Online Appendix for

Does Variance Risk Have Two Prices? Evidence from the Equity and Option Markets

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A Data Description

A.1 Predictive Variables

We provide more detail on the definition of the macro-finance variables used to capture the dynamics of the equity and option VRPs. The PE ratio is downloaded from Robert Shiller's webpage and is defined as the price of the SP500 divided by the 10-year trailing moving average of aggregate earnings. The quarterly inflation rate is computed from the Producer Price Index (PPI), aggregate employment is measured by the total number of employees in the nonfarm sector (seasonally-adjusted), and the default spread is defined as the yield differential between Moody's BAA- and AAA-rated bonds. These three series are downloaded from the Federal Reserve Bank of St. Louis.

Tables I and II report the unconditional moments and correlation matrix of the predictors over the long sample between 1970 and 2014 (179 quarterly observations) and over the short sample between 1992 and 2014 (92 quarterly observations). Overall, the summary statistics for the macro-finance studies are similar to those reported in previous studies. The two broker-dealer variables contain information at different frequencies—the leverage ratio is a slow-moving predictor, whereas the PBI return captures the short-term reaction of intermediaries to aggregate losses.

[TABLE I HERE]

[TABLE II HERE]

A.2 The Set of Equity Portfolios

A.2.1 Portfolio Formation

We use the approach developed by Ang, Hodrick, Xing, and Zhang (2006) to form the cross-section of 25 variance risk-sensitive portfolios. First, we estimate the market and variance betas of individual stocks each month using daily returns over the previous month. Using a daily frequency allows us to pin down the conditional risk loadings without specifying the conditioning information (see Lewellen and Nagel (2006) for a detailed discussion). For each stock with at least 17 daily observations, we regress its return on the CRSP market return $r_{m,d}$ and the innovation of the SP500 realized variance $u_{v,d}$. Computing a model-free variance innovation based on intraday return observations is not feasible because this data is only available in the latter part of the sample. To address this issue, we model the daily conditional variance of the SP500 return using a standard GARCH (1,1): $\sigma_d^2 = \gamma + \alpha\sigma_{d-1}^2 + \beta\varepsilon_d^2$, where ε_d^2 is the daily squared SP500 return. After estimating the parameters γ, α, and β using daily returns over a one-year rolling window, we compute $u_{v,d}$ as $\varepsilon_d^2 - \hat{\sigma}_{d-1}^2$, where $\hat{\sigma}_{d-1}^2$ is the conditional variance estimated on the previous day.[1]

Second, we sort stocks according to their exposures to the market and variance factors. Since short-window regressions can produce large estimation errors, we rank each stock i based on its beta t-statistics, $\hat{t}_{im,t} = \hat{b}_{im,t}/\hat{\sigma}_{b_{im,t}}$ and $\hat{t}_{iv,t} = \hat{b}_{iv,t}/\hat{\sigma}_{b_{iv,t}}$, where $\hat{\sigma}_{b_{im,t}}$, $\hat{\sigma}_{b_{iv,t}}$ denote the estimated volatilities of the estimated betas $\hat{b}_{im,t}$ and $\hat{b}_{iv,t}$.[2] Stocks are ranked first into quintiles based on their market t-statistic, and then into quintiles based on their variance t-statistic.

Third, we compute the average return of all stocks in each group. To mitigate liquidity concerns, we apply a value-weighting scheme and exclude NASDAQ stocks. Repeating these three steps each month over the entire sample period, we obtain the return time-series of the 25 variance portfolios.

A.2.2 Summary Statistics over the Short Sample

Table III summarizes the properties of the variance portfolios (Low, 2, 3, 4, High) over the short sample (1992-2014). Consistent with the results in Table 1 of the paper, Panel A

[1] Whereas Ang, Hodrick, Xing, and Zhang (2006) use the daily change in the VIX index to measure $u_{v,d}$, we follow a different approach for two reasons. First, as noted by these authors, the VIX is a noisy proxy of the variance innovation because it also captures changes in the risk premium itself. Second, data on the VIX is only available in the early 1990s whereas our sample begins in 1970.

[2] Several papers (e.g., Kosowski, Timmerman, Wermers, and White (2006)) show that the t-statistic allows for an improved ranking because it controls for the precision of the estimated coefficient. Consistent with these studies, we find that ranking based on t-statistics largely improves the post-ranking characteristics of the variance portfolios (see Section F.1).

reveals that both average returns and post-formation variance betas vary monotonically across portfolios. The spreads in average returns and variance betas between the high- and low-variance portfolios are both higher than the ones observed during the full sample (-5.09% vs -3.11% per year for returns, 1.49 vs 0.73 for betas). Panel B shows that the rejections of the commonly-used asset pricing models are stronger during the short sample. Across the four tested models, the estimated annual alphas of the high minus low variance portfolio range between -5.97% (CAPM) and -4.67% (Fama-French and liquidity) and are all highly significant.

[TABLE III HERE]

B Estimation Procedure

B.1 The Equity Market

B.1.1 Two-Pass Regression in a Conditional Setting

This section provides additional information on the procedure for estimating the Variance Risk Premium (VRP) projection in the equity market using the conditional two-pass regression approach developed by Gagliardini, Ossola, and Scaillet (2015). In the first step, we estimate, for each equity portfolio p ($p = 1, ..., n$), the coefficients of the following time-series regression:

$$r^e_{p,t+1} = -c'_p z_t + b_{pv} \cdot rv_{t+1} + b_{pm} \cdot f_{m,t+1} + e_{p,t+1}, \tag{B1}$$

where $r^e_{p,t+1}$ is the excess return of portfolio p, z_t is the J-vector of lagged predictors (including a constant), rv_{t+1} is the realized market variance, and $f_{m,t+1}$ is the market factor. The $(J+2)$-vector of coefficients $\beta_p = (-c'_p, b_{pv}, b_{pm})'$ is equal to $E[x_{t+1}x'_{t+1}]^{-1}E[x_{t+1}r^e_{p,t+1}]$, where $x_{t+1} = (z_t', rv_{t+1}, f_{m,t+1})'$. The OLS estimator of β_p is given by

$$\hat{\beta}_p = \left(\sum_{t=1}^{T} x_{t+1} x_{t+1}' \right)^{-1} \sum_{t=1}^{T} x_{t+1} r_{p,t+1}^e, \tag{B2}$$

where T is the total number of return observations.

In the second step, we compute the estimator of the $2J$-vector $V^e = (V_v^{e\prime}, V_m^{e\prime})'$ that drives the risk-neutral expectations of the two risk factors (variance and market). Specifically, we use a WLS approach to estimate the following cross-sectional regression:

$$c_p = B_p V^e, \tag{B3}$$

where B_p a $J \times 2J$ matrix equal to $[b_{pv} \cdot I_J, b_{pm} \cdot I_J]$, and I_J is the $J \times J$ identity matrix. For each portfolio p, we compute a $J \times J$ matrix of weights $w_p = diag(v_p)^{-1}$, where v_p is the covariance matrix of the J-vector of standardized errors $\sqrt{T}(\hat{c}_p - \hat{B}_p V^e)$. This matrix is equal to $v_p = C_{V^e}' Q_x^{-1} S_{pp} Q_x^{-1} C_{V^e}$, where $Q_x = E[x_{t+1} x_{t+1}']$, S_{pp} is a $(J+2) \times (J+2)$ matrix equal to $E[e_{p,t+1}^2 x_{t+1} x_{t+1}']$, C_{V^e} is a $(J+2) \times J$ matrix defined as $[E_1' - (I_J \otimes V^{e\prime}) J_A E_2']'$ with $E_1 = [I_J, \mathbf{0}_{J\times 2}]'$, $E_2 = [\mathbf{0}_{2\times J}, I_2]'$, $J_A = W_{J,J\cdot 2}(I_2 \otimes vec(I_J))$, $\mathbf{0}_{J\times 2}$ is a $J \times 2$ matrix of zeros, and $W_{J,J\cdot 2}$ is a $(J, J \cdot 2)$-commutation matrix.[3] The empirical counterpart of v_p is given by

$$\widehat{v}_p = C_{\hat{V}_1^e}' \hat{Q}_x^{-1} \hat{S}_p^{-1} \hat{Q}_x^{-1} C_{\hat{V}_1^e}, \tag{B4}$$

where $\hat{Q}_x = \frac{1}{T} \sum_{t=1}^{T} x_{t+1} x_{t+1}'$, $\widehat{S}_{pp} = \frac{1}{T} \sum_{t=1}^{T} \hat{e}_{p,t+1}^2 x_{t+1} x_{t+1}'$, $\hat{e}_{p,t+1} = r_{p,t+1}^e - \hat{\beta}_p' x_{t+1}$, $C_{\widehat{V}_1^e} = [E_1' - (I_J \otimes \hat{V}_1^{e\prime}) J_A E_2']'$, and $\hat{V}_1^e$ is the first-step OLS estimator of V^e obtained using unit weights, i.e., $\hat{V}_1^e = \left(\sum_{p=1}^{n} \hat{B}_p' \hat{B}_p \right)^{-1} \sum_{p=1}^{n} \hat{B}_p' \hat{c}_p$. Using the estimated matrix of weights

[3] The commutation matrix $W_{n,m}$ of order $n \cdot m \times n \cdot m$ is defined such that $W_{n,m} vec(A) = vec(A')$ for any matrix $A \in R^{m\times n}$.

$\hat{w}_p$, we obtain the following estimator of V^e :

$$\widehat{V}^e = \left(\sum_{p=1}^{n} \hat{B}_p' \hat{w}_p \hat{B}_p \right)^{-1} \sum_{p=1}^{n} \hat{B}_p' \hat{w}_p \hat{c}_p. \tag{B5}$$

Third, we turn to the estimation of the vector of the linear forecasts of the risk factors defined as $proj(f_{t+1}|\, z_t) = F'z_t$, where $f_{t+1} = (rv_{t+1}, f_{m,t+1})'$, and $F = [F_v, F_m]$ is a $J \times 2$ matrix of coefficients equal to $E[z_t z_t']^{-1} E[z_t f_{t+1}']$. These coefficients are obtained from an OLS regression of the factors on the lagged predictors, i.e.,

$$\hat{F} = \left(\sum_{t=1}^{T} z_t z_t' \right)^{-1} \sum_{t=1}^{T} z_t f_{t+1}'. \tag{B6}$$

Combining equations (B5) and (B6), we compute the projections of the variance and market risk premia as

$$\begin{aligned} \hat{\lambda}_{v,t}^e(z) &= \left(\hat{F}_v - \hat{V}_v^e \right)' z_t, \\ \hat{\lambda}_{m,t}^e(z) &= \left(\hat{F}_m - \hat{V}_m^e \right)' z_t, . \end{aligned} \tag{B7}$$

B.1.2 Distribution of the Estimated Coefficients

In an unconditional setting, Jagannathan and Wang (1998) show that the estimated vector of unconditional risk premia is consistent and asymptotically normally distributed. Its covariance matrix Σ_λ is equal to $\Sigma_f + \frac{1}{n}\Sigma_V$, where Σ_f is the covariance matrix of the risk factors, and Σ_{V^e} is the covariance matrix of the estimated risk factor expectations under the risk-neutral measure. Gagliardini, Ossola, and Scaillet (2015) demonstrate that a similar result holds in a conditional setting. Specifically, the $2J$-vector that drives the vector of conditional risk premia, $\hat{\Lambda}^e = vec(\hat{F}) - \hat{V}^e$, is consistent and asymptotically normally distributed, i.e.,

$$\sqrt{T} \left(\hat{\Lambda}^e - \Lambda^e \right) \Rightarrow N(\mathbf{0}_{2J\times 1}, \Sigma_{\Lambda^e}). \tag{B8}$$

The $2J \times 2J$ covariance matrix Σ_{Λ^e} is the sum of two terms, Σ_F and $\frac{1}{n}\Sigma_{V^e}$, defined as

$$\Sigma_F = (I_J \otimes Q_z^{-1})\Sigma_u(I_J \otimes Q_z^{-1}), \tag{B9}$$

$$\Sigma_{V^e} = \left(\frac{1}{n}B'WB\right)^{-1} \frac{1}{n}B'WVWB \left(\frac{1}{n}B'WB\right)^{-1}, \tag{B10}$$

where Σ_u is a $2J \times 2J$ matrix equal to $E(u_{t+1}u'_{t+1} \otimes z_t z'_t)$ with $u_{t+1} = f_{t+1} - F'z_t$, B is a $Jn \times 2J$ matrix defined as $[B'_1, ..., B'_n]'$, W is a $Jn \times Jn$ block diagonal matrix with elements $[w_p]_{p=1,...,n}$ on its diagonal, and V is a $Jn \times Jn$ matrix composed of $J \times J$ submatrices $[V_{pk}]_{p,k=1,...,n}$ with $V_{pk} = C'_{V^e}Q_x^{-1}S_{pk}Q_x^{-1}C_{V^e}$, and $S_{pk} = E[e_{p,t+1}e_{k,t+1}x_{t+1}x'_{t+1}]$. A consistent estimator of Σ_{Λ^e} can be obtained by replacing Σ_u, Q_z^{-1}, B, W, and V with their empirical counterparts.

B.1.3 Joint Test of Correct Specification

To determine whether the two-factor model is correctly specified, we use the test statistic proposed by Kan, Robotti, and Shanken (2013). Under the null hypothesis of correct specification, the sum of the squared pricing errors, $Q = \sum_{p=1}^{n} (c_p - B_p V^e)' (c_p - B_p V^e)$, is equal to zero and its estimated counterpart multiplied by T is asymptotically distributed as

$$T\hat{Q} = \frac{T}{n}\sum_{p=1}^{n} \hat{\zeta}'_p \hat{w}_p \hat{\zeta}_p \xrightarrow{d} \frac{1}{n}\sum_{p=1}^{nJ-2J} eig_p \cdot \chi^2_p, \tag{B11}$$

where $\hat{\zeta}_p$ is the J-vector of estimated errors computed as $\hat{c}_p - \hat{B}_p\hat{V}^e$, eig_p $(p = 1, ..., nJ-2J)$ are the non-zero eigenvalues of the matrix $D = V^{1/2}(W - WB(B'WB)^{-1}B'W)V^{1/2}$, and χ^2_p $(p = 1, ..., nJ - 2J)$ are i.i.d. chi-square variables with one degree of freedom.

