Option-Implied Correlations, Factor Models, and Market Risk*

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Implied correlation and variance risk premium stand out in predicting market returns. However, while the predictive ability of implied correlation lasts for up to a year, the variance risk premium predicts market returns only for one quarter ahead. Contrary to the accepted view, implied correlation predicts the market return not through a diversification risk (average correlation) channel, but by predicting a concentration of market exposure, which defines the level of non-diversifiable *market* risk. Economy-wide implied correlation built exclusively from option prices of nine sector ETFs and the S&P500 efficiently predicts future market returns and systematic diversification risk in the form of market betas dispersion. Newly developed implied correlations for economic sectors provide industry-related information and are used to extract option-implied risk factors from sector-based covariances.

Keywords: Implied correlation, factor model, market factor, factor exposure

JEL: G11, G12, G13, G17

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1 Introduction

Return co-movement, typically measured by correlation, is one of the most fundamental concepts in financial economics and plays a crucial role in portfolio choice, risk management, and asset pricing. Importantly, correlations tend to increase during market crashes,[1] so that the instability of correlations, or correlation risk, negatively affects investor welfare by making diversification more difficult in expensive states of nature. Related and widely used in finance are linear factor models of returns implying a specific correlation matrix between the assets. Typically, the direct estimation of a correlation matrix or its estimation through a linear factor model entails the use of historical data and may not reflect current market expectations.

This paper addresses two major issues: First, we construct an *ex ante* covariance (correlation) matrix from option prices without using historical information, which allows us to identify and estimate a linear factor model implied by current option prices. Second, our study questions, through which channel implied correlation predicts market returns.

Throughout the whole paper, we make options the main source of information. That is, as it was already documented, current option prices subsume current market expectations about future investment opportunities (e.g., Vanden (2008)), hence, option-implied information often works well in predicting the future asset dynamics (see Poon and Granger (2003), Christoffersen, Jacobs, and Chang (2011) for review). However, while a number of variables can be easily extracted from options, constructing an implied correlation matrix is a daunting task: there are many degrees of freedom (as all pairwise correlations have to be pinned down), and only one identifying restriction that equates the index variance to the variance of the portfolio of index components. To overcome this problem, one can either assume the equal correlations as in Driessen, Maenhout, and Vilkov (2005) and Skinzi and Refenes (2005), or rely on the historical correlation structure and adjust it by a parametric correlation premium, as in Buss and Vilkov (2012). We propose a new method that allows for extracting a block-diagonal heterogeneous

[1] E.g., Roll (1988), Jorion (2000), and Longin and Solnik (2001).

correlation matrix exclusively from option prices on the S&P500, on economic sector ETFs, and on index (and hence, ETF) components.

Our main results can be summarized as follows: (i) variance and correlation risk premiums vary across different sectors of the economy, that is, stocks in sectors have heterogeneous exposure to underlying factors; (ii) implied correlations predict market factor realizations, and, interestingly, even implied correlations constructed from only nine sectors perform comparable to implied correlations based on all S&P500 constituents; (iii) implied correlations predict not the future correlations per se, but a more dense clustering of market betas around the mean, and a non-diversifiable market component of the portfolio variance; and (iv) an option-implied covariance matrix based on implied correlations within and between economic sectors can be used to extract statistical factors that explain more of the stock return dynamics than traditional Fama and French (1993, 2015), and Carhart (1997) factors.

More specifically, we document the magnitudes of implied correlations, correlation and variance risk premiums for major U.S. indices, economic sectors, and their individual components. We find that there is a significant correlation risk premium for stocks in major indices, which tends to increase with time to maturity. Smaller indices show higher levels of correlations but similar levels of correlation risk premiums. There is also a visible heterogeneity in the levels of average correlation among economic indices: health, consumer discretionary, and technology show the three lowest correlations (0.42, 0.42, and 0.44 for 30 days), while energy, finance, and materials show the three top ones (0.70, 0.63, and 0.52 for 30 days). Consumer staples, however, demonstrate the largest correlation risk premium of 0.10 for 30 days, followed by finance and technology (0.08 and 0.08). A sector rotation investment strategy is based on the fact that sectors behave differently across various stages of business cycles (e.g., Beber, Brandt, and Kavajecz (2011))—some sectors are more protective (like consumer staples) in expensive states of nature, while some sectors (like technology and finance) are more exposed to business cycle risk. The diversification in and between economic sectors is valued quite differently from general diversification over a broad universe, while the size of this universe is not crucial—it is more important that it contains assets representing all sectors of the economy.

The literature has already shown that, from many option-based variables, two stand out in predicting market return: variance risk premium, and implied correlation. Evidence shows that variance risk premium has the best performance at a quarterly horizon (e.g., Bollerslev, Tauchen, and Zhou (2009)), and implied correlation works at horizons up to a year (e.g, Driessen, Maenhout, and Vilkov (2005), Bernales and Valenzuela (2016), Faria, Kosowski, and Wang (2016), among others). It is established that both correlation and variance risks contribute to the market variance risk, and hence to the variance risk premium,[2] but these two variables are not redundant, and it is not clear through which channel implied correlation predicts future risk, and how it is different from the channel of variance risk premium. Variance risk premium is shown to be related to tail risk (e.g., Bollerslev and Todorov (2011), and Trojani and Schneider (2015)). Correlations are linked to uncertainty: Buraschi, Trojani, and Vedolin (2014) show that the correlation risk premium is positively related to the disagreement risk; Faria, Kosowski, and Wang (2016) document the dependence of the correlation risk premium on macroeconomic uncertainty and related variables. Intuitively, an increasing correlation reduces diversification, and if it really constitutes the risk channel through which correlation is linked to the equity risk premium, implied correlation is supposed to predict levels of realized correlation better than other variables. We find that implied correlation does not do a good job in predicting future realized correlation for horizons longer than a quarter, and that the historical correlation considerably outperforms the implied one as a predictor. We find, however, that implied correlation predicts the dispersion of factor betas in the future, specifically, a high implied correlation predicts a lower dispersion of betas at horizons from one to 12 months, and hence a higher non-diversifiable portfolio risk. Lower dispersion of market betas makes it hard to find "a place to hide" from the market risk (similar to "no place to hide" from the

[2]Driessen, Maenhout, and Vilkov (2009) show that pricing of index variance risk depends on the pricing of individual variance risk and correlation risk, Cosemans (2011) presents evidence that the predictive power of the market variance risk premium is mainly driven by the correlation risk premium and the systematic component of the average variance risk premium in individual constituents. Pollet and Wilson (2010) study the predictive qualities of realized correlations and show that the realized correlation provides more information on true aggregate risk than the market variance.

correlation risk in Buraschi, Kosowski, and Trojani (2014)), hence requiring the market factor exposure be compensated by a higher risk premium. Thus, implied correlation predicts not just any diversification, but specifically a systematic diversification.

Ait-Sahalia and Xiu (2016) show that a covariance matrix of a large portfolio of U.S. equities is well represented by a low rank common structure with a sparse (block-diagonal) residual matrix from factors explaining sector dynamics. Their starting point is a positive-definite matrix, which is used as input for the factor identification procedure, so that the covariance matrix is rebuilt from a small number of common factors and a number of sector-specific ones. We do not rebuild a covariance matrix from extracted factors—it's the opposite; we extract factors from a covariance matrix constructed using a block-diagonal correlation matrix of implied correlations in and between economic sectors in the S&P500, and individual stock volatilities. A covariance matrix with reduced structure inferred from option prices provides plenty of information about expected joint stock dynamics—the extracted factors explain more variability in future individual stock returns than statistical factors from a historical covariance matrix or even from a heterogenous implied covariance matrix of Buss and Vilkov (2012).

The remainder of the paper is structured as follows: Section 2 contains the economic motivation and reasoning for our analysis and introduces the identification of various implied correlation matrices. Section 3 discusses data preparation procedures, and in Section 4 the properties of implied correlations and variance risk premiums for different indices, economic sectors, and individual stocks are analyzed. Section 5 shows that one can extract a factor structure from a full sector-based covariance matrix and that it improves the out-of-sample linear factor model fit for individual stocks. Section 6 contains a number of robustness tests, and Section 7 concludes the analysis.

2 Model and Identification of Implied Correlations

In finance one often starts from specifying a return-generating process as a linear factor model with a number of systematic factors and an idiosyncratic noise, so that for each asset i the return is

$$r_{i,t+1} = \mu_{i,t} + \sum_{k=1}^{K} \beta_{ik,t} F_{k,t+1} + \varepsilon_{i,t+1}, \tag{1}$$

where $\mu_{i,t}$ is the asset's expected return, each $F_{k,t+1}$ denotes a mean zero systematic factor, $\beta_{ik,t}$ denotes the sensitivity of the return on asset i to the innovations in factor k, and $\varepsilon_{i,t+1}$ is the "nonsystematic" risk component with $E[\varepsilon_{i,t+1}|F_{k,t+1}] = 0, \forall k$. One then looks for potential factors, either economically or statistically motivated, and tests the pricing of these factors using a number of traditional routines—portfolio sorting, two-stage Fama and MacBeth (1973) regressions, and others. The recent hunt for factors has resulted in a large number of asset pricing findings, which might be false (see Harvey, Liu, and Zhu (2015)) or redundant (Kogan and Tian (2012)).

One of the tools for factor identification is the factor analysis, which also started as a linear model (e.g., a brief history of factor analysis in Mulaik (2009)) and can be explained in very simple terms: it assumes that linear dependencies (that is, correlations) between variables are generated by the exposure to a set of common factors. Thus, a result of factor analysis applied to asset returns, for example, is the mathematical structure describing the rules that govern the composition of the returns of their components.

The maximum number of identifiable factors equals the rank of the covariance or the correlation matrix used as an input; however, one typically considers only "important" factors explaining the largest part of the total variance, and demotes the rest of components to idiosyncratic noise (Bartlett (1950, 1951)). Idiosyncratic noise is also a "factor," though explaining only the residual variance of one given stock. The task of estimating a covariance matrix from a factor model is well-specified:

$$\Sigma = B\Sigma^F B^\top + D, \tag{2}$$

where B is the $N \times K$ matrix of K factor betas for N stocks, Σ^F is the covariance matrix of factors, and D is the diagonal matrix of residual variances. The inverse problem, that is, finding the factor betas and factor variances from an estimated covariance matrix, is slightly more complicated, and depends on the approach taken. For the principal component analysis (PCA) based on eigen-decomposition of a (symmetric and well-defined) covariance matrix, the answer will be unique up to the set of basis factors, explaining the joint variance in a descending order.

It is assumed that residuals in model (1) are not correlated and hence all covariances are formed by systematic factors affecting several assets. Moreover, the largest part of the joint dependency is typically isolated into a "market factor," which represents just the average directional movement of the asset universe. Taking the factor model to heart, we thus know that the correlation is induced by the exposure of assets to common factors, that is, derived from systematic covariance $B\Sigma^F B^\top$. Consider the market model, in which the market is the only factor, and the factor covariance Σ^F is equal to market variance σ_M^2. The correlation between any two stocks i, j is created by the interaction of betas, namely

$$\rho_{i,j} = \sigma_M^2 \frac{\beta_{M,i}\beta_{M,j}}{\sigma_i \sigma_j}, \tag{3}$$

where $\sigma_i = \sqrt{\beta_{M,i}^2 \sigma_M^2 + \varepsilon_i^2}$ is the total volatility of stock i. The (value-weighted) mean market beta is equal to one by definition, and keeping the volatilities in (3) constant we expect that the average correlation between assets is decreasing in the dispersion of betas around their mean:

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

where we assumed that market betas are distributed around their mean with the same variance, that is, $\beta_M \sim Dist(1, \sigma_\epsilon^2)$. Moreover the covariance between the deviation of betas from the mean is expected to be negative, because their mean does not change, and an increasing beta is necessarily compensated by a decreasing one. We label the effect of the factor beta distribution on the correlation by *systematic diversification effect.* The correlations can also change due to a change in the total stock volatility, or, rather, due to changes in the stock volatility composition in terms of how much of it is due to an idiosyncratic component. When the σ_ϵ^2 diminishes to zero, the pairwise correlation converges to one, and it does not depend on the distribution of the betas anymore. The effect of the volatility composition on correlation is labeled by *diversification effect.*

We aim at extracting correlation matrices from option prices, full or partially, under different assumptions about the structure of a correlation matrix, and analyze what is important to take into account in such a procedure not to lose information contained in correlations.

Correlations are constructed using several methods: (i) equicorrelations under the assumption that at every time period all pairwise correlations are equal; we use the terms "implied correlation" (IC) for the risk-neutral, and "realized correlation" (RC) for the realized equicorrelations;[3] (ii) sector-based correlations under the assumption that pairwise correlations are all equal for stocks in the same economic sector, and that pairwise correlations between any two stocks belonging to different sectors are all equal as well; and (iii) heterogenous correlations under the assumption that the pairwise correlation risk premium is proportional to the distance between the maximum correlation of one and the expected pairwise correlation under the objective measure (as in Buss and Vilkov (2012)). The first method always gives a positive-definite matrix when correlation is non-negative; the second method leads to a block-diagonal correlation matrix, which is positive-definite when the correlation between sectors is low enough, and the third one leads to a positive definite correlation matrix if the input expected correlation matrix under the P measure is positive definite. Later, in Section 5 we discuss option-implied factor structure and also suggest how one can adjust covariance matrix from sector-based or heterogenous correlation matrices to make it positive-definite.

