Expected Stock Returns and the Correlation Risk Premium*

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Abstract

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Keywords: correlation risk premium, out-of-sample return predictability, option-implied information, trading strategy, diversification, factor risk

JEL: G11, G12, G13, G17

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I. Introduction

It is long recognized that the variance of the aggregate market return is stochastic, and that investors are ready to pay a premium to hedge against changes in variance—the variance risk premium—which, to a large extent, serves as compensation for bearing jump risk.[1] Correlations between individual stocks are also time-varying, and correlation risk, i.e., the risk of deteriorating diversification benefits, also carries a risk premium. Particularly, by pricing index options using relatively higher expected variance than for individual options, investors are essentially willing to pay a correlation risk premium to hedge against changes in correlation.[2]

Importantly, both, aggregate index variance and average correlation, are co-moving negatively with the market return, i.e., they tend to increase during bear markets, and, hence, should contribute to the equity risk premium.[3] However, while the relation between the variance risk premium and the equity risk premium has been extensively studied, there is little evidence that the correlation risk premium contributes to the equity risk premium. Thus, in this paper, we are going to focus on the *correlation risk premium* and try to answer the following questions: Is the return on the aggregate market predictable by the correlation risk premium? How does the correlation risk premium compare to the variance risk premium in predicting aggregate market returns? Can the variance risk premium and the correlation risk premium predict the market return *out-of-sample*? What are the economic forces and risk factors that give rise to the correlation risk premium?

In answering these questions, we make four major contributions. First, in a stylized model with multiple stocks and priced correlation risk, we decompose the equity risk premium into three components: (i) the variance risk premium (VRP); (ii) the correlation risk premium (CRP); and (iii) an orthogonal component. This "beta representation" allows us to derive a

[1]See Carr and Wu (2009) and Bollerslev, Tauchen, and Zhou (2009) for evidence on the variance risk premium and Todorov (2009), Bollerslev and Todorov (2011) and Todorov and Tauchen (2011) for evidence on jump risk.

[2]See Driessen, Maenhout, and Vilkov (2009), Buraschi, Kosowski, and Trojani (2014), Mueller, Stathopoulos, and Vedolin (2017), and Krishnan, Petkova, and Ritchken (2009).

[3]Christie (1982), Roll (1988), Bekaert and Wu (2000) and Longin and Solnik (2001) document a negative correlation between the market return and index variance (equal to −0.77 in our sample). Bollerslev, Tauchen, and Zhou (2009), Carr and Wu (2016), and Bandi and Renò (2016) relate the variance risk premium to the equity risk premium. For our sample period, we document a correlation of −0.61 between the market return and implied correlation.

theoretically founded forecasting equation for the market return. Second, we demonstrate that the variance and correlation betas of the pricing equation can be estimated using a simple, contemporaneous regression that relies on increments of the respective risk-neutral quantities (implied index variance and implied correlation) as well as realized market returns.

Third, we show how these betas can be used, together with the variance and correlation risk premiums, for *out-of-sample* forecasts of the aggregate market return. Empirically, we document out-of-sample R^2's of up to 13% at a quarterly, and up to 7% at an annual horizon, with the predictive power at the annual horizon stemming exclusively from the correlation risk premium. In contrast, the predictability by the variance risk premium peaks at quarterly horizon and fades away quickly after that. In summary, the predictive power of the variance risk premium is far more short-lived than that of the correlation risk premium. These predictability results imply highly significant economic benefits for a representative investor, mostly attributable to the correlation risk premium and crucially depend on the use of the new estimation methodology discussed above.

Fourth, we study the risks the correlation risk premium compensates for, and the economic channels through which the correlation risk premium arises. Particularly, we try to differentiate between explanations for the equity premium predictability by the correlation risk premium that are risk-based, in the form of the Intertemporal CAPM (I-CAPM), and explanations that are based on investor disagreement. Our results suggest that a risk-based explanation is better supported by the data. Particularly, we find that expected correlations, that would serve as a state variable in the I-CAPM, predict future diversification benefits for horizons up to one year, measured by the average future correlation among stocks (with R^2's of up to 29.97% using lagged realized correlation and R^2's of up to 35.44% using implied correlation as predictors), and measured by the non-diversifiable market risk in a portfolio, i.e., the future dispersion of market betas (with R^2's that peak at the nine-months horizon with a value of 32.30%). Similar to the predictability results, variances (implied or realized) have a shorter predictability horizon for future risks. In contrast, the positive link between disagreement and the correlation risk premium established in Buraschi, Trojani, and Vedolin (2014) for a sample period from 1996 to July 2007, turns negative for our extended sample period until April 2016.

Our paper is related to several strands of the literature. First, the literature that uses option-implied information to predict the return on the aggregate market. Bollerslev, Tauchen, and Zhou (2009), for the U.S., and Bollerslev, Marrone, Xu, and Zhou (2014), in an international setting, show that the variance risk premium is a strong and robust predictor of aggregate market returns. Particularly, they show that the return predictability of the variance risk premium lasts up to one quarter and depends crucially on the use of "model-free" implied variances. In contrast, evidence on return predictability using the correlation risk premium is scarce. That is, while several existing studies document return predictability by correlations itself for a horizon of up to one year, e.g., Driessen, Maenhout, and Vilkov (2005, 2012) and Faria, Kosowski, and Wang (2016) based on implied correlations as well as Pollet and Wilson (2010) based on realized correlations, only Cosemans (2011) finds some in-sample return predictability based on the correlation risk premium.

We contribute to this literature by showing, in a simple, stylized model, that the correlation risk premium should contribute to the equity risk premium because of its negative correlation with the market return, and by confirming this relation empirically—in-sample and out-of-sample for a horizon of up to one year. We highlight that the out-of-sample performance critically relies on the use of a new methodology to estimate the pricing equation parameters by the joint dynamics of market returns and option-implied variables instead of traditionally used regressions of long-term returns on past predictors.

Second, we are related to the literature that studies correlation risk (premiums) as well as its sources. Particularly, while our reduced-form model is agnostic about the reasons for priced correlation risk, the literature offers several, alternative explanations. Garleanu, Pedersen, and Poteshman (2009) offer a demand-based model that can explain the differential pricing of index and individual options and gives rise to a non-zero correlation risk premium. Driessen, Maenhout, and Vilkov (2009) provide a risk-based explanation based on Merton's (1973) I-

CAPM. In this case, the average correlation serves as a state variable that has predictive power for the future market risks in a portfolio and, thus, is priced. Similarly, Buraschi, Kosowski, and Trojani (2014) relate the correlation risk to the existence of a "no-place-to-hide" state variable. Finally, in Buraschi, Trojani, and Vedolin (2014) a correlation risk premium arises due to investor disagreement about the parameters of the economy. Particularly, due to uncertainty about future dividends, measured by differences in beliefs, agents implicitly expect stocks to behave more like the market in the future, thus, increasing the expected correlation under the pricing probability measure. Hence, a higher correlation risk premium would predict a higher equity risk premium in the future.

We contribute to this literature by identifying the channel through which the correlation risk premium affects the equity risk premium and, thus, future market returns. Particularly, we concentrate on the risk-based and disagreement-based explanations. While we find that both—high uncertainty and high correlations—command a higher equity risk premium, our results suggest that the correlation risk premium cannot serve as a proxy for uncertainty or disagreement because it is negatively related to uncertainty (measured by the economic policy uncertainty index) and disagreement (measured by the aggregate difference in beliefs proxy). In contrast, we show that the risk-based explanation can rationalize the observed patters of return predictability because expected correlations (implied and realized) predict future average realized correlations well.

Thus, our paper is also related to the rich literature discussing pricing of uncertainty and disagreement risk in the economy. Varian (1985) shows that disagreement is associated with a positive risk premium in an economy with agents who have different subjective probabilities. Abel (1989) also stresses the importance of heterogeneous beliefs for an increase in the equity premium. Further theoretical work has confirmed these findings, and an extensive survey can be found in Basak (2005). Dumas, Kurshev, and Uppal (2009) show that the long-run price of risk can be decomposed into two components, with a second term stemming from future disagreement. Collin-Dufresne, Johannes, and Lochstoer (2016) demonstrate that parameter uncertainty has profound effects on the equity risk premium.[4] Empirically, most studies find that investors require a compensation for both economic uncertainty and disagreement.[5] Carlin, Longstaff, and Matoba (2014) directly measure the level of disagreement among Wall Street mortgage dealers about prepayment speeds, and show that higher disagreement is associated with higher expected returns. Likewise, Boehme, Danielsen, Kumar, and Sorescu (2009) demonstrate a positive relationship between dispersion of beliefs and expected returns, after controlling for short-interest and investor recognition as proxied by institutional ownership.

The remainder of the paper is oraganized as follows: Section II contains the derivation of a pricing equation linking the equity risk premium to variance and correlation risk premiums, as well as the introduction of a new estimation method for variance and correlation betas. Section III discusses data preparation procedures, and in Section IV we look in detail at empirical analysis including properties of the variance and correlation risk premiums, estimation of model parameters, and in-sample and out-of-sample market return predictability. Section V analyses the economic channels behind the predictability of market returns by the correlation risk premium. Section VI contains a number of robustness tests, and Section VII concludes the analysis.

II. Model Setup

We start from building a reduced-form model of a market index with several risky stocks, where each stock is driven by a diffusion process with stochastic volatility, and the correlation between each stock is stochastic. The expected correlations between stocks are interpreted as the proxy for disagreement risk, and the correlation risk premium—as compensation for

[4]Note that in theoretical and empirical literature *uncertainty* and *disagreement* are often used interchangeably, and uncertainty-type models are tested using forecasters-based disagreement proxies (see Jurado, Ludvigson, and Ng (2015) for a discussion). In theory, an increase in disagreement can occur when there is no change in uncertainty—if at least some agents change their expectation, but all are no less sure about the likely outcome. Lahiri and Sheng (2010) show that aggregate forecast uncertainty is equal to the disagreement among the forecasters plus the expected variability of future aggregate shocks. Thus the reliability of disagreement as a proxy for uncertainty will be determined by the stability of the forecasting environment and the length of the forecast horizon. In the data forecaster disagreement often co-moves with other measures of economic uncertainty (e.g., economic uncertainty proxy based on the news), however, one should be careful in determining the correct testing environment.

[5]One important exception in this literature is Miller (1977), who posits that in the presence of short-sale constraints disagreement should have a positive effect on stock prices. These predictions have been tested in several empirical studies, e.g., Diether, Malloy, and Scherbina (2002), and have been shown to be plausible.

the disagreement risk. We show how to decompose the equity risk premium into variance, correlation, and orthogonal components, and use the resulting pricing equation to predict future market returns. Section II.B develops a novel method of estimating variance and correlation exposures using contemporaneous regressions of daily market returns on changes in implied variance and correlation, which is then used to test the pricing equation in later sections.

A. Equity Risk Premium and its Link to Correlation Risk

We build upon the structure in Driessen, Maenhout, and Vilkov (2012) to derive the process of the aggregate market index from the individual asset processes. At this stage we stay agnostic about the reasons for correlation risk being priced, and the potential explanations include the link between the correlation risk premium and uncertainty as derived in a general equilibrium economy by Buraschi, Trojani, and Vedolin, or an ICAPM-type reasoning, where correlation is a priced state variable predicting changes in the future investment opportunity set.

Specifically, we assume that each individual asset follows a diffusion process with a stochastic variance, and that all the pairwise correlations between stocks are driven by one state variable. Specifically, the stock market index is composed of N stocks. Under the physical probability measure P, the price of stock i, S_i, follows an Ito process with drift $\mu_i(t)$ and diffusion $\phi_i(t)$:

$$dS_i = \mu_i S_i dt + \phi_i S_i dW_i, \tag{1}$$

where W_i is a standard Wiener process.[6] The special case of $\phi_i(t)$ being constant simplifies (1) to the standard Black-Scholes set-up. More generally, the instantaneous variance $\phi_i^2(t)$ is an Ito process, driven by a standard scalar Wiener process W_{ϕ_i}. Denoting the drift of $\phi_i^2(t)$ by γ_i, and the diffusion scaling parameter (which will determine the "vol of vol") by ς_i, the instantaneous variance process of the individual stock return, under the physical P measure is

$$d\phi_i^2 = \gamma_i dt + \varsigma_i \phi_i dW_{\phi_i}. \tag{2}$$

[6]We omit time as an argument for notational convenience throughout, except when placing particular emphasis.

We assume that the individual variance can be correlated with the stock Wiener, though the correlation is expected to be of a smaller magnitude than for the index.[7] More importantly, the instantaneous correlation between individual stocks $i, j,\ i \neq j$ is modeled as:

$$E_t \left[dW_i dW_j\right] = \rho_{ij} \left(t\right) dt = \rho(t)dt, \tag{3}$$

where a single state variable $\rho\left(t\right)$ is driving all pairwise correlations. While this assumption may seem restrictive, it has been used in empirical and theoretical literature before;[8] and it has been shown to be able to capture the correlation risk in the most parsimonious way.

Under the physical probability measure P, the correlation state variable $\rho\left(t\right)$ is assumed to follow a mean-reverting process with long-run mean $\overline{\rho}$, mean-reversion parameter λ and diffusion parameter σ_ρ:[9]

$$d\rho = \lambda\left(\overline{\rho} - \rho\right)dt + \sigma_\rho \sqrt{\rho\left(1-\rho\right)} dW_\rho. \tag{4}$$

Such a setup guarantees the positive definiteness of the resulting correlation and variance-covariance matrices (See proposition 1, appendix B in Driessen, Maenhout, and Vilkov (2012)).

When individual stocks are aggregated into the market index with the respective weights $w_i, \forall i = 1 \ldots N$, the aggregate market process inherits important properties from the individual stock and from the correlation processes. Specifically, we obtain an index process:[10]

$$\begin{cases} \frac{dS_I}{S_I} & = \mu_I dt + \phi_I dW_I \\ d\phi_I^2 & = \delta_\phi dt + \nu_\phi d\rho + \iota_I dW_{\phi_I} \\ d\rho & = \lambda\left(\overline{\rho} - \rho\right)dt + \sigma_\rho \sqrt{\rho\left(1-\rho\right)} dW_\rho, \end{cases} \tag{5}$$

[7] This is consistent with the empirical findings of Dennis, Mayhew, and Stivers (2006), who obtain a much smaller leverage effect for individual stock returns than for the index.

[8] One of the first references using this type of correlations under physical probability measure is Elton and Gruber (1973), while under the risk-neutral measure the option-implied correlations between multiple stocks were introduced in Driessen, Maenhout, and Vilkov (2005, 2009, 2012) and Skinzi and Refenes (2005); later literature also used the term "equicorrelation."

[9] Collin-Dufresne and Goldstein (2001) discuss a similar model of correlation dynamics. The process is of the Wright-Fisher type, used extensively in genetics (see e.g. Karlin and Taylor (1981)), and also in financial economics (Cochrane, Longstaff, and Santa-Clara (2003)).

