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, and including a wide variety of state variables that proxy for the intertemporal hedging demand component of the ICAPM. Risk premium induced by the conditional covariation of individual stocks with the market portfolio remains economically and statistically significant after controlling for risk premiums 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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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, and including a wide variety of state variables that proxy for the intertemporal hedging demand component of the ICAPM. Risk premium induced by the conditional covariation of individual stocks with the market portfolio remains economically and statistically significant after controlling for risk premiums 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, the existing literature has not yet reached an agreement on the existence of a positive risk-return tradeoff for stock market indices. 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 (assuming that hedging demands are not too large). 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]

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, 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.

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 premiums 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 premiums.

To explore how macroeconomic variables vary with the investment opportunity and test whether covariations of Dow 30 stocks with them induce additional risk premiums, 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.

In a series of papers, Fama and French (1992, 1993, 1995, 1996, 1997) 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 premiums on Dow 30 stocks.[2] 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

[2] 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).

significant predictive power for one day ahead returns on Dow stocks. In other words, the level and innovations in the size and momentum 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 premiums 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 review

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.[3]

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

[3] 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.[4]

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:

$$\mu = A \cdot COV_m + B \cdot COV_x , \tag{1}$$

where μ denotes the expected excess return on a vector of *n* risky assets, *A* reflects the average relative risk aversion of market investors, COV_m denotes the covariance between excess returns on the *n* risky assets and the market portfolio *m*, B measures the market's aggregate reaction to shifts in a *k*-dimensional state vector that governs the stochastic investment opportunity, and COV_x measures the covariance between excess returns on the *n* risky assets and the *k* state variables *x*.

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[4] 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.

For any risky asset *i*, the relation becomes

$$\mu_i - r = A \cdot \sigma_{im} + B \cdot \sigma_{ix} , \quad (2)$$

where σ_{im} denotes the covariance between the excess returns on the risky asset *i* and the market portfolio *m*, and σ_{ix} denotes a ($1 \times k$) row of covariances between the excess returns on risky asset *i* and the *k* state variables *x*. Equation (2) states that in equilibrium, investors are compensated in terms of expected return, for bearing market (systematic) risk and for bearing the risk of unfavorable shifts in the investment opportunity set.

Many empirical studies focus on the time-series implication of the equilibrium relation in eq. (2) and apply it narrowly to the market portfolio. Without the hedging demand component ($\sigma_{ix} = 0$), this focus leads to the following risk-return relation:

$$\mu_m - r = A \cdot \sigma_m^2 . \quad (3)$$

When considering stochastic investment opportunity, the literature often implicitly or explicitly projects the covariance vector σ_{ix} linearly to the state variables *x* to obtain the following relation:

$$\mu_m - r = A \cdot \sigma_m^2 + B \cdot x . \quad (4)$$

Our work in this article differs from the above literature in two major ways. First, we estimate the intertemporal relation eq. (2) not on the single series of the market portfolio, but simultaneously on Dow 30 stocks, and constrain all these stocks to have the same cross-sectionally consistent proportionality coefficients *A* and *B*. Second, we directly estimate the conditional covariances σ_{im} and σ_{ix} using the dynamic conditional correlation model of Engle (2002). We do not make any linear projection assumptions on the state variables.

In the Merton (1973) original setup, the two conditional covariances (σ_{im}, σ_{ix}) are assumed to be constant. Nevertheless, the empirical literature has estimated the relation assuming time-varying covariances. We do the same in this paper. In principle, if the covariances are stochastic, they would represent additional sources of variation in the investment opportunity and induce extra intertemporal hedging demand terms.

The second term in eq. (2) reflects the investors' demand for the asset as a vehicle to hedge against unfavorable shifts in the investment opportunity set. An "unfavorable" shift in the investment opportunity set variable *x* is defined as a change in *x* such that future consumption *c* will fall for a given level of future wealth. That is, an unfavorable shift is an increase in *x* if $\partial c/\partial x < 0$ and a decrease in *x* if $\partial c/\partial x > 0$.

Merton (1973) shows that all risk-averse utility maximizers will attempt to hedge against such shifts in the sense that if $\partial c/\partial x < 0$ ($\partial c/\partial x > 0$), then, ceteris paribus, they will demand more of an asset, the more positively (negatively) correlated the asset's return is with changes in *x*. Thus, if the ex post opportunity set is less favorable than was anticipated, the investor will expect to be compensated by a higher level of wealth through the positive correlation of the returns. Similarly, if the ex post returns are lower, he will expect a more favorable investment environment.

In this paper, we focus on the sign and statistical significance of the common slope coefficient (*A*) on σ_{im} in the following risk-return relation:

$$\mu_i - r = C_i + A \cdot \sigma_{im} + B \cdot \sigma_{ix} . \quad (5)$$

According to the original ICAPM of Merton (1973), the relative risk aversion coefficient *A* is restricted to be the same across all risky assets and it should be positive and statistically significant, implying a positive risk-return tradeoff.

Another implication of the ICAPM is that the intercepts (C_i) in eq. (5) should not be jointly different from zero assuming that the covariances of risky assets with the market portfolio and with the innovations in states variables have enough predictive power for the time-series variation in expected returns. To determine whether σ_{im} and σ_{ix} have significant explanatory power, we test the joint hypothesis that H_0: $C_1 = C_2 = ... = C_n = 0$ assuming that we have *n* risky assets in the portfolio.

We think that macroeconomic variables such as the fed funds rate, default spread, and term spread, financial factors such as the size, book-to-market, and momentum factors of Fama and French, and the well-known volatility measures such as the options implied, GARCH, and range volatility can be viewed as potential state variables that may affect the stochastic investment opportunity set. Hence, we investigate whether the positive coefficient on σ_{im} remains intact after controlling for the conditional covariances of risky assets with the aforementioned state variables. First, we test the statistical significance of the common slope coefficient (*B*) on σ_{ix} in eq. (5) and then examine whether the common slope (*A*) on σ_{im} remains positive and significant after including σ_{ix} to the risk-return relation.

3.1. Data

Our study is based on the latest stock composition of the Dow Jones Industrial Average. 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.[5] 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 Corp. (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 Corp. (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 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

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[5] 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.

Several studies find that macroeconomic variables associated with business cycle fluctuations can predict the stock market.[6] The commonly chosen variables include Treasury bill rates, federal funds rate, default spread, term spread, and dividend-price ratios. We study how variations in the fed funds rate, default spread, and term spread predict variations in the investment opportunity set and how incorporating conditional covariances of individual stock returns with these variables affects the intertemporal risk-return relation.[7]

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. 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

Fama and French (1993) introduce two financial factors related to firm size and the ratio of book value of equity to market value of equity. In a series of papers, Fama and French (1992, 1993, 1995, 1996, 1997) show the importance of these two factors. To form these factors, Fama and French first construct six portfolios according to the rankings on market equity (ME) and book-to-market (BM) ratios. In June of each year, they rank all NYSE stocks in CRSP based on ME. Then they use the median NYSE size to split NYSE, AMEX, and NASDAQ stocks into two groups, small and big (S and B). They also break NYSE, AMEX, and NASDAQ stocks into three BM groups based on the breakpoints for bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of BM for NYSE stocks. They construct the *SMB* (small minus big) factor as the difference between the returns on the portfolio of small size stocks and the returns on the portfolio of large size stocks, and the *HML* (high minus low) factor as the difference between the returns on the portfolio of high BM stocks and the returns on the

[6] See Fama and Schwert (1977), Keim and Stambaugh (1986), Chen, Roll, and Ross (1986), Campbell and Shiller (1988), Fama and French (1988, 1989), Schwert (1989, 1990), Fama (1990), Campbell (1987, 1991), Ferson and Harvey (1991, 1999), Ferson and Schadt (1996), Goyal and Santa-Clara (2003), Ghysels, Santa-Clara, and Valkanov (2005), Bali, Cakici, Yan, and Zhang (2005), and Guo and Whitelaw (2006).

[7] 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.

portfolio of low BM stocks. We use the *SMB* and *HML* portfolios of Fama and French that are constructed daily.

The momentum (*MOM*) factor of Fama and French is constructed from six value-weighted portfolios formed using independent sorts on size and prior return of NYSE, AMEX, and NASDAQ stocks. *MOM* is the average of the returns on two (big and small) high prior return portfolios minus the average of the returns on two low prior return portfolios. The portfolios are constructed daily. Big means a firm is above the median market cap on the NYSE at the end of the previous day; small firms are below the median NYSE market cap. Prior return is measured from day –250 to –21. Firms in the low prior return portfolio are below the 30th NYSE percentile. Those in the high portfolio are above the 70th NYSE percentile.

The daily, monthly, and annual returns on these three factors (*SMB*, *HML*, *MOM*) 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

We test whether the risk-aversion coefficient on the conditional covariance of individual stocks with the market portfolio remains positive and significant after controlling for risk premiums induced by conditional covariation of individual stocks with alternative measures of market volatility. We use options implied, GARCH, and range based volatility estimators.

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 is introduced by the CBOE on September 22, 2003. The VIX is obtained from the European style S&P 500 index option prices and incorporates information from the volatility skew by using a wider range of strike prices rather 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 premiums 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:

$$Range_{m,t} = Max(\ln P_{m,t}) - Min(\ln P_{m,t}) \;, \tag{6}$$

where $Max(\ln P_{m,t})$ and $Min(\ln P_{m,t})$ are the highest and lowest log 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 (6) 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.

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

$$R_{i,t+1} = \alpha_0^i + \alpha_1^i R_{i,t} + \varepsilon_{i,t+1} \,, \tag{7}$$

$$E_t\left[\varepsilon_{i,t+1}^2\right] \equiv \sigma_{i,t+1}^2 = \beta_0^i + \beta_1^i \varepsilon_{i,t}^2 + \beta_2^i \sigma_{i,t}^2 \,, \tag{8}$$

where $R_{i,t+1}$ denotes total excess return on stock *i* that can be decomposed into expected and idiosyncratic components. $E_t\left[R_{i,t+1}\right] = \hat{\alpha}_0^i + \hat{\alpha}_1^i R_{i,t}$ is the expected excess return on stock *i* conditional on time *t* information and $\varepsilon_{i,t+1}$ is the idiosyncratic (or firm-specific) excess return on stock *i*. $\sigma_{i,t+1}^2$ in eq. (8) is the time-*t* expected conditional variance of $\varepsilon_{i,t+1}$ that can be viewed as conditional idiosyncratic volatility.

