Correlation Risk

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ABSTRACT

Investors hold portfolios of assets with different risk-reward profiles for diversification benefits. Conditional on the volatility of assets, diversification benefits can vary over time depending on the correlation structure among asset returns. The correlation of returns between assets has varied substantially over time. To insure against future "low diversification" states, investors might demand securities that offer higher payouts in these states. If this is the case, then correlation would be a systematic risk factor, and investors would pay a premium for securities that offer higher payouts in regimes in which the correlation is high. We empirically test this hypothesis and find that correlation carries a statistically and economically significant negative price of risk, after controlling for the volatility of the assets and other risk factors that have been found to affect stock returns.

(*Time-varying Correlation; Price of Correlation Risk*)

Diversification benefits depend on the correlation structure among asset returns. There is now considerable evidence that correlations among asset returns change over time, that they generally increase during financial crises, and, more generally, they increase in bear markets.[1] Li (2002) finds that macroeconomic variables can account for a small but statistically significant portion of the time varying correlation between asset returns. In particular, this correlation is positively related to inflation risk. When inflation risk is high, asset returns tend to be more volatile, and in such regimes investors have a stronger incentive to diversify. However, in these very regimes, Li's result implies that correlations are high and diversification opportunities are low, thus leading him to Murphy's Law of Diversification: *"diversification opportunities are least available when they are most needed."*

If diversification opportunities diminish in regimes when they are most needed, investors could pay a premium to insure against such states. In other words, if correlation between assets is a systematic risk factor, all things being equal, investors would pay a premium for securities that offer higher payouts in states where asset correlations are high. This paper empirically tests this hypothesis. Specifically, we investigate whether time varying correlation between individual assets carries a significant price of risk in the cross-section of stock returns.

However, before we examine whether there exists a significant price of correlation risk in the cross-section of stock returns, we are faced with the following important issues. First, we need to determine an aggregate measure of correlation, or more specifically, correlation innovation. Clearly, this measure is influenced by pair-wise correlations among securities, and there are many asset classes to choose. Second, we need to be careful in relating increasing correlation to reduced diversification benefits. An alternative explanation could be that correlation is just a business cycle indicator. For example, correlations may be related to unanticipated inflation, as Li's result implies, to the market return, to T-bill rates and to industrial production, all of which are business cycle variables that define the investment opportunity set. Any analysis would clearly have to carefully control for or remove these business cycle effects, before assessing whether correlation risk is priced. Third, increasing correlation, per se, does not necessarily mean lower diversification benefits. Diversification opportunities increase when the correlations among assets decrease, conditional on the volatility of assets remaining the same or increasing. Indeed, Campbell, Lettau, Malkiel and Xu (2001) examine the 1962-1997 period and show that the benefits of diversification among U.S. stocks changed because of two effects: changing average standard deviation of the returns of individual stocks and changing average correlation of returns between any two stocks. Thus, in any analysis for determining the price of correlation risk, we need to control for volatility of assets.

Several strands of literature have examined correlation between asset returns. The first strand, already alluded to, focuses on understanding the time varying nature of aggregate stock-

[1] See, for example, Bollerslev, Chou and Kroner (1992).

bond correlation and its link with macroeconomic factors. Beltratti and Shiller (1992), extending Campbell and Shiller's (1988) model, price stocks and bonds jointly and find that the resulting theoretical correlations are smaller than the empirical ones. Li (2002), and d'Addona and Kind (2005) use affine asset pricing models to jointly value stocks and bonds that allow the development of correlations endogenously. These models are helpful in explaining how macroeconomic factors influence the correlation between asset returns. These studies conclude that uncertainty in expected inflation is a key determinant of correlation.[2] Other studies, including Rouwenhorst (1995), have examined the effects of business cycles on asset returns and concluded that they are significant. Schwert (1989), for example, shows that they can explain much of the time series variations in volatility. Therefore, a natural question to ask is how correlation varies at different stages in the business cycle. Li (2002) examines this issue and finds that the business cycle does not have any significant effect on this correlation, either in the US or in the $G7$ economies. Li (2002) also documents significant variations in stock-bond correlations in $G7$ countries and concludes that correlations in the different countries appear to follow similar mean reverting processes.

A second strand of literature focuses on understanding the covariances or correlations among asset returns. Goetzmann, Li and Rouwenhorst (2005) examine the major world equity markets, and find that correlations vary considerably through time, are highest during periods of economic and financial integration such as the late 19th and 20th centuries, and, because of the time varying nature of correlations, diversification benefits are not constant. Moskowitz (2003) documents the link between firm characteristics and the contemporaneous and future covariance structure of returns, and examines the strength of this relationship across business cycles. He finds that a size factor is most closely linked to covariance risk. Scruggs and Glabadanidis (2003) reject models with constant correlation restrictions on the covariance matrix between stocks and bonds. They include a long-term Government bond index as an additional factor in the Intertemporal Capital Asset Pricing Model (ICAPM) for the aggregate market return, and model the joint time-series dynamics of the stock and bond markets. They find that intertemporal risk-reward relationships are sensitive to the dynamic covariance matrix.

A third strand of research studies correlation risk in the equity market using derivatives. Driessen, Maenhout and Vilkov (2005) develop a model for equity prices with priced correlation risk, and empirically measure the magnitude of the risk premium. In their model, asset prices follow geometric Wiener processes where the correlations are connected through a simple one factor model. The dynamics of this common factor under the risk neutral measure are identified by specifying the structure for the correlation risk premium. They show that incorporating stochastic correlations in an option pricing model has the potential for removing many of the

[2]Additional studies along these lines include Campbell and Ammer (1993), Bekaert, Engstrom, and Granadier (2004) and Mamaysky (2002).

option pricing anomalies. They observe that the price of correlation risk is significantly negative and plays an important role in removing well-known biases in option models.

The final strand of related literature examines, concurrently, the volatility of stocks and the correlation between stocks. Campbell, Lettau, Malkiel and Xu (2001) show that firm level stock variance shows an increasing trend in the period 1962-1997. However, the correlations between the individual stocks decreased during this period, as a result of which the market as a whole did not become more volatile. The implication of this study is that increasing correlations between stocks by itself need not necessarily mean decreasing diversification opportunities because the stock volatilities might have decreased concurrently to offset the effect of increasing correlations.

To the best of our knowledge no study has addressed whether time-varying correlation between individual stocks carries a significant price of risk in the cross-section of stock returns, which is our objective in this paper. Of course, a number of studies have examined multi-factor models in which risk is measured by covariances with common factors. The risk factors could be extracted from the covariance matrix of returns, as in Roll and Ross (1980), be based on macroeconomic variables, as in Chen, Roll and Ross (1986), or be based on stock market and bond market portfolios and characteristics. Fama and French (1992, 1993, 1995, 1996) show that the market portfolio and portfolios related to size and book-to-market are important factors for stock returns. Fama and French (1993) also show that stock returns have shared common variation due to bond market factors related to maturity and default. Ang, Hodrick, Xing and Zhang (2006) examine the pricing of market volatility risk. We claim that, in addition to the market characteristics, the correlation between assets is also an important risk factor capturing changing diversification opportunities.

What we need to make clear is that our objective in this paper is *not* to study correlation risk as a replacement for covariance risk in a standard CAPM setting. Research along these lines, including work on lower partial co-moments and downside risk, has been done by others. The goal of our paper is unrelated to this literature; rather, we examine whether correlation between individual stocks is a priced risk factor in a multifactor model that includes other well-known risk factors such as liquidity and volatility factors.

We analyze correlations between assets over a 40-year period from 1963 to 2003. We first select assets that represent different risk-return profiles. As the first set of representative assets, we use 5 of the 25 Fama-French portfolios that have been sorted by size and book-to-market. These 5 portfolios include the four extremes in the double sort, namely, small-value, small-growth, large-value, and large-growth, as well as the medium size-medium book-to-market portfolio. In an alternate selection of representative stock portfolios, we include 5 industry portfolios based on broad industry definitions–consumer goods, manufacturing, hi-tech, health care, and others. For each of the alternative sets of representative assets, we compute the time series of monthly pairwise correlations, from which we compute the monthly correlation innovations and purge them of the effects of macrovariables to obtain correlation innovations. We use the same procedure to obtain the asset volatility innovations. We then examine whether the principal components that account for most of the variability in pair-wise correlation innovations are priced in the cross-section of returns, after controlling for the effect of asset volatility innovations.

We find that, controlling for asset volatility, correlation between assets carries a significantly negative price of risk. The negative price of correlation risk suggests that investors prefer stocks that have higher payouts in states in which a portfolio is effectively less diversified. The demand for such stocks is then reflected in lower expected returns. The explanatory power of correlation for stock returns is robust to the presence of the market return, size factor, book-to-market factor, default premium, aggregate market volatility innovation, liquidity and other risk factors, and to controlling for the effects of macroeconomic variables. We find that the significantly negative market price of correlation risk persists even after we allow for time variation in the factor loadings of assets or if we use different sets of representative assets to compute correlations. We continue to find significantly negative market price of correlation risk if we use the average correlation innovation residual rather than the principal components of correlation innovations.

The remainder of the paper is organized as follows. In section 1, we describe our data and extract the time series of correlations. In section 2, we test our factor model using cross-sectional regressions. In section 3, we perform several robustness checks. Section 4 concludes.