B.2 The Option Market

B.2.1 Treatment of Samples with Unequal Lengths

This section explains how to estimate the VRP projection in the option market. To compute the J-vector of risk-neutral coefficients V_v^o, we run a time-series regression of the squared VIX index vix_t^2 on the predictors. The main issue is that the periods over which the variables are observed have unequal lengths: the realized variance and predictors are available since 1970 (long sample), whereas the VIX index is only observed since the early 1990's (short sample). To exploit the information contained in the long sample, we use an extension of the Generalized Method of Moments (GMM) developed by Lynch and Wachter (2013). To begin, we denote by $g(V_{v,S}^o)$ and $g(F_{v,S})$ the J-vectors of moments associated with V_v^o and F_v over the short sample, and by $g(F_v)$ the J-vector of moments associated with F_v over the long sample:

$$\begin{aligned} g(V_{v,S}^o) &= \frac{1}{\lambda T}\sum^{\lambda T} f_t(V_{v,S}^o) = \frac{1}{\lambda T}\sum^{\lambda T} z_t u_{vix,t+1} = \frac{1}{\lambda T}\sum^{\lambda T} z_t(vix_t^2 - V_v^{o\prime} z_t), \\ g(F_{v,S}) &= \frac{1}{\lambda T}\sum^{\lambda T} f_t(F_{v,S}) = \frac{1}{\lambda T}\sum^{\lambda T} z_t u_{v,t+1} = \frac{1}{\lambda T}\sum^{\lambda T} z_t(rv_{t+1} - F_v' z_t), \\ g(F_v) &= \frac{1}{T}\sum^{T} f_t(F_v) = \frac{1}{T}\sum^{T} z_t u_{v,t+1} = \frac{1}{T}\sum^{T} z_t(rv_{t+1} - F_v' z_t), \end{aligned} \quad \text{(B12)}$$

where λT is the number of observations over the short sample. The procedure proposed by Lynch and Wachter (2013) consists of using a new set of moments to estimate V_v^o:

$$g(V_v^o) = g(V_{v,S}^o) - B_{V_v^o,F_v}(g(F_v) - g(F_{v,S})), \quad \text{(B13)}$$

where each row of the $J \times J$ matrix $B_{V_v^o,F_v}$ contains the coefficients of a regression of each element in $g(V_{v,S}^o)$ on the J-vector $g(F_{v,S})$. To compute these coefficients, we estimate the vectors V_v^o and F_v over the short sample. Then, we use equations (B12) to compute the J-vectors $f_t(\hat{V}_{v,S}^o)$ and $f_t(\hat{F}_{v,S})$ at each time t, and run a time-series regression of each element in $f_t(\hat{V}_{v,S}^o)$ on $f_t(\hat{F}_{v,S})$.

By construction, the estimated vector of long sample moments $g(\hat{F}_v)$ equals zero because we use it to compute $\hat{F}_v$, while the estimated short sample moment $g(\hat{F}_{v,S})$ is given by $\frac{1}{\lambda T} Z'(Y_{rv} - Z\hat{F}_v)$, where $Z = [z'_{(1-\lambda)T+1}, ..., z'_T]'$, and $Y_{rv} = [rv_{(1-\lambda)T+2}, ..., rv_{T+1}]'$.

Plugging these estimates into equation (B13), we have:

$$\begin{aligned} g(V_v^o) &= \frac{1}{\lambda T} Z'(Y_{vix} - ZV_v^o) - \hat{B}_{V_v^o,F_v} \left(\frac{1}{\lambda T} Z'(Y_{rv} - Z\hat{F}_v) \right) \\ &= \frac{1}{\lambda T} \left(Z'(Y_{vix} - ZV_v^o) - \hat{B}_{V_v^o,F_v} Z'(Y_{rv} - Z\hat{F}_v) \right), \end{aligned} \quad \text{(B14)}$$

where $Y_{vix} = [vix^2_{(1-\lambda)T+1}, ..., vix^2_T]'$. Therefore, the adjusted estimated vector given by

$$\hat{V}_v^o = (Z'Z)^{-1} \left(Z'Y_{vix} - \hat{B}_{V_v^o,F_v} Z'(Y_{rv} - Z\hat{F}_v) \right) = \hat{V}_{v,S}^o - \hat{A}, \quad \text{(B15)}$$

where $\hat{A}$ is the adjustment factor given by $(Z'Z)^{-1} \hat{B}_{V_v^o,F_v} Z'(Y_{rv} - Z\hat{F}_v)$.

B.2.2 Distribution of the Estimated Coefficients

Exploiting the results derived by Lynch and Wachter (2013), we can determine the properties of the $2J$-vector of estimated coefficients $\hat{C}^o = [\hat{F}_v', \hat{V}_v^{o\prime}]'$. Specifically, it is consistent and asymptotically normally distributed, i.e.,

$$\sqrt{\lambda T} \left(\hat{C}^o - C^o \right) \Rightarrow N(\mathbf{0}_{2J\times 1}, \Sigma_{C^o}). \quad \text{(B16)}$$

The $2J \times 2J$ covariance matrix Σ_{C^o} is equal to

$$\Sigma_{C^o} = (I_2 \otimes E[z_t z_t']^{-1}) S^A (I_2 \otimes E[z_t z_t']^{-1}), \quad \text{(B17)}$$

where S^A is defined as

$$S^A = \begin{bmatrix} \lambda S_{F_v} & \lambda S_{F_v,V_v^o} \\ \lambda S_{V_v^o,F_v} & S_{V_v^o} - (1-\lambda) S_{V_v^o,F_v} S_{F_v}^{-1} S_{F_v,V_v^o} \end{bmatrix}, \quad \text{(B18)}$$

with $S_{F_v} = \sum_{\tau=-\infty}^{\infty} E[f_t(F_v) f_{t-\tau}(F_v)']$, $S_{F_v,V_v^o} = \sum_{\tau=-\infty}^{\infty} E[f_t(F_v) f_{t-\tau}(V_v^o)']$, and $S_{V_v^o} = \sum_{\tau=-\infty}^{\infty} E[f_t(V_v^o) f_{t-\tau}(V_v^o)']$. To estimate these elements, we build on the procedure described by Stambaugh (1997) and Lynch and Wachter (2013). First, we use the White estimator to compute $\hat{S}_{F_v}$ over the full sample. Then, we use the estimated coefficient matrix $\widehat{B}_{V_v^o,F_v}$ and the estimated residual covariance matrix $\hat{\Sigma}$ from the regression of $f_t(\hat{V}_{v,S}^o)$ on $f_t(\hat{F}_{v,S})$ to compute the remaining terms:

$$\hat{S}_{F_v,V_v^o} = \hat{S}_{F_v}' \hat{B}_{V_v^o,F_v}', \tag{B19}$$

$$\hat{S}_{V_v^o} = \hat{\Sigma} + \hat{B}_{V_v^o,F_v} \hat{S}_{F_v} \hat{B}_{V_v^o,F_v}'. \tag{B20}$$

This approach guarantees that the estimator of $\hat{S}^A$ is positive-definite. Plugging this estimator in equation (B18) and replacing $E[z_t z_t']$ with its estimated value over the long sample, $\hat{Q}_z = \frac{1}{T}\sum_{t=1}^{T} z_t z_t'$, we obtain a consistent estimator of Σ_{C^o}.

Based on these results, we can determine the properties of the coefficients that affect the dynamics of the option VRP. Specifically, the J-vector of estimated coefficients $\hat{\Lambda}_v^o = \hat{F}_v - \hat{V}_v^o$ is asymptotically distributed as

$$\sqrt{\lambda T}(\hat{\Lambda}_v^o - \Lambda_v^o) \Rightarrow N(\mathbf{0}_{J\times 1}, \Sigma_{\Lambda_v^o}). \tag{B21}$$

The $J \times J$ covariance matrix $\Sigma_{\Lambda_v^o}$ is given by

$$\Sigma_{\Lambda_v^o} = \Sigma_{C^o}^1 + \Sigma_{C^o}^2 - 2\Sigma_{C^o}^{1,2}, \tag{B22}$$

where $\Sigma_{C^o}^1$ is the $J \times J$ upper block of Σ_{C^o}, $\Sigma_{C^o}^2$ is the $J \times J$ lower block of Σ_{C^o}, and $\Sigma_{C^o}^{1,2}$ is the off-diagonal block of Σ_{C^o}.

B.3 t-Statistics for the Difference in Estimated Coefficients

The difference between the equity and option VRPs is defined as $d_v' z_t$, where d_v is a J-vector equal to $V_v^o - V_v^e$. To determine whether each element of the estimated vector $\widehat{d_v}$ is significantly different from zero, we implement a bootstrap procedure. Consistent with the specification chosen to estimate both VRPs, we model the dynamics of the excess return of each equity portfolio p ($p = 1, ..., n$), the predictors, the market return, the realized variance, and the squared VIX index as

$$\begin{aligned}
r^e_{p,t+1} &= -(b_{pv} \cdot V^{e\prime}_v + b_{pm} \cdot V^{e\prime}_m) z_t + b_{pv} \cdot rv_{t+1} + b_{pm} \cdot f_{m,t+1} + e_{p,t+1}, \\
z_{t+1} &= \Phi z_t + u_{z,t+1}, \\
rv_{t+1} &= F^{\prime}_v z_t + u_{v,t+1}, \\
f_{m,t+1} &= F^{\prime}_m z_t + u_{m,t+1}, \\
vix^2_t &= V^{o\prime}_v z_t + u_{vix,t}. \qquad \text{(B23)}
\end{aligned}$$

After estimating the different coefficients in the system of equations (B23), we build a $\lambda T \times N$ matrix of estimated residuals, $\widehat{R} = [\hat{e}, \hat{u}_z, \hat{u}_v, \hat{u}_m, \hat{u}_{vix}]$, where λT is the number of observations over the short sample, and N is equal to $n + (J - 1) + 3$. We have $\hat{e} = [\hat{e}^{\prime}_{(1-\lambda)T+2}, ..., \hat{e}^{\prime}_{T+1}]^{\prime}$ with $\hat{e}_t = [\hat{e}_{1,t}, ..., \hat{e}_{n,t}]$, $\hat{u}_z = [\hat{u}^{\prime}_{z,(1-\lambda)T+2}, ..., \hat{u}^{\prime}_{z,T+1}]^{\prime}$, $\hat{u}_v = [\hat{u}_{v,(1-\lambda)T+2}, ..., \hat{u}_{v,T+1}]^{\prime}$, $\hat{u}_m = [\hat{u}_{m,(1-\lambda)T+2}, ..., \hat{u}_{m,T+1}]^{\prime}$, and $\hat{u}_{vix} = [\hat{u}_{vix,(1-\lambda)T+1}, ..., \hat{u}_{vix,T}]^{\prime}$.

For each bootstrap iteration b ($b = 1, ..., 1,000$), we first draw with replacement a set of T rows from the matrix $\widehat{R}$. This procedure allows us to preserve the cross-sectional correlation between the residuals. Second, we plug the estimated coefficients and the bootstrapped residuals into equations (B23) to build, for each time t ($t = 1, ..., T$), the J-vector of predictors $z_t(b)$, the excess return of the variance portfolios $r^e_{p,t+1}(b)$, the realized variance $f_{v,t+1}(b)$, and the market return $f_{m,t+1}(b)$. Third, we construct the squared VIX $vix^2_t(b)$ using the bootstrapped residuals over the short sample. Fourth, we take all of these bootstrapped time-series and re-estimate the J-vectors of coefficients $\hat{V}^e_v(b)$ and $\hat{V}^o_v(b)$ using the approaches proposed by Gagliardini, Ossola, and Scaillet (2015) and Lynch and Wachter (2013), and compute $\hat{d}_v(b)$ as $\hat{V}^o_v(b) - \hat{V}^e_v(b)$. After repeating these four steps 1,000 times, we compute the t-statistic of each element, $\hat{d}_{v,j}$ ($j = 1, ..., J$), as $\frac{\hat{d}_{v,j}}{\hat{\sigma}_{d_{v,j}}}$, where $\hat{\sigma}_{d_{v,j}}$ is the standard deviation of the 1,000 bootstrapped values.

C Construction of the Variance Mimicking Portfolio

This section explains how we form a mimicking portfolio that tracks the market variance payoff based on the return information contained in the 25 equity portfolios. Specifically, we can use equation (B1) to write the (market-hedged) excess return of each portfolio as $r^e_{p,t+1} = -b_{pv} \cdot p^e_{rv,t} + b_{pv} \cdot rv_{t+1} + \epsilon_{p,t+1}$, where $p^e_{rv,t}$ is the forward price of the realized variance formed in the equity market, and $\epsilon_{p,t+1}$ is the idiosyncratic component. Whereas we do not observe $p^e_{rv,t}$, we can replace it by its projection implied by the two-factor model $proj(p^e_{rv,t} \middle| z_t) = V^{e\prime}_v z_t$, and form a strategy that invests: (i) one dollar in portfolio p financed at the risk-free rate; (ii) $\frac{b_{pv} \cdot proj(p^e_{rv,t} | z_t)}{(1+r_{ft})}$ dollars at the risk-free rate. The resulting payoff is equal to

$$x^e_{p,t+1} = r^e_{p,t+1} + b_{pv} \cdot proj(p^e_{rv,t} \middle| z_t) = b_{pv} \cdot rv_{t+1} + e_{p,t+1}, \qquad \text{(C1)}$$

where $e_{p,t+1}$ is equal to $\epsilon_{p,t+1} + b_{pv}(proj(p^e_{rv,t} | z_t) - p^e_{rv,t})$. After stacking the portfolio payoffs and variance betas to form the vectors $x^e_{t+1} = [x^e_{1,t+1}, ..., x^e_{n,t+1}]'$ and $b_v = [b_{1v}, ..., b_{nv}]'$, we can construct the variance-mimicking equity portfolio by solving the following minimization problem:

$$\min_b \; var(rv_{t+1} - b' x^e_{t+1}) \quad \text{s.t. } b' b_v = 1. \qquad \text{(C2)}$$

The optimal coefficient b^* is given by

$$b^* = E(x^e_{t+1} x^{e\prime}_{t+1})^{-1} \left[E(x^e_{t+1} rv_{t+1}) - q b_v \right], \qquad \text{(C3)}$$

where the constant q is equal to $\frac{b'_v \left[E(x^e_{t+1} x^{e\prime}_{t+1})^{-1} E(x^e_{t+1} rv_{t+1}) \right] - 1}{b'_v E(x^e_{t+1} x^{e\prime}_{t+1})^{-1} b_v}$. The final payoff of this portfolio is equal to the sum of the realized variance and a residual term, i.e.,

$$x^e_{s,t+1} = b^{*\prime} x^e_{t+1} = rv_{t+1} + b^{*\prime} e_{t+1}, \qquad \text{(C4)}$$

and its excess return is given by

$$r^e_{s,t+1} = b^{*\prime} r^e_{t+1} = rv_{t+1} + b^{*\prime} e_{t+1} - proj(p^e_{rv,t} \big| z_t), \tag{C5}$$

where $e_{t+1} = [e_{1,t+1}, ..., e_{n,t+1}]'$ and $r^e_{t+1} = [r^e_{1,t+1}, ..., r^e_{n,t+1}]'$. To compute the optimal vector b^* from the data, we first use equation (C1) and measure the payoff vector x^e_{t+1} as $r^e_{t+1} + \hat{b}_v \cdot \hat{V}^{e\prime}_v z_t$, where the estimated vector $\hat{b}_v$ is obtained from the time-series regression of the two-factor model with all predictors, and $\hat{V}^e_v$ is the estimated equity vector estimated using the conditional two-pass regression. Second, we replace $E(x^e_{t+1} x^{e\prime}_{t+1})$ with $\frac{1}{T}\sum_{t=1}^{T} x^e_{t+1} x^{e\prime}_{t+1}$, $E(x^e_{t+1} rv_{t+1})$ with $\frac{1}{T}\sum_{t=1}^{T} x^e_{t+1} rv_{t+1}$, and b_v with $\hat{b}_v$ in equation (C3) to compute b^*. Third, we compute the payoff and excess return the mimicking portfolio as $\hat{b}^{*\prime} x^e_{t+1}$ and $\hat{b}^{*\prime} r^e_{t+1}$, respectively.