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

$$Range_{i,t} = Max(\ln P_{i,t}) - Min(\ln P_{i,t}), \tag{9}$$

where $Max(\ln P_{i,t})$ and $Min(\ln P_{i,t})$ are the highest and lowest log 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.

3.2. Estimating Time-Varying Conditional Covariances

We estimate the conditional covariance between excess returns on asset *i* and the market portfolio *m* based on the following bivariate GARCH(1,1) specification:

$$R_{i,t+1} = \alpha_0^i + \alpha_1^i R_{i,t} + \varepsilon_{i,t+1}, \tag{10}$$

$$R_{m,t+1} = \alpha_0^m + \alpha_1^m R_{m,t} + \varepsilon_{m,t+1}, \tag{11}$$

$$E_t\left[\varepsilon_{i,t+1}^2\right] \equiv \sigma_{i,t+1}^2 = \beta_0^i + \beta_1^i \varepsilon_{i,t}^2 + \beta_2^i \sigma_{i,t}^2, \tag{12}$$

$$E_t\left[\varepsilon_{m,t+1}^2\right] \equiv \sigma_{m,t+1}^2 = \beta_0^m + \beta_1^m \varepsilon_{m,t}^2 + \beta_2^m \sigma_{m,t}^2, \tag{13}$$

$$E_t\left[\varepsilon_{i,t+1}\varepsilon_{m,t+1}\right] \equiv \sigma_{im,t+1} = \rho_{im,t+1} \cdot \sigma_{i,t+1} \cdot \sigma_{m,t+1}, \tag{14}$$

where $R_{i,t+1}$ and $R_{m,t+1}$ denote the time (*t*+1) excess return on asset *i* and the market portfolio *m* over a risk-free rate, respectively, and $E_t[.]$ denotes the expectation operator conditional on time *t* information. $\sigma_{i,t+1}^2$ is the time-*t* expected conditional variance of $R_{i,t+1}$, $\sigma_{m,t+1}^2$ is the time-*t* expected conditional variance of $R_{m,t+1}$, and $\sigma_{im,t+1}$ is the time-*t* expected conditional covariance between $R_{i,t+1}$ and $R_{m,t+1}$. $\rho_{im,t+1}$ is the conditional correlation between $R_{i,t+1}$ and $R_{m,t+1}$.[8]

The GARCH specifications in equations (10)-(14) do not arise directly from the ICAPM model, but they provide a parsimonious approximation of the form of conditional heteroskedasticity typically encountered with financial time-series data (e.g., Bollerslev, Chou, and Kroner (1992) and Bollerslev, Engle, and Nelson (1994)). As an alternative to bivariate GARCH specifications, earlier studies define the conditional covariances (or betas) as a function of some macroeconomic variables and then use a two-stage ordinary least squares (OLS) or generalized method of moments (GMM) estimation methodology to generate conditional risk measures (e.g., Harvey (1989), Ferson and Harvey (1991), and Jagannathan and Wang (1996)).

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[8] Similar conditional covariance specifications are used by Baillie and Bollerslev (1992), Bollerslev (1990), Bollerslev, Engle, and Wooldridge (1988), Bollerslev and Wooldridge (1992), Ding and Engle (2001), Engle and Kroner (1995), Engle and Mezrich (1996), Engle, Ng, and Rothschild (1990), and Kroner and Ng (1998). These specifications can be viewed as multivariate generalizations of the univariate GARCH models developed by Engle (1982) and Bollerslev (1986).

When considering stochastic investment opportunities governed by a set of state variables, we estimate the conditional covariance between each stock i and each state variable x, σ_{ix}, using an analogous bivariate GARCH specification:

$$R_{i,t+1} = \alpha_0^i + \alpha_1^i R_{i,t} + \varepsilon_{i,t+1}, \tag{15}$$

$$x_{t+1} = \alpha_0^x + \alpha_1^x x_t + \varepsilon_{x,t+1}, \tag{16}$$

$$E_t\left[\varepsilon_{i,t+1}^2\right] \equiv \sigma_{i,t+1}^2 = \beta_0^i + \beta_1^i \varepsilon_{i,t}^2 + \beta_2^i \sigma_{i,t}^2, \tag{17}$$

$$E_t\left[\varepsilon_{x,t+1}^2\right] \equiv \sigma_{x,t+1}^2 = \beta_0^x + \beta_1^x \varepsilon_{x,t}^2 + \beta_2^x \sigma_{x,t}^2, \tag{18}$$

$$E_t\left[\varepsilon_{i,t+1}\varepsilon_{x,t+1}\right] \equiv \sigma_{ix,t+1} = \rho_{ix,t+1} \cdot \sigma_{i,t+1} \cdot \sigma_{x,t+1}. \tag{19}$$

We assume that the excess returns on individual stocks and the market portfolio as well as the states variables follow an autoregressive of order one AR(1) process given in equations (10), (11), and (16). At an earlier stage of the study, we consider alternative specifications of the conditional mean. More specifically, the excess returns are assumed to follow a moving average of order one MA(1) process ($R_{i,t+1} = \alpha_0^i + \alpha_1^i \varepsilon_{i,t} + \varepsilon_{i,t+1}$), ARMA(1,1) process ($R_{i,t+1} = \alpha_0^i + \alpha_1^i R_{i,t} + \alpha_2^i \varepsilon_{i,t} + \varepsilon_{i,t+1}$), and a constant ($R_{i,t+1} = \alpha_0^i + \varepsilon_{i,t+1}$). As will be discussed in the paper, our main findings are not sensitive to the choice of conditional mean specification.

We estimate the conditional covariances of each stock with the market portfolio and state variables ($\sigma_{im,t+1}, \sigma_{ix,t+1}$) based on the mean-reverting dynamic conditional correlation (DCC) model of Engle (2002). Engle defines the conditional correlation between two random variables r_1 and r_2 that each has zero mean as

$$\rho_{12,t} = \frac{E_{t-1}\left(r_{1,t} \cdot r_{2,t}\right)}{\sqrt{E_{t-1}\left(r_{1,t}^2\right) \cdot E_{t-1}\left(r_{2,t}^2\right)}}, \tag{20}$$

where the returns are defined as the conditional standard deviation times the standardized disturbance:

$$\sigma_{i,t}^2 = E_{t-1}\left(r_{i,t}^2\right), \qquad r_{i,t} = \sigma_{i,t} \cdot u_{i,t}, \qquad i = 1,2 \tag{21}$$

where $u_{i,t}$ is a standardized disturbance that has zero mean and variance one for each series. Equations (20) and (21) indicate that the conditional correlation is also the conditional covariance between the standardized disturbances:

$$\rho_{12,t} = \frac{E_{t-1}\left(u_{1,t} \cdot u_{2,t}\right)}{\sqrt{E_{t-1}\left(u_{1,t}^2\right) \cdot E_{t-1}\left(u_{2,t}^2\right)}} = E_{t-1}\left(u_{1,t} \cdot u_{2,t}\right). \tag{22}$$

The conditional covariance matrix of returns is defined as

$$H_t = D_t \cdot \rho_t \cdot D_t, \quad \text{where } D_t = diag\left\{\sqrt{\sigma_{i,t}^2}\right\}, \tag{23}$$

where ρ_t is the time-varying conditional correlation matrix

$$E_{t-1}\left(u_t \cdot u_t'\right) = D_t^{-1} \cdot H_t \cdot D_t^{-1} = \rho_t, \quad \text{where } u_t = D_t^{-1} \cdot r_t \tag{24}$$

Engle (2002) introduces a mean-reverting DCC model:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} \cdot q_{jj,t}}}, \tag{25}$$

$$q_{ij,t} = \overline{\rho}_{ij} + a_1 \cdot \left(u_{i,t-1} \cdot u_{j,t-1} - \overline{\rho}_{ij}\right) + a_2 \cdot \left(q_{ij,t-1} - \overline{\rho}_{ij}\right) \tag{26}$$

where $\overline{\rho}_{ij}$ is the unconditional correlation between $u_{i,t}$ and $u_{j,t}$. Equation (26) indicates that the conditional correlation is mean reverting towards $\overline{\rho}_{ij}$ as long as $a_1 + a_2 < 1$.

Engle (2002) assumes that each asset follows a univariate GARCH process and writes the log likelihood function as:

$$\begin{aligned} L &= -\frac{1}{2}\sum_{t=1}^{T}\left(n\ln(2\pi) + \ln\left|H_t\right| + r_t' H_t^{-1} r_t\right) \\ &= -\frac{1}{2}\sum_{t=1}^{T}\left(n\ln(2\pi) + 2\ln\left|D_t\right| + r_t' D_t^{-1} D_t^{-1} r_t - u_t' u_t + \ln\left|\rho_t\right| + u_t' \rho_t^{-1} u_t\right) \end{aligned} \tag{27}$$

As shown in Engle (2002), letting the parameters in D_t be denoted by *θ* and the additional parameters in ρ_t be denoted by *φ*, equation (27) can be written as the sum of a volatility part and a correlation part:

$$L(\theta, \varphi) = L_V(\theta) + L_C(\theta, \varphi). \tag{28}$$

The volatility term is

$$L_V(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\left(n\ln(2\pi) + \ln\left|D_t\right|^2 + r_t' D_t^{-2} r_t\right), \tag{29}$$

and the correlation component is

$$L_C(\theta, \varphi) = -\frac{1}{2}\sum_{t=1}^{T}\left(\ln\left|\rho_t\right| + u_t' \rho_t^{-1} u_t - u_t' u_t\right). \tag{30}$$

The volatility part of the likelihood is the sum of individual GARCH likelihoods:

$$L_V(\theta) = -\frac{1}{2}\sum_t \sum_{i=1}^{n}\left(\ln(2\pi) + \ln(\sigma_{i,t}^2) + \frac{r_{i,t}^2}{\sigma_{i,t}^2}\right), \tag{31}$$

which is jointly maximized by separately maximizing each term. The second part of the likelihood is used to estimate the correlation parameters. The two-step approach to maximizing the likelihood is to find

$$\hat{\theta} = \arg\max\{L_V(\theta)\} \tag{32}$$

and then take this value as given in the second stage:

$$\max_{\varphi}\{L_C(\hat{\theta},\varphi)\}. \tag{33}$$

We estimate the conditional covariances of each stock with the market portfolio and with each state variable using the maximum likelihood method described above.