1 Data

Our sample period is from July 1963 to December 2003. We begin in July 1963 so as to examine the same period as the Fama-French (1992, 1993) papers and other papers in this literature. This would make our results comparable to studies that have found other factors to be important for explaining the cross-section of expected stock returns.

We use three sets of data. The first set consists of broad asset classes that we use to measure the correlation risk. These are 5 stock portfolios sorted by size and book-to-market: the small-growth, small-value, medium, large-growth, and large-value portfolios within the set of 25 Fama-French portfolios sorted on the same basis. The daily returns of these asset classes come form Ken French's web site.[3] Alternatively, as a robustness check, we include 5 industry-sorted stock portfolios to the 5 stock portfolios sorted by size and book-to-market.

The second data set consists of test assets that we use to examine our factor model. These are the 25 Fama-French portfolios sorted by size and book-to-market. Their monthly returns are obtained from Ken French's web site as well. We choose these portfolios since they have become the benchmark in testing competing asset pricing models. In addition, these portfolios

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data-library.html

are amongst the most challenging set of assets for existing models.

The third data set consists of variables that we use as risk factors in our model. These include:

Fama-French Factors

We collect data on the Fama-French (1993) book-to-market and size factors, HML and SMB. These factors are very successful at explaining the cross-section of returns sorted by size and book-to-market. The monthly returns of HML and SMB come from Ken French's web site.

Default Risk Premium

Following Fama and French (1993), who show that bond returns have explanatory power for stock returns, we collect data on a variable that controls for the returns on Government and risky corporate bonds. The variable is the default risk premium, DEF, defined as

$$DEF_t = R_{LG,t} - R_{LT,t},$$

where $R_{LG,t}$ is the total return on a low grade corporate bond and $R_{LT,t}$ is the total return on a long term Treasury bond from the Ibbotson database.

Unanticipated Inflation

Following Chen, Roll and Ross (1986) and Brennan, Wang, and Xia (2004), we collect data on unanticipated inflation as an additional risk factor. We first obtain the Consumer Price Index (CPI) data from the FRED database of the Federal Reserve Bank of St. Louis. Then, we define unanticipated inflation as

$$UI_t = I_t - E_{t-1}(I_t),$$

where I_t is the realized monthly first difference of the natural logarithm of CPI for period t, and $E_{t-1}(I_t)$ is the date $t-1$ expected inflation. The expected inflation series are the fitted values of an AR(3) process on monthly CPI.

Growth in Industrial Production

Vassalou (2003) uses GDP as an explanatory variable for stock returns. However, the data on GDP is available only quarterly, while we conduct our analysis on a monthly basis. Therefore, we collect data on the growth rate of US industrial production, GIP. This data is obtained from the FRED database of the Federal Reserve Bank of St. Louis. If IP_t denotes the rate of industrial production in month t, then the monthly growth rate is

$$GIP_t = ln(IP_t) - ln(IP_{t-1}).$$

Aggregate Market Volatility

Ang, Hodrick, Xing, and Zhang (2006) examine the pricing of aggregate volatility risk in the cross-section of stock returns. In our tests, we also control for a factor related to market volatility. We follow French, Schwert, and Stambaugh (1987) and calculate the monthly volatility of the CRSP value-weighted portfolio, s, by using the daily returns of the index within each month. Schwert (1989) relates stock market volatility to a number of economic variables, including inflation rates and industrial production growth. To remove the effects of macroeconomic variables on volatility, we first regress s on a vector of variables, including the market return, inflation, growth rate of industrial production, the real rate, and past volatility realizations. The residual from the regression, $MVOL$, which represents innovations in volatility, is used as a control factor in our cross-sectional tests. That is, we remove the effects of macroeconomic variables and then focus on the innovations in volatility.

Liquidity

Pastor and Stambaugh (2003) show that stocks with high liquidity betas have higher average returns. Since they show that liquidity is a systematic risk factor, we control for this factor in our cross-sectional analysis. We use the monthly returns of the aggregate liquidity measure, LIQ.[4]

In addition, we collect monthly data on real rates, defined as the one-month T-bill rate minus expected inflation. The CRSP value-weighted portfolio is our proxy for the market portfolio. Whenever we use excess returns we define them as simple total returns minus the nominal rate of one-month T-Bills.

Our test of whether aggregate correlation is priced in the cross-section of returns proceeds in three main steps. The first step involves estimating the time-series of pair-wise correlations between different assets, and then constructing an aggregate correlation measure. The second step involves estimating individual asset's loadings with respect to correlation risk. The third step examines whether asset loadings with respect to correlation risk are important determinants of average returns.

1.1 Constructing An Aggregate Correlation Measure

This section describes three separate steps involved in computing the aggregate correlation measure. First, we compute the time series of sample correlations between individual assets. Second, we purge the estimated sample correlations from the effects of different control variables and thus derive correlation innovation series. Third, we perform a principal component analysis on the set of correlation innovations to derive one aggregate measure of asset correlation. Below

[4]We thank Rob Stambaugh for providing the data.

we describe these steps.

We need to construct an aggregate measure of correlation. Since computing the correlation between each pair of stocks and then taking the average is virtually impossible, we reduce the dimensionality of the problem by choosing a set of 5 representative portfolios. We use the daily returns of 5 stock portfolios sorted by size and book-to-market to compute monthly pair-wise correlations. More specifically, the correlation number for each month between a pair of portfolios is computed as the sample correlation between the daily return series within the month. The advantage of this method is that the correlation number each month is not model-dependent. We compute all $\binom{5}{2} = 10$ time series of correlations. Rather than work with these values, which, by construction, are bounded by $[-1, 1]$, we transform them to Fisher correlations defined by:

$$FCorr = 0.5ln[(1 + Corr)/(1 - Corr)]. \quad (1)$$

This function is continuous and monotonic, and there is a one-to-one mapping between the actual and Fisher-transformed correlations.

Next, we perform a principal component analysis on the pair-wise correlations between assets. Such an analysis uncovers the weights assigned to each pair-wise correlation in an aggregate measure that best captures the variation in correlations. We are interested in the principal components that explain a significant portion of the variation in correlations. The first principal component explains 61 percent, while the second principal component explain an additional 13 percent. Panels A and B of Figure 1 plot the first two principal components derived from the matrix of pair-wise portfolio correlations. Correlation, on average, increases in recessionary periods. In Panel A, the difference, on average, in correlation between the recessionary and non-recessionary periods is 0.40, which is statistically significant with a t-statistic of 4.52.

Figure 1 here

Our objective is to test whether aggregate correlation risk is priced in the cross-section of returns. The first two principal components based on Fisher correlations are good candidates to represent correlation risk. However, we first need to purge them from the effects of variables that are known to affect asset correlation. That is, we need to derive correlation innovations. To do this, we regress the Fisher correlation for each asset pair on its lagged value, the market return, expected inflation, unanticipated inflation, the growth rate of industrial production, and the real rate as in the following time series regression

$$\rho_{i,t} = b_{i,0} + b_{i,1}\rho_{i,t-1} + b_{i,2}R_{m,t} + b_{i,3}E_{t-1}(I_t) + b_{i,4}UI_t + b_{i,5}GIP_t + b_{i,6}RealRate_t + u_{i,t}, \quad (2)$$

where i represents an individual asset pair. The first variable in the equation above, $\rho_{i,t-1}$, controls for autocorrelation effects in the correlation time-series. We include the market return,

$R_{m,t}$, since other studies have shown that correlations among assets tend to increase in bad market states. Finally, we control for unexpected and expected inflation, as well as the real interest rate, motivated by Li (2002), who shows that these variables affect stock-bond correlations.

Since there are 10 different time-series of pair-wise correlations, we have 10 different regressions corresponding to equation (2). Table 1 reports the F-statistics and the adjusted R^2s from the regressions described above. We present estimates for the model with and without the lagged correlation term, to examine the effect of the macroeconomic variables alone on correlations. When lagged correlation is excluded from the model, the average adjusted R^2 across all 10 regressions is around 10.81%. The effect of macroeconomic variables on the correlations between assets is statistically significant but economically small. When lagged correlation is included in the model, the adjusted R^2s increase in all cases and the average is 22.40%. Therefore, lagged correlation adds a substantial explanatory power to the model over and above the macroeconomic variables. However, the portion of the variation in asset return correlations not explained by macroeconomic variables and by lagged correlation remains large.

Table 1 here

Next, we store the 10 time-series of residuals, $u_{i,t}$ from equation (2). They represent innovations in the realized correlation series for each pair of assets. If correlation is a systematic risk factor, then innovations in this factor should be priced in the cross-section of returns. Next we conduct a principal-components analysis on these pair-wise correlation innovations. We are interested in the principal components that explain a significant portion of the variation. We find that the first principal component explains 55 percent, the second principal component an additional 14 percent, with a big drop-off thereafter.

Panels A and B of Figure 2 show the time-series of the first two principal components based on the correlation innovations. Panel A shows that the variation in the first principal component of correlation innovations is reduced once we purge them of the effects of macroeconomic variables (comparing Panel A of Figure 2 with Panel A of Figure 1). For instance, for the recessionary periods, the difference, on average, between the non-purged correlation in Panel A of Figure 1 and the purged correlation in Panel A of Figure 2 is 0.26, which is significant with a t-statistic of 2.35. In other words, once purged of macroeconomic variables that are related to the business cycle, high values of correlation in recessionary periods gets somewhat muted. Nevertheless, correlation still shows a time-varying pattern even after controlling for macroeconomic effects.