[10] The derivations of the index variance ϕ_I^2 under the P measure are given in Driessen, Maenhout, and Vilkov (2012), Proposition 2. The coefficients in the index variance expression are are given by $\nu_\phi \equiv \sum_{i=1}^{N} \sum_{j \neq i} w_i w_j \phi_i \phi_j$, $\iota_i \equiv \left(w_i^2 + \frac{1}{2}\rho \sum_{j\neq i} w_i w_j \frac{\phi_j}{\phi_i}\right)\phi_i \varsigma_i$ *and* $\delta_\phi \equiv \frac{1}{2}\sum_{i=1}^{N}\left[\left(2w_i^2 + \rho\sum_{j\neq i} w_i w_j \frac{\phi_j}{\phi_i}\right)\gamma_i - \frac{1}{4}\rho\sum_{j\neq i} w_i w_j \frac{\phi_j}{\phi_i}\varsigma_i^2\right]$.

where we defined a new Wiener dW_{ϕ_I} such as $\iota_I dW_{\phi_I} = \sum_{i=1}^N \iota_i dW_{\phi_i}$. The index variance is driven by two stochastic components: $d\rho$ is inherited from the pairwise correlation process, and dW_{ϕ_I}—from the individual variances.[11] The two-component stochastic volatility process is widely used in literature for option pricing and has also been shown to play important role in predicting market risk premium (e.g., for long-run risk models in Zhou and Zhu (2015), or with non-expected preference specifications in Schreindorfer (2016), among others). Linking the correlation and average individual variance dynamics to a slow, and a faster-moving variance components, respectively, represents an interesting venue for future research. Cosemans (2011) showed that correlation and average (systematic) individual variance premiums capture orthogonal parts of the aggregate variance premium.

The index-driving Wiener W_I is correlated with both correlation and individual variances, and by decomposing it into three components

$$dW_I = \varrho_1 dW_{\phi_I} + \varrho_2 dW_\rho + \varrho_3 dW_\perp, \tag{6}$$

such that $(\varrho_1 dW_{\phi_I} + \varrho_2 dW_\rho + \varrho_3 dW_\perp)^2/dt = 1$, and Wieners W_{ϕ_I} and W_ρ being orthogonal to $W_\perp$, we rewrite the market index SDE as

$$\frac{dS_I}{S_I} = \mu_I dt + \phi_I \varrho_1 dW_{\phi_I} + \phi_I \varrho_2 dW_\rho + \phi_I \varrho_3 dW_\perp. \tag{7}$$

Express from equation (5) the individual Wieners in terms of market variance and the correlation state variable:

$$\begin{cases} dW_{\phi_I} & = -\frac{\delta_\phi}{\iota_I} dt + \frac{1}{\iota_I} d\phi_I^2 - \frac{\nu_\phi}{\iota_I} d\rho \\ dW_\rho & = -\frac{\lambda(\bar{\rho}-\rho)}{\sigma_\rho\sqrt{\rho(1-\rho)}} dt + \frac{1}{\sigma_\rho\sqrt{\rho(1-\rho)}} d\rho, \end{cases} \tag{8}$$

[11] Note that by straightforward extension of an aggregation from individual level one can introduce jumps on the index level. We will just need to include systematic (correlated) jumps in individual stock processes, which are not diversified away in a basket. Because jumps are shown to be responsible for the most of the variance risk premium (up to 3/4 of it according to Bollerslev and Todorov (2011)), it makes sense theoretically; empirically, if a proxy for quadratic variation includes variation due to jumps, we can acknowledge that our exposure to variance includes jump risk.

and substitute them for the original Wieners in the market process (7) to obtain the final desired system of SDEs for the market index, driven by variance, and correlation shocks directly:

$$\begin{cases} \frac{dS_I}{S_I} &= \hat{\mu}_I dt + \hat{\sigma}_\phi d\phi_I^2 + \hat{\sigma}_\rho d\rho + \phi_I \varrho_3 dW_\perp \\ d\phi_I^2 &= \delta_\phi dt + \nu_\phi d\rho + \iota_I dW_{\phi_I} \\ d\rho &= \lambda\left(\overline{\rho} - \rho\right) dt + \sigma_\rho \sqrt{\rho\left(1-\rho\right)} dW_\rho, \end{cases} \tag{9}$$

where the drift is $\hat{\mu}_I = \mu_I - \frac{\phi_I \varrho_1 \delta_\phi}{\iota_I} - \frac{\phi_I \varrho_2 \lambda(\overline{\rho}-\rho)}{\sigma_\rho \sqrt{\rho(1-\rho)}}$, market index diffusion coefficient is $\hat{\sigma}_\phi = \frac{\phi_I \varrho_1}{\iota_I}$, and the correlation state variable diffusion is $\hat{\sigma}_\rho = \frac{\phi_I \varrho_2}{\sigma_\rho \sqrt{\rho(1-\rho)}} - \frac{\phi_I \varrho_1 \nu_\phi}{\iota_I}$; the remaining coefficients δ_ϕ, ν_ϕ, and ι_I are defined in footnote (10).

We assume that there exists a stochastic discount factor (SDF) ξ, and that all sources of risk entering the system (9) are potentially priced, i.e., they are entering the SDF expression with non-zero prices of risk: λ_{ϕ_I} for the index variance, λ_ρ for the correlation state variable, and $\lambda_\perp$ for the orthogonal Wiener.[12] Specified in this form, the prices of risk give the change in drift by the change of measure for the index variance and correlation processes, as well as for the orthogonal Wiener:

$$\frac{d\xi}{\xi} \times \begin{cases} d\phi_I^2 &= -\lambda_{\phi_I} dt \\ d\rho &= -\lambda_\rho dt \\ dW_\perp &= -\lambda_\perp dt, \end{cases} \tag{10}$$

and when we compute the covariance between the SDF and the respective process integrated over a time interval, we end up with the respective risk premiums—for variance (e.g., Carr and Wu (2009)), correlation (e.g., Driessen, Maenhout, and Vilkov (2009)), and orthogonal risks. The market risk premium is given by the covariance between the market return and the SDF:

$$E^P\left[\frac{dS_I}{S_I}\right] - E^Q\left[\frac{dS_I}{S_I}\right] = \frac{dS_I}{S_I}\frac{d\xi}{\xi} = -\hat{\sigma}_\phi \lambda_{\phi_I} dt - \hat{\sigma}_\rho \lambda_\rho dt - \phi_I \varrho_3 \lambda_\perp dt, \tag{11}$$

and hence it can be directly linked to the price of variance and correlation risks.

Following recent literature (e.g., Bollerslev, Tauchen, and Zhou (2009), Driessen, Maenhout, and Vilkov (2009)) and for reasons of easier interpretation, we define discrete variance (VRP)

[12]While it is conventional to specify an SDF in terms of standard Wieners and the respective prices of risk, we can always re-formulate it in terms of correlated sources of risk.

and correlation (CRP) risk premiums with the opposite sign, i.e., as integrated process under Q measure minus the respective process under P. Then the market risk premium can be inferred from the following pricing equation:

$$E_t[r_{t+1}] - r_{f,t} = \beta_{t,VRP} E_t[-VRP_{t,t+1}] + \beta_{t,CRP} E_t[-CRP_{t,t+1}] + \beta_{t,\perp} E_t[\omega_{t,t+1}], \qquad (12)$$

where ω is the risk premium for a factor "orthogonal" to the index variance and the correlation state variable, and betas are related to diffusion coefficients of the market index process in (9).

B. Estimation Strategy

To predict the market excess return using the pricing equation (12), we need first to estimate the conditional betas with respect to the variance, correlation, and orthogonal risks. It can be done in a traditional way, when one runs a regression of the realized excess return from $t - \Delta$ up to time t on the VRP, CRP, and other regressors, and then uses the obtained betas to predict the future return. However, because one should not use information arriving in the period of return realization, the last observation of the regressors should come from time $t - \Delta$, and it might diminish the model performance in predicting future returns relative to t. This traditional approach is best suited for explanatory in-sample regressions, and it has been used in a number of studies for these purposes.

Recall that the model underlying the pricing equation (12) is the system of SDEs (9), and the betas in the pricing equation represent the estimates of the diffusion coefficients in the dynamics dS_I/S_I, and can be obtained empirically by regressing the random return component $dS_I/S_I - E[dS_I/S_I]$ on the shocks to the index variance $d\phi_I$, to the pairwise correlation $d\rho$, and to the orthogonal risk component $dW_\perp$. Moreover, from Girsanov theorem (see, e.g., (Karatzas and Shreve, 1991, page 190)) follows that by the change of the measure from actual P to risk-neutral Q only the drift of the process changes, while the diffusion parts stay intact. This result is very important, because due to invariance of the stochastic part we can estimate the betas from shocks to variables under any equivalent probability measure, physical P, or risk-neutral Q.

Let us reconcile the need for particular variables in the estimation, and the feasibility of estimating these variables empirically. Under the actual measure, the random (discrete) shock to a predictor z can be approximated by the difference between its realization and its conditional expectation $z_{t+1} - E_t[z]$, and that is the path pursued by Pyun (2016) for the estimation of the contemporaneous variance betas. From high-frequency data one can observe a realization of the variance, and one can use different models to get a conditional expectation of the variance over a period. Using the same procedure to obtain a pairwise correlation shock for the next day is tricky, when one deals with a large number of stocks—data availability and microstructural issues may pose a problem.

Under the risk-neutral measure we can obtain implied variances (IV) and correlations (IC), which are the risk-neutral expected integrated variance and correlation, respectively, over a period of time from t until the maturity of the options T:

$$IV(t,T) = E_t^Q \left[\int_t^T \phi_I^2(s) ds \right] \tag{13}$$

$$IC(t,T) = E_t^Q \left[\int_t^T \rho(s) ds \right]. \tag{14}$$

The integrated expected variance is highly persistent—first-order autocorrelations in our data are between 0.97 and 0.994 for different maturities and for short time increments it is well approximated by a martingale, e.g., Filipović, Gourier, and Mancini (2016) find that a "martingale model provides relatively accurate forecasts for the one-day horizon ..., but its forecasting accuracy largely deteriorates when moving to the ten-day horizon." While we are not aware of a similar study on correlation swaps, IC is also highly persistent (first autocorrelations between 0.97 and 0.993), with average daily increments statistically not different from zero, and we assume that it also can be approximated by a martingale for short (daily) time increments. We can get more intuition by looking at the following decomposition for the implied variance:

$$IV(t,T) = E_t^Q\left[\int_t^T \phi_I^2(s)ds\right] = E_t^Q\left[E_{t+1}^Q\left[\int_{t+1}^T \phi_I^2(s)ds\right]\right] + E_t^Q\left[\int_t^{t+1} \phi_I^2(s)ds\right] \tag{15}$$

$$= E_t^Q\left[IV(t+1,T)\right] + E_t^Q\left[\int_t^{t+1} \phi_I^2(s)ds\right], \tag{16}$$

and implied correlation:

$$IC(t,T) = E_t^Q\left[\int_t^T \rho(s)ds\right] = E_t^Q\left[E_{t+1}^Q\left[\int_{t+1}^T \rho(s)ds\right]\right] + E_t^Q\left[\int_t^{t+1} \rho(s)ds\right] \tag{17}$$

$$= E_t^Q\left[IC(t+1,T)\right] + E_t^Q\left[\int_t^{t+1} \rho(s)ds\right]. \tag{18}$$

Hence, the daily increment in IV and IC are indeed close to the unexpected random shock due to a change in filtration over time:

$$\begin{cases} \Delta IV(t+1,T) & = IV(t+1,T) - E_t^Q\left[IV(t+1,T)\right] - E_t^Q\left[\int_t^{t+1} \phi_I^2(s)ds\right] \\ \Delta IC(t+1,T) & = IC(t+1,T) - E_t^Q\left[IC(t+1,T)\right] - E_t^Q\left[\int_t^{t+1} \rho(s)ds\right]. \end{cases} \tag{19}$$

Assuming that the last terms in the equations above,—expected integrated variance and correlation over one day,—are small and relatively constant over time, they will not have much an effect on the estimation of the covariances or betas. Thus, we can use the currently observed IV and IC as the conditional expectations of tomorrow's IV and IC, and the daily increments in IV and IC can then be used as a proxy for the daily (or other short interval) random shock to variance and correlation, accordingly:

$$\begin{cases} \Delta IV(t+1,T) \approx IV(t+1,T) - E_t[IV(t+1,T)] & \approx \zeta_\phi \times \Delta\phi_I^2 \\ \Delta IC(t+1,T) \approx IC(t+1,T) - E_t[IC(t+1,T)] & \approx \zeta_\rho \times \Delta\rho, \end{cases} \tag{20}$$

where ζ_ϕ and ζ_ρ are adjustments factors, stemming from the fact that on the right hand-side we have a short-period shock to the variance or correlation, while on the left-hand side we have changes in variance and correlations integrated over time up to option expiration, and hence the integrated effect of a short-term shock.

Thus, we obtain the conditional betas for pricing equation (12) by estimating a discrete version of the first equation in system (9), using on both sides of the regression increments of the respective variables under the risk-neutral measure:

$$r_{t+1} - r_{f,t} = \alpha + \beta_{t,\Delta IV} \Delta IV(t+1,T) + \beta_{t,\Delta IC} \Delta IC(t+1,T) + \Xi_{t+1}, \tag{21}$$

where Ξ_{t+1} is a proxy for the orthogonal shock (when used).

Note that before using the resulting betas from (21) in the pricing equation (12), we need to adjust them for the difference in magnitude of the regressors used for the betas estimation and predictors in the pricing equation; i.e., we need to determine the adjustment factors ζ_ϕ and ζ_ρ. We will deal with these issues in the empirical section.

III. Data and Preparation of Variables

We describe the data sources, and the procedures to select, filter, and merge the data from different datasets—CRSP, Compustat, I/B/E/S and OptionMetrics. This section also briefly discusses the construction of variables used in our empirical analysis in Section IV—disagreement proxy, implied and realized variances, implied and realized correlations, as well as variance and correlation risk premiums.

A. Data Preparation

We work with three major indices, and their constituents, namely, S&P500, S&P100, and DJ Industrial Average (DJ30). We obtain their composition from Compustat and merge it with CRSP through the CCM Linking Table using GVKEY and IID to link to PERMNO, following the second best method from Dobelman, Kang, and Park (2014). The data on returns and market capitalization are obtained from CRSP, and as a proxy for index weights on each day, we use the relative market cap (for S&P500 and S&P100) or price (for DJ30) of each stock in an index from the previous day. For realized second moments of the indices we also use intraday futures data at one-minute frequency. As market proxy we use the S&P500 index.

Matching the historical data with options works through the historical CUSIP link provided by OptionMetrics. S&P500, S&P100, and DJ Industrial Average indices are directly used as underlying for options. PERMNO is used as the main identifier in our merged database, and the data availability statistics is provided in Table I. For computing the option-based variables we rely on the Surface File from OptionMetrics, selecting for each underlying the options with 30, 91, 182, 273, and 365 days to maturity and (absolute) delta smaller or equal to 0.5. While the surface data is not suitable for testing trading strategies due to extensive inter- and extrapolations of the market data, it still can be used in asset pricing tests or in generating signals for trading (e.g., DeMiguel, Plyakha, Uppal, and Vilkov (2013), among others). The options for S&P500 and S&P100 are available from 1996, and for DJ30—from October 1997; all options data is available until April 2016.