Table 1 reports parameter estimates of the mean-reverting DCC model.[9] 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. 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.[10] 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

[9] 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.

[10] The conditional correlation estimates in Figure 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.

evidence for reasonable conditional variance and covariance estimates from the mean-reverting DCC model.

3.3. Estimating the intertemporal relation between risk and return

Given the conditional covariances, we estimate the intertemporal relation from the following system of equations,

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B \cdot \sigma_{ix,t+1} + e_{i,t+1}, \qquad i = 1, 2, ..., n, \tag{34}$$

where n denotes the number of individual stocks and also the number of equations in the estimation. In this paper, we simultaneously estimate n = 30 equations as our focus is on the daily risk-return tradeoff for Dow 30 stocks. We constrain the slope coefficients (A, B) to be the same across all stocks for cross-sectional consistency. We allow the intercepts C_i to differ across different stocks. Under the null hypothesis of ICAPM, the intercepts should be jointly zero. We use deviations of the intercept estimates from zero as a test against the validity and sufficiency of the ICAPM specification.[11]

We estimate the system of equations using a weighted least square method that allows us to place constraints on coefficients across equations. We compute the t-statistics of the parameter estimates accounting for heteroskedasticity and autocorrelation as well as contemporaneous cross-correlations in the errors from different equations. The estimation methodology can be regarded as an extension of the seemingly unrelated regression (SUR) method, the details of which are in Appendix C.[12]

In addition to the SUR method, we use Rogers' (1983, 1993) contemporaneous cross-sectional correlation adjusted standard errors. To compute Rogers' standard errors, we first acquire regression errors (e_t) from the panel data. Then, the variance-covariance matrix of the coefficient estimates is computed as $\left(X'X\right)^{-1}\sum_{t=1}^{T}\left(X_t'\hat{e}_t\hat{e}_t'X_t\right)\left(X'X\right)^{-1}$, where X is the matrix of independent variables, $\hat{e}_t$ is the estimated error terms, and subscript t denotes a part of the data in a certain time period t. The standard errors obtained from Rogers' methodology are also known as "clustered" standard errors.[13]

4. Empirical Results

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[11] In somewhat different contexts of conditional asset pricing models, similar tests on the intercepts are used by Ferson, Kandel, and Stambaugh (1987), Gibbons, Ross, and Shanken (1989), Harvey (1989), Shanken (1990), and Ferson and Harvey (1999).

[12] At an earlier stage of the study, we also use the ordinary least squares (OLS) and weighted least squares (WLS) methodology in estimating the system of equations. 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. We should note that the t-statistics from OLS and WLS turn out to be significantly larger than those reported in our tables.

[13] OLS, WLS, and SUR estimates are obtained from the commonly used econometrics softwares called STATA, EVIEWS, and WINRATS. The clustered standard errors are obtained from STATA.

First, we present the estimation results on the intertemporal risk-return tradeoff assuming zero intertemporal hedging demand. Second, 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 premiums 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 and average firm-specific intercepts along with the *t*-statistics from the following system of equations:

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + e_{i,t+1}, \qquad i = 1, 2, ..., n = 30. \tag{35}$$

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.

As shown in the last column of Table 2, 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.[14]

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 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 variation in expected returns so that we fail to reject the null hypothesis. The second column of Table 2 shows that the cross-sectional averages of C_i (denoted by $\overline{C}$) are small ranging from -1.53×10^{-4} to -2.34×10^{-4}. The average *t*-statistics of C_i are also very small, between –0.51 and –0.73, implying statistically insignificant daily abnormal returns.

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[14] Appendix D provides further robustness checks for the significance of positive risk-return tradeoff. The results from the clustered standard errors and the panel estimation with the standardized residuals indicate a positive and significant intertemporal relation between expected returns and risk for Dow 30 stocks.

Figure 3 presents the magnitude and statistical significance of daily abnormal returns (intercepts) that differ across stocks. 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. In all cases, the daily abnormal returns turn out to be insignificant, both economically and statistically. These results indicate that it is not only the average intercepts and average *t*-statistics reported in Table 2, but the magnitude and *t*-statistics of the intercepts are estimated to be very small for each individual stock as well.

4.1.1. Controlling for the October 1987 crash

Table 3 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:

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B \cdot X_t + e_{i,t+1}, \tag{36}$$

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 3 presents positive and highly significant common slope coefficients (*A*) on $\sigma_{im,t+1}$.

Table 4 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 4, 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 4 reports very small Wald statistics from testing the joint hypothesis of all intercepts equal zero. The second column of Table 4 presents economically and statistically insignificant average abnormal returns. Overall, the panel regression results in Tables 3 and 4 indicate that the economically and statistically significant relation between risk and return remains intact after controlling for the October 1987 crash.

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

Table 5 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 5 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 5 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.[15]

4.1.3. Subsample analysis

Table 6 investigates whether the positive relation between expected return and risk remains economically and statistically significant for different subsample periods.[16] 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.

4.1.4. Alternative specifications of the conditional mean

As shown in equations (10) and (11), 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 given in equation (34). As presented in Table 7, 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

[15] 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).

[16] To save space, starting with Table 6 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 6 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.

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 7 presents very small Wald statistics from testing the joint hypothesis of all intercepts equal zero. The second column of Table 7 reports insignificant average abnormal returns. Overall, the parameter estimates in Table 7 indicate that the economically and statistically significant relation between risk and return is not sensitive to the choice of conditional mean specification.

4.1.5. Alternative specification of the conditional covariance process

As discussed earlier, the conditional covariances are estimated based on the mean-reverting dynamic conditional correlation (DCC) model of Engle (2002). As a robustness check, we now estimate the conditional covariance between excess returns on stock *i* and the market portfolio *m* based on the following bivariate GARCH(1,1) specification:

$$R_{i,t+1} = \alpha_0^i + \varepsilon_{i,t+1}, \quad (37)$$

$$R_{m,t+1} = \alpha_0^m + \varepsilon_{m,t+1}, \quad (38)$$

$$E_t\left[\varepsilon_{i,t+1}^2\right] \equiv \sigma_{i,t+1}^2 = \beta_0^i + \beta_1^i \varepsilon_{i,t}^2 + \beta_2^i \sigma_{i,t}^2, \quad (39)$$

$$E_t\left[\varepsilon_{m,t+1}^2\right] \equiv \sigma_{m,t+1}^2 = \beta_0^m + \beta_1^m \varepsilon_{m,t}^2 + \beta_2^m \sigma_{m,t}^2, \quad (40)$$

$$E_t\left[\varepsilon_{i,t+1}\varepsilon_{m,t+1}\right] \equiv \sigma_{im,t+1} = \beta_0^{im} + \beta_1^{im} \varepsilon_{i,t}\varepsilon_{m,t} + \beta_2^{im} \sigma_{im,t}, \quad (41)$$

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 (41), 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 ($\sigma_{im,t}$).

As shown in the last column of Appendix E, 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.[17] The common slope estimates are stable across different market portfolios, between 2.99 and 3.70. The first column of Appendix E shows that the Wald statistics (with 30 degrees of freedom) are very small, failing to reject the null hypothesis of all intercepts equal zero. The second column of Appendix E shows that the cross-

[17] As shown in equations (37)-(38), the conditional mean of daily excess returns on individual stocks and the market portfolio is assumed to be constant. We should note that at an earlier stage of the study, we consider alternative specifications of the conditional mean and estimate the conditional covariances with the AR(1), MA(1), ARMA(1,1) specifications. Overall, the economic and statistical significance of the common slope coefficients turn out to be insensitive to the choice of conditional mean. Similar to our findings in Table 7, the statistical significance of the risk-aversion coefficient is found to be somewhat lower with constant mean as compared to AR(1), MA(1), and ARMA(1,1) specifications. Thus, Appendix E presents conservative results.

sectional averages of the intercepts are very small ranging from 5.03×10^{-5} to 1.34×10^{-4}. The average *t*-statistics of the intercepts are also very small, between 0.17 and 0.48, implying statistically insignificant daily abnormal returns.

4.1.6. 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 8 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 8 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 8 is that the common slope (*B*) on the lagged macroeconomic variables is found to statistically insignificant, except for some marginal significance for the change in federal funds rate.[18] 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.

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

[18] 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.

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) 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 (or total) volatility has any influence on the risk-return tradeoff. The significance of firm-level volatility is tested by estimating the following system of equations:

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B \cdot VOL_{i,t+1} + e_{i,t+1}, \tag{42}$$

where $VOL_{i,t+1}$ is the time-t expected conditional volatility of $R_{i,t+1}$. We consider two alternative measures of firm-level volatility: (1) $VOL_{i,t+1}$ is the conditional variance of the daily excess returns on stock i at time t+1 ($\sigma^2_{i,t+1}$) estimated using the AR(1)-GARCH(1,1) model and can be interpreted as the conditional idiosyncratic volatility of individual stock; (2) $VOL_{i,t+1}$ is the range daily standard deviation of individual stocks defined as $Max(\ln P_{i,t}) - Min(\ln P_{i,t})$, and can be interpreted as the conditional total volatility of individual stock.

Table 9 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 idiosyncratic volatility of individual stocks as well as the conditional range-based total volatility of individual stocks. The first column of Table 9 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 3.60, and highly significant with the t-statistics ranging from 5.82 to 7.13. Another notable point in Table 9 is that the common slope (B) on the GARCH-based idiosyncratic volatility is estimated to be positive but marginally significant, whereas the slope on the range-based total volatility is positive and statistically significant. These results suggest that an increase in daily firm-specific volatility of a Dow stock leads to an increase in the stock's one day ahead expected returns.