Identification for all three methods is based on the same restriction that the variance of a basket I is equal to the variance of the portfolio, which this basket represents:

$$\sigma_I^2(t) = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_i(t) \sigma_j(t) \rho_{ij}(t). \tag{4}$$

This restriction holds under both objective P and risk-neutral Q measures. For the first method, given the time-series of variances for an index (or a sector) $\sigma_I^2(t)$ and its components $\sigma_i^2(t), i = 1 \dots N$, as well as the index weights $\{w_i\}$, the equicorrelation $\rho_{ij}(t) = \rho(t)$ is calculated for

[3] 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 (2009) and Skinzi and Refenes (2005); later literature also used the term "equicorrelation."

each day t as

$$\rho(t) = \frac{\sigma_I^2(t) - \sum_{i=1}^{N} w_i^2 \sigma_i^2(t)}{\sum_{i=1}^{N} \sum_{j \neq i} w_i w_j \sigma_i(t) \sigma_j(t)}, \tag{5}$$

and the resulting correlation matrix at time t is

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

IC and RC use risk-neutral and realized variances, respectively, and both are computed for all indices and all economic sectors. To construct the block-diagonal correlation matrix we first estimate the sector equicorrelations by applying equation (5) to each sector:

$$\Omega_{sect} = \begin{pmatrix} 1 & \rho_{sect} & \dots & \rho_{sect} \\ \rho_{sect} & 1 & \dots & \rho_{sect} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{sect} & \rho_{sect} & \dots & 1 \end{pmatrix},$$

and then use the identifying restriction (4) with known within-sector equicorrelations to determine the remaining correlation $\rho_{off-diag}(t)$ between stocks from different sectors:

$$\sigma_I^2(t) = \sum_{sect=1}^{Nsect} \sum_{i \in sect} \sum_{j \in sect} w_i w_j \sigma_i(t) \sigma_j(t) \rho_{sect}(t) + \sum_{i=1}^{N} \sum_{j: sect(i) \neq sect(j)} w_i w_j \sigma_i(t) \sigma_j(t) \rho_{off-diag}(t),$$

which leads to the desired off-diagonal correlation:

$$\rho_{off-diag} = \frac{\sigma_I^2(t) - \sum_{sect=1}^{Nsect} \sum_{i \in sect} \sum_{j \in sect} w_i w_j \sigma_i(t) \sigma_j(t) \rho_{sect}(t)}{\sum_i^N \sum_{j: sect(i) \neq sect(j)} w_i w_j \sigma_i(t) \sigma_j(t)}. \tag{6}$$

Combining sector equicorrelations and correlation $\rho_{off-diag}$ between sectors gives a *full sector-based (FSB)* correlation matrix:

$$\Omega_{FSB}^Q = \begin{pmatrix} \Omega_{sect1}^Q & \rho_{off-diag} & \cdots & \rho_{off-diag} \\ \rho_{off-diag} & \Omega_{sect2}^Q & \cdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{off-diag} & \cdots & \cdots & \Omega_{sectN}^Q \end{pmatrix}.$$

We also construct the *reduced sector-based* correlations for the S&P500 index using not all of its individual components, but only nine sector ETFs, that is, using (5) directly. The sector weights are set equal to the weights of all their individual components relative to the weight of all stocks in the S&P500.

The third method uses the following parametric form for implied correlations $\rho_{ij}^Q(t)$:

$$\rho_{ij}^Q(t) = \rho_{ij}^P(t) - \alpha(t)(1 - \rho_{ij}^P(t)), \tag{7}$$

where $\rho_{ij}^P(t)$ is the expected correlation under the objective measure, and $\alpha(t)$ denotes the parameter to be identified. Substituting the implied correlations (7) into restriction (4), one can compute $\alpha(t)$ in closed form:

$$\alpha_t = -\frac{(\sigma_I^Q(t))^2 - \sum_{i=1}^N \sum_{j=1}^N w_i w_j \sigma_i^Q(t)\sigma_j^Q(t)\rho_{ij}^P(t)}{\sum_{i=1}^N \sum_{j=1}^N w_i w_j \sigma_i^Q(t)\sigma_j^Q(t)(1 - \rho_{ij}^P(t))},$$

and then use equation (7) to identify the implied correlation matrix $\Omega^Q(t)$, with elements $\rho_{ij}^Q(t)$.

Thus, correlation matrices used in further analysis are equicorrelations Ω_{EC}^M under two measures $M \in \{P, Q\}$; heterogeneous correlations Ω^P estimated as traditional correlation under the P measure and adjusted for the risk premium Ω_{BV}^Q as in Buss and Vilkov and two versions of implied sector-based correlations, Ω_{RSB}^Q for the reduced sector-based matrix, and Ω_{FSB}^Q for the full sector-based matrix. The corresponding covariance matrices Σ follow from pre- and post-multiplying the correlation matrices by the diagonal matrices of volatilities, either realized (physical P measure), or implied (risk-neutral Q measure) ones.

3 Data and Preparation of Variables

Implied correlations are estimated by comparing the index variance with the variance of the portfolio of index components. We work with a number of major indices, and their constituents, namely, S&P500, S&P100, DJ Industrial Average (DJ30), and economic sector indices based on the S&P500. We obtain the composition of all the indices and economic sectors 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). We then group stocks to correspond to the composition of nine Select Sector SPDR ETFs, as shown in the Table 1. 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. A market weight within each sector in the S&P500 is calculated as a value weight as well, in which the total market cap of the sector equals to the aggregate market cap of all its available constituents.

Matching the historical data with options happens through the historical CUSIP link provided by OptionMetrics. S&P500, S&P100, and DJ Industrial Average indices are directly used as underlying for options, while SPDR ETFs serve as proxy for nine economic sectors. PERMNO is used as the main identifier in our merged database, and the data availability statistics is provided in Table 1. For computing the option-based variables we rely on the Surface File from OptionMetrics, selecting for each underlying the options with 30, 91 and 365 days to maturity and (absolute) delta lower or equal to 0.5. While the surface data is not suitable for testing trading rules due to extensive inter- and extrapolations of the market data, it proved to be a valuable source of information that can be used in asset pricing tests or in generating signals for trading (e.g., DeMiguel, Plyakha, Uppal, and Vilkov (2013), Driessen, Maenhout, and Vilkov (2005), among others).

Option-implied second moments are computed as model-free implied variance (Dumas (1995), Britten-Jones and Neuberger (2000), Bakshi, Kapadia, and Madan (2003)) and as simple variance swap (Martin (2013)). The simple variance swaps are used in the main analysis, and the log contracts are checked out in robustness exercises. The options for S&P500 and S&P100 are available from 1996, while for DJ30 they become available from October 1997, and for Sector SPDRs from mid-December 1998. The data on options are available until April 2016.

For realized variances we use daily returns for a window length of a month, a quarter, or a year. The variance risk premium (VRP) is computed in an *ex ante* version as risk-neutral variance observed at the end of day t minus realized variance from $t - \Delta t$ to t. The implied correlations and covariance matrices are constructed following methods discussed in Section 2. The correlation risk premium (CRP) is constructed also in an *ex ante* version as an implied correlation at the end of day t minus the corresponding realized correlation from $t - \Delta t$ to t.

4 Properties of Correlations

4.1 The Price of Variance and Correlation Risks

The correlations and risk premiums for 30, 90, and 365 days, estimated for major indices as equicorrelations and for S&P500 also as full and reduced sector-based correlations are provided in Table 2. The correlations and correlation risk premiums for S&P500 sectors are shown in Table 3. With small deviations, two main messages emerge: first, there is a significant correlation risk premium for stocks in major indices, and, second, this risk premium tends to grow with time to maturity. Smaller indices typically show higher levels of correlations, but similar levels of correlation risk premiums. Reduced sector-based correlations for S&P500 are seemingly too high (almost two times higher than the corresponding S&P500 equicorrelations or full sector-based correlations). There is also a visible heterogeneity in the levels of average correlation among economic indices, which may be a sign of different average levels of idiosyncratic (that is, firm-specific) noise across sectors. Health, consumer discretionary, and technology show the three lowest correlations (0.42, 0.42, and 0.44 for 30 days), while energy, finance, and materials show the three top ones (0.70, 0.63, and 0.52 for 30 days). Consumer staples, however, demonstrate the largest correlation risk premium of 0.10 for 30 days, followed by finance and technology (0.08 and 0.08). Consumer staples is traditionally a safe sector used by conservative investors, and intra-sector diversification is highly valued; finance and technology are more aggressive areas, and diversification is important for hedging the tails. For utilities a 30-day implied correlation is even lower than a realized one, although it looks more like an outlier, because for longer maturities we regain status quo.

The joint dynamics of implied and realized equicorrelations for S&P500 and other major indices and sectors in Table 4 reveal that in major indices the correlations tend to co-move extremely closely (with an exception of reduced sector-based correlations); however, within the S&P500 the correlations in the sectors are linked less strongly, and demonstrate a great amount of heterogeneity in dynamics. The correlations between 30-day IC for S&P500 and major indices are all above 0.96, while for S&P500 and sectors the correlations between IC's range from 0.31 to 0.80. Other maturities and realized correlations demonstrate a similar picture.

Thus, the diversification in and between economic sectors is valued quite differently from general diversification over a broad universe, while the size of this universe does not matter so much—more important is that it contains stocks representing all sectors of the economy. The documented heterogeneity in the correlation matrix increases our chances at extracting option-implied factors directly from a sector-based approach.

Tables 5 and 6 provide a complementary view on the variance risk premiums for individual stocks within a number of indices and sectors and for the indices and sectors 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, 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. It is consistent with the evidence on the correlation risk premium for a broad stock universe. For the individual sectors the results are mixed, and we observe a lot of heterogeneity in the variance risk premium sign and significance. For example, for individual stocks within the finance sector (*fin*) the average realized variance is higher than the implied one, while for the sector as a whole the VRP is not significant. The difference is absorbed by the correlation risk premium as seen above. A more detailed analysis of implications of the variance risk premium heterogeneity across sectors, and its link to the observed correlation risk premium is left for further research.

4.2 Predictability of Risks and Returns by Implied Correlation

A number of option-implied variables are able to predict future stock returns, especially in the cross-section of assets (e.g., Christoffersen, Jacobs, and Chang (2011) for a review), but two variables stand out in predicting market risk premium—variance risk premium and implied correlations. We retest this claim using the market factor as computed in the Kenneth French data library compounded over 30, 91, and 365 calendar days, and applying just three regressors, namely lagged realized (historical RC) correlations and implied correlation from the major indices (computed as equicorrelations for all index components, and as correlations between sectors for S&P500 sample, both reduced and full sector-based ones), and variance risk premium for the same indices.[4] Note that in these regressions we do not explicitly control for traditional predictors of market return—it has been shown in previous research that both implied correlation and variance risk premiums are robust to including a large number of such traditional estimators.[5] The results in Table 7 do not only confirm past results about RC, VRP, and IC predictability (e.g., Driessen, Maenhout, and Vilkov (2005), Faria, Kosowski, and Wang (2016) for implied variables, and Pollet and Wilson (2010) for realized correlation), but also deliver two new facts. First, for predicting returns one does not need to work out IC for a very large index (in terms of number of constituents) using all underlying stocks—it is enough to have a "small" index with broad economic coverage (like DJ30 with 30 stocks); moreover, it is even enough to consider sectors as underlying standalone assets within the scope of the S&P500 index, that is, work with a "large" index of only nine sectors. Second, working with longer-maturity IC and VRP in predictive regressions, IC alone always delivers better results than VRP, and it is always significant in stand-alone and joint regressions. VRP, however, loses significance in stand-alone regressions predicting 365-day market factor realizations, and in joint regressions its sign turns to to be significantly negative. IC delivers an impressive R^2 of more than 22% for the annual horizon. Moreover, for the DJ30-based IC, the R^2 grows to over 32%, and for the S&P500 reduced sector-based IC, the R^2 stays at about the same level of

[4]We include an intercept in each regression but do not report it in the table for lack of space.

[5]See, for example, Driessen, Maenhout, and Vilkov (2005), Faria, Kosowski, and Wang (2016), among others.

29%. Thus, it is the average correlation between different sectors of the economy that matters, and not just the average level of correlation between stocks. Realized equicorrelations perform worse than implied ones in all cases but two: a reduced sector-based RC for an S&P500 sample performs slightly better than the corresponding IC for longer-term market factor realizations (R^2's of 0.117 vs. 0.115 for 91 days and 0.307 vs. 0.291 for 365 days, respectively).