Our construction of the mimicking equity portfolio is closely related to the one examined by Ferson, Siegel, and Xu (2006) and Lamont (2001), in which they maximize the correlation between the risk factor and the mimicking portfolio return conditional on a set of predictors z_t. Applying their approach to the variance factor, we obtain a mimicking portfolio whose excess return is given by $b' r^e_{t+1}$, where b is the coefficient vector from the following time-series regression: $rv_{t+1} = c' z_t + b' r^e_{t+1} + e_{t+1}$. The optimization problem in equation (C2) is similar except that we impose two restrictions: (i) the variance beta of the mimicking portfolio is equal to one (to make it comparable to the variance-mimicking option portfolio); (ii) the intercept $c' z_t$ is consistent with the model restriction, i.e., $c' z_t = proj(p^e_{rv,t} \big| z_t) = V^{e\prime}_v z_t$.

D Specification Tests

D.1 The Market Risk Premium

As discussed in Section B, the estimation procedure yields an estimate of the Market Risk Premium (MRP) projection. Studying its properties provides an additional specification test of the two-factor model. This test uses the restriction that the market factor $f_{m,t+1}$ is an excess return which has, by construction, a zero forward price ($p^e_{fm,t} = 0$). Therefore, if the two-factor model is correctly specified, the linear projection of the MRP must be equal to the linear projection of the market factor, i.e.,

$$\lambda^e_{m,t}(z) = proj(f_{m,t+1}|\, z_t) = F'_m z_t. \tag{D1}$$

A testable implication of this restriction is that each element of the risk-neutral vector V^e_m equals zero. The empirical evidence in Table IV reveals that the equality $V^e_m = 0$ is not rejected by the data because none of the estimated coefficients is statistically significant.

We also examine the relationships between the predictors and the MRP projection by reporting the estimated vector $\hat{F}_m - \hat{V}^e_m$ in Table V. Panel A reveals that the PE ratio is the most important explanatory variable with a negative and significant coefficient of -1.96. The resulting premium is strongly countercyclical, as depicted in Figure I which plots its time variation over the long sample (1970-2014). Overall, the properties of the market risk premium are consistent with those documented in the previous literature (e.g., Fama and French (1989) and Keim and Stambaugh (1986)).

[TABLE IV HERE]

[TABLE V HERE]

[FIGURE I HERE]

D.2 Comparison of the Portfolio Return Projections

To further assess the specification of the two-factor model, we study the properties of the projection of the equity portfolio returns on the space spanned by the predictors, defined as

$$proj(r^e_{p,t+1}|\, z_t) = h'_p z_t, \tag{D2}$$

where the coefficient vector h_p is obtained from a time-series regression of the portfolio excess return on the predictors. This projection is unconstrained in the sense that it can be estimated without specifying the identity and/or the number of risk factors. As such, it can be compared with the constrained version implied by the two-factor model:

$$proj^M(r^e_{p,t+1} \big| z_t) = b_{pv}\lambda^e_{v,t}(z) + b_{pm}\lambda^e_{m,t}(z) = b_{pv}(F_v - V^e_v)' z_t + b_{pm}(F_m - V^e_m)' z_t. \quad \text{(D3)}$$

If the two-factor model omits relevant risk factors, we expect the two projections to follow different patterns. To examine this issue, we run a time-series regression of the estimated value of $proj(r^e_{p,t+1} \big| z_t)$ on that of $proj^M(r^e_{p,t+1} \big| z_t)$ for the five quintile portfolios described in Table 1 of the paper. Table VI reveals that the constrained version tracks its unconstrained counterpart almost perfectly, with adjusted R^2s ranging between 0.95 and 0.98. This analysis provides further evidence that the two-factor model performs well at capturing the dynamics of the equity portfolio returns.

[TABLE VI HERE]

D.3 Hedging Errors of the Variance-Mimicking Portfolio

If the two-factor model is correctly specified, two predictions can be made on the hedging error of the variance-mimicking equity portfolio. First, its volatility must be small because the idiosyncratic term is largely diversified away. We find that the volatility of the hedging error represents only 19% of the average residual volatility of the 25 equity portfolios. To visualize this result, we plot the payoff of the mimicking equity portfolio, alongside with that of its option-based counterpart. Whereas the former logically exhibits greater volatility because of the residual term, Figure II shows that it is able to closely track realized variance with a correlation coefficient of 0.80.

Second, the hedging error should be uncorrelated with the macro-finance and broker-dealer variables because the difference between the forward price $p^e_{rv,t}$ and its model-based projection $V_v^{e\prime} z_t$ is unpredictable. Consistent with this prediction, the regression analysis reveals that none of the coefficients is statistically significant.

[FIGURE II HERE]

D.4 Additional Risk Factors

We examine whether our main results change when we include additional risk factors that could potentially drive the cross-section of equity portfolio returns. To begin, we consider three extensions of the two-factor model that include commonly-used risk factors:

$$\begin{aligned} r^e_{p,t+1} &= -c_p' z_t + b_p' f_{t+1} + s_p \cdot r_{smb,t+1} + h_p \cdot r_{hml,t+1} + e_{p,t+1}, \\ r^e_{p,t+1} &= -c_p' z_t + b_p' f_{t+1} + s_p \cdot r_{smb,t+1} + h_p \cdot r_{hml,t+1} + m_p \cdot r_{mom,t+1} + e_{p,t+1}, \\ r^e_{p,t+1} &= -c_p' z_t + b_p' f_{t+1} + s_p \cdot r_{smb,t+1} + h_p \cdot r_{hml,t+1} + l_p \cdot r_{liq,t+1} + e_{p,t+1}, \end{aligned} \tag{D4}$$

where $b_p = [b_{pv}, b_{pm}]'$, $f_{t+1} = [rv_{t+1}, f_{m,t+1}]'$, $r_{smb,t+1}$, $r_{hml,t+1,}$ $r_{mom,t+1}$, $r_{liq,t+1}$ are the returns on zero-investment factor-mimicking portfolios for size, book-to-market, momentum, and liquidity obtained from Kenneth French's and Lubos Pastor's websites, and s_p, h_p, m_p, l_p are the associated risk loadings.

Next, we allow the equity portfolios to load differently on the different components of the market realized variance. We build on previous work by Adrian and Rosenberg (2008) and consider a three-factor model that distinguishes between the low- and high-frequency components of the realized variance denoted by $rv_{1,t+1}$ and $rv_{2,t+1}$, respectively. Both components are extracted from the daily squared returns of the SP500 using the Hodrick–Prescott filter and their sum is equal to rv_{t+1}. The resulting three-factor model can be written as

$$r^e_{p,t+1} = -c_p' z_t + b_{pv} \cdot rv_{t+1} + b_{pv2} \cdot rv_{2,t+1} + b_{pm} \cdot f_{m,t+1} + e_{p,t+1}. \tag{D5}$$

Finally, we allow for a non-linear relationship between the equity portfolio returns and the realized variance. If we model the variance beta as a linear function of rv_{t+1}, we obtain the following three-factor model:

$$r^e_{p,t+1} = -c_p' z_t + b_{pv} \cdot rv_{t+1} + b_{pv2} \cdot rv^2_{t+1} + b_{pm} \cdot f_{m,t+1} + e_{p,t+1}. \tag{D6}$$

For each model, we use the conditional two-pass regression to compute the VRP equity projection, and compare the coefficients for the broker-dealer variables in the equity and option markets. The results in Table VII confirm that the two variables continue to play a significantly different role in the equity and option markets. In addition, the alternative equity VRP projections are all similar to the baseline projection with pairwise correlations ranging between 0.75 and 0.97.

[TABLE VII HERE]

D.5 Time-Varying Portfolio Betas

We model the time variation of the variance and market betas as linear functions of each predictor $z_{j,t} : b_{pv,t} = b_{pv} + b_{pv,j} z_{j,t-1}$ and $b_{pm,t} = b_{pm} + b_{pm,j} z_{j,t-1}$ (for $j = 1, ..., J$). In this case, the factor model can be written as

$$\begin{aligned} r^e_{p,t+1} &= -c_{pt}' z_t + b_{pv,t} \cdot rv_{t+1} + b_{pm,t} \cdot f_{m,t+1} + e_{p,t+1}, \\ &= -c_{pt}' z_t + b_{pv} \cdot rv_{t+1} + b_{pm} \cdot f_{m,t+1} + b_{pv,j} \cdot f_{1,t+1} + b_{pm,j} \cdot f_{2,t+1} + e_{p,t+1}, \end{aligned} \tag{D7}$$

where $f_{1,t+1} = z_{j,t} rv_{t+1}$, $f_{2,t+1} = z_{j,t} f_{m,t+1}$, and the equilibrium value for c_{pt} is given by $b_{pv,t} \cdot V_v^{e\prime} + b_{pm,t} \cdot V_m^{e\prime}$.

To measure the degree of time variation of the portfolio betas, we estimate the coefficients $b_{pv,j}$ and $b_{pm,j}$ for each portfolio and each predictor (realized variance, PE ratio, default spread, inflation, employment, leverage, and PBI return). In Table VIII, we report the coefficient t-statistics for the variance factor and find little evidence of time variation in betas. Only 10% of the coefficients are significant at the 5% level, and these occurrences are evenly distributed across predictors. For the market factor, Table IX shows that the proportion of significant coefficients is slightly higher at 18% and most of them are attributed to the PE ratio. Despite this higher concentration, its impact on the coefficients associated with the broker-dealer variables, $\widehat{v}_v^e(lev)$ and $\widehat{v}_v^e(pbi)$, is expected to be small. The reason is that the magnitude of the bias of these coefficients for each portfolio depends on the three covariances between the omitted factor $f_{2,t+1}$ and lev_t, pbi_t, $f_{m,t+1}$, which are all statistically indistinguishable from zero.

[TABLE VIII HERE]

[TABLE IX HERE]

E Potential Impact of Jump Risk

E.1 The Peso Problem

As discussed by Ang, Hodrick, Xing, and Zhang (2006), the estimation of the VRP can be affected by the Peso problem, i.e., the occurrence of large but infrequent variance jumps. To illustrate, suppose that we want to estimate the average option VRP defined as the difference between the average realized variance $\widehat{rv}$ and the average squared VIX $\widehat{vix}^2$. If the number of variance spikes during the sample is smaller than the option market expected ex-ante (measured by the risk-neutral expectation), $\widehat{rv}$ is lower than $\widehat{vix}^2$ and the magnitude of the estimated VRP is inflated.

In our setting, $\widehat{rv}$ is replaced with the more general expression $\hat{F}_v' z_t$ but the analysis remains unchanged. Therefore, the equity and option VRPs should be interpreted with some caution. However, the VRP difference $\hat{D}_t(z)$ mitigates this problem because the term $\hat{F}_v' z_t$ cancels out (see equation (4) in the paper). Therefore, as long as the risk-neutral equity expectation $\hat{V}_v^{e\prime} z_t$ is not systematically biased—a point discussed below—, $\hat{D}_t(z)$ provides meaningful information about the price difference in both markets.

E.2 Jump Risk and the Omitted-Factor Bias

The equity vector $\hat{V}_v^e$ can potentially be biased if jump risk is required for explaining the cross-section of equity portfolio returns. Although our previous analysis strongly suggests that the two-factor is correctly specified, we carefully examine the theoretical properties of the bias from omitting the jump risk factor.[4] Without loss of generality, we focus on leverage and assume that its (true) risk-neutral coefficients are the same in the equity and option markets (i.e., $v_v^e(lev) = v_v^o(lev)$). Then, we then determine under which conditions $\hat{v}_v^e(lev)$ is positively biased and leads to the negative difference between $\hat{v}_v^o(lev)$ and $\hat{v}_v^e(lev)$ documented in Table 3 of the paper (Panel B).

To summarize our theoretical analysis presented in Section G, we demonstrate that the jump risk premium must be sensitive to leverage (similar to the VRP). In addition, the jump and variance betas must have opposite signs which implies that equity portfolios must combine two properties difficult to reconcile: their returns must be positive when variance is high, but negative when a jump occurs. Assuming that these conditions hold, we further examine whether the bias can quantitatively reproduce the results in Table 3 using a Monte-Carlo simulation analysis that matches the salient features of the data. We find that the sensitivity of the jump risk premium to leverage must be economically large and the portfolio betas on the jump and variance risks must be highly negatively correlated. To summarize, the bias of $\hat{v}_v^e(lev)$ can only explain the observed VRP difference under strong theoretical and empirical conditions that are unlikely to be met.

E.3 Extreme Variance Observations

Besides the Peso problem, it is well known that a single large data observation can have a disproportionate impact on estimated coefficients in linear regression models. To evaluate this impact, we repeat the analysis after winsorizing 2.5% and 5% of the most extreme

[4]Whereas we mainly focus on the jump risk factor, the theoretical analysis of the bias presented in Section G is general and applies to any omitted factor.

market variance observations (1% and 2.5% in each tail). Table X reveals that the estimated coefficients associated with the two broker-dealer variables remain statistically significant in the option market. Therefore, the ability of these variables to explain the VRP difference is not driven by a few extreme observations.

[TABLEX HERE]

E.4 The SVIX Index

When the market is subject to large price movements, the squared VIX computed from option prices is not necessarily equal to the forward price of the realized variance. To address this issue, we examine the properties of the SVIX index that is robust to market jumps (see Martin (2013)). In Table XI, we examine the relationships between this index and the different predictors between January 1996 and January 2012 (period during which the SVIX index is available). Similar to the VIX index, the results confirm the important role played by the two broker-dealer variables in the option market as their estimated coefficients remain both negative and significant.

[TABLE XI HERE]

F Further Evidence

F.1 Alternative Approaches for Forming Equity Portfolios

We consider alternative procedures that could reasonably be used to form the set of variance risk-sensitive portfolios. To begin, we construct these portfolios after modifying the population of stocks in two ways. First, we remove tiny stocks as an alternative to excluding NASDAQ stocks (All but tiny stocks). Similar to Fama and French (2008), we define a stock as tiny if its monthy market capitalization falls below the 20th percentile of the market capitalization for NYSE stocks. Second, we include all existing stocks (All stocks) to address the concern that relevant information on the market VRP is lost when specific stocks are excluded (All stocks).

