Investigating ICAPM with Dynamic Conditional Correlations*

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ABSTRACT

This paper examines the intertemporal relation between expected return and risk for 30 stocks in the Dow Jones Industrial Average. The mean-reverting dynamic conditional correlation model of Engle (2002) is used to estimate a stock's conditional covariance with the market and test whether the conditional covariance predicts time-variation in the stock's expected return. The risk-aversion coefficient, restricted to be the same across stocks in panel regression, is estimated to be between two and four and highly significant. This result is robust across different market portfolios, different sample periods, alternative specifications of the conditional mean and covariance processes, different data sets including book-to-market portfolios and stocks in the S&P 100 index, and including a wide variety of state variables that proxy for the intertemporal hedging demand component of the ICAPM. The risk premium induced by the conditional covariation of individual stocks with the market portfolio remains economically and statistically significant after controlling for risk premia induced by conditional covariation with macroeconomic variables (federal funds rate, default spread, and term spread), financial factors (size, book-to-market, and momentum), and volatility measures (implied, GARCH, and range volatility).

JEL classifications: G12; G13; C51.

Keywords: ICAPM; Dynamic conditional correlation; ARCH; Risk aversion; Dow Jones.

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This paper examines the intertemporal relation between expected return and risk for 30 stocks in the Dow Jones Industrial Average. The mean-reverting dynamic conditional correlation model of Engle (2002) is used to estimate a stock's conditional covariance with the market and test whether the conditional covariance predicts time-variation in the stock's expected return. The risk-aversion coefficient, restricted to be the same across stocks in panel regression, is estimated to be between two and four and highly significant. This result is robust across different market portfolios, different sample periods, alternative specifications of the conditional mean and covariance processes, different data sets including book-to-market portfolios and stocks in the S&P 100 index, and including a wide variety of state variables that proxy for the intertemporal hedging demand component of the ICAPM. The risk premium induced by the conditional covariation of individual stocks with the market portfolio remains economically and statistically significant after controlling for risk premia induced by conditional covariation with macroeconomic variables (federal funds rate, default spread, and term spread), financial factors (size, book-to-market, and momentum), and volatility measures (implied, GARCH, and range volatility).

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1. Introduction

Merton (1973) introduces an intertemporal capital asset pricing model (ICAPM) in which an asset's expected return depends on its covariance with the market portfolio and with state variables that proxy for changes in investment opportunity set. A large number of studies test the significance of an intertemporal relation between expected return and risk in the aggregate stock market. However, even the existence of a positive risk-return tradeoff for market indices has not been universally found in the existing literature. Due to the fact that the conditional mean and volatility of stock market returns are not observable, different approaches and specifications used by previous studies in estimating the two conditional moments are largely responsible for the conflicting empirical evidence.

Our study extends time-series tests of the ICAPM to many risky assets. The prediction of Merton (1980) that expected returns should be related to conditional risk applies not only to the market portfolio but also to individual stocks. Expected returns for any stock should vary through time with the stock's conditional covariance with the market portfolio as well as the hedging demands. To be internally consistent, the relation should be the same for all stocks, i.e., the predictive slope on the conditional covariance represents the average relative risk aversion of market investors. We exploit this cross-sectional consistency condition and estimate the common time-series relation across 30 stocks in the Dow Jones Industrial Average.[1,2]

Using daily data from July 1986 to September 2007, we estimate the mean-reverting dynamic conditional correlation (DCC) model of Engle (2002) and generate the time-varying conditional covariances between daily excess returns on each stock and the market portfolio. Then, we estimate a system of time-series regressions of the stocks' excess returns on their conditional covariances with the market, while constraining all regressions to have the same slope coefficient. Our estimation based on Dow 30 stocks and alternative measures of the market portfolio generates positive and highly significant risk aversion coefficients, with magnitudes between two and four. The identified positive risk-return tradeoff at daily frequency is robust to different market portfolios, different sample periods, alternative specifications of the conditional mean and covariance processes, different data sets including book-to-market portfolios and stocks in the S&P 100 index, and including a wide variety of state variables that proxy for the intertemporal hedging demand component of the ICAPM.

[1] There are two reasons why we focus on the 30 stocks in the Dow Jones Industrial Average. First, we have to reduce the dimension of the estimation problem. An obvious requirement with the maximum likelihood and panel regression estimation is that the parameter convergence occurs reasonably quickly. Unfortunately, it has been our experience while running the estimation procedures that parameter estimation can be very tedious and takes very long time. In view of these difficulties, we restricted our sample to 30 stocks. Second, Dow stocks have large market capitalization, they are liquid and they have relatively low idiosyncratic risk. Hence, they represent a significant and systematic portion of the aggregate market portfolio.

[2] To check whether our results are sensitive to the choice of stocks in a particular index or driven by survivorship bias, we apply the same statistical tests to individual stocks in the S&P 100 index and to book-to-market portfolios. As will be discussed in the paper, the qualitative results turn out to be insensitive to the choice of financial assets.

When the investment opportunity is stochastic, investors adjust their investment to hedge against unfavorable shifts in the investment opportunity set and achieve intertemporal consumption smoothing. Hence, covariations with state of the investment opportunity induce additional risk premium on an asset. We identify a series of macroeconomic, financial, and volatility factors and examine whether their conditional covariances with individual stocks induce additional risk premia.

To explore how macroeconomic variables vary with the investment opportunity and test whether covariations of Dow 30 stocks with them induce additional risk premia, we first estimate the conditional covariances of these variables with daily excess returns on each stock and then analyze how the stocks' excess returns respond to their conditional covariances with macroeconomic factors. Because of data availability at daily frequency, we use the level and changes in federal funds rates, default, and term spreads as potential factors that may affect the investment opportunity set. The parameter estimates show that incorporating the covariances of stock returns with the aforementioned macroeconomic variables does not alter the magnitude and statistical significance of the relative risk aversion coefficients. The common slope on the market covariance remains positive and highly significant. The results also indicate that the slope coefficients on the conditional covariances with macroeconomic variables are statistically insignificant, implying that the level and innovations in macro variables do not contain any systematic risks rewarded in the stock market at daily frequency.

Fama and French (1992, 1993) provide evidence on the significance of size and book-to-market variables in predicting the cross-sectional and time-series variation in stock and portfolio returns. Jegadeesh and Titman (1993, 2001) and Carhart (1997) present evidence on the significance of past returns (or momentum) in predicting the cross-sectional and time-series variation in future returns on individual stocks and portfolios. We examine whether the size (*SMB*), book-to-market (*HML*), and momentum (*MOM*) factors of Fama and French move closely with investment opportunities and whether covariations of individual stocks with these three factors induce additional risk premia on Dow 30 stocks.[3] Estimation shows that the covariances of daily excess returns on Dow stocks and the *HML* factor (or value premium) generate significantly positive slope coefficients. Hence, an increase in a stock's covariance with *HML* predicts a higher excess return on the stock. The results also indicate that the covariances of stocks with the *SMB* and *MOM* factors do not have significant predictive power for one day ahead returns on Dow stocks. In other words, the level and innovations in the size and momentum

[3] The *SMB* (small minus big) factor is the difference between the returns on the portfolio of small size stocks and the returns on the portfolio of large size stocks. The average return on the *SMB* factor is positive because small stocks generate higher average returns than big stocks. The *HML* (high minus low) factor is the difference between the returns on the portfolio of high book-to-market stocks and the returns on the portfolio of low book-to-market stocks. The average return on the *HML* factor is positive because value stocks with high book-to-market ratio generate higher average returns than growth stocks with low book-to-market ratio. The positive return difference on the portfolios of value and growth stocks is referred to as value premium. The *MOM* (winner minus loser) factor is the difference between the returns on the portfolio of stocks with higher past 2- to 12-month cumulative returns (winners) and the returns on the portfolio of stocks with lower past 2- to 12-month cumulative returns (losers).

factors are not priced in the ICAPM framework. Consistent with recent empirical evidence provided by Campbell and Vuolteenaho (2004), Brennan, Wang, and Xia (2004), Petkova and Zhang (2005), and Petkova (2006) as well as recent theoretical models of Gomes, Kogan, and Zhang (2003) and Zhang (2005), our results suggest that the *HML* (or value premium) is a priced risk factor and can be viewed as a proxy for investment opportunities.

Campbell (1993, 1996) provides a two-factor ICAPM in which unexpected increase in market volatility represents deterioration in the investment opportunity set or decrease in optimal consumption. In this setting, a positive covariance of returns with volatility shocks (or innovations in market volatility) predicts a lower return on the stock. In the context of Campbell's ICAPM, an increase in market volatility predicts a decrease in optimal consumption and hence an unfavorable shift in the investment opportunity set. Risk-averse investors will demand more of an asset, the more positively correlated the asset's return is with changes in market volatility because they will be compensated by a higher level of wealth through positive correlation of the returns. That asset can be viewed as a hedging instrument. In other words, an increase in the covariance of returns with volatility risk leads to an increase in the hedging demand, which in equilibrium reduces expected return on the asset.

Following Campbell (1993, 1996), we assume that investors want to hedge against the changes in the forecasts of future market volatilities. In this paper, we use three alternative measures of market volatility to test whether stocks that have higher correlation with the changes in market volatility yield lower expected return: (1) the conditional volatility of S&P 500 index returns based on the generalized autoregressive conditional heteroskedasticity (GARCH) model, (2) the options implied volatility of S&P 500 index returns obtained from the Chicago Board Options Exchange (CBOE), and (3) the range volatility of S&P 500 index returns based on the maximum and minimum values of the S&P 500 index over a sampling interval of one day. The panel regression results indicate that daily risk premium induced by the conditional covariation of Dow stocks with the market portfolio remains economically and statistically significant after controlling for risk premia induced by conditional covariation with changes in GARCH, implied, and range based volatility estimators. The results also provide strong evidence for a significantly negative relation between expected return and volatility risk. For all measures of market volatility, we find that stocks with higher association with the changes in expected future market volatility give lower expected return.

The paper is organized as follows. Section 2 briefly discusses earlier studies on the intertemporal relation between expected return and risk. Section 3 describes the data and estimation methodology. Section 4 presents the empirical results. Section 5 concludes.

2. Literature on the Risk-Return Tradeoff

Dynamic asset pricing models starting with Merton's (1973) ICAPM provide a theoretical framework that gives a positive equilibrium relation between the conditional first and second moments of excess returns on the aggregate market portfolio. However, Abel (1988), Backus and Gregory (1993), and Gennotte and Marsh (1993) develop models in which a negative relation between expected return and volatility is consistent with equilibrium. Similarly, empirical studies are still not in agreement on the direction of a time-series relation between expected return and risk.[4]

Many studies fail to identify a statistically significant intertemporal relation between risk and return of the market portfolio. French, Schwert, and Stambaugh (1987) find that the coefficient estimate is not significantly different from zero when they use past daily returns to estimate the monthly conditional variance. Goyal and Santa-Clara (2003) obtain similar insignificant results using the same conditional variance estimator but over a longer sample period. Chan, Karolyi, and Stulz (1992) employ a bivariate GARCH-in-mean model to estimate the conditional variance, and they also fail to obtain a significant coefficient estimate for the United States. Baillie and DeGennaro (1990) replace the normal distribution assumption in the GARCH-in-mean specification with a fat-tailed t-distribution. Their estimates remain insignificant. Campbell and Hentchel (1992) use the quadratic GARCH (QGARCH) model of Sentana (1995) to determine the existence of a risk-return tradeoff within an asymmetric GARCH-in-mean framework. Their estimate is positive for one sample period and negative for another sample period, but neither is statistically significant. Glosten, Jagannathan, and Runkle (1993) use monthly data and find a negative but statistically insignificant relation from two asymmetric GARCH-in-mean models. Based on semi-nonparametric density estimation and Monte Carlo integration, Harrison and Zhang (1999) find a significantly positive risk and return relation at one-year horizon, but they do not find a significant relation at shorter holding periods such as one month. Using a sample of monthly returns and implied and realized volatilities for the S&P 500 index, Bollerslev and Zhou (2006) find an insignificant intertemporal relation between expected return and realized volatility, whereas the relation between return and implied volatility turns out to be significantly positive.

Several studies even find that the intertemporal relation between risk and return is negative. Examples include Campbell (1987), Breen, Glosten, and Jagannathan (1989), Turner, Startz, and Nelson (1989), Nelson (1991), Glosten, Jagannathan, and Runkle (1993), Whitelaw (1994), and Harvey (2001). Using a regime switching model, Whitelaw (2000) finds a negative unconditional relation between the mean and variance of excess returns on the market portfolio. Using a latent vector autoregression approach, Brandt and Kang (2004) show that although the conditional correlation between the mean and

[4] See, e.g., Ghysels, Santa-Clara, and Valkanov (2005) and Christoffersen and Diebold (2006).

volatility of market portfolio returns is negative, the unconditional correlation is positive due to the lead-lag correlations.

Some studies do provide evidence supporting a positive risk-return relation. Chou (1988) finds a significantly positive relation with weekly data based on the symmetric GARCH model of Bollerslev (1986). Bollerslev, Engle, and Wooldridge (1988) use a multivariate GARCH-in-mean process to model the conditional mean and the conditional covariance of returns on stocks, bonds, and bills with the excess market return. They find a small but significant risk-return tradeoff. Scruggs (1998) includes the long-term government bond returns as a second factor of the bivariate GARCH-in-mean model and find the partial relation between the conditional mean and variance to be positive and significant.[5]

Ghysels, Santa-Clara, and Valkanov (2005) introduce a new variance estimator that uses past daily squared returns, and they conclude that the monthly data are consistent with a positive relation between conditional expected excess return and conditional variance. Bali and Peng (2006) examine the intertemporal relation between risk and return using high-frequency data. Based on realized, GARCH, implied, and range-based volatility estimators, they find a positive and significant link between the conditional mean and conditional volatility of market returns at daily frequency. Guo and Whitelaw (2006) develop an asset pricing model based on Merton's (1973) ICAPM and Campbell and Shiller's (1988) log-linearization method, and find a positive relation between stock market risk and return within their newly proposed ICAPM framework. Using a long history of monthly data from 1836 to 2003, Lundblad (2007) estimates alternative specifications of the GARCH-in-mean model, and finds a positive and significant risk-return tradeoff for the aggregate market portfolio. Using a long history of monthly data from 1926 to 2002, Bali (2008) identifies a positive and significant relation between expected return and risk on the size/book-to-market and industry portfolios of Fama and French (1993, 1997).

3. The intertemporal relation between expected return and risk

Merton's (1973) ICAPM implies the following equilibrium relation between risk and return:

$$\mu_{t+1} - r_{f,t} = A \circ Cov_t\left(r_{t+1}, r_{m,t+1}\right) + Cov_t\left(r_{t+1}, x_{t+1}\right) \circ B \tag{1}$$

where $r_{f,t}$ is the risk free rate, $\mu_{t+1} = E(r_{t+1})$ is the $n \times 1$ vector conditional mean of stock returns r_{t+1}, $r_{m,t+1}$ is the market return, and x_{t+1} is a vector of k state variables that shift the investment opportunity set. The covariances are conditional on information available at the time the assets are evaluated. Important restrictions implied by the theory are the fact that intercepts in this equation are zero and that the slope coefficient A is a scalar that is appropriate for all assets and B is a $k \times 1$ vector that prices all assets. This representation is equivalent to non-existence of arbitrage when the pricing kernel is a linear

[5] Scruggs (1998) assumes that the conditional correlation between stock returns and bond returns is constant. Once they relax this assumption, Scruggs and Glabadanidis (2003) fail to identify a positive risk-return tradeoff.

function of the market aggregate return. Additional factors could be added and will be examined in the empirical work. There is no restriction in the theory that the parameters *A* and *B* are time invariant although this is commonly applied and is completely reasonable when the state variables are included to measure shifts in investment opportunity sets.

In the original Merton model, the parameters of the system and the covariances were all interpreted as constant but the ability to model time variation in covariances makes it natural to include these directly in the analysis. The empirical literature has generally recognized that the parameters may be time varying but not in a parametric fashion. In principle, if the covariances are stochastic, they would represent additional sources of variation in the investment opportunity set and potential hedging demand terms.

The expression in (1) can now be written as

$$V_t \begin{pmatrix} r_{t+1} \\ r_{t+1}^m \\ x_{t+1} \end{pmatrix} = \begin{pmatrix} H_{r,r,t} & H_{r,m,t} & H_{r,x,t} \\ H_{m,r,t} & H_{m,m,t} & H_{m,x,t} \\ H_{x,r,t} & H_{x,m,t} & H_{x,x,t} \end{pmatrix} \tag{2}$$

$$\begin{aligned} E_t(r_{t+1}) &= r_{f,t} + A \circ H_{r,m,t} + H_{r,x,t} \circ B \\ E_t(r_{m,t+1}) &= r_{f,t} + A \circ H_{m,m,t} + H_{m,x,t} \circ B \end{aligned} \tag{3}$$

If normality is assumed, then the first two moments are sufficient to completely define the distribution hence equations (2) and (3) define the process regardless of how many assets are being priced.

Various parameterizations of the covariance matrix have been used in the literature. In this paper, several versions of the DCC model are employed as this is very stable and parsimonious and is manageable for large numbers of assets. Furthermore, it is clear from (3) that the full dynamic covariance matrix of returns does not enter the pricing equation. Thus a simplified estimation approach is employed for most of the analyses in this paper. In particular, the covariances $H_{r,m,t}$ and $H_{r,x,t}$ can be estimated first and used in a seemingly unrelated regression estimate of returns in (3). This is described in more detail in Section 3.2.

In each case, we test the hypothesis that the individual intercepts are jointly zero. We test the hypothesis that *A* is zero and also test the hypothesis that *A* is the same for all assets. We find that for most state variables *B* is not significantly different from zero and do not affect the estimates of *A*. However, volatilities, however they are measured, are highly significant but still do not alter our estimates for *A*. Allowing the state variables x_{t+1} to enter (3) directly does not change the estimates appreciably.