The results lead us to pose another question: through which channel does the IC predict the market return? We know from Bollerslev, Tauchen, and Zhou (2009), for example, that VRP can be linked to long-run consumption risk, and that market risk and variance risk premiums share a common component. Bollerslev and Todorov (2011), Trojani and Schneider (2015), Andersen, Fusari, and Todorov (2016), among others, show that the VRP is largely due to the tail risk, and thus tail risk is a predictability channel for market excess returns by VRP. Conventional wisdom tells us that correlation is linked to diversification, and hence implied correlation should be a forward-looking indicator of diversification risk. In this case, IC should be able to predict the future realized correlation between stocks in the economy.

We have tested a hypothesis that IC predicts future risks for horizons of 30, 91, and 365 days, where risks are formulated in different forms. First, we put the RC for a given index (corresponding to the predictors) on the left-hand side, anticipating that hight IC predicts increasing risk in the form of higher RC and thus lower diversification benefits. Second, we take the average R^2 from a one factor model, and we expect that high IC reflects a higher systematic risk, that is, a better fit of a factor model on individual stock level, so that the IC coefficient should be positive again. Third, we look at the cross-sectional dispersion of market betas, hypothesizing that lower diversification is related to how all stocks move together, and especially how they become aligned with the market factor. A higher IC should lead to lower dispersion of market betas. It is similar to the “no place to hide” story of Buraschi, Kosowski, and Trojani (2014), but instead of hedge funds we analyze individual stocks, and instead of the correlation factor we just see how market betas behave. Last but not least, we test if the realized variance (RV) can be predicted by one of our risk measures. In all the regressions we compare the predictive abilities of lagged RC, current IC, and ex ante VRP for the corresponding horizons.

Table 8 shows the results of risk predictive regressions for 30, 91, and 365 calendar days in Panels A, B, and C, respectively. The major insights are that with increasing predictability horizon the lagged RC does a progressively better job in predicting R^2 form the one factor model, and in predicting future realized correlations (RC), and that while for 30-day horizon IC results in a higher (or similar) R^2's compared to the lagged RC, for 90-day horizon the RC mostly outperforms IC with a large gap. For 30 days there is one case where IC is taking a significant lead—it is the full sector-based IC. At the annual horizon (365 days) lagged RC dominates in predicting the fit of factor model and the level of realized correlations; and hence, a superior performance of IC in predicting future market factor realizations does not come through its predicting diversification benefits. However, IC excels in predicting the cross-sectional dispersion of market betas, and except for the DJ30 sample, we fail to reject a negative relationship between the level of IC and future $\sigma^2(\beta_M)$. The relationship is especially strong for longer horizons, where the R^2 in univariate regressions of dispersion in betas on an intercept and IC goes up to 0.55 for reduced sector-based IC (it is 0.41 for full sector-based IC, and 0.29 for just S&P500 IC). Thus, IC predicts not just the level of diversification, and not just the fit of the factor models, but it predicts the level of "systematic" diversification. Higher IC indicates closer clustering of market betas around the mean for a given sample, and higher correlation due to market exposure. In extreme cases the market betas of all stocks converge to one, which can interfere with plans of keeping target market exposure (e.g., market-neutral strategies or long-only strategies with reduced market risk).[6] As already conjectured RV can be predicted well for all indices by the VRP for a 30-day horizon but explains less in terms of R^2 for horizons longer 91 days.

[6]VRP is related to the future factor model fit and RC only marginally, so its risk predictive qualities work though a different channel.

5 Implied Factors and Factor Exposures

There are several important take-aways from the previous sections: (i) implied correlations predict future market factor realizations, and by constructing the implied correlation proxy it is crucial to take into account the structure of the economy, that is, identify correlations between sectors and not just as many components as possible; (ii) implied correlations predict not the diversification risk, but the systematic diversification risk (or the level of the non-diversifiable part of portfolio risk) though the negative link to the future cross-sectional dispersion of market betas; and (iii) variance and correlation risk premiums vary a lot across different sectors of the economy, that is, stocks in the sectors have heterogenous exposure to the underlying driving factors.

These results inspire us to work more with our correlation (covariance) matrices, first, to see how well they can predict future market exposure, and, second, to extract from them statistical factors and see how well these factors can predict future joint stock dynamics. While Buss and Vilkov (2012) use an option-implied covariance matrix constructed by combining historical and option-based inputs to predict market betas, we go one step further and exclude historical component from the estimation. Further analysis concentrates on using a traditional historical covariance matrix Σ^P, a heterogenous implied covariance matrix Σ^Q_{BV} by Buss and Vilkov (2012), and a full sector-based (option-implied and hence ex ante) covariance matrix Σ^Q_{FSB} in two applications: (i) infer factor structure of returns in the form of principal components and see how well these factors fit the future individual return dynamics and (ii) estimate and compare market factor betas.

At the end of each month we construct three covariance matrices; the historical covariance matrix is based on daily returns for the last 251 trading days, Σ^Q_{BV} is based on the historical covariance matrix and on 30-, 91-, or 365-day options, and Σ^Q_{FSB} is based only on data from options of respective maturities.[7]

[7]Note that all three matrices are not necessarily positive definite by construction, although one can make them positive definite, by taking longer time series for estimation of Σ^P, by using a positive definite matrix as

Following Ait-Sahalia and Xiu (2016) who identified three to five statistical factors in similar settings, from each matrix we extract five leading principal components (i.e., with highest eigenvalues) and normalize them to add up to one, so that we can treat them as factor weights. Using daily stock returns, we create the daily realizations of each factor for the next month. The first principal component-based factor from any of the matrices is typically a long-only and well diversified portfolio of all stocks that roughly corresponds to the U.S. market factor. Its time-series correlation to the S&P500 return and to the market factor are about 0.95, with values slightly increasing from Σ^P to Σ^Q_{BV} and to Σ^Q_{FSB}-based principal components. The time-series average of the $L2$ norm of the difference between the market (value-based) and statistical factor weights is approximately 0.08 for all three methods and maturities of options used. The first factors from all three matrices are also very highly correlated. One can treat the first statistical factor as a market factor adjusted to be orthogonal to the other "sector-specific" ones.

Statistical factors beyond the first one are harder to interpret. We extract them at the end of each month, and the order of importance in terms of explained variance (eigenvalue of each factor) changes in time, for example, factor #2, explaining materials and consumer staples sectors today may not be factor #2 in a month. Thus, we cannot easily attribute each factor for each month to a particular place, and the exploration of such a procedure is left for later.

The matrices give us statistical factors, and comparing the explanatory power of these factors with respect to stock returns, we can judge if option-implied correlations help to identify the future factor structure of returns. Moreover, comparing a historical with a hybrid and then with a factor-based matrices we can see if using only option-implied information about sectors is enough for pinning down the dynamics of asset returns. After getting daily factor realizations, each month we regress daily returns for each stock in CRSP on the constant and a set of factors, starting with the first (market-alike) one, and sequentially adding the next ones. The adjusted R^2's for regressions are averaged cross-sectionally each month, and then the time-series average

input for Σ^Q_{BV}, and by shrinking the full sector-based correlation matrix toward identity matrix (e.g., Ledoit and Wolf (2003, 2004)).

R^2 is reported for each combination of factors. To compare with the traditional approach, we carry out the same procedure with Fama and French (1993, 2015) and Carhart (1997) factors, adding them sequentially to the monthly regressions. The results are provided in Table 9.

The most striking result is that using the historical structure of the covariance matrix either by itself or enriched by option-implied information, is not essential for inferring the factor structure of returns. Having the ex ante covariance with the structure implied by the correlations in and between sectors, however, is enough for extracting factor structure that improves the factor model fit of future stock returns. Compared to factors from Σ^P or Σ^Q_{BV}, the principal components from full sector-based matrix Σ^Q_{FSB} deliver up to 2.3% higher adjusted R^2 with one factor and up to 2.1% higher R^2 with five factors.

Consistent with Ait-Sahalia and Xiu (2016) we observe that leading factors uncovered by PCA explain a larger fraction of the total variation of asset returns than that explained by traditional economically-motivated factors. Five Fama-French factors and momentum explain 26.1% of variation, while five statistical factors show R^2 of up to 32.8%.

Note that a full sector-based covariance matrix is not necessarily positive-definite, and hence a number of factors with positive eigenvalues may be smaller than the number of assets in our universe. To construct the positive-definite matrix as required for portfolio allocation and other similar applications, a number of solutions is available. For example, one can use decomposition (2) and after computing the systematic part of the covariance $B\Sigma^F B^\top$ (with a selected number of factors), replace the diagonal elements with the total variance, in effect adding the residual stock variance D to the systematic part. Another way would be to use the regularization method of Zumbach (2009a,b), that is, to reconstruct a covariance matrix using all eigenvectors, but replacing the value of all eigenvalues below a specified threshold by the threshold itself. A simpler shrinkage approach (e.g., Ledoit and Wolf (2003, 2004)) is also a well-accepted option. These experiments as well as possible applications of the resulting covariance matrix are left for further research.

6 Robustness Tests

We carry out a number of robustness tests to see how sensitive our analysis is regarding assumptions about computational procedures, inputs, and sample periods. Specifically, we look at the following: (i) instead of applying index weights for computing the correlations in formulas (5) and (6), use equal weights for underlying assets; (ii) for computing implied correlations use not the simple variance swap as in Martin (2013), which are especially well suited for estimating implied correlations, according to Ian Martin, but log contract (model-free implied variance as in Britten-Jones and Neuberger (2000), Bakshi, Kapadia, and Madan (2003)), (iii) check the validity of the major results for subperiods. All tables for robustness tests are collected in the (Internet) Appendix A1.

We can expect large discrepancies in the results by using equal weights assumption, while the model free implied variance should not have much an effect. As evident from Table 4, the time-series correlations between the base version of IC and equal-weighted IC are between 0.95 (for 30 days) and 0.72 (for 365 days), while the correlations between base and model free implied variance versions are all above 0.97.

The results for equal weights assumption are provided in Tables A101 to A104. Our interest here is to see if a much simpler procedure for computing the equicorrelations with equal instead of true index weights results in correlations with comparable qualities. The equal weighting produces similar correlation risk premiums across indices and sectors, with a slight change in the magnitude of the correlations. The differences are seemingly lower for correlations based on a larger number of assets, such as S&P500 with all individual assets involved. For reduced sector-based correlations, that is, IC and RC based on nine sector ETFs used as assets, the bias from using equal weights is large. The worst news is that the performance of IC and RC in predicting future market return and risk deteriorates significantly for all indices and horizons of predictability, more so for longer horizons.

The results for using log variance swaps (MFIV) as a proxy for integrated risk-neutral variance are provided in Tables A105 to A111. Most results on the dynamics and on magnitudes of correlations, variances, and the respective risk premiums come through the choice of variance swaps, and there are no particularly interesting discoveries. Important messages come from the tables on returns and risk predictability: the SMFIV-based IC works much better in predicting both market returns and risks, and the improvement is especially large for longer horizons. For example, the R^2 in regressing annual market return on IC is reduced by $2-3\%$ for all indices and methods when MFIV is used; the reduction in performance in predicting risk measures is even larger for most regression specifications. Thus, as Martin (2013) claimed, using simple variance swaps indeed delivers a more informative implied correlations.

7 Conclusion

Implied correlation uses forward-looking information from option markets, and it is typically interpreted as an indicator of uncertainty and diversification risk in the future. We study implied correlations inferred from major U.S. stock indices and economic sectors.

We show that by constructing an implied correlation proxy it is crucial to use the structure of the economy, that is, one shall identify correlations between economic sectors and not just between as many assets as possible. Only nine sector ETFs and S&P500 options are enough to obtain an implied correlation, which works well as a predictor of future market return and systematic diversification risk. The latter can be thought of as a heterogeneity or dispersion of market betas, and it represents the channel though which implied correlation is linked to future risk. Note that implied correlation predicts the average realized correlation (that is, total diversification benefits) worse compared to past realized correlation.

Sector option data reveal sector-specific implied correlations and risk premiums, and they are vastly heterogenous. Their analysis can be helpful in understanding premiums for diversification risk along different stages of a business cycle. Heterogeneity of sector-based correlations also allows for construction of a sector-based covariance matrix for S&P500 components, and for extracting statistical factors from it. These factors explain future return dynamics of individual stocks better than traditional economic factors, and also better than statistical factors extracted from a historical covariance matrix, or from a heterogenous option-implied covariance matrix (Buss and Vilkov (2012)).

Implied correlation from any broad index (in terms of coverage of different sectors) predicts future market returns, and its predictability horizon (up to a year) is longer than that of the market variance risk premium (about a quarter). We show that an implied correlation is related to future systematic diversification risk and not just to a level of future realized correlations. High implied correlation significantly predicts lower dispersion in market betas for all studies horizons, thus making risk in individual names more concentrated around the market factor.

