KOÇ UNIVERSITY-TÜSİAD ECONOMIC RESEARCH FORUM
WORKING PAPER SERIES

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Robert F. Engle
Yi Tang

Working Paper 1305
February 2013

KOÇ UNIVERSITY-TÜSİAD ECONOMIC RESEARCH FORUM
Rumelifeneri Yolu 34450 Sarıyer/Istanbul

# Dynamic Conditional Beta is Alive and Well in the Cross-Section of Daily Stock Returns

Turan G. Bali*
*Georgetown University*

Robert F. Engle†
*New York University*

Yi Tang‡
*Fordham University*

This draft: October 8, 2012

**Abstract**

This paper investigates the significance of dynamic conditional beta in predicting the cross-sectional variation in expected stock returns. The results indicate that the time-varying conditional beta is alive and well in the cross-section of daily stock returns. Portfolio-level analyses and firm-level cross-sectional regressions indicate a positive and significant relation between dynamic conditional beta and future returns on individual stocks. An investment strategy that goes long stocks in the highest conditional beta decile and shorts stocks in the lowest conditional beta decile produces average returns and alphas of 8% per annum. These results are robust to controls for size, book-to-market, momentum, short-term reversal, liquidity, co-skewness, idiosyncratic volatility, and preference for lottery-like assets.

**JEL classification code:** G10, G11, C13

**Keywords:** Dynamic conditional beta, conditional CAPM, ICAPM, and expected stock returns.

*Turan G. Bali is the Robert S. Parker Professor of Finance at the McDonough School of Business, Georgetown University, Washington, D.C. 20057. Phone: (202) 687-5388, Fax: (202) 687-4031, E-mail: tgb27@georgetown.edu.

†Robert F. Engle is the Michael Armellino Professor of Finance at New York University Stern School of Business, 44 West Fourth Street, Suite 9-62, New York, NY 10012, Phone: (212) 998-0710, Fax : (212) 995-4220, Email: rengle@stern.nyu.edu.

‡Yi Tang is an Assistant Professor of Finance at the Schools of Business, Fordham University, 1790 Broadway, New York, NY 10019, Phone: (646) 312-8292, Fax: (646) 312-8295, E-mail: ytang@fordham.edu.

We thank Andrew Ang, Tim Bollerslev, Stephen Brown, Frank Diebold, Eugene Fama, Eric Ghysels, and Robert Whitelaw for their extremely helpful comments and suggestions. We also benefited from discussions with George Comer, Sandeep Dahiya, Ozgur Demirtas, Allan Eberhart, George Panayotov, Lee Pinkowitz, Rohan Williamson, and seminar participants at the Federal Reserve Bank of New York and Georgetown University.

## 1. Introduction

The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) indicates that the expected return on a security in excess of the risk-free rate is related to market beta, positively and linearly, through equation (1):

$$E(R_i) - r_f = \beta_i \left[ E(R_m) - r_f \right], \tag{1}$$

where $E(R_i) - r_f$ and $E(R_m) - r_f$ denote, respectively, the expected excess return on the security and the market portfolio, and $\beta_i$ is the market beta defined as the covariance between the excess returns on the security and the market, divided by the variance of the excess market returns.

The primary implication of the CAPM is that there exists a positive linear relation between expected returns on securities and their market betas, and variables other than beta do not capture the cross-sectional variation in expected returns.[1] The CAPM also implies that the beta premium is positive and equals the expected market return minus the risk-free rate.[2]

As a theory, the CAPM is well received because it provides a powerful and economically sensible notion that any risk-averse investors would demand higher expected returns to compensate for taking higher risk. However, the model is unsuccessful in empirical tests. Very early work by Fama, Fisher, Jensen, and Roll (1969) and Blume (1970) investigate the model's empirical validity and they find supporting evidence for the CAPM's security market line. A few years later, more formal empirical tests are conducted to assess the model's performance. The results indicate a positive cross-sectional relation between beta and average return, but the relation is too flat (see, e.g., Black, Jensen, and Scholes (1972), Miller and Scholes (1972), Fama and MacBeth (1973), and Blume and Friend (1973)).[3]

[1] However, over the last four decades, a large number of studies show that firm characteristics and risk factors such as firm size, value-to-price ratios, past returns, and liquidity have significant predictive power for average stock returns, while market beta has no power.

[2] The familiar CAPM equation in (1) assumes that all investors can borrow and lend at a given riskless rate of interest. However, unrestricted risk-free borrowing and lending is an unrealistic assumption. Black (1972) introduces a version of the CAPM without risk-free borrowing or lending, and shows that the CAPM's key result can be obtained by allowing unrestricted short sales of risky securities.