3.1. Data

Our study is based on the latest stock composition of the Dow Jones Industrial Average.[6] The ticker symbols and company names are presented in Appendix A. In our empirical analyses, we use daily excess returns on Dow 30 stocks for the longest common sample period from July 10, 1986 to September 28, 2007, yielding a total of 5,354 daily observations.

For the market portfolio, we use five different stock market indices: (1) the value-weighted NYSE/AMEX/NASDAQ index, also known as the value-weighted index of the Center for Research in Security Prices (CRSP), can be viewed as the broadest possible stock market index used in earlier studies, (2) New York Stock Exchange (NYSE) index, (3) Standard and Poor's 500 (S&P 500) index, (4) Standard and Poor's 100 (S&P 100) index, and (5) Dow Jones Industrial Average (DJIA) can be viewed as the smallest possible stock market index used in earlier studies.

Appendix B reports the mean, median, maximum, minimum, and standard deviation of the daily excess returns on Dow 30 Stocks.[7] As shown in Panel A, in terms of the sample mean, General Motors (GM) has the lowest average daily excess return of –0.0059%, whereas Intel (INTC) has the highest average daily excess return of 0.0408%. In terms of the sample standard deviation, Exxon Mobil (XOM) has the lowest unconditional volatility of 1.89% per day, whereas Intel (INTC) has the highest unconditional volatility of 3.12% per day. In terms of the daily maximum excess return, E.I. DuPont de Nemours (DD) has the lowest daily maximum of 9.86%, whereas Honeywell (HON) has the highest daily maximum of 31.22%. In terms of the daily minimum excess return, Altria (MO, was Philip Morris) has the lowest daily minimum of –75.03%, whereas Home Depot (HD) has the highest daily minimum of –46.23%.

Panel B of Appendix B reports the mean, median, maximum, minimum, and standard deviation of the daily excess returns on the value-weighted NYSE/AMEX/NASDAQ, NYSE, S&P 500, S&P 100, and DJIA indices. To be consistent with the firm-level data, the descriptive statistics are computed for the sample period from July 10, 1986 to September 28, 2007. In terms of the sample mean, the S&P 500 index has the lowest average daily excess return of 0.022%, whereas the NYSE/AMEX/NASDAQ index has the highest average daily excess return of 0.030%. In terms of the sample standard deviation, the NYSE index has the lowest unconditional volatility of 0.96% per day, whereas the S&P 100 index has the highest unconditional volatility of 1.11% per day. In terms of the daily maximum excess return, the NYSE/AMEX/NASDAQ index has the lowest daily maximum of 8.63%, whereas the DJIA index has the highest daily maximum of 10.12%. In terms of the daily minimum excess return, the DJIA index has the

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[6] To determine whether our results are driven by survivorship bias or a particular data set, we apply our tests to a different composition of Dow stocks trading earlier. We also replicate our main findings with individual stocks in the S&P 100 index.

[7] Excess returns on Dow 30 stocks are obtained by subtracting the returns on 1-month Treasury bills from the raw returns on Dow stocks. The daily returns on 1-month T-bill are obtained from Kenneth French's online data library.

lowest daily minimum of –22.64%, whereas the NYSE/AMEX/NASDAQ index has the highest daily minimum of –17.16%.

For state variables, we consider the commonly used macroeconomic variables (the federal funds rate, default spread, and term spread), financial factors (size, book-to-market, and momentum), and volatility measures (options implied, GARCH, and range).

3.1.1. Macroeconomic Variables

We obtain daily data on the federal funds rate, 3-month Treasury bill, 10-year Treasury bond yields, BAA-rated and AAA-rated corporate bond yields from the H.15 database of the Federal Reserve Board. The federal funds rate is the interest rate at which a depository institution lends immediately available funds (balances at the Federal Reserve) to another depository institution overnight. It is a closely watched barometer of the tightness of credit market conditions in the banking system and the stance of monetary policy. In addition to the fed funds rate, we use the term and default spreads as control variables. The term spread (TERM) is calculated as the difference between the yields on the 10-year Treasury bond and the 3-month Treasury bill. The default spread is computed as the difference between the yields on the BAA-rated and AAA-rated corporate bonds.[8] As a final set of variables, we include the lagged excess return on the market portfolio as well as the lagged excess return on Dow 30 stocks to control for the serial correlation in daily returns that might spuriously affect the risk-return tradeoff.

3.1.2. Size, book-to-market, and momentum factors

The daily, monthly, and annual returns on the three factors (*SMB*, *HML*, *MOM*) of Fama and French are available at Kenneth French's online data library, and the daily data cover the period from July 1, 1963 to September 28, 2007. In our empirical analyses, we use them for our longest common sample from July 10, 1986 to September 28, 2007.

3.1.3. Alternative Measures of Market Volatility

Implied volatilities are considered to be the market's forecast of the volatility of the underlying asset of an option. Specifically, the Chicago Board Options Exchange (CBOE)'s VXO implied volatility index provides investors with up-to-the-minute market estimates of expected volatility by using real-time S&P 100 index option bid/ask quotes. The VXO is a weighted index of American implied volatilities calculated from eight near-the-money, near-to-expiry, S&P 100 call and put options based on the Black-Scholes (1973) pricing formula.

As an alternative to the VXO index, we could have used the newer VIX index, which was introduced by the CBOE on September 22, 2003. The VIX is obtained from the European style S&P 500

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[8] We could not include the aggregate dividend yield (or the dividend-price ratio) because the data on dividends are available only at the monthly frequency while our empirical analyses are based on the daily data.

index option prices and incorporates information from the volatility skew by using a wider range of strike prices than just at-the-money series. However, the daily data on VIX starts from January 2, 1990, which does not cover our full sample period (7/10/1986–9/28/2007). Hence, we use the daily data on VXO that starts from January 2, 1986 and spans the full sample period of Dow 30 stocks.

We estimate the conditional variance of daily excess returns on the S&P 500 index using a GARCH(1,1) model and then generate the DCC-based conditional covariances between daily excess returns on Dow 30 stocks and the change in daily conditional volatility. Our objective is to test whether unexpected news in market volatility is priced in the stock market and then to check robustness of risk-aversion coefficient after controlling for risk premium induced by the conditional covariation of individual stocks with the GARCH volatility of the market portfolio.

The range volatility that utilizes information contained in the high frequency intraday data is defined as:

$$Range_{m,t} = \ln(P_{m,t}^{\max}) - \ln(P_{m,t}^{\min}) \,, \tag{4}$$

where $P_{m,t}^{\max}$ and $P_{m,t}^{\min}$ are the highest and lowest stock market index levels on day *t*. In our empirical analysis, we use the maximum and minimum values of the S&P 500 index over a sampling interval of one day. Equation (4) can be viewed as a measure of daily standard deviation of the market portfolio. Alizadeh, Brandt, and Diebold (2002) and Brandt and Diebold (2006) point out several advantages of using range volatility estimators: The range-based volatility is highly efficient, approximately Gaussian and robust to certain types of microstructure noise such as bid-ask bounce. In addition, range data are available for many assets including Dow 30 stocks and major stock market indices over a long sample period.

3.1.4. Conditional Idiosyncratic/Total Volatility of Individual Stocks

Recent studies on idiosyncratic and total risk of individual stocks provide conflicting evidence on the direction and significance of a cross-sectional relation between firm-level volatility and expected returns. The existing literature is also not in agreement about the significance of a time-series relation between aggregate idiosyncratic volatility and excess returns on the market portfolio. Hence, we examine the significance of conditional idiosyncratic and total volatility of individual stocks in the ICAPM framework and test if the intertemporal relation between expected returns and market risk remains significantly positive after controlling for firm-level volatility measures.

To measure total risk of individual stocks, we use the following range volatility:

$$Range_{i,t} = \ln(P_{i,t}^{\max}) - \ln(P_{i,t}^{\min}) \,, \tag{5}$$

where $P_{i,t}^{\max}$ and $P_{i,t}^{\min}$ are the highest and lowest prices of stock *i* on day *t*. The maximum and minimum prices of Dow 30 stocks are used over a sampling interval of one day to compute range volatility estimators.

The conditional total volatility of Dow 30 stocks is estimated based on the following AR(1)-GARCH(1,1) model:

$$R_{i,t+1} = \alpha_0^i + \alpha_1^i R_{i,t} + \varepsilon_{i,t+1}, \tag{6}$$

$$E_t\left[\varepsilon_{i,t+1}^2\right] \equiv \sigma_{i,t+1}^2 = \beta_0^i + \beta_1^i \varepsilon_{i,t}^2 + \beta_2^i \sigma_{i,t}^2 , \tag{7}$$

where $R_{i,t+1}$ denotes excess return on stock *i* and $\sigma_{i,t+1}^2$ in eq. (7) is the time-*t* expected conditional variance of $\varepsilon_{i,t+1}$ that can be viewed as the conditional total risk of stock *i*.

Following Spiegel and Wang (2005) and Fu (2008), the conditional idiosyncratic volatility of Dow 30 stocks is estimated based on the there-factor Fama-French (1993) model:

$$R_{i,t+1} = \alpha_0^i + \alpha_1^i R_{m,t+1} + \alpha_2^i SMB_{t+1} + \alpha_3^i HML_{t+1} + \varepsilon_{i,t+1}, \tag{8}$$

$$E_t\left[\varepsilon_{i,t+1}^2\right] \equiv \sigma_{i,t+1}^2 = \beta_0^i + \beta_1^i \varepsilon_{i,t}^2 + \beta_2^i \sigma_{i,t}^2 , \tag{9}$$

where total excess return on stock *i* can be decomposed into expected and idiosyncratic components using the excess market return (R_m), size (*SMB*) and book-to-market (*HML*) factors. $\varepsilon_{i,t+1}$ is the idiosyncratic (or firm-specific) excess return on stock *i*. $\sigma_{i,t+1}^2$ in eq. (9) is the time-*t* expected conditional variance of $\varepsilon_{i,t+1}$ that can be viewed as the conditional idiosyncratic volatility.

3.2. Estimating Time-Varying Conditional Covariances

The DCC model of Engle (2002) parameterizes the volatilities and correlations separately. The general specification we use is

$$y_{t+1} \equiv \begin{pmatrix} r_{t+1} \\ r_{t+1}^m \\ x_{t+1} \end{pmatrix} = \alpha_0 + \alpha_1 y_t + \mu_t + \varepsilon_{t+1},\ V_t\left(\varepsilon_{t+1}\right) = D_{t+1}\rho_{t+1}D_{t+1} \tag{10}$$

where the mean is given by equation (1) for asset returns, and *D* is the diagonal matrix of conditional standard deviations given by

$$D_{t+1}^2 = \beta_0 + \beta_1 y_t^2 + \beta_2 D_t^2, \quad \alpha_0, \alpha_1, \alpha_2, \beta_0, \beta_1, \beta_2, D_t \ \ diagonal. \tag{11}$$

The correlations are given by

$$\rho_t = diag\left(Q_t\right)^{-1/2} Q_t diag\left(Q_t\right)^{-12} \tag{12}$$

where

$$Q_{t+1} = \overline{\rho} + a_1 \circ \left(u_t u_t ' - \overline{\rho} \right) + a_2 \circ \left(Q_t - \overline{\rho} \right)$$
$$u_t = D_t^{-1} \varepsilon_t ,\ \overline{\rho} = \frac{1}{T} \sum_{t=1}^{T} u_t u_t ' \tag{13}$$

In many applications, a_1 and a_2 are considered to be scalars as in Engle (2002) and Engle (2008a,b), however we consider a more flexible specification where these are symmetric positive definite matrices and multiplication is element by element or Hadamard. This is shown by Ding and Engle (2001) to imply positive definiteness of the matrix Q and consequently of the correlation matrix. In this way each return may have different parameters. Our estimation strategy does not enforce positive definiteness as it consists of a series of bivariate estimations, but it does insure that all correlations used in estimation lie in the interval (-1,1).

The likelihood function for this problem is constructed assuming conditional normality of the dependent variables. As is generally true for multivariate GARCH models, this estimator is consistent even if the normality assumption is invalid as long as the first two moment equations are correctly specified [see Bollerslev and Wooldridge (1992) for a proof].

Our estimation approach proceeds in steps.

1) We take out any autoregressive elements in returns and estimate univariate GARCH models for all returns and state variables.
2) We construct standardized returns and compute bivariate DCC estimates of the correlations between each stock and the market and between each stock and the state variables using the bivariate likelihood function.
3) We estimate the expected return equation as a panel with the conditional covariances as regressors. The error covariance matrix specified as seemingly unrelated related regression (SUR). A weighted least squares alternative divides each equation by its estimated conditional standard deviation before estimating the panel by SUR.

In one case we jointly estimate the entire system and get very similar results.[9]

Table 1 reports parameter estimates of the mean-reverting DCC model.[10] For all stocks in the Dow Jones Industrial Average, both parameters ($0 < a_1, a_2 < 1$) are estimated to be positive, less than one, and highly significant. Similar to the findings of Engle (2002), the magnitude of a_1 is small, in the range of 0.0075 to 0.0581, whereas a_2 is found to be large, ranging from 0.9326 to 0.9904. The persistence of the conditional correlations of each stock with the market portfolio is measured by the sum of a_1 and a_2.

[9] The panel estimation methodology with SUR takes into account heteroskedasticity and autocorrelation as well as contemporaneous cross-correlations in the error terms.
[10] The parameter estimates in Table 1 are based on the market portfolio measured by the DJIA. The results from alternative measures of the market portfolio are very similar and they are available upon request.

For all stocks, the estimated value of (a_1+a_2) is less than one, in the range of 0.9880 to 0.9982, implying mean reversion in the conditional correlation estimates.

Figure 1 displays the conditional correlations between the daily excess returns on Dow 30 stocks and the market portfolio over the sample period of July 10, 1986 to September 28, 2007. A notable point in Figure 1 is that the conditional correlations exhibit significant time variation for all stocks and the correlations are pulled back to some long-run average level over time, indicating strong mean reversion. A common observation in Figure 1 is that when the level of conditional correlation is high, mean reversion tends to cause it to have a negative drift, and when it is low, mean reversion tends to cause it to have a positive drift.

To test whether the mean-reverting DCC model generates reasonable conditional covariance estimates, we compute the equal-weighted and price-weighted averages of the conditional covariances of Dow 30 stocks with the market portfolio. Then, we compare the weighted average conditional covariances with the benchmark of the conditional market variance. In Panel A (Panel B) of Figure 2, the dashed line denotes the equal-weighted (price-weighted) average of the conditional covariances of daily excess returns on Dow 30 stocks with daily excess returns on the market portfolio. The solid line in both panels denotes the conditional variance of daily excess returns on the market portfolio. The weighted-average covariances are in the same range as the conditional variance of the market portfolio. The two series in both panels move very closely together. In fact, it is almost impossible to visually distinguish the two series in Figure 2. Specifically, in Panel A the sample correlation between the equal-weighted average covariance and the market variance is 0.9931 and in Panel B the sample correlation between the price-weighted average covariance and the market variance is 0.9932. The affinity in magnitudes and time-series fluctuations between the weighted average covariances and market portfolio variance provides evidence for reasonable conditional variance and covariance estimates from the mean-reverting DCC model.

4. Empirical Results

First, we present the estimation results on the intertemporal risk-return tradeoff assuming zero intertemporal hedging demand. Second, we test whether our results are driven by survivorship bias or by a particular data set. Third, we present results from the one-step estimation of the ICAPM model with DCC. Fourth, we check the robustness of our main findings across different sample periods, and after controlling for the October 1987 crash, macroeconomic variables, the lagged returns on individual stocks and the market portfolio, the conditional volatility of individual stocks and the market portfolio, and alternative specifications of the conditional mean and covariance processes. Finally, we estimate the intertemporal relation by including additional risk premia induced by the conditional covariation of Dow 30 stocks with various macroeconomic, financial, and volatility factors.

4.1. Risk-return tradeoff without intertemporal hedging demand

Table 2 reports the common slope estimates (A) along with the t-statistics from the following system of equations:

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + e_{i,t+1}, \qquad i = 1, 2, ..., n = 30. \tag{14}$$

Estimation is based on daily excess returns on Dow 30 stocks (n=30) and five alternative measures of the market portfolio over the sample period of July 10, 1986 to September 28, 2007. Each row of Table 2 presents estimates based on a market portfolio measured by the value-weighted NYSE/AMEX/NASDAQ, NYSE, S&P 500, S&P 100, and DJIA indices.

The second column of Table 2 shows that, with the SUR methodology, the risk-return coefficient on $\sigma_{im,t+1}$ is estimated to be positive and highly significant with the t-statistics ranging from 5.44 to 7.03. The common slope estimates are stable across different market portfolios, between 2.25 and 3.26. Based on the relative risk aversion interpretation, the magnitudes of these estimates are economically sensible as well.

To gain some insight about the economic significance of risk-return coefficients, we can rewrite eq. (14) in a static CAPM framework:

$$E(R_i) = C_i + \left(A \cdot \sigma_m^2\right) \cdot \left(\frac{\sigma_{im}}{\sigma_m^2}\right) = C_i + \left(A \cdot \sigma_m^2\right) \cdot \beta_i = C_i + E(R_m) \cdot \beta_i, \tag{15}$$

where expected excess return on stock i, $E(R_i)$, is a linear function of market beta, β_i, and $(A \cdot \sigma_m^2)$ is a measure of expected excess return on the market portfolio, i.e., $E(R_m) = A \cdot \sigma_m^2$. As shown in Panel B of Appendix B, the standard deviation of excess return on the market portfolio is about 1% per day, implying that the daily variance of the market portfolio, σ_m^2, is about 0.0001. As reported in Table 2, the common slope, A, is estimated in the range of 2.25 and 3.26, which corresponds to $A \cdot \sigma_m^2$ = 5.67% and 8.22% per annum annualized expected market risk premium assuming 252 trading days in a year.

In estimating the system of time-series relations, we allow the intercepts to be different for different stocks. These intercepts capture the daily abnormal returns on each stock that cannot be explained by the conditional covariances with the market portfolio. The first column of Table 2 reports the Wald statistics and the p-values in square brackets from testing the joint hypothesis of all intercepts equal zero; H_0: $C_1 = C_2 = ... = C_{30} = 0$. The Wald statistics from the SUR estimation turn out to be very small, between 5.86 and 7.87, indicating that the conditional covariances of Dow 30 stocks with the market portfolio have significant predictive power for the time-series and cross-sectional variation in expected returns so that we fail to reject the null hypothesis.