Figure 2 here

Table 2 shows the sample correlations of different risk factors with correlation risk. The factors include the market return, MKT, HML, SMB, default premium, DEF, unanticipated inflation, UI, growth rate of industrial production, GIP, the NBER recession dummy, CYCLE, aggregate market volatility innovations, MVOL, and liquidity, LIQ. The first 2 rows of the table correspond to the principal components based on Fisher correlations. The results indicate that asset correlations tend to go up in recessions (the correlations with the CYCLE variable are positive). The next 2 rows of the table correspond to the principal components based on correlation innovations. They show that once the effects of macroeconomic variables have been removed, the correlation measures are generally uncorrelated with the CYCLE variable. This suggests that correlation innovations carry information independent of the business cycle. The last two rows of the table correspond to the principal components based on asset volatility innovations. The first principal component has relatively high correlations with the market return and market volatility.

The last two columns of Table 2 report the adjusted R^2s and F-statistics from multiple regressions of each correlation and volatility measure on the set of risk factors. The results show that while the effects of the variables on the first principal components of correlation are significant (rows 1 and 3), their explanatory power is relatively small. This indicates that the correlation factor contains information not spanned by the set of well-known risk factors and therefore, it might represent a separate risk factor in the cross-section of returns.

Table 2 Here

1.2 Asset Volatility Measure

The principal components based on correlation innovations represent our summary measures of aggregate correlation risk in the economy. It is a measure that conveys information about the diversification benefits facing investors. Increasing correlation, per se, however does not necessarily mean lower diversification benefits. Diversification opportunities increase when the correlations among assets decrease, conditional on the volatility of assets remaining the same or increasing. Therefore, in our empirical analysis for determining the price of correlation risk we need to control for the average volatility of assets. Next, we describe how the asset volatility measure is constructed.

We follow French, Schwert, and Stambaugh (1987) and calculate the monthly volatility of each of the 5 asset classes by using the daily returns within each month. To remove the effects of macroeconomic variables on volatility, we first regress each volatility series on a vector of variables, including the market return, inflation, growth rate of industrial production, real rate, and past volatility. We run 5 such regressions since there are 5 asset classes under consideration. Next, we perform a principal component analysis on the residuals from these regressions. The first principal component explains 83 percent of the variation in asset volatility innovations, while the second one explains 13 percent. Therefore, the way we derive asset volatility innovations is consistent with the way we derive the correlation innovations. We use the first two principal components as control variables in our subsequent tests. We denote the volatility factors with $AVOL$.

2 The Basic Factor Model

If investment opportunities change over time, then factor models like the Intertemporal CAPM (ICAPM) of Merton (1973) and the Arbitrage Pricing Theory Model(APT) of Ross (1976) predict that there should be risk premia associated with assets' exposures to state variables that describe time-variation in investment opportunities.[5] Time-varying correlation between assets proxies for changing diversification benefits and, thus, affect the investment opportunity set available to investors. Risk-averse investors want to hedge against changes in the investment opportunity set, as in Merton (1973). However, the effect of time-varying inter-asset correlation on the investment opportunity set depends on the asset volatilities. For instance, if the asset volatilities are low, the effect of changing inter-asset correlation on the investment opportunity set would also be low. So, we examine whether inter-asset correlation, after controlling for the volatility of assets, is a systematic risk factor. The model specification that we consider is:

$$R_{i,t} = \alpha_i + \beta_{i,F} F_t + \beta_{i,AVOL} PC_{AVOL,t} + \beta_{i,\rho} PC_{\rho,t} + \epsilon_{i,t}, \tag{3}$$

where $R_{i,t}$ is the return on asset i in excess of the risk-free rate at the end of period t, F_t is a vector of realizations for the other risk factors at the end of period t (which we specify below), $PC_{\rho,t}$ is the correlation factor based on the principal component measure and $PC_{AVOL,t}$ is the asset volatility factor based on the principal component measure, as described above,. [6] The betas are the slope coefficients from the above return-generating process.

The unconditional expected excess return on asset is given by:

$$E(R_i) = \gamma_F \beta_{i,F} + \gamma_{AVOL} \beta_{i,AVOL} + \gamma_\rho \beta_{i,\rho}, \tag{4}$$

where γ_F is a vector of risk prices associated with factors that have been documented to significantly affect asset returns, and γ_ρ is the price of risk for the correlation factor. The implication of the factor model in equation (4) is that assets with different loadings with respect to correlation risk have different average returns.

[5] The following is a short list of papers that examine empirically the predictions of ICAPM or APT-type models: Chen, Roll, and Ross (1986), Shanken (1990), Campbell (1996), Fama and French (1993, 1995, 1996), Chen (2003), Brennan, Wang, and Xia (2004), Campbell and Vuolteenaho (2004), Ang, Hodrick, Xing, and Zhang (2006). These papers examine the price of risk associated with a range of different risk factors.

[6] Initially, we check whether the first two principal components are both priced, and after showing the second principal component of correlation innovations in not priced in the cross section of asset returns, we focus only on the first principal component.

We proceed to test the basic model defined in equations (3) and (4). In the first specification that we use, the vector F contains the following variables: the excess market return, R_m, HML, and SMB. The other variables in the model are the first 2 principal components based on pair-wise correlation innovations, and the first 2 principal components of asset volatility innovations. This model assumes away time variation in the factor loadings of the assets. We relax this assumption later in the paper and examine time-varying risk loadings.

We conduct our tests in two steps: first, we examine a time-series regression for each test asset to estimate the factor loadings; second, we conduct cross-sectional regressions to compute the factor prices of risk. We use the standard Fama-MacBeth (1973) regression analysis.

We begin with the following equation, in which the test assets are the 25 Fama-French portfolios sorted by size and book-to-market. Specifically, for portfolios i = 1, ..., 25:

$$R_{i,t} = \alpha_i + \beta_{i,m} R_{m,t} + \beta_{i,HML} R_{HML,t} + \beta_{i,SMB} R_{SMB,t} + \beta_{i,AVOL} PC_{AVOL,t} + \beta_{i,\rho} PC_{\rho,t} + \epsilon_{i,t}, \quad (5)$$

where the left-hand sight variable represents a return in excess of the riskfree rate and PC_ρ is a vector of the first two principal components for correlation innovations and PC_{AVOL} is a vector of the first two principal components variance innovations, derived as discussed before.

The second step of the Fama-MacBeth procedure involves relating the average excess returns of all assets to their exposures to the risk factors in the model. We specify the cross-sectional relation:

$$R_{i,t} = \gamma_0 + \gamma_m \widehat{\beta}_{i,m} + \gamma_{HML} \widehat{\beta}_{i,HML} + \gamma_{SMB} \widehat{\beta}_{i,SMB} + \gamma_{AVOL} \widehat{\beta}_{i,AVOL} + \gamma_\rho \widehat{\beta}_{i,\rho} + e_{i,t}, \quad (6)$$

for all $i = 1, ..., 25$ and for each month. If assets' loadings with respect to the risk factors are important determinants of average returns, then the γ terms that represent the prices of risk for each factor should be significant.

Since the betas are estimated from the time-series regression in equation (5), they represent generated regressors in equation (6). This is the classical errors-in-variables problem, arising from the two-pass nature of this approach. Following Shanken (1992), we use a correction procedure that accounts for the errors-in-variables problem. Shanken's correction is designed to adjust for the overstated precision of the Fama-MacBeth standard errors. It assumes that the error terms from the time-series regression are independently and identically distributed over time, conditional on the time-series of observations for the risk factors. Jagannathan and Wang (1998) argue that if the error terms are heteroskedastic, then the Fama-MacBeth procedure does not necessarily result in smaller standard errors of the cross-sectional coefficients.

Table 3 presents the results from the estimation of equation (6). As the table shows, the price of risk associated with the first principal component of correlation innovations is negative in magnitude and statistically significant. This result is robust to the errors-in-variables adjustment. The price of risk for the second principal component of correlation innovations is not significant. The risk premium associated with the value factor, HML, is significant and its magnitude is positive. Neither of the first 2 principal components of asset volatility innovations is significant. The adjusted R^2 value shows that the basic model is able to explain a large portion of the cross-sectional variation in average returns.

Table 3 Here

Based on the observation that the second principal component of correlation innovations is not priced in the cross-section of returns, we do not consider the second principal component in further analysis. Table 3 reports the basic specification in the absence of the second principal component of both the correlation innovations and the asset volatility innovations. The results show that the explanatory power of the model is very similar to our previous specification. The price of correlation innovation risk for the first principal component continues to be negative and significant.

Since the dependent variables in the cross-sectional regression are excess returns, the intercept term, γ_0, should be equal to zero, for a well-specified model. This hypothesis cannot be rejected in the case of the model presented in equation (6). Overall the results from our basic model indicate that correlation risk is priced in the cross-section of average returns. The estimated negative price for correlation risk suggests that assets that pay more when the general level of correlation is high are valued more and hence, have lower expected returns.