[3] These studies find that the intercept in the cross-sectional regressions is greater than the average risk-free rate and the slope coefficient on beta is less than the average excess market return. Similar evidence that the relation between beta and average return is too flat is obtained from time-series tests as well (see, e.g., Friend and Blume (1970), Black, Jensen, and Scholes (1972), and Stambaugh (1982)). The intercepts in time-series regressions of excess asset returns on the excess market return are positive for assets with low beta and negative for assets with high beta (see Black (1993)).

Although very early work do not seem to put a fork in the CAPM, most of the later studies reject the model's empirical validity and practicality (see, e.g., Roll (1977), Basu (1977, 1983), Stattman (1983), Banz (1981), Rosenberg, Reid, and Lanstein (1985), Bhandari (1988), and Fama and French (1992)). Since then, the CAPM is declared dead by many practitioners and academics.[4]

The aforementioned studies examine the static (or unconditional) version of the CAPM because the original model is developed in a hypothetical economy in which all investors are single-period risk-averse utility of terminal wealth maximizers. However, in the real world, investors live for many periods and their investment decisions change through time according to their expectations about the future return distributions. The early empirical tests of the CAPM also make the assumption that the betas of the assets remain constant over time or over the estimation period. However, this is not a plausible assumption because the relative riskiness of a firm's cash flow is likely to vary over the business cycle. Also, to the extent that the business cycle is induced by technology or taste shocks, the relative share of different sectors in the economy fluctuates, causing significant time-series variation in the betas of firms in these sectors. This also implies that during recessionary or expansionary periods, correlations of firms with the market may increase or decrease depending on the industries to which firms belong. Hence, expected returns and betas typically depend on the information available at any given point in time and vary over time.[5]

Based on this evidence, we examine the significance of dynamic conditional beta in predicting the cross-sectional variation in stock returns. We rely on a time-varying conditional version of the CAPM that relates the conditionally expected excess returns on risky assets to the conditionally expected excess return on the market portfolio:

$$E\left[R_{i,t+1} - r_{f,t+1} | \Omega_t\right] = E\left[\beta_{i,t+1} | \Omega_t\right] \cdot E\left[R_{m,t+1} - r_{f,t+1} | \Omega_t\right], \tag{2}$$

where $\Omega_t$ denotes the information set at time $t$ that investors use to form expectations about future returns and betas. $E\left[R_{i,t+1} - r_{f,t+1} | \Omega_t\right]$ and $E\left[R_{m,t+1} - r_{f,t+1} | \Omega_t\right]$ are the expected excess return on

[4] The interested reader may wish to consult Fama and French (2004) who provide an excellent, comprehensive review of the CAPM literature.

[5] More direct evidence is provided by Bollerslev, Engle, and Wooldridge (1988), Harvey (1989), Jaganathan and Wang (1996), Lewellen and Nagel (2006), Bali (2008), Bali and Engle (2010), and Engle (2012) who find significant time-series variation in the conditional betas of equity portfolios.

the risky asset $i$ and the market portfolio $m$ at time $t+1$ conditional on the information set at time $t$. $E[\beta_{i,t+1}|\Omega_t]$ is the time-$t$ expected conditional beta of asset $i$ defined as the ratio of the time-$t$ expected conditional covariance between $R_{i,t+1} - r_{f,t+1}$ and $R_{m,t+1} - r_{f,t+1}$ to the time-$t$ expected variance of $R_{m,t+1} - r_{f,t+1}$:

$$E[\beta_{i,t+1}|\Omega_t] = \frac{cov[R_{i,t+1} - r_{f,t+1}, R_{m,t+1} - r_{f,t+1}|\Omega_t]}{var[R_{m,t+1} - r_{f,t+1}|\Omega_t]}. \quad (3)$$

Bollerslev, Engle, and Wooldridge (1988), Bali (2008), and Bali and Engle (2010) allow both conditional expected returns and conditional betas to vary over time and they find a positive and significant intertemporal relation between expected returns and risk for equity portfolios. However, they do not investigate the cross-sectional relation between expected returns and time-varying conditional betas, nor do they examine the risk-return tradeoff at the individual firm level. In this paper, we test the significance of dynamic conditional betas in predicting the cross-section of future returns on individual stocks.