Next, we consider three approaches for measuring the stock exposures to market and variance risk. First, it is well-known that OLS coefficients are sensitive to outliers (e.g., Martin and Simin (2003)). To address this issue, we compute robust beta t-statictics (Robust betas) using the Huber loss function (Huber (1981)). Second, we expand the time-horizon over which betas are estimated from monthly to quarterly (Quarterly betas). Third, we rank stocks according to their estimated betas to evaluate the importance of controling for estimation errors using t-statistics (No t-statistics).

Finally, nonsynchronous price movements can have a significant impact on stock betas measured at the daily frequency (see Lo and MacKinlay (1990)). In the spirit of Dimson (1979), we therefore add the lagged daily market return $r_{m,d-1}$ and lagged variance innovation $u_{v,d-1}$ in the time-series regresssions performed each month (Lagged factors): $r_{i,d} = \gamma + b^1_{im,t} r_{m,d} + b^2_{im,t} r_{m,d-1} + b^1_{irv,t} u_{v,d} + b^2_{irv,t} u_{v,d-1} + \epsilon_{i,d}$, where $r_{i,d}$ is the return of stock i on day d. The estimated market and variance betas are then computed as $\hat{b}_{im,t} = \hat{b}^1_{im,t} + \hat{b}^2_{im,t}$ and $\hat{b}_{irv,t} = \hat{b}^1_{irv,t} + \hat{b}^2_{irv,t}$, respectively. Alternatively, we also exclude the daily return observations equal to zero for each month and each stock (Zero returns). This approach is motivated by Bekaert, Harvey, and Lundblad (2007) who use the number of zero daily returns as their main illiquidity measure.

Table XIII reports the coefficients for the broker-dealer variables in the equity and option markets. In all of these cases, we still find that the leverage ratio is a key determinant of the difference between the two VRPs. For the PBI return, the difference between the estimated coefficients remains highly significant in all but two cases. When stocks are ranked based on the estimated betas (no t-statistics), the negative relationship between variance betas and average returns weakens and the correlation with the baseline equity VRP drops to 0.44. These results highlight the importance of using t-statistics to reduce estimation errors in short-window regressions. Similar results are obtained with quarterly betas, which is consistent with Ang, Hodrick, Xing, and Zhang (2006) who note that using longer windows reduces the information content of the beta estimates.

[TABLE XII HERE]

F.2 Broker-Dealer Variables in the Equity Market

In Table 3 of the paper, we show that the broker-dealer variables (leverage and PBI return) play no role in driving the time variation of the equity VRP projection. To visualize this result, we plot in Figure III the projections with and without the broker-dealer variables and confirm that they are nearly indistinguishable.

[FIGURE III HERE]

F.3 Alternative Predictive Variables

In this section, we measure whether the impact of the broker-dealer variables (leverage and PBI return) on the equity and option VRPs changes with the identity of the macro-finance variables. First, we replace the PE ratio with the dividend yield computed from the CRSP index. Second, we replace the quarterly growth rate in employment with two alternative indicators of real activity: the seasonally-adjusted quarterly growth rate in industrial production and the business cycle indicator constructed by Aruoba, Diebold, and Scotti (2009) which aggregates information regarding employment, industrial production, and interest rates. Third, we take the initial set of macro-finance variables and add two commonly-used interest rate variables: the 3-month T-bill rate and the term spread, defined as the difference between the 10- and 1-year T-bond yields. Fourth, we add the quarterly variance of the inflation rate following recent work by Paye (2012) who finds that this variable helps to predict the future quarterly volatility. For each specification, Table XIII reports the coefficients for the broker-dealer variables in the equity and option markets. In all of these cases, the two broker-dealer variables continue to play a significantly different role in the equity and option markets.

We also consider alternative specifications in which we add to the baseline set of predictors the squared values of the macro-finance variables. The motivation for these tests is to determine whether the explanatory power of the broker-dealer variables stems from their ability to capture any non-linear relationships between the macro-finance variables and the VRPs. The results documented in Table XIV show that it is not the case.

[TABLE XIII HERE]

[TABLE XIV HERE]

F.4 Implied Individual Stock Variance and Correlation

The market variance is equal to the sum of the individual stock variances and their covariances. Therefore, the VIX index contains information about the prices of both individual stock variance risk (changes in individual stock variances) and correlation risk (changes in the correlation structure of stocks). In this section, we examine how the broker-dealer variables affect each of these two prices. We extract the price of individual stock variance from individual option prices as the equally-weighted average of the implied variances of the SP500 stocks. For correlation risk, its price is measured by the implied correlation among SP500 stocks computed from index and individual option prices. Both series are computed monthly and are available between January 1996 and August 2013.[5]

The relationships between the broker-dealer variables and the implied stock variance is reported in Panel B of XV (first row). Contrary to the squared VIX, the coefficient associated with leverage is positive and is not statistically significant when considered jointly with the PBI return (with a t-statistic of 1.47). This finding is consistent with the empirical role played by intermediaries in the option market. Whereas the VIX is inferred from index options, the implied stock variance is computed from individual stock options whose supply is not dominated by financial intermediaries (see Garleanu, Pedersen, and Poteshman (2009)). Changes in their risk-bearing capacity are therefore less likely to

[5] Driessen, Maenhout, and Vilkov (2009) provide a detailed description of the construction of these variables.

drive the prices of these options.

Repeating this analysis for the implied correlation, we observe in Panel B (second row) that it shares strong similarities with the squared VIX as the leverage coefficient is both negative and highly significant. Therefore, periods when intermediaries deleverage are associated with an increase in the prices of both aggregate variance and correlation risks. This similarity resonates with the study by Driessen, Maenhout, and Vilkov (2009) which finds that the market VRP is mostly attributed to correlation risk.

[TABLE XV HERE]

F.5 Analysis based on Monthly Data

In this section, we re-estimate the equity and option VRPs over a monthly time-horizon using the same estimation procedure as the one described in Section B. All of the variables (risk factors, portfolio returns, predictors) are available at the monthly frequency, except for the leverage ratio of broker-dealers. To address this issue, we linearly interpolate the quarterly leverage values (similar to Kan, Robotti, and Shanken (2013), and Vissing-Jorgensen and Attanasio (2003)). We also replace the quarterly VIX with its monthly counterpart computed from the prices of one-month SP500 options.

Table XVI examines the explanatory power of the predictors on the monthly VRPs and reveals that the two broker-dealer variables remain the only significant drivers of the VRP difference (the t-statistics are equal -4.26 for leverage and -5.08 for the PBI return). We observe that the explanatory power of the PBI return becomes stronger at the monthly horizon, consistent with the fact that changes in this variable are short-lived. For the equity market, using monthly data seems to introduce some noise in the relationship between the macro-finance variables and the VRP as the t-statistics decrease and the model is marginally rejected (when the 10% threshold is used). However, the coefficients share strong commonalities with their quarterly-based counterparts. In most cases, their signs remain the same and their ratios are close to one third.

[TABLE XVI HERE]

F.6 Analysis based on Individual Stocks

F.6.1 Estimation Procedure

The analysis of the equity VRP presented in the paper is based on a set of variance risk-sensitive equity portfolios. An alternative procedure advocated, among others, by Ang, Liu, and Schwarz (2010), and Gagliardini, Ossola, and Scaillet (2015) is to directly use individual stock data as inputs for estimation. Whereas the extended two-pass regression is similar to the one presented in Section B, Gagliardini, Ossola, and Scaillet (2015) explain that two important differences must be properly accounted for. First, the panel of individual stock returns is unbalanced and contains stocks with short-return histories. These stocks may yield regression coefficients that are either highly volatile or impossible to compute (if the matrix inversion cannot be performed). To address this issue, it is necessary to introduce an appropriate trimming mechanism to reduce the cross-section of stocks. Second, the number of individual stocks is extremely large (more than 7,000 in our sample). The econometric theory must account for this feature by letting both the number of return observations and the number of stocks grow large (double asymptotics). It implies that the asymptotic distributions of the estimated coefficients and the test statistic differ from those obtained with portfolios.

The estimation procedure can be summarized as follows. In the first step, we compute, for each individual stock i ($i = 1, ..., m$), the OLS estimator of the $(J+2)$-vector of coefficients $\beta_i = (-c_i', b_{iv}, b_{im})'$ as

$$\hat{\beta}_i = \left(\sum_{t=1}^{T} I_{i,t} x_t x_t' \right)^{-1} \sum_{t=1}^{T} I_{i,t} x_t r_{i,t}^e, \tag{F1}$$

where $r_{i,t}^e$ is the stock excess return, x_{t+1} is a $(J+2)$-vector defined as $(z_t', rv_{t+1}, f_{m,t+1})'$, T is the total number of observations, and $I_{i,t}$ is a indicator function equal to 1 if $r_{i,t}^e$ is observed. Following Gagliardini, Ossola, and Scaillet (2015), we introduce a trimming device that keeps stock i in the cross-section only if $CN(\hat{Q}_{x,i}) \leq \chi_{1,T}$ and $\tau_{i,T} \leq \chi_{2,T}$, where $CN(\hat{Q}_{x,i}) = \left(eig_{\max}(\hat{Q}_{x,i})/eig_{\min}\left(\hat{Q}_{x,i}\right)\right)^{\frac{1}{2}}$ denotes the condition number of $\hat{Q}_{x,i} = \frac{1}{T}\sum_{t=1}^{T} I_{i,t}x_t x_t'$, $\tau_{i,T} = \frac{T}{T_i}$, and $T_i = \sum_{t=1}^{T} I_{i,t}$ is the total number of return observations for stock i. As advocated by Gagliardini, Ossola, and Scaillet (2015), we set $\chi_{1,T} = 15$ and $\chi_{2,T} = 2.275$ (which implies a minimum of 80 quarterly return observations).[6]

In the second step, we compute the estimator of the $2J$-vector $V^e = (V_v^{e\prime}, V_m^{e\prime})'$ that drives the risk-neutral expectations of the two risk factors (variance and market) using the non-trimmed stocks only. Similar to the portfolio approach, we use a WLS approach in which the $J \times J$ matrix of estimated weights for each stock i is computed as $\hat{w}_i = diag(1_i^{\chi}\hat{v}_i)^{-1}$, where $\hat{v}_i$ is given by equation (B4), and 1_i^{χ} is $J \times J$ matrix whose diagonal elements are equal to one if stock i is kept in the cross-section and zero otherwise. Using the estimated matrix of weights $\hat{w}_i$, we obtain the following estimator of V^e :

$$\widehat{V}_{stock}^{e} = \left(\sum_{i=1}^{m} \hat{B}_i'\hat{w}_i\hat{B}_i\right)^{-1}\sum_{i=1}^{m} \hat{B}_i'\hat{w}_i\hat{c}_i, \tag{F2}$$

where $\hat{B}_i$ a $J \times 2J$ matrix equal to $[\hat{b}_{iv} \cdot I_J, \hat{b}_{im} \cdot I_J]$. The J-vector of estimated coefficients $\widehat{V}_{v,stock}^{e}$ can be then plugged in equation (B7) to obtain the VRP projection in the equity market, $\hat{\lambda}_{v,t}^{e}(z) = \left(\hat{F}_v - \hat{V}_{v,stock}^{e}\right)' z_t$.

When T and m grows large and the two-factor model is correctly specified, Gagliardini, Ossola, and Scaillet (2015) demonstrate that the $2J$-vector $\hat{\Lambda}_{stock}^{e} = vec(\hat{F}) - \hat{V}_{stock}^{e}$ is consistent and normally distributed, i.e.,

$$\sqrt{T}\left(\hat{\Lambda}_{stock}^{e} - \Lambda^e\right) \Rightarrow N(\mathbf{0}_{2J\times 1}, \Sigma_F). \tag{F3}$$

where $\Sigma_F = (I_J \otimes Q_z^{-1})\Sigma_u(I_J \otimes Q_z^{-1})$. As discussed above, the asymptotic distribution

[6] Specifically, Gagliardini, Ossola, and Scaillet (2015) conduct a Monte-Carlo analysls based on $T = 546$ monthly observations, and note that $\chi_{2,T}$ must be equal to 2.275 $\left(\frac{546}{200}\right)$ in order to estimate the risk premium coefficients and the model test statistic (see p. 38). In our sample, T is equal to 179, which implies that each stock must have at least 80 return observations $\left(\text{i.e., } \frac{179}{80} = 2.23\right)$.

of $\hat{\Lambda}^e_{stock}$ differs from its portfolio-based counterpart because its covariance matrix only depends on the variance of the coefficients in the factor predictive regressions (i.e., the term $\frac{1}{n}\Sigma_{V^e}$ that appears in equation (B8) vanishes here).

The statistic for testing whether the two-factor model is correctly specified is also different from its portfolio-based counterpart in equation (B11). The test developed by Gagliardini, Ossola, and Scaillet (2015) is based on the statistic $\hat{\xi}_{m,T}$ defined as $T\sqrt{m}(\hat{Q}-\frac{1}{T}J)$, where $\hat{Q} = \frac{1}{m}\sum_{i=1}^{m}\hat{\zeta}_i'\hat{w}_i\hat{\zeta}_i$, and $\hat{\zeta}_i = \hat{c}_i - \hat{B}_i\hat{V}^e_{stock}$. As T and n grow large, it can be shown that

$$\hat{\xi}_{m,T} \Rightarrow N(0,\Sigma_\xi). \tag{F4}$$

The variance term is defined as

$$\Sigma_\xi = 2\lim_{m\to\infty} E\left[\frac{1}{n}\sum_{i,j}\frac{\tau^2_{i,T}\tau^2_{j,T}}{\tau^2_{i,j,T}} trace\left[\left(C'_{V^e}Q^{-1}_{x,i}S_{ij}Q^{-1}_{x,j}C_{V^e}\right)w_i\left(C'_{V^e}Q^{-1}_{x,j}S_{ji}Q^{-1}_{x,i}C_{V^e}\right)w_j\right]\right],$$

where $\tau_{i,j,T} = \frac{1}{T}\sum_{t=1}^{T} I_{i,t}I_{j,t}$. To implement this test, we simply need to replace C_{V^e}, $Q_{x,i}$, $Q_{x,j}$, S_{ij}, w_i, and w_j with their empirical counterparts to obtain a consistent estimator of Σ_ξ. Finally, we use the same bootstrap procedure as the one outlined in Section B.3 to examine the VRP difference between the equity and option markets. To make the bootstrap approach tractable, we assume that the return residuals from the two-factor model are uncorrelated across stocks.

F.6.2 Empirical Results

The results in Table XVII reveal that our main results hold again with individual stocks. The leverage ratio and PBI return remain the most important drivers of the VRP difference with t-statistics equal to -3.66 and -6.36, respectively. Similar to the results documented by Gagliardini, Ossola, and Scaillet (2015) for commonly-used asset pricing models (e.g., CAPM, Fama-French), our specification test largely rejects the null hypothesis that the two-factor model is able to price individual stocks. This finding resonates with the previous literature that highlights the challenges of explaining the cross-section of individual stock returns as (i) individual stocks are likely to be exposed to a wide range of risk factors (e.g., Lewellen, Nagel, and Shanken (2010), Daniel and Titman (2012)); (ii) their betas are likely to change over time (e.g., Andersen, Bollerslev, Diebold, and Wu (2006)).[7] The rejection of the two-factor model contrasts with its ability to explain the cross-section of portfolio returns used in our baseline specification. Therefore, the portfolio-based approach described in Section B allows for a more accurate estimation of the equity VRP.