2.1 Including Additional Risk Factors in the Basic Model

Does the price of correlation risk continue to be significantly negative even in the presence of other known risk factors? To examine this, we include additional risk factors in the basic model. These are risk factors that have been shown to be important determinants of the cross-section of returns. They include market volatility innovations (MVOL), default premium (DEF), unexpected inflation (UI), and growth rate of industrial production (GIP). We examine the following specification:

$$\begin{aligned} R_{i,t} &= \gamma_0 + \gamma_m \widehat{\beta}_{i,m} + \gamma_{HML} \widehat{\beta}_{i,HML} + \gamma_{SMB} \widehat{\beta}_{i,SMB} + \\ &\quad \gamma_{MVOL} \widehat{\beta}_{i,MVOL} + \gamma_{DEF} \widehat{\beta}_{i,DEF} + \gamma_{UI} \widehat{\beta}_{i,UI} + \gamma_{GIP} \widehat{\beta}_{i,GIP} + \\ &\quad \gamma_{AVOL} \widehat{\beta}_{i,AVOL} + \gamma_\rho \widehat{\beta}_{i,\rho} + e_{i,t}, \end{aligned} \tag{7}$$

for all $i = 1, ..., 25$ and for each time period. The results are presented in Table 4.

Table 4 Here

The results are presented in Table 4. The price of correlation innovation risk is still negative in magnitude and significant after the Shanken adjustment. The risk premium of HML is positive and significant. The intercept term from the regression is not significant and the adjusted R square indicates that the explanatory power of the model has increased.

Next, we include Pastor and Stambaugh (2003) liquidity factor, LIQ, as an additional risk factor in the above regression specification. As discussed before, correlation tends to be high in bear markets, and these are the very times when liquidity tends to be low. Therefore, high aggregate correlation could potentially capture the price of liquidity risk. Hence, in our tests we explicitly control for the presence of the aggregate liquidity factor. We present the corresponding results in a separate table, Table 5, since the sample period used to test the expanded specification is from July 1968 to December 2003.

Table 5 Here

The price of correlation innovation risk continues to be negative in magnitude and significant after the Shanken adjustment. In the presence of the liquidity factor, only the risk premium of HML is positive and significant. The intercept term from the regression is not significant and the adjusted R square indicates that the explanatory power of the model is very high.

Overall, the results thus far show that correlation innovation risk is significantly priced in the cross-section of expected returns. This result is robust to the presence of other well-known risk factors and macroeconomic variables and to the errors-in-variables adjustment.

3 Robustness Checks

3.1 Incorporating Time-Varying Information

The models examined so far assume that the betas with respect to the risk factors remain unchanged over the entire sample period. As shown by Jagannathan and Wang (1996), Lettau and Ludvigson (2001), and Ferson and Harvey (1999), among others, asset betas tend to vary over time. As a result, we relax the assumption of constant betas by estimating factor loadings that vary through time. The time-varying betas are estimated using a standard approach. With this approach, we account for time variation in the factor loadings of the assets by following Shanken (1990) and Ferson and Harvey (1999). They impose a simple structure on the time variation of the assets' factor loadings. In particular, let

$$\alpha_{i,t-1} = a_{i0} + a_{i1} Z_{t-1},$$
$$\beta_{i,t-1} = b_{i0} + b_{i1} Z_{t-1},$$

where Z_{t-1} is a conditioning variable available to investors at time t. Our conditioning variable is the term premium, $TERM$, defined as the spread in yields between a 10-year and a 1-year Treasury bond (taken from the Federal Reserve Bank of St. Louis web site). The choice of this variable is motivated by the time-series literature on return predictability. Fama and French (1989), for example, show that the term spread predicts that the expected market returns are low during expansions and high during recessions. They document that the term spread is able to track the short-term fluctuations in the business cycle.[7]

Substituting the expressions for alpha and beta above in equation (5) and excluding the SMB factor (as it is not found to be significant), we get the following return-generating process

$$\begin{aligned} R_{i,t} &= a_{i0} + a_{i1} Z_{t-1} + b_{i0,m} R_{m,t} + b_{i1,m*Z}(R_{m,t} Z_{t-1}) + \\ & b_{i0,HML} R_{HML,t} + b_{i1,HML*Z}(R_{HML,t} Z_{t-1}) + b_{i0,AVOL} R_{AVOL,t} + \\ & b_{i1,AVOL*Z}(R_{AVOL,t} Z_{t-1}) + b_{i0,\rho} PC_{\rho,t} + b_{i1,\rho*Z}(PC_{\rho,t} Z_{t-1}) + \epsilon_{i,t}, \end{aligned} \tag{8}$$

over all time periods and for each test portfolio $i = 1, 2.., 25$. This return-generating process corresponds to the following cross-sectional regression:

$$\begin{aligned} R_{i,t} &= \gamma_0 + \gamma_Z Z_{t-1} + \gamma_m \widehat{b}_{i0,m} + \gamma_{mz} \widehat{b}_{i1,m*Z} + \\ & \gamma_{HML} \widehat{b}_{i0,HML} + \gamma_{HMLz} \widehat{b}_{i1,HML*Z} + \gamma_{AVOL} \widehat{b}_{i0,AVOL} + \gamma_{VARz} \widehat{b}_{i1,AVOL*Z} + \\ & \gamma_\rho \widehat{b}_{i0,\rho} + \gamma_{\rho z} \widehat{b}_{i1,\rho*Z} + e_{i,t}, \end{aligned} \tag{9}$$

for all test portfolios $i = 1, 2, ..., 25$ and for each time period, t. We use term premium as a proxy for Z. We focus only on the first principal component of correlation residuals in these regressions. Likewise, $AVOL$ is also the first principal component of volatility residuals.

The results are presented in Table 6. The price of correlation risk continues to be negative in magnitude and statistically significant. The interaction term between correlation and default premium is also significant, which indicates that there is time-variation in assets' loadings with respect to correlation risk. The two terms pertaining to correlation innovation risk are jointly significant, as indicated by the small p-value shown in the last row of the table. The book-to-market factor is also significant. The terms associated with asset volatility innovations are not significant. Overall, the conclusion that emerges from Table 6 is that the price of correlation risk is negative and significant. Furthermore, assets' exposures to correlation risk vary over time.

Table 6 Here

[7] Also see Keim and Stambaugh (1986) and Campbell (1987).

3.2 Using a Different Set of Base Assets to Measure Aggregate Correlation

As a different robustness check, we change the initial set of assets that span the risk-return spectrum. So far we have used a set of 5 "extreme" portfolios of the 25 Fama-French portfolios sorted by size and book-to-market. In this section, we include 5 industry portfolios to the 5 stock portfolios. The industry groups are defined as Consumer, Manufacturing, Hi-Tech, Health, and Other, and their daily returns come from Ken French's web site. Therefore, we evaluate whether our results are sensitive to the choice of the initial set of stock portfolios used to compute pair-wise correlations.

Table 7 reports the results for the case in which correlation risk is derived from the set of industry and size & book-to-market portfolios. The specification in the table allows for time-variation in the assets' loadings with respect to correlation risk. The price of correlation risk is significant, the price of time-varying correlation risk is negative, and these two terms pertaining to correlation innovation risk are jointly significant, as indicated by the small p-value shown in the last row of the table. Therefore, our previous results are not driven by the choice of base equity asset classes.

Table 7 Here

3.3 Using Average Correlation Innovations

We examine 3 different specifications of the following model:

$$\begin{aligned} R_{i,t} \quad = \quad & \gamma_0 + \gamma_m \widehat{\beta}_{i,m} + \gamma_{HML} \widehat{\beta}_{i,HML} + \gamma_{SMB} \widehat{\beta}_{i,SMB} + \\ & \gamma_{MVOL} \widehat{\beta}_{i,MVOL} + \gamma_{LIQ} \widehat{\beta}_{i,LIQ} + \gamma_{DEF} \widehat{\beta}_{i,DEF} + \gamma_{UI} \widehat{\beta}_{i,UI} + \\ & \gamma_{GIP} \widehat{\beta}_{i,GIP} + \gamma_{AVOL} \widehat{\beta}_{i,AVOL} + \gamma_\rho \widehat{\beta}_{i,\rho} + e_{i,t}, \end{aligned} \tag{10}$$

for all $i = 1, ..., 25$ and for each time period, where we now use the average correlation innovations instead of the first principal component of the correlation innovations, as the correlation factor. Correspondingly, we use the average asset volatility innovation instead of the first principal component of the asset volatility innovations. The results are presented in Table 8.

Table 8 Here

The results show that in all 3 specifications examined, the price of correlation innovation risk is still negative and significant after the Shanken adjustment. The risk premium of HML is positive and significant. The intercept term from the regression is not significant.

3.4 Portfolio Returns Sorted by Market and Correlation Loadings

How do the returns of portfolios sorted by correlation-risk loadings look? To examine this, we construct a set of risk-sorted portfolios as follows. Each month, each stock's risk loadings are computed from a multiple regression of excess returns over the previous 60 months on the factors in the factor model over the same 60 months. The factors are the excess market return and the excess return on a portfolio that mimics correlation risk.