4.1.8. 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:

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B \cdot VOL_{m,t+1} + e_{i,t+1}, \tag{43}$$

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: (1) $VOL_{m,t+1}$ is the conditional variance of daily excess returns on the market portfolio at time t+1 ($\sigma^2_{m,t+1}$) 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 $Max(\ln P_{m,t}) - Min(\ln P_{m,t})$; and (3) $VOL_{m,t+1}$ is the implied market volatility (VXO_t) obtained from the S&P 100 index options.

Table 10 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 10 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.

4.2. 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 premiums 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).

4.2.1. Risk premiums 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 premiums, 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 11 reports the common slope estimates (A, B_1, B_2, B_3) and the average firm-specific intercepts (C_i) along with their t-statistics from the following system of equations:

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B_1 \cdot \sigma_{i,DEF,t+1} + B_2 \cdot \sigma_{i,TERM,t+1} + B_3 \cdot \sigma_{i,FED,t+1} + e_{i,t+1}, \tag{44}$$

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 11 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.

4.2.2. Risk premiums induced by conditional covariation with SMB, HML, and MOM

When the investment opportunity is stochastic, investors adjust their investment to hedge against future shifts in the investment opportunity and achieve intertemporal consumption smoothing. Hence, covariations with state of the investment opportunity induce additional risk premiums on an asset. 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 premiums on Dow 30 stocks. We measure the conditional covariance of each stock with these three factors and estimate the following system of equations:

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B_1 \cdot \sigma_{i,SMB,t+1} + B_2 \cdot \sigma_{i,HML,t+1} + B_3 \cdot \sigma_{i,MOM,t+1} + e_{i,t+1}\,, \tag{45}$$

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 12 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 premiums 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 12 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).[19]

[19] 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

4.2.3. Risk premiums 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,

$$R_{i,t+1} = C_i + A \cdot \sigma_{im,t+1} + B \cdot \sigma_{i,\Delta VOL_m,t+1} + e_{i,t+1}, \tag{46}$$

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) $\Delta VOL_{m,t+1}$ 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 $(\Delta Range_{m,t+1})$.

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 significant. As shown in Table 13, 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

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 using these changes in the ICAPM framework.

negative intertemporal relation between expected return and volatility risk.[20] 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, and the conditional mean/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 premiums 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 premiums 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 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.

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[20] 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.

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 premiums. 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.

Appendix A (continued)

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

Consider a system of n equations, of which the typical ith equation is

$$y_i = X_i \beta_i + u_i \,, \tag{1}$$

where y_i is a $N \times 1$ vector of time-series observations on the ith dependent variable, X_i is a $N \times k_i$ matrix of observations of k_i independent variables, β_i is a $k_i \times 1$ vector of unknown coefficients to be estimated, and u_i is a $N \times 1$ vector of random disturbance terms with mean zero. Parks (1967) proposes an estimation procedure that allows the error term to be both serially and cross-sectionally correlated. In particular, he assumes that the elements of the disturbance vector u follow an AR(1) process:

$$u_{it} = \rho_i u_{it-1} + \varepsilon_{it} \,; \quad \rho_i < 1 \,, \tag{2}$$

where ε_{it} is serially independently but contemporaneously correlated:

$$Cov(\varepsilon_{it}\varepsilon_{jt}) = \sigma_{ij} \,, \ \forall i, j \,, \text{ and } \ Cov(\varepsilon_{it}\varepsilon_{js}) = 0, \text{ for } s \neq t \tag{3}$$

Equation (1) can then be written as

$$y_i = X_i \beta_i + P_i \varepsilon_i \,, \tag{4}$$

with

$$P_i = \begin{bmatrix} \left(1-\rho_i^2\right)^{-1/2} & 0 & 0 \ \dots \ 0 \\ \rho_i \left(1-\rho_i^2\right)^{-1/2} & 1 & 0 \ \dots \ 0 \\ \rho_i^2 \left(1-\rho_i^2\right)^{-1/2} & \rho_i & 0 \ \dots \ 0 \\ . & & \\ . & & \\ . & & \\ \rho_i^{N-1} \left(1-\rho_i^2\right)^{-1/2} & \rho_i^{N-2} & \rho_i^{N-3} \ \dots 1 \end{bmatrix}. \tag{5}$$

Under this setup, Parks presents a consistent and asymptotically efficient three-step estimation technique for the regression coefficients. The first step uses single equation regressions to estimate the parameters of autoregressive model. The second step uses single equation regressions on transformed equations to estimate the contemporaneous covariances. Finally, the Aitken estimator is formed using the estimated covariance,

$$\hat{\beta} = \left(X^T \Omega^{-1} X\right)^{-1} X^T \Omega^{-1} y \,, \tag{6}$$

where $\Omega \equiv E[uu^T]$ denotes the general covariance matrix of the innovation. In our application, we use the aforementioned methodology with the slope coefficients restricted to be the same for all stocks. In particular, we use the same three-step procedure and the same covariance assumptions as in equations (2) to (5) to estimate the covariances and to generate the t-statistics for the parameter estimates.

Appendix D. Alternative Panel Estimation Methodology

Assuming that the errors in panel regression are cross-sectionally uncorrelated 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 robustness check, we use Rogers' (1983, 1993) robust 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

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

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 replicate our findings reported in Table 2 using Rogers (1983, 1993) or clustered standard errors. As shown in the first column of the table below, 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 further 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 (35) by the conditional standard deviation of individual stocks, $\sigma_{i,t+1}$, we obtain the following system of equations:

$$R^*_{i,t+1} = C^*_i + A\cdot\left(\rho_{im,t+1}\cdot\sigma_{m,t+1}\right) + e^*_{i,t+1}, \qquad i = 1, 2, ..., n = 30. \tag{35'}$$

where the new dependent variable is the standardized residual for stock *i*, $R^*_{i,t+1} = \left(R_{i,t+1} - E_t\left[R_{i,t+1}\right]\right)/\sigma_{i,t+1}$, obtained from equations (10) and (12), 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 (35') with standardized residuals is not exactly the same as estimating (35) with raw data, the results provide further robustness check for the significance of positive risk-return tradeoff. The last column of the table below shows that the common slope coefficients from the standardized residuals are estimated to be in the range of 2.00 and 2.84 with the *t*-statistics between 2.57 and 3.17.

Market Portfolio	Common slope (A) with clustered standard error	Common slope (A) from standardized residuals
NYSE/AMEX/NASDAQ	3.6433	2.6968
	(4.51)	(3.09)
NYSE	3.4065	2.8429
	(4.44)	(3.17)
S&P 500	3.2599	2.0715
	(4.38)	(2.63)
S&P 100	2.8191	2.0061
	(4.60)	(2.59)
DJIA	2.8717	2.0040
	(4.03)	(2.57)

Appendix E. Alternative Specification of the Conditional Covariance Process

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

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

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 $R_{m,t+1}$ obtained from equations (37)-(41). 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 – 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 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 presents the cross-sectional averages of C_i (denoted by $\overline{C}$) and the average t-statistics of C_i in parentheses. 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.

Market Portfolio	Wald Test	$\overline{C}$	A
NYSE/AMEX/NASDAQ	19.63	7.94×10^{-5}	3.6996
	[0.93]	(0.29)	(6.18)
NYSE	20.95	1.34×10^{-4}	3.1953
	[0.89]	(0.48)	(5.82)
S&P 500	18.97	5.03×10^{-5}	3.5384
	[0.94]	(0.17)	(6.19)
S&P 100	19.54	9.48×10^{-5}	2.9933
	[0.93]	(0.34)	(5.58)
DJIA	19.97	6.80×10^{-5}	3.3290
	[0.92]	(0.23)	(6.05)

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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:

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

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

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

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

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

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

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), average intercepts, and their t-statistics (in parentheses) from the following system of equations,

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

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 – 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 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 presents the cross-sectional averages of C_i (denoted by $\overline{C}$) and the average t-statistics of C_i in parentheses. 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.

Market Portfolio	Wald Test	$\overline{C}$	A
NYSE/AMEX/NASDAQ	6.92 [1.00]	-2.34×10^{-4} (–0.76)	3.2590 (6.56)
NYSE	5.94 [1.00]	-1.58×10^{-4} (–0.53)	2.5868 (5.45)
S&P 500	7.27 [1.00]	-2.31×10^{-4} (–0.76)	2.9480 (6.57)
S&P 100	7.87 [1.00]	-2.32×10^{-4} (–0.76)	2.6339 (7.03)
DJIA	5.86 [1.00]	-1.53×10^{-4} (–0.51)	2.2516 (5.44)

Table 3
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 4
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	$\overline{C}$	A
NYSE/AMEX/NASDAQ	4.35 [1.00]	-1.48×10^{-4} (–0.46)	2.9540 (3.63)
NYSE	4.37 [1.00]	-1.20×10^{-4} (–0.38)	2.7530 (3.00)
S&P 500	4.23 [1.00]	-1.17×10^{-4} (–0.37)	2.4397 (3.25)
S&P 100	4.30 [1.00]	-8.89×10^{-5} (–0.29)	1.9353 (3.25)
DJIA	5.86 [1.00]	-9.11×10^{-5} (–0.30)	2.1794 (2.91)

Table 5
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 6
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	$\overline{C}$	A
1/4/1988 – 9/28/2007	4.35 [1.00]	-1.48×10^{-4} (–0.46)	2.9540 (3.63)
7/10/1986 – 2/6/1997	9.67 [0.99]	-6.42×10^{-5} (–0.20)	2.7480 (4.86)
2/7/1997 – 9/28/2007	6.58 [1.00]	-3.41×10^{-4} (–0.72)	3.1244 (3.17)

Table 7
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 second column presents the cross-sectional averages of C_i (denoted by $\overline{C}$) and the average *t*-statistics of C_i in parentheses. 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	$\overline{C}$	A
Constant	6.42 [1.00]	-2.11×10^{-4} (–0.69)	3.0612 (5.97)
AR(1)	6.92 [1.00]	-2.34×10^{-4} (–0.76)	3.2590 (6.56)
MA(1)	7.40 [1.00]	-2.45×10^{-4} (–0.80)	3.3219 (6.64)
ARMA(1,1)	8.96 [0.99]	-2.63×10^{-4} (–0.86)	3.5775 (7.16)

Table 8
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 9
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 conditional variance of the daily excess returns on stock *i* at time *t*+1 ($\sigma^2_{i,t+1}$) estimated using the AR(1)-GARCH(1,1) model and can be interpreted as the conditional idiosyncratic volatility of individual stocks. $VOL_{i,t+1}$ is the range daily standard deviation of individual stocks defined as $Max(\ln P_{i,t}) - Min(\ln P_{i,t})$ and can be interpreted as the conditional total 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
$\sigma_{im,t+1}$	GARCH volatility	Range volatility	Dum_month
3.0611	0.0238		
(6.02)	(1.85)		
3.7091	0.0215		–0.0113
(7.13)	(1.67)		(–5.01)
2.9717		0.0105	
(5.82)		(2.24)	
3.5992		0.0111	–0.0116
(6.92)		(2.36)	(–5.12)

Table 10
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 the daily excess returns on the market portfolio at time *t*+1 ($\sigma^2_{m,t+1}$) 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 $Max(\ln P_{m,t}) - Min(\ln P_{m,t})$; 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 11
Risk Premiums 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 12
Risk Premiums 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 13
Risk Premiums 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).