We pay particular attention to the magnitude and statistical significance of daily abnormal returns (intercepts) that differ across stocks. At an earlier stage of the study, the intercepts and their t-statistics are plotted for Dow 30 stocks as a scattered diagram for each market portfolio measured by the value-weighted CRSP, NYSE, S&P 500, S&P 100, and DJIA indices. Although not presented in the paper to save space, in all cases, the daily abnormal returns turn out to be insignificant, both economically and statistically.

In addition to the SUR methodology, we use the ordinary least squares (OLS) and weighted least squares (WLS) in estimating the system of equations in eq. (14). The *t*-statistics from OLS are not adjusted for heteroskedasticity, autocorrelation, or contemporaneous cross-correlations in the errors. The *t*-statistics from WLS are adjusted only for heteroskedasticity. As expected, the *t*-statistics of the common slope estimates (A) from OLS and WLS turn out to be significantly larger than those for the SUR. As shown in Table 2, the common slope coefficients from OLS are in the range of 2.82 to 3.64 with the *t*-statistics ranging from 10.19 to 10.97. The common slopes from WLS are estimated to be between 3.18 and 4.11 with the *t*-statistics between 11.79 and 12.52. Similar to our findings from SUR, these results indicate a positive and highly significant relation between expected return and risk on Dow stocks. The Wald statistics from OLS and WLS turn out to be larger than those for the SUR, but the corresponding *p*-values in square brackets cannot reject the null hypothesis of all intercepts equal zero.

Assuming that the errors in panel regression are cross-sectionally uncorrelated (as in the case of OLS and WLS) can yield standard errors that are biased downwards. This bias is due to the fact that error correlations are often systematically related to the explanatory variables. To resolve this problem, we use an extended SUR methodology that accounts for heteroscedasticity, first-order serial correlation, and contemporaneous cross-correlations in the error terms. As a further robustness check, we use Rogers' (1983, 1993) robust standard errors (the so-called *clustered* standard errors) that yield asymptotically correct standard errors for the OLS and WLS estimators under a general cross-correlation structure.

Assuming that the errors are independent across cross-sections, Rogers (1983, 1993) write the variance-covariance matrix of the coefficient estimates as

$$\left(X'X\right)^{-1}\sum_{t=1}^{T}\left[X_t'\Omega_t X_t\right]\left(X'X\right)^{-1}, \tag{16}$$

where X denotes the panel of explanatory variables, Ω is the covariance matrix of the panel of errors, and X_t and Ω_t denote a single cross-section of explanatory variables and the corresponding error covariance matrix, respectively. Since $X_t'\Omega_t X_t = E\left[X_t' e_t e_t' X_t\right]$, Rogers substitutes estimated errors for true errors to get a variance estimator of regression coefficients: $\left(X'X\right)^{-1}\sum_{t=1}^{T}\left(X_t'\hat{e}_t\hat{e}_t'X_t\right)\left(X'X\right)^{-1}$, where e_t denotes the regression errors and $\hat{e}_t$ is the estimated errors. Rogers indicates that the standard errors are consistent in T under plausible assumptions. That is, they converge as the time dimension of the panel grows. This is not a concern for our study since we have long time-series with 5,354 daily observations.

We re-estimate the system of equations in (14) using Rogers (1983, 1993) or clustered standard errors. The common slope coefficients are estimated to positive, in the range of 2.82 to 3.64, and highly significant with the *t*-statistics ranging from 4.03 to 4.60.

As a final robustness check, we use standardized residuals as the dependent variable in the panel regression instead of raw data on daily excess returns. Dividing both sides of equation (14) by the conditional standard deviation of individual stocks, $\sigma_{i,t+1}$, we obtain the following system of equations:

$$R^*_{i,t+1} = C^*_i + A \cdot \left(\rho_{im,t+1} \cdot \sigma_{m,t+1}\right) + e^*_{i,t+1}, \qquad (14')$$

where the new dependent variable is the standardized residual for stock *i*, $R^*_{i,t+1} = \left(R_{i,t+1} - E_t\left[R_{i,t+1}\right]\right)/\sigma_{i,t+1}$, and the new explanatory variable is the conditional correlation times the conditional volatility of the market portfolio, $\sigma_{im,t+1}/\sigma_{i,t+1} = \left(\rho_{im,t+1} \cdot \sigma_{m,t+1}\right)$.

Although estimating (14') with the standardized residuals is not exactly the same as estimating (14) with raw data, the results provide further evidence for the significance of positive risk-return tradeoff. The common slope coefficients from the standardized residuals are estimated to be in the range of 2.07 and 2.93 with the *t*-statistics between 3.08 and 3.97.

Overall, the results from SUR, OLS, WLS, and Rogers' clustered methodology point out a positive and significant intertemporal relation between expected return and risk. For the remainder of the paper, to save space we present parameter estimates only based on the SUR methodology that accounts for heteroskedasticity and autocorrelation as well as contemporaneous cross-correlations in the errors from different equations.

4.2. Survivorship Bias and Stocks in the S&P 100 Index

As discussed earlier, the sample considered in the paper consists of the 30 stocks that are *currently* in the Dow Jones index. Since poorly performing firms are periodically taken out of the index in favor of firms that have performed better, the current index is likely to be comprised of firms that have high average past returns. Although there is no theory as to why survivorship bias would affect the intertemporal relation between expected return and risk, rather than just the level of average returns, some readers may be concerned about the possibility that the bias would affect the risk-return tradeoff as well.

To relieve concerns about the survivorship bias, we drop the top four performing firms over the 1986-2007 sample period (Microsoft, Intel, Home Depot, and Hewlett-Packard) that were added to the index in 1997 and 1999, approximately midway through the sample. These four firms are replaced by Chevron, Goodyear Tire & Rubber, Eastman Kodak, and International Paper.[11] With this new sample, we

[11] We tried to drop more firms in our current sample, and include Bethlehem Steel, Texaco, Westinghouse Electric, Woolworth, and Union Carbide. However, we could not find data for these firms over the sample period of July 1986 to September 2007.

re-estimate the intertemporal relation in eq. (14) using the CRSP value-weighted index as a proxy for the market portfolio. The risk-return coefficient on $\sigma_{im,t+1}$ is found to be 2.91 with the *t*-statistic of 5.92, indicating a positive and significant risk-return tradeoff. We also test the joint hypothesis of all intercepts equal zero and the Wald statistic is about 5.78 with a *p*-value of one. The results turn out to be very similar to our original findings reported in Table 2, indicating that the survivorship bias does not have any influence over the intertemporal risk-return relation.

As a further robustness check about the choice of a particular set of stocks or particular index, we replicate our main findings using individual stocks in the S&P 100 index. Out of 100 stocks currently in the S&P 100 index, 71 stocks (listed in Appendix C) have daily data from July 10, 1986 to September 28, 2007. We first estimate the DCC based conditional covariances of each stock with the market portfolio (proxied by the CRSP value-weighted index) and then estimate the SUR panel regression based on this new sample of 71 stocks. The common slope coefficient on $\sigma_{im,t+1}$ is found to be 4.58 with the *t*-statistic of 7.50, indicating a positive and highly significant relation between expected return and risk on S&P 100 stocks. We also test the joint hypothesis of all intercepts equal zero and the Wald statistic is about 56.14 with a *p*-value of 0.91. The results provide evidence that the significantly positive relation between risk and return is robust across different stock samples.

4.3. One-Step Estimation with Dow Stocks and Book-to-Market Portfolios

We have so far estimated the risk aversion coefficient in two steps; first obtain the conditional covariances with DCC and then use the covariance estimates in the panel regression with a common slope coefficient. Some readers might be concerned that the covariance matrices implied by the DCC model were not used in estimating risk premia or in computing their standard errors. A common worry in testing asset pricing models is that time-varying covariances are measured with error. Since this is the first study that utilizes DCC based conditional covariances in examining an asset pricing model, we are not aware of the significance of measurement errors in covariances.

As pointed out by earlier studies, estimating multivariate GARCH-in-mean models with time-varying conditional correlations is an extremely difficult task, especially if the number of cross-sections gets bigger. Early work on time-varying covariances in large dimensions was carried out by Bollerslev (1990) in his constant correlation model, where the volatilities of each asset were allowed to vary through time but the correlations were time invariant (see Tse (2000) and Engle (2008a) for a review of this topic). Recently, the DECO model of Engle and Kelly (2007) and the MacGyver estimation method of Engle (2008b) deal with the computation of correlations for a large number of assets with an assumption that the correlation amongst assets changes through time but is constant across the cross-section of assets.[12] We should note that estimating time-varying correlations based on a multivariate GARCH model with a constant mean is easier than estimating time-varying correlations based on a multivariate GARCH-in-mean model. In this paper, we estimate in one step the time-varying conditional correlations as well as the parameters of time-varying conditional mean in a multivariate GARCH-in-mean framework.

To ease the parameter convergence, we use correlation targeting assuming that the time-varying correlations mean reverts to the sample correlations. To reduce the overall time of maximizing the conditional log-likelihood, we first estimate all pairs of bivariate GARCH-in-mean model and then use the median values of A, a_1 and a_2 as starting values along with the bivariate GARCH-in-mean estimates of variance parameters (β_0, β_1, β_2). Even after going through these steps to increase the speed of parameter convergence, it takes very long time to obtain the full set of parameters in the multivariate GARCH-in-mean model with 30 stocks and 5,354 time-series observations.

The common slope and the intercepts are estimated using daily returns on the Dow 30 stocks for the period July 10, 1986 to September 28, 2007. The market portfolio is proxied by the value-weighted CRSP index. The risk-return coefficient (A) on $\sigma_{im,t+1}$ is estimated to be 3.97 with the t-statistic of 5.84. The magnitude and statistical significance of the common slope turns out to be similar to our earlier findings from the two-step estimation. As shown in Table 2, the risk aversion parameter (A) is estimated to be 3.26 with t-stat. = 6.56 from the SUR panel regression. We test the joint hypothesis of all intercepts equal zero in the multivariate GARCH-in-mean model. The Wald statistic is found to be 26.72 with a p-value of 0.64. Overall, the one-step and two-step estimation results provide similar evidence such that there is a significantly positive relation between risk and return on Dow stocks and the abnormal daily returns are economically and statistically insignificant.

To the best of our knowledge, this is the first study that examines ICAPM using individual stocks. The existing literature generally focuses on well-diversified portfolios. Although measurement errors in conditional covariances do not have any significant effects on the magnitude and statistical significance of risk aversion coefficients, we decide to compare the one-step and two-step estimation results using different test assets that are more common in the literature. Specifically, we use daily returns on the value-weighted book-to-market (BM) portfolios available in Kenneth French's online data library. The longest available sample period is from July 1, 1963 to December 31, 2007. Results are reported for the entire sample as well as the shorter sample from July 10, 1986 to September 28, 2007, corresponding to the period of Dow 30 stocks.

[12] An alternative method was suggested by Engle (2008b) where he fit many pairs of bivariate estimators, governed by simple dynamics, and then took a median of these estimators. This method is known as the MacGyver estimation strategy. Engle, Shephard, and Shephard (2008) introduce a new estimation methodology that has some similarities to the MacGyver strategy, but it is more efficient.

Using 10 book-to-market portfolios and the value-weighted CRSP index as a proxy for the market portfolio, we estimate the common slope coefficient (A) and the intercepts in one step based on the multivariate GARCH-in-mean model with DCC. As reported in Panel A of Table 3, the risk aversion coefficient is estimated to be 2.90 with t-stat. = 5.43 for the long sample period 1963-2007 and 2.46 with t-stat. = 3.81 for the shorter sample period 1986-2007. The Wald statistic from testing the joint hypothesis of all intercepts equal zero in the multivariate GARCH-in-mean model turns out to be 28.84 with *p*-value of 0.13% for the long sample 1963-2007, whereas the Wald statistic is 8.20 with *p*-value of 61% for the shorter sample 1986-2007. These results indicate a positive and significant relation between expected return and risk on the value-weighted book-to-market portfolios for both sample periods. The abnormal returns are jointly zero for the short sample, suggesting validity of the ICAPM. However, for the long sample, the conditional covariances cannot fully explain the time-series and cross-sectional variation in portfolio returns since the null hypothesis is strongly rejected.

In addition to testing the significance of common slope and intercepts, we examine whether there is a significant difference between the average risk-adjusted returns of value (high BM) and growth (low BM) portfolios. Panel A shows that for the long sample, the average risk-adjusted return difference between the value and growth portfolios is about 0.000266 [= 0.000194 – (–0.000072)] per day, corresponding to 6.70% per annum. This difference is also statistically significant with the Wald stat. = 14.25 (*p*-value = 0.02%). However, for the short sample, the average risk-adjusted return difference between the value and growth portfolios is statistically insignificant. More specifically, the difference is about 0.000189 [= 0.000225 – 0.000036] per day, corresponding to 4.76% per annum. The Wald statistic from testing the differences between intercepts on high BM and low BM portfolios is about 2.56 with *p*-value of 11%.

We now compare the magnitude and statistical significance of the parameters from the one-step and two-step estimation methodology based on the value-weighted book-to-market portfolios. First, we estimate the DCC based conditional covariances of each BM portfolio with the market and then use the covariance estimates in the SUR panel regression with a common slope coefficient. As presented in Panel B of Table 3, the risk aversion coefficient is estimated to be 2.15 with t-stat. = 4.88 for the long sample 1963-2007 and 1.95 with t-stat. = 3.28 for the shorter sample 1986-2007. The Wald statistic from testing the joint hypothesis of all intercepts equal zero in the multivariate GARCH-in-mean model turns out to be 26.19 with *p*-value of 0.35% for the long sample 1963-2007, whereas the Wald statistic is 18.52 with *p*-value of 4.68% for the shorter sample 1986-2007. These results indicate a positive and significant relation between expected return and risk on the value-weighted book-to-market portfolios for both sample periods. The abnormal returns from the two-step estimation are also large in magnitude and jointly different from zero for both sample periods, implying that the conditional covariances cannot fully explain the time-series and cross-sectional variation in portfolio returns.

Based on the estimates from the two-step methodology, we examine if there is a significant difference between the average risk-adjusted returns of value and growth portfolios. Panel B shows that for the long sample, the average risk-adjusted return difference between the value and growth portfolios is about 0.000276 [= 0.000262 – (–0.000014)] per day, corresponding to 6.96% per annum. This difference is statistically significant with the Wald stat. = 5.23 (p-value = 2.22%). However, for the short sample, the average risk-adjusted return difference between the value and growth portfolios is statistically insignificant. Specifically, the difference is 0.000193 [= 0.000299 – 0.000106] per day, corresponding to 4.86% per annum. The Wald statistic from testing the differences between the intercepts on high BM and low BM portfolios is about 1.01 with p-value of 31%.

Overall, the results in Table 3 indicate that the one-step and two-step estimation methods generate similar conclusions about the significance and validity of ICAPM. The benefit of using the two-step estimation methodology is that we can easily test the robustness of our findings by including a number of other covariances between returns and factors or state variables. Unfortunately, we cannot test whether macroeconomic, financial and volatility factors are priced in the ICAPM framework based on the one-step estimation. With the current state of technology, we could not estimate the maximum likelihood parameters after including the hedging demand component of the ICAPM. Hence, from now on, we will present evidence from the two-step estimation with SUR.

4.4. Robustness Check

4.4.1. Controlling for the October 1987 crash

Table 4 presents results from testing the significance of an intertemporal risk-return tradeoff after controlling for the October 1987 crash. The following system of equations is estimated for Dow 30 stocks:

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B \cdot X_t + e_{i,t+1}, \qquad (17)$$

where X_t denotes a day, week, and month dummy for October 1987. Dum_day equals one for the day of October 19, 1987 and zero otherwise; Dum_week equals one for the week of October 19, 1987 – October 23, 1987 and zero otherwise; and Dum_month equals one for the month of October 1, 1987 – October 30, 1987 and zero otherwise. As expected, for all measures of the market portfolio, the common slope (B) on X_t is estimated to be negative and highly significant for the day, week, and month dummy. Each panel of Table 4 presents positive and highly significant common slope coefficients (A) on $\sigma_{im,t+1}$.

Table 5 checks the robustness of our main findings for the sample period of January 4, 1988 to September 28, 2007 that excludes October 1987. As shown in the last column of Table 5, the risk-return coefficient on $\sigma_{im,t+1}$ is estimated to be positive and highly significant for all measures of the market portfolio. The first column of Table 5 reports very small Wald statistics from testing the joint hypothesis of all intercepts equal zero. The second column of Table 5 presents economically and statistically insignificant average abnormal returns. Overall, the panel regression results in Tables 4 and 5 indicate that the economically and statistically significant relation between risk and return remains intact after controlling for the October 1987 crash.

4.4.2. Controlling for the lagged returns on individual stocks and the market portfolio

Table 6 examines the significance of common slope on the conditional covariance of Dow 30 stocks with the market portfolio after controlling for the lagged daily excess returns on individual stocks $(R_{i,t})$, the lagged daily excess return on the market portfolio $(R_{m,t})$, and the crash dummy. The first column of each panel in Table 6 provides strong evidence for a significantly positive relation between expected return and market risk after controlling for the lagged returns and the October 1987 crash. The risk-return coefficient (A) is stable across different market portfolios and highly significant with the t-statistics ranging from 5.20 to 7.94. Another notable point in Table 6 is that the common slope (B) on the lagged returns is found to be negative and statistically significant, indicating negative first-order autocorrelation in daily stock returns.[13]

4.4.3. Subsample analysis

Table 7 investigates whether the positive relation between expected return and risk remains economically and statistically significant for different subsample periods.[14] For the sample period of January 4, 1988 – September 28, 2007 (excluding the October 1987 crash), the common slope (A) is estimated to be 2.95 with the t-statistic of 3.63. For the full sample period of July 10, 1986 – September 28, 2007, A is estimated to be 3.26 with the t-statistic of 6.56. We break the entire sample into two and re-estimate the intertemporal relation for two subsamples. For the first subsample of July 10, 1986 – February 6, 1997, the risk-return coefficient is about 2.75 with t-stat. = 4.86. For the second subsample of February 7, 1997 – September 28, 2007, the risk aversion coefficient turns out to be somewhat higher at 3.12 with t-stat. = 3.17.