A simple way to construct a mimicking portfolio is to regress aggregate correlation (the first principal component of correlation innovations) on a set of base asset returns, as suggested in Breeden, Gibbons and Litzenberger (1989). We use this approach in creating the correlation-mimicking factor, $R_{\rho,t}$:

$$\rho_{mb,t} = c' B_t + e_t. \tag{11}$$

Here B_t represents the set of base portfolio returns in excess of the risk free rate. The return on the mimicking portfolio, $R_{\rho,t}$, is then equal to $c' B_t$. The base assets are the six value-weighted portfolios, constructed by Fama and French, from the intersection of two size and three book-to-market portfolios. These portfolios are created from a separate sorting of the assets relative to the 25 size and book-to-market test portfolios.

Our objective in this section is to form portfolios that have a large spread in their betas with respect to the market and the correlation factor. To accomplish this, we perform a double sort on market beta and on the beta with respect to correlation risk. That is, we first form 5 groups by sorting all stocks on market beta, and then sort stocks in each market beta group into 5 groups on correlation beta. This produces a total of 25 portfolios. The value-weighted returns of these portfolios are then recorded, for the period from July 1968 to December 2003.

Figure 3 shows the bar plots of the average returns of our new set of 25 portfolios of stocks. In this figure, the five major groups of bars are based on market returns loadings, and five bars in each major group are based on correlation loadings. The average returns of stocks with different correlation loadings follow a very regular pattern: within each market beta group, average returns of firms are almost always decreasing in their correlation loadings.

Figure 3 Here

Within each beta-sorted portfolio group, we compute the return difference between the extreme portfolios that are based on correlation loadings. Each return difference represents the monthly return on a zero-investment strategy that is based on aggregate correlation. We then regress these returns on the monthly returns of the HML and SMB portfolios and find that the resulting time-series alphas are positive and strongly significant. On average, the monthly return from this zero-investment strategy that is not explained by the size or value factors is almost 7% per annum. This result is interesting because the market and correlation loadings have been estimated without a look-ahead bias: they have been estimated from the information investors have at the beginning of each month. Thus, firms that are most exposed to aggregate correlation provide the best hedges against states with poor diversification benefits for portfolio managers, are more valuable, and therefore, have lower average returns.

4 Conclusion

We address the following research questions in this paper: are innovations in return correlations an important determinant of expected returns? Is the correlation factor, purged of macroeconomic factors, priced even in the presence of loadings with respect to well-known risk factors? The answer to these two research questions is an emphatic yes. Controlling for asset volatility, correlation carries a statistically and economically significant negative price of risk that cannot be explained by the market return, size, book-to-market, volatility, default spread, unexpected inflation, liquidity, and other risk factors. The market price of correlation risk is significant after accounting for macroeconomic variables that are known to influence the dynamics of asset correlations. The market price of correlation risk is significant whether we construct the aggregate correlation factor as the first principal component based on correlation innovations or as the average correlation innovation. The market price of correlation risk is significantly negative when we allow for time variation in the factor loadings of the assets. Finally, the market price of correlation risk is robust to the choice of the set of initial assets for which we compute pair-wise correlations.

The implication of our result is as follows. When investment opportunities are changing, risk premia should reflect how assets covary with portfolios that best hedge changes in investment opportunities. Controlling for other risk factors and for asset volatility, we find that as the correlation between assets that span the risk-return spectrum increases, investors lose at least part of the diversification benefit. Stocks that pay out more in states where asset correlations are high are more attractive and the expected returns on these securities are lower. Thus, the market price of correlation risk is significantly negative.

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Table 1
Correlation Innovations

This table reports the F-statistic and the adjusted R^2 for the following model

$$\rho_{i,t} = b_{i,0} + b_{i,1}\rho_{i,t-1} + b_{i,2}R_{m,t} + b_{i,3}E(I_t) + b_{i,4}UI_t + b_{i,5}GIP_t + b_{i,6}RealRate_t + u_{it},$$

where $\rho_{i,t}$ is the Fisher-transformed correlation time-series for an individual asset pair. There are 10 such pair-wise correlations based on 5 portfolios sorted by size and book-to-market (small-growth, small-value, medium, large-growth, and large-value). The independent variables in the regression are the past level of the correlation, the excess market return, $R_{m,t}$, expected inflation, $E(I_t)$, unanticipated inflation, UI_t, the growth rate of industrial production, GIP_t, and the real interest rate. The time-series of monthly correlations for any asset pair are computed using daily returns. The sample period is from July 1963 to December 2003. We report the *F*-statistic and the adjusted R^2 for the model with and without $\rho_{i,t-1}$.

Asset Pairs	Model without $\rho_{i,t-1}$		Full model	
	F-value	Adjusted R^2	*F*-value	Adjusted R^2
small-growth, small-value	21.58***	17.36	31.65***	27.68
small-growth, medium	26.99***	21.00	32.64***	31.54
small-growth, large-growth	10.33***	8.60	14.76***	18.86
small-growth, large-value	17.30***	14.24	17.30***	23.74
small-value, medium	19.74***	16.05	17.22***	25.73
small-value, large-growth	6.02***	4.73	9.26***	16.69
small-value, large-value	11.72***	9.78	10.95***	20.80
medium, large-growth	5.65***	4.38	9.18***	19.22
medium, large-value	10.92***	9.10	8.78***	19.73
large-growth, large-value	4.00***	2.81	8.31***	20.00
Average		10.81		22.40

*, **, and *** denote *p*-value is significant at the 10%, 5% and 1% levels respectively.

Table 2
Factor Correlations

This table reports the correlations between well-known risk factors and different measures of aggregate correlation. To compute the aggregate correlation we start with a base set of 5 portfolios sorted by size and book-to-market (small-growth, small-value, medium, large-growth, and large-value). We consider the following measures of correlation: (a) the first principal component of the 10 Fisher-transformed correlations (first row), (b) the second principal component of the 10 Fisher-transformed correlations (second row), (c) the first principal component of the matrix of Fisher correlation innovations, which are obtained after removing the effects of macroeconomic variables (market return, expected inflation, unexpected inflation, real rate, growth rate of industrial production, past correlation levels) from each pair-wise Fisher-transformed correlation (third row), and (d) the second principal component of the matrix of Fisher correlation innovations (fourth row). The variables that we consider in the different columns of the table are the excess market return, MKT, the Fama-French factors (HML and SMB), market volatility (MVOL), liquidity factor return (LIQ), default premium, DEF (defined as a low grade bond return minus a long term Treasury bond return), unexpected inflation, UI, the monthly growth rate of industrial production, GIP, and the NBER recession dummy, CYCLE. The last two columns show the adjusted R^2 values and the *F*-statistics from multiple regressions of each correlation measure on MKT, HML, SMB, LIQ, MVOL, DEF, UI, GIP, and CYCLE.

	MKT	HML	SMB	LIQ	MVOL	DEF	UI	GIP	CYCLE	R^2	F
1st Principal Component based on Fisher Correlations	0.04	-0.05	-0.02	0.00	0.05	0.24	0.03	-0.11	0.18	4.90	3.40***
2nd Principal Component based on Fisher Correlations	0.00	0.04	0.00	-0.02	0.08	0.05	-0.04	-0.04	0.09	-0.40	0.78
1st Principal Component based on Fisher Correlation Innovation	0.00	-0.10	-0.10	0.01	0.24	0.20	0.00	0.00	0.05	10.03	6.24***
2nd Principal Component based on Fisher Correlation Innovation	0.00	0.03	-0.09	0.02	0.13	0.03	0.00	0.00	0.00	0.00	1.01

*, **, and *** denote *p*-value is significant at the 10%, 5% and 1% levels respectively.

Table 3
Cross-Sectional Prices of Risk: The Basic Model

This table reports cross-sectional γ coefficients of 2 specifications of the following Fama-MacBeth regression

$$R_{i,t} = \gamma_0 + \gamma_m \hat{\beta}_{i,m} + \gamma_{HML} \hat{\beta}_{i,HML} + \gamma_{SMB} \hat{\beta}_{i,SMB} + \gamma_{AVOL} \hat{\beta}_{i,AVOL} + \gamma_\rho \hat{\beta}_{i,\rho} + e_{i,t}$$

that uses the excess returns on 25 portfolios sorted by book-to-market and size as the dependent variables, where γ_m is the market risk premium, γ_{HML} and γ_{SMB} are the risk premia associated with HML and SMB, γ_{AVOL} is/are the coefficient(s) associated with asset volatility innovations, and γ_ρ is/are the coefficient(s) associated with correlation innovations. To compute asset correlations, we use a base set of 5 portfolios sorted by size and book-to-market (small-growth, small-value, medium, large-growth, and large-value). Our measure of correlation is the first two principal components of the matrix of asset correlation innovations (after removing the effects of macroeconomic variables from each pair-wise Fisher-transformed correlation). The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression. The coefficients are expressed in decimals per month. The adjusted R^2 follows Jagannathan and Wang (1996) and is reported in decimals. The t-statistics are adjusted for errors-in-variables, following Shanken (1992), and are reported in parenthesis. Bold numbers denote t-statistics that are significant at the 5 percent level. The sample period is from July 1963 to December 2003.