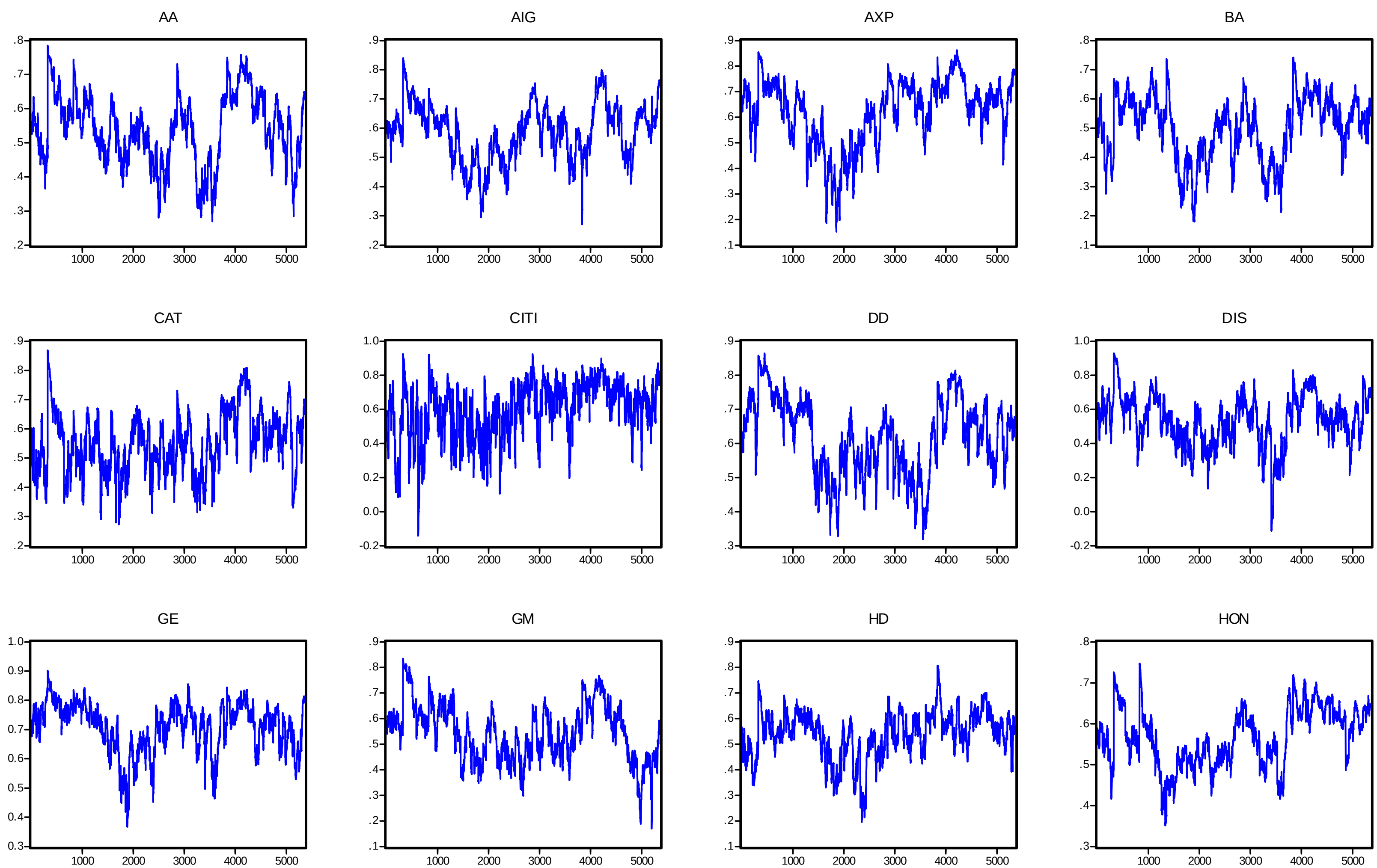


Figure 1 (continued)

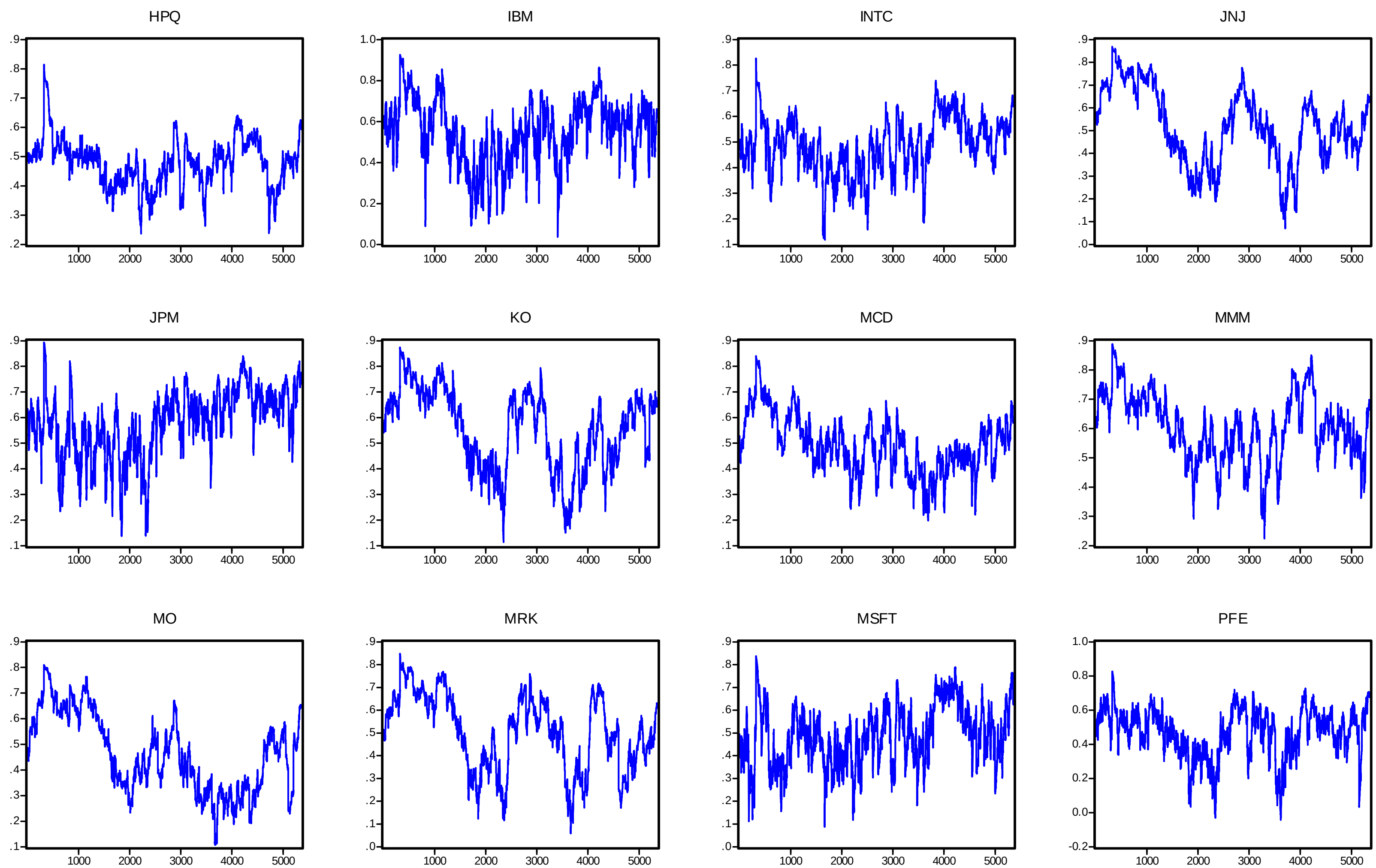


Figure 1 (continued)