We use the proxy of economic policy uncertainty (EPU) by Baker, Bloom, and Davis (2016),[13] and also construct a proxy for the disagreement (or, difference in beliefs), based on the earnings forecasts for individual firms. For the disagreement proxy (DIB) we use the Unadjusted Summary History file for U.S. firms from I/B/E/S. Following Diether, Malloy, and Scherbina (2002) we define firm-specific DIB as the standard deviation of earnings-per-share forecasts for the fiscal year one scaled by the absolute value of the forecasts. For the market-wide disagreement we use an equal-weighted average of the individual DIBs, which according to Buraschi, Trojani, and Vedolin (2014) has a correlation of almost one with the proxy based on market capitalization weights. We also take into account a number of traditional predictors of the market return borrowed from Goyal and Welch (2008) study.[14] All these variables are used at monthly frequency.

B. Variances and Correlations

Option-implied variances (IV) are computed using log contracts (model-free implied variance by Dumas (1995), Britten-Jones and Neuberger (2000), Bakshi, Kapadia, and Madan (2003), and others) or as simple variance swaps (Martin (2013)). Because we need a proxy for the total

[13]We appreciate having an opportunity to download updated series of the Economic Policy Uncertainty Index from the web-site of the authors www.policyuncertainty.com/.

[14]We are grateful to Amit Goyal for making the updated data available on his web-site www.hec.unil.ch/agoyal/.

quadratic variation due to diffusion and jump components, we use simple swaps in the main analysis, and the log contracts are left for robustness exercises.[15]

Realized variances (RV) are estimated from daily returns for a specified window Δ. The *ex ante* variance risk premium (VRP) is computed as implied variance observed at the end of day t minus realized variance from $t - \Delta t$ to t. In most cases we will consider the 30-day VRP for predicting returns and risks, because it demonstrates a better performance compared to the longer-term VRP. The VRP for the period matching the future return or risk horizon will be discussed in the robustness section.

Following our assumption set in equation (3), that all pairwise correlations are driven by the same state variable, correlations are constructed as equicorrelations, i.e., all the pairwise correlations are set equal. We use the terms "implied correlation" (IC) for the risk-neutral, and "realized correlation" (RC) for the realized equicorrelations.[16] Important is that this method always gives a positive-definite covariance matrix when the equicorrelation is non-negative, which is typically the case for large baskets.[17]

The identification of the pairwise correlations is based on the restriction that the variance of an index (or a basket) I is equal to the variance of the portfolio of its individual components:

$$\sigma_I^2(t) = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_i(t) \sigma_j(t) \rho_{ij}(t). \tag{22}$$

This restriction holds under both objective P and risk-neutral Q measures. Given the time-series of variances for an index $\sigma_I^2(t)$ and its components $\sigma_i^2(t), i = 1 \ldots N$, as well as the index

[15] In earlier versions of the paper Ian Martin discussed the issue of estimating implied correlations, and came to conclusions that implied correlations/ correlation swaps should be estimated using simple variance swaps as opposed to model-free variance.

[16] One of the first references using this type of correlations under physical probability measure is Elton and Gruber (1973), while under the risk-neutral measure the option-implied correlations between multiple stocks were introduced in Driessen, Maenhout, and Vilkov (2005) and Skinzi and Refenes (2005); later literature also used the term "equicorrelation."

[17] See proposition 1, appendix B in Driessen, Maenhout, and Vilkov (2012).

weights $\{w_i\}$, the equicorrelation $\rho_{ij}(t) = \rho(t)$ is calculated for each day t as

$$\rho(t) = \frac{\sigma_I^2(t) - \sum_{i=1}^{N} w_i^2 \sigma_i^2(t)}{\sum_{i=1}^{N} \sum_{j \neq i} w_i w_j \sigma_i(t) \sigma_j(t)}, \tag{23}$$

thus, assuming that the correlation matrix at time t looks as

$$\Omega_{EC} = \begin{pmatrix} 1 & \rho & \dots & \rho \\ \rho & 1 & \dots & \rho \\ \vdots & \vdots & \ddots & \vdots \\ \rho & \rho & \dots & 1 \end{pmatrix}. \tag{24}$$

By plugging in risk-neutral (implied) variances in formula (23), we get implied correlation (IC) as output, and by using expected actual variances (or realized ones), we obtain the realized correlation (RC). The *ex ante* correlation risk premium (CRP) is constructed as the implied correlation for options' maturity $t + \Delta$ observed at the end of day t minus the corresponding realized correlation from $t - \Delta t$ to t.

IV. Price of Correlation Risk and Return Predictability

We test for the presence of variance and correlation risk premiums in index options for three major indices, and for the variance risk premium in individual options on all constituent stocks. Then in Section IV.B we proceed with testing the main pricing equation (12), paying special attention to its out-of-sample performance; for parameter estimation we use a new methodology developed in Section II.B. Finally, in Section V.B we investigate additional predictions of the the model about the link between CRP and future dispersion of market betas, and carry out additional diagnostics of the connection between CRP and market uncertainty/disagreement proxies.

A. The Price of Variance and Correlation Risks

The correlations and variances for major indices co-move very closely, and hence potentially contain (or, reveal) similar information. The joint dynamics of equicorrelations and variances for S&P500 and other major indices in Table III reveal that in major indices each set of variables (implied and realized correlations, as implied and realized variances) tend to be strongly correlated. For example, the correlations between 30-day IC for S&P500 and other indices are all above 0.96. Other variables demonstrate a similar picture for all maturities. In what follows, we concentrate on analyzing variables extracted from S&P500 data, and provide results for S&P100 and DJ30 for completeness.

The correlations and risk premiums for all maturities are provided in Table II with two main observations: First, there is a significant correlation risk premium for stocks in all the major indices, and, second, this risk premium tends to grow with time to maturity; moreover, this CRP grows happens exclusively due to increasing IC with maturity. Both correlations (IC and RC) within an index and the CRP decrease as the number of its components grows.

Tables IV and V provide a complementary view on the variance risk premiums for individual stocks within a number of indices and for the indices themselves. As shown in previous studies (e.g., Driessen, Maenhout, and Vilkov (2005)), the variance risk premium at the individual level is typically not significantly different from zero (with point estimate being negative for maturities longer than 30 days for S&P500 components and for all maturities of the S&P500 and DJ30 components), while at the index level the implied variance is always greater than the realized one, and the difference is highly significant with p-values ranging from less than 0.01 to 0.09 - exceeding 0.05 only twice. Observe, however, from Table V that on individual level variance risk premiums demonstrate a lot of heterogeneity, and for some stocks we still observe a systematic and significant deviation of risk-neutral variance from its counterpart under the physical P measure.

Overall, we confirm the findings of Driessen, Maenhout, and Vilkov (2005) that the index variance is priced predominantly due to priced correlation component, though the dynamics of the individual variance risk premiums should not be neglected. Hence, both correlation and index variance risk premiums potentially contain non-redundant information.

B. Return Predictability: Out-of-sample Testing

It has been demonstrated in several studies that the variance risk premium is able to predict market returns, and the predictability is stronger at the intermediate quarterly return horizon (e.g., Bollerslev, Tauchen, and Zhou (2009), Bollerslev, Marrone, Xu, and Zhou (2014)). As for correlations, interestingly, a vast majority of existing studies documented return predictability by implied correlations, where the predictability is stronger at relatively longer horizons up to one year (e.g., Driessen, Maenhout, and Vilkov (2005, 2012), Faria, Kosowski, and Wang (2016)), and we are aware of only one previous study by Cosemans (2011) that used correlation risk premium in an in-sample market return predictability testing. Theoretically, consistent with our pricing equation (12), one should use the CRP to explain the equity risk premium.

We replicate the in-sample predictability exercise for S&P500 excess returns using VRP and CRP for three different indices, and a slightly longer sample period compared to earlier studies. From Table VI we observe that the VRP indeed has a strong predictive power for future returns, with the R^2 reaching its maximum at the quarterly horizon (9.60%), and then fading away pretty quickly. CRP gains its significance starting from a monthly horizon and delivers a decent R^2 for all considered horizons longer than one month (e.g., 7.26% for quarterly and 9.87% for 9-month horizons). In joint tests the CRP behaves in a predatory way for horizons longer than one quarter, and steals the significance from the VRP. The predictors survive a number of standard controls (e.g., from Goyal and Welch (2008)), and we discuss these results in the robustness section.

Motivated by our model predictions and the in-sample regression results, we concentrate now on the out-of-sample forecasting of market returns, and here we are especially interested in the potential difference in horizons, at which VRP and CRP show the best performance. We reproduce below the three key equations from the Section II: (i) index dynamics equation–first equation from the system (9), (ii) estimation equation (21), and (iii) pricing equation (12):

$$dS_I/S_I = \hat{\mu}_I dt + \hat{\sigma}_\phi d\phi_I^2 + \hat{\sigma}_\rho d\rho + \phi_I \varrho_3 dW_\perp$$

$$\Downarrow$$

$$r_{t+1} - r_{f,t} = \alpha + \beta_{t,\Delta IV}\Delta IV(t+1,T) + \beta_{t,\Delta IC}\Delta IC(t+1,T) + \beta_{t,\perp}\Xi_{t+1}$$

$$\Downarrow$$

$$E_t[r_{t+1}] - r_{f,t} = \beta_{t,VRP}E_t[-VRP_{t,t+1}] + \beta_{t,CRP}E_t[-CRP_{t,t+1}] + \beta_{t,\perp}E_t[\omega_{t,t+1}].$$

Motivated by the index dynamics from the first equation above, we are using the estimation equation (the second one above) to obtain the market index betas with respect to variance and correlation risks, and then apply these betas in the pricing equation to get the market forecast.

Note that before we can apply the betas from the estimation equation to predict market returns for a specified horizon, we need to carry out some adjustments. Specifically, note that betas in the estimation and pricing equations represent the correlation between return on the left-hand side and a specific variable on the right-hand side, multiplied by the ratio of their volatilities. Correlation is a unit-less measure of linear dependency between random shocks to return and either correlation or variance process, and hence it should be the same in the estimation and pricing equations. The volatilities are different, however, due to two reasons: first, in the estimation equation we use daily returns on the left-hand side, while in the pricing equation we predict longer-period excess returns, and, second, in the estimation equation we use daily increments of correlation or variance integrated over some period, which do not always correspond to "daily" shocks to these variables. Also, because we define VRP and CRP as risk-neutral quantities minus physical ones, and the expected excess return is basically the difference between the physical and risk-neutral measures, we need either to use $-CRP$ and $-VRP$ in pricing equations, or to multiply the betas by -1.

For example, when we use 30-day options to extract annualized implied variance, we first compute the simple swap rate for 30 days, and then scale it up by factor 365/30. Hence the increments in the annualized 30-day IV are $365/30 \approx 12.17$ times larger in magnitude than a

1-day shock to variance we should use to match daily returns. As a result, the denominator in the ratio of volatilities is $\sqrt{365/30} \approx 3.49$ times larger (or numerator is 3.49 times smaller) than it is supposed to be for matching-period increments of the left- and right-hand side variable, and the beta needs to be adjusted upwards by factor 3.49.[18] Now we can use this adjusted beta with annualized VRP from monthly options to predict matching-period monthly returns. If we want to predict two-month returns using the same 30-day annualized VRP, we need to multiply it by two to match the duration of the return.

Note that we cannot apply the same trick for adjusting the correlation betas, because integrated correlations are not annualized and they do not scale up or down with time linearly. One way to address the issue would be to adjust the beta by the ratio of the volatility of the right-hand side variable used in estimation relative to the volatility of the predictor. For example, for predicting monthly market return we use monthly CRP, and knowing that the volatility of ΔIC is typically 2-3 times lower than that of monthly CRP, we need adjust the beta downwards by multiplying it by scaling factor $\frac{\sigma_{\Delta IC}}{\sigma_{CRP}}$:

$$\beta_{t,CRP} = \frac{\rho_{I,CRP} \times \sigma_I}{\sigma_{CRP}} = \frac{\rho_{I,\rho} \times \sigma_I}{\sigma_{\Delta IC}} \times \frac{\sigma_{\Delta IC}}{\sigma_{CRP}} = \beta_{t,\Delta IC} \times \frac{\sigma_{\Delta IC}}{\sigma_{CRP}}. \tag{25}$$

The underlying assumption is again that the correlations between index return and correlation processes are estimated correctly and do not require adjustments, i.e., $\rho_{I,CRP} = \rho_{I,\rho}$. We estimate the appropriate scaling factor over the same backward window, over which we run the correlation beta estimation.

To predict the market excess return at time t for a horizon τ_r, we regress, at t, daily excess returns on daily increments of the annualized τ_{IV}-day implied variance and/or of the τ_{IC}-day implied correlation to get initial variance and correlation betas $\beta_{t,\Delta IV}$ and $\beta_{t,\Delta IC}$. We use a historical window of one year. We scale the resulting betas by $\sqrt{365/\tau_{IV}}$ for variance, and by $\frac{\sigma_{\Delta IC}}{\sigma_{CRP}}$ for the correlation, to get $\beta_{t,VRP}$ and $\beta_{t,CRP}$. The correlation scaling factor is estimated

[18] This discussion and the suggested solution are based on the silent assumption that one can scale up variance linearly by time. It is not exactly correct, and depending on the return process assumptions, by applying linear scaling one can believe in overestimating variability as in Diebold, Hickman, Inoue, and Schuermann (1997), or underestimating it as in Danielsson and Zigrand (2006).

over the same rolling window using the sample volatilities of IC and CRP, both for τ_{IC} tenor. Using a particular combination of predictors, we obtain a predicted return for model $j = 0 \dots 3$ at time t for horizon τ_r:

$$\begin{cases} \text{Model 0:} & \hat{r}_{j,t,\tau_r} = \hat{r}_t \\ \text{Model 1:} & \hat{r}_{j,t,\tau_r} = \beta_{t,VRP} \times VRP(t) \\ \text{Model 2:} & \hat{r}_{j,t,\tau_r} = \beta_{t,CRP} \times CRP(t) \\ \text{Model 3:} & \hat{r}_{j,t,\tau_r} = \beta_{t,VRP} \times VRP(t) + \beta_{t,CRP} \times CRP(t), \end{cases} \tag{26}$$

where $\hat{r}_t$ is the historical mean of the market excess return. While theoretically one should select the VRP and CRP for the same horizon as predicted returns, we noticed that 30-day IV/VRP delivers the strongest results, and we are always using 30-day IV to estimate betas and 30-day VRP to predict returns (so it need to be scaled up by $\frac{\tau_r}{30}$ to match the return horizon). IC and CRP are matched in horizon to predicted returns. For each model j, each point in time t, and each horizon τ_r we define the forecast error as $e_{j,t,\tau_r} := \hat{r}_{j,t,\tau_r} - r_{t,t+\tau_r}$. Let $\hat{r}_{j,\tau_r}$ denote the vector of predicted returns for horizon τ_r, and e_{j,τ_r} denotes the vector of rolling OOS errors from model j.