	Specification 1	Specification 2
Risk Factor	Price of Risk	Price of Risk
MKT	-0.0050 (-0.78)	-0.0052 (-0.93)
HML	**0.0046** **(3.25)**	**0.0045** **(3.21)**
SMB	0.0026 (1.72)	0.0025 (1.65)
AVOL 1st Principal Component	0.7434 (1.67)	0.6974 (1.77)
AVOL 2nd Principal Component	0.3882 (1.29)	
ρ 1st Principal Component	**-0.8718** **(-2.61)**	**-0.7726** **(-2.93)**
ρ 2nd Principal Component	0.0819 (0.49)	
Intercept	0.0090 (1.43)	0.0097 (1.82)
Adjusted R^2	81.64	82.14

Table 4
Cross-Sectional Prices of Risk: Controlling for Other Risk Factors

This table reports cross-sectional γ coefficients from the following Fama-MacBeth regression

$$R_{i,t} = \gamma_0 + \gamma_m \hat{\beta}_{i,m} + \gamma_{HML} \hat{\beta}_{i,HML} + \gamma_{SMB} \hat{\beta}_{i,SMB} + \gamma_{MVOL} \hat{\beta}_{i,MVOL} + \gamma_{DEF} \hat{\beta}_{i,DEF} + \gamma_{UI} \hat{\beta}_{i,UI} + \gamma_{GIP} \hat{\beta}_{i,GIP} + \gamma_{AVOL} \hat{\beta}_{i,AVOL} + \gamma_{\rho} \hat{\beta}_{i,\rho} + e_{i,t}$$

that uses the excess returns on 25 portfolios sorted by book-to-market and size as the dependent variables, where γ_m is the market risk premium, γ_{HML}, γ_{SMB}, γ_{DEF}, γ_{MVOL} are the risk premia associated with HML, SMB, default, and market volatility innovations, γ_{AVOL} is the coefficient associated with asset volatility innovations, and γ_{ρ} is the coefficient associated with correlation innovations. To compute the aggregate correlation we start with a base set of 5 portfolios sorted by size and book-to-market (small-growth, small-value, medium, large-growth, and large-value). Our measure of correlation is the 1st principal components of the matrix of asset correlation innovations (after removing the effects of macroeconomic variables from each pair-wise Fisher-transformed correlation). The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression. The coefficients are expressed in decimals per month. The adjusted R^2 follows Jagannathan and Wang (1996) and is reported in decimals. The t-statistics are adjusted for errors-in-variables, following Shanken (1992), and are reported in parenthesis. Bold numbers denote t-statistics that are significant at the 5 percent level. The sample period is from July 1963 to December 2003.

Risk Factor	Price of Risk
MKT	-0.0037 (-0.52)
HML	**0.0045** **(3.15)**
SMB	0.0029 (1.88)
MVOL	-0.0010 (-0.46)
DEF	-0.0010 (-1.06)
UI	-0.0008 (-1.50)
GIP	0.0012 (0.64)
AVOL 1st Principal Component	0.4527 (1.01)
ρ 1st Principal Component	**-0.7478** **(-2.26)**
Intercept	0.0073 (1.07)
Adjusted R^2	89.74

Table 5
Cross-Sectional Prices of Risk: Controlling for Liquidity Risk as Well

This table reports cross-sectional γ coefficients from the following Fama-MacBeth regression

$$R_{i,t} = \gamma_0 + \gamma_m\hat{\beta}_{i,m} + \gamma_{HML}\hat{\beta}_{i,HML} + \gamma_{SMB}\hat{\beta}_{i,SMB} + \gamma_{MVOL}\hat{\beta}_{i,MVOL} + \gamma_{LIQ}\hat{\beta}_{i,LIQ} + \gamma_{DEF}\hat{\beta}_{i,DEF} + \gamma_{UI}\hat{\beta}_{i,UI} + \gamma_{GIP}\hat{\beta}_{i,GIP} + \gamma_{AVOL}\hat{\beta}_{i,AVOL} + \gamma_\rho\hat{\beta}_{i,\rho} + e_{i,t}$$

that uses the excess returns on 25 portfolios sorted by book-to-market and size as the dependent variables, where γ_m is the market risk premium, γ_{HML}, γ_{SMB}, γ_{DEF}, γ_{MVOL}, γ_{LIQ} are the risk premia associated with HML, SMB, default, market volatility innovation, and liquidity risk, γ_{AVOL} is the coefficient associated with asset volatility innovations, and γ_ρ is the coefficient associated with correlation innovations. To compute the aggregate correlation we start with a base set of 5 portfolios sorted by size and book-to-market (small-growth, small-value, medium, large-growth, and large-value). Our measure of correlation is the 1st principal components of the matrix of asset correlation innovations (after removing the effects of macroeconomic variables from each pair-wise Fisher-transformed correlation). The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression. The coefficients are expressed in decimals per month. The adjusted R^2 follows Jagannathan and Wang (1996) and is reported in decimals. The t-statistics are adjusted for errors-in-variables, following Shanken (1992), and are reported in parenthesis. Bold numbers denote t-statistics that are significant at the 5 percent level. The sample period is from July 1968 to December 2003.

Risk Factor	Price of Risk
MKT	-0.0028 (-0.42)
HML	**0.0048** **(2.81)**
SMB	0.0016 (0.90)
LIQ	0.0061 (0.80)
MVOL	0.0002 (0.08)
DEF	-0.0011 (-1.21)
UI	-0.0007 (-1.43)
GIP	0.0004 (0.19)
AVOL 1st Principal Component	0.2413 (0.60)
ρ 1st Principal Component	**-0.5067** **(-2.18)**
Intercept	0.0064 (1.02)
Adjusted R^2	86.37

Table 6
Cross-Sectional Prices of Risk: The Conditional Beta Approach

This table reports cross-sectional γ coefficients from the following Fama-MacBeth regression:

$$R_{i,t} = \gamma_0 + \gamma_z Z_{t-1} + \gamma_m \hat{\beta}_{i,m} + \gamma_{mz}\hat{\beta}_{i,m*Z_{t-1}} + \gamma_{HML}\hat{\beta}_{i,HML} + \gamma_{HMLz}\hat{\beta}_{i,HML*Z_{t-1}}$$
$$+ \gamma_{AVOL}\hat{\beta}_{i,AVOL} + \gamma_{AVOLz}\hat{\beta}_{i,AVOL*Z_{t-1}} + \gamma_\rho \hat{\beta}_{i,\rho} + \gamma_{\rho z}\hat{\beta}_{i,\rho * Z_{t-1}} + e_{i,t}$$

that uses the excess returns on 25 portfolios sorted by book-to-market and size as the dependant variables, where Z_{t-1} is a conditioning variable known to the market at time t, γ_{mz} is the price of risk related to time-variation in the market risk premium, γ_{HMLz} is the price of risk related to time-variation in HML, γ_{AVOLz} is the coefficient associated with time-variation in asset volatility innovations, γ_ρ is the measure of price of correlation innovation risk, and $\gamma_{\rho z}$ is the price of risk related to time-variation in correlation innovations. To compute the aggregate correlation we start with a base set of 5 portfolios sorted by size and book-to-market (small-growth, small-value, medium, large-growth, and large-value). We use the first principal component of the matrix of asset correlation innovations (after removing the effects of macroeconomic variables from each pair-wise Fisher-transformed correlation). Our conditioning variable, $Z_{t-1,}$ is TERM, defined as the yield spread between a 10-year and a 1-year Government bond. The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression. The coefficients are expressed in decimals per month. The adjusted R^2 follows Jagannathan and Wang (1996) and is reported in decimals. The t-statistics are adjusted for errors-in-variables, following Shanken (1992), and are reported in parenthesis. Bold numbers denote t-statistics that are significant at the 5 percent level. The last row reports the p-value for the test that γ_ρ and $\gamma_{\rho z}$ are jointly equal to zero. The table examines the sample period from July 1963 to December 2003.

Risk Factor	Price of Risk
MKT	-0.0013 (-0.20)
MKT* Z_{t-1}	-0.0000 (-0.03)
HML	**0.0046** **(3.24)**
HML* Z_{t-1}	0.0001 (0.82)
AVOL 1st Principal Component	0.4410 (1.33)
AVOL* Z_{t-1}	0.0086 (1.34)
ρ 1st Principal Component	**-0.6709** **(-2.33)**
ρ * Z_{t-1}	**-0.0074** **(-2.00)**
Z_{t-1}	0.0065 (1.71)
Intercept	0.0057 (0.93)
Adjusted R^2	83.93
p-value	0.03

Table 7
Cross-Sectional Prices of Risk: The Conditional Beta Approach
(Including Industry Portfolios)

This table reports cross-sectional γ coefficients from the following Fama-MacBeth regression:

$$R_{i,t} = \gamma_0 + \gamma_z Z_{t-1} + \gamma_m \hat{\beta}_{i,m} + \gamma_{mz} \hat{\beta}_{i,m*Z_{t-1}} + \gamma_{HML} \hat{\beta}_{i,HML} + \gamma_{HMLz} \hat{\beta}_{i,HML*Z_{t-1}}$$
$$+ \gamma_{AVOL} \hat{\beta}_{i,AVOL} + \gamma_{AVOLz} \hat{\beta}_{i,AVOL*Z_{t-1}} + \gamma_{\rho} \hat{\beta}_{i,\rho} + \gamma_{\rho z} \hat{\beta}_{i,\rho*Z_{t-1}} + e_{i,t}$$

that uses the excess returns on 25 portfolios sorted by book-to-market and size as the dependant variables, where Z_{t-1} is a conditioning variable known to the market at time t, γ_{mz} is the price of risk related to time-variation in the market risk premium, γ_{HMLz} is the price of risk related to time-variation in HML, γ_{AVOLz} is the coefficient associated with time-variation in asset volatility innovations, γ_{ρ} is the measure of price associated with correlation innovation risk, and $\gamma_{\rho z}$ is the price of risk related to time-variation in correlation. To compute the aggregate correlation we start with a base set of 10 assets: 5 portfolios sorted by size and book-to-market (small-growth, small-value, medium, large-growth, and large-value) and 5 industry portfolios (consumer goods, manufacturing, hi-tech, healthcare, and others). We use the first principal component of the matrix of asset correlation residuals (after removing the effects of macroeconomic variables from each pair-wise Fisher-transformed correlation). Our conditioning variable, $Z_{t-1,}$ is TERM, defined as the yield spread between a 10-year and a 1-year Government bond. The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression. The coefficients are expressed in decimals per month. The adjusted R^2 follows Jagannathan and Wang (1996) and is reported in decimals. The t-statistics are adjusted for errors-in-variables, following Shanken (1992), and are reported in parenthesis. Bold numbers denote t-statistics that are significant at the 5 percent level. The last row reports the p-value for the test that γ_{ρ} and $\gamma_{\rho z}$ are jointly equal to zero.