[TABLE XVII HERE]

G Analysis of the Omitted-Factor Bias

G.1 Theoretical Analysis

In this section, we study the potential impact of omitting a relevant factor on the estimated risk-neutral equity vector $\hat{V}_v^e$. Whereas we focus on the coefficient associated with leverage, $\hat{v}_v^e(lev)$, the same analysis applies to the PBI return. Without loss of generality, we make several assumptions to make our presentation as simple as possible. First, we assume that the portfolio returns are driven by the standardized leverage lev_t and two demeaned factors, the realized variance rv_{t+1} and an additional factor $f_{1,t+1}$. To allow for a non-zero correlation ρ between the two factors, we write $f_{1,t+1}$ as $\rho rv_{t+1} + b_\varepsilon \varepsilon_{1,t+1}$, where b_ε is equal to $\sqrt{(1-\rho^2)}$ and the factor $\varepsilon_{1,t+1}$ is uncorrelated with rv_{t+1}. Second,

[7] In theory, we could incorporate several sources of risk and explicitly specify the beta dynamics. However, such models are difficult to estimate because of the large number of parameters. In addition, Ghysels (1998) shows that a wrong specification of time-varying betas may result in large pricing errors (possibly greater than those produced by a constant beta model).

we define the covariance matrix of the vector $[lev_t, rv_{t+1}, \varepsilon_{1,t+1}]'$ as

$$\Omega = \begin{bmatrix} 1 & f_v^e(lev) & f_\varepsilon^e(lev) \\ f_v^e(lev) & \sigma^2 & 0 \\ f_\varepsilon^e(lev) & 0 & \sigma^2 \end{bmatrix}, \tag{G1}$$

where the volatilities of rv_{t+1}, $\varepsilon_{1,t+1}$ (and thus $f_{1,t+1}$) are captured by the same parameter σ. Based on the coefficients in equation (G1), we can write the projections of the two factors on the space spanned by leverage as

$$proj(rv_{t+1}|\, z_t) = f_v^e(lev) \cdot lev_t, \qquad proj(f_{1,t+1}|\, z_t) = (\rho f_v^e(lev) + b_\varepsilon f_\varepsilon^e(lev)) \cdot lev_t. \tag{G2}$$

Similarly, we define the projections of the forward factor prices as

$$proj(p_{rv,t}^e|\, z_t) = v_v^e(lev) \cdot lev_t, \qquad proj(p_{f1,t}^e|\, z_t) = (\rho v_v^e(lev) + b_\varepsilon v_\varepsilon^e(lev)) \cdot lev_t. \tag{G3}$$

Third, we assume that the vector of portfolio betas on rv_{t+1} and $f_{1,t+1}$, denoted by $b_p = [b_{pv}, b_{pf}]'$, is drawn from a bivariate normal distribution with a zero mean and a covariance matrix Ω_b in which the variance terms are both equal to σ_b^2 and the covariance is given by $\rho_b \sigma_b^2$. The correlation coefficient ρ_b provides a convenient way to examine different scenarios regarding the signs of the betas: if ρ_b is positive, b_{pv} and b_{pf} tend to have the same signs, while the opposite holds if ρ_b is negative. The resulting factor representation of the excess return of each portfolio is defined as

$$r_{p,t+1}^e = -c_p \cdot lev_t + b_{pv} \cdot rv_{t+1} + b_{pf} \cdot f_{1,t+1} + e_{p,t+1}, \tag{G4}$$

where the restriction imposed by the model on the intercept is given by

$$c_p = b_{pv} \cdot v_v^e(lev) + b_{pf} \cdot (\rho v_v^e(lev) + b_\varepsilon v_\varepsilon^e(lev)). \tag{G5}$$

We study the properties of $\hat{v}_v^e(lev)$ when the model used for estimation includes lev_t and rv_{t+1}, but omits the relevant factor $f_{1,t+1}$. Standard results on regression analysis reveal that the estimated coefficient vector $\hat{\beta}_p = (-\hat{c}_p, \hat{b}_{pv})'$ is biased, i.e.,

$$bias(\hat{\beta}_p) = \Omega_{lev,rv}^{-1} \begin{bmatrix} cov(lev_t, \rho rv_{t+1}) \\ cov(rv_{t+1}, \rho rv_{t+1}) \end{bmatrix} b_{pf} + \Omega_{lev,rv}^{-1} \begin{bmatrix} cov(lev_t, b_\varepsilon \varepsilon) \\ cov(rv_{t+1}, b_\varepsilon \varepsilon) \end{bmatrix} b_{pf}, \quad \text{(G6)}$$

where $\Omega_{lev,rv}$ denotes the covariance matrix of lev_t and rv_{t+1}. From equation (G6), the average values of the two estimated coefficient can be written as

$$\begin{aligned} c_p^* &= E(\hat{c}_p) = c_p - \frac{\sigma^2 b_\varepsilon f_\varepsilon^e(lev)}{\sigma^2 - f_v^e(lev)^2} b_{pf}, \\ b_{pv}^* &= E(\hat{b}_{pv}) = b_{pv} + \rho b_{pf} - \frac{b_\varepsilon f_\varepsilon^e(lev) f_v^e(lev)}{\sigma^2 - f_v^e(lev)^2} b_{pf}. \end{aligned} \quad \text{(G7)}$$

Any bias in the coefficient vector $\hat{\beta}_p$ across portfolios can potentially affect the average value of $\hat{v}_v^e(lev)$ because the latter is obtained from the cross-sectional regression of the vector $c^* = [c_1^*, ..., c_n^*]'$ on the vector $b_v^* = [b_{1v}^*, ..., b_{nv}^*]'$, i.e.,

$$v_v^e(lev)^* = E(\hat{v}_v^e(lev)) = \left(b_v^{*\prime} b_v^*\right)^{-1} b_v^{*\prime} c^*. \quad \text{(G8)}$$

Intuitively, $v_v^e(lev)^*$ can be interpreted as a cross-sectional average of the portfolio pseudo-values, where each pseudo-value, $v_v^e(lev)_p^*$, is defined such that the equilibrium condition applied to the misspecified model holds (for $p = 1, ..., n$):

$$c_p^* = b_{pv}^* \cdot v_v^e(lev)_p^*. \quad \text{(G9)}$$

Therefore, we can determine the properties of the bias of $\hat{v}_v^e(lev)$ by studying the difference between the pseudo-value $v_v^e(lev)_p^*$ and the true value $v_v^e(lev)$. Taking the difference between the LHSs and RHSs of equations (G5) and (G9) and rearranging terms, we can express the difference between $v_v^e(lev)_p^*$ and $v_v^e(lev)$ as

$$\frac{b_{pf}}{b_{pv}^*}\left[b_\varepsilon\left(v_\varepsilon^e(lev) - \frac{\sigma^2 + f_\varepsilon^e(lev)f_v^e(lev)}{\sigma^2 - f_v^e(lev)^2}f_\varepsilon^e(lev)\right)\right] = v_v^e(lev)_p^* - v_v^e(lev). \quad \text{(G10)}$$

This expression can be simplified if we set $f_v^e(lev)$ equal to zero—an assumption consistent with the fact that the estimated coefficient $\hat{f}_v^e(lev)$ is not significant (see Table 2 of the paper). In this case, b_{pv}^* is equal to $b_{pv} + \rho b_{pf}$ and we have

$$\frac{b_{pf}}{b_{pf}(\rho_b + \rho) + \varepsilon_b}\left[b_\varepsilon(v_\varepsilon^e(lev) - f_\varepsilon^e(lev))\right] = v_v^e(lev)_p^* - v_v^e(lev), \quad \text{(G11)}$$

where b_{pv} is decomposed into its two orthogonal components, $b_{pf}\rho_b$ and ε_b.

Equation (G11) reveals three cases where the estimated leverage coefficient is unbiased. First, $bias(\hat{v}_v^e(lev))$ equals zero if the risk premium of the orthogonal factor $\varepsilon_{1,t+1}$, $\lambda_{\varepsilon,t}(z)$, is unrelated to leverage. This condition implies that $v_\varepsilon^e(lev) - f_\varepsilon^e(lev)$ is null and that $v_v^e(lev)_p^*$ equals $v_v^e(lev)$ for each portfolio. Second, we obtain the same result if the factor correlation ρ tends to ± 1 because $b_\varepsilon = \sqrt{(1-\rho^2)}$ tends to zero. Third, $\hat{v}_v^e(lev)$ is unbiased when the sum of the correlations, $\rho_b + \rho$, is equal to zero. In this case, the first term on the LHS becomes $\frac{b_{pf}}{\varepsilon_b}$ and the two elements of this ratio are uncorrelated. Because $\frac{b_{pf}}{\varepsilon_b}$ randomly takes negative and positive values, the cross-portfolio differences between $v_v^e(lev)_p^*$ and $v_v^e(lev)$ offset one another and $\hat{v}_v^e(lev)$ is unbiased.

If none of these conditions is met, $\hat{v}_v^e(lev)$ is biased either positively or negatively depending on the signs of: (i) the ratio $\frac{b_{pf}}{b_{pv}^*}$ (as measured by the sign of $\rho_b + \rho$); (ii) the coefficient $v_\varepsilon^e(lev) - f_\varepsilon^e(lev)$ that relates leverage to $\lambda_{\varepsilon,t}(z)$. If both terms are positive or negative for most portfolios, the LHS of equation (G11) is positive, which implies that the bias is positive, i.e., $\hat{v}_v^e(lev)$ is, on average, higher than $v_v^e(lev)$. On the other hand, if the two sums have opposite signs for most portfolios, the LHS of equation (G11) is negative and the resulting bias is negative, i.e., $\hat{v}_v^e(lev)$ is, on average, lower than $v_v^e(lev)$.

G.2 Simulation Analysis

To quantify the magnitude of this bias, we recourse to a Monte-Carlo simulation analysis. The parameter values are chosen according to our empirical findings. The factor volatility σ is equal to 0.012 (the standard deviation of the realized variance), and the beta volatility σ_b is equal to 0.51 (the cross-sectional standard deviation of the variance betas). Importantly, we set $v_v^e(lev)$ equal to -0.37 so that the equity VRP, defined here as $(f_v^e(lev) - v_v^e(lev))\, lev_t = -v_v^e(lev) lev_t$, exhibits the same relationship with leverage as the one estimated in the option market (see Table 3 of the paper). Therefore, the (true) impact of leverage on the equity and option VRPs is exactly the same. In both markets, a decrease in leverage increases the compensation for hedging against variance risk (i.e., both VRPs decrease).

The simulation analysis is conducted over 1,000 trials, where each trial s ($s = 1, ..., 1,000$) includes three steps. First, we randomly draw, for each portfolio p ($p = 1, ..., 25$), the beta vector b_p^s from the bivariate normal distribution. Second, we compute the values taken by the two coefficients $c_p^{*,s}$ and $b_{p,v}^{*,s}$ for each portfolio using equations (G7). Third, we create the two vectors $c^{*,s} = [c_1^{*,s}, ..., c_{25}^{*,s}]'$ and $b_v^{*,s} = [b_{1v}^{*,s}, ..., b_{25v}^{*,s}]'$, and use equation (G8) to compute $v_v^e(lev)^{*,s}$. After repeating these three steps over 1,000 draws of portfolio betas, we compute $bias(\hat{v}_v^e(lev))$ as $\frac{1}{1,000}\sum_{s=1}^{1,000} v_v^e(lev)^{*,s} - v_v^e(lev)$.

In our first scenario, we interpret the omitted factor $f_{1,t+1}$ as a jump risk factor that has the same premium properties as those of the realized variance by setting $f_f^e(lev) = 0$ and $v_f^e(lev) = -0.37$. The negative value for $v_f^e(lev)$ implies that the jump risk premium, $\left(f_f^e(lev) - v_f^e(lev)\right) lev_t$, is strongly negative when intermediaries' leverage is low (similar to the VRP itself). In addition, a jump factor is positively correlated with realized variance by construction (Todorov (2010)). To account for this positive relationship, we set ρ is equal to 0.55 (the correlation between the realized variance and the high-frequency variance component computed by Adrian and Rosenberg (2008)). In Panel A of Figure IV, we plot the relative bias, defined as $\frac{bias(\hat{v}_v^e(lev))}{abs(v_v^e(lev))}$, across different values for the beta correlation ρ_b ranging between -0.9 and 0.9. Because $v_\varepsilon^e(lev) - f_\varepsilon^e(lev)$ is negative, we have a positive bias when $\rho_b + \rho$ is negative (i.e., $\frac{b_{pf}}{b_{pv}^*}$ tends to be negative). At $\rho_b = -0.53$, the sum $\rho_b + \rho$ is null and the resulting bias is equal to zero. Finally, the bias becomes negative when $\rho_b > -0.53$ because $\frac{b_{pf}}{b_{pv}^*}$ tends to be positive. All of these results are consistent with the predictions of equation (G11).

This analysis is important for interpreting the main result of the paper that leverage drives the option VRP, but not the equity VRP. To attribute this result to the omission of a jump risk factor, $v_v^e(lev)^*$ must be equal to zero. Given that $v_v^e(lev)$ equals -0.37, the relative bias must therefore be positive and equal to 100%. However, Panel A reveals that the highest bias is close to 90%. A bias of 100% is achievable if we are willing to assume that the risk premium of $f_{1,t+1}$ is extremely sensitive to leverage. For instance, suppose that the term $v_\varepsilon^e(lev) - f_\varepsilon^e(lev)$ is doubled from -0.37 to -0.74 so that a one-standard deviation decline in leverage increases the magnitude of the jump premium by 3.0% per year. In this case, Panel A shows that the bias reaches 100% provided that portfolio betas have opposite signs 79% of the time (i.e., ρ_b must be equal to -0.80).[8] This condition implies that the equity portfolios must combine two properties that are difficult to reconcile: their returns must be high (low) when the realized variance is high and, at the same time, low (high) when the market return exhibits a jump.