In our empirical analysis, we estimate the conditional betas for the S&P 500 stocks based on the dynamic conditional correlation (DCC) model of Engle (2002) using one year of daily data. We then ask if these dynamic conditional betas have predictive power for the cross-section of individual stock returns over the next one to five days. The sample period is from July 1963 to December 2009. Confirming the findings of earlier studies, we first show that there is no significant link between the unconditional beta and the cross-section of expected returns. Then, we provide comprehensive analyses of the cross-sectional relation between the dynamic conditional betas and future stock returns.

The results from the time-varying conditional betas are remarkable. Univariate portfolio level analyses indicate that a trading strategy that goes long stocks in the highest conditional beta decile and shorts stocks in the lowest conditional beta decile yields average returns and alphas of 8% per annum. Firm-level, cross-sectional regressions that control for well-known pricing effects, including size, book-to-market (Fama and French (1992, 1993)), momentum (Jegadeesh and Titman (1993)), short-term reversal (Jegadeesh (1990)), liquidity (Amihud (2002)), co-skewness (Harvey and Siddique (2000)), volatility (Ang, Hodrick, Xing, and Zhang (2006, 2009)), and preference for lottery-like assets (Bali, Cakici, and Whitelaw (2011)) generate very similar results.

As robustness checks, we test whether the positive relation between the dynamic conditional beta and the cross-section of expected returns holds in bivariate dependent sorts and using the size, book-to-market, and momentum matched benchmark portfolios similar to Daniel and Titman (1997). In addition to the S&P 500 sample, we replicate our results using the largest 500 and 1,000 stocks as well as the most liquid 500 stocks in the U.S. equity market. Throughout our empirical analysis, the evidence is consistent with significant pricing effects generated by the outperformance of stocks with high conditional beta and the underperformance of stocks with low conditional beta. Overall, our results indicate that the unconditional beta is dead, but the dynamic conditional beta is alive and powerful in the cross-section of daily stock returns.

The paper is organized as follows. Section 2 presents the conditional intertemporal capital asset pricing model. Section 3 contains the data and variable definitions. Section 4 presents evidence of cross-sectional predictability in the context of univariate portfolio sorts and also looks more closely at the characteristics of the stocks within these portfolios. Section 5 provides bivariate portfolio level analyses, controlling for size, book-to-market, momentum, short-term reversal, liquidity, co-skewness, volatility, and extreme returns, while also examining the predictive power of the conditional beta using the characteristic matched portfolios and firm-level cross-sectional regressions. Section 6 provides additional robustness checks, and Section 7 concludes the paper.

## 2. The Conditional Intertemporal Capital Asset Pricing Model

Merton's (1973) intertemporal capital asset pricing model (ICAPM) implies the following equilibrium relation between expected return and risk for any risky asset $i$:

$$\mu_i - r_f = A \cdot \sigma_{im} + B \cdot \sigma_{ix}, \tag{4}$$

where $\mu_i - r_f$ denotes the unconditional expected excess return on risky asset $i$, $\sigma_{im}$ denotes the unconditional covariance between the excess returns on the risky asset $i$ and the market portfolio $m$, and $\sigma_{ix}$ denotes a $(1 \times k)$ row of unconditional covariances between the excess returns on the risky asset $i$ and the $k$-dimensional state variables $x$. $A$ is the relative risk aversion of market investors and $B$ measures the market's aggregate reaction to shifts in a $k$-dimensional state vector that governs the stochastic investment opportunity set. Equation (4) states that in equilibrium, investors are compensated in terms of expected return for bearing market risk and for bearing the risk of unfavorable shifts in the investment opportunity set.

The second term in equation (4) 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 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 is anticipated, investors will expect to be compensated by a higher level of wealth through the positive correlation of the returns.

Merton (1973) uses the example of stochastic interest rate to illustrate the role of intertemporal hedging demand. He points out that a positive covariance of asset returns with interest rate shocks (or innovations in interest rate) predicts a lower return on the risky asset. In the context of Merton's ICAPM, an increase in interest rate predicts a decrease in investment demand (since the cost of borrowing is high) and a decrease in optimal consumption, which leads to 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 the changes in interest rate 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 interest rate risk leads to an increase in the hedging demand, which in equilibrium reduces expected return on the asset.