The standard way of testing the out-of-sample performance is to evaluate the sequence of out-of-sample forecasts by a loss function that is either an economically meaningful criterion, such as utility or profits (e.g., Leitch and Tanner (1991), West, Edison, and Cho (1993), Della Corte, Sarno, and Tsiakas (2009)), or using some statistical criterion (e.g., Diebold and Mariano (1995), McCracken (2007)); these approaches have recently been unified and extended by Giacomini and White (2006), who developed out-of-sample tests to compare the predictive ability of competing forecasts, given a general loss function under conditions of possibly misspecified models.

Our out-of-sample performance measures are computed as follows. First, the OOS R^2 is defined relative to the prediction based on the historical average return (model $j = 0$):

$$R^2_{j,\tau_r} = 1 - \frac{MSE_{j,\tau_r}}{MSE_{0,\tau_r}}, \text{ where } MSE_{j,\tau_r} = \frac{1}{N} e^{\top}_{j,\tau_r} \times e_{j,\tau_r}, j = 0, \dots, 3, \tag{27}$$

where N is the number of predictions or errors in a vector. Second, the average square-error loss δ, again defined relative to the prediction from model $j = 0$:

$$\delta_{j,\tau_r} = MSE_{j,\tau_r} - MSE_{0,\tau_r}, \tag{28}$$

which is one of the loss functions underlying the Diebold-Mariano tests. Third, we compute the gain in the certainty equivalent return of a mean-variance investor (similar to Campbell and Thompson (2008)) following the predictions of a given model $j = 1, 2, 3$ relative to the prediction based on the historical average return. For this purpose at the end of each month t we derive an optimal portfolio consisting of market and risk-free investment, $w_{t,\tau,j} = \frac{\hat{r}_{j,t,\tau_r}}{\sigma^2}$ for a myopic mean-variance investor with horizon τ_r, risk aversion $\gamma = 1$, and using as inputs a one-year historical variance and the predicted excess market return $\hat{r}_{j,t,\tau_r}$.[19] Then we construct the rolling realized returns $r^{MV}_{j,\tau}$ for each model and horizon, and compute the mean-variance certainty equivalent CE_{j,τ_r}. The gain in the certainty equivalent return is then defined as

$$\Delta CE_j, \tau_r = CE_{j,\tau_r} - CE_{0,\tau_r}, \text{ where } CE_{,\tau_r} = E[r^{MV}_{j,\tau_r}] - \frac{\gamma}{2}\sigma^2(r^{MV}_{j,\tau_r}), \tag{29}$$

and it measures the true economic benefit from being able to construct a better performing portfolio. We also compute a certainty equivalent improvement relative to model using CRP as a predictor, i.e., $CE_{j,\tau_r} - CE_{CRP,\tau_r}$.

A particular model out-performs the prediction by average return when R^2_{j,τ_r} is significantly different from zero, and when δ_{j,τ_r} and $\Delta CE_{j,\tau_r}$ are significantly positive. Due to a short sample period of less than 20 years and tested return predictability at horizons up to a year, the asymptotic testing procedures may not be very accurate, and we resort to boostrapping our statistics. Specifically, we use the moving-block bootstrap by Künsch (1989),[20] where we randomly resample with replacement from the time-series of predictions made by each model, of the market return realizations following each observation, and of the respective errors.[21] For

[19] Following Campbell and Thompson (2008), we restrict the optimal weights to be in $[0, 1.5]$ range.

[20] MBB is shown (e.g., in Lahiri (1999)) to be comparable in performance to other widely used methods like stationary bootstrap by Politis and Romano (1994) or circular block bootstrap from their 1992 paper, while constant block size leads to smaller mean-squared errors than with random block size as in stationary bootstrap.

[21] We draw 10,000 random samples of size equal to 200 blocks, with blocks of twelve observations (i.e., one-year blocks) to preserve the autocorrelation in the data, which is at maximum equal to eleven lags for annual prediction horizon due to overlapping observations each month.

these random samples we compute OOS performance measures, and then construct a bootstrapped distribution for each of them. Testing the null is then equivalent to checking the value of a cumulative density function at zero value of a given statistic.

The results of the market return prediction using contemporaneous betas approach are collected in Table VII. From Panel A we observe that using VRP alone generates significant R^2 for monthly and quarterly horizons, and CRP produces significant R^2's for all horizons, reaching the maximum of 8.1% for one quarter and decreasing slightly to 7.0% for one year returns. Jointly VRP and CRP generate a stellar 13.1% out-of-sample R^2 at the quarterly horizon. The Diebold-Mariano statistic is consistent with the R^2 results. The improvements in certainty equivalent returns are shown in Panel B, and we observe that VRP alone significantly improves the certainty equivalent by 2.4% p.a. for monthly and quarterly horizons, and by 1.3% for the 6-month horizon. The CRP shows improvement of 3.9% for the monthly horizon, then around 2% for 3-, 6-, and 9-month horizons, and slightly less than a percent for one year. Thus, as before, the predictive power of CRP is economically and statistically significant for a longer period compared to the VRP. Looking directly at the CE improvement relative to the CRP model ($CE_{j,\tau_r} - CE_{CRP,\tau_r}$), we also see that CRP performs statistically better than VRP for horizons of one, six, and nine months with improvement of 1.6%, 0.8%, and 2% p.a., respectively.

We also run the standard predictive procedure, where we use a 3-year rolling window at each time t to estimate a regression of a form:

$$r_t - r_{f,t-1} = \beta_{t-1,VRP} VRP_{t-1,t} + \beta_{t-1,CRP} CRP_{t-1,t}, \tag{30}$$

and then apply the resulting betas to currently observed explanatory variables $VRP_{t,t+1}$ and $CRP_{t,t+1}$ to get an excess return forecast $r_{t+1} - r_{f,t}$ for the next time period. We apply then the same evaluation criteria to the prediction as we did before for the contemporaneous betas approach. The results for OOS R^2 and Diebold-Mariano loss function δ_{j,τ_r} shown in Table VIII are weaker than with contemporaneous betas approach for the VRP (R^2 for one month is very negative, and for three months—5.4%, and then again negative for longer horizons), and they are a lot weaker for the CRP—most R^2's are not significant. The improvements in the certainty equivalent reported in Panel B are also smaller than in Table VII. Remember that with the traditional approach, when we estimate the betas in (30) for time t, the latest observation of the predictive variables comes from $t-1$, i.e., for predicting annual returns we do not use any option-implied information from the past year. Figure 1 contrasts the VRP and CRP betas estimated at each point in time for the next-period prediction. We observe that the variance and correlation betas are quite dynamic, and just skipping the last year of data certainty has a profound (and negative) effect on the prediction quality. For longer-term CRP the difference in betas is quite large, with contemporaneous betas being much more stable compared to the standard ones. Stability of betas adds to the stability of the forecast; moreover, visually, traditional betas seem to overreact to large occurrences of return and/ or predictive variables. Using high-frequency (daily) returns and variance/ correlation increments for contemporaneous approach mitigates the effect of outliers on the estimated quadratic covariation and on the resulting betas.

Thus, three important messages emerge: (i) VRP and CRP perform better than the past average return statistically, and the improvements in predictability have clear economic benefits; (ii) VRP's performance peaks at quarterly horizon, and then fades away quickly, while the CRP shows stable significant predictability for horizons up to a year; and (iii) using contemporaneous betas approach is important, especially for longer-term prediction.

V. What Does Correlation Risk Stand For?

A. Correlation Risk Premium and Uncertainty: Empirical Link

The only to us known attempt to explain the correlation risk premium in general equilibrium settings has been used by Buraschi, Trojani, and Vedolin (2014). The authors linked the correlation risk premium to uncertainty in the economy, measured empirically as the aggregated difference in beliefs regarding the future companies' earnings. Moreover, they provided solid empirical support to their theoretical claims, showing that ex-post correlation risk premium is positively related to the aggregated difference in beliefs.

Intuitively, a positive link between the uncertainty and correlation risk premium fits out our empirical results: both correlation risk premium and uncertainty are associated with a positive compensation for risk, and hence potentially the correlation risk premium can be used as a proxy for disagreement or uncertainty.

When we compute a correlation between the aggregate DIB for the end of each month and ex-post correlation risk premium also estimated for the end of each month (though with a look-ahead bias), it is indeed positive for all CRP maturities for the sample period 1996-07/2007 used in Buraschi, Trojani, and Vedolin (2014), ranging from 0.11 for 30-day CRP to 0.06 for 365-day CRP. However, for our whole sample from 1996 until 04/2016, the correlation for 30-day CRP is literally zero at 0.008, turning negative for longer maturities, and reaching -0.19 for 365-day CRP.

To understand the link between uncertainty and CRP, we plot in Figure 2 the 3-year rolling window correlations between the uncertainty measures (difference in beliefs DIB and economic policy uncertainty index EPU) and the ex post CRP for various maturities. It is clear from the picture that the correlation between uncertainty and CRP is quite unstable, and that over time it tends to decrease. For DIB the correlation stays mostly negative after 2007, and for both uncertainty measures we observe very significant downward swings, during which correlation reaches about -0.55 for both measures. For early years, however, the link between DIB and CRP was rather positive, while for EPU and CRP is was on average around zero and exhibited very high volatility.

Investigating empirically the dynamics of the link between uncertainty and CRP is an interesting venue for future research, but for now we find that the extended empirical data does not support a clean and appealing theoretical picture suggested by Buraschi, Trojani, and Vedolin (2014).

B. Correlation Risk Premium and Future Market Risk

One of the potential motivations for the existence of the correlation risk premium is the role of the correlation as a state variable predicting future investment opportunities. Intuitively, increasing correlations decrease the potential diversification benefits, and thus increase the total risk in an equity portfolio. The average correlation between stocks matters by affecting the number of stocks required to reach a well-diversified portfolio, and the differences in correlations for different stock pairs matter by defining the lowest attainable bound of the systematic risk (as a proportion of the market factor risk) in a well-diversified portfolio. Our correlation measures (IC and RC) represent the average correlations among stocks, and to proxy for the distribution of individual pairwise correlations we use the cross-sectional variance of the realized market betas.

We can illustrate the link between the dispersion of betas and correlation in a stylized market model, in which each stock is driven by the market and an idiosyncratic components. The correlation between any two stocks i, j is created by the interaction of betas, and when idiosyncratic components for each asset gets more aligned with the market factor, it converges to one:

$$\lim_{\varepsilon_i^2, \varepsilon_j^2 \to 0} \rho_{i,j} = \lim_{\varepsilon_i^2, \varepsilon_j^2 \to 0} \sigma_M^2 \frac{\beta_{M,i}\beta_{M,j}}{\sqrt{\beta_{M,i}^2\sigma_M^2 + \varepsilon_i^2}\sqrt{\beta_{M,j}^2\sigma_M^2 + \varepsilon_j^2}} = 1. \quad (31)$$

In general, we expect the average correlation between assets to increase when betas get more clustered around one, i.e., when their cross-sectional dispersion around their mean gets smaller. Keeping the volatilities in (31) constant, and assuming that market betas are distributed around mean one with the same variance, that is, $\beta_M = 1 + \epsilon_M \sim Dist(1, \sigma_\epsilon^2)$, we obtain:

$$E[\rho_{i,j}] \propto E[\beta_{M,i}\beta_{M,j}] = E[(1 + \epsilon_{M,i})(1 + \epsilon_{M,j})] = 1 + cov(\epsilon_{M,i}, \epsilon_{M,j}) = 1 - \sigma_\epsilon^2, \quad (32)$$

where the covariance between the deviation of betas from the mean is negative, because their mean does not change, and an increasing beta is necessarily compensated by a decreasing one.

We can illustrate the effect of dispersion of betas as the bound of non-diversifiable risk for a simple equal-weighted portfolio of N stocks. A typical contribution to portfolio variance of stock i is $w_i^2\sigma_i^2 = \left(\frac{1}{N}\right)^2 \sigma_i^2$, and the total number of variance terms is certainly N. A typical covariance between two stocks i and j adds to the portfolio variance $w_i\, w_j \sigma_{ij} = \left(\frac{1}{N}\right)^2 \sigma_{ij}$ (for all $i \neq j$), and the total number of such covariance terms (off-diagonal terms) is $N^2 - N$. Add all the terms to get the portfolio variance:

$$\sigma_p^2 = \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij} = \sum_{i=1}^{N}\left(\frac{1}{N}\right)^2 \sigma_{ii} + \sum_{i=1}^{N}\sum_{j\neq i}^{N}\left(\frac{1}{N}\right)^2 \sigma_{ij} \tag{33}$$

$$= \left(\frac{1}{N}\right)\left(\frac{1}{N}\sum_{i=1}^{N}\sigma_i^2\right) + \left(\frac{N^2 - N}{N^2}\right)\left(\frac{1}{N^2 - N}\sum_{i=1}^{N}\sum_{j\neq i}^{N}\sigma_{ij}\right). \tag{34}$$

As N becomes very large, the contribution of the variance terms to the portfolio variance tends to zero, and the contribution of covariance terms tends to the average covariance σ_{ij}, where in an one-factor model as described above the covariance is a function of stock market betas:

$$\sigma_{ij} = \beta_{M,i}\beta_{M,j}\sigma_M^2. \tag{35}$$

Thus, the portfolio's expected non-diversifiable risk relative to the market risk is $E[\beta_{M,i}\beta_{M,j}]$, which is decreasing in the dispersion of betas as we demonstrated in (32) above. Intuitively, it is clear, because with all market betas collapsing to their grand mean of one, the lowest risk boundary in the portfolio is the market variance itself.

Table IX provides the regression results for predicting a particular future risk measure (dispersion of market betas $\sigma^2(\beta_M)$, realized correlation RC, and the realized market variance (RV) by one of the four predictors, namely, lagged realized variance and current implied variances (RV and IV), and lagged realized and current implied correlations (RC and IC). The numbers allow us to disentangle the roles of variance and correlation as state variables defining future investment opportunities, and thus understand why variance and correlation risk premiums predict returns over different horizons.

First, correlation, and especially implied correlation, predicts future dispersion of market betas, and its explanatory power is increasing with the horizon. Higher implied correlation predicts lower dispersion and hence a higher lower bound of non-diversifiable risk. The R^2 is modest 10.70% for monthly horizon, and it goes up to around 30% for six-month and longer horizons. Second, a similar picture is with predicting future realized correlations—here past realized correlation delivers a very high R^2 for all horizons—all between 23% and 30%. Implied correlations show its best performance in predicting shorter-term realized correlations (with R^2 of 35% for the monthly horizon), though its R^2 for the annual horizon is still above 15%. Third, both correlations do a very poor job in predicting future market variance.