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List of Tables

Table 1: Index Data Composition Summary

In this table, we report the statistics on the composition of major indices and economic sectors. "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	Sector	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
S&P500 Sectors											
Materials (*mat*)	SPDR	XLB	110007	15	128798	27	33	26	31	0.831	0.987
Hlth Care (*hea*)	SPDR	XLV	110008	35	128859	27	51	26	51	0.779	1.000
Cons Stapl (*cst*)	SPDR	XLP	110009	30	128898	33	41	31	40	0.806	0.997
Cons Discr (*cdi*)	SPDR	XLY	110010	25	128940	77	87	69	84	0.804	0.982
Energy (*ene*)	SPDR	XLE	110011	10	129001	23	29	22	29	0.830	0.997
Finance (*fin*)	SPDR	XLF	110012	40	129021	55	80	56	79	0.831	0.990
Industr (*ind*)	SPDR	XLI	110013	20	129039	51	64	51	61	0.869	1.000
Inf Tech (*tec*)	SPDR	XLK	110014	45, 50	129059	33	71	40	71	0.765	0.917
Utilities (*utl*)	SPDR	XLU	110015	55	129218	29	35	27	33	0.826	1.000

Table 2: 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 difference between them (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 three different maturities—30, 91, 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 (5). Full sector-based correlations for SP500 sample are correlations between economic sectors in the index, computed using equation (6). Reduced sector-based are estimated from using sectors as underlying assets directly from equation (5). Model-free 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	365	30	91	365	30	91	365
SP500 Sample									
Mean	0.387	0.423	0.459	0.327	0.326	0.327	0.060	0.097	0.133
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.375	0.423	0.464	0.298	0.308	0.308	0.060	0.094	0.142
StDev	0.126	0.113	0.099	0.145	0.125	0.115	0.103	0.084	0.076
SP100 Sample									
Mean	0.423	0.463	0.498	0.356	0.357	0.358	0.067	0.106	0.140
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.412	0.466	0.509	0.331	0.344	0.341	0.066	0.103	0.144
StDev	0.130	0.114	0.101	0.152	0.129	0.116	0.114	0.090	0.093
DJ30 Sample									
Mean	0.464	0.497	0.528	0.371	0.373	0.377	0.082	0.112	0.137
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.456	0.503	0.539	0.352	0.363	0.359	0.078	0.102	0.141
StDev	0.148	0.129	0.105	0.169	0.148	0.141	0.130	0.102	0.090
SP500 Sample (full sector-based)									
Mean	0.358	0.396	0.436	0.314	0.314	0.320	0.044	0.082	0.116
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.349	0.403	0.449	0.289	0.302	0.302	0.046	0.085	0.122
StDev	0.137	0.125	0.114	0.151	0.131	0.117	0.100	0.077	0.071
SP500 Sample (reduced sector-based)									
Mean	0.663	0.719	0.751	0.634	0.646	0.661	0.028	0.074	0.089
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000
Median	0.701	0.762	0.789	0.658	0.672	0.696	0.028	0.068	0.095
StDev	0.195	0.167	0.156	0.186	0.166	0.147	0.159	0.115	0.094

Table 3: Sector 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 difference between them (IC-RC), for components of S&P500 sector indices and for sectors within S&P500, for the sample period from 1996 to 04/2016, and from 10/1997 to 04/2016, respectively, and for three different maturities—30, 91, 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 (5). Model-free 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	365	30	91	365	30	91	365
Sector: mat									
Mean	0.520	0.520	0.549	0.483	0.480	0.477	0.038	0.041	0.080
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.151	0.144	0.139	0.154	0.122	0.094	0.141	0.115	0.110
Sector: hea									
Mean	0.415	0.397	0.433	0.367	0.363	0.359	0.048	0.035	0.075
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.007	0.000
StDev	0.136	0.108	0.111	0.173	0.145	0.115	0.182	0.126	0.101
Sector: cst									
Mean	0.476	0.445	0.491	0.375	0.364	0.359	0.102	0.081	0.135
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.141	0.108	0.106	0.163	0.118	0.086	0.207	0.132	0.106
Sector: cdi									
Mean	0.416	0.438	0.475	0.384	0.376	0.377	0.038	0.065	0.102
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.123	0.107	0.093	0.147	0.119	0.097	0.137	0.103	0.081
Sector: ene									
Mean	0.702	0.715	0.717	0.693	0.694	0.695	0.009	0.022	0.024
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.351	0.077	0.164
StDev	0.184	0.170	0.148	0.187	0.163	0.145	0.164	0.127	0.107
Sector: fin									
Mean	0.628	0.643	0.680	0.551	0.551	0.552	0.078	0.092	0.130
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.136	0.103	0.090	0.146	0.113	0.095	0.144	0.107	0.101
Sector: ind									
Mean	0.504	0.523	0.554	0.451	0.448	0.454	0.054	0.076	0.104
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.167	0.157	0.147	0.196	0.161	0.147	0.160	0.106	0.086
Sector: tec									
Mean	0.441	0.463	0.501	0.366	0.362	0.366	0.075	0.099	0.129
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.146	0.119	0.096	0.151	0.124	0.117	0.165	0.121	0.105
Sector: utl									
Mean	0.487	0.548	0.649	0.535	0.531	0.534	-0.049	0.016	0.111
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.131	0.000
StDev	0.166	0.157	0.164	0.179	0.155	0.136	0.187	0.114	0.128

Table 4: Link between Correlations for S&P500 and other indices

The table reports time-series correlations between correlations (implied and realized) for the S&P500, and other major indices, and sector subindices. 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 three different maturities—30, 91, 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 (5). Full sector-based correlations for S&P500 sample are correlations between economic sectors in the index, computed using equation (6). Reduced sector-based are estimated by using sectors as underlying assets directly from equation (5). Robustness contains ICs for S&P500 index computer either under assumption of equal index weights, oder using MFIV (Bakshi, Kapadia, and Madan (2003)) as a proxy of expected integrated variance.

	IC			*RC*		
	30	91	365	30	91	365
SP100	0.983	0.979	0.895	0.987	0.990	0.992
DJ30	0.963	0.974	0.963	0.958	0.972	0.991
SP500 Sample (reduced sector-based)	0.788	0.840	0.888	0.838	0.842	0.854
SP500 Sample (full sector-based)	0.993	0.992	0.992	0.995	0.995	0.997
Sector: mat	0.535	0.571	0.599	0.615	0.656	0.694
Sector: hea	0.619	0.837	0.844	0.613	0.614	0.739
Sector: cst	0.310	0.592	0.347	0.601	0.650	0.729
Sector: cdi	0.718	0.777	0.704	0.747	0.784	0.859
Sector: ene	0.331	0.366	0.469	0.369	0.365	0.467
Sector: fin	0.586	0.525	0.168	0.732	0.748	0.779
Sector: ind	0.797	0.843	0.896	0.770	0.827	0.874
Sector: tec	0.385	0.329	0.023	0.749	0.714	0.711
Sector: utl	0.490	0.621	0.620	0.455	0.565	0.682
Robustness						
SP500, equal weights	0.953	0.943	0.717			
SP500, model free implied variance	0.998	0.992	0.967			

Table 5: Individual and Index Variances, and Variance Risk Premiums

The table reports the time-series averages of realized ($\sqrt{RV}$) and model-free implied variances ($\sqrt{MFIV}$), expressed in volatility terms, and the difference between them ($VRP = MFIV - RV$), 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, and 365 (calendar) days. For individual stocks the variances are equally-weighted cross-sectional averages across all constituent stocks. Model-free implied variance ($MFIV$) 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 $MFIV$. Model-free implied variances are computed as simple variance swaps Martin (2013). All variances (volatilities) 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	$\sqrt{MFIV}$	$\sqrt{RV}$	VRP	$p-val$	$\sqrt{MFIV}$	$\sqrt{RV}$	VRP	$p-val$
SP500 Sample								
30	0.400	0.398	0.001	0.757	0.211	0.187	0.006	0.004
91	0.383	0.397	-0.011	0.144	0.211	0.186	0.006	0.044
365	0.367	0.395	-0.021	0.164	0.216	0.186	0.008	0.089
SP100 Sample								
30	0.364	0.371	-0.005	0.333	0.211	0.188	0.005	0.004
91	0.351	0.368	-0.013	0.105	0.212	0.187	0.006	0.029
365	0.341	0.365	-0.017	0.204	0.218	0.187	0.009	0.061
DJ30 Sample								
30	0.323	0.327	-0.002	0.434	0.207	0.177	0.007	0.000
91	0.311	0.325	-0.009	0.154	0.207	0.176	0.007	0.006
365	0.307	0.319	-0.008	0.461	0.213	0.176	0.010	0.038

Table 6: Individual and Sector Variances, and Variance Risk Premiums

The table reports the time-series averages of realized ($\sqrt{RV}$) and model-free implied variances ($\sqrt{MFIV}$), expressed in volatility terms, and the difference between them ($VRP = MFIV - RV$), expressed as a difference in variances, for nine samples of stocks—components of economic sectors based on S&P500 index, for the sample period from 12/1998 to 04/2016 and for three different maturities—30, 91, and 365 (calendar) days. For individual stocks the variances are equally-weighted cross-sectional averages across all constituent stocks. Model-free implied variance ($MFIV$) 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 $MFIV$. Model-free implied variances are computed as simple variance swaps Martin (2013). All variances (volatilities) 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	$\sqrt{MFIV}$	$\sqrt{RV}$	VRP	$p-val$	$\sqrt{MFIV}$	$\sqrt{RV}$	VRP	$p-val$
Sector:mat								
30	0.385	0.377	0.006	0.147	0.264	0.250	0.005	0.055
91	0.369	0.375	-0.005	0.479	0.252	0.250	-0.000	0.923
365	0.359	0.372	-0.010	0.479	0.251	0.251	-0.001	0.903
Sector:hea								
30	0.364	0.348	0.011	0.000	0.199	0.185	0.005	0.021
91	0.351	0.348	0.002	0.518	0.192	0.185	0.002	0.380
365	0.345	0.349	-0.002	0.696	0.198	0.185	0.004	0.186
Sector:cst								
30	0.303	0.285	0.010	0.000	0.179	0.155	0.007	0.000
91	0.290	0.284	0.003	0.136	0.172	0.155	0.005	0.000
365	0.290	0.281	0.005	0.222	0.186	0.155	0.010	0.000
Sector:cdi								
30	0.404	0.388	0.012	0.000	0.239	0.229	0.005	0.010
91	0.388	0.388	0.000	0.998	0.237	0.229	0.004	0.215
365	0.375	0.384	-0.007	0.562	0.243	0.230	0.005	0.385
Sector:ene								
30	0.404	0.402	0.001	0.849	0.275	0.281	-0.005	0.374
91	0.390	0.400	-0.008	0.441	0.269	0.280	-0.007	0.367
365	0.377	0.393	-0.013	0.476	0.268	0.280	-0.007	0.518
Sector:fin								
30	0.400	0.436	-0.030	0.036	0.308	0.313	-0.006	0.350
91	0.374	0.432	-0.046	0.051	0.293	0.311	-0.014	0.233
365	0.351	0.421	-0.055	0.189	0.286	0.313	-0.019	0.429
Sector:ind								
30	0.366	0.352	0.010	0.001	0.233	0.216	0.007	0.000
91	0.351	0.352	-0.000	0.932	0.228	0.216	0.004	0.086
365	0.345	0.349	-0.003	0.741	0.233	0.217	0.006	0.236
Sector:tec								
30	0.500	0.503	-0.004	0.498	0.286	0.265	0.010	0.011
91	0.484	0.504	-0.019	0.024	0.283	0.265	0.007	0.143
365	0.456	0.505	-0.047	0.029	0.285	0.266	0.006	0.493
Sector:utl								
30	0.331	0.312	0.012	0.072	0.204	0.193	0.004	0.150
91	0.299	0.311	-0.007	0.367	0.194	0.193	-0.000	0.966
365	0.284	0.309	-0.015	0.322	0.209	0.193	0.006	0.143

Table 7: Market Return Predictability: Correlations and VRP

The table shows the coefficients (and corresponding p-values) and the R^2 of the market predictive regressions, for the sample period from 10/1997 to 04/2016 for DJ30-based variables, and from 01/1996 to 04/2016 for S&P500 and S&P100. We regress overlapping market factor compounded over a specified horizon (30, 91, and 365 calendar days) on a constant and a given set of explanatory variables, which are the realized (historical) equicorrelation (RC) for 30, 91, and 365 calendar days, implied correlation (IC) for the same maturities, and the variance risk premium, which equals to the difference between model-free implied variance and lagged realized variance computed over the matching period (VRP) of 30, 91, and 365 calendar days. Model-free 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.