In the original Merton (1973) model, the parameters of expected returns and covariances are all interpreted as constant, but the ability to model time variation in expected returns and covariances makes it natural to include time-varying parameters directly in the analysis (see Bali and Engle (2010)), which gives the following conditional intertemporal capital asset pricing model (the conditional ICAPM):

$$E\left[R_{i,t+1}-r_{f,t+1}|\Omega_t\right]=A\cdot cov\left[R_{i,t+1}-r_{f,t+1},R_{m,t+1}-r_{f,t+1}|\Omega_t\right]+B\cdot cov\left[R_{i,t+1}-r_{f,t+1},\Delta X_{t+1}|\Omega_t\right], \tag{5}$$

where $cov\left[R_{i,t+1}-r_{f,t+1},R_{m,t+1}-r_{f,t+1}|\Omega_t\right]$ is the time-$t$ expected conditional covariance between the excess returns on the risky asset $i$ and the market portfolio $m$, and $cov\left[R_{i,t+1}-r_{f,t+1},\Delta X_{t+1}|\Omega_t\right]$ is the time-$t$ expected conditional covariance between the excess return on the risky asset $i$ and the innovations in the state variable $X$, proxied by the change in $X$ ($\Delta X_{t+1}=X_{t+1}-X_t$). In equation (5), $A$ is the reward-to-risk ratio and interpreted as the Arrow-Pratt relative risk-aversion coefficient. The parameter $B$ represents the price of risk for innovations or unexpected changes in the state variable $X$.[6]

To point out the differences between the conditional CAPM in equation (2) and the conditional ICAPM in equation (5), we replace the conditional covariances with the conditional betas in equation (6):

$$E\left[R_{i,t+1}-r_{f,t+1}|\Omega_t\right]=\tilde{A}\cdot E\left[\beta_{im,t+1}|\Omega_t\right]+\tilde{B}\cdot E\left[\beta_{ix,t+1}|\Omega_t\right], \tag{6}$$

where $E\left[\beta_{im,t+1}|\Omega_t\right]$ is the time-$t$ expected conditional market beta of asset $i$ that measures time-varying sensitivity of asset $i$ to the fluctuations in the market portfolio, and $E\left[\beta_{ix,t+1}|\Omega_t\right]$ is the time-$t$ expected conditional beta of asset $i$ against the state variable $X$ that measures time-varying exposure of asset $i$ to the changes in $X$. In equation (6), $\tilde{A}$ is the time-$t$ expected conditional market risk premium and $\tilde{B}$ is the time-$t$ expected conditional risk premium of $X$.

The difference between the conditional CAPM in equation (2) and the conditional ICAPM in equation (6) is the intertemporal hedging demand component, $E\left[\beta_{ix,t+1}|\Omega_t\right]$, which implies that, contrary to the conditional CAPM, expected returns on risky assets in equation (6) may differ from the risk-

[6] Bali and Engle (2010) provide a time-series investigation of the conditional ICAPM in equation (5). Their results indicate a positive and significant intertemporal relation between expected returns and risk for equity portfolios. They also find that the conditional covariances of equity portfolios with the changes in default spread, the changes in term spread, and the changes in implied market volatility are priced in the conditional ICAPM framework. Their findings provide evidence for the significance of intertemporal hedging demand, implying that investors care about the portfolios' covariation with future investment opportunities.

less rate even when they have no market risk.[7] The conditional ICAPM indicates that the dynamic conditional beta does not provide a complete description of an asset's systematic risk. To explain the cross-sectional differences in expected returns, in addition to the asset's covariation with the market portfolio, one needs to account for the asset's covariation with future investment opportunities as well.

The central prediction of the conditional CAPM is that there exists a positive linear relation between expected returns on securities and their conditional market betas, and variables other than the conditional beta should not capture the cross-sectional variation in stock returns. As will be discussed later in the paper, we find a positive and significant link between the conditional beta and the cross-section of expected returns. However, after controlling for the conditional beta, some of the usual suspects (e.g., firm size, past returns, and idiosyncratic volatility) strongly predict the cross-section of expected returns. This provides a potential explanation for the empirical failures of the static and the conditional CAPM. Our results point to the need for a more complicated asset pricing model along the lines of the conditional ICAPM.

The static CAPM is built on an implausible assumption that investors care only about the mean and variance of single-period portfolio returns. However, in practice, investors make decisions for multiple periods and they revise their portfolio and risk management decisions over time based on the expectations about future investment opportunities. In Merton's (1973) ICAPM, investors are concerned not only with the terminal wealth that their portfolio produces, but also with the investment and consumption opportunities that they will have in the future. Hence, when choosing a portfolio at time $t$, ICAPM investors consider how their wealth at time $t+1$ might vary with future state variables. This implies that like CAPM investors, ICAPM investors prefer high expected return and low return variance, but they are also concerned with the covariances of portfolio returns with state variables that affect future investment opportunities.[8]

[7] A cross-sectional implication of the conditional ICAPM is that even when $E\left[\beta_{im,t+1}|\Omega_t\right] = 0$ in equation (6), expected returns differ across risky assets because of the differences in the assets' conditional covariances with future investment opportunities, i.e., because of the differences in $E\left[\beta_{ix,t+1}|\Omega_t\right]$ across assets.