Risk Factor	Price of Risk
MKT	-0.0027 (-0.52)
MKT* Z_{t-1}	0.0001 (0.35)
HML	**0.0041** **(2.90)**
HML* Z_{t-1}	0.0001 (0.73)
AVOL 1st Principal Component	0.7464 (1.71)
AVOL* Z_{t-1}	0.0088 (1.10)
ρ 1st Principal Component	**-0.9645** **(-2.01)**
ρ* Z_{t-1}	-0.0096 (-1.64)
Z_{t-1}	0.0069 (1.88)
Intercept	0.0075 (1.49)
Adjusted R^2	81.19
p-value	0.05

Table 8
Cross-Sectional Prices of Risk: Using Average Correlation Innovations

This table reports cross-sectional γ coefficients of 3 specifications from the following Fama-MacBeth regression:

$$R_{i,t} = \gamma_0 + \gamma_m \hat{\beta}_{i,m} + \gamma_{HML} \hat{\beta}_{i,HML} + \gamma_{SMB} \hat{\beta}_{i,SMB} + \gamma_{MVOL} \hat{\beta}_{i,MVOL} + \gamma_{LIQ} \hat{\beta}_{i,LIQ} + \gamma_{DEF} \hat{\beta}_{i,DEF} + \gamma_{UI} \hat{\beta}_{i,UI} + \gamma_{GIP} \hat{\beta}_{i,GIP} + \gamma_{AVOL} \hat{\beta}_{i,AVOL} + \gamma_{\rho} \hat{\beta}_{i,\rho} + e_{i,t}$$

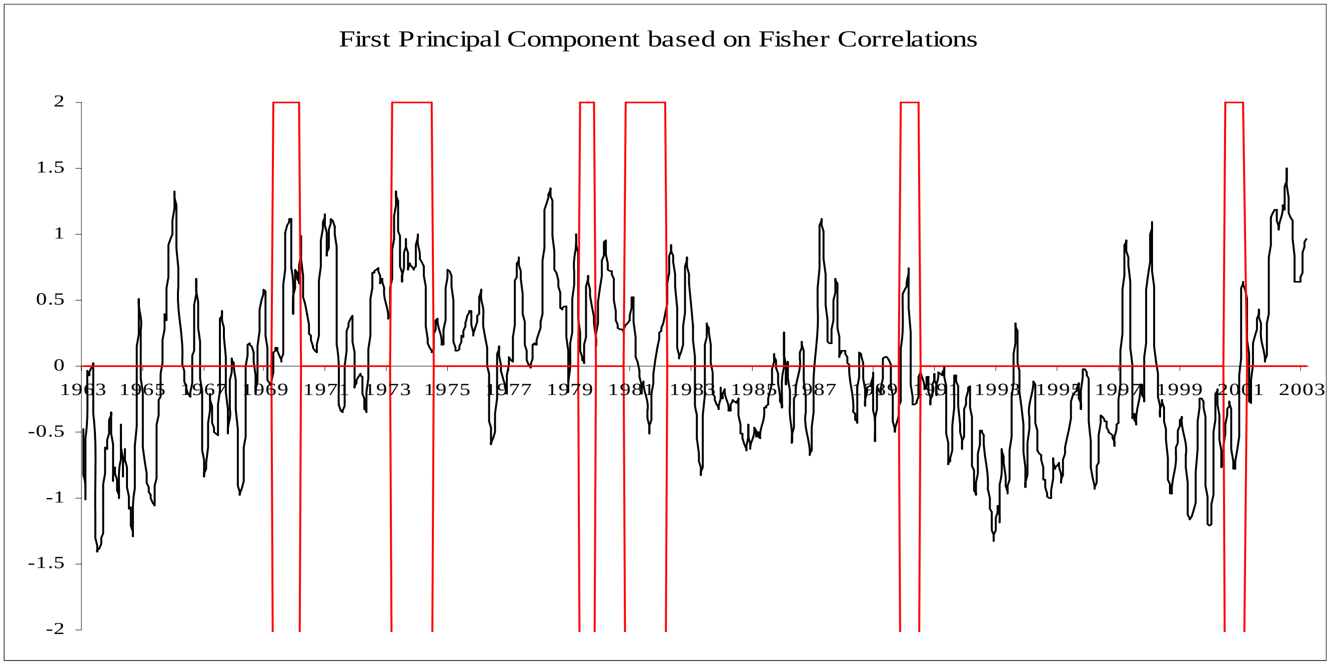
that uses the excess returns on 25 portfolios sorted by book-to-market and size as the dependent variables, where γ_m is the market risk premium, γ_{HML}, γ_{SMB}, γ_{DEF}, γ_{MVOL}, γ_{LIQ} are the risk premia associated with HML, SMB, default, market volatility innovation, and liquidity risk, γ_{AVOL} is the coefficient associated with asset volatility innovations, and γ_{ρ} is the coefficient associated with correlation innovation risk. To compute the aggregate correlation we start with a base set of 5 portfolios sorted by size and book-to-market (small-growth, small-value, medium, large-growth, and large-value). Our measure of correlation is based on the average correlation residuals (after removing the effects of macroeconomic variables from each pair-wise Fisher-transformed correlation). The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression. The coefficients are expressed in decimals per month. The adjusted R^2 follows Jagannathan and Wang (1996) and is reported in decimals. The t-statistics are adjusted for errors-in-variables, following Shanken (1992), and are reported in parenthesis. Bold numbers denote t-statistics that are significant at the 5 percent level. The sample period for the first 2 specifications is from July 1963 to December 2003, and for the 3rd specification is from July 1968 to December 2003.

	Specification 1	Specification 2	Specification 3
Risk Factor	Price of Risk	Price of Risk	Price of Risk
MKT	-0.0043 (-0.80)	-0.0047 (-0.62)	-0.0025 (-0.39)
HML	**0.0048** **(3.40)**	**0.0046** **(3.18)**	**0.0049** **(2.88)**
SMB	0.0022 (1.43)	0.0029 (1.90)	0.0018 (0.99)
MVOL		-0.0014 (-0.68)	0.0000 (0.01)
DEF		-0.0010 (-0.97)	-0.0009 (-1.08)
UI		-0.0007 (-1.31)	-0.0007 (-1.52)
GIP		0.0012 (0.57)	-0.0001 (0.06)
LIQ			0.0096 (1.18)
AVOL Average	-0.3695 (-1.17)	-0.4197 (-0.93)	-0.4895 (-1.36)
ρ Average	**-0.2786** **(-2.46)**	**-0.3762** **(-2.26)**	**-0.2071** **(-2.18)**
Intercept	0.0088 (1.74)	0.0083 (1.12)	0.0066 (1.08)
Adjusted R^2	76.62	86.58	80.47

Figure 1
Correlation Plots

This figure shows the time-series plots of the first two principal components based on the correlation matrix of asset returns. The asset classes include 5 portfolios sorted by size and book-to-market (small-growth, small-value, medium, large-growth, and large-value). The principal component analysis is performed on the matrix of Fisher-transformed asset correlations. Panel A plots the resulting 1st principal component, while Panel B plots the resulting 2nd principal component. The vertical lines indicate recession periods as defined by NBER. The sample period is from July 1963 to December 2003.