	Market return, 30 days				Market return, 91 days				Market return, 365 days			
SP500 Sample												
RC	0.030				0.111				0.403			
	0.111				0.037				0.093			
IC		0.067		0.072		0.255		0.259		0.851		0.849
		0.000		0.000		0.000		0.000		0.000		0.000
VRP			0.210	0.228			0.444	0.478			-0.738	-0.699
			0.003	0.001			0.001	0.000			0.231	0.186
R^2	0.008	0.030	0.023	0.057	0.029	0.125	0.029	0.159	0.064	0.216	0.012	0.227
SP100 Sample												
RC	0.027				0.087				0.332			
	0.134				0.089				0.209			
IC		0.058		0.062		0.240		0.245		0.864		0.897
		0.001		0.000		0.000		0.000		0.000		0.000
VRP			0.215	0.230			0.527	0.556			-0.589	-0.990
			0.003	0.002			0.000	0.000			0.394	0.039
R^2	0.007	0.024	0.023	0.050	0.019	0.113	0.037	0.153	0.045	0.232	0.008	0.254
DJ30 Sample												
RC	0.026				0.089				0.531			
	0.126				0.058				0.000			
IC		0.059		0.062		0.226		0.230		0.982		0.973
		0.000		0.000		0.000		0.000		0.000		0.000
VRP			0.215	0.229			0.540	0.574			-1.253	-1.105
			0.005	0.003			0.000	0.000			0.078	0.048
R^2	0.008	0.032	0.019	0.053	0.025	0.125	0.033	0.162	0.158	0.329	0.029	0.351
SP500 Sample (reduced sector-based)												
RC	0.049				0.170				0.700			
	0.000				0.000				0.000			
IC		0.048		0.047		0.167		0.165		0.642		0.634
		0.000		0.000		0.000		0.000		0.000		0.000
VRP			0.205	0.205			0.405	0.390			-1.550	-1.446
			0.005	0.004			0.003	0.005			0.015	0.027
R^2	0.034	0.035	0.024	0.059	0.117	0.115	0.027	0.140	0.307	0.291	0.058	0.342
SP500 Sample (full sector-based)												
RC	0.040				0.138				0.730			
	0.039				0.011				0.000			
IC		0.066		0.071		0.230		0.240		0.872		0.844
		0.000		0.000		0.000		0.000		0.000		0.000
VRP			0.205	0.226			0.412	0.484			-1.468	-1.147
			0.005	0.002			0.003	0.000			0.015	0.071
R^2	0.015	0.034	0.024	0.063	0.049	0.123	0.028	0.161	0.219	0.296	0.054	0.328

Table 8: Risk Predictability: Correlations and VRP

The table shows the coefficients (with corresponding p-values) and the R^2 of the risk predictive regressions, for the sample period from 10/1997 to 04/2016 for DJ30-based variables, and from 01/1996 to 04/2016 for S&P500 and S&P100. We regress risk measures for a specified horizon of 30, 91, and 365 calendar days (in Panels A, B, and C, respectively) on a constant and a given set of explanatory variables, which are implied correlation (IC) for 30, 91, and 365 calendar days, and the variance risk premium, which equals to the difference between model-free implied variance and lagged realized variance computed over the matching period (VRP) of 30, 91, and 365 calendar days. The risk measures are the realized variance (RV), the average 1-factor model R^2 for all stocks in a given index, cross-sectional variance of market betas $\sigma^2(\beta_M)$ for all stocks in an index, and realized equicorrelation (RC), also defined for a given index. Model-free 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: 30-day horizon

	RV			1-factor R^2			$\sigma^2(\beta_M)$			RC		
SP500 Sample												
RC	0.150			0.507			-0.531			0.510		
	0.002			0.000			0.000			0.000		
IC		0.143			0.616			-0.783			0.688	
		0.001			0.000			0.000			0.000	
VRP			-0.829			-0.690			0.188			-0.674
			0.001			0.000			0.573			0.001
R^2	0.110	0.074	0.200	0.303	0.335	0.033	0.066	0.107	0.000	0.260	0.354	0.027
SP100 Sample												
RC	0.122			0.468			-0.315			0.470		
	0.003			0.000			0.000			0.000		
IC		0.126			0.587			-0.422			0.647	
		0.001			0.000			0.000			0.000	
VRP			-0.761			-0.657			0.272			-0.628
			0.004			0.001			0.403			0.013
R^2	0.086	0.067	0.167	0.267	0.307	0.026	0.028	0.036	0.001	0.221	0.306	0.020
DJ30 Sample												
RC	0.102			0.441			-0.089			0.522		
	0.005			0.000			0.368			0.000		
IC		0.100			0.560			-0.153			0.671	
		0.001			0.000			0.175			0.000	
VRP			-0.638			-0.712			0.164			-0.847
			0.014			0.000			0.520			0.000
R^2	0.086	0.063	0.120	0.276	0.332	0.025	0.003	0.008	0.000	0.273	0.338	0.025
SP500 Sample (reduced sector-based)												
RC	0.066			0.363			-0.610			0.365		
	0.049			0.000			0.000			0.000		
IC		0.048			0.341			-0.585			0.369	
		0.014			0.000			0.000			0.000	
VRP			-0.871			-0.613			0.179			-0.665
			0.001			0.000			0.593			0.002
R^2	0.031	0.018	0.217	0.258	0.249	0.030	0.143	0.143	0.000	0.214	0.239	0.028
SP500 Sample (full sector-based)												
RC	0.148			0.493			-0.576			0.513		
	0.004			0.000			0.000			0.000		
IC		0.129			0.644			-0.811			0.696	
		0.002			0.000			0.000			0.000	
VRP			-0.873			-0.614			0.174			-0.665
			0.001			0.000			0.604			0.002
R^2	0.102	0.064	0.218	0.314	0.443	0.029	0.084	0.137	0.000	0.280	0.425	0.028

…Table 8 continued

Panel B: 91-day horizon

	RV			1-factor R^2			$\sigma^2(\beta_M)$			*RC*		
SP500 Sample												
RC	0.099			0.591			-0.226			0.544		
	0.002			0.000			0.008			0.000		
IC		0.044			0.549			-0.487			0.548	
		0.068			0.000			0.000			0.000	
VRP			-0.474			-0.807			-0.845			-0.646
			0.000			0.000			0.000			0.000
R^2	0.049	0.008	0.073	0.359	0.255	0.042	0.030	0.116	0.027	0.300	0.251	0.027
SP100 Sample												
RC	0.081			0.558			-0.097			0.523		
	0.004			0.000			0.200			0.000		
IC		0.033			0.527			-0.296			0.512	
		0.173			0.000			0.001			0.000	
VRP			-0.439			-0.720			-0.885			-0.580
			0.000			0.000			0.000			0.003
R^2	0.039	0.005	0.060	0.328	0.228	0.029	0.006	0.046	0.028	0.277	0.207	0.018
DJ30 Sample												
RC	0.069			0.546			0.044			0.609		
	0.004			0.000			0.549			0.000		
IC		0.036			0.508			-0.073			0.558	
		0.070			0.000			0.338			0.000	
VRP			-0.323			-0.830			-1.234			-0.920
			0.000			0.000			0.000			0.000
R^2	0.043	0.009	0.034	0.387	0.256	0.032	0.002	0.005	0.075	0.373	0.239	0.030
SP500 Sample (reduced sector-based)												
RC	-0.004			0.413			-0.510			0.372		
	0.900			0.000			0.000			0.000		
IC		-0.012			0.358			-0.470			0.344	
		0.502			0.000			0.000			0.000	
VRP			-0.510			-0.686			-0.837			-0.632
			0.000			0.000			0.000			0.000
R^2	-0.000	0.001	0.081	0.314	0.240	0.035	0.241	0.209	0.026	0.238	0.207	0.027
SP500 Sample (full sector-based)												
RC	0.084			0.577			-0.342			0.553		
	0.015			0.000			0.001			0.000		
IC		0.029			0.602			-0.534			0.575	
		0.249			0.000			0.000			0.000	
VRP			-0.505			-0.723			-0.814			-0.649
			0.000			0.000			0.000			0.000
R^2	0.034	0.003	0.080	0.377	0.376	0.038	0.068	0.151	0.025	0.327	0.324	0.029

…Table 8 continued

Panel C: 365-day horizon

	RV			1-factor R^2			$\sigma^2(\beta_M)$			*RC*		
SP500 Sample												
RC	0.050			0.668			-0.231			0.514		
	0.007			0.000			0.008			0.000		
IC		-0.025			0.565			-0.643			0.440	
		0.066			0.000			0.000			0.000	
VRP			0.099			-1.136			-0.183			-0.780
			0.029			0.000			0.348			0.000
R^2	0.022	0.004	0.005	0.426	0.228	0.071	0.049	0.286	0.002	0.286	0.157	0.038
SP100 Sample												
RC	0.044			0.615			-0.055			0.440		
	0.020			0.000			0.495			0.000		
IC		-0.048			0.397			-0.414			0.267	
		0.001			0.000			0.000			0.000	
VRP			0.099			-1.025			-0.218			-0.609
			0.005			0.000			0.256			0.000
R^2	0.020	0.017	0.005	0.367	0.116	0.058	0.003	0.150	0.003	0.216	0.060	0.023
DJ30 Sample												
RC	0.023			0.531			0.022			0.577		
	0.095			0.000			0.731			0.000		
IC		-0.042			0.346			-0.179			0.354	
		0.001			0.000			0.008			0.000	
VRP			0.152			-1.298			-0.038			-1.419
			0.001			0.000			0.871			0.000
R^2	0.008	0.017	0.012	0.354	0.091	0.071	0.001	0.050	-0.000	0.319	0.073	0.065
SP500 Sample (reduced sector-based)												
RC	-0.019			0.382			-0.434			0.258		
	0.098			0.000			0.000			0.000		
IC		-0.052			0.340			-0.613			0.233	
		0.000			0.000			0.000			0.000	
VRP			0.126			-0.625			-0.160			-0.450
			0.028			0.001			0.475			0.022
R^2	0.004	0.038	0.007	0.255	0.225	0.026	0.246	0.547	0.001	0.117	0.106	0.014
SP500 Sample (full sector-based)												
RC	0.029			0.594			-0.338			0.471		
	0.092			0.000			0.001			0.000		
IC		-0.040			0.587			-0.710			0.443	
		0.001			0.000			0.000			0.000	
VRP			0.121			-0.788			-0.120			-0.589
			0.026			0.000			0.580			0.002
R^2	0.006	0.012	0.007	0.367	0.336	0.039	0.097	0.405	0.000	0.237	0.196	0.022

Table 9: Factor Models: Individual Stocks

The table shows the average market betas and the R^2's for one-, three, five-, and six-factor models (Fama and French (1993, 2015), Carhart (1997)) and average betas on the first leading factor and R^2's for the explanatory regressions of individual stock returns on one to five leading factors extracted from one of three covariance matrices, namely, historical covariance matrix for S&P500 components Σ^P estimated over the last 251 trading days, heterogenous implied covariance matrix Σ^Q_{BV} from Buss and Vilkov (2012) estimated using Σ^P as input and 30-/91-/365-day options, and full sector-based covariance matrix Σ^Q_{FSB} constructed from 30-/91-/365-day options as discussed in Section 2. Model-free implied variances are computed as simple variance swaps Martin (2013). The principal components are extracted at the end of each month, and daily factor realizations for the next month are constructed from daily stock returns and corresponding normalized eigenvectors. One regression per stock in CRSP is then performed for the sample period from 01/1996 to 08/2016.

Factors	β_{mkt}	R^2
Economic factors		
mkt	0.997	0.208
mkt+smb+hml	1.068	0.236
mkt+smb+hml+rmw+cma	1.043	0.253
mkt+smb+hml+rmw+cma+mom	1.042	0.261

	30-day		91-day		365-day	
Factors	β_{PC1}	R^2	β_{PC1}	R^2	β_{PC1}	R^2
Covariance Matrix: Σ^P						
PC1	0.844	0.231	0.844	0.230	0.849	0.235
PC1-2	0.829	0.262	0.830	0.262	0.840	0.266
PC1-3	0.827	0.279	0.828	0.279	0.838	0.284
PC1-4	0.826	0.291	0.827	0.290	0.839	0.295
PC1-5	0.826	0.300	0.827	0.299	0.840	0.305
Covariance Matrix: Σ^Q_{BV}						
PC1	0.883	0.232	0.883	0.232	0.907	0.237
PC1-2	0.898	0.261	0.881	0.262	0.904	0.268
PC1-3	0.884	0.277	0.885	0.279	0.905	0.286
PC1-4	0.885	0.288	0.882	0.291	0.912	0.299
PC1-5	0.882	0.297	0.881	0.298	0.908	0.307
Covariance Matrix: Σ^Q_{FSB}						
PC1	0.878	0.247	0.875	0.247	0.910	0.260
PC1-2	0.887	0.272	0.882	0.274	0.919	0.289
PC1-3	0.875	0.287	0.870	0.288	0.917	0.305
PC1-4	0.865	0.297	0.870	0.300	0.913	0.317
PC1-5	0.873	0.306	0.877	0.310	0.924	0.328

A1 Internet Appendix: Tables for Robustness Tests

Tables with IC/RC under assumption of equal index weights

Table A101: (Equal Weights) 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 difference between them (IC-RC), for three samples of stocks—components of S&P500, S&P100 and DJ30 indices, for the sample period from 1996 to 08/2015, and from 10/1997 to 08/2015, respectively, and for three different maturities—30, 91, 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 (5) under assumptions that all indices are equal-weighted ones. Full sector-based correlations for SP500 sample are correlations between economic sectors in the index, computed using equation (6) with equal asset weights. Reduced sector-based are estimated from using sectors as underlying assets directly from equation (5) with equal sector weights. The p-values for significance of the means are computed with Newey and West (1987) adjustments for autocorrelation.