Variances (especially the implied one) predict best the future market variances; for short horizons the explanatory power is impressive—R^2 of almost 50% for one-month prediction. For longer horizons the R^2 goes down quickly and gets to about 12% for one-year future variance. Variances can also predict future realized correlations, with a much more modest R^2 of 15.93% for one month, and less than 5% for one year. Most interestingly, the variances predict the dispersion of future market betas with the *positive* sign, and an impressive R^2 of almost 21% for one-year horizon. It means that a higher expected variance predicts higher future market variance, but at the same time it predicts better diversification (i.e., better lower bound on non-diversifiable market risk) for large and well-diversified portfolios at longer horizons like one year.

Thus, variance predicts the shorter-term risk in the form of the market variance, and for longer terms it predicts higher market risk, but better diversification at the same time, so investors having access to broad market can hedge against the increasing market variance by increasing the number of stocks in the portfolio, especially with more disperse market betas. Correlation, on the other hand, plays an important role in determining longer-term risks in the form of diversification and lower bound of non-diversifiable risks. Following Buraschi, Kosowski, and Trojani (2014) we can label correlation as the "no-place-to-hide" state variable, which predicts risks and returns at longer horizons compared to the variance. Such an interpretation is fully consistent with our empirical results on market return predictability.

VI. Robustness Tests

We carry out a number of additional tests to check if our results are robust to modifications in the procedures. The additional tables are provided in the Internet Appendix.

Table A101 reports the results of the in-sample return predictability using CRP and VRP, both computed to match the horizon instead of always using 30-day VRP as in the main text. The results for VRP are typically far worse, consistent with what we claimed earlier. Again, in the main analysis we use 30-day VRP, which is most beneficial for this predictor.

We also test in Table A102 how the option-based variables compare in predicting future market return with a number of fundamental variables, shown elsewhere to be successful predictors of market return. While there is a myriad of possible explanatory variables used in different studies (e.g., Goyal and Welch (2008), Ferreira and Santa-Clara (2011), among others), we limit our choice to only five of them, but so that they are largely non-redundant in terms of economic information they encompass. Specifically, we use the Earnings Price Ratio ($EP12$), the Term Spread (TMS), the Default Yield Spread (DFY), the Book-to-Market Ratio (BM), and the Net Equity Expansion ($NTIS$). We construct these variables from the data and following the procedures from the study of Goyal and Welch (2008). $EP12$ is defined as the difference between the log of earnings and the log of prices; TMS is the difference between the long term yield on government bonds and the Treasury-bill; DFY is the difference between BAA and AAA-rated corporate bond yields; BM is the ratio of book value to market value for the Dow Jones Industrial Average, and $NTIS$ is the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. The results indicate that while a number of fundamental variables successfully improve explaining future market returns, they typically do not change the sign or significance of the correlation risk premium. In some cases adding term and default spreads improves the significance of CRP, e.g., for 9- and 12-month prediction.

We also carry out the ouf-of-sample prediction using the VRP for the period matching the predicted return period instead of always using 30-day VRP. The results in Table A103 show that in general using the longer-term VRP decreases the prediction quality: for 3-month horizon the R^2 decreases from 10.9% with 30-day VRP to 7.9%, and then sharply turns negative for longer horizons.

Thus, the additional checks show that in general our results are robust to standard controls and changes in procedures.

VII. Conclusion

Implied correlation uses forward-looking information from option markets, and is typically interpreted as an indicator of diversification risk in the future. In this paper, we show that the correlation risk premium, inferred from major U.S. stock indices, is able to predict market excess returns in-sample and out-of-sample at horizons of up to one year. In contrast, the predictability of the variance risk premium peaks already at the quarterly frequency.

We first derive, in a reduced-form model, a beta representation of the equity risk premium that links it to the variance and correlation risk premiums. Next, we develop a new methodology for estimating the exposures with respect to variance and correlation risk, using daily increments of option-implied variance and correlation as well as daily returns of the market. Our methodology substantially improves the out-of-sample predictability of market returns, and leads to an out-of-sample R^2 of 13% using both variance risk premium and correlation risk premium as predictors at the quarterly horizon, and to an out-of-sample R^2 of 7% using the correlation risk premium as the only predictor at the annual horizon. These predictability results imply considerable statistical and economic gains in portfolio optimization, measured by the certainty equivalent of an optimizing mean-variance investor.

Analyzing the link between correlation and uncertainty as well as future risks, we find that the average correlation can be interpreted as a "no-place-to-hide" state variable, that predicts future diversification risks for horizons up to one year. Particularly, implied and realized correlations predict future realized correlations and non-diversifiable market risk in equity portfolios in the form of dispersion of market betas. Variances perform better only in predicting shorter-term risks. This allows an interpretation of market variance and average correlation as state variables in the form of the I-CAPM (or proxies of state variables) that predict future investment opportunities, and hence bear risk premiums as compensation. Intuitively, while correlations predict risks for a longer term compared to the variance, they are able to predict returns for longer terms as well.

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Table I Index Data Composition Summary

In this table, we report the statistics on the composition of major indices used in our analysis. "Data/ options" columns contain information on underlying instruments for option data from OptionMetrics (OM). "Data/ CCM" columns show the economic sector designation for sector-type securities, and index identifier (Gvkeyx) from Compustat. "#, total" gives minimum and median (mdn) number of assets in each index after our matching procedure, "#, w/options" gives the number of components with available option data, and "w w/options" shows the weight of components with options data for a given index.

Sample	Data/ OM			Data/ CCM	#, total		#, w/options		w w/options	
	Type	Ticker	Secid	Gvkeyx	min	mdn	min	mdn	min	mdn
Indices										
SP500	Index	SPX	108105	000003	498	500	405	491	0.832	0.978
SP100	Index	OEX	109764	000664	99	100	92	98	0.921	0.974
DJ30	Index	DJX	102456	000005	26	30	24	29	0.839	0.980

Table II Index Implied and Realized Correlations: Summary

The table reports summary statistics (time-series mean, p-value for the mean, median, and the standard deviation) for the implied correlation (IC), realized correlation (RC), and for the correlation risk premium ($CRP = IC - RC$), for three samples of stocks—components of S&P500, S&P100 and DJ30 indices, for the sample period from 1996 to 04/2016, and from 10/1997 to 04/2016, respectively, and for five different maturities—30, 91, 182, 273, and 365 (calendar) days. $IC(t)$ ($RC(t)$) are calculated from daily observations of implied (realized) variances for the index and for all index components. Implied variances are computed as simple variance swaps (Martin (2013)). The p-values for significance of the means are computed with Newey and West (1987) adjustments for autocorrelation.

	IC					*RC*					*IC-RC*				
	30	91	182	273	365	30	91	182	273	365	30	91	182	273	365
SP500															
Mean	0.387	0.423	0.446	0.454	0.459	0.327	0.326	0.327	0.328	0.327	0.060	0.097	0.123	0.130	0.133
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.375	0.423	0.454	0.462	0.464	0.298	0.308	0.310	0.307	0.308	0.060	0.094	0.126	0.140	0.142
StDev	0.126	0.113	0.106	0.104	0.099	0.145	0.125	0.119	0.116	0.115	0.103	0.084	0.081	0.080	0.076
SP100															
Mean	0.423	0.463	0.485	0.494	0.498	0.356	0.357	0.359	0.359	0.358	0.067	0.106	0.126	0.135	0.140
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.412	0.466	0.496	0.506	0.509	0.331	0.344	0.339	0.342	0.341	0.066	0.103	0.125	0.144	0.144
StDev	0.130	0.114	0.106	0.103	0.101	0.152	0.129	0.122	0.119	0.116	0.114	0.090	0.090	0.094	0.093
DJ30															
Mean	0.464	0.497	0.523	0.529	0.528	0.371	0.373	0.376	0.378	0.377	0.082	0.112	0.138	0.140	0.137
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.456	0.503	0.535	0.541	0.539	0.352	0.363	0.368	0.359	0.359	0.078	0.102	0.134	0.144	0.141
StDev	0.148	0.129	0.118	0.113	0.105	0.169	0.148	0.143	0.142	0.141	0.130	0.102	0.095	0.094	0.090

Table III Link between Correlations and Variances for S&P500 and other indices

The table reports time-series correlations between correlations (implied and realized), and variances (implied and realized) for the S&P500, and other major indices. We use components of the S&P500, S&P100 and DJ30 indices, for the sample period from 1996 to 04/2016, and from 10/1997 to 04/2016, respectively, and for five different maturities—30, 91, 182, 273, and 365 (calendar) days. $IC(t)$ ($RC(t)$) are calculated from daily observations of model-free implied (realized) variances for the index and for all index components, using (23). Implied variance (IV) is computed as simple variance swap (Martin (2013)) on each day using out-of-the money options with the respective maturity, and realized variance RV is calculated on each day from daily returns over a respective window, corresponding to the maturity of IV.

	IC					*RC*				
	30	91	182	273	365	30	91	182	273	365
SP100	0.983	0.979	0.952	0.927	0.895	0.987	0.990	0.991	0.991	0.992
DJ30	0.963	0.974	0.974	0.972	0.963	0.958	0.972	0.982	0.988	0.991

	IV					*RV*				
	30	91	182	273	365	30	91	182	273	365
SP100	0.994	0.992	0.984	0.968	0.960	0.996	0.996	0.995	0.995	0.994
DJ30	0.987	0.985	0.986	0.983	0.980	0.990	0.994	0.995	0.995	0.995

Table IV Individual and Index Variances, and Variance Risk Premiums

The table reports the time-series averages of realized (RV) and model-free implied variances (IV), expressed in volatility terms, and the difference between them ($VRP = IV - RV$), expressed as a difference in variances, for three samples of stocks—components of S&P500, S&P100, and DJ30 indices, for the sample period from 1996 to 04/2016, and from 10/1997 to 04/2016, respectively, and for three different maturities—30, 91, 182, 273, and 365 (calendar) days. For individual stocks the variances are equal-weighted cross-sectional averages across all constituent stocks. Implied variance (IV) is computed as simple variance swap (Martin (2013)) on each day using out-of-the money options with the respective maturity, and realized variance RV is calculated on each day from daily returns over a respective window, corresponding to the maturity of IV. All numbers are expressed in annual terms. The p-value is for the null hypothesis that implied and realized variances are on average equal; the p-values are computed from standard errors with Newey and West (1987) adjustments for autocorrelation.

	Individual Stocks				Indices			
Days	$\sqrt{IV}$	$\sqrt{RV}$	VRP	$p-val$	$\sqrt{IV}$	$\sqrt{RV}$	VRP	$p-val$
SP500 Sample								
30	0.398	0.397	0.001	0.807	0.210	0.185	0.005	0.007
91	0.381	0.395	-0.011	0.125	0.210	0.184	0.006	0.049
182	0.371	0.393	-0.017	0.115	0.211	0.184	0.007	0.087
273	0.368	0.392	-0.019	0.154	0.213	0.184	0.007	0.090
365	0.365	0.392	-0.020	0.171	0.215	0.185	0.008	0.078
SP100 Sample								
30	0.361	0.368	-0.005	0.309	0.210	0.186	0.005	0.007
91	0.348	0.366	-0.012	0.095	0.211	0.185	0.006	0.034
182	0.342	0.363	-0.015	0.115	0.212	0.185	0.007	0.055
273	0.340	0.361	-0.015	0.175	0.214	0.185	0.008	0.067
365	0.339	0.361	-0.016	0.217	0.217	0.186	0.009	0.053
DJ30 Sample								
30	0.320	0.325	-0.003	0.314	0.206	0.175	0.006	0.000
91	0.308	0.323	-0.009	0.121	0.206	0.175	0.007	0.007
182	0.302	0.320	-0.011	0.231	0.208	0.175	0.008	0.023
273	0.303	0.317	-0.009	0.349	0.210	0.175	0.009	0.032
365	0.304	0.316	-0.007	0.476	0.212	0.175	0.010	0.032

Table V Individual Variance Risk Premiums

The table reports the results of individual tests of variance risk premiums, for three samples of stocks–components of S&P500, S&P100, and DJ30 indices, for the sample period from 01/1996 to 04/2016 for S&P500 and S&P100, and from 10/1997 to 04/2016 for DJ30, and five three different maturities – 30, 91, 182, 273 and 365 (calendar) days. The table shows the number of stocks, for which the respective hypothesis is either rejected ($IV - RV \geq 0$ and $IV - RV \leq 0$), or failed to be rejected ($IV = RV$). Implied variance (IV) is computed on each day using out-of-the money options with the respective maturity, and realized variance (RV) is calculated on each day from daily returns over a respective window, corresponding to the maturity of IV. The test statistics for each stock are based on Newey-West (1987) autocorrelation consistent standard errors with lags equal to the number of overlapping observations (20, 62, 125, 188 or 251, respectively).

Days	$IV - RV \geq 0$	$IV = RV$	$IV - RV \leq 0$
SP500 Sample			
30	54	669	344
91	70	824	171
182	83	839	143
273	86	810	168
365	95	765	197
SP100 Sample			
30	12	150	51
91	9	173	25
182	16	176	25
273	13	166	30
365	12	159	40
DJ30 Sample			
30	3	38	7
91	4	42	4
182	2	41	4
273	1	39	10
365	0	37	10

Table VI In-sample Market Return Predictability: Correlation and Variance Risk Premiums

The table shows the coefficients (and corresponding p-values) and the R^2 of the market predictive regressions, for the sample period from 01/1996 to 04/2016 for S&P500 and S&P100, and from 10/1997 to 04/2016 for DJ30-based variables. We regress overlapping excess market returns compounded over a specified horizon (30, 91, 182, 273, and 365 calendar days) on a constant and a given set of explanatory variables, which are the correlation risk premium (CRP) for 30, 91, 182, 273, and 365 calendar days, and the variance risk premium (VRP), which equals to the difference between the 30-day implied variance and lagged realized variance computed over the historical period of 30 calendar days. Implied variances are computed as simple variance swaps (Martin (2013)). The p-values (under the coefficients) for the null hypothesis that the coefficients are equal zero are computed using Newey and West (1987) standard errors. The adjusted R^2 are given as percentages.