Panel A



Panel B

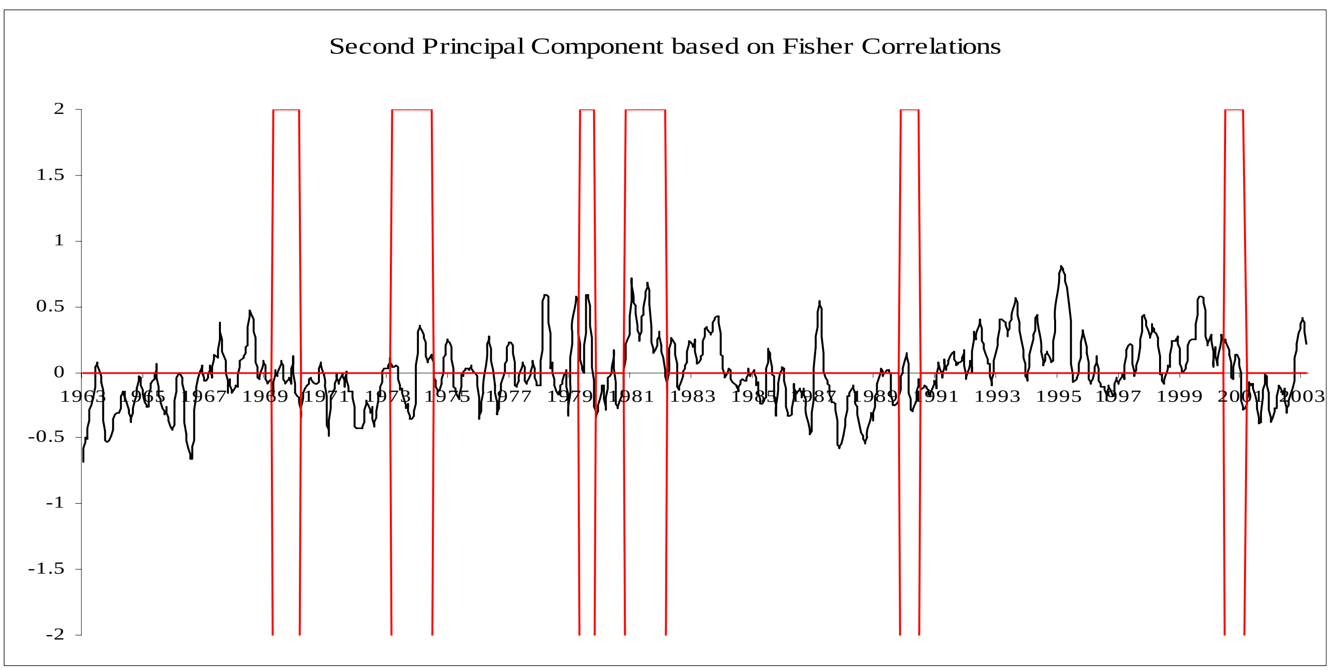
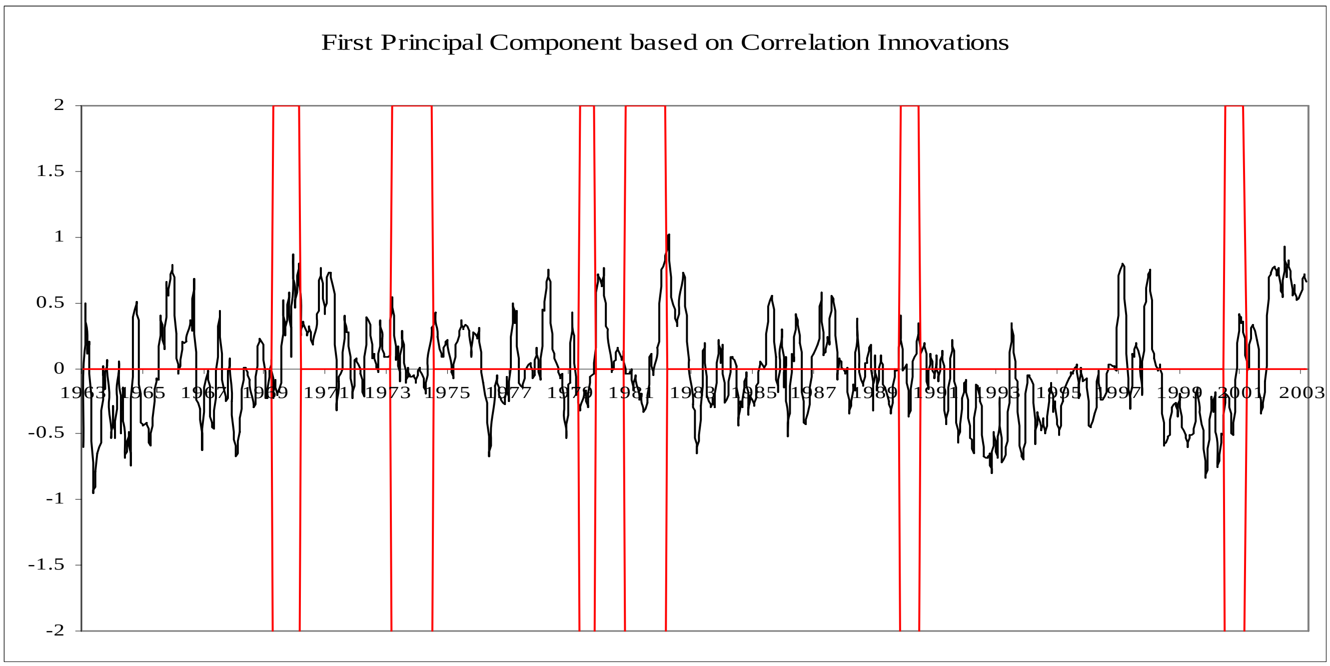


Figure 2
Correlation Innovation Plots

This figure shows the time-series plots of the first two principal components based on the correlation innovation matrix of asset returns. The asset classes include 5 portfolios sorted by size and book-to-market (small-growth, small-value, medium, large-growth, and large-value). The principal component analysis is performed on the matrix of Fisher-transformed correlation residuals. Correlation residuals are obtained after removing the effects of macroeconomic variables (market return, expected inflation, unexpected inflation, real rate, growth rate of industrial production, past correlation levels) from each pair-wise Fisher-transformed correlation. Panel A plots the resulting 1st principal component, while Panel B plots the resulting 2nd principal component. The vertical lines indicate recession periods as defined by NBER. The sample period is from July 1963 to December 2003.

Panel A



Panel B

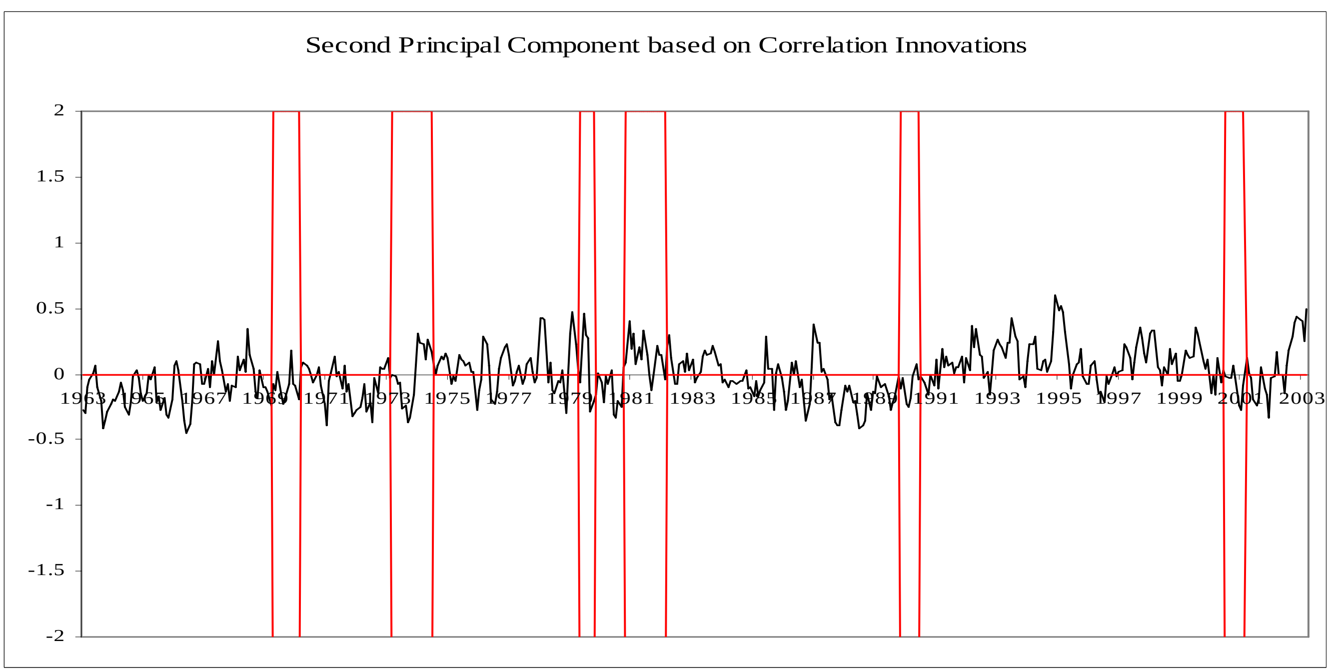


Figure 3
Portfolio Returns Sorted by Market and Correlation Loadings

This figure shows plots of the average returns of 25 portfolios of stocks for the period from July 1968 to December 2003. These 25 portfolios are constructed as follows. Each month, each stock's risk loadings are computed from a multiple regression of returns over the previous 60 months on the factors over the same 60 months. The factors are the excess market return, and the excess return on a portfolio that mimics the first principal component of correlation residuals. The assets used to obtain the mimicking portfolio returns are the 6 Fama-French portfolios double-sorted on size and book-to-market. 5 groups are formed by sorting stocks on market beta. Each market beta group is further sorted into 5 groups based on correlation betas. Thus, the 5 major groups of bars in the figure below are based on market returns loadings, while the 5 bars in each major group are based on correlation loadings.