	IC			*RC*			*IC-RC*		
	30	91	365	30	91	365	30	91	365
SP500 Sample									
Mean	0.305	0.347	0.404	0.263	0.259	0.262	0.041	0.088	0.142
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.290	0.340	0.399	0.245	0.245	0.261	0.040	0.081	0.144
StDev	0.106	0.104	0.105	0.111	0.090	0.079	0.090	0.083	0.089
SP100 Sample									
Mean	0.365	0.408	0.463	0.306	0.305	0.307	0.058	0.103	0.156
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.357	0.411	0.461	0.288	0.292	0.304	0.056	0.097	0.153
StDev	0.118	0.112	0.117	0.127	0.104	0.094	0.101	0.088	0.103
DJ30 Sample									
Mean	0.421	0.460	0.513	0.330	0.331	0.335	0.085	0.121	0.165
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.410	0.457	0.498	0.312	0.327	0.334	0.078	0.108	0.160
StDev	0.134	0.127	0.119	0.144	0.119	0.104	0.128	0.112	0.112
SP500 Sample (full sector-based)									
Mean	0.278	0.318	0.381	0.247	0.244	0.252	0.030	0.075	0.129
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.267	0.319	0.374	0.229	0.235	0.250	0.032	0.072	0.130
StDev	0.102	0.093	0.100	0.110	0.089	0.078	0.086	0.072	0.082
SP500 Sample (reduced sector-based)									
Mean	0.698	0.752	0.816	0.663	0.673	0.690	0.034	0.078	0.126
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.725	0.773	0.829	0.678	0.688	0.712	0.026	0.060	0.132
StDev	0.182	0.139	0.110	0.179	0.148	0.132	0.164	0.130	0.101

Table A102: (Equal Weights) Sector 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 difference between them (IC-RC), for components of S&P500 sector indices and for sectors within S&P500, for the sample period from 1996 to 08/2015, and from 10/1997 to 08/2015, respectively, and for three different maturities—30, 91, 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 (5) under assumption that all indices are equal-weighted ones. The p-values for significance of the means are computed with Newey and West (1987) adjustments for autocorrelation.

	IC			*RC*			*IC-RC*		
	30	91	365	30	91	365	30	91	365
Sector: mat									
Mean	0.479	0.501	0.524	0.449	0.445	0.449	0.031	0.057	0.082
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
StDev	0.154	0.150	0.141	0.152	0.122	0.093	0.145	0.117	0.120
Sector: hea									
Mean	0.319	0.319	0.360	0.290	0.280	0.277	0.029	0.038	0.083
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000
StDev	0.111	0.096	0.105	0.141	0.107	0.081	0.154	0.105	0.098
Sector: cst									
Mean	0.377	0.376	0.427	0.307	0.292	0.288	0.070	0.084	0.139
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.123	0.088	0.087	0.138	0.095	0.061	0.179	0.115	0.096
Sector: cdi									
Mean	0.352	0.384	0.428	0.335	0.325	0.331	0.026	0.065	0.099
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000
StDev	0.098	0.089	0.079	0.130	0.103	0.082	0.127	0.107	0.099
Sector: ene									
Mean	0.465	0.486	0.502	0.466	0.466	0.470	-0.000	0.021	0.036
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.953	0.044	0.033
StDev	0.137	0.126	0.112	0.151	0.131	0.108	0.122	0.098	0.088
Sector: fin									
Mean	0.563	0.606	0.649	0.518	0.514	0.520	0.045	0.091	0.126
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.140	0.118	0.103	0.156	0.119	0.106	0.153	0.118	0.114
Sector: ind									
Mean	0.422	0.458	0.502	0.389	0.383	0.390	0.033	0.075	0.115
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.146	0.145	0.142	0.162	0.139	0.133	0.133	0.091	0.090
Sector: tec									
Mean	0.325	0.355	0.398	0.273	0.266	0.268	0.052	0.087	0.125
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.104	0.099	0.088	0.114	0.090	0.078	0.127	0.109	0.097
Sector: utl									
Mean	0.420	0.513	0.583	0.493	0.486	0.484	-0.074	0.025	0.090
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.032	0.000
StDev	0.154	0.161	0.180	0.187	0.161	0.138	0.198	0.121	0.112

Table A103: (Equal Weights) Market Return Predictability: Correlations and VRP

The table shows the coefficients (and corresponding p-values) and the R^2 of the market predictive regressions, for the sample period from 10/1997 to 08/2015 for DJ30-based variables, and from 01/1996 to 08/2015 for S&P500 and S&P100. We regress overlapping market factor compounded over a specified horizon (30, 91, and 365 calendar days) on a constant and a given set of explanatory variables, which are the realized (historical) equicorrelation (RC) for 30, 91, and 365 calendar days, implied correlation (IC) for the same maturities, and the variance risk premium, which equals to the difference between model-free implied variance and lagged realized variance computed over the matching period (VRP) of 30, 91, and 365 calendar days. 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.

	Market return, 30 days				Market return, 91 days				Market return, 365 days			
SP500 Sample												
RC	0.041				0.212				0.716			
	0.071				0.000				0.000			
IC		0.084		0.078		0.286		0.270		0.632		0.760
		0.000		0.000		0.000		0.000		0.000		0.000
VRP			0.227	0.207			0.469	0.226			-0.191	-1.313
			0.002	0.005			0.001	0.128			0.599	0.001
R^2	0.008	0.032	0.023	0.051	0.053	0.130	0.027	0.136	0.107	0.143	0.001	0.178
SP100 Sample												
RC	0.035				0.155				0.410			
	0.047				0.000				0.000			
IC		0.072		0.068		0.254		0.236		0.543		0.646
		0.000		0.000		0.000		0.000		0.000		0.000
VRP			0.232	0.214			0.548	0.342			-0.001	-1.135
			0.002	0.005			0.001	0.016			0.999	0.001
R^2	0.008	0.029	0.022	0.048	0.038	0.119	0.032	0.131	0.049	0.131	-0.000	0.156
DJ30 Sample												
RC	0.037				0.144				0.755			
	0.022				0.000				0.000			
IC		0.075		0.069		0.237		0.220		0.604		0.717
		0.000		0.000		0.000		0.000		0.000		0.000
VRP			0.248	0.208			0.580	0.249			-0.433	-1.617
			0.004	0.010			0.001	0.113			0.328	0.001
R^2	0.011	0.040	0.023	0.056	0.043	0.129	0.035	0.134	0.185	0.164	0.003	0.207
SP500 Sample (reduced sector-based)												
RC	0.040				0.162				0.656			
	0.010				0.000				0.000			
IC		0.043		0.040		0.173		0.161		0.568		0.639
		0.000		0.001		0.000		0.000		0.000		0.000
VRP			0.222	0.205			0.436	0.301			-0.591	-1.165
			0.004	0.006			0.003	0.030			0.132	0.002
R^2	0.020	0.025	0.024	0.045	0.083	0.085	0.025	0.096	0.230	0.118	0.008	0.150
SP500 Sample (full sector-based)												
RC	0.051				0.211				1.086			
	0.048				0.000				0.000			
IC		0.100		0.096		0.334		0.318		0.739		0.882
		0.000		0.000		0.000		0.000		0.000		0.000
VRP			0.221	0.206			0.441	0.248			-0.506	-1.526
			0.004	0.007			0.002	0.094			0.187	0.000
R^2	0.013	0.041	0.024	0.062	0.052	0.142	0.026	0.150	0.228	0.169	0.006	0.221

Table A104: (Equal Weights) Risk Predictability: Correlations and VRP

The table shows the coefficients (with corresponding p-values) and the R^2 of the risk predictive regressions, for the sample period from 10/1997 to 08/2015 for DJ30-based variables, and from 01/1996 to 08/2015 for S&P500 and S&P100. We regress risk measures for a specified horizon of 30, 91, and 365 calendar days (in Panels A, B, and C, respectively) on a constant and a given set of explanatory variables, which are implied correlation (IC) for 30, 91, and 365 calendar days, and the variance risk premium, which equals to the difference between model-free implied variance and lagged realized variance computed over the matching period (VRP) of 30, 91, and 365 calendar days. The risk measures are the average 4- and 1-factor model R^2 for all stocks in a given index, cross-sectional variance of market betas $\sigma^2(\beta_M)$ for all stocks in an index, and realized equicorrelation (RC), also defined for a given index. 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: 30-day horizon

	4-factor R^2			1-factor R^2			$\sigma^2(\beta_M)$			RC		
SP500 Sample												
RC	0.420			0.516			-0.619			0.373		
	0.000			0.000			0.000			0.000		
IC		0.430			0.568			-0.887			0.533	
		0.000			0.000			0.000			0.000	
VRP			-0.493			-0.515			0.014			-0.159
			0.004			0.025			0.972			0.472
R^2	0.177	0.171	0.022	0.184	0.205	0.016	0.053	0.100	-0.000	0.138	0.260	0.002
SP100 Sample												
RC	0.389			0.481			-0.414			0.380		
	0.000			0.000			0.000			0.000		
IC		0.447			0.592			-0.604			0.547	
		0.000			0.000			0.000			0.000	
VRP			-0.455			-0.467			0.252			-0.176
			0.020			0.082			0.504			0.400
R^2	0.192	0.217	0.017	0.200	0.260	0.012	0.031	0.057	0.001	0.144	0.255	0.002
DJ30 Sample												
RC	0.335			0.436			-0.245			0.433		
	0.000			0.000			0.029			0.000		
IC		0.324			0.451			-0.382			0.520	
		0.000			0.000			0.002			0.000	
VRP			-0.519			-0.545			0.180			-0.295
			0.008			0.043			0.519			0.172
R^2	0.185	0.145	0.020	0.202	0.182	0.014	0.020	0.040	0.000	0.188	0.227	0.004
SP500 Sample (reduced sector-based)												
RC	0.226			0.294			-0.402			0.201		
	0.000			0.000			0.000			0.000		
IC		0.180			0.244			-0.423			0.239	
		0.000			0.000			0.000			0.000	
VRP			-0.422			-0.445			0.043			-0.216
			0.020			0.065			0.914			0.303
R^2	0.141	0.093	0.019	0.156	0.112	0.014	0.056	0.065	-0.000	0.109	0.161	0.005
SP500 Sample (full sector-based)												
RC	0.449			0.565			-0.715			0.394		
	0.000			0.000			0.000			0.000		
IC		0.601			0.785			-1.097			0.600	
		0.000			0.000			0.000			0.000	
VRP			-0.423			-0.446			0.037			-0.216
			0.020			0.065			0.925			0.304
R^2	0.209	0.323	0.019	0.217	0.361	0.014	0.067	0.136	-0.000	0.157	0.316	0.005

...Table A104 continued

Panel B: 91-day horizon

	4-factor R^2			1-factor R^2			$\sigma^2(\beta_M)$			*RC*		
SP500 Sample												
RC	0.599			0.678			-0.304			0.404		
	0.000			0.000			0.003			0.000		
IC		0.270			0.344			-0.521			0.343	
		0.001			0.000			0.000			0.000	
VRP			-0.553			-0.569			-0.970			0.033
			0.004			0.010			0.000			0.855
R^2	0.222	0.060	0.019	0.244	0.083	0.018	0.027	0.107	0.029	0.165	0.159	-0.000
SP100 Sample												
RC	0.567			0.634			-0.152			0.476		
	0.000			0.000			0.060			0.000		
IC		0.340			0.423			-0.393			0.412	
		0.000			0.000			0.000			0.000	
VRP			-0.435			-0.420			-0.930			0.059
			0.057			0.116			0.000			0.766
R^2	0.264	0.110	0.010	0.278	0.143	0.008	0.009	0.072	0.024	0.229	0.200	0.000
DJ30 Sample												
RC	0.488			0.575			-0.114			0.484		
	0.000			0.000			0.130			0.000		
IC		0.186			0.257			-0.286			0.306	
		0.008			0.001			0.000			0.000	
VRP			-0.498			-0.532			-1.060			0.234
			0.013			0.019			0.002			0.223
R^2	0.253	0.040	0.013	0.287	0.063	0.012	0.011	0.081	0.051	0.236	0.104	0.003
SP500 Sample (reduced sector-based)												
RC	0.318			0.384			-0.302			0.224		
	0.000			0.000			0.000			0.000		
IC		0.144			0.179			-0.156			0.172	
		0.010			0.003			0.070			0.000	
VRP			-0.440			-0.450			-0.986			-0.028
			0.036			0.062			0.000			0.865
R^2	0.180	0.032	0.014	0.214	0.041	0.012	0.065	0.015	0.029	0.141	0.073	-0.000
SP500 Sample (full sector-based)												
RC	0.660			0.761			-0.429			0.445		
	0.000			0.000			0.001			0.000		
IC		0.520			0.626			-0.672			0.417	
		0.000			0.000			0.000			0.000	
VRP			-0.479			-0.500			-0.954			-0.037
			0.017			0.030			0.000			0.817
R^2	0.277	0.186	0.017	0.300	0.220	0.015	0.047	0.126	0.027	0.201	0.192	-0.000