	Return, 30 days			Return, 91 days			Return, 181 days			Return, 273 days			Return, 365 days		
SP500 Sample															
CRP	0.076	-	0.027	0.254	-	0.165	0.381	-	0.343	0.588	-	0.575	0.559	-	0.559
	0.027	-	0.362	0.002	-	0.031	0.051	-	0.095	0.067	-	0.095	0.150	-	0.166
VRP	-	0.322	0.289	-	0.663	0.514	-	0.473	0.220	-	0.421	0.101	-	0.230	0.000
	-	0.004	0.007	-	0.000	0.000	-	0.007	0.178	-	0.060	0.705	-	0.430	0.999
R^2	2.48	6.90	6.81	7.26	9.60	11.99	6.90	2.24	7.02	9.87	0.74	9.55	5.43	-0.18	5.02
SP100 Sample															
CRP	0.051	-	0.011	0.234	-	0.154	0.363	-	0.313	0.561	-	0.551	0.527	-	0.517
	0.076	-	0.678	0.004	-	0.042	0.047	-	0.089	0.042	-	0.063	0.082	-	0.098
VRP	-	0.333	0.319	-	0.701	0.563	-	0.718	0.528	-	0.500	0.103	-	0.403	0.124
	-	0.004	0.006	-	0.000	0.000	-	0.000	0.002	-	0.052	0.725	-	0.219	0.696
R^2	1.27	6.68	6.35	6.74	9.75	12.08	7.24	4.24	9.23	12.18	1.01	11.87	7.60	0.25	7.27
DJ30 Sample															
CRP	0.040	-	0.010	0.205	-	0.128	0.273	-	0.227	0.330	-	0.306	0.150	-	0.132
	0.117	-	0.675	0.007	-	0.068	0.123	-	0.230	0.243	-	0.313	0.642	-	0.689
VRP	-	0.292	0.277	-	0.727	0.582	-	0.555	0.330	-	0.468	0.249	-	0.285	0.212
	-	0.005	0.005	-	0.000	0.000	-	0.007	0.105	-	0.085	0.463	-	0.405	0.536
R^2	0.90	4.53	4.16	6.27	9.42	11.25	4.47	2.39	4.91	3.93	0.73	3.80	0.11	-0.15	-0.19

Table VII Out of Sample Predictability - Continuous Beta Approach

The table reports the Out-of-Sample R^2_{j,τ_r} and the Diebold-Mariano test statistic δ_{j,τ_r} in Panel A, and the improvement of the certainty equivalent of a mean-variance investor optimizing her portfolio using forecasts by a specific model instead of either using the past mean market return (Model 0), or CRP as a predictor, in Panel B. The variance and correlation risk premiums are computed as the difference between implied and lagged realized variances ($VRP = IV - RV$), and as the difference between implied and lagged realized correlations ($CRP = IC - RC$), for three samples of stocks—components of S&P500, S&P100, and DJ30 indices, for the sample period from 1996 to 04/2016 for S&P500, S&P100, and from 10/1997 to 04/2016 for DJ30, and for five different maturities—30, 91, 182, 273, and 365 (calendar) days. Implied variance (IV) is computed as the simple variance swap (Martin (2013)) on each day using out-of-the money options with maturity of 30 days, and realized variance (RV) is calculated on each day from daily returns over a 30-day historical window. The p-values are obtained from a bootstrapped distribution using moving-block bootstrap by Künsch (1989) with 10,000 samples.

Panel A: OOS R^2 and δ

	R^2_{j,τ_r}			δ_{j,τ_r}		
Days	VRP	CRP	VRP+CRP	VRP	CRP	VRP+CRP
SP500 Sample						
30	0.091	0.025	0.095	-0.000	-0.000	-0.000
	0.000	0.000	0.000	0.000	0.000	0.000
91	0.111	0.081	0.131	-0.001	-0.001	-0.001
	0.000	0.000	0.000	0.000	0.000	0.000
182	0.005	0.067	0.047	-0.000	-0.001	-0.001
	0.379	0.000	0.002	0.381	0.000	0.002
273	-0.131	0.079	-0.080	0.003	-0.002	0.002
	0.000	0.000	0.018	0.000	0.000	0.017
365	-0.304	0.070	-0.215	0.011	-0.003	0.008
	0.000	0.001	0.000	0.000	0.001	0.000
SP100 Sample						
30	0.085	0.012	0.084	-0.000	-0.000	-0.000
	0.000	0.015	0.000	0.000	0.015	0.000
91	0.113	0.072	0.127	-0.001	-0.000	-0.001
	0.000	0.000	0.000	0.000	0.000	0.000
182	0.024	0.055	0.052	-0.000	-0.001	-0.001
	0.065	0.000	0.000	0.067	0.000	0.000
273	-0.119	0.066	-0.090	0.003	-0.002	0.002
	0.001	0.000	0.007	0.001	0.000	0.007
365	-0.241	0.070	-0.191	0.009	-0.003	0.007
	0.000	0.001	0.001	0.000	0.001	0.001
DJ30 Sample						
30	0.061	-0.004	0.063	-0.000	0.000	-0.000
	0.000	0.283	0.000	0.000	0.283	0.000
91	0.086	0.064	0.094	-0.001	-0.000	-0.001
	0.000	0.000	0.000	0.000	0.000	0.000
182	-0.030	0.049	-0.013	0.000	-0.001	0.000
	0.120	0.001	0.295	0.118	0.001	0.290
273	-0.203	0.028	-0.179	0.005	-0.001	0.005
	0.000	0.092	0.000	0.000	0.094	0.000
365	-0.348	0.008	-0.317	0.013	-0.000	0.012
	0.000	0.387	0.000	0.000	0.390	0.000

...Table VII continued

Panel B: Certainty Equivalent Improvement

	$CE_{j,\tau_r} - CE_{0,\tau_r}$			$CE_{j,\tau_r} - CE_{CRP,\tau_r}$		
Days	VRP	CRP	VRP+CRP	VRP	CRP	VRP+CRP
SP500 Sample						
30	0.024	0.039	0.024	-0.016	-	-0.016
	0.003	0.000	0.002	0.001	-	0.003
91	0.024	0.022	0.024	0.002	-	0.002
	0.000	0.001	0.000	0.410	-	0.402
182	0.013	0.021	0.011	-0.008	-	-0.010
	0.019	0.000	0.031	0.052	-	0.018
273	0.000	0.020	0.001	-0.020	-	-0.019
	0.469	0.000	0.434	0.001	-	0.001
365	0.003	0.007	0.002	-0.005	-	-0.005
	0.324	0.086	0.347	0.204	-	0.184
SP100 Sample						
30	0.026	0.024	0.020	0.002	-	-0.004
	0.001	0.000	0.012	0.378	-	0.276
91	0.021	0.027	0.025	-0.005	-	-0.002
	0.000	0.000	0.000	0.159	-	0.362
182	0.008	0.021	0.008	-0.013	-	-0.012
	0.099	0.000	0.079	0.015	-	0.016
273	-0.001	0.017	-0.000	-0.018	-	-0.017
	0.434	0.002	0.491	0.004	-	0.006
365	0.002	0.011	0.002	-0.009	-	-0.009
	0.372	0.039	0.342	0.100	-	0.109
DJ30 Sample						
30	0.010	-0.015	0.017	0.025	-	0.032
	0.181	0.087	0.049	0.000	-	0.000
91	0.013	0.013	0.010	-0.000	-	-0.003
	0.045	0.034	0.112	0.486	-	0.227
182	0.008	0.017	0.007	-0.009	-	-0.010
	0.212	0.013	0.246	0.090	-	0.065
273	-0.011	0.013	-0.011	-0.025	-	-0.025
	0.165	0.015	0.169	0.001	-	0.001
365	-0.014	-0.008	-0.015	-0.007	-	-0.007
	0.093	0.144	0.083	0.157	-	0.133

Table VIII Out of Sample Predictability - Traditional Beta Approach

The table reports the Out-of-Sample R^2_{j,τ_r} and the Diebold-Mariano test statistic δ_{j,τ_r} in Panel A, and the improvement of the certainty equivalent of a mean-variance investor optimizing her portfolio using forecasts by a specific model instead of either using past mean market return (Model 0), or CRP as a predictor, in Panel B. The VRP and CRP betas are computed by the traditional predictive approach using a 36-month historical rolling window for estimation. The variance and correlation risk premiums are computed as the difference between implied and lagged realized variances ($VRP = IV - RV$), and as a difference between implied and lagged realized correlations ($CRP = IC - RC$), for three samples of stocks—components of S&P500, S&P100, and DJ30 indices, for the sample period from 1996 to 04/2016 for S&P500, S&P100, and from 10/1997 to 04/2016 for DJ30, and for five different maturities—30, 91, 182, 273, and 365 (calendar) days. Implied variance (IV) is computed as the simple variance swap (Martin (2013)) on each day using out-of-the money options with maturity of 30 days, and realized variance (RV) is calculated on each day from daily returns over a 30-day historical window. The p-values are obtained from a bootstrapped distribution using moving-block bootstrap by Künsch (1989) with 10,000 samples.

Panel A: OOS R^2 and δ

	R^2_{j,τ_r}			δ_{j,τ_r}		
Days	VRP	CRP	VRP+CRP	VRP	CRP	VRP+CRP
SP500 Sample						
30	-0.396	-0.023	-0.576	0.001	0.000	0.001
	0.000	0.000	0.000	0.000	0.000	0.000
91	0.054	0.053	0.063	-0.000	-0.000	-0.000
	0.000	0.001	0.000	0.000	0.001	0.000
182	-0.027	0.004	-0.129	0.001	-0.000	0.003
	0.008	0.433	0.000	0.008	0.436	0.000
273	-0.097	-0.375	-0.743	0.004	0.014	0.027
	0.000	0.000	0.000	0.000	0.000	0.000
365	-0.518	-0.540	-1.181	0.030	0.031	0.068
	0.000	0.000	0.000	0.000	0.000	0.000
SP100 Sample						
30	-0.337	-0.038	-0.492	0.001	0.000	0.001
	0.000	0.000	0.000	0.000	0.000	0.000
91	0.025	0.039	0.045	-0.000	-0.000	-0.000
	0.025	0.029	0.002	0.025	0.029	0.002
182	0.028	-0.047	-0.156	-0.001	0.001	0.003
	0.000	0.160	0.004	0.000	0.158	0.004
273	-0.056	-0.322	-0.517	0.002	0.012	0.020
	0.000	0.000	0.000	0.000	0.000	0.000
365	-0.395	-0.469	-1.002	0.023	0.027	0.058
	0.000	0.000	0.000	0.000	0.000	0.000
DJ30 Sample						
30	-0.611	-0.045	-0.863	0.001	0.000	0.002
	0.000	0.000	0.000	0.000	0.000	0.000
91	-0.126	0.016	-0.082	0.001	-0.000	0.001
	0.000	0.191	0.000	0.000	0.193	0.000
182	-0.283	-0.075	-0.593	0.006	0.001	0.012
	0.000	0.000	0.000	0.000	0.000	0.000
273	-0.208	-0.435	-1.051	0.007	0.015	0.036
	0.000	0.000	0.000	0.000	0.000	0.000
365	-1.337	-0.951	-3.072	0.069	0.049	0.158
	0.000	0.000	0.000	0.000	0.000	0.000

...Table VIII continued

Panel B: Certainty Equivalent Improvement

	$CE_{j,\tau_r} - CE_{0,\tau_r}$			$CE_{j,\tau_r} - CE_{CRP,\tau_r}$		
Days	VRP	CRP	VRP+CRP	VRP	CRP	VRP+CRP
SP500 Sample						
30	0.003	0.011	0.009	-0.008	-	-0.002
	0.391	0.099	0.151	0.115	-	0.319
91	-0.004	0.014	0.011	-0.018	-	-0.003
	0.169	0.000	0.010	0.000	-	0.232
182	0.006	0.014	0.016	-0.009	-	0.001
	0.003	0.002	0.001	0.028	-	0.104
273	0.005	0.018	0.013	-0.013	-	-0.005
	0.018	0.012	0.041	0.038	-	0.000
365	0.012	0.001	0.006	0.011	-	0.005
	0.000	0.414	0.079	0.037	-	0.000
SP100 Sample						
30	0.007	0.007	-0.006	0.001	-	-0.012
	0.235	0.101	0.277	0.462	-	0.038
91	-0.003	0.014	0.004	-0.017	-	-0.011
	0.228	0.001	0.225	0.000	-	0.000
182	0.004	0.023	0.023	-0.019	-	0.000
	0.015	0.000	0.000	0.001	-	0.459
273	0.004	0.017	0.023	-0.014	-	0.006
	0.046	0.006	0.000	0.023	-	0.007
365	0.004	-0.000	0.004	0.005	-	0.005
	0.014	0.450	0.073	0.173	-	0.000
DJ30 Sample						
30	-0.005	0.015	-0.010	-0.020	-	-0.025
	0.301	0.000	0.161	0.004	-	0.001
91	-0.015	0.001	-0.008	-0.016	-	-0.009
	0.000	0.377	0.034	0.000	-	0.004
182	-0.012	-0.010	-0.014	-0.002	-	-0.004
	0.008	0.003	0.000	0.387	-	0.000
273	0.005	-0.009	-0.013	0.015	-	-0.004
	0.018	0.032	0.005	0.003	-	0.000
365	0.016	-0.002	-0.002	0.018	-	0.000
	0.000	0.241	0.273	0.000	-	0.059

Table IX Risk Predictability

The table shows the coefficients (with corresponding p-values) and the R^2 of the risk predictive regressions, for the sample period from 01/1996 to 04/2016 for S&P500 and S&P100, and from 10/1997 to 04/2016 for DJ30-based variables. We regress risk measures for a specified future horizon of 30, 91, 181, 273, and 365 calendar days on a constant and one of the explanatory variables, which are the lagged realized and current implied variances (RV and IV), and lagged realized and current implied correlations (RC and IC) for 30, 91, 181, 273, and 365 calendar days. The risk measures are the cross-sectional variance of market betas $\sigma^2(\beta_M)$ for all stocks in an index in Panel A, realized equicorrelation (RC) in Panel B, and realized market variance (RV) for a given index in Panel C. Implied variances are computed as simple variance swaps Martin (2013). The p-values (under the coefficients) for the null hypothesis that the coefficients are equal zero are computed using Newey and West (1987) standard errors.

