat{\beta}_i^{UV}$					
0.01	0.02	0.03	0.05	0.08	0.09	0.10	0.11	0.12	0.12	0.11
(4.14)	*(4.20)*	*(3.50)*	*(3.74)*	*(4.01)*	*(3.87)*	*(3.58)*	*(3.40)*	*(3.16)*	*(2.88)*	*(2.30)*
					R^2_{adj}					
5.10	5.64	4.82	6.28	7.09	6.25	5.64	5.11	4.68	4.21	1.97

Table A.1 – *Continued*

Panel B) Volatility Loadings in the Stock Market (January 1990-December 2014)

	Book-to-Market Equity (BE/ME) Quintiles									
Size Quintiles	*Low*	*2*	*3*	*4*	*High*	*Low*	*2*	*3*	*4*	*High*
			$\hat{\alpha}_i$					*t-stats for* $\hat{\alpha}_i$		
Small	-0.53	0.30	0.29	0.60	0.62	*(-1.67)*	*(1.07)*	*(1.41)*	*(2.81)*	*(2.86)*
2	-0.19	0.22	0.39	0.38	0.34	*(-0.82)*	*(1.24)*	*(2.32)*	*(2.27)*	*(1.54)*
3	-0.10	0.26	0.28	0.40	0.54	*(-0.50)*	*(1.84)*	*(2.00)*	*(2.51)*	*(2.78)*
4	0.11	0.24	0.19	0.45	0.12	*(0.71)*	*(2.02)*	*(1.30)*	*(3.20)*	*(0.63)*
Big	0.01	0.14	0.23	-0.15	0.09	*(0.09)*	*(1.37)*	*(1.64)*	*(-0.86)*	*(0.42)*
			$\hat{\beta}_i^m$					*t-stats for* $\hat{\beta}_i^m$		
Small	1.34	1.13	0.99	0.91	0.95	*(17.31)*	*(16.46)*	*(19.66)*	*(17.44)*	*(18.00)*
2	1.33	1.05	0.93	0.93	1.08	*(23.28)*	*(23.86)*	*(22.62)*	*(22.78)*	*(20.13)*
3	1.26	1.06	0.94	0.90	1.01	*(24.95)*	*(30.34)*	*(27.92)*	*(22.96)*	*(21.19)*
4	1.20	0.97	0.96	0.89	1.05	*(30.88)*	*(33.18)*	*(26.44)*	*(25.90)*	*(22.34)*
Big	0.98	0.90	0.80	0.92	1.08	*(44.81)*	*(37.00)*	*(23.77)*	*(21.33)*	*(19.98)*
			$\hat{\beta}_i^{UV}$					*t-stats for* $\hat{\beta}_i^{UV}$		
Small	-0.48	-0.44	-0.32	-0.28	-0.41	*(-2.56)*	*(-2.68)*	*(-2.62)*	*(-2.25)*	*(-3.21)*
2	-0.23	-0.34	-0.29	-0.24	-0.32	*(-1.66)*	*(-3.25)*	*(-2.88)*	*(-2.41)*	*(-2.45)*
3	-0.25	-0.16	-0.15	-0.25	-0.23	*(-2.07)*	*(-1.91)*	*(-1.83)*	*(-2.59)*	*(-2.02)*
4	-0.18	-0.20	-0.25	-0.27	-0.19	*(-1.87)*	*(-2.81)*	*(-2.84)*	*(-3.20)*	*(-1.63)*
Big	0.14	0.06	-0.05	-0.05	0.05	*(2.68)*	*(1.01)*	*(-0.55)*	*(-0.44)*	*(0.39)*

	Book-to-Market Equity (BE/ME) Quintiles				
Size Quintiles	*Low*	*2*	*3*	*4*	*High*
			R_{adj}^2		
Small	57.70	55.56	63.45	57.61	60.33
2	69.71	71.96	69.59	69.44	64.29
3	72.77	79.52	76.72	69.91	66.06
4	80.06	82.57	75.43	74.94	67.96
Big	88.48	84.28	69.71	64.89	61.05

Table A.2: Additional Unconditional Tests

I estimate the factors' risk premia using the Fama-MacBeth (1973) procedure for the following asset pricing model:

$$E\left(R_{i,t+1}^{e}\right)=\lambda_0+\lambda_m\beta_i^m+\sum_{s=1}^{S}\lambda_s\beta_i^s ,$$

where λ_m is the market price of risk and λ_s is the price of risk associated with the generic factor *s*. The left-hand side variable is a vector of monthly excess returns for the 11 maturity-sorted Treasury portfolios and the 25 size- and value-sorted portfolios, and the betas represent factors' loadings estimated in the corresponding time series models. *UV* represents unexpected volatility, and is the residual from an *AR(1)* model applied to the time series of realized stock market volatility. Δ*VIX* represents month-to-month innovations in implied volatility index, and Δ*SKEW* represents month-to-month innovations in the *SKEW* index, and captures tail risk. *Mkt_dn* represents downside risk and *Mkt_up* is upside risk (downside risk reflects the covariance of asset returns with the market return, conditional on the latter being below its unconditional mean; a similar definition holds for upside risk). *HML* and *SMB* are mimicking portfolios for book-to-market equity and size (zero-investment portfolios). Data cover the period January 1990 to December 2014 in Panels A and B, and they cover the period January 1952 to December 2014 for Panel C. I report the Fama-MacBeth *t-statistics* in parentheses. I report the root MSE for each model and the R^2_{adj} in percentages.

Panel A) Results with ΔVIX

Model	$\hat{\lambda}_0$	$\hat{\lambda}_m$	$\hat{\lambda}_{\Delta VIX}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	*Avg MSE*	R^2_{adj}
FF-3 & ΔVIX	0.23	0.36	-1.60	0.19	0.27		1.83	80.31
	(5.87)	*(1.40)*	*(-2.39)*	*(0.97)*	*(1.48)*			
Carhart & ΔVIX	0.13	0.64	-0.92	0.14	0.29	3.38	1.75	91.25
	(3.64)	*(2.53)*	*(-1.41)*	*(0.72)*	*(1.60)*	*(5.63)*		

Panel B) Results with ΔSKEW

Model	$\hat{\lambda}_0$	$\hat{\lambda}_m$	$\hat{\lambda}_{UV}$	$\hat{\lambda}_{SKEW}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	*Avg MSE*	R^2_{adj}
CAPM, UV & ΔSKEW	0.26	0.41	-0.94	2.52				2.55	71.31
	(5.58)	*(1.58)*	*(-2.04)*	*(1.24)*					
FF-3 & ΔSKEW	0.20	0.42		2.48	0.17	0.31		1.95	78.91
	(5.02)	*(1.62)*		*(1.95)*	*(0.88)*	*(1.69)*			
Carhart & ΔSKEW	0.12	0.68		0.17	0.12	0.31	3.59	1.84	90.82
	(3.20)	*(2.64)*		*(0.13)*	*(0.62)*	*(1.71)*	*(5.32)*		

Panel C) Results with Downside and Upside Risks

Model	$\hat{\lambda}_0$	$\hat{\lambda}_{m\_dn}$	$\hat{\lambda}_{m\_up}$	*Avg MSE*	R^2_{adj}
Mkt_dn & Mkt_up	0.16	0.52	0.01	2.98	68.02
	(4.02)	*(1.34)*	*(0.03)*		