These estimates are relatively stable across different sample periods. The t-statistics show that all estimates are highly significant. The consistent estimates and high t-statistics across different market portfolios, sample periods, and after controlling for the lagged returns and the crash dummy suggest that the identified positive risk-return tradeoff is not only significant, but also robust.

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[13] Jegadeesh (1990), Lehman (1990), Lo and MacKinlay (1990), and Boudoukh, Richardson, and Whitelaw (1994) provide evidence for the significance of short-term reversal (or negative autocorrelation in short-term returns).

[14] To save space, starting with Table 7 we only present results based on the market portfolio measured by the value-weighted NYSE/AMEX/NASDAQ index. At an earlier stage of the study, we replicate our findings reported in Table 7 and follow-up tables using the NYSE, S&P 500, S&P 100, and DJIA indices. The results from these alternative measures of the market portfolio turn out to be very similar and they are available upon request.

4.4.4. Alternative specifications of the conditional mean

As shown in equation (10), the conditional mean of daily excess returns on individual stocks and the market portfolio is assumed to follow an AR(1) process. In this section, we consider alternative specifications of the conditional mean and re-estimate the system of equations in (14). As presented in Table 8, when the daily excess returns on Dow 30 stocks and the market portfolio are assumed to be constant, the risk aversion parameter is estimated to be 3.06 with *t*-stat. = 5.97. When the conditional mean is parameterized as an MA(1) process ($R_{i,t+1} = \alpha_0^i + \alpha_1^i \varepsilon_{i,t} + \varepsilon_{i,t+1}$), the common slope (*A*) on $\sigma_{im,t+1}$ is found to be 3.32 with the *t*-statistic of 6.64. When the conditional mean of daily excess returns is modeled with ARMA(1,1) process ($R_{i,t+1} = \alpha_0^i + \alpha_1^i R_{i,t} + \alpha_2^i \varepsilon_{i,t} + \varepsilon_{i,t+1}$), the risk-return coefficient is about 3.58 with *t*-stat. = 7.16. The common slope estimates are stable across different specifications of the conditional mean, between 3.06 and 3.58, with the *t*-statistics ranging from 5.97 to 7.16. The first column of Table 8 presents very small Wald statistics from testing the joint hypothesis of all intercepts equal zero. The second column of Table 8 reports insignificant average abnormal returns. Overall, the parameter estimates in Table 8 indicate that the economically and statistically significant relation between risk and return is not sensitive to the choice of conditional mean specification.[15]

4.4.5. Controlling for macroeconomic variables

To determine whether the level or changes in macroeconomic variables can influence time-series variation in stocks returns and hence may affect the risk-return tradeoff, we directly incorporate the lagged macroeconomic variables to the system of equations:

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B \cdot X_t + e_{i,t+1},$$

where X_t denotes a vector of control variables including the default spread (DEF_t), term spread $(TERM_t)$, federal funds rate (FED_t), and the crash dummy (Dum_month) that equals one for the month of October 1, 1987 – October 30, 1987 and zero otherwise.

Table 9 tests the significance of common slope (*A*) on the conditional covariance of Dow 30 stocks with the market portfolio after controlling for DEF_t, $TERM_t$, and FED_t as well as their first differences denoted by ΔDEF_t, $\Delta TERM_t$, and ΔFED_t. The first column of Table 9 provides strong evidence for a significantly positive relation between expected return and market risk after controlling for macroeconomic variables and the October 1987 crash. The risk-return coefficient (*A*) is stable across different controls, in the range of 3.25 to 3.90, and it is highly significant with the *t*-statistics ranging from 6.54 to 7.69. An interesting observation in Table 9 is that the common slope (*B*) on the lagged

[15] Appendix D provides evidence that the significantly positive relation between risk and return is robust across different conditional covariance specifications as well.

macroeconomic variables is found to statistically insignificant, except for some marginal significance for the change in federal funds rate.[16] The slope on ΔFED_t is found to be between –0.08 and –0.09 with the *t*-statistics ranging from –1.64 to –1.74. This result suggests that an unexpected increase (decrease) in the fed funds rate will reduce (raise) stock prices over the next trading day, implying a negative relation between stock returns and interest rates in the short run. In fact, this is what we commonly observe in the U.S. stock market after the Federal Reserve's unexpected increase or decrease in interest rates.

4.4.6. Controlling for the conditional idiosyncratic and total volatility of individual stocks

Several asset pricing models, e.g., Levy (1978) and Merton (1987), show that limited diversification results in an equilibrium where expected returns compensate not only for market risk but also for idiosyncratic risk. Motivated by these theoretical models and investors' preferences for holding less than perfectly diversified portfolios, recent empirical studies investigate the cross-sectional relation between expected stock returns and idiosyncratic and total volatility. Ang, Hodrick, Xing and Zhang (2006) find a strong negative relation between idiosyncratic volatility and the cross-section of expected stock returns. Spiegel and Wang (2005) and Fu (2008) use conditional measures of idiosyncratic volatility and find a positive and significant relation between idiosyncratic risk and expected returns. Bali and Cakici (2008) focus on the methodological differences that led the previous studies to develop conflicting evidence. Goyal and Santa-Clara (2003) and Bali, Cakici, Yan, and Zhang (2005) investigate the significance of a time-series relation between aggregate idiosyncratic volatility and excess market returns. After testing if the equal-weighted and value-weighted average idiosyncratic volatility of individual stocks can predict the one month ahead returns on the market portfolio, these studies provide conflicting evidence as well. Overall, the existence and direction of both time-series and cross-sectional relations between idiosyncratic volatility and expected returns is still a subject of an intense debate.

Within the ICAPM framework, we examine if the conditional idiosyncratic and total volatility of individual stocks can predict time-series variation in one day ahead returns on Dow 30 stocks. We also check whether the conditional idiosyncratic and total volatility have any influence on the risk-return tradeoff. The significance of firm-level volatility is tested by estimating the following system of equations:

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B \cdot VOL_{i,t+1} + e_{i,t+1}, \qquad (18)$$

[16] Although one would think that unexpected news in macroeconomic variables could be viewed as risks that would be rewarded in the stock market, we find that the level and changes in term and default spreads do not affect time-series variation in daily stock returns. Our interpretation is that it would be very difficult for macroeconomic variables (except for the overnight fed funds rate) to explain daily variations in stock returns. If we examined the risk-return tradeoff at lower frequency (such as monthly or quarterly frequency), we might observe significant impact of macroeconomics variables on monthly or quarterly variations in stock returns.

where $VOL_{i,t+1}$ is the time-*t* expected conditional volatility of $R_{i,t+1}$. We consider three alternative measures of firm-level volatility: (1) The range daily standard deviation is defined in eq. (5), $\ln(P_{i,t}^{\max}) - \ln(P_{i,t}^{\min})$, that can be interpreted as the total risk of an individual stock; (2) The conditional variance of daily excess returns is estimated using the AR(1)-GARCH(1,1) model given in eqs. (6)-(7) and it can be viewed as the conditional total volatility of individual stocks; and (3) The conditional variance of daily excess returns is estimated using the three-factor Fama-French (1993) model given in eqs. (8)-(9) and it is considered as the conditional idiosyncratic volatility of individual stocks.

Table 10 tests the significance of common slope (*A*) on the conditional covariance of Dow 30 stocks with the market portfolio after controlling for the conditional GARCH-based total and idiosyncratic volatility of individual stocks as well as the range-based volatility. The first column of Table 10 provides strong evidence for a significantly positive relation between expected return and market risk after controlling for firm-level volatility and the October 1987 crash. The risk-return coefficient estimates (*A*) are found to be in the range of 2.97 to 3.85, and highly significant with the *t*-statistics ranging from 5.82 to 7.13. The second and third columns of Table 10 show that the common slope (*B*) on the range-based total volatility is positive and statistically significant, whereas the slope on the GARCH-based total risk is positive but marginally significant. A notable point in Table 10 is that the common slope on the GARCH-based conditional idiosyncratic volatility is estimated to be positive, but statistically insignificant. These results suggest that an increase in firm-specific total volatility (not idiosyncratic volatility) of a Dow stock leads to an increase in the stock's one day ahead expected returns.

4.4.7. Controlling for the conditional volatility of the market portfolio

Earlier studies examine the significance of an intertemporal relation between the conditional mean and conditional volatility of excess returns on the market portfolio. The results from testing whether the conditional volatility of the market portfolio predicts time-series variation in future returns on the market portfolio have so far been inconclusive. In this section, we investigate if the conditional volatility of the market portfolio can predict time-series variation in individual stock returns. We also check whether the conditional volatility of the market portfolio has any impact on the daily risk-return tradeoff. The significance of market volatility is determined by estimating the following system of equations:

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B \cdot VOL_{m,t+1} + e_{i,t+1}, \tag{19}$$

where $VOL_{m,t+1}$ is the time-*t* expected conditional volatility of $R_{m,t+1}$ obtained from the GARCH, Range, and Option Implied Volatility models, i.e., $VOL_{m,t+1}$ is (1) the conditional variance of daily excess returns on the market portfolio estimated using the AR(1)-GARCH(1,1) model; (2) the range daily standard deviation of the market portfolio defined in eq. (4) as $\ln(P_{m,t}^{\max}) - \ln(P_{m,t}^{\min})$; and (3) the implied market volatility (VXO_t) obtained from the S&P 100 index options.

Table 11 provides strong evidence for a significant link between expected returns on individual stocks and their conditional covariances with the market even after controlling for the conditional volatility of the market portfolio. For all measures of market volatility, the risk-return coefficients (*A*) are estimated to be positive, in the range of 2.84 to 3.41, and highly significant with the *t*-statistics ranging from 5.39 to 6.49. Another notable point in Table 11 is that the common slope (*B*) on the GARCH, range, and implied volatility estimators of the market portfolio is found to be positive and statistically significant with and without the October 1987 crash dummy. These results indicate that an increase in daily market volatility brings about an increase in expected returns on Dow 30 stocks over the next trading day.

4.5. Risk-return tradeoff with intertemporal hedging demand

This section tests the significance of risk premium induced by the conditional variation with the market portfolio after controlling for risk premia induced by the conditional covariation of individual stocks with macroeconomic variables (fed funds rate, default spread, and term spread), financial factors (size, book-to-market, and momentum), and volatility measures (implied, GARCH, and range volatility).

4.5.1. Risk premia induced by conditional covariation with macroeconomic variables

Financial economists often choose certain macroeconomic variables to control for stochastic shifts in the investment opportunity set. The widely used variables include the short-term interest rates, default spreads on corporate bond yields, and term spreads on Treasury yields. To investigate how these macroeconomic variables vary with the investment opportunity and whether covariations of individual stocks with them induce additional risk premia, we first estimate the conditional covariance of these variables with excess returns on each stock and then analyze how the stocks' excess returns respond to their conditional covariance with these economic factors. In estimating the conditional covariances, we use the level and changes in daily federal funds rates, the level and changes in daily default spreads, and the level and changes in term spreads, as described in Section 3.1.1.

Table 12 reports the common slope estimates (A, B_1, B_2, B_3) and their *t*-statistics from the following system of equations:

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B_1 \cdot \sigma_{i,DEF,t+1} + B_2 \cdot \sigma_{i,TERM,t+1} + B_3 \cdot \sigma_{i,FED,t+1} + e_{i,t+1}, \quad (20)$$

where $\sigma_{i,DEF,t+1}$ is the conditional covariance between daily excess returns on stock i and the level or change in daily default spreads, $\sigma_{i,TERM,t+1}$ is the conditional covariance between daily excess returns on stock i and the level or change in daily term spreads, and $\sigma_{i,FED,t+1}$ is the conditional covariance between daily excess returns on stock i and the level or change in daily fed funds rate.

The parameter estimates in Table 12 reveal several important results. First, incorporating the covariance of stock returns with any of these macroeconomic variables does not alter the magnitude and statistical significance of the risk aversion estimates. In all cases, the common slope coefficient (A) on $\sigma_{im,t+1}$ is positive, in the range of 3.00 and 3.28, and highly significant with the t-statistics between 5.25 and 6.60. Second, the slope coefficient (B_1) on $\sigma_{i,DEF,t+1}$ is positive, but statistically insignificant. If B_1 were statistically significant, the positive slope would indicate that the upward movements in default spread predict favorable shifts in the investment opportunity set. Third, the common slopes (B_2, B_3) on $\sigma_{i,TERM,t+1}$ and $\sigma_{i,FED,t+1}$ are negative, but their t-statistics are extremely low. If B_2 and B_3 were statistically significant, the negative coefficients would imply that an increase in term spread and fed funds rate predicts a downward shift in optimal consumption or unfavorable shifts in the investment opportunity set. However, we cannot draw any of these conclusions because the conditional covariances of individual stocks with macro variables turn out to be very poor predictors of future stock returns.

4.5.2. Risk premia induced by conditional covariation with SMB, HML, and MOM

In this subsection, we take the size (*SMB*), book-to-market (*HML*), and momentum (*MOM*) factors of Fama and French to describe the state of the investment opportunity, and we investigate whether covariations of individual stocks with these three factors induce additional risk premia on Dow 30 stocks. We measure the conditional covariance of each stock with the financial factors and estimate the following system of equations:

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B_1 \cdot \sigma_{i,SMB,t+1} + B_2 \cdot \sigma_{i,HML,t+1} + B_3 \cdot \sigma_{i,MOM,t+1} + e_{i,t+1}, \quad (21)$$

where $\sigma_{i,SMB,t+1}$, $\sigma_{i,HML,t+1}$, and $\sigma_{i,MOM,t+1}$ measure the time-t expected conditional covariance between the time-(t+1) excess return on stock i and the level and change in *SMB*, *HML*, and *MOM*, respectively. From the estimates of B_1, B_2, and B_3, we can learn how investors react to the covariations of stock returns with financial factors.

Table 13 provides strong evidence for a significant link between expected returns on Dow 30 stocks and their conditional covariances with the market after controlling for risk premia induced by the conditional covariation with *SMB*, *HML*, and *MOM*. The risk-return coefficients (A) are estimated to be in the range of 3.25 to 4.84 and highly significant with the t-statistics ranging from 4.66 to 6.88. The conditional covariances of stock returns with the size and momentum factors do not have significant predictive power for one day ahead returns on Dow 30 stocks. In other words, the level and innovations in the *SMB* and *MOM* factors are not priced in the stock market. Another notable point in Table 13 is that the common slope (B_2) on $\sigma_{i,HML,t+1}$ is found to be positive and statistically significant for all risk-return specifications considered in the paper. Thus, an increase in the covariance of a stock return with the *HML* factor predicts an increase in the stock's expected excess return over the next trading day.

The positive slope estimates on $\sigma_{i,HML,t+1}$ suggest that upward movements in the *HML* factor predict favorable shifts in the investment opportunity set, implying that the *HML* (or value premium) is a priced risk factor that is correlated with innovations in investment opportunities. These results are also consistent with the recent empirical evidence provided by Campbell and Vuolteenaho (2004), Brennan, Wang, and Xia (2004), Petkova and Zhang (2005), and Petkova (2006) as well as with the recent theoretical models of Gomes, Kogan, and Zhang (2003) and Zhang (2005).[17]

4.5.3. Risk premium induced by conditional covariation with unexpected market volatility

Following Campbell (1993, 1996), we assume that investors want to hedge against unexpected change in future market volatility defined here as the first-difference of the GARCH conditional volatility of S&P 500 index return $(\Delta GARCH_{m,t+1})$, the first-difference of the options implied volatility of S&P 500 index return $(\Delta VXO_{m,t+1})$, and the first-difference of the range volatility of S&P 500 index return $(\Delta Range_{m,t+1})$. In this section, we test whether stocks that have higher correlation with the change in market volatility yield lower expected return.

When considering stochastic investment opportunities governed by innovations in future market volatility, we estimate the intertemporal relation from the following system of equations,

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B \cdot \sigma_{i,\Delta VOL_m,t+1} + e_{i,t+1}, \tag{22}$$

where $\sigma_{i,\Delta VOL_m,t+1}$ measures the time-*t* expected conditional covariance between $R_{i,t+1}$ and the change in the conditional volatility of the market portfolio denoted by $\Delta VOL_{m,t+1}$. We use three alternative measures of $\Delta VOL_{m,t+1}$: (1) The change in the GARCH conditional volatility of S&P 500 index return $(\Delta GARCH_{m,t+1})$; (2) The change in the option implied volatility of S&P 500 index return $(\Delta VXO_{m,t+1})$; and (3) The change in the range volatility of S&P 500 index return $(\Delta Range_{m,t+1})$.

Under the null hypothesis of Campbell's (1993, 1996) ICAPM, the common slope (A) on $\sigma_{im,t+1}$ should be positive and significant, and the common slope (B) on $\sigma_{i,\Delta VOL_m,t+1}$ should be negative and

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[17] We should note that the explanation of value premium within the conditional CAPM framework is still a subject of an intense debate. Lettau and Ludvigson (2001) and Ang and Chen (2007) find that the conditional CAPM helps explain the return difference of value and growth stocks. However, Lewellen and Nagel (2006) provide evidence that is not in agreement with the findings of Ang and Chen (2007). Fama and French (2006) are also skeptical about the empirical performance of the conditional CAPM to explain value premium. Chen (2003) tests whether superior returns to value stocks can be explained by exposures to time-variations in the forecasts of future market returns and future market volatilities and his results indicate that value premium cannot be explained in the ICAPM framework.

significant. As shown in Table 14, the risk-return coefficient (*A*) on $\sigma_{im,t+1}$ is estimated to be in the range of 1.41 to 3.02 with the *t*-statistics ranging from 2.02 to 5.53, implying a positive intertemporal relation between expected return and market risk. For the GARCH and range-based volatility of the market portfolio, the common slope (*B*) on $\sigma_{i,\Delta VOL_m,t+1}$ is estimated to be between –0.26 and –0.29 and highly significant. For the options implied volatility of the market portfolio, the common slope (*B*) on $\sigma_{i,\Delta VOL_m,t+1}$ is estimated to be between –0.41 and –0.51 and highly significant. These results imply a negative intertemporal relation between expected return and volatility risk.[18] In other words, stocks that have higher correlation with the changes in expected future market volatility yield lower expected return.