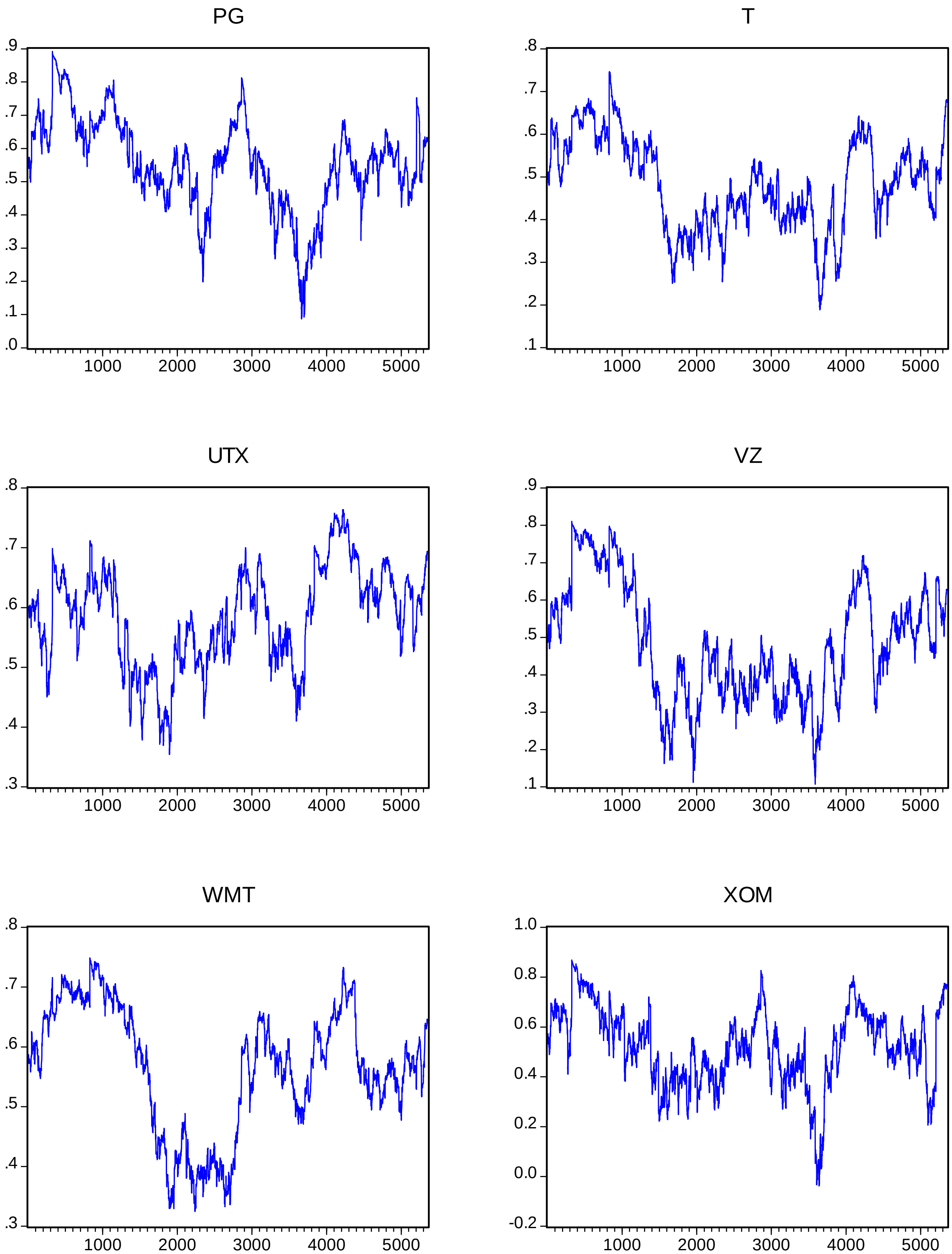
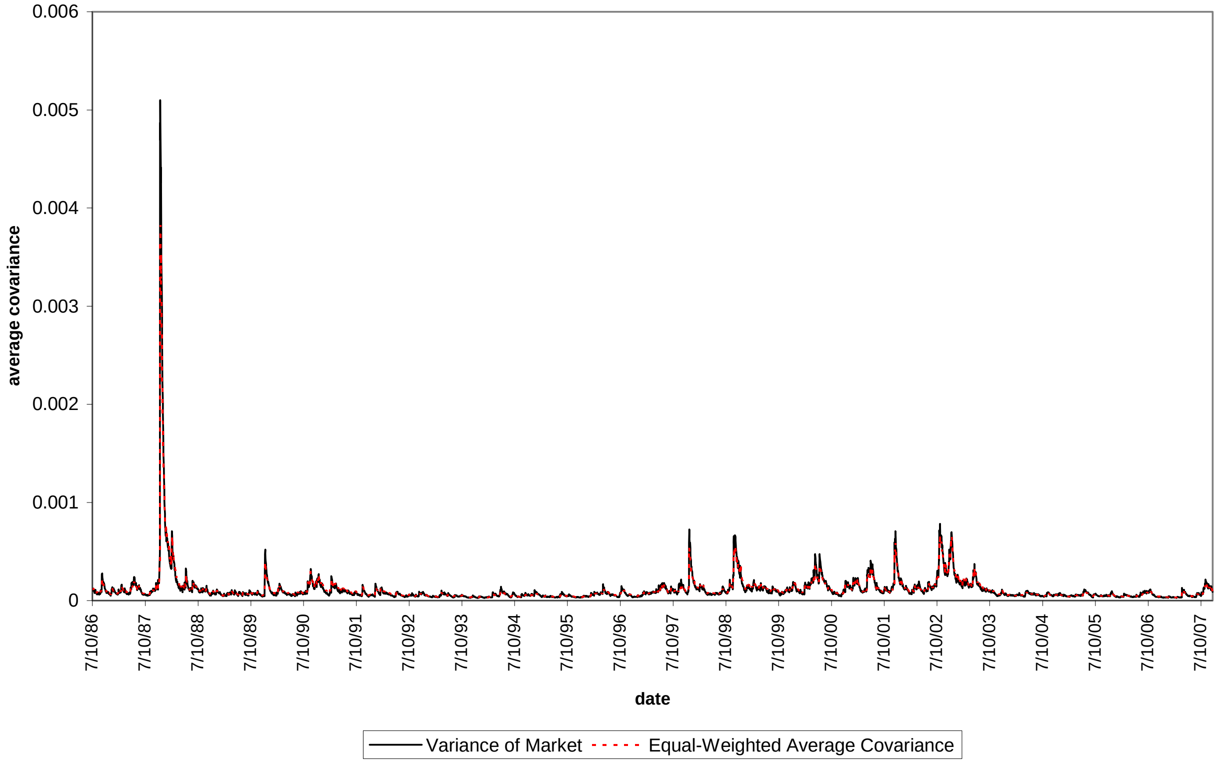


Figure 2. Weighted Average Conditional Covariance vs. Conditional Variance of the Market

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.

Panel A. Equal-Weighted Average Conditional Covariance vs. Conditional Variance of the Market



Panel B. Price-Weighted Average Conditional Covariance vs. Conditional Variance of the Market

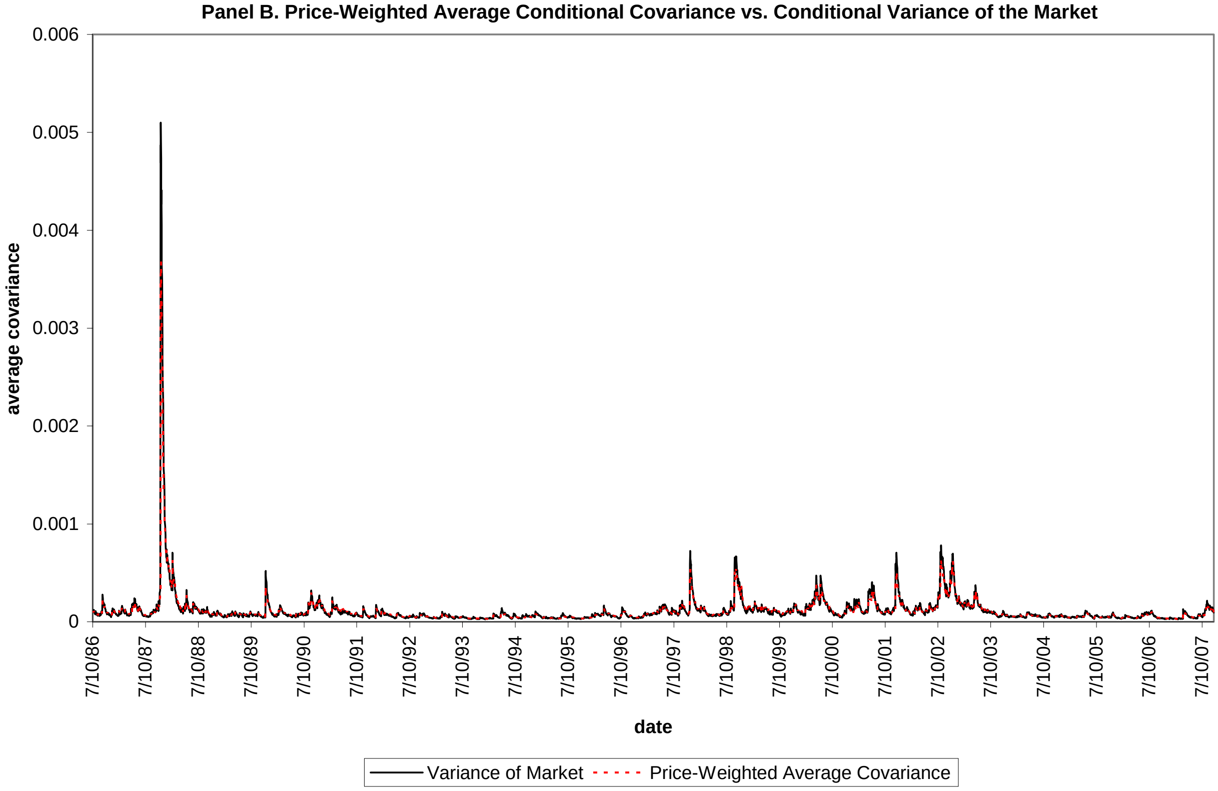
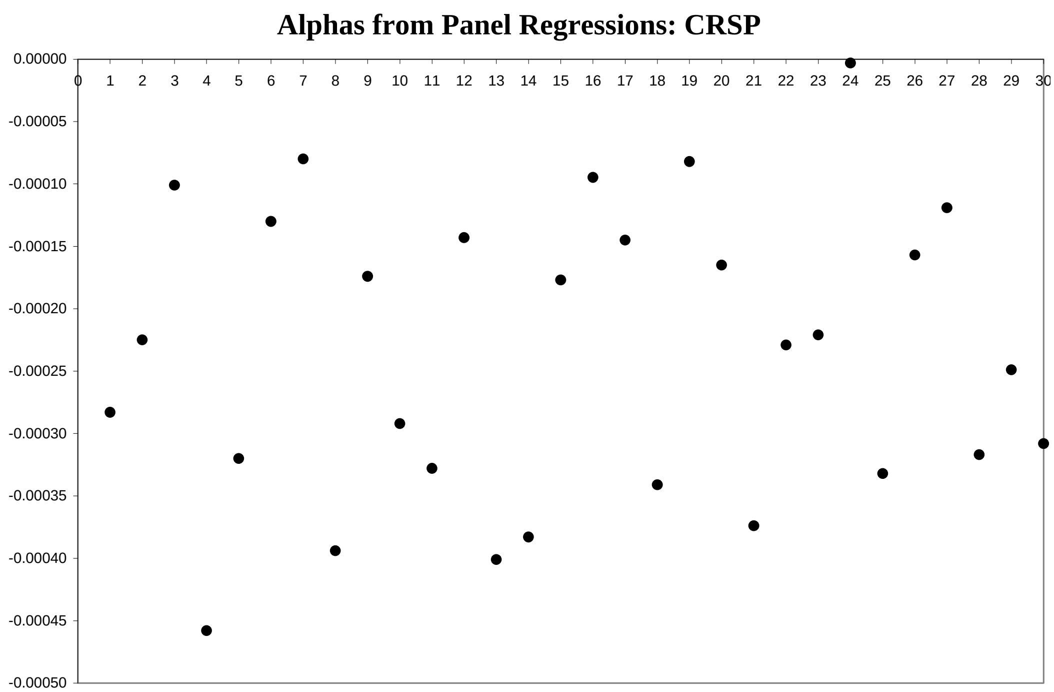


Figure 3. Daily Abnormal Returns on Dow 30 Stocks

This figure presents the magnitude and statistical significance of daily abnormal returns on Dow 30 stocks. Intercepts (denoted by C_i) that differ across stocks are obtained from estimating the system of equations in (10)-(14) over the sample period July 10, 1986–September 28, 2007. The market portfolio is measured by the value-weighted NYSE/AMEX/NASDAQ (CRSP), NYSE, S&P 500, S&P 100, and Dow Jones Industrial Average (DJIA) indices.