...Table A104 continued

Panel C: 365-day horizon

	4-factor R^2			1-factor R^2			$\sigma^2(\beta_M)$			RC		
SP500 Sample												
RC	0.741			0.813			-0.225			0.417		
	0.000			0.000			0.043			0.000		
IC		0.180			0.194			-0.445			0.213	
		0.024			0.030			0.000			0.000	
VRP			-0.309			-0.470			-0.263			-0.035
			0.247			0.100			0.196			0.840
R^2	0.293	0.028	0.006	0.306	0.029	0.011	0.022	0.144	0.003	0.199	0.085	-0.000
SP100 Sample												
RC	0.692			0.742			-0.008			0.468		
	0.000			0.000			0.924			0.000		
IC		0.193			0.219			-0.276			0.251	
		0.009			0.006			0.001			0.000	
VRP			-0.250			-0.362			-0.304			0.068
			0.310			0.170			0.108			0.738
R^2	0.363	0.041	0.003	0.356	0.045	0.006	-0.000	0.081	0.005	0.254	0.106	0.000
DJ30 Sample												
RC	0.604			0.676			-0.080			0.543		
	0.000			0.000			0.237			0.000		
IC		-0.048			-0.066			-0.189			0.039	
		0.457			0.361			0.000			0.539	
VRP			-0.510			-0.762			0.164			-0.696
			0.051			0.008			0.500			0.004
R^2	0.298	0.002	0.012	0.314	0.004	0.023	0.009	0.065	0.002	0.291	0.002	0.028
SP500 Sample (reduced sector-based)												
RC	0.314			0.363			-0.257			0.195		
	0.000			0.000			0.002			0.000		
IC		0.281			0.314			-0.431			0.202	
		0.000			0.000			0.000			0.000	
VRP			0.105			-0.030			-0.246			0.058
			0.719			0.923			0.265			0.765
R^2	0.160	0.082	0.001	0.182	0.088	-0.000	0.068	0.124	0.003	0.108	0.075	0.000
SP500 Sample (full sector-based)												
RC	0.688			0.792			-0.369			0.448		
	0.000			0.000			0.005			0.000		
IC		0.381			0.418			-0.600			0.267	
		0.000			0.000			0.000			0.000	
VRP			-0.035			-0.193			-0.213			-0.010
			0.902			0.520			0.318			0.957
R^2	0.259	0.118	-0.000	0.286	0.118	0.002	0.051	0.201	0.002	0.202	0.106	-0.000

Tables with implied moments from MFIV

Table A105: (MFIV) Index Implied and Realized Correlations: Summary Statistics

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 difference between them (IC-RC), for three samples of stocks—components of S&P500, S&P100 and DJ30 indices, for the sample period from 1996 to 08/2015, and from 10/1997 to 08/2015, respectively, and for three different maturities—30, 91, 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 (5). Full sector-based correlations for SP500 sample are correlations between economic sectors in the index, computed using equation (6). Reduced sector-based are estimated from using sectors as underlying assets directly from equation (5). The p-values for significance of the means are computed with Newey and West (1987) adjustments for autocorrelation.

	IC			*RC*			*IC-RC*		
	30	91	365	30	91	365	30	91	365
SP500 Sample									
Mean	0.393	0.432	0.483	0.325	0.323	0.325	0.069	0.110	0.158
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.380	0.434	0.489	0.296	0.306	0.306	0.065	0.104	0.162
StDev	0.131	0.120	0.114	0.143	0.124	0.115	0.104	0.092	0.100
SP100 Sample									
Mean	0.429	0.474	0.526	0.354	0.354	0.356	0.075	0.120	0.170
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.419	0.479	0.531	0.331	0.342	0.339	0.071	0.115	0.174
StDev	0.134	0.119	0.115	0.150	0.127	0.116	0.114	0.096	0.114
DJ30 Sample									
Mean	0.467	0.505	0.552	0.369	0.370	0.374	0.088	0.123	0.162
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.457	0.510	0.549	0.350	0.360	0.356	0.080	0.110	0.161
StDev	0.152	0.135	0.118	0.167	0.146	0.140	0.135	0.113	0.120
SP500 Sample (full sector-based)									
Mean	0.362	0.400	0.455	0.311	0.310	0.318	0.051	0.091	0.138
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.352	0.409	0.466	0.286	0.296	0.298	0.050	0.092	0.146
StDev	0.141	0.127	0.122	0.150	0.130	0.119	0.100	0.082	0.090
SP500 Sample (reduced sector-based)									
Mean	0.657	0.705	0.767	0.631	0.641	0.658	0.025	0.064	0.109
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.000
Median	0.694	0.741	0.791	0.655	0.667	0.687	0.021	0.049	0.114
StDev	0.199	0.165	0.153	0.187	0.167	0.148	0.165	0.127	0.104

Table A106: (MFIV) Sector Implied and Realized Correlations: Summary Statistics

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 difference between them (IC-RC), for components of S&P500 sector indices and for sectors within S&P500, for the sample period from 1996 to 08/2015, and from 10/1997 to 08/2015, respectively, and for three different maturities—30, 91, 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 (5). The p-values for significance of the means are computed with Newey and West (1987) adjustments for autocorrelation.

	IC			*RC*			*IC-RC*		
	30	91	365	30	91	365	30	91	365
Sector: mat									
Mean	0.530	0.535	0.549	0.472	0.470	0.470	0.059	0.067	0.087
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.158	0.152	0.142	0.149	0.119	0.093	0.149	0.120	0.120
Sector: hea									
Mean	0.420	0.405	0.434	0.360	0.356	0.353	0.060	0.049	0.081
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001
StDev	0.142	0.119	0.121	0.171	0.142	0.113	0.189	0.137	0.116
Sector: cst									
Mean	0.494	0.467	0.494	0.371	0.360	0.354	0.123	0.108	0.143
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.151	0.119	0.111	0.163	0.117	0.085	0.216	0.139	0.112
Sector: cdi									
Mean	0.425	0.452	0.486	0.382	0.375	0.377	0.049	0.081	0.110
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.128	0.117	0.107	0.147	0.120	0.099	0.141	0.111	0.097
Sector: ene									
Mean	0.724	0.741	0.724	0.698	0.699	0.701	0.025	0.043	0.027
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.011	0.002	0.180
StDev	0.192	0.179	0.150	0.190	0.167	0.150	0.172	0.135	0.117
Sector: fin									
Mean	0.632	0.655	0.675	0.546	0.546	0.548	0.085	0.108	0.128
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.134	0.106	0.089	0.145	0.112	0.095	0.149	0.114	0.112
Sector: ind									
Mean	0.512	0.539	0.572	0.445	0.442	0.449	0.067	0.098	0.126
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.173	0.170	0.157	0.193	0.160	0.149	0.161	0.109	0.098
Sector: tec									
Mean	0.443	0.472	0.512	0.357	0.353	0.359	0.086	0.118	0.147
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
StDev	0.149	0.118	0.102	0.150	0.124	0.117	0.166	0.127	0.130
Sector: utl									
Mean	0.510	0.588	0.643	0.530	0.527	0.528	-0.022	0.059	0.109
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.061	0.000	0.000
StDev	0.182	0.179	0.183	0.180	0.157	0.135	0.197	0.123	0.118

Table A107: (MFIV) Individual and Index Variances, and Variance Risk Premiums

The table reports the time-series averages of realized ($\sqrt{RV}$) and model-free implied variances ($\sqrt{MFIV}$), expressed in volatility terms, and the difference between them ($VRP = MFIV - RV$), 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 8/2015, and from 10/1997 to 8/2015, respectively, and for three different maturities—30, 91, and 365 (calendar) days. For individual stocks the variances are equally-weighted cross-sectional averages across all constituent stocks. Model-free implied variance ($MFIV$) 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 $MFIV$. All variances (volatilities) 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	$\sqrt{MFIV}$	$\sqrt{RV}$	VRP	$p-val$	$\sqrt{MFIV}$	$\sqrt{RV}$	VRP	$p-val$
SP500 Sample								
30	0.408	0.398	0.007	0.065	0.216	0.187	0.008	0.000
91	0.393	0.397	-0.003	0.621	0.219	0.186	0.009	0.000
365	0.375	0.395	-0.015	0.232	0.224	0.186	0.012	0.004
SP100 Sample								
30	0.372	0.371	0.001	0.856	0.216	0.188	0.008	0.000
91	0.362	0.368	-0.004	0.461	0.220	0.187	0.010	0.000
365	0.348	0.365	-0.012	0.287	0.226	0.187	0.012	0.002
DJ 30 Sample								
30	0.334	0.327	0.005	0.035	0.212	0.177	0.009	0.000
91	0.327	0.325	0.001	0.777	0.216	0.176	0.011	0.000
365	0.312	0.319	-0.005	0.599	0.221	0.176	0.013	0.001

Table A108: (MFIV) Individual and Sector Variances, and Variance Risk Premiums

The table reports the time-series averages of realized ($\sqrt{RV}$) and model-free implied variances ($\sqrt{MFIV}$), expressed in volatility terms, and the difference between them ($VRP = MFIV - RV$), expressed as a difference in variances, for nine samples of stocks—components of economic sectors based on S&P500 index, for the sample period from 12/1998 to 8/2015 and for three different maturities—30, 91, and 365 (calendar) days. For individual stocks the variances are equally-weighted cross-sectional averages across all constituent stocks. Model-free implied variance ($MFIV$) 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 $MFIV$. All variances (volatilities) 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	$\sqrt{MFIV}$	$\sqrt{RV}$	VRP	$p-val$	$\sqrt{MFIV}$	$\sqrt{RV}$	VRP	$p-val$
Sector:mat								
30	0.392	0.378	0.011	0.006	0.275	0.254	0.011	0.000
91	0.378	0.376	0.002	0.747	0.266	0.253	0.006	0.045
365	0.365	0.375	-0.008	0.492	0.260	0.254	0.003	0.553
Sector:hea								
30	0.368	0.349	0.014	0.000	0.202	0.187	0.006	0.001
91	0.357	0.349	0.006	0.050	0.198	0.186	0.005	0.020
365	0.346	0.351	-0.004	0.559	0.203	0.185	0.006	0.103
Sector:cst								
30	0.308	0.285	0.014	0.000	0.184	0.157	0.009	0.000
91	0.294	0.284	0.006	0.002	0.179	0.156	0.008	0.000
365	0.289	0.283	0.004	0.399	0.188	0.156	0.010	0.000
Sector:cdi								
30	0.415	0.390	0.020	0.000	0.247	0.233	0.009	0.000
91	0.403	0.389	0.011	0.002	0.249	0.233	0.009	0.001
365	0.387	0.387	0.000	0.978	0.254	0.233	0.010	0.090
Sector:ene								
30	0.401	0.391	0.008	0.195	0.281	0.283	-0.000	0.926
91	0.390	0.389	0.001	0.920	0.279	0.281	-0.001	0.908
365	0.376	0.388	-0.009	0.521	0.275	0.281	-0.003	0.745
Sector:fin								
30	0.420	0.441	-0.018	0.137	0.322	0.319	0.001	0.865
91	0.402	0.438	-0.030	0.116	0.314	0.317	-0.004	0.720
365	0.374	0.428	-0.044	0.229	0.301	0.319	-0.012	0.583
Sector:ind								
30	0.375	0.354	0.015	0.000	0.242	0.219	0.010	0.000
91	0.362	0.354	0.006	0.072	0.240	0.219	0.010	0.000
365	0.351	0.352	-0.000	0.956	0.245	0.220	0.011	0.011
Sector:tec								
30	0.511	0.510	0.002	0.769	0.295	0.270	0.013	0.000
91	0.497	0.510	-0.013	0.132	0.295	0.270	0.013	0.007
365	0.470	0.512	-0.041	0.037	0.294	0.271	0.010	0.275
Sector:utl								
30	0.340	0.314	0.017	0.012	0.211	0.195	0.006	0.012
91	0.313	0.312	0.000	0.941	0.204	0.195	0.004	0.199
365	0.296	0.311	-0.009	0.443	0.210	0.194	0.006	0.092

Table A109: (MFIV) Market Return Predictability: Correlations and VRP

The table shows the coefficients (and corresponding p-values) and the R^2 of the market predictive regressions, for the sample period from 10/1997 to 08/2015 for DJ30-based variables, and from 01/1996 to 08/2015 for S&P500 and S&P100. We regress overlapping market factor compounded over a specified horizon (30, 91, and 365 calendar days) on a constant and a given set of explanatory variables, which are the realized (historical) equicorrelation (RC) for 30, 91, and 365 calendar days, implied correlation (IC) for the same maturities, and the variance risk premium, which equals to the difference between model-free implied variance and lagged realized variance computed over the matching period (VRP) of 30, 91, and 365 calendar days. 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.