5. Conclusion

We estimate the daily intertemporal relation between expected return and risk using a cross section of 30 stocks in the Dow Jones Industrial Average. By so doing, we not only guarantee the cross-sectional consistency of the estimated intertemporal relation, but also gain statistical power by pooling multiple time series together for a joint estimation with common slope coefficients. The average relative risk aversion is estimated to be positive, highly significant, and robust to variations in the market portfolios, sample periods, data sets, estimation methodologies, and the conditional mean and covariance specifications. The positive risk-return tradeoff at daily frequency remains intact after controlling for (*i*) the level and changes in macroeconomic variables, (*ii*) the October 1987 crash, (*iii*) the lagged returns on individual stocks and the market portfolio, (*iv*) the conditional idiosyncratic and total volatility of individual stocks, and (*v*) the conditional volatility of the market portfolio. The magnitude of the risk-return coefficient is also economically sensible, ranging from two to four.

When investigating the intertemporal hedging demands and the associated risk premia induced by the conditional covariation of Dow 30 stocks with a set of macroeconomic variables, we find that the common slope coefficients on the conditional covariances with the fed funds rate, default and term spreads are statistically insignificant, implying that the level and innovations in macro variables do not contain any systematic risks rewarded in the stock market at daily frequency. We investigate whether the *SMB*, *HML*, and *MOM* factors of Fama and French move closely with investment opportunities and whether covariations with these three factors induce additional risk premia on Dow 30 stocks. The results indicate that although the *SMB* and *MOM* factors are not priced in the ICAPM framework, the *HML* is a priced risk factor and can be viewed as a proxy for investment opportunities. Finally, we assume that investors want to hedge against the changes in future market volatility and we use three different

[18] Bakshi and Kapadia (2003) find the volatility risk premium to be negative in index options markets. We examine whether the volatility risk premium is negative within the ICAPM framework of Campbell (1993, 1996) using individual stocks.

measures (GARCH, implied, range) to test whether stocks that have higher correlation with the innovations in market volatility yield lower expected return. The parameter estimates provide strong evidence for a significantly negative relation between expected return and volatility risk. However, incorporating the conditional covariation with any of these state variables does not change the positive risk premium induced by the conditional covariation with the market portfolio.

By pooling the time series and cross section together, we find that the mean-reverting DCC-based conditional covariance estimates predict the time-series variation in stock returns and they generate significant and reasonable risk premium. We also find that the intertemporal risk-return tradeoff is significantly positive at daily frequency and the relative risk aversion estimates are within a reasonable range. The robust, significant and sensible estimates highlight the added benefits of using the conditional measures of covariance risk and simultaneously maintaining the cross-sectional consistency in estimating the ICAPM.

Appendix A. Stocks in the Dow Jones Industrial Average

According to Dow Jones, the industrial average started out with 12 stocks in 1896: American Cotton Oil (traces remain in CPC International), American Sugar (eventually became Amstar Holdings), American Tobacco (killed by antitrust action in 1911), Chicago Gas (absorbed by Peoples Gas), Distilling and Cattle Feeding (evolved into Quantum Chemical), General Electric (the only survivor), Laclede Gas (now Laclede Group but not in the index), National Lead (now NL Industries but not in the index), North American (group of utilities broken up in 1940s), Tennesee Coal and Iron (gobbled up by U.S. Steel), U.S. Leather preferred (vanished around 1952), and U.S. Rubber (became Uniroyal, in turn bought by Michelin).

The number of stocks was increased to 20 in 1916. The 30-stock average made its debut in 1928, and the number has remained constant ever since.

Here are some of the recent changes.

- On March 17, 1997, Hewlett-Packard, Johnson & Johnson, Travelers Group, and Wal-Mart joined the average, replacing Bethlehem Steel, Texaco, Westinghouse Electric and Woolworth.
- In 1998, Travelers Group merged with CitiBank, and the new entity, CitiGroup, replaced the Travelers Group.
- On November 1, 1999, Home Depot, Intel, Microsoft, and SBC Communications joined the average, replacing Union Carbide, Goodyear Tire & Rubber, Sears, and Chevron.
- Between 1999 and 2004, several stocks in the index merged and/or changed names: Exxon became Exxon-Mobil after their merger; Allied-Signal merged with Honeywell and kept the Honeywell name; JP Morgan became JP Morgan Chase after their merger; Minnesota Mining and Manufacturing officially became 3M Corp; and Philip Morris renamed itself to Altria.
- On April 8, 2004, American International Group, Pfizer, and Verizon joined the average, replacing AT&T, Eastman Kodak, and International Paper.
- In 2007 SBC renamed itself to AT&T after completing the acquisition of that company.

This study is based on the latest stock composition of the Dow Jones Industrial Average. The ticker symbols and company names are reported in the following table.

MMM	3M Corporation	HD	Home Depot
AA	Alcoa	HON	Honeywell
MO	Altria (was Philip Morris)	INTC	Intel Corp.
AXP	American Express	IBM	International Business Machines
AIG	American Int'l Group	JNJ	Johnson & Johnson
T	AT&T Inc. (was SBC)	JPM	JP Morgan Chase
BA	Boeing	MCD	McDonalds
CAT	Caterpillar	MRK	Merck
C	CitiGroup	MSFT	Microsoft
KO	Coca Cola	PFE	Pfizer
DD	E.I. DuPont de Nemours	PG	Procter and Gamble
XOM	Exxon Mobil	UTX	United Technologies
GE	General Electric	VZ	Verizon Communications
GM	General Motors	WMT	Wal-Mart Stores
HPQ	Hewlett-Packard	DIS	Walt Disney Co.

Appendix B. Descriptive Statistics

Panel A. Daily Excess Returns on Dow 30 Stocks

This table presents summary statistics for the daily excess returns on Dow 30 Stocks. Mean, median, maximum, minimum, and standard deviation are reported for each stock. The descriptive statistics are computed for the longest common sample period from July 10, 1986 to September 28, 2007 (5,354 daily observations). The sample ends in September 28, 2007 for all series, but the start date is different and shown in the second column.

Stock	Start Date	Mean	Median	Maximum	Minimum	Std. Dev.
MMM	1/2/1970	0.000012	-0.000180	0.1104	-0.5086	0.0190
AA	1/2/1962	0.000155	-0.000210	0.1403	-0.5126	0.0236
MO	1/2/1970	0.000186	0.000136	0.1598	-0.7503	0.0232
AXP	4/1/1977	0.000159	-0.000210	0.1853	-0.6550	0.0238
AIG	9/7/1984	-0.000037	-0.000200	0.1102	-0.5169	0.0213
T	7/19/1984	-0.000057	-0.000190	0.1124	-0.6490	0.0212
BA	1/2/1962	0.000153	-0.000190	0.1525	-0.4905	0.0207
CAT	1/2/1962	0.000207	-0.000200	0.1453	-0.5116	0.0230
C	1/3/1977	0.000065	-0.000210	0.1831	-0.4896	0.0248
KO	1/2/1962	0.000124	-0.000160	0.1965	-0.4979	0.0202
DD	1/2/1962	0.000002	-0.000220	0.0986	-0.6786	0.0205
XOM	1/2/1970	0.000120	-0.000120	0.1788	-0.5029	0.0189
GE	1/2/1962	0.000027	-0.000180	0.1244	-0.6683	0.0221
GM	1/2/1962	-0.000059	-0.000300	0.1810	-0.5017	0.0219
HPQ	1/2/1962	0.000268	-0.000175	0.1728	-0.4901	0.0275
HD	8/20/1984	0.000289	-0.000150	0.1288	-0.4623	0.0258
HON	1/2/1970	0.000179	-0.000200	0.3122	-0.4976	0.0230
INTC	7/9/1986	0.000408	-0.000180	0.2010	-0.5319	0.0312
IBM	1/2/1962	0.000034	-0.000180	0.1314	-0.5092	0.0210
JNJ	1/2/1970	0.000088	-0.000140	0.1101	-0.5126	0.0207
JPM	12/30/1983	0.000100	-0.000200	0.1603	-0.5092	0.0234
MCD	1/2/1970	0.000044	-0.000195	0.1083	-0.5204	0.0213
MRK	1/2/1970	0.000052	-0.000140	0.1302	-0.6750	0.0227
MSFT	3/13/1986	0.000370	-0.000120	0.1955	-0.5350	0.0299
PFE	1/4/1982	-0.000019	-0.000200	0.1022	-0.6572	0.0235
PG	1/2/1970	0.000087	-0.000110	0.2216	-0.5039	0.0212
UTX	1/2/1970	0.000193	-0.000185	0.1004	-0.5184	0.0210
VZ	11/21/1983	-0.000052	-0.000200	0.1402	-0.5005	0.0192
WMT	8/25/1972	0.000110	-0.000200	0.1244	-0.4899	0.0230
DIS	1/2/1962	0.000143	-0.000180	0.1907	-0.7409	0.0241

Panel B. Daily Excess Returns on the Market Portfolio

This table presents summary statistics for the daily excess returns on the value-weighted NYSE/AMEX/NASDAQ, NYSE, S&P 500, S&P 100, and Dow Jones Industrial Average (DJIA). Mean, median, maximum, minimum, and standard deviation are reported for each index. To be consistent with the stock data, the descriptive statistics are computed for the sample period from July 10, 1986 to September 28, 2007 (5,354 daily observations).

Market Portfolio	Mean	Median	Maximum	Minimum	Std. Dev.
NYSE/AMEX/NASDAQ	0.00030	0.00070	0.0863	-0.1716	0.0099
NYSE	0.00023	0.00046	0.0898	-0.1920	0.0096
S&P 500	0.00022	0.00041	0.0907	-0.2049	0.0106
S&P 100	0.00023	0.00036	0.0888	-0.2119	0.0111
DJIA	0.00026	0.00039	0.1012	-0.2264	0.0107

Appendix C. Stocks in the S&P 100 Index for the Period of 1986-2007

Out of 100 stocks currently in the S&P 100 index, 71 stocks listed below have daily data from July 10, 1986 to September 28, 2007.

MMM	3M Corporation	HAL	Halliburton Company
ABT	Abbott Laboratories	HPQ	Hewlett-Packard
AA	Alcoa	HNZ	HJ Heinz
MO	Altria (was Philip Morris)	HD	Home Depot
AIG	American Int'l Group	HON	Honeywell
AEP	American Electric Power	IBM	International Business Machines
AXP	American Express	INTC	Intel
AMGN	Amgen	IP	International Paper
BUD	Anheuser-Busch Companies	JNJ	Johnson & Johnson
AAPL	Apple	JPM	JP Morgan Chase
T	AT&T	LTD	Limited Brands
AVP	Avon Products	MCD	McDonalds
BK	Bank of New York Mellon	MDT	Medtronic
BAC	Bank of America	MRK	Merck
BAX	Baxter International	MER	Merrill Lynch
BA	Boeing	MSFT	Microsoft
BMY	Bristol Mysers Squibb	NSC	Norfolk Southern
BNI	Burlington Northern Santa Fe	ORCL	Oracle
CPB	Campbell Soup	PEP	Pepsico
CAT	Caterpillar	PFE	Pfizer
CVX	Chevron	PG	Procter and Gamble
CI	Cigna	RTN	Raytheon
KO	Coca Cola	SLE	Sara Lee
CL	Colgate Palmolive	SLB	Schlumberger
CMCSA	Comcast	SO	Southern Co.
COP	ConocoPhillips	TGT	Target
CVS	CVS Caremark	TYC	Tyco International
DIS	Walt Disney	UTX	United Technologies
DOW	Dow Chemical	USB	US Bancorp
DD	E.I. DuPont de Nemours	VZ	Verizon Communications
EXC	Exelon	WMT	Wal-Mart Stores
FDX	FedEx	WFC	Wells Fargo
F	Ford Motor	WY	Weyerhaeuser
GD	General Dynamics	WMB	Williams Companies
GE	General Electric	XRX	Xerox
GM	General Motors		

Appendix D. Alternative Specification of the Conditional Covariance Process

Section 4 provides evidence from the conditional covariances estimated with the mean-reverting DCC model of Engle (2002). As a robustness check, in this appendix, we estimate the conditional covariance between excess returns on stock *i* and the market portfolio *m* based on the following bivariate GARCH(1,1) specification:

$$R_{i,t+1} = \alpha_0^i + \varepsilon_{i,t+1} \tag{D.1}$$

$$R_{m,t+1} = \alpha_0^m + \varepsilon_{m,t+1} \tag{D.2}$$

$$E_t\left[\varepsilon_{i,t+1}^2\right] \equiv \sigma_{i,t+1}^2 = \beta_0^i + \beta_1^i \varepsilon_{i,t}^2 + \beta_2^i \sigma_{i,t}^2 \tag{D.3}$$

$$E_t\left[\varepsilon_{m,t+1}^2\right] \equiv \sigma_{m,t+1}^2 = \beta_0^m + \beta_1^m \varepsilon_{m,t}^2 + \beta_2^m \sigma_{m,t}^2 \tag{D.4}$$

$$E_t\left[\varepsilon_{i,t+1}\varepsilon_{m,t+1}\right] \equiv \sigma_{im,t+1} = \beta_0^{im} + \beta_1^{im} \varepsilon_{i,t}\varepsilon_{m,t} + \beta_2^{im} \sigma_{im,t} \tag{D.5}$$

where $\sigma_{im,t+1}$ is the time-*t* expected conditional covariance between $R_{i,t+1}$ and $R_{m,t+1}$ at time (*t*+1). As shown in equation (D.5), the conditional covariance at time (*t*+1) is a function of the product of the time-*t* residuals ($\varepsilon_{i,t}\varepsilon_{m,t}$) and the time-*t* conditional covariance ($\sigma_{im,t}$).

The table below reports the common slope estimates (*A*) and their *t*-statistics (in parentheses) from the system of equations, $R_{i,t+1} = C_i + A\sigma_{im,t+1} + e_{i,t+1}$. As shown in the last column, the risk-return coefficient on $\sigma_{im,t+1}$ is estimated to be positive and highly significant with the *t*-statistics ranging from 5.58 to 6.19. The common slope estimates are stable across different market portfolios, between 2.99 and 3.70. The first column shows that the Wald statistics (with 30 degrees of freedom) are very small, failing to reject the null hypothesis of all intercepts equal zero.

Market Portfolio	Wald Test	*A*
NYSE/AMEX/NASDAQ	19.63 [0.93]	3.6996 (6.18)
NYSE	20.95 [0.89]	3.1953 (5.82)
S&P 500	18.97 [0.94]	3.5384 (6.19)
S&P 100	19.54 [0.93]	2.9933 (5.58)
DJIA	19.97 [0.92]	3.3290 (6.05)

References

Abel, A. B., 1988. Stock prices under time-varying dividend risk: An exact solution in an infinite-horizon general equilibrium model. *Journal of Monetary Economics* 22, 375–393.

Alizadeh, S., Brandt, M. W., Diebold, F. X., 2002. Range-based estimation of stochastic volatility models, *Journal of Finance* 57, 1047–1092.

Ang, A., Chen, J., 2007. CAPM over the long-run: 1926–2001. *Journal of Empirical Finance* 14, 1–40.

Ang, A., Hodrick, R. J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. *Journal of Finance* 61, 259–299.

Backus, D. K., Gregory, A. W., 1993. Theoretical relations between risk premiums and conditional variance. *Journal of Business and Economic Statistics* 11, 177–185.

Baillie, R. T., DeGennaro, R. P., 1990. Stock returns and volatility. *Journal of Financial and Quantitative Analysis* 25, 203–214.

Bakshi, G, Kapadia, N., 2003. Delta hedged gains and the negative market volatility risk premium. *Review of Financial Studies* 16, 527–566.

Bali, T. G., 2008. The intertemporal relation between expected returns and risk, *Journal of Financial Economics* 87, 101–131.

Bali, T. G., and Cakici, N., 2008. Idiosyncratic volatility and the cross-section of expected returns, *Journal of Financial and Quantitative Analysis* 43, 29–58.

Bali, T. G., Cakici, N., Yan, X., Zhang, Z., 2005. Does idiosyncratic risk really matter? *Journal of Finance* 60, 905–929.

Bali, T. G., Peng, L., 2006. Is there a risk-return tradeoff? Evidence from high frequency data. *Journal of Applied Econometrics* 21, 1169–1198.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. *Journal of Political Economy* 81, 637–654.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 31, 307–327.

Bollerslev, T., 1990. Modeling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. *Review of Economics and Statistics* 72, 498–505.

Bollerslev, T., Engle, R. F., Wooldridge, J. M., 1988. A capital asset pricing model with time-varying covariances. *Journal of Political Economy* 96, 116–131.

Bollerslev, T., Wooldridge, J. M., 1992. Quasi-maximum likelihood estimation and inference in dynamic models with time varying covariances. *Econometric Reviews* 11, 143–172.

Bollerslev, T., Zhou, H., 2006. Volatility puzzles: a simple framework for gauging return-volatility regressions *Journal of Econometrics* 131, 123–150.

Boudoukh, J., Richardson, M., Whitelaw, R. F., 1994. Insights on autocorrelations of short-horizon stock returns. *Review of Financial Studies* 7, 539–573.

Brandt, M. W., Diebold, F. X., 2006. A no-arbitrage approach to range-based estimation of return covariances and correlations, *Journal of Business* 79, 61–73.

Brandt, M. W., Kang, Q., 2004. On the relationship between the conditional mean and volatility of stock returns: a latent VAR approach, *Journal of Financial Economics* 72, 217–257.