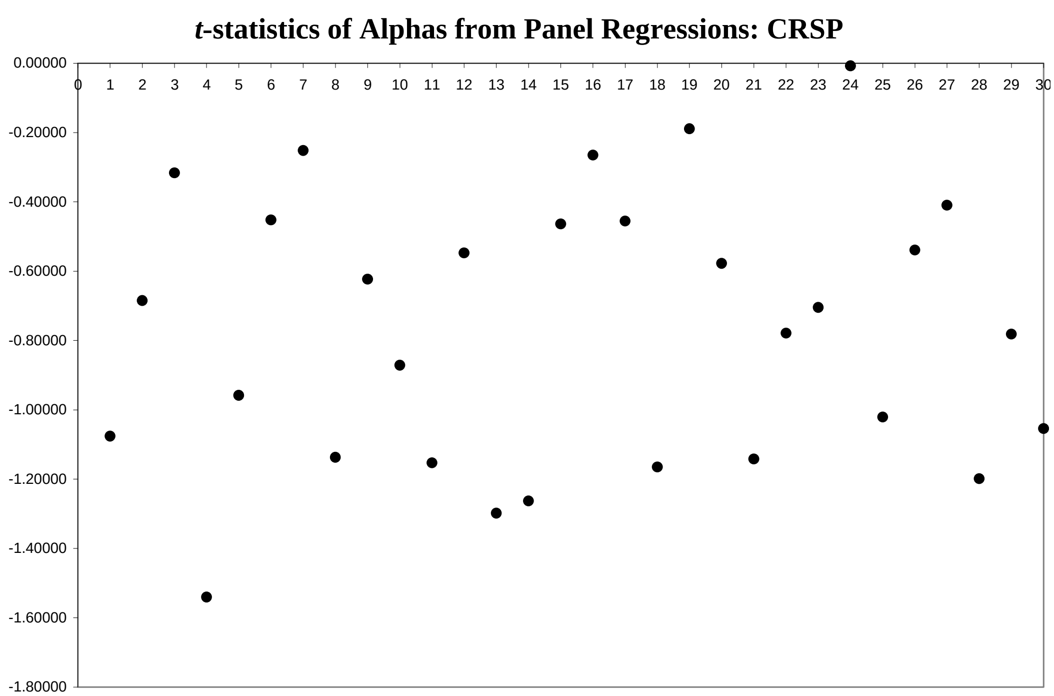
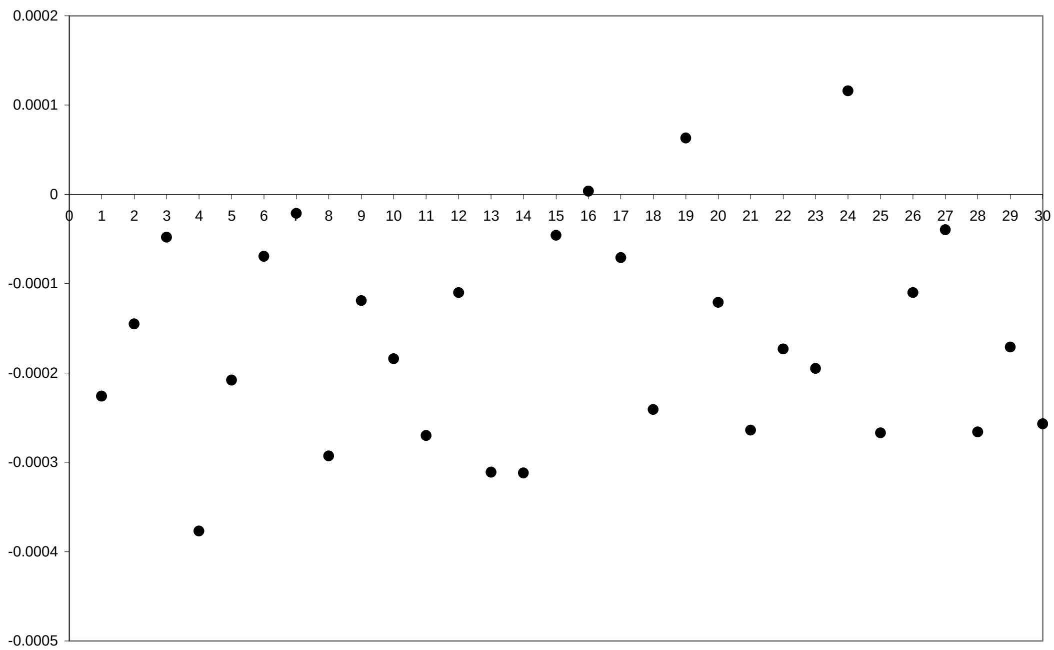


Figure 3 (continued)

Alphas from Panel Regressions: NYSE



t-statistics of Alphas from Panel Regressions: NYSE

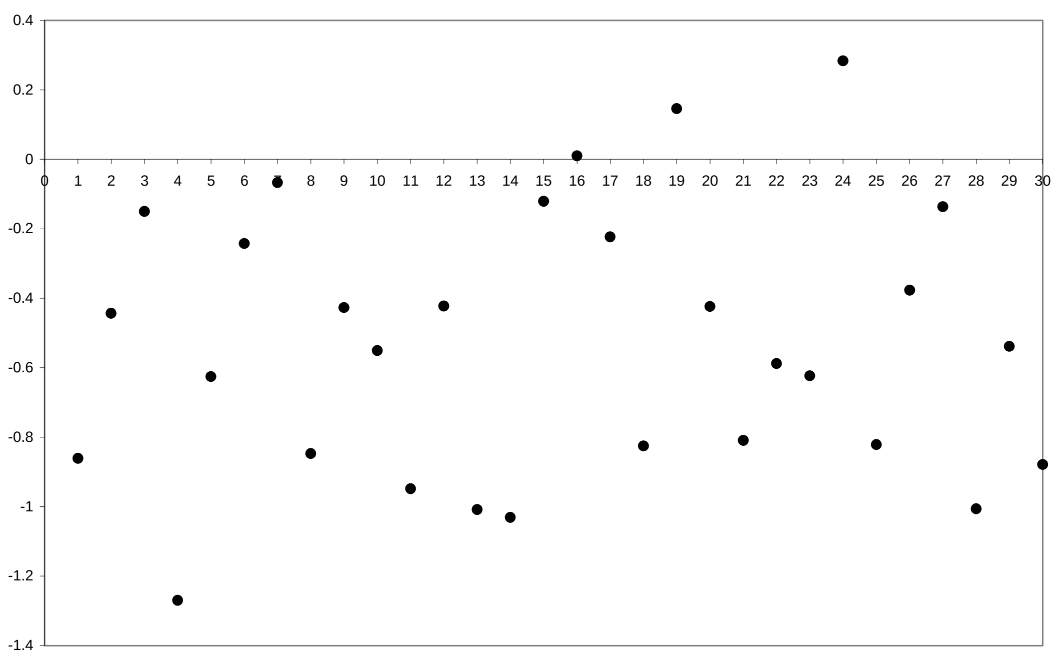
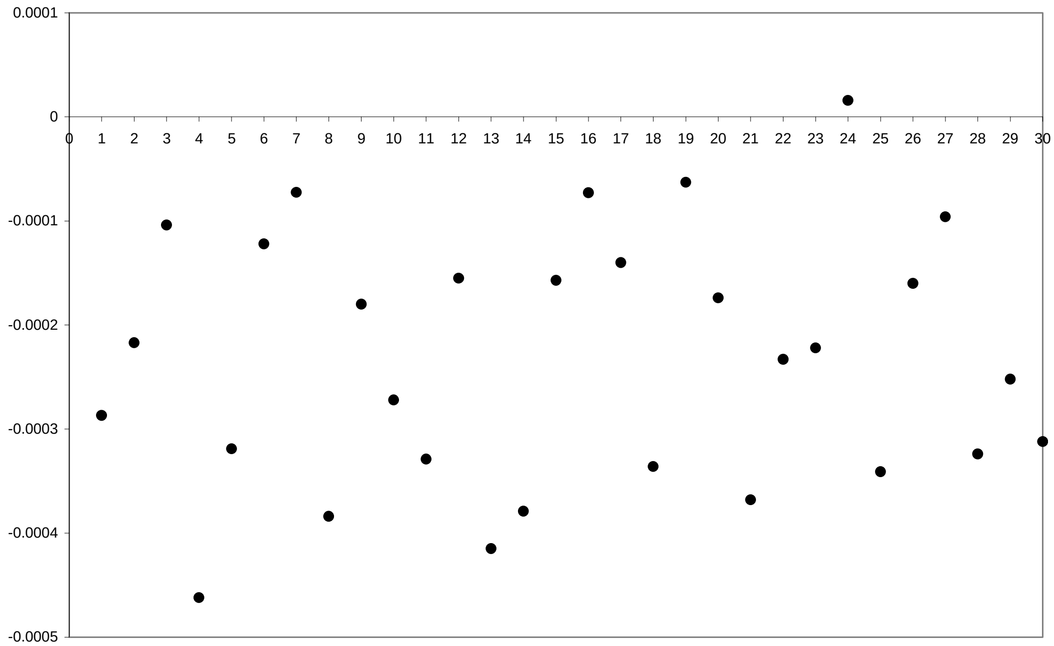