In the second scenario, we assume that $f_{1,t+1}$ has the opposite premium properties to the ones of the realized variance, i.e., $f_f^e(lev) = 0$ and $v_f^e(lev) = 0.37$. The omitted factor can be interpreted as a recession risk factor whose premium, $\left(f_f^e(lev) - v_f^e(lev)\right) lev_t$, increases when intermediaries' leverage is below average (contrary to the VRP). The main difference with the previous scenario is that $v_\varepsilon^e(lev) - f_\varepsilon^e(lev)$ turns positive, which produces a positive relationship between ρ_b and $bias(\hat{v}_v^e(lev))$. To plot this relationship, we set $v_f^e(lev)$ equal to 0.37 and ρ equal to -0.41 (the average correlation between the realized variance and the market return). The results in Panel B reveal that the bias

[8] This proportion is obtained by simulating a large number of draws for the beta vector $b_p = [b_{pv}, b_{pf}]'$ from the bivariate normal distribution (with $\rho_b = -0.85$), and then counting the number of times b_{pv} and b_{pf} have different signs.

reaches 100% only if the portfolio betas have the same sign 85% of the time (i.e., ρ_b must be equal to 0.89). Similar to the first scenario, this last condition implies that the portfolios must combine two properties that are difficult to reconcile: they must perform well (poorly) both when the realized variance is high and when the recession hits. If we are willing to double $v_f^e(lev)$ from 0.37 to 0.74, the required beta correlation remains high at 0.73.

[FIGURE IV HERE]

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Table I: Unconditional Moments of the Predictive Variables

Panel A reports the first four moments as well as the first-, and second-order partial autocorrelation coefficients of the predictors used to capture the dynamics of the Variance Risk Premium (VRP) over the long sample from 1970 to 2014 (179 quarterly observations). The set of predictors (all expressed in log form) includes the lagged realized variance (RV), the price/earnings ratio (PE), the default spread (DEF), the quarterly inflation rate of the producer price index (PPI), the quarterly growth rate of the seasonally-adjusted number of employees in the nonfarm sector (EMP), the leverage ratio of broker-dealers (LEV), and the quarterly return of the prime broker index (PBI). Panel B reports the same statistics over the short sample from 1992 to 2014 (92 quarterly observations).

Panel A: Long Sample (1970-2014)

	Mean	Std.	Skew.	Kurt.	AC1	AC2
Lagged Realized Variance (RV)	−5.34	0.79	0.96	4.57	0.66	0.14
Price/Earnings Ratio (PE)	2.86	0.45	-0.14	2.18	0.98	−0.14
Default Spread (DEF)	1.01%	0.41%	1.85	8.29	0.83	−0.11
Producer Price Index (PPI)	0.92%	1.28%	0.20	6.22	0.41	0.21
Employment Growth (EMP)	0.37%	0.56%	−0.83	4.84	0.75	0.04
Broker-Dealer Leverage (LEV)	2.71	0.60	0.06	2.20	0.96	0.12
Prime Broker Index (PBI)	1.98%	17.6%	−0.57	4.62	0.05	−0.14

Panel B: Short Sample (1992-2014)

	Mean	Std.	Skew.	Kurt.	AC1	AC2
Lagged Realized Variance (RV)	−5.26	0.89	0.76	3.41	0.72	0.13
Price/Earnings Ratio (PE)	3.22	0.24	0.49	3.22	0.94	−0.19
Default Spread (DEF)	0.89%	0.40%	3.21	17.00	0.81	−0.24
Producer Price Index (PPI)	0.55%	1.09%	−1.24	10.09	0.14	0.00
Employment Growth (EMP)	0.27%	0.47%	−1.71	6.79	0.82	0.17
Broker-Dealer Leverage (LEV)	3.20	0.31	1.08	6.38	0.84	0.03
Prime Broker Index (PBI)	2.07%	16.3%	−1.31	6.19	0.05	−0.10

Table II: Correlation Matrix of the Predictive Variables

Panel A reports the correlation matrix of the predictors over the long sample from 1970 to 2014 (179 quarterly observations). The set of predictors (all expressed in log form) includes the lagged realized variance (RV), the price/earnings ratio (PE), the default spread (DEF), the quarterly inflation rate of the producer price index (PPI), the quarterly growth rate of the seasonally-adjusted number of employees in the nonfarm sector (EMP), the leverage ratio of broker-dealers (LEV), and the quarterly return of the prime broker index (PBI). Panel B reports the same statistics over the short sample from 1992 to 2014 (92 quarterly observations).

Panel A: Long Sample (1970-2012)

	PE	DEF	PPI	EMP	LEV	PBI
Lagged Realized Variance (RV)	0.06	0.41	−0.08	−0.44	0.11	−0.28
Price/Earnings Ratio (PE)		−0.53	−0.30	−0.02	0.78	0.04
Default Spread (DEF)			−0.09	−0.52	−0.22	−0.04
Producer Price Index (PPI)				0.14	−0.30	−0.02
Employment Growth (EMP)					−0.22	−0.04
Broker-Dealer Leverage (LEV)						−0.07

Panel B: Short Sample (1992-2014)

	PE	DEF	PPI	EMP	LEV	PBI
Lagged Realized Variance (RV)	0.05	0.62	−0.20	−0.53	0.40	−0.45
Price/Earnings Ratio (PE)		−0.47	0.10	0.39	0.19	0.21
Default Spread (DEF)			−0.35	−0.76	−0.32	−0.40
Producer Price Index (PPI)				0.23	0.04	0.15
Employment Growth (EMP)					−0.27	0.21
Broker-Dealer Leverage (LEV)						−0.30

Table III: Summary Statistics for the Equity Portfolios: Short Sample

Panel A shows the annualized excess mean, standard deviation, size (in log form), Book-to-Market (BM) ratio, and the pre-, post-rank variance betas of the quarterly returns of quintile portfolios formed by equally weighting all portfolios in the same variance beta quintile (Low, 2, 3, 4, High). For each quintile portfolio, the pre-rank beta is defined as the mean of the variance betas across stocks on the portfolio formation dates. The post-rank variance beta is computed from the time-series regression of the portfolio return on the variance and market factors (including all predictors). Panel B reports the annualized estimated alpha of each quintile portfolio using the CAPM, the Fama-French (FF) model that includes the market, size, and BM factors, and two extensions that include momentum and liquidity factors, respectively. The figures in parentheses report the heteroskedasticity-robust t-statistics. ***, **, and * designate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Unconditional Moments, Characteristics, and Variance Betas

Quintile	Mean (% p.a.)	St. Dev. (% p.a.)	Size	BM	Pre-rank beta		Post-rank beta	
Low	10.29	14.74	9.33	0.54	−0.65	(−2.25)	−1.66***	(−4.55)
2	9.45	15.52	9.44	0.55	−0.29	(−0.82)	−1.01***	(−2.91)
3	7.47	14.93	9.49	0.52	−0.02	(−0.06)	−0.99***	(−2.83)
4	5.54	14.86	9.44	0.54	0.25	(0.70)	−0.59**	(−2.15)
High	5.19	16.35	9.46	0.53	0.61	(2.15)	−0.17	(−0.48)
High-Low	−5.09	8.31	0.13	−0.01	1.22	(4.40)	1.49***	(3.32)

Panel B: Alphas

Quintile	CAPM (% p.a.)		Fama-French (FF) (% p.a.)		FF+Momentum (% p.a.)		FF+Liquidity (% p.a.)	
Low	4.07**	(2.76)	2.40*	(1.73)	2.64*	(1.94)	1.54	(1.28)
2	2.95*	(1.72)	1.62	(1.17)	0.96	(0.58)	1.30	(0.87)
3	0.94	(0.73)	−0.04	(−0.38)	0.04	(0.03)	−0.06	(−0.61)
4	−0.99	(−0.84)	−2.07**	(−2.26)	−2.37***	(−2.63)	−2.49***	(−2.58)
High	−1.90**	(−1.31)	−2.96**	(−2.31)	−2.92**	(−2.01)	−3.13**	(−2.24)
High-Low	−5.97***	(−3.13)	−5.36***	(−2.72)	−5.56***	(−2.83)	−4.67**	(−2.42)

Table IV: Market Factor: Risk Neutral Expectation

Panel A reports the estimated coefficients that drive the risk-neutral expectation of the market factor for the set of macro-finance variables that includes the lagged realized variance (RV), the price/earnings ratio (PE), the default spread (DEF), the quarterly inflation rate (PPI), and the quarterly employment rate (EMP). The coefficients determine the impact of a one-standard deviation change in the variables on the risk-neutral expectation of the market factor and are obtained from the conditional two-pass regression. Panel B examines the incremental predictive power of the broker-dealer leverage ratio (LEV) and the quarterly return of the prime broker index (PBI) in the presence of the macro-finance variables. The figures in parentheses report the heteroskedasticity-robust t-statistics.

Panel A: Macro-Finance Variables

	Mean	R. Var. (RV)	PE ratio (PE)	Default (DEF)	Inflation (PPI)	Employ. (EMP)
Risk Neutral Expectation	0.01 (0.08)	−0.18 (−1.19)	−0.12 (−0.48)	−0.02 (−0.08)	−0.01 (−0.10)	−0.22 (−1.32)

Panel B: Contribution of Broker-Dealer Variables

			Combined	
	Leverage (LEV)	PB Index (PBI)	Leverage (LEV)	PB Index (PBI)
Risk Neutral Expectation	−0.14 (−1.02)	0.16 (1.35)	−0.11 (−0.77)	0.14 (1.14)

Table V: Market Factor: Risk Premium

Panel A examines the relationships between the macro-finance variables and the Market Risk Premium (MRP). The set of variables includes the lagged realized variance (RV), the price/earnings ratio (PE), the default spread (DEF), the quarterly inflation rate (PPI), and the quarterly employment rate (EMP). The coefficients determine the impact of a one-standard deviation change in the variables on the MRP and are obtained from the conditional two-pass regression. Panel B examines the incremental predictive power of the broker-dealer leverage ratio (LEV) and the quarterly return of the prime broker index (PBI) in the presence of the macro-finance variables. The figures in parentheses report the heteroskedasticity-robust t-statistics. ***, **, and * designate statistical significance at the 1%, 5%, and 10% levels.

Panel A: Macro-Finance Variables

	Mean	R. Var. (RV)	PE ratio (PE)	Default (DEF)	Inflation (PPI)	Employ. (EMP)
Market Risk Premium	1.70^{**}	0.68	-1.96^{**}	-1.40	-1.17	-1.62^{**}
	(2.55)	(0.88)	(-1.96)	(-1.02)	(-1.29)	(-1.98)

Panel B: Contribution of Broker-Dealer Variables

	Leverage (LEV)	PB Index (PBI)	Combined Leverage (LEV)	Combined PB Index (PBI)
Market Risk Premium	-0.56	0.91	-0.34	0.83
	(-0.62)	(1.26)	(-0.34)	(1.01)

Table VI: Constrained versus Unconstrained Portfolio Return Projections

This table reports the slope and adjusted R^2 of a time-series regression of the unconstrained return projection on the model-implied projection for each quintile portfolio formed by equally weighting all equity portfolios in the same variance beta quintile (Low, 2, 3, 4, High). The unconstrained expectation is expressed as a linear function of the set of predictors that includes the lagged realized variance, the price/earnings ratio, the default spread, the quarterly inflation rate, the quarterly employment rate, the broker-dealer leverage ratio, and the quarterly return of the prime broker index. The constrained version is computed from the estimated coefficients of the two-factor model. The figures in parentheses report the heteroskedasticity-robust t-statistics. ***, **, and * designate statistical significance at the 1%, 5%, and 10% level, respectively.

	Equity Portfolios				
Quintile	Low	2	3	4	High
Slope	1.03***	0.88***	1.02***	1.03***	1.17***
	(52.92)	(94.91)	(89.21)	(69.41)	(53.58)
R^2	0.96	0.98	0.98	0.96	0.95

Table VII: Alternative Factor Models for the Equity Market

This table examines the robustness of the explanatory power of the broker-dealer variables to changes in the factor model used in the equity market. The first specification includes the initial factors (realized variance (RV) and market return), and the Fama-French size and Book-to-Market (BM) factors. The second and third specifications add the momentum and liquidity factors to the previous specification. The fourth specification includes the initial factors and the high-frequency RV component obtained from the Hodrick-Prescott filter. The fifth specification includes the initial factors and the squared RV. For each specification, the first column reports the correlation between the equity Variance Risk Premium (VRP) projection and its baseline counterpart presented in the paper. The remaining columns contain the estimated coefficients that drive the equity and option VRPs (as well as their difference) for the broker-dealer leverage ratio (LEV) and the quarterly return of the prime broker index (PBI) in the presence of the macro-finance variables. The coefficients determine the impact of a one-standard deviation change in the predictors on the equity and option VRPs, as well as their difference. The figures in parentheses report the heteroskedasticity-robust t-statistics. ***, **, and * designate statistical significance at the 1%, 5%, and 10% levels, respectively.

		Equity VRP		Option VRP		VRP Difference	
	Corr. Baseline	Leverage (LEV)	PB Index (PBI)	Leverage (LEV)	PB Index (PBI)	Leverage (LEV)	PB Index (PBI)
Size+BM	0.75	−0.18	−0.09	0.37***	0.17**	−0.55***	−0.26**
		(−0.90)	(−0.48)	(4.68)	(2.03)	(−6.43)	(−2.03)
Size+BM +Momentum	0.79	−0.14	−0.06	0.37***	0.17**	−0.51***	−0.23*
		(−0.67)	(−0.30)	(4.67)	(2.03)	(−5.84)	(−1.79)
Size+BM +Liquidity	0.75	−0.17	−0.05	0.37***	0.17**	−0.54***	−0.22*
		(−0.84)	(−0.23)	(4.67)	(2.03)	(−6.24)	(−1.70)
High-frequency RV	0.97	−0.26	−0.09	0.37***	0.17**	−0.63***	−0.26**
		(−1.17)	(−0.47)	(4.67)	(2.03)	(−7.27)	(−2.11)
Squared RV	0.97	−0.19	−0.14	0.37***	0.17**	−0.56***	−0.31**
		(−0.83)	(−0.71)	(4.67)	(2.03)	(−6.54)	(−2.53)

Table VIII: Time-Varying Betas: Variance Factor

This table reports, for each equity portfolio sorted along the Market (M) and Variance (V) dimensions, the t-statistic of the coefficients measuring the sensitivity of the variance beta to changes in the lagged realized variance (RV), the price/earnings ratio (PE), the default spread (DEF), the quarterly inflation rate (PPI), the quarterly employment rate (EMP), the broker-dealer leverage ratio (LEV) and the quarterly return of the prime broker index (PBI). * designates statistical significance at the 5% level or lower.