Brennan, M., Wang, A., Xia, Y., 2004. Estimation and test of a simple model of intertemporal asset pricing. *Journal of Finance* 59, 1743–1775.

Breen, W., Glosten, L. R., Jagannathan, R., 1989. Economic significance of predictable variations in stock index returns. *Journal of Finance* 44, 1177–1189.

Campbell, J. Y., 1987. Stock returns and the term structure. *Journal of Financial Economics* 18, 373–399.

Campbell, J. Y., 1993. Intertemporal asset pricing without consumption data. *American Economic Review* 83, 487–512.

Campbell, J. Y., 1996. Understanding risk and return. *Journal of Political Economy* 104, 298–345.

Campbell, J. Y., Hentchel, L., 1992. No news is good news: an asymmetric model of changing volatility in stock returns. *Journal of Financial Economics* 31, 281–318.

Campbell, J. Y., Shiller, R., 1988. The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies* 1, 195–228.

Campbell, J. Y., Vuolteenaho, T., 2004. Bad Beta, Good Beta, *American Economic Review* 94, 1249–1275.

Carhart, M. M., 1997. On persistence in mutual fund performance. *Journal of Finance* 52, 57–82.

Chan, K. C., Karolyi, G. A., Stulz, R. M., 1992. Global financial markets and the risk premium on US equity. *Journal of Financial Economics* 32, 137–167.

Chen, J., 2003. Intertemporal CAPM and the cross-section of stock returns. Working Paper, University of Southern California.

Chou, R. Y., 1988. Volatility persistence and stock valuations: some empirical evidence using GARCH. *Journal of Applied Econometrics* 3, 279–294.

Christoffersen, P. F., Diebold, F. X., 2006. Financial asset returns, direction-of-change, forecasting, and volatility dynamics. *Management Science* 52, 1273–1287.

Ding, Z., Engle, R. F., 2001. Large-scale conditional covariance matrix modeling, estimation, and testing. *Academia Economic Papers* 2, 157–184.

Engle, R. F., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics* 20, 339–350.

Engle, R. F., 2008a. *Anticipating Correlations*. Princeton University Press. Forthcoming.

Engle, R. F., 2008b. High dimensional dynamic correlations. In J. L. Castle and N. Shephard (Eds.), The Methodology and Practice of Econometrics: Papers in Honour of David F Hendry. Oxford University Press. Forthcoming.

Engle, R. F., Kelly, B., 2007. Dynamic equicorrelation. Working Paper, Stern School of Business, New York University.

Engle, R. F., Shephard, N., Shephard K., 2008. Fitting and testing vast dimensional time-varying covariance models. Working Paper, New York University and University of Oxford.

Fama, E. F., French, K. R., 1992. Cross-section of expected stock returns. *Journal of Finance* 47, 427–465.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3–56.

Fama, E. F., French, K. R., 2006. The value premium and the CAPM. *Journal of Finance* 61, 2163–2185.

French, K. R., Schwert, G. W., Stambaugh, R., 1987. Expected stock returns and volatility. *Journal of Financial Economics* 19, 3–29.

Fu, F., 2008. Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics* forthcoming.

Gennotte, G., Marsh, T. A., 1993. Variations in economic uncertainty and risk premiums on capital assets. *European Economic Review* 37, 1021–1041.

Ghysels, E., Santa-Clara, P., Valkanov, R., 2005. There is a risk-return trade-off after all. *Journal of Financial Economics* 76, 509–548.

Glosten, L. R., Jagannathan, R., Runkle, D. E., 1993. On the relation between the expected value and the volatility of the nominal excess returns on stocks. *Journal of Finance* 48, 1779–1801.

Gomes, J., Kogan, L., Zhang, L., 2003. Equilibrium cross section of returns. *Journal of Political Economy* 111, 693–732.

Goyal, A., Santa-Clara, P., 2003. Idiosyncratic risk matters! *Journal of Finance* 58, 975–1008.

Guo, H., Whitelaw, R. F., 2006. Uncovering the risk-return relation in the stock market. *Journal of Finance* 61, 1433–1463.

Harrison, P., Zhang, H., 1999. An investigation of the risk and return relation at long horizons. *Review of Economics and Statistics* 81, 399–408.

Harvey, C. R., 2001. The specification of conditional expectations. *Journal of Empirical Finance* 8, 573–637.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. *Journal of Finance* 45, 881–898.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48, 65–91.

Jegadeesh, N., Titman, S., 2001. Profitability of momentum strategies: an evaluation of alternative explanations. *Journal of Finance* 56, 699–720.

Lettau, M., Ludvigson, S., 2001. Resurrecting the (C)CAPM: a cross-sectional test when risk premia are time-varying. *Journal of Political Economy* 109, 1238–1287.

Lehman, B., 1990. Fads, martingales, and market efficiency. *Quarterly Journal of Economics* 105, 1–28.

Levy, H., 1978. Equilibrium in an imperfect market: a constraint on the number of securities in the portfolio. *American Economic Review* 68, 643–658.

Lewellen, J., Nagel, S., 2006. The conditional CAPM does not explain asset-pricing anomalies. *Journal of Financial Economics* 82, 289–314.

Lo, A. W., MacKinlay, A. C., 1990. When are contrarian profits due to stock market overreaction? *Review of Financial Studies* 3, 175–205.

Lundblad, C., 2007. The risk return tradeoff in the long run: 1836–2003. *Journal of Financial Economics* 85, 123–150.

Merton, R. C., 1973. An intertemporal asset pricing model. *Econometrica* 41, 867–887.

Merton, R. C., 1980. On estimating the expected return on the market: an exploratory investigation. *Journal of Financial Economics* 8, 323–361.

Merton, R. C. 1987. A simple model of capital market equilibrium with incomplete information. *Journal of Finance* 42, 483–510.

Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: a new approach.*Econometrica* 59, 347–370.

Petkova, R., 2006, Do the Fama-French factors proxy for innovations in predictive variables? *Journal of Finance* 61, 581–612.

Petkova, R., and Zhang, L., 2005. Is value riskier than growth? *Journal of Financial Economics* 78, 187–202.

Rogers, William H., 1983, Analyzing complex survey data, Rand Corporation memorandum, Santa Monica, CA.

Rogers, William H., 1993, Regression standard errors in clustered samples, Stata Technical Bulletin Reprints STB-13, STB-18, 88–94.

Scruggs, J. T., 1998. Resolving the puzzling intertemporal relation between the market risk premium and conditional market variance: a two-factor approach. *Journal of Finance* 53, 575–603.

Scruggs, J., Glabadanidis, P., 2003. Risk premia and the dynamics covariance between stock and bond returns. *Journal of Financial and Quantitative Analysis* 37, 27–62.

Sentana, E., 1995. Quadratic ARCH models. *Review of Economic Studies* 62, 639–661.

Spiegel, M., Wang, X., 2005. Cross-sectional variation in stock returns: liquidity and idiosyncratic risk. Yale ICF Working Paper No. 05-13.

Tse, Y., 2000. A test for constant correlations in a multivariate GARCH model. *Journal of Econometrics* 98, 107–127.

Turner, C. M., Startz, R., Nelson, C. R., 1989. A markov model of heteroskedasticity, risk, and learning in the stock market. *Journal of Financial Economics* 25, 3–22.

Whitelaw, R. F., 1994. Time variations and covariations in the expectation and volatility of stock market returns. *Journal of Finance* 49, 515–541.

Whitelaw, R. F., 2000. Stock market risk and return: an equilibrium approach. *Review of Financial Studies* 13, 521–547.

Zhang, L., 2005. The value premium. *Journal of Finance* 60, 67–103.

Table 1
Maximum Likelihood Estimates of the Mean-Reverting DCC Parameters

Entries report the maximum likelihood parameter estimates (a_1, a_2) of the mean-reverting DCC model:

$$R_{i,t+1} = \alpha_0^i + \alpha_1^i R_{i,t} + \sigma_{i,t+1} u_{i,t+1}$$

$$R_{m,t+1} = \alpha_0^m + \alpha_1^m R_{m,t} + \sigma_{m,t+1} u_{m,t+1}$$

$$E_t\left[\varepsilon_{i,t+1}^2\right] \equiv \sigma_{i,t+1}^2 = \beta_0^i + \beta_1^i \sigma_{i,t}^2 u_{i,t}^2 + \beta_2^i \sigma_{i,t}^2$$

$$E_t\left[\varepsilon_{m,t+1}^2\right] \equiv \sigma_{m,t+1}^2 = \beta_0^m + \beta_1^m \sigma_{m,t}^2 u_{m,t}^2 + \beta_2^m \sigma_{m,t}^2 ,$$

$$E_t\left[\varepsilon_{i,t+1}\varepsilon_{m,t+1}\right] \equiv \sigma_{im,t+1} = \rho_{im,t+1} \cdot \sigma_{i,t+1} \cdot \sigma_{m,t+1} ,$$

$$\rho_{im,t+1} = \frac{q_{im,t+1}}{\sqrt{q_{ii,t+1} \cdot q_{mm,t+1}}}, \quad q_{im,t+1} = \bar{\rho}_{im} + a_1 \cdot \left(u_{i,t} \cdot u_{m,t} - \bar{\rho}_{im}\right) + a_2 \cdot \left(q_{im,t} - \bar{\rho}_{im}\right)$$

where $\bar{\rho}_{im}$ is the unconditional correlation between $u_{i,t}$ and $u_{m,t}$. The conditional correlations between the excess returns on the market portfolio and on each of the Dow 30 stocks are estimated based on daily returns from July 10, 1986 to September 28, 2007. The *t*-statistics of the parameter estimates are presented in parentheses.

Dow 30 Stocks	a_1	a_2	$a_1 + a_2$
MMM	0.0170 (11.93)	0.9779 (521.90)	0.9949
AA	0.0148 (7.83)	0.9791 (339.71)	0.9939
MO	0.0118 (9.69)	0.9865 (636.12)	0.9982
AXP	0.0201 (8.78)	0.9752 (308.45)	0.9953
AIG	0.0155 (7.96)	0.9790 (344.85)	0.9945
T	0.0102 (6.13)	0.9871 (438.40)	0.9973
BA	0.0157 (7.07)	0.9784 (280.78)	0.9942
CAT	0.0238 (15.11)	0.9669 (468.67)	0.9907
C	0.0581 (32.14)	0.9326 (327.32)	0.9907
KO	0.0183 (10.14)	0.9783 (425.03)	0.9965
DD	0.0175 (8.35)	0.9786 (342.16)	0.9960
XOM	0.0215 (10.37)	0.9730 (342.71)	0.9945

Table 1 (continued)

Dow 30 Stocks	a_1	a_2	$a_1 + a_2$
GE	0.0207 (9.48)	0.9686 (248.85)	0.9893
GM	0.0172 (7.03)	0.9778 (282.74)	0.9951
HPQ	0.0112 (8.42)	0.9816 (374.89)	0.9928
HD	0.0174 (6.69)	0.9740 (202.64)	0.9914
HON	0.0090 (5.69)	0.9858 (353.95)	0.9948
INTC	0.0197 (9.94)	0.9704 (246.95)	0.9901
IBM	0.0357 (12.67)	0.9561 (257.63)	0.9918
JNJ	0.0149 (7.79)	0.9823 (415.98)	0.9972
JPM	0.0278 (11.12)	0.9639 (311.53)	0.9917
MCD	0.0166 (6.44)	0.9788 (281.89)	0.9955
MRK	0.0156 (12.23)	0.9814 (614.52)	0.9970
MSFT	0.0299 (10.77)	0.9592 (233.43)	0.9891
PFE	0.0276 (10.77)	0.9604 (248.02)	0.9880
PG	0.0144 (10.67)	0.9828 (556.31)	0.9972
UTX	0.0091 (8.69)	0.9884 (591.79)	0.9974
VZ	0.0136 (7.70)	0.9846 (462.85)	0.9982
WMT	0.0075 (11.47)	0.9904 (769.31)	0.9979
DIS	0.0298 (11.31)	0.9633 (257.96)	0.9931

Table 2
Risk-Return Tradeoff without Intertemporal Hedging Demand

Entries report the common slope estimates (A) and their t-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A\sigma_{im,t+1} + e_{i,t+1}, \qquad i = 1, 2, ..., n,$$

where $R_{i,t+1}$ denotes the daily excess return on stock i at time t+1, $R_{m,t+1}$ denotes the daily excess return on the market portfolio at time t+1, and $\sigma_{im,t+1}$ is the time-t expected conditional covariance between $R_{i,t+1}$ and $R_{m,t+1}$. C_i is the intercept for stock i and A is the common slope coefficient. Estimation is based on daily data on Dow 30 stocks (n=30) and five alternative measures of the market portfolio over the sample period of July 10, 1986 to September 28, 2007. Each row reports the estimates based on a market portfolio proxied by the value-weighted NYSE/AMEX/NASDAQ, NYSE, S&P 500, S&P 100, and DJIA indices. The first two columns present the SUR estimates of panel regression in which the t-statistics are corrected for heteroskedasticity and autocorrelation for each series and contemporaneous cross-correlations among the error terms. The next two columns report the OLS estimates of panel regression in which the t-statistics are not corrected for heteroskedasticity, autocorrelation, or contemporaneous cross-correlations in the errors. The last two columns show the WLS estimates of panel regression that correct the t-statistics only for heteroskedasticity. For each estimation methodology, the first column reports the Wald statistics and the p-values in square brackets from testing the joint hypothesis of all intercepts equal zero. The second column displays the common slope coefficients and the t-statistics of A in parentheses.

	SUR		*OLS*		*WLS*	
Market Portfolio	Wald Test	*A*	Wald Test	*A*	Wald Test	*A*
NYSE/AMEX/NASDAQ	6.92	3.2590	20.64	3.6432	29.39	4.1109
	[1.00]	(6.56)	[0.89]	(10.97)	[0.50]	(12.52)
NYSE	5.94	2.5868	17.73	3.4065	26.12	3.8938
	[1.00]	(5.45)	[0.96]	(10.53)	[0.67]	(12.19)
S&P 500	7.27	2.9480	20.05	3.2599	28.75	3.6852
	[1.00]	(6.57)	[0.92]	(10.80)	[0.53]	(12.36)
S&P 100	7.87	2.6339	19.38	2.8191	27.83	3.1799
	[1.00]	(7.03)	[0.93]	(10.83)	[0.58]	(12.44)
DJIA	5.86	2.2516	15.88	2.8717	23.56	3.2892
	[1.00]	(5.44)	[0.98]	(10.19)	[0.79]	(11.79)

Table 3
One-Step versus Two-Step Estimation of the ICAPM with DCC Using Book-to-Market Portfolios

Entries report the intercepts (C_i) and common slope estimates (A) along with their t-statistics from the one-step (Panel A) and two-step (Panel B) estimation methodology. Estimation is based on daily returns on the ten value-weighted book-to-market portfolios and the value-weighted NYSE/AMEX/NASDAQ index proxying for the market portfolio. Results are presented for the entire sample period July 1, 1963 to December 31, 2007 and the shorter sample period July 10, 1986 to September 28, 2007. For each estimation methodology, the table reports the Wald statistics and the p-values in square brackets from testing the joint hypothesis of all intercepts equal zero (H_0: $C_i = 0$). For each estimation methodology, the table reports the Wald statistics and the p-values in square brackets from testing the statistical difference between average risk-adjusted returns on value (high BM) and growth (low BM) portfolios (H_0: $C_1=C_{10}$).

Panel A. One-Step Estimation of ICAPM with DCC

	July 1, 1963 – December 31, 2007				July 10, 1986 – September 28, 2007			
	Intercept	t-stat.	Common Slope	t-stat.	Intercept	t-stat.	Common Slope	t-stat.
Low BM	-0.000072	-0.6455	2.8952	5.4318	0.000036	0.2097	2.4559	3.8120
2	-0.000025	-0.2499			0.000051	0.3126		
3	0.000002	0.0188			0.000102	0.6713		
4	0.000019	0.2071			0.000112	0.7544		
5	0.000020	0.2230			0.000119	0.8402		
6	0.000074	0.8469			0.000107	0.7715		
7	0.000122	1.4179			0.000193	1.4206		
8	0.000142	1.7157			0.000135	1.0693		
9	0.000164	1.8462			0.000179	1.2912		
High BM	0.000194	2.0516			0.000225	1.5748		
	Wald	p-value			Wald	p-value		
H_0: $C_i = 0$	28.84	0.0013			8.20	0.6097		
	Wald	p-value			Wald	p-value		
H_0: $C_1=C_{10}$	14.25	0.0002			2.56	0.1096		

Table 3 (continued)

Panel B. Two-Step Estimation of ICAPM with DCC Using SUR Panel Regression

	July 1, 1963 – December 31, 2007				July 10, 1986 – September 28, 2007			
	Intercept	t-stat.	Common Slope	t-stat.	Intercept	t-stat.	Common Slope	t-stat.
Low BM	-0.000014	-0.1540	2.1522	4.8763	0.000106	0.7621	1.9536	3.2759
2	0.000053	0.5973			0.000147	1.0608		
3	0.000074	0.8482			0.000192	1.3875		
4	0.000089	1.0255			0.000197	1.4268		
5	0.000090	0.9910			0.000200	1.4503		
6	0.000073	1.5879			0.000187	1.3602		
7	0.000138	2.1254			0.000268	1.9536		
8	0.000202	2.3355			0.000204	1.4890		
9	0.000228	2.6205			0.000255	1.8570		
High BM	0.000262	3.0175			0.000299	2.1782		
	Wald	*p*-value			Wald	*p*-value		
H_0: $C_i = 0$	26.19	0.0035			18.52	0.0468		
	Wald	*p*-value			Wald	*p*-value		
H_0: $C_1 = C_{10}$	5.23	0.0222			1.01	0.3144		

Table 4
Risk-Return Tradeoff after Controlling for the October 1987 Crash

Entries report the common slope estimates and the t-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A\sigma_{im,t+1} + BX_t + e_{i,t+1},$$

where $R_{i,t+1}$ denotes the daily excess return on stock i at time t+1, $R_{m,t+1}$ denotes the daily excess return on the market portfolio at time t+1, and $\sigma_{im,t+1}$ is the time-t expected conditional covariance between $R_{i,t+1}$ and $R_{m,t+1}$. C_i is the intercept for stock i , and A and B are the common slope coefficients. X_t denotes a crash dummy for October 1987: Dum_day equals one for the day of October 19, 1987 and zero otherwise; Dum_week equals one for the week of October 19, 1987 – October 23, 1987 and zero otherwise; and Dum_month equals one for the month of October 1, 1987 – October 30, 1987 and zero otherwise. Each panel reports the common slope coefficient estimates based on a market portfolio proxied by the value-weighted NYSE/AMEX/NASDAQ, NYSE, S&P 500, S&P 100, and DJIA indices. The t-statistics are adjusted for heteroskedasticity and autocorrelation for each series and contemporaneous cross-correlations among the error terms in panel regression.