Figure 3 (continued)

Alphas from Panel Regressions: S&P 500



t-statistics of Alphas from Panel Regressions: S&P 500

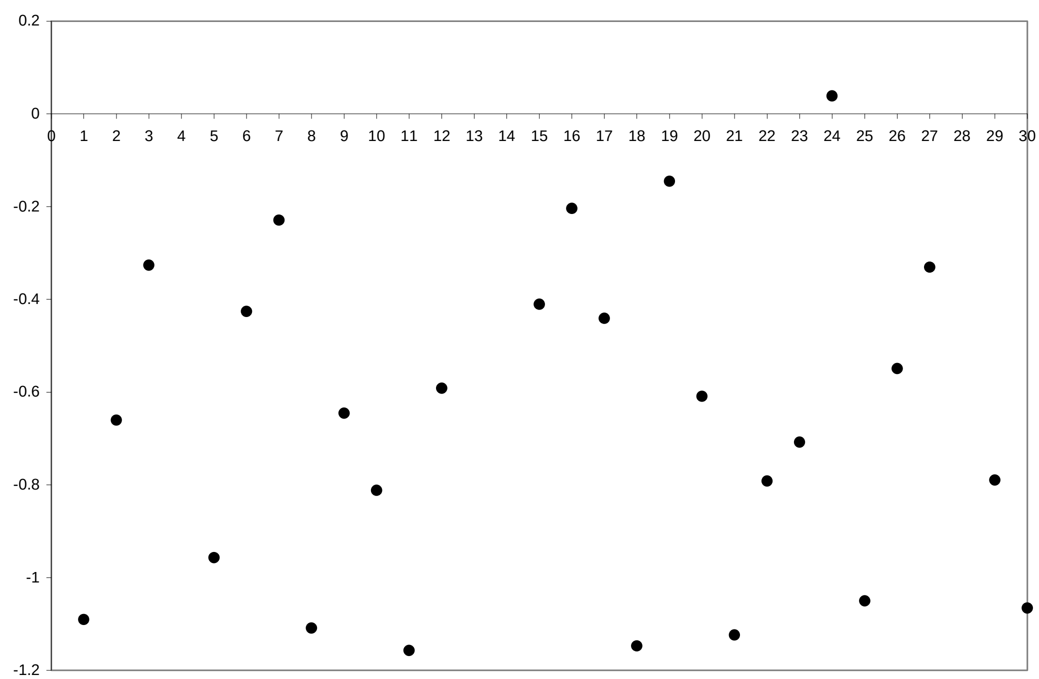
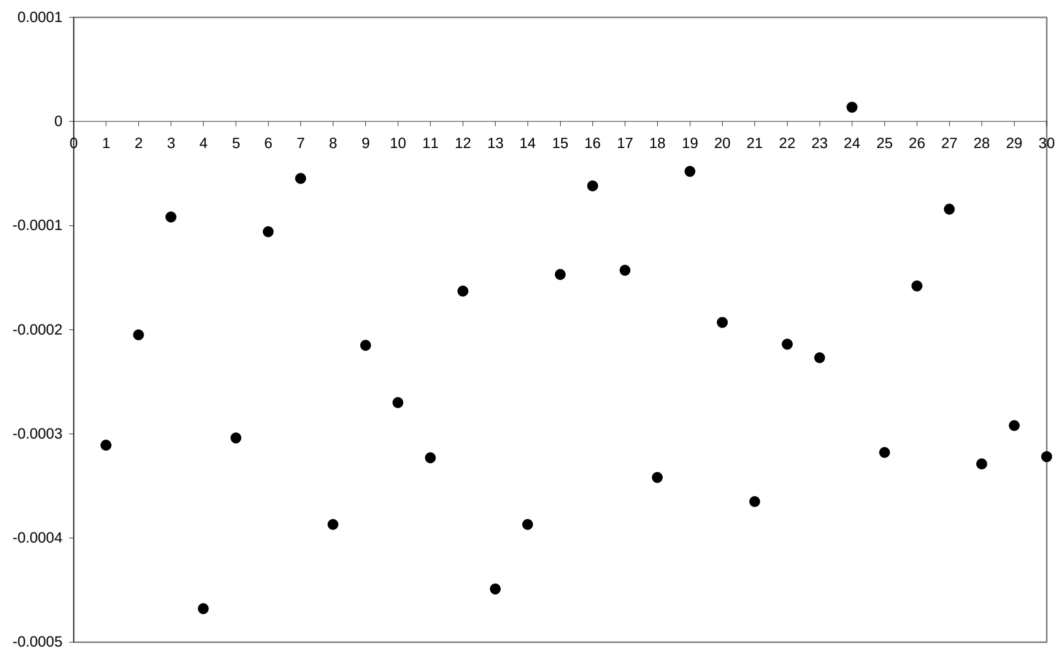


Figure 3 (continued)

Alphas from Panel Regressions: S&P 100



***t*-statistics of Alphas from Panel Regressions: S&P 100**

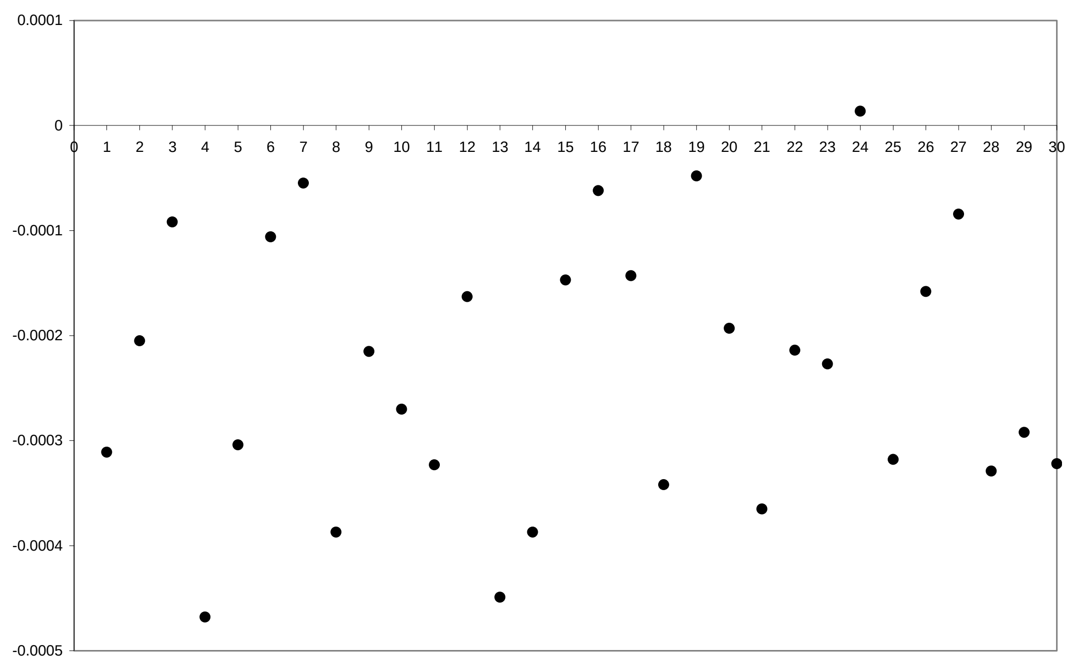
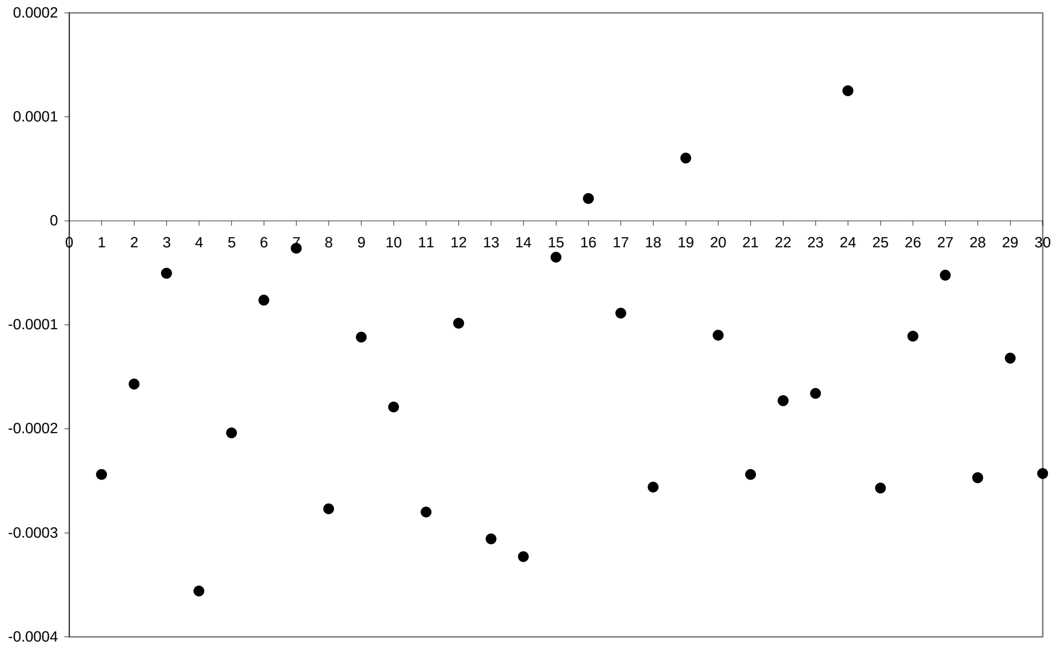


Figure 3 (continued)

Alphas from Panel Regressions: DJIA



***t*-statistics of Alphas from Panel Regressions: DJIA**