	R. Var. (RV)	PE Ratio (PE)	Default (DEF)	Inflation (PPI)	Employ. (EMP)	Leverage (LEV)	PB Index (PBI)
M1V1	−1.98*	−0.50	1.36	−1.15	0.47	−0.88	0.38
M1V2	−0.83	1.33	0.25	−1.41	−0.16	0.44	−0.22
M1V3	−1.13	−1.03	1.05	1.09	0.53	0.46	−0.89
M1V4	−3.43*	1.10	−0.65	−1.70	0.84	0.01	−0.84
M1V5	−2.64*	−0.50	−0.66	−2.44*	2.85*	−1.17	1.88
M2V1	−3.95*	0.24	−1.95	−1.85	2.72*	−1.26	0.78
M2V2	−0.21	1.64	0.46	−2.10	0.81	0.26	0.22
M2V3	−1.37	−0.19	1.02	−0.70	−0.89	0.15	1.21
M2V4	-1.74	1.02	0.96	−0.62	0.00	0.28	0.36
M2V5	0.43	−0.35	1.58	0.58	−0.35	2.06*	1.46
M3V1	−2.59*	−0.58	0.67	−1.26	0.66	−1.87	1.61
M3V2	0.89	−0.96	0.39	−0.50	0.42	0.83	−0.18
M3V3	−2.05*	−0.67	−2.00*	−1.02	3.00*	0.37	0.20
M3V4	-0.64	−0.15	1.24	−0.29	0.10	−0.32	1.35
M3V5	−0.42	0.31	−0.73	0.47	0.93	1.54	−1.69
M4V1	−0.99	−0.17	1.44	−0.42	−1.46	1.60	0.18
M4V2	−2.73*	−0.24	0.03	−0.91	0.00	−1.96*	0.00
M4V3	0.15	−1.80	4.17*	0.62	−2.35*	1.02	0.73
M4V4	0.02	−0.05	1.37	−0.31	0.67	1.91	1.34
M4V5	0.19	−1.66	1.43	−0.45	−0.60	4.07*	−0.96
M5V1	−1.19	−1.47	−0.31	−0.62	0.11	−1.29	−0.29
M5V2	-0.68	−0.19	0.57	−1.92	0.56	0.05	0.74
M5V3	−0.54	1.50	−0.53	−0.86	1.19	0.31	−0.22
M5V4	0.52	−0.46	1.80	−0.26	−0.64	1.08	0.88
M5V5	1.77	−1.23	1.69	1.15	−0.61	0.82	0.00

Table IX: Time-Varying Betas: Market Factor

This table reports, for each equity portfolio sorted along the Market (M) and Variance (V) dimensions, the t-statistic of the coefficients measuring the sensitivity of the market beta to changes in the lagged realized variance (RV), the price/earnings ratio (PE), the default spread (DEF), the quarterly inflation rate (PPI), the quarterly employment rate (EMP), the broker-dealer leverage ratio (LEV) and the quarterly return of the prime broker index (PBI). * designates statistical significance at the 5% level or lower.

	R. Var. (RV)	PE Ratio (PE)	Default (DEF)	Inflation (PPI)	Employ. (EMP)	Leverage (LEV)	PB Index (PBI)
M1V1	−2.81*	−2.61*	0.91	0.94	1.22	−0.98	2.79*
M1V2	−2.45*	−2.15*	1.26	2.40	−0.08	0.59	0.12
M1V3	−2.22*	−1.94	1.69	4.65	0.26	−0.43	−0.03
M1V4	−2.34*	−2.87*	1.48	1.55	−0.56	0.48	−0.15
M1V5	−1.88	−2.28*	0.96	−0.04	0.86	−0.16	1.08
M2V1	−2.18*	−2.63*	1.49	−0.25	0.44	−0.10	1.78
M2V2	−1.89	−1.63	0.70	0.25	1.41	−0.30	1.43
M2V3	−1.92	−2.23*	1.50	0.71	0.08	−0.31	0.94
M2V4	−3.44*	−4.48*	0.79	2.98*	0.86	0.15	0.39
M2V5	−1.49	−2.28*	1.19	2.14*	−0.70	1.21	1.42
M3V1	−1.79	−4.50*	2.13*	1.28	−0.90	−0.74	1.93
M3V2	−0.31	−2.24*	−0.06	2.13*	0.81	0.32	−0.36
M3V3	−1.41	−1.54	−0.11	0.63	0.64	0.82	0.09
M3V4	−1.41	−2.77*	2.29*	0.99	0.29	−1.01	1.59
M3V5	−1.26	−2.17*	0.78	0.91	0.80	−0.07	−0.82
M4V1	−1.18	−1.77	1.10	−0.34	−0.02	1.42	1.40
M4V2	−2.79*	−4.07*	1.68	1.39	1.00	0.13	1.16
M4V3	−3.94*	−2.54*	1.22	0.14	0.01	1.09	0.13
M4V4	−0.14	−1.35	1.21	−0.19	1.15	0.88	1.94
M4V5	−0.71	−1.93	1.69	0.17	−0.73	3.53*	1.05
M5V1	−0.39	−1.44	0.83	0.84	−1.53	−0.44	−0.03
M5V2	0.98	−2.10*	1.56	0.55	0.27	1.59	0.11
M5V3	0.49	−0.96	0.53	−1.64	0.51	2.59*	−2.55*
M5V4	−1.21	0.12	−0.03	−0.87	−0.24	1.31	0.35
M5V5	1.42	0.09	1.53	−0.92	−0.61	0.71	0.32

Table X: Winsorized Variance Observations

This table examines the robustness of the explanatory power of the broker-dealer variables to winsorizing extreme observations of the realized variance. For each threshold (1% and 2.5% of observations winsorized at each end), the columns report the estimated coefficients that drive the equity and option Variance Risk Premia (VRPs), as well as their difference for the broker-dealer leverage ratio (LEV) and the quarterly return of the prime broker index (PBI) in the presence of the macro-finance variables. The coefficients determine the impact of a one-standard deviation change in the predictors on the equity and option VRPs, as well as their difference. The figures in parentheses report the heteroskedasticity-robust t-statistics. ***, **, and * designate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Equity VRP		Option VRP		VRP Difference	
	Leverage (LEV)	PB Index (PBI)	Leverage (LEV)	PB Index (PBI)	Leverage (LEV)	PB Index (PBI)
2% winsorized	−0.15	−0.12	0.32***	0.15*	−0.47***	−0.27***
	(−0.61)	(−0.63)	(4.03)	(1.75)	(−6.12)	(−2.53)
5% winsorized	−0.07	−0.09	0.20***	0.11	−0.27***	−0.20***
	(−0.71)	(−0.99)	(3.66)	(1.37)	(−4.50)	(−2.91)

Table XI: The Squared SVIX Index: Period 1996-2012

Panel A reports the estimated coefficients and the adjusted R^2 of the regression of the quarterly squared SVIX index on the set of macro-finance variables that includes the lagged realized variance (RV), the price/earnings ratio (PE), the default spread (DEF), the quarterly inflation rate (PPI), the quarterly employment rate (EMP). The coefficients determine the impact of a one-standard deviation change in the variables on the squared SVIX and are computed using the GMM for samples of unequal lengths. Panel B examines the incremental predictive power of the broker-dealer leverage ratio (LEV) and the quarterly return of the prime broker index (PBI) in the presence of the macro-finance variables. The figures in parentheses report the heteroskedasticity-robust t-statistics. ***, **, and * designate statistical significance at the 1%, 5%, and 10% levels.

Panel A: Macro-Finance Variables

	Mean	R. Var. (RV)	PE ratio (PE)	Default (DEF)	Inflation (PPI)	Employ. (EMP)	R^2
Squared SVIX	1.18^{***}	0.69^{***}	-0.11	0.15^{**}	-0.05	0.11	0.76
	(31.50)	(10.31)	(-1.37)	(2.29)	(-0.87)	(1.58)	

Panel B: Contribution of Broker-Dealer Variables

					Combined		
	Leverage (LEV)	R^2	PB Index (PBI)	R^2	Leverage (LEV)	PB Index (PBI)	R^2
Squared SVIX	-0.09^{**}	0.76	-0.12^{**}	0.77	-0.15^{***}	-0.17^{***}	0.78
	(-2.57)		(-2.17)		(-4.37)	(-3.08)	

Table XII: Alternative Approaches for Forming Portfolios

This table examines the robustness of the explanatory power of the broker-dealer variables to changes in the portfolio formation procedure. The first specification includes all but tiny stocks, whereas the second includes all stocks in the population. The third, fourth, and fifth specifications rank stocks each month based on their robust beta t-statistics, their quarterly beta t–statistics, and their estimated betas. The sixth and seventh specifications account for nonsynchronous trading by including the lagged factors in the stock return regressions, and by excluding return observations equal to zero. For each specification, the first column reports the correlation between the equity Variance Risk Premium (VRP) projection and its baseline counterpart presented in the paper. The remaining columns contain the estimated coefficients that drive the equity and option VRPs (as well as their difference) for the broker-dealer leverage ratio (LEV) and the quarterly return of the prime broker index (PBI) in the presence of the macro-finance variables. The coefficients determine the impact of a one-standard deviation change in the predictors on the equity and option VRPs, as well as their difference. The figures in parentheses report the heteroskedasticity-robust t-statistics. ***, **, and * designate statistical significance at the 1%, 5%, and 10% levels, respectively.

		Equity VRP		Option VRP		VRP Difference	
	Corr. Baseline	Leverage (LEV)	PB Index (PBI)	Leverage (LEV)	PB Index (PBI)	Leverage (LEV)	PB Index (PBI)
All but Tiny Stocks	0.82	−0.08	−0.11	0.37***	0.17**	−0.45***	−0.28**
		(−0.34)	(−0.34)	(4.67)	(2.03)	(−3.32)	(−2.10)
All Stocks	0.81	0.00	−0.23	0.37***	0.17**	−0.37***	−0.40***
		(0.02)	(−1.18)	(4.67)	(2.03)	(−3.55)	(−2.96)
Robust Betas	0.97	−0.08	0.03	0.37***	0.17**	−0.45***	−0.14
		(−0.33)	(0.16)	(4.67)	(2.03)	(−5.40)	(−1.30)
Quarterly Betas	0.44	−0.04	−0.28	0.37***	0.17**	−0.42***	−0.45***
		(−0.17)	(−1.19)	(4.67)	(2.03)	(−4.63)	(−3.69)
No t-statistics	0.62	−0.23	0.08	0.37***	0.17**	−0.60***	−0.09
		(−1.14)	(0.54)	(4.67)	(2.03)	(−8.50)	(−1.40)
Lagged Factors	0.76	−0.21	−0.23	0.37***	0.17**	−0.52***	−0.41***
		(−1.25)	(−1.34)	(4.67)	(2.03)	(−7.04)	(−3.58)
Zero Returns	0.86	−0.23	−0.15	0.37***	0.17**	−0.61***	−0.32***
		(−0.86)	(−0.77)	(4.67)	(2.03)	(−7.28)	(−2.83)

Table XIII: Alternative Set of Macro-Finance Variables

This table examines the robustness of the explanatory power of the broker-dealer variables to changes in the set of macro-finance variables. The first specification replaces the price/earnings ratio with the dividend yield. The second and third specifications replace the quarterly growth rate in employment with the quarterly growth rate in industrial production and the business cycle indicator proposed by Aruoba, Diebold, and Scotti (2009), respectively. The fourth, fifth, and sixth specifications add two bond variables (the three-month T-Bill rate and the term spread), and the quarterly volatility of the inflation rate to the initial set of predictors. For each specification, the columns report the estimated coefficients that drive the equity and option Variance Risk Premia (VRPs) (as well as their difference) for the broker-dealer leverage ratio (LEV) and the quarterly return of the prime broker index (PBI) in the presence of the macro-finance variables. The coefficients determine the impact of a one-standard deviation change in the predictors on the equity and option VRPs, as well as their difference. The figures in parentheses report the heteroskedasticity-robust t-statistics ***, **, and * designate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Equity VRP		Option VRP		VRP Difference	
	Leverage (LEV)	PB Index (PBI)	Leverage (LEV)	PB Index (PBI)	Leverage (LEV)	PB Index (PBI)
Dividend Yield	−0.05	−0.05	0.41***	0.18**	−0.41***	−0.24**
	(−0.02)	(0.27)	(4.59)	(2.16)	(−3.42)	(−1.95)
Industrial Production	−0.17	−0.12	0.36***	0.17**	−0.54***	−0.30**
	(−0.70)	(−0.64)	(4.57)	(2.04)	(−3.93)	(−2.28)
Business Cycle	−0.07	−0.12	0.31***	0.19**	−0.38***	−0.30**
	(−0.31)	(−0.60)	(4.20)	(2.31)	(−3.93)	(−2.32)
Short Rate	−0.11	−0.12	0.38***	0.17**	−0.48***	−0.30**
	(0.48)	(−0.65)	(4.62)	(2.07)	(−3.68)	(−2.27)
Term Spread	−0.17	−0.13	0.38***	0.18**	−0.55***	−0.31**
	(−0.69)	(−0.65)	(4.76)	(2.18)	(−4.05)	(−2.30)
Vol. Inflation	−0.16	−0.10	0.35***	0.16**	−0.52***	−0.26**
	(−0.68)	(−0.53)	(4.56)	(1.97)	(−3.91)	(−2.06)

Table XIV: Squared Macro-Finance Variables

This table examines the robustness of the explanatory power of the broker-dealer variables to changes in the set of macro-finance variables. The specifications include the initial set of predictors (lagged realized variance, the price/earnings ratio, the default spread, the quarterly inflation rate, the quarterly employment rate) and their squared values taken one at a time. For each specification, the columns report the estimated coefficients that drive the equity and option Variance Risk Premia (VRPs) (as well as their difference) for the broker-dealer leverage ratio (LEV) and the quarterly return of the prime broker index (PBI) in the presence of the macro-finance variables. The coefficients determine the impact of a one-standard deviation change in the predictors on the equity and option VRPs, as well as their difference. The figures in parentheses report the heteroskedasticity-robust t-statistics. ***, **, and * designate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Equity VRP		Option VRP		VRP Difference	
	Leverage (LEV)	PB Index (PBI)	Leverage (LEV)	PB Index (PBI)	Leverage (LEV)	PB Index (PBI)
Realized Variance^2	−0.09	−0.16	0.35***	0.18***	−0.43***	−0.34***
	(−0.36)	(0.80)	(4.33)	(2.32)	(−3.54)	(−2.74)
PE Ratio^2	−0.18	−0.07	0.26***	0.18**	−0.45***	−0.25**
	(−0.78)	(0.34)	(3.56)	(2.19)	(−3.46)	(−2.01)
Default Spread^2	−0.14	−0.08	0.37***	0.15*	−0.51***	−0.23*
	(−0.57)	(−0.41)	(4.80)	(1.86)	(−3.76)	(−1.73)
Inflation^2	−0.14	−0.09	0.35***	0.19**	−0.49***	−0.28**
	(−0.58)	(−0.44)	(4.45)	(2.38)	(−3.69)	(−2.14)
Employment^2	−0.18	−0.14	0.35***	0.22***	−0.54***	−0.37***
	(−0.74)	(−0.75)	(4.54)	(2.65)	(−4.06)	(−2.80)

Table XV: Implied Stock Variance and Implied Correlation

Panel A reports the estimated coefficients and adjusted R^2 of regressions of the equally-weighted average of the monthly implied variances of individual stocks (Implied Stock Variance) and the monthly implied correlation (Implied Correlation) on the set of macro-finance predictors that include the lagged realized variance (RV), the price/earnings ratio (PE), the default spread (DEF), the quarterly inflation rate (PPI), and the quarterly employment rate (EMP). The coefficients determine the impact of a one-standard deviation change in the variables on Implied Stock and Implied Correlation, and are computed using the GMM for samples of unequal lengths. Panel B examines the incremental predictive power of the orthogonalized broker-dealer variables, the broker-dealer leverage ratio (LEV) and the quarterly return of the prime broker index (PBI), in the presence of the macro-finance variables. The figures in parentheses report the heteroskedasticity-robust t-statistics. ***, **, and * designate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Macro-Finance Variables