Panel A. NYSE/AMEX/NASDAQ

$\sigma_{im,t+1}$	Dum_day	Dum_week	Dum_month
3.5912	–0.1917		
(7.32)	(–19.06)		
4.0027		–0.0214	
(7.76)		(–4.44)	
3.8947			–0.0115
(7.67)			(–5.07)

Panel B. NYSE

$\sigma_{im,t+1}$	Dum_day	Dum_week	Dum_month
2.9301	–0.1915		
(6.23)	(–19.04)		
3.3187		–0.0203	
(6.69)		(–4.21)	
3.1962			–0.0110
(6.57)			(–4.85)

Panel C. S&P 500

$\sigma_{im,t+1}$	Dum_day	Dum_week	Dum_month
3.2482	–0.1917		
(7.33)	(–19.05)		
3.6268		–0.0215	
(7.78)		(–4.46)	
3.5193			–0.0114
(7.67)			(–5.06)

Panel D. S&P 100

$\sigma_{im,t+1}$	Dum_day	Dum_week	Dum_month
2.8849	–0.1919		
(7.79)	(–19.07)		
3.1713		–0.0213	
(8.17)		(–4.45)	
3.0728			–0.0113
(8.05)			(–5.03)

Panel E. Dow Jones Industrial Average (DJIA)

$\sigma_{im,t+1}$	Dum_day	Dum_week	Dum_month
2.5261	–0.1913		
(6.17)	(–19.01)		
2.8533		–0.0199	
(6.63)		(–4.13)	
2.7634			–0.0109
(6.53)			(–4.81)

Table 5
Risk-Return Tradeoff after Eliminating the October 1987 Crash: 1/4/1988 – 9/28/2007

Entries report the common slope estimates (*A*), average intercepts, and their *t*-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A\sigma_{im,t+1} + e_{i,t+1},$$

where $R_{i,t+1}$ denotes the daily excess return on stock *i* at time *t*+1, $R_{m,t+1}$ denotes the daily excess return on the market portfolio at time *t*+1, and $\sigma_{im,t+1}$ is the time-*t* expected conditional covariance between $R_{i,t+1}$ and $R_{m,t+1}$. C_i is the intercept for stock *i* , and *A* is the common slope coefficient. The results are presented for the sample period of January 4, 1988 – September 28, 2007 (that excludes October 1987). The *t*-statistics are adjusted for heteroskedasticity and autocorrelation for each series and contemporaneous cross-correlations among the error terms in panel regression.

Market Portfolio	Wald Test	*A*
NYSE/AMEX/NASDAQ	4.35	2.9540
	[1.00]	(3.63)
NYSE	4.37	2.7530
	[1.00]	(3.00)
S&P 500	4.23	2.4397
	[1.00]	(3.25)
S&P 100	4.30	1.9353
	[1.00]	(3.25)
DJIA	5.86	2.1794
	[1.00]	(2.91)

Table 6
Risk-Return Tradeoff after Controlling for Lagged Return and October 1987 Crash

Entries report the common slope estimates and the *t*-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A\sigma_{im,t+1} + BX_t + e_{i,t+1},$$

where $R_{i,t+1}$ denotes the daily excess return on stock i at time t+1, $R_{m,t+1}$ denotes the daily excess return on the market portfolio at time t+1, and $\sigma_{im,t+1}$ is the time-t expected conditional covariance between $R_{i,t+1}$ and $R_{m,t+1}$. C_i is the intercept for stock i, and A and B are the common slope coefficients. X_t denotes a vector of control variables including the lagged daily excess return on stock i $(R_{i,t})$, the lagged daily excess return on the market portfolio $(R_{m,t})$, and the crash dummy (Dum_month) equals one for the month of October 1, 1987 – October 30, 1987 and zero otherwise. Each panel reports the common slope estimates based on a market portfolio proxied by the value-weighted NYSE/AMEX/NASDAQ, NYSE, S&P 500, S&P 100, and DJIA indices. The *t*-statistics are adjusted for heteroskedasticity and autocorrelation for each series and contemporaneous cross-correlations among the error terms in panel regression.

Panel A. NYSE/AMEX/NASDAQ

$\sigma_{im,t+1}$	$R_{i,t}$	$R_{m,t}$	Dum_month
3.1643	–0.0119		
(6.37)	(–4.76)		
3.1869		–0.0412	
(6.41)		(–2.89)	
3.8011	–0.0115		–0.0119
(7.48)	(–5.07)		(–4.77)
3.8390		–0.0466	–0.0120
(7.56)		(–3.27)	(–5.29)

Panel B. NYSE

$\sigma_{im,t+1}$	$R_{i,t}$	$R_{m,t}$	Dum_month
2.4751	–0.0119		
(5.20)	(–4.76)		
2.5399		–0.0259	
(5.33)		(–1.74)	
3.0846	–0.0119		–0.0110
(6.33)	(–4.75)		(–4.85)
3.1559		–0.0310	–0.0113
(6.48)		(–2.09)	(–4.99)

Panel C. S&P 500

$\sigma_{im,t+1}$	$R_{i,t}$	$R_{m,t}$	Dum_month
2.8746	–0.0120		
(6.41)	(–4.80)		
2.8991		–0.0323	
(6.46)		(–2.41)	
3.4474	–0.0120		–0.0115
(7.52)	(–4.82)		(–5.08)
3.4807		–0.0364	–0.0118
(7.59)		(–2.72)	(–5.22)

Panel D. S&P 100

$\sigma_{im,t+1}$	$R_{i,t}$	$R_{m,t}$	Dum_month
2.5835	–0.0121		
(6.89)	(–4.83)		
2.5913		–0.0246	
(6.91)		(–2.27)	
3.0240	–0.0121		–0.0114
(7.92)	(–4.86)		(–5.05)
3.0343		–0.0268	–0.0116
(7.94)		(–2.48)	(–5.13)

Panel E. Dow Jones Industrial Average (DJIA)

$\sigma_{im,t+1}$	$R_{i,t}$	$R_{m,t}$	Dum_month
2.1818	–0.0121		
(5.27)	(–4.83)		
2.2028		–0.0318	
(5.31)		(–2.39)	
2.6948	–0.0121		–0.0109
(6.37)	(–4.84)		(–4.82)
2.7232		–0.0358	–0.0112
(6.43)		(–2.69)	(–4.96)

Table 7
Risk-Return Tradeoff in Three Subsamples

Entries report the common slope estimates (A), average intercepts, and their t-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A\sigma_{im,t+1} + e_{i,t+1},$$

where $R_{i,t+1}$ denotes the daily excess return on stock i at time t+1, $R_{m,t+1}$ denotes the daily excess return on the market portfolio at time t+1, and $\sigma_{im,t+1}$ is the time-t expected conditional covariance between $R_{i,t+1}$ and $R_{m,t+1}$. C_i is the intercept for stock i , and A is the common slope coefficient. The results are presented for the sample period of January 4, 1988 – September 28, 2007 (that excludes October 1987) as well as two subsample periods: July 10, 1986 – February 6, 1997 and February 7, 1997 – September 28, 2007. The t-statistics are adjusted for heteroskedasticity and autocorrelation for each series and contemporaneous cross-correlations among the error terms in panel regression.

Sample Period	Wald Test	A
1/4/1988 – 9/28/2007	4.35	2.9540
	[1.00]	(3.63)
7/10/1986 – 2/6/1997	9.67	2.7480
	[0.99]	(4.86)
2/7/1997 – 9/28/2007	6.58	3.1244
	[1.00]	(3.17)

Table 8
The Intertemporal Risk-Return Relation with Alternative Specifications of the Conditional Mean

Entries report the common slope estimates and the *t*-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A\sigma_{im,t+1} + e_{i,t+1}, \qquad i = 1, 2, ..., n,$$

where $R_{i,t+1}$ denotes the daily excess return on stock *i* at time *t*+1, $R_{m,t+1}$ denotes the daily excess return on the market portfolio at time *t*+1, and $\sigma_{im,t+1}$ is the time-*t* expected conditional covariance between $R_{i,t+1}$ and $R_{m,t+1}$. C_i is the intercept for stock *i* and *A* is the common slope coefficient. Estimation is based on daily data on Dow 30 stocks (*n*=30) over the sample period of July 10, 1986 to September 28, 2007. The market portfolio is proxied by the value-weighted NYSE/AMEX/NASDAQ index. Each row reports the estimates based on a constant, AR(1), MA(1), and ARMA(1,1) specification of the conditional mean of $R_{i,t+1}$ and $R_{m,t+1}$. The first column reports the Wald statistics and the *p*-values in square brackets from testing the joint hypothesis of all intercepts equal zero. The last column displays the common slope coefficients and the *t*-statistics of *A* in parentheses. The *t*-statistics are adjusted for heteroskedasticity and autocorrelation for each series and contemporaneous cross-correlations among the error terms in panel regression.

Conditional Mean	Wald Test	*A*
Constant	6.42	3.0612
	[1.00]	(5.97)
AR(1)	6.92	3.2590
	[1.00]	(6.56)
MA(1)	7.40	3.3219
	[1.00]	(6.64)
ARMA(1,1)	8.96	3.5775
	[0.99]	(7.16)

Table 9
Risk-Return Tradeoff after Controlling for Macroeconomic Variables

Entries report the common slope estimates and the *t*-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A\sigma_{im,t+1} + BX_t + e_{i,t+1},$$

where $R_{i,t+1}$ denotes the daily excess return on stock *i* at time *t*+1, $R_{m,t+1}$ denotes the daily excess return on the market portfolio at time *t*+1, and $\sigma_{im,t+1}$ is the time-*t* expected conditional covariance between $R_{i,t+1}$ and $R_{m,t+1}$. C_i is the intercept for stock i, and A and B are the common slope coefficients. X_t denotes a vector of control variables including the default spread (DEF_t) defined as the difference between the daily yields on BAA- and AAA-rated corporate bonds, the term spread $(TERM_t)$ defined as the difference between the yields on 10-year Treasury bond and 3-month Treasury bill, the daily federal funds rate (FED_t), and the crash dummy (Dum_month) equals one for the month of October 1, 1987 – October 30, 1987 and zero otherwise. ΔDEF_t, $\Delta TERM_t$, and ΔFED_t denote the first-difference in DEF_t, $TERM_t$, and FED_t. The *t*-statistics are adjusted for heteroskedasticity and autocorrelation for each series and contemporaneous cross-correlations among the error terms in panel regression.

$\sigma_{im,t+1}$	DEF_t	$TERM_t$	FED_t	ΔDEF_t	$\Delta TERM_t$	ΔFED_t	Dum_month
3.2613	–0.0059						
(6.55)	(–0.09)						
3.8892	0.0078						–0.0115
(7.64)	(0.13)						(–5.07)
3.2497				0.6934			
(6.54)				(0.98)			
3.8843				0.6499			–0.0114
(7.65)				(0.92)			(–5.06)
3.2884		–0.0202					
(6.62)		(–1.64)					
3.9037		–0.0160					–0.0112
(7.69)		(–1.32)					(–4.93)
3.2707					–0.2203		
(6.59)					(–1.01)		
3.9018					–0.1847		–0.0114
(7.69)					(–0.85)		(–5.04)
3.2575			0.0026				
(6.56)			(0.39)				
3.8984			0.0050				–0.0116
(7.68)			(0.76)				(–5.11)
3.2538						–0.0833	
(6.55)						(–1.64)	
3.8915						–0.0858	–0.0115
(7.67)						(–1.71)	(–5.08)
3.8872	0.0289	–0.0176	–0.0003				–0.0112
(7.64)	(0.44)	(–1.16)	(–0.03)				(–4.89)
3.8887				0.6479	–0.2031	–0.0875	–0.0114
(7.66)				(0.92)	(–0.93)	(–1.74)	(–5.04)

Table 10
Risk-Return Tradeoff after Controlling for the Conditional Volatility of Individual Stock

Entries report the common slope estimates and the *t*-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B \cdot VOL_{i,t+1} + e_{i,t+1},$$

where $R_{i,t+1}$ denotes the daily excess return on stock *i* at time *t*+1, $R_{m,t+1}$ denotes the daily excess return on the market portfolio at time *t*+1, $\sigma_{im,t+1}$ is the time-*t* expected conditional covariance between $R_{i,t+1}$ and $R_{m,t+1}$, and $VOL_{i,t+1}$ is the time-*t* expected conditional volatility of $R_{i,t+1}$. $VOL_{i,t+1}$ is the range daily standard deviation of individual stocks defined as $\ln(P_{i,t}^{\max}) - \ln(P_{i,t}^{\min})$ and can be interpreted as the total risk of individual stocks. $VOL_{i,t+1}$ is the conditional variance of the daily excess returns on stock *i* estimated using the AR(1)-GARCH(1,1) model and can be interpreted as the conditional total volatility of individual stocks. $VOL_{i,t+1}$ is the conditional variance of the daily excess returns on stock *i* estimated using the 3-factor Fama-French (1993) model and can be interpreted as the conditional idiosyncratic volatility of individual stocks. C_i is the intercept for stock *i* , and A and B are the common slope coefficients. Dum_month is the crash dummy that equals one for the month of October 1, 1987 – October 30, 1987 and zero otherwise. The market portfolio is measured by the value-weighted NYSE/AMEX/NASDAQ index. The *t*-statistics are adjusted for heteroskedasticity and autocorrelation for each series and contemporaneous cross-correlations among the error terms in panel regression.

$Cov_t(R_{i,t+1}, R_{m,t+1})$	$VOL_{i,t+1}$			October 1987 crash
$\sigma_{im,t+1}$	Range total volatility	GARCH total volatility	GARCH idiosyncratic volatility	Dum_month
2.9717	0.0105			
(5.82)	(2.24)			
3.5992	0.0111			–0.0116
(6.92)	(2.36)			(–5.12)
3.0611		0.0238		
(6.02)		(1.85)		
3.7091		0.0215		–0.0113
(7.13)		(1.67)		(–5.01)
3.2024			0.0096	
(6.38)			(0.79)	
3.8470			0.0077	–0.0114
(7.50)			(0.64)	(–5.05)

Table 11
Risk-Return Tradeoff after Controlling for the Conditional Volatility of Market Portfolio

Entries report the common slope estimates and the *t*-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B \cdot VOL_{m,t+1} + e_{i,t+1},$$

where $R_{i,t+1}$ denotes the daily excess return on stock *i* at time *t*+1, $R_{m,t+1}$ denotes the daily excess return on the market portfolio at time *t*+1, $\sigma_{im,t+1}$ is the time-*t* expected conditional covariance between $R_{i,t+1}$ and $R_{m,t+1}$, and $VOL_{m,t+1}$ is the time-*t* expected conditional volatility of $R_{m,t+1}$ obtained from the GARCH, Range, and Option Implied Volatility models: (1) $VOL_{m,t+1}$ is the conditional variance of daily excess returns on the market portfolio estimated using the AR(1)-GARCH(1,1) model; (2) $VOL_{m,t+1}$ is the range daily standard deviation of the market portfolio defined as $\ln(P_{m,t}^{\max}) - \ln(P_{m,t}^{\min})$; and (3) $VOL_{m,t+1}$ is the implied market volatility (VXO_t) obtained from the S&P 100 index options. C_i is the intercept for stock i, and A and B are the common slope coefficients. Dum_month is the crash dummy that equals one for the month of October 1, 1987 – October 30, 1987 and zero otherwise. The market portfolio is measured by the value-weighted NYSE/AMEX/NASDAQ index. The *t*-statistics are adjusted for heteroskedasticity and autocorrelation for each series and contemporaneous cross-correlations among the error terms in panel regression.

$Cov_t(R_{i,t+1}, R_{m,t+1})$	$VOL_{m,t+1}$			October 1987 crash
$\sigma_{im,t+1}$	GARCH volatility	Range volatility	Implied volatility	Dum_month
2.8868	1.9843			
(5.39)	(2.02)			
3.0829	4.9089			–0.0162
(5.74)	(4.55)			(–6.50)
2.8831		0.0401		
(5.55)		(2.32)		
3.4092		0.0602		–0.0131
(6.49)		(3.42)		(–5.66)
2.8432			0.0045	
(5.46)			(2.49)	
3.3565			0.0069	–0.0134
(6.39)			(3.73)	(–5.78)

Table 12
Risk Premia Induced by Conditional Covariation with Macroeconomic Variables

Entries report the common slope estimates and the *t*-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B_1 \cdot \sigma_{i,DEF,t+1} + B_2 \cdot \sigma_{i,TERM,t+1} + B_3 \cdot \sigma_{i,FED,t+1} + e_{i,t+1},$$

where $\sigma_{im,t+1}$ measures the time-*t* expected conditional covariance between the excess returns on each stock $(R_{i,t+1})$ and the market portfolio $(R_{m,t+1})$, $\sigma_{i,DEF,t+1}$ measures the time-*t* expected conditional covariance between $R_{i,t+1}$ and the level and changes in the default spread $(DEF_t, \Delta DEF_t)$, $\sigma_{i,TERM,t+1}$ is the time-*t* expected conditional covariance between $R_{i,t+1}$ and the level and changes in the term spread $(TERM_t, \Delta TERM_t)$, and $\sigma_{i,FED,t+1}$ is the time-*t* expected conditional covariance between $R_{i,t+1}$ and the level and changes in the federal funds rate $(FED_t, \Delta FED_t)$. C_i is the intercept for stock i, and A, B_1, B_2, and B_3 are the common slope coefficients. The *t*-statistics are adjusted for heteroskedasticity and autocorrelation for each series and contemporaneous cross-correlations among the error terms in panel regression.