Panel A: Dispersion of Market Betas – $\sigma^2(\beta_M)$

	$\sigma^2(\beta_M)$, 30			$\sigma^2(\beta_M)$, 91			$\sigma^2(\beta_M)$, 181			$\sigma^2(\beta_M)$, 273			$\sigma^2(\beta_M)$, 365		
	β	$p-val$	R^2	β	$p-val$	R^2	β	$p-val$	R^2	β	$p-val$	R^2	β	$p-val$	R^2
SP500 Sample															
RV	-0.117	0.573	0.05	0.761	0.011	6.80	1.390	0.000	14.64	1.214	0.004	12.90	1.004	0.026	9.97
IV	-0.148	0.651	0.02	1.328	0.005	7.62	1.818	0.000	11.26	2.105	0.000	15.63	2.334	0.000	20.93
RC	-0.531	0.000	6.59	-0.226	0.097	3.04	-0.255	0.188	4.61	-0.251	0.276	5.06	-0.231	0.351	4.91
IC	-0.783	0.000	10.70	-0.487	0.002	11.59	-0.677	0.001	28.54	-0.684	0.004	32.30	-0.643	0.020	28.58
SP100 Sample															
RV	0.224	0.425	0.23	0.987	0.006	11.08	1.473	0.000	26.81	1.417	0.000	24.53	1.210	0.005	17.08
IV	0.672	0.120	0.97	1.765	0.001	14.27	2.161	0.000	23.71	2.460	0.000	29.36	2.421	0.000	30.74
RC	-0.315	0.000	2.77	-0.097	0.421	0.61	-0.017	0.929	0.00	-0.020	0.928	0.02	-0.055	0.811	0.33
IC	-0.422	0.000	3.64	-0.296	0.046	4.55	-0.399	0.062	10.84	-0.454	0.061	16.30	-0.414	0.130	15.02
DJ30 Sample															
RV	0.294	0.258	0.46	1.219	0.000	22.26	1.779	0.000	35.26	1.520	0.000	30.70	1.305	0.001	24.57
IV	0.696	0.064	1.30	1.781	0.000	21.71	2.263	0.000	32.67	2.406	0.000	41.02	2.501	0.000	46.27
RC	-0.089	0.368	0.35	0.044	0.706	0.24	0.029	0.827	0.14	0.020	0.898	0.07	0.022	0.899	0.10
IC	-0.153	0.175	0.78	-0.073	0.551	0.54	-0.205	0.165	6.14	-0.213	0.188	7.50	-0.179	0.331	4.98

Panel B: Realized Correlation – RC

	RC, 30			RC, 91			RC, 181			RC, 273			RC, 365		
	β	$p-val$	R^2	β	$p-val$	R^2	β	$p-val$	R^2	β	$p-val$	R^2	β	$p-val$	R^2
SP500 Sample															
RV	0.768	0.000	12.09	0.650	0.000	8.43	0.529	0.014	2.80	0.485	0.023	2.50	0.637	0.002	4.70
IV	1.359	0.000	15.93	1.200	0.000	10.58	0.854	0.052	3.30	0.646	0.256	1.78	0.558	0.398	1.38
RC	0.510	0.000	26.03	0.544	0.000	29.97	0.493	0.000	23.12	0.529	0.000	27.58	0.514	0.000	28.60
IC	0.688	0.000	35.44	0.548	0.000	25.05	0.451	0.000	16.88	0.422	0.001	15.01	0.440	0.003	15.67
SP100 Sample															
RV	0.757	0.000	9.97	0.610	0.000	6.40	0.268	0.169	1.02	0.216	0.318	0.57	0.392	0.134	1.72
IV	1.278	0.000	12.80	1.065	0.000	7.87	0.526	0.150	1.62	0.216	0.676	0.21	0.112	0.853	0.04
RC	0.470	0.000	22.10	0.523	0.000	27.74	0.425	0.000	18.55	0.447	0.000	21.10	0.440	0.001	21.62
IC	0.647	0.000	30.64	0.512	0.000	20.69	0.386	0.001	11.90	0.297	0.026	7.20	0.267	0.075	6.04
DJ30 Sample															
RV	0.861	0.000	8.89	0.703	0.000	5.38	0.471	0.155	1.14	0.389	0.204	0.77	0.601	0.120	1.93
IV	1.245	0.000	9.13	0.879	0.016	3.83	0.156	0.833	0.05	-0.281	0.763	0.20	-0.475	0.660	0.60
RC	0.522	0.000	27.28	0.609	0.000	37.30	0.560	0.000	28.65	0.593	0.000	31.97	0.577	0.000	31.91
IC	0.671	0.000	33.79	0.558	0.000	23.85	0.454	0.000	14.11	0.380	0.015	9.41	0.354	0.069	7.27

...Table IX continued

Panel C: Realized Variance – RV

	RV, 30			RV, 91			RV, 181			RV, 273			RV, 365		
	β	$p-val$	R^2	β	$p-val$	R^2	β	$p-val$	R^2	β	$p-val$	R^2	β	$p-val$	R^2
SP500 Sample															
RV	0.694	0.000	48.09	0.464	0.000	21.61	0.401	0.002	10.03	0.256	0.058	5.00	0.167	0.107	2.62
IV	1.074	0.000	48.54	0.847	0.000	26.44	0.754	0.000	15.91	0.645	0.000	12.83	0.569	0.000	11.87
RC	0.150	0.002	10.97	0.099	0.038	4.93	0.059	0.221	2.01	0.059	0.264	2.48	0.050	0.333	2.22
IC	0.143	0.001	7.43	0.044	0.201	0.80	-0.029	0.319	0.41	-0.040	0.162	0.97	-0.025	0.348	0.39
SP100 Sample															
RV	0.681	0.000	46.29	0.458	0.000	20.97	0.311	0.005	9.72	0.219	0.081	4.84	0.162	0.156	2.65
IV	1.023	0.000	47.09	0.796	0.000	25.60	0.639	0.000	16.89	0.539	0.000	11.68	0.484	0.000	10.70
RC	0.122	0.003	8.60	0.081	0.060	3.85	0.056	0.220	2.24	0.054	0.296	2.47	0.044	0.413	1.96
IC	0.126	0.001	6.67	0.033	0.342	0.47	-0.021	0.518	0.23	-0.061	0.073	2.46	-0.048	0.120	1.74
DJ30 Sample															
RV	0.660	0.000	43.56	0.436	0.000	19.07	0.385	0.002	9.23	0.237	0.073	4.21	0.136	0.212	1.68
IV	0.960	0.000	45.34	0.723	0.000	23.92	0.626	0.000	14.01	0.513	0.000	10.59	0.442	0.000	9.18
RC	0.102	0.005	8.61	0.069	0.061	4.32	0.038	0.337	1.52	0.034	0.408	1.45	0.023	0.556	0.82
IC	0.100	0.001	6.29	0.036	0.193	0.86	-0.033	0.203	0.88	-0.048	0.094	2.14	-0.042	0.144	1.72

Figure 1. Betas Comparison: Contemporaneous vs. Standard Approach

The figure shows the time series of betas w.r.t. the variance (VRP) and correlation (CRP) risks, estimated using contemporaneous (Contemp Beta) and standard predictive (Standard Beta) approaches. The contemporaneous approach uses 12-month historical window, and the standard approach uses expanding historical window of 60 months and longer. We depict betas for 30, 91, 182, and 365-day VRP and CRP.

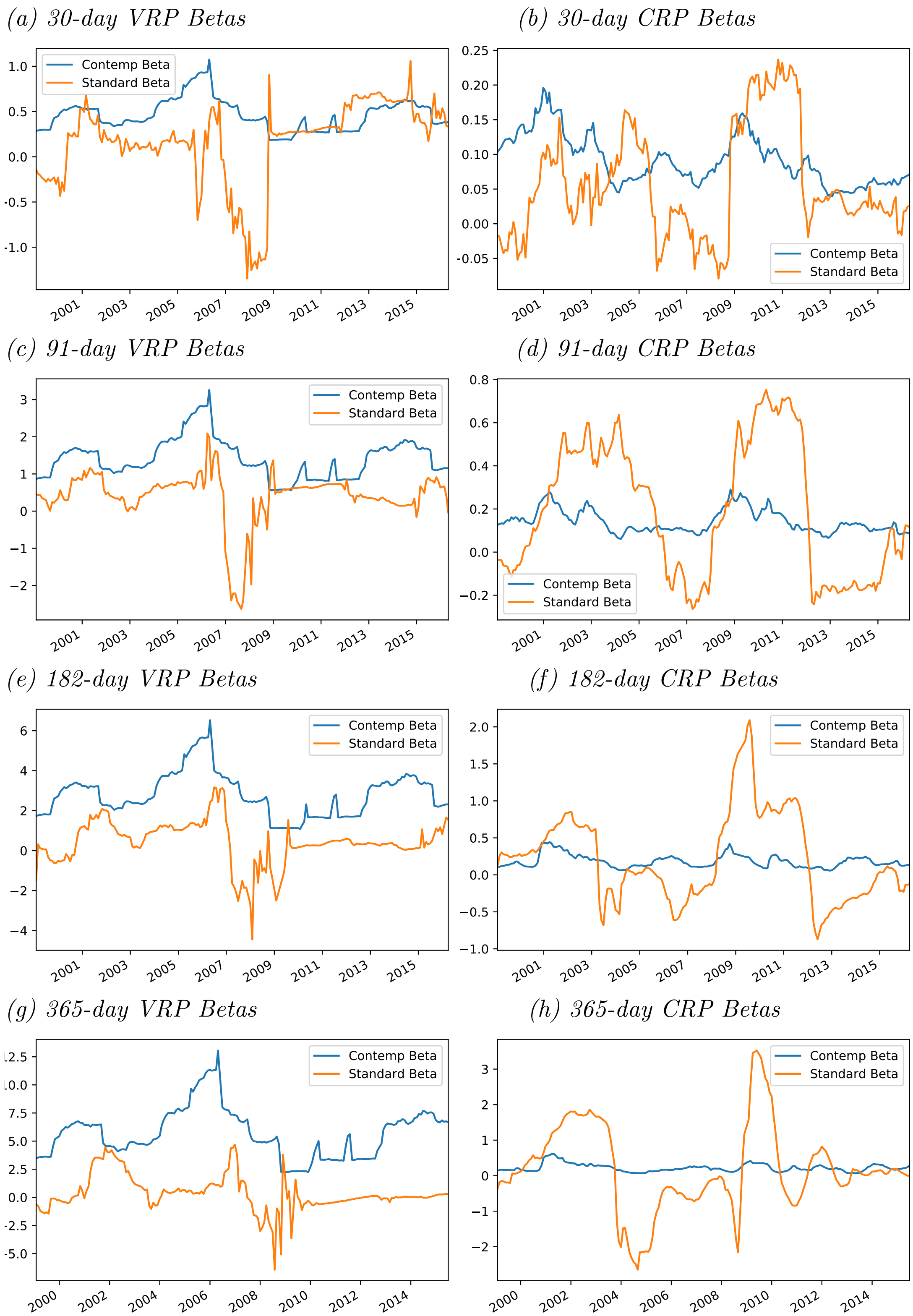
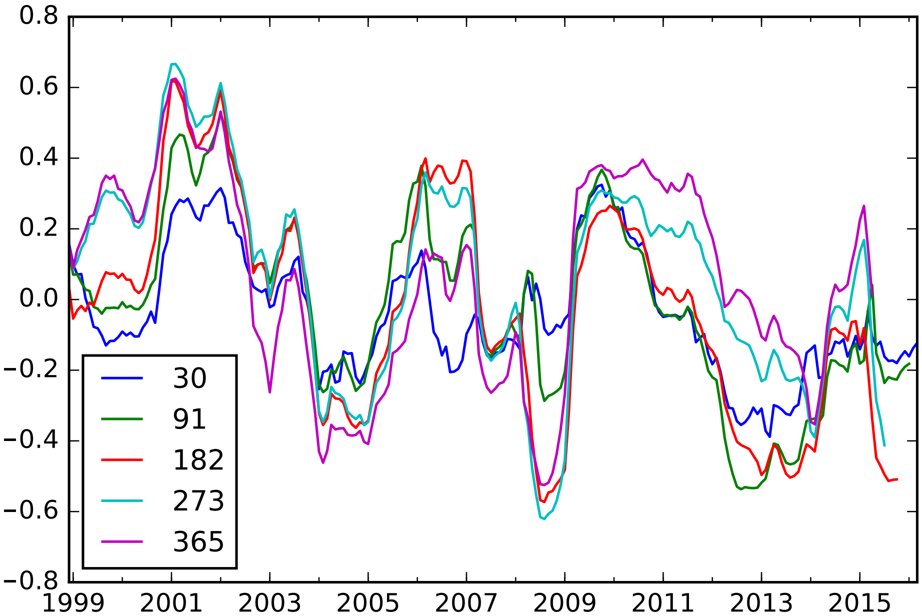


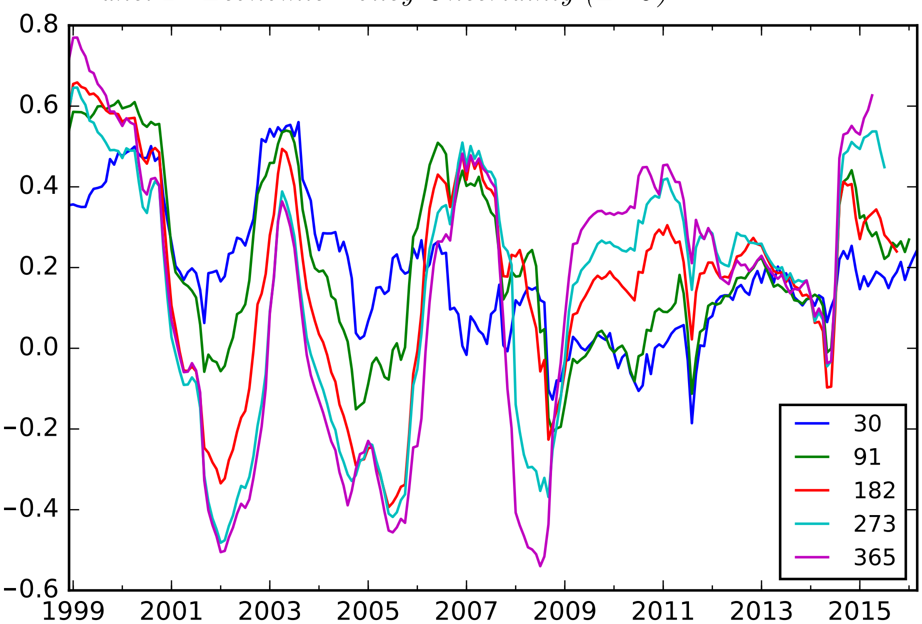
Figure 2. Uncertainty vs. Correlation Risk Premium

The figure shows the rolling window correlations between a particular uncertainty proxy (Difference in Beliefs in Panel A, and Economic Policy Uncertainty Index in Panel B) and the ex-post correlation risk premium (i.e., implied correlation for a given period minus realized correlation over the same period) based on S&P500 index, for five different maturities, from 30 to 365 days. The correlations are computed for each date from monthly data using a 3-year historical window.

Panel A: Difference in Beliefs (DIB)



Panel B: Economic Policy Uncertainty (EPU)



A1. Internet Appendix: Tables for Robustness Tests

Table A101 In-sample Market Return Predictability: Correlation and Variance Risk Premiums

The table shows the coefficients (and corresponding p-values) and the R^2 of the market predictive regressions, for the sample period from 01/1996 to 04/2016 for S&P500 and S&P100, and from 10/1997 to 04/2016 for DJ30-based variables. We regress overlapping excess market returns compounded over a specified horizon (30, 91, 182, 273, and 365 calendar days) on a constant and a given set of explanatory variables, which are the correlation risk premium (CRP) for 30, 91, 182, 273, and 365 calendar days, and the variance risk premium (VRP), which equals to the difference between implied variance and lagged realized variance computed over the matching period of 30, 91, 182, 273, and 365 calendar days. Implied variances are computed as simple variance swaps (Martin (2013)). The p-values (under the coefficients) for the null hypothesis that the coefficients are equal zero are computed using Newey and West (1987) standard errors. The adjusted R^2 are given as percentages.