[8] Fama (1996) points out that Merton's (1973) ICAPM generalizes the logic of the CAPM. Fama (1996) shows that optimal portfolios of ICAPM investors are multifactor efficient, which means ICAPM investors have the largest possible expected returns, given their return variances and the covariances of their returns with the relevant state variables.

Merton's (1973) ICAPM is deduced from the portfolio selection behavior of risk-averse investors who maximize the expected utility of lifetime consumption and who can trade *continuously in time*. Hence, it is important to note that Merton's ICAPM is originally developed in a continuous-time framework, but the empirical test of the ICAPM requires discrete-time data. Clearly, the discrete-time approximation of the continuous-time model may potentially generate large approximation errors depending on the frequency of data used to measure expected returns and betas. Merton (1973) points out in his seminal paper (p. 869, footnote 9) that daily frequency is sufficiently small to make the continuous-time assumption a good approximation.

We follow Merton's (1973) remark and estimate the time-varying conditional betas using daily data and investigate their predictive power for the cross-section of daily stock returns. By sampling the return process more frequently (than monthly data, for example), we increase the accuracy of the conditional beta estimates and measure the cross-sectional risk-return relationship at daily frequency.[9]

Another reason that we investigate the cross-section of daily stock returns is the significant upward trend in daily trading volume and daily turnover of the S&P 500 stocks used in the paper. Figure 1 depicts the aggregate daily dollar trading volume of the S&P 500 stocks (in $millions) over the sample period July 1964−December 2009. Figure 2 plots the average daily turnover of the S&P 500 stocks (defined as the ratio of trading volume to the number of shares outstanding), and Figure 3 presents the relative volume and relative turnover for the same period. In Figure 3, RVOLD is the ratio of aggregate daily trading volume of S&P 500 stocks to the total daily trading volume of the market, and RTURN the ratio of the S&P 500 stocks' daily turnover to the daily turnover of all stocks trading at NYSE, Amex, and Nasdaq.

In Appendix A, we present the corresponding values for five decades in our sample: July 1964−June 1973, July 1973−June 1983, July 1983−June 1993, July 1993−June 2003, and July 2003−December 2009. A notable point in Figures 1−3 and Appendix A is that the daily trading volume and the daily share turnover of the S&P 500 stocks as well as the relative volume and relative turnover increased

[9] Andersen, Bollerslev, Diebold, and Labys (2003) and Barndorff-Nielsen and Shephard (2004) provide theoretical and empirical evidence that the measurement of conditional variance and covariance of a time-series becomes more precise as the sampling frequency increases.

over time significantly. As reported in Appendix A, the aggregate daily trading volume of the S&P 500 stocks is about $226 million for the first decade in our sample (1964−1973), whereas the corresponding figure increased to $88 billion for the most recent period (2003−2009). Similarly, the relative volume and relative turnover of the S&P 500 stocks (with respect to all stocks in the U.S. equity market) are, respectively, 0.47 and 0.67 for the period 1964−1973, whereas the corresponding figures increased to 0.70 and 1.39, respectively. These results indicate substantial rises in the trading activity of big and liquid stocks at daily frequency.

Since stocks with greater trading volume and turnover adjust faster to information, prices converge to their true, full information value more quickly, i.e., prices become more efficient. As pointed out by Merton (1987), big stocks are in general less susceptible to market frictions such as information costs. Hence, by investigating the cross-section of daily returns on these big and liquid stocks, we identify an economically important risk-return relation that market professionals can exploit because of low trading costs.

## 3. Data and Variable Definitions

Our main sample is made up of the S&P 500 index components obtained from the Center for Research in Securities Prices database (CRSP). The daily return and daily trading volume data come from the CRSP. We adjust stock returns for delisting in order to avoid survivorship bias (Shumway (1997)).[10] The accounting data are obtained from the Merged CRSP/Compustat database. The sample covers the period from July 1963 to December 2009.

In addition to the S&P 500 stocks, we use three different datasets to check the robustness of our findings; the largest 500 and 1,000 stocks in the CRSP that are obtained by ranking individual stocks based on their market capitalization as of the end of June of each year from 1963 to 2009. We also use

[10] Specifically, when a stock is delisted, we use the delisting return from CRSP, if available. Otherwise, we assume the delisting return is -100%, unless the reason for delisting is coded as 500 (reason unavailable), 520 (went to OTC), 551-573