$\sigma_{im,t+1}$	$\sigma_{i,DEF,t+1}$	$\sigma_{i,TERM,t+1}$	$\sigma_{i,FED,t+1}$	$\sigma_{i,\Delta DEF,t+1}$	$\sigma_{i,\Delta TERM,t+1}$	$\sigma_{i,\Delta FED,t+1}$
3.1687	0.1399					
(6.23)	(0.83)					
3.1356				0.0788		
(6.02)				(0.78)		
3.1454		–0.0219				
(5.96)		(–0.65)				
3.0124					–0.0083	
(5.30)					(–0.89)	
3.2838			–0.0053			
(6.60)			(–0.69)			
3.1201						–0.0047
(6.11)						(–1.10)
3.0494	0.1474	–0.0286	–0.0074			
(5.67)	(0.88)	(–0.82)	(–0.93)			
2.9956				0.0446	–0.0028	–0.0036
(5.25)				(0.40)	(–0.25)	(–0.77)

Table 13
Risk Premia Induced by Conditional Covariation with Financial Risk Factors

Entries report the common slope estimates and the *t*-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B_1 \cdot \sigma_{i,SMB,t+1} + B_2 \cdot \sigma_{i,HML,t+1} + B_3 \cdot \sigma_{i,MOM,t+1} + e_{i,t+1},$$

where $\sigma_{im,t+1}$ measures the time-*t* expected conditional covariance between the excess returns on each stock $(R_{i,t+1})$ and the market portfolio $(R_{m,t+1})$, $\sigma_{i,SMB,t+1}$ measures the time-*t* expected conditional covariance between $R_{i,t+1}$ and the level and change in the size factor $(SMB_t, \Delta SMB_t)$, $\sigma_{i,HML,t+1}$ is the time-*t* expected conditional covariance between $R_{i,t+1}$ and the level and change in the book-to-market factor $(HML_t, \Delta HML_t)$, and $\sigma_{i,MOM,t+1}$ is the time-*t* expected conditional covariance between $R_{i,t+1}$ and the level and change in the momentum factor $(MOM_t, \Delta MOM_t)$. C_i is the intercept for stock i, and A, B_1, B_2, and B_3 are the common slope coefficients. The *t*-statistics are adjusted for heteroskedasticity and autocorrelation for each series and contemporaneous cross-correlations among the error terms in panel regression.

$\sigma_{im,t+1}$	$\sigma_{i,SMB,t+1}$	$\sigma_{i,HML,t+1}$	$\sigma_{i,MOM,t+1}$	$\sigma_{i,\Delta SMB,t+1}$	$\sigma_{i,\Delta HML,t+1}$	$\sigma_{i,\Delta MOM,t+1}$
3.4870	0.7383					
(4.85)	(0.43)					
3.2519				–0.0473		
(4.66)				(–0.03)		
3.8854		4.4342				
(6.39)		(2.03)				
3.9328					5.2897	
(6.78)					(2.17)	
3.5711			–1.0799			
(6.83)			(–1.54)			
3.5932						–1.1013
(6.88)						(–1.60)
4.8407	1.7139	5.3628	–1.1602			
(5.23)	(0.92)	(1.97)	(–1.63)			
4.5013				0.5628	5.6825	–1.1700
(5.30)				(0.32)	(2.21)	(–1.64)

Table 14
Risk Premium Induced by Conditional Covariation with Unexpected News in Market Volatility

Entries report the common slope estimates and the *t*-statistics (in parentheses) from the following system of equations,

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B \cdot \sigma_{i,\Delta VOL_m,t+1} + e_{i,t+1},$$

where $\sigma_{im,t+1}$ measures the time-*t* expected conditional covariance between the excess returns on each stock $(R_{i,t+1})$ and the market portfolio $(R_{m,t+1})$, where $R_{m,t+1}$ is proxied by the value-weighted NYSE/AMEX/NASDAQ index. $\sigma_{i,\Delta VOL_m,t+1}$ measures the time-*t* expected conditional covariance between $R_{i,t+1}$ and the change in the conditional volatility of the market portfolio denoted by $\Delta VOL_{m,t+1}$: (1) $\Delta VOL_{m,t+1}$ is the change in the GARCH conditional volatility of S&P 500 index return $(\Delta GARCH_{m,t+1})$; (2) $\Delta VOL_{m,t+1}$ is the change in the option implied volatility of S&P 500 index return $(\Delta VXO_{m,t+1})$; and (3) $\Delta VOL_{m,t+1}$ is the change in the range volatility of S&P 500 index return $(\Delta Range_{m,t+1})$. C_i is the intercept for stock i, and A and B are the common slope coefficients. Dum_month is the crash dummy that equals one for the month of October 1, 1987 – October 30, 1987 and zero otherwise. The *t*-statistics are adjusted for heteroskedasticity and autocorrelation for each series and contemporaneous cross-correlations among the error terms in panel regression.

$Cov_t(R_{i,t+1}, R_{m,t+1})$	$Cov_t(R_{i,t+1}, \Delta VOL_{m,t+1})$			October 1987 crash
$\sigma_{im,t+1}$	$\Delta GARCH_{m,t+1}$	$\Delta Range_{m,t+1}$	$\Delta VXO_{m,t+1}$	Dum_month
2.4589	–0.2559			
(4.56)	(–3.73)			
3.0190	–0.2890			–0.0123
(5.53)	(–4.20)			(–5.41)
2.0336		–0.2583		
(3.47)		(–4.23)		
2.5894		–0.2812		–0.0118
(4.35)		(–4.60)		(–5.23)
1.4102			–0.4106	
(2.02)			(–3.80)	
1.6675			–0.5145	–0.0128
(2.38)			(–4.74)	(–5.62)

Figure 1. Mean-Reverting Dynamic Conditional Correlations

This figure presents the time-varying conditional correlations of daily excess returns on Dow 30 stocks with daily excess returns on the market portfolio. The market portfolio is measured by the Dow Jones Industrial Average (DJIA). The conditional correlations are obtained from the mean-reverting DCC model over the sample period of July 10, 1986 to September 28, 2007 (5,354 daily observations).

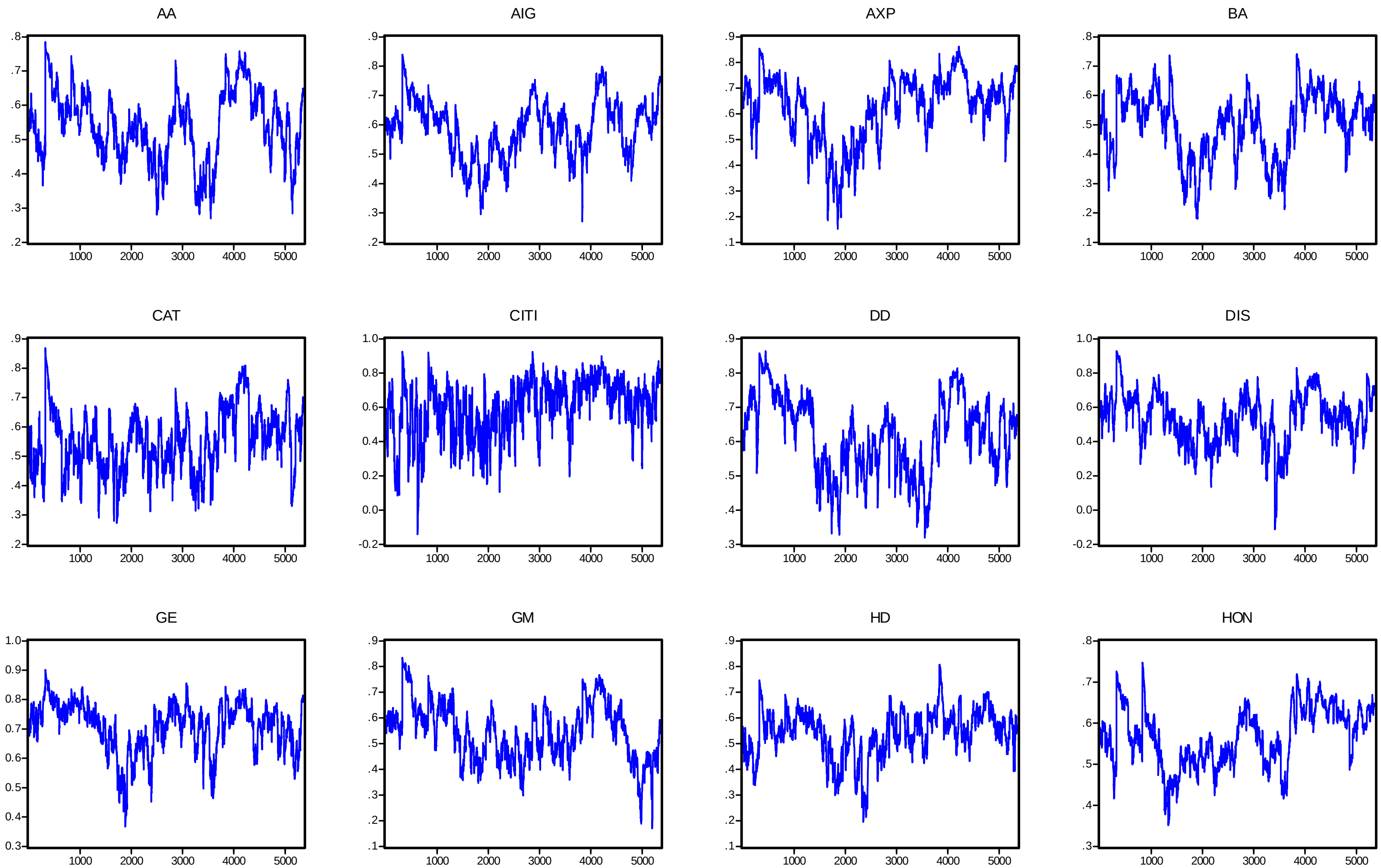

Figure 1 (continued)

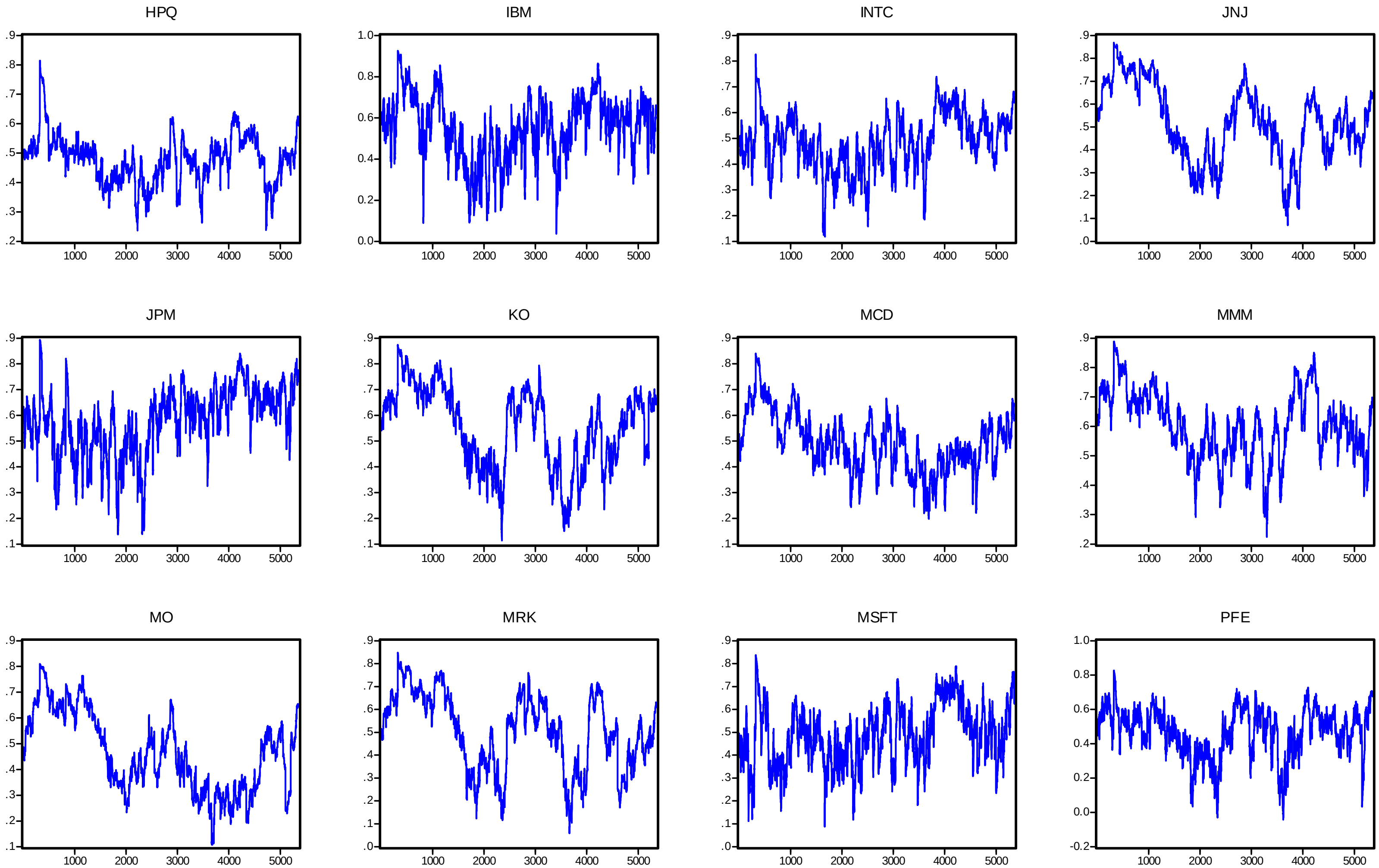

Figure 1 (continued)

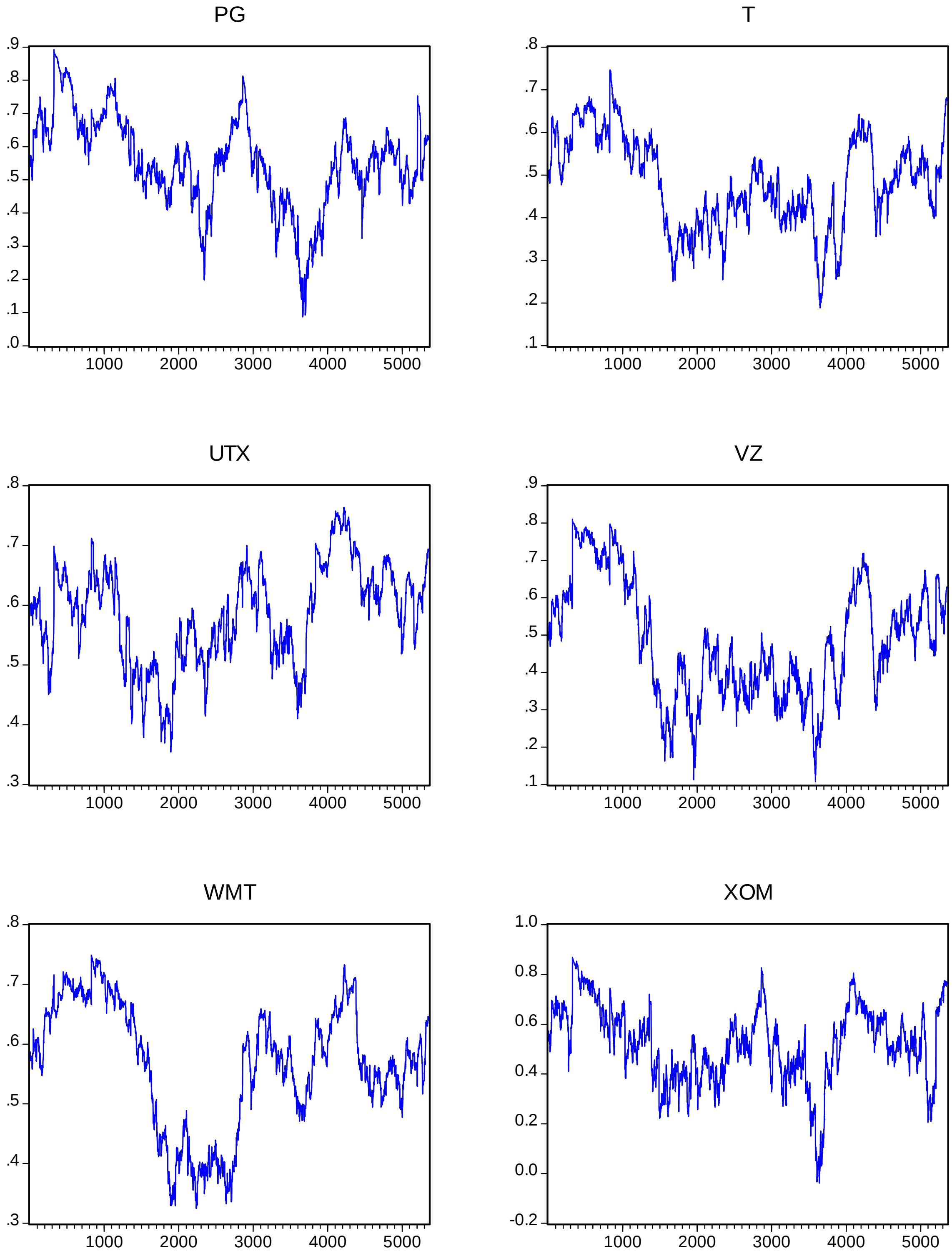

Figure 2. Weighted Average Conditional Covariance vs. Conditional Variance of the Market

In Panel A (Panel B), the dashed line denotes the equal-weighted (price-weighted) average of the conditional covariances of daily excess returns on Dow 30 stocks with daily excess returns on the market portfolio. The solid line in both panels denotes the conditional variance of daily excess returns on the market portfolio. The market portfolio is measured by the Dow Jones Industrial Average (DJIA). The conditional variance-covariance estimates are obtained from the mean-reverting DCC model.