	Market return, 30 days				Market return, 91 days				Market return, 365 days			
SP500 Sample												
RC	0.037				0.156				0.509			
	0.056				0.000				0.000			
IC		0.073		0.071		0.269		0.259		0.725		0.801
		0.000		0.000		0.000		0.000		0.000		0.000
VRP			0.227	0.220			0.469	0.330			-0.191	-1.147
			0.002	0.002			0.001	0.015			0.599	0.001
R^2	0.011	0.037	0.023	0.058	0.055	0.154	0.027	0.167	0.113	0.223	0.001	0.251
SP100 Sample												
RC	0.034				0.137				0.436			
	0.059				0.000				0.000			
IC		0.067		0.065		0.267		0.255		0.735		0.848
		0.000		0.000		0.000		0.000		0.000		0.000
VRP			0.232	0.224			0.548	0.405			-0.001	-1.345
			0.002	0.004			0.001	0.005			0.999	0.000
R^2	0.010	0.032	0.022	0.053	0.045	0.148	0.032	0.165	0.084	0.236	-0.000	0.271
DJ30 Sample												
RC	0.031				0.127				0.617			
	0.073				0.000				0.000			
IC		0.065		0.062		0.245		0.232		0.797		0.866
		0.000		0.000		0.000		0.000		0.000		0.000
VRP			0.248	0.228			0.580	0.397			-0.433	-1.431
			0.004	0.004			0.001	0.005			0.328	0.001
R^2	0.011	0.039	0.023	0.058	0.049	0.156	0.035	0.172	0.230	0.287	0.003	0.324
SP500 Sample (reduced sector-based)												
RC	0.050				0.189				0.722			
	0.001				0.000				0.000			
IC		0.050		0.047		0.181		0.174		0.620		0.652
		0.000		0.000		0.000		0.000		0.000		0.000
VRP			0.222	0.204			0.436	0.311			-0.591	-1.119
			0.004	0.006			0.003	0.020			0.132	0.002
R^2	0.035	0.039	0.024	0.059	0.146	0.132	0.025	0.145	0.356	0.273	0.008	0.303
SP500 Sample (full sector-based)												
RC	0.046				0.174				0.787			
	0.024				0.000				0.000			
IC		0.074		0.073		0.257		0.251		0.784		0.841
		0.000		0.000		0.000		0.000		0.000		0.000
VRP			0.221	0.218			0.441	0.366			-0.506	-1.226
			0.004	0.003			0.002	0.006			0.187	0.001
R^2	0.019	0.043	0.024	0.066	0.076	0.157	0.026	0.175	0.276	0.285	0.006	0.322

Table A110: (MFIV) Risk Predictability: Correlations and VRP

The table shows the coefficients (with corresponding p-values) and the R^2 of the risk predictive regressions, for the sample period from 10/1997 to 08/2015 for DJ30-based variables, and from 01/1996 to 08/2015 for S&P500 and S&P100. We regress risk measures for a specified horizon of 30, 91, and 365 calendar days (in Panels A, B, and C, respectively) on a constant and a given set of explanatory variables, which are implied correlation (IC) for 30, 91, and 365 calendar days, and the variance risk premium, which equals to the difference between model-free implied variance and lagged realized variance computed over the matching period (VRP) of 30, 91, and 365 calendar days. The risk measures are the average 4- and 1-factor model R^2 for all stocks in a given index, cross-sectional variance of market betas $\sigma^2(\beta_M)$ for all stocks in an index, and realized equicorrelation (RC), also defined for a given index. 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: 30-day horizon

	4-factor R^2			1-factor R^2			$\sigma^2(\beta_M)$			RC		
SP500 Sample												
RC	0.425			0.524			-0.516			0.524		
	0.000			0.000			0.000			0.000		
IC		0.449			0.587			-0.765			0.649	
		0.000			0.000			0.000			0.000	
VRP			-0.493			-0.515			0.014			-0.464
			0.004			0.025			0.972			0.123
R^2	0.302	0.282	0.022	0.316	0.332	0.016	0.061	0.112	-0.000	0.274	0.352	0.012
SP100 Sample												
RC	0.385			0.482			-0.339			0.481		
	0.000			0.000			0.000			0.000		
IC		0.423			0.568			-0.460			0.615	
		0.000			0.000			0.000			0.000	
VRP			-0.455			-0.467			0.252			-0.404
			0.020			0.082			0.504			0.230
R^2	0.262	0.253	0.017	0.279	0.309	0.012	0.029	0.043	0.001	0.231	0.301	0.007
DJ30 Sample												
RC	0.352			0.452			-0.081			0.528		
	0.000			0.000			0.432			0.000		
IC		0.386			0.517			-0.145			0.623	
		0.000			0.000			0.183			0.000	
VRP			-0.519			-0.545			0.180			-0.634
			0.008			0.043			0.519			0.039
R^2	0.272	0.265	0.020	0.290	0.307	0.014	0.003	0.007	0.000	0.279	0.313	0.013
SP500 Sample (reduced sector-based)												
RC	0.276			0.367			-0.621			0.367		
	0.000			0.000			0.000			0.000		
IC		0.233			0.320			-0.548			0.350	
		0.000			0.000			0.000			0.000	
VRP			-0.422			-0.445			0.043			-0.464
			0.020			0.065			0.914			0.124
R^2	0.231	0.184	0.019	0.268	0.229	0.014	0.148	0.129	-0.000	0.225	0.230	0.013
SP500 Sample (full sector-based)												
RC	0.401			0.512			-0.583			0.530		
	0.000			0.000			0.000			0.000		
IC		0.481			0.634			-0.814			0.677	
		0.000			0.000			0.000			0.000	
VRP			-0.423			-0.446			0.037			-0.465
			0.020			0.065			0.925			0.125
R^2	0.310	0.395	0.019	0.332	0.450	0.014	0.083	0.143	-0.000	0.299	0.432	0.013

…Table A110 continued

Panel B: 91-day horizon

	4-factor R^2			1-factor R^2			$\sigma^2(\beta_M)$			*RC*		
SP500 Sample												
RC	0.535			0.605			-0.210			0.551		
	0.000			0.000			0.019			0.000		
IC		0.382			0.468			-0.481			0.473	
		0.000			0.000			0.000			0.000	
VRP			-0.553			-0.569			-0.970			-0.362
			0.004			0.010			0.000			0.138
R^2	0.338	0.161	0.019	0.371	0.207	0.018	0.025	0.122	0.029	0.309	0.212	0.007
SP100 Sample												
RC	0.497			0.564			-0.100			0.520		
	0.000			0.000			0.221			0.000		
IC		0.369			0.466			-0.347			0.444	
		0.000			0.000			0.000			0.000	
VRP			-0.435			-0.420			-0.930			-0.226
			0.057			0.116			0.000			0.418
R^2	0.306	0.146	0.010	0.333	0.197	0.008	0.006	0.063	0.024	0.275	0.173	0.002
DJ30 Sample												
RC	0.469			0.540			0.066			0.603		
	0.000			0.000			0.369			0.000		
IC		0.333			0.411			-0.077			0.452	
		0.000			0.000			0.255			0.000	
VRP			-0.498			-0.532			-1.060			-0.544
			0.013			0.019			0.002			0.029
R^2	0.350	0.149	0.013	0.379	0.186	0.012	0.006	0.006	0.051	0.366	0.174	0.010
SP500 Sample (reduced sector-based)												
RC	0.337			0.416			-0.513			0.372		
	0.000			0.000			0.000			0.000		
IC		0.251			0.323			-0.420			0.320	
		0.000			0.000			0.000			0.000	
VRP			-0.440			-0.450			-0.986			-0.350
			0.036			0.062			0.000			0.160
R^2	0.257	0.138	0.014	0.321	0.188	0.012	0.239	0.156	0.029	0.246	0.176	0.007
SP500 Sample (full sector-based)												
RC	0.507			0.595			-0.334			0.565		
	0.000			0.000			0.001			0.000		
IC		0.470			0.573			-0.541			0.544	
		0.000			0.000			0.000			0.000	
VRP			-0.479			-0.500			-0.954			-0.376
			0.017			0.030			0.000			0.118
R^2	0.353	0.285	0.017	0.396	0.345	0.015	0.062	0.153	0.027	0.346	0.301	0.008

…Table A110 continued

Panel C: 365-day horizon

	4-factor R^2			1-factor R^2			$\sigma^2(\beta_M)$			*RC*		
SP500 Sample												
RC	0.604			0.671			-0.227			0.510		
	0.000			0.000			0.012			0.000		
IC		0.302			0.340			-0.508			0.268	
		0.000			0.000			0.000			0.000	
VRP			-0.309			-0.470			-0.263			-0.307
			0.247			0.100			0.196			0.219
R^2	0.408	0.095	0.006	0.435	0.105	0.011	0.047	0.222	0.003	0.290	0.075	0.005
SP100 Sample												
RC	0.581			0.633			-0.080			0.443		
	0.000			0.000			0.349			0.000		
IC		0.203			0.241			-0.386			0.150	
		0.005			0.002			0.000			0.016	
VRP			-0.250			-0.362			-0.304			-0.162
			0.310			0.170			0.108			0.492
R^2	0.386	0.046	0.003	0.392	0.055	0.006	0.007	0.159	0.005	0.223	0.025	0.001
DJ30 Sample												
RC	0.466			0.520			0.033			0.555		
	0.000			0.000			0.609			0.000		
IC		0.105			0.103			-0.099			0.117	
		0.107			0.155			0.055			0.148	
VRP			-0.510			-0.762			0.164			-0.786
			0.051			0.008			0.500			0.016
R^2	0.333	0.012	0.012	0.349	0.010	0.023	0.003	0.019	0.002	0.309	0.010	0.019
SP500 Sample (reduced sector-based)												
RC	0.319			0.378			-0.430			0.256		
	0.000			0.000			0.000			0.000		
IC		0.308			0.362			-0.612			0.264	
		0.000			0.000			0.000			0.000	
VRP			0.105			-0.030			-0.246			-0.014
			0.719			0.923			0.265			0.960
R^2	0.211	0.191	0.001	0.251	0.226	-0.000	0.244	0.483	0.003	0.117	0.122	-0.000
SP500 Sample (full sector-based)												
RC	0.512			0.598			-0.357			0.473		
	0.000			0.000			0.001			0.000		
IC		0.430			0.495			-0.650			0.369	
		0.000			0.000			0.000			0.000	
VRP			-0.035			-0.193			-0.213			-0.152
			0.902			0.520			0.318			0.574
R^2	0.329	0.230	-0.000	0.374	0.254	0.002	0.110	0.362	0.002	0.244	0.148	0.001

Table A111: (MFIV) Factor Models: Individual Stocks

The table shows the average market betas and the R^2's for one-, three, five-, and six-factor models (Fama and French (1993, 2015), Carhart (1997)) and average betas on the first leading factor and R^2's for the explanatory regressions of individual stock returns on one to five leading factors extracted from one of three covariance matrices, namely, historical covariance matrix for S&P500 components Σ^P estimated over the last 251 trading days, heterogenous implied covariance matrix Σ^Q_{BV} from Buss and Vilkov (2012) estimated using Σ^P as input and 30-/91-/365-day options, and full sector-based covariance matrix Σ^Q_{FSB} constructed from 30-/91-/365-day options as discussed in Section 2. The principal components are extracted at the end of each month, and daily factor realizations for the next month are constructed from daily stock returns and corresponding normalized eigenvectors. One regression per stock in CRSP is then performed for the sample period from 01/1996 to 08/2015.

Factors	β_{mkt}	R^2
Economic factors		
mkt	0.997	0.208
mkt+smb+hml	1.068	0.236
mkt+smb+hml+rmw+cma	1.043	0.253
mkt+smb+hml+rmw+cma+mom	1.042	0.261

	30-day		91-day		365-day	
Factors	β_{PC1}	R^2	β_{PC1}	R^2	β_{PC1}	R^2
Covariance Matrix: Σ^P						
PC1	0.844	0.231	0.844	0.230	0.849	0.235
PC1-2	0.829	0.262	0.830	0.262	0.840	0.266
PC1-3	0.827	0.279	0.828	0.279	0.838	0.284
PC1-4	0.826	0.291	0.827	0.290	0.839	0.295
PC1-5	0.826	0.300	0.827	0.299	0.840	0.305
Covariance Matrix: Σ^Q_{BV}						
PC1	0.881	0.232	0.882	0.232	0.899	0.236
PC1-2	0.879	0.260	0.880	0.261	0.894	0.267
PC1-3	0.881	0.278	0.886	0.278	0.901	0.284
PC1-4	0.873	0.290	0.883	0.290	0.903	0.297
PC1-5	0.873	0.297	0.885	0.298	0.903	0.305
Covariance Matrix: Σ^Q_{FSB}						
PC1	0.877	0.246	0.875	0.247	0.905	0.260
PC1-2	0.885	0.271	0.883	0.273	0.913	0.288
PC1-3	0.874	0.287	0.872	0.287	0.911	0.303
PC1-4	0.868	0.298	0.868	0.298	0.909	0.314
PC1-5	0.827	0.307	0.877	0.307	0.911	0.325