	Mean	R. Var. (RV)	PE ratio (PE)	Default (DEF)	Inflation (PPI)	Employ. (EMP)	R^2
Implied Stock Variance	1.74*** (36.49)	0.67*** (10.91)	0.50*** (5.41)	0.51*** (5.84)	−0.01 (−0.15)	0.25*** (−3.39)	0.69
Implied Correlation	40.63*** (67.51)	8.67*** (12.20)	−10.62*** (−8.65)	−5.15*** (−4.96)	−1.39** (−2.05)	3.26*** (4.04)	0.50

Panel B: Contribution of Broker-Dealer Variables

					Combined		
	Leverage (LEV)	R^2	PB Index (PBI)	R^2	Leverage (LEV)	PB Index (PBI)	R^2
Implied Stock Variance	0.18*** (2.68)	0.73	−0.21*** (−3.94)	0.71	0.10 (1.47)	−0.18*** (−3.38)	0.73
Implied Correlation	−1.16** (−2.34)	0.51	0.26 (0.43)	0.50	−1.45*** (−2.91)	−0.54 (−0.86)	0.51

Table XVI: Variance Risk Premia: Monthly Analysis

Panel A examines the relationships between the macro-finance variables and the equity Variance Risk Premium (VRP), the option VRP, and their difference at the monthly frequency. The set of variables includes the lagged realized variance (RV), the price/earnings ratio (PE), the default spread (DEF), the quarterly inflation rate (PPI), and the quarterly employment rate (EMP). The coefficients determine the impact of a one-standard deviation change in the variables on the VRPs and their difference. The equity- and option-based coefficients are obtained from the conditional two-pass regression approach and the GMM for samples of unequal lengths, respectively. Panel B examines the incremental predictive power of the broker-dealer leverage ratio (LEV) and the quarterly return of the prime broker index (PBI) in the presence of the macro-finance variables. The figures in parentheses report the heteroskedasticity-robust t-statistics. The J-statistic of the joint test and associated p-values in brackets determine whether the two-factor equity model is correctly specified. ***, **, and * designate statistical significance at the 1%, 5%, and 10% levels.

Panel A: Macro-Finance Variables

	Mean	R. Var. (RV)	PE ratio (PE)	Default (DEF)	Inflation (PPI)	Employ. (EMP)	J-stat.
Equity VRP	−0.09	−0.06	0.09	0.04	0.14*	0.07	5.76
	(−1.15)	(−0.56)	(0.78)	(0.34)	(1.75)	(0.77)	[0.04]
Option VRP	−0.13***	−0.09***	0.08***	0.06***	0.05***	−0.01	
	(−12.34)	(−5.87)	(4.36)	(2.87)	(3.08)	(−0.79)	
Difference	0.04	0.04	0.01	−0.02	0.08	0.08	
	(0.49)	(0.59)	(0.14)	(−0.16)	(1.45)	(1.09)	

Panel B: Contribution of Broker-Dealer Variables

					Combined		
	Leverage (LEV)	J-stat.	PB Index (PBI)	J-stat.	Leverage (LEV)	PB Index (PBI)	J-stat.
Equity VRP	0.02	6.90	−0.20***	6.76	−0.05	−0.20**	7.71
	(0.24)	[0.03]	(−2.58)	[0.04]	(−0.47)	(−2.49)	[0.04]
Option VRP	0.07***		0.00		0.08***	0.03**	
	(3.56)		(0.32)		(4.37)	(2.07)	
Difference	−0.05*		−0.20***		−0.13***	−0.23***	
	(−1.67)		(−4.53)		(−4.26)	(−5.08)	

Table XVII: Variance Risk Premia: Individual Stocks

Panel A examines the relationships between the macro-finance variables and the equity Variance Risk Premium (VRP) inferred from individual stocks, the option VRP, and their difference. The set of variables includes the lagged realized variance (RV), the price/earnings ratio (PE), the default spread (DEF), the quarterly inflation rate (PPI), and the quarterly employment rate (EMP). The coefficients determine the impact of a one-standard deviation change in the variables on the VRPs and their difference. The equity- and option-based coefficients are obtained from the conditional two-pass regression applied to individual stocks and the GMM for samples of unequal lengths, respectively. Panel B examines the incremental predictive power of the broker-dealer leverage ratio (LEV) and the quarterly return of the prime broker index (PBI) in the presence of the macro-finance variables. The figures in parentheses report the heteroskedasticity-robust t-statistics. The J-statistic of the joint test and associated p-values in brackets determine whether the two-factor equity model is correctly specified. ***, **, and * designate statistical significance at the 1%, 5%, and 10% levels.

Panel A: Macro-Finance Variables

	Mean	R. Var. (RV)	PE ratio (PE)	Default (DEF)	Inflation (PPI)	Employ. (EMP)	J-stat.
Equity VRP	0.05	0.01	0.07	0.01	0.08	0.22***	4.29
	(0.68)	(0.08)	(0.67)	(0.10)	(0.82)	(3.26)	[0.00]
Option VRP	−0.45***	−0.34***	0.35***	0.01	0.19**	−0.07	
	(−8.01)	(−3.70)	(3.42)	(0.12)	(2.22)	(−0.72)	
Difference	0.50**	0.34***	−0.29***	0.00	−0.11*	0.28***	
	(2.52)	(3.41)	(−3.56)	(−0.01)	(−1.72)	(3.47)	

Panel B: Contribution of Broker-Dealer Variables

					Combined		
	Leverage (LEV)	J-stat.	PB Index (PBI)	J-stat.	Leverage (LEV)	PB Index (PBI)	J-stat.
Equity VRP	0.21	4.55	−0.25***	4.28	0.14	−0.22**	4.79
	(0.89)	[0.00]	(−4.41)	[0.00]	(−0.52)	(−2.11)	[0.00]
Option VRP	0.31***		0.07		0.37***	0.17**	
	(3.84)		(0.83)		(4.68)	(2.03)	
Difference	−0.09*		−0.32***		−0.23***	−0.39***	
	(−1.68)		(−5.05)		(−3.66)	(−6.36)	

Figure I: Market Risk Premium

This figure reports the path of the quarterly Market Risk Premium (MRP) projection obtained with the set of macro-finance predictors that includes the lagged realized variance, the price/earnings ratio, the default spread, the quarterly inflation rate, and the quarterly employment rate. Shaded areas correspond to NBER recession periods. The y-axis is in percent per quarter.

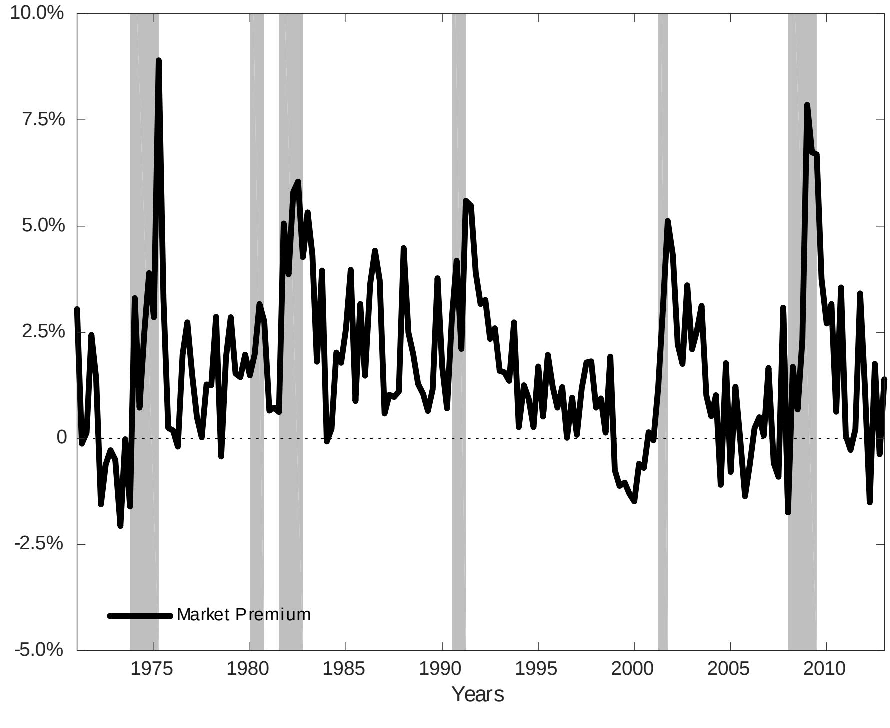

Figure II: Payoffs of the Variance Mimicking Portfolios

This figure plots the quarterly payoffs of the mimicking portfolios formed in the equity and option markets. The construction of the mimicking option portfolio (solid line) is based on the approach developed by Carr and Wu (2009). The mimicking equity portfolio (dashed line) is obtained from a linear combination of the equity portfolios inferred from the two-factor model. The quarterly realized variance is almost identical to the payoff of the option portfolio and is therefore not shown.

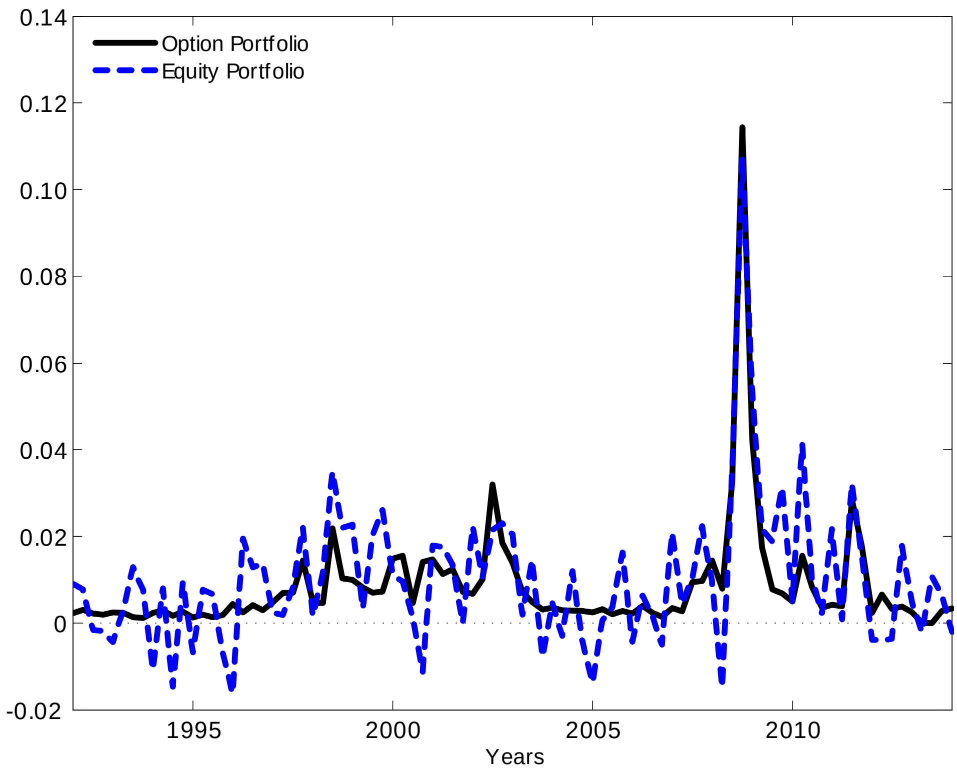

Figure III: Equity Variance Risk Premium: Impact of the Broker-Dealer Variables

This figure compares the paths followed by two versions of the quarterly equity Variance Risk Premium (VRP) projection. The first version is based on the set of macro-finance variables that includes the lagged realized variance, the price/earnings ratio, the default spread, the quarterly inflation rate, and the quarterly employment rate. The second version is obtained using the macro-finance predictors as well as the two broker-dealer variables, which are the leverage ratio of broker-dealers and the quarterly return of the prime broker index. The y-axis is in percent per quarter.

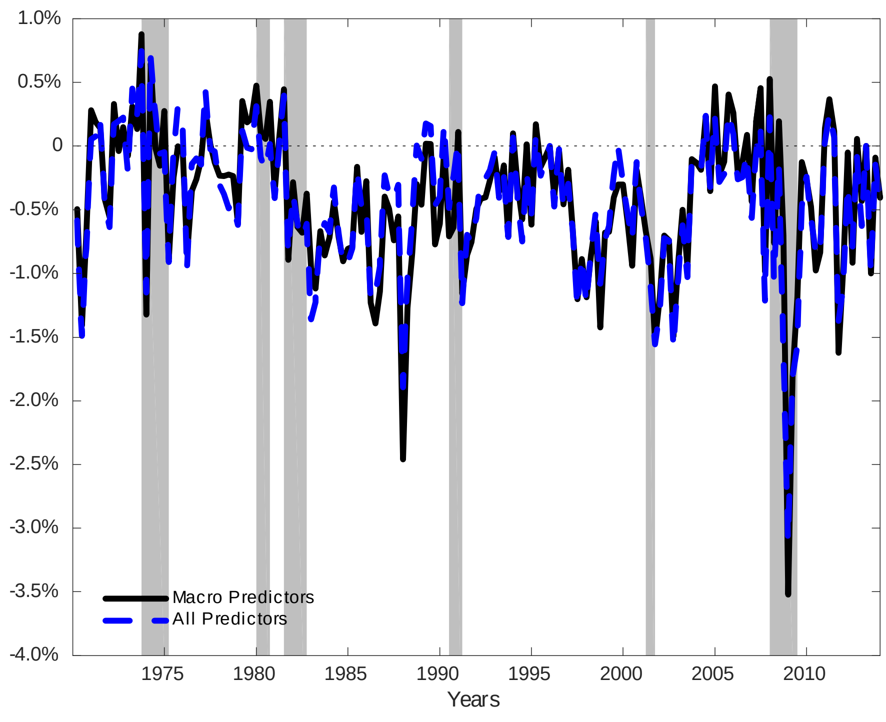

Figure IV: Simulated Omitted-Factor Bias

Panel A reports the bias of the estimated risk-neutral leverage coefficient for the equity Variance Risk Premium (VRP), $\hat{v}_v^e(lev)$, when the asset pricing model omits a factor whose risk premium is negatively related to leverage. The bias is defined in relative terms as a fraction of the true leverage coefficient $v_v^e(lev)$, which is set equal to -0.37 (similar to the option-based estimate in Table 3 of the paper). For each value taken by the correlation between the portfolio betas (on the variance and omitted factors), we compute the bias via a simulation analysis that replicates the salient feature of the data (1,000 trials are used for each scenario). We consider two different values for the coefficient that relates leverage to the quarterly risk premium of the omitted factor: -0.37% (solid line), and -0.74% (dashed line). Panel B repeats the analysis for an omitted factor whose risk premium is positively related to leverage.