	Return, 30 days			Return, 91 days			Return, 181 days			Return, 273 days			Return, 365 days		
SP500 Sample															
CRP	0.076	-	0.027	0.254	-	0.195	0.381	-	0.729	0.588	-	1.108	0.559	-	1.071
	0.027	-	0.362	0.002	-	0.027	0.051	-	0.002	0.067	-	0.002	0.150	-	0.031
VRP	-	0.322	0.289	-	0.562	0.270	-	-0.304	-1.606	-	-0.599	-2.554	-	-0.740	-2.501
	-	0.004	0.007	-	0.002	0.175	-	0.553	0.000	-	0.380	0.000	-	0.253	0.028
R^2	2.48	6.90	6.81	7.26	5.08	7.73	6.90	0.15	16.20	9.87	0.81	23.90	5.43	0.85	14.77
SP100 Sample															
CRP	0.051	-	0.011	0.234	-	0.161	0.363	-	0.647	0.561	-	1.029	0.527	-	0.994
	0.076	-	0.678	0.004	-	0.062	0.047	-	0.003	0.042	-	0.001	0.082	-	0.017
VRP	-	0.333	0.319	-	0.652	0.400	-	-0.270	-1.567	-	-0.437	-2.642	-	-0.467	-2.645
	-	0.004	0.006	-	0.001	0.042	-	0.683	0.006	-	0.592	0.001	-	0.518	0.031
R^2	1.27	6.68	6.35	6.74	6.07	8.10	7.24	-0.03	15.10	12.18	0.21	26.16	7.60	0.08	17.28
DJ30 Sample															
CRP	0.040	-	0.010	0.205	-	0.133	0.273	-	0.545	0.330	-	0.741	0.150	-	0.581
	0.117	-	0.675	0.007	-	0.120	0.123	-	0.018	0.243	-	0.017	0.642	-	0.198
VRP	-	0.292	0.277	-	0.679	0.420	-	-0.436	-1.718	-	-0.942	-2.690	-	-1.323	-2.628
	-	0.005	0.005	-	0.000	0.044	-	0.475	0.008	-	0.236	0.004	-	0.079	0.072
R^2	0.90	4.53	4.16	6.27	6.06	7.51	4.47	0.40	12.33	3.93	1.86	15.64	0.11	2.81	7.85

Table A102 In-sample Market Return Predictability with Controls: Correlation and Variance Risk Premiums

The table shows the coefficients (and corresponding p-values) and the R^2 of the market predictive regressions, for the sample period from 01/1996 to 04/2016 for S&P500 and S&P100, and from 10/1997 to 04/2016 for DJ30-based variables. We regress excess market return compounded over a specified horizon (30, 91, 182, 273, and 365 calendar days) and observed at the end of each month (i.e., overlapping by its horizon in months-1) on a constant and a given set of explanatory variables, which are the ex ante correlation risk premium (CRP) for 30, 91, 182, 273, and 365 calendar days, the variance risk premium (VRP), which equals the difference between implied variance and lagged realized variance computed over the matching period of 30 calendar days, and a number of control variables as defined and used in the study by Goyal and Welch (2008). The p-values (under the coefficients) for the null hypothesis that the coefficients are equal zero are computed using Newey and West (1987) standard errors.

Days	CRP	VRP	EP12	TMS	DFY	BM	NTIS	R^2
SP500 Sample								
30	0.027	0.292	-	-	-	-	-	6.92
-	0.379	0.007	-	-	-	-	-	-
30	0.026	0.313	0.010	0.075	0.517	-	-	6.31
-	0.386	0.010	0.275	0.733	0.677	-	-	-
30	0.029	0.267	-0.004	-0.189	-	0.104	0.245	7.42
-	0.342	0.010	0.765	0.443	-	0.125	0.229	-
91	0.169	0.516	-	-	-	-	-	12.30
-	0.030	0.000	-	-	-	-	-	-
91	0.202	0.589	0.021	0.093	2.704	-	-	12.66
-	0.007	0.000	0.338	0.855	0.259	-	-	-
91	0.183	0.379	-0.044	-1.060	-	0.463	1.229	22.47
-	0.009	0.000	0.118	0.079	-	0.000	0.042	-
182	0.353	0.221	-	-	-	-	-	7.38
-	0.091	0.182	-	-	-	-	-	-
182	0.524	0.512	0.030	0.093	9.068	-	-	11.72
-	0.002	0.013	0.460	0.919	0.032	-	-	-
182	0.305	0.060	-0.122	-2.486	-	1.100	3.131	37.05
-	0.028	0.766	0.007	0.028	-	0.000	0.005	-
273	0.575	0.101	-	-	-	-	-	9.55
-	0.095	0.705	-	-	-	-	-	-
273	0.954	0.407	0.044	1.290	14.576	-	-	20.91
-	0.002	0.063	0.453	0.288	0.001	-	-	-
273	0.522	-0.310	-0.167	-2.281	-	1.502	4.142	45.26
-	0.018	0.367	0.016	0.125	-	0.000	0.004	-
365	0.559	0.000	-	-	-	-	-	5.02
-	0.166	0.999	-	-	-	-	-	-
365	1.149	0.595	0.083	3.434	18.670	-	-	22.81
-	0.004	0.026	0.301	0.038	0.002	-	-	-
365	0.469	-0.373	-0.150	-0.850	-	1.633	4.830	42.69
-	0.180	0.358	0.055	0.607	-	0.000	0.008	-

...Table A102 continued

Days	CRP	VRP	EP12	TMS	DFY	BM	NTIS	R^2
SP100 Sample								
30	0.008	0.324	-	-	-	-	-	6.42
-	0.745	0.006	-	-	-	-	-	-
30	0.009	0.341	0.010	0.069	0.421	-	-	5.81
-	0.725	0.009	0.274	0.758	0.735	-	-	-
30	0.011	0.295	-0.003	-0.189	-	0.099	0.244	6.86
-	0.682	0.009	0.826	0.448	-	0.144	0.232	-
91	0.158	0.566	-	-	-	-	-	12.42
-	0.040	0.000	-	-	-	-	-	-
91	0.197	0.639	0.026	0.018	2.870	-	-	12.95
-	0.009	0.000	0.249	0.973	0.235	-	-	-
91	0.179	0.417	-0.041	-1.119	-	0.471	1.157	22.45
-	0.013	0.000	0.144	0.066	-	0.000	0.055	-
182	0.324	0.534	-	-	-	-	-	9.75
-	0.083	0.002	-	-	-	-	-	-
182	0.544	0.803	0.053	-0.104	11.068	-	-	16.27
-	0.000	0.000	0.192	0.906	0.001	-	-	-
182	0.329	0.214	-0.124	-2.619	-	1.166	2.818	38.64
-	0.007	0.371	0.009	0.023	-	0.000	0.015	-
273	0.551	0.103	-	-	-	-	-	11.87
-	0.063	0.725	-	-	-	-	-	-
273	0.970	0.501	0.079	1.033	18.937	-	-	27.52
-	0.000	0.021	0.175	0.340	0.000	-	-	-
273	0.560	-0.271	-0.166	-2.272	-	1.569	3.567	47.49
-	0.002	0.480	0.016	0.115	-	0.000	0.018	-
365	0.517	0.124	-	-	-	-	-	7.27
-	0.098	0.696	-	-	-	-	-	-
365	1.065	0.675	0.117	3.266	21.918	-	-	28.68
-	0.000	0.002	0.150	0.033	0.000	-	-	-
365	0.520	-0.304	-0.151	-0.699	-	1.690	4.196	44.44
-	0.027	0.500	0.052	0.663	-	0.000	0.028	-

Days	CRP	VRP	EP12	TMS	DFY	BM	NTIS	R^2
DJ30 Sample								
30	0.008	0.282	-	-	-	-	-	4.27
-	0.721	0.005	-	-	-	-	-	-
30	0.010	0.304	0.010	0.126	0.322	-	-	3.58
-	0.672	0.013	0.310	0.566	0.806	-	-	-
30	0.010	0.259	-0.005	-0.188	-	0.116	0.253	5.17
-	0.674	0.010	0.737	0.445	-	0.104	0.257	-
91	0.128	0.590	-	-	-	-	-	11.53
-	0.069	0.000	-	-	-	-	-	-
91	0.170	0.686	0.030	0.355	2.956	-	-	12.83
-	0.010	0.000	0.189	0.478	0.230	-	-	-
91	0.154	0.457	-0.040	-0.877	-	0.499	1.059	23.18
-	0.010	0.001	0.138	0.143	-	0.000	0.094	-
182	0.230	0.339	-	-	-	-	-	5.11
-	0.226	0.101	-	-	-	-	-	-
182	0.425	0.677	0.053	0.529	10.680	-	-	11.97
-	0.007	0.002	0.185	0.552	0.004	-	-	-
182	0.264	0.121	-0.131	-2.406	-	1.241	2.781	39.94
-	0.020	0.623	0.001	0.033	-	0.000	0.018	-
273	0.306	0.249	-	-	-	-	-	3.80
-	0.313	0.463	-	-	-	-	-	-
273	0.807	0.641	0.092	2.033	19.174	-	-	21.86
-	0.003	0.001	0.102	0.074	0.000	-	-	-
273	0.446	-0.256	-0.187	-2.178	-	1.772	3.569	50.29
-	0.012	0.518	0.002	0.139	-	0.000	0.020	-
365	0.132	0.212	-	-	-	-	-	-0.19
-	0.689	0.536	-	-	-	-	-	-
365	1.004	0.997	0.145	4.453	25.359	-	-	25.43
-	0.006	0.000	0.068	0.010	0.000	-	-	-
365	0.401	-0.187	-0.178	-0.713	-	1.941	3.976	47.81
-	0.117	0.709	0.007	0.660	-	0.000	0.036	-

Table A103 Out of Sample Predictability - Continuous Beta Approach

The table reports the Out-of-Sample R^2_{j,τ_r} and the Diebold-Mariano test statistic δ_{j,τ_r} in Panel A, and the improvement of the certainty equivalent of a mean-variance investor optimizing her portfolio using forecasts by a specific model instead of either using past mean market return (Model 0), or CRP as a predictor, in Panel B. The variance and correlation risk premiums are computed as the difference between implied and lagged realized variances ($VRP = IV - RV$), and as the difference between implied and lagged realized correlations ($CRP = IC - RC$), for three samples of stocks—components of S&P500, S&P100, and DJ30 indices, for the sample period from 1996 to 04/2016 for S&P500, S&P100, and from 10/1997 to 04/2016 for DJ30, and for five different maturities—30, 91, 182, 273, and 365 (calendar) days. Implied variance (IV) is computed as the simple variance swap (Martin (2013)) on each day using out-of-the money options with with the respective maturity, and realized variance (RV) is calculated on each day from daily returns over a 30-day historical window. The p-values are obtained from a bootstrapped distribution using moving-block bootstrap by Künsch (1989) with 10,000 samples.

Panel A: OOS R^2 and δ

	R^2_{j,τ_r}			δ_{j,τ_r}		
Days	VRP	CRP	VRP+CRP	VRP	CRP	VRP+CRP
SP500 Sample						
30	0.091	0.025	0.095	-0.000	-0.000	-0.000
	0.000	0.000	0.000	0.000	0.000	0.000
91	0.079	0.081	0.069	-0.001	-0.001	-0.000
	0.000	0.000	0.000	0.000	0.000	0.000
182	-0.010	0.067	-0.045	0.000	-0.001	0.001
	0.372	0.000	0.085	0.372	0.000	0.083
273	-0.252	0.079	-0.388	0.006	-0.002	0.010
	0.000	0.000	0.000	0.000	0.000	0.000
365	-0.334	0.070	-0.616	0.012	-0.003	0.022
	0.000	0.001	0.000	0.000	0.001	0.000
SP100 Sample						
30	0.085	0.012	0.084	-0.000	-0.000	-0.000
	0.000	0.015	0.000	0.000	0.015	0.000
91	0.094	0.072	0.083	-0.001	-0.000	-0.001
	0.000	0.000	0.000	0.000	0.000	0.000
182	-0.081	0.055	-0.119	0.001	-0.001	0.002
	0.042	0.000	0.011	0.042	0.000	0.011
273	-0.227	0.066	-0.390	0.006	-0.002	0.010
	0.001	0.000	0.000	0.001	0.000	0.000
365	-0.298	0.070	-0.493	0.011	-0.003	0.018
	0.000	0.001	0.000	0.000	0.001	0.000
DJ30 Sample						
30	0.061	-0.004	0.063	-0.000	0.000	-0.000
	0.000	0.283	0.000	0.000	0.283	0.000
91	0.079	0.064	0.058	-0.001	-0.000	-0.000
	0.000	0.000	0.000	0.000	0.000	0.000
182	-0.057	0.049	-0.126	0.001	-0.001	0.002
	0.014	0.001	0.000	0.014	0.001	0.000
273	-0.277	0.028	-0.468	0.007	-0.001	0.012
	0.000	0.092	0.000	0.000	0.094	0.000
365	-0.382	0.008	-0.688	0.014	-0.000	0.025
	0.000	0.387	0.000	0.000	0.390	0.000

...Table A103 continued

Panel B: Certainty Equivalent Improvement

	$CE_{j,\tau_r} - CE_{0,\tau_r}$			$CE_{j,\tau_r} - CE_{CRP,\tau_r}$		
Days	VRP	CRP	VRP+CRP	VRP	CRP	VRP+CRP
SP500 Sample						
30	0.024	0.039	0.024	-0.016	-	-0.016
	0.003	0.000	0.002	0.001	-	0.003
91	0.028	0.022	0.027	0.007	-	0.005
	0.000	0.001	0.000	0.041	-	0.104
182	0.029	0.021	0.030	0.008	-	0.009
	0.000	0.000	0.000	0.013	-	0.007
273	0.016	0.020	0.016	-0.004	-	-0.004
	0.011	0.000	0.015	0.303	-	0.306
365	-0.006	0.007	-0.011	-0.013	-	-0.018
	0.229	0.086	0.083	0.049	-	0.016
SP100 Sample						
30	0.026	0.024	0.020	0.002	-	-0.004
	0.001	0.000	0.012	0.378	-	0.276
91	0.031	0.027	0.028	0.005	-	0.001
	0.000	0.000	0.000	0.048	-	0.394
182	0.026	0.021	0.025	0.005	-	0.005
	0.000	0.000	0.000	0.080	-	0.122
273	0.014	0.017	0.013	-0.003	-	-0.005
	0.016	0.002	0.030	0.346	-	0.285
365	-0.001	0.011	-0.005	-0.012	-	-0.016
	0.476	0.039	0.300	0.104	-	0.051
DJ30 Sample						
30	0.010	-0.015	0.017	0.025	-	0.032
	0.181	0.087	0.049	0.000	-	0.000
91	0.017	0.013	0.013	0.004	-	0.001
	0.020	0.034	0.048	0.087	-	0.411
182	0.015	0.017	0.011	-0.002	-	-0.006
	0.056	0.013	0.128	0.368	-	0.172
273	-0.005	0.013	-0.009	-0.018	-	-0.022
	0.357	0.015	0.249	0.026	-	0.013
365	-0.039	-0.008	-0.041	-0.032	-	-0.033
	0.002	0.144	0.002	0.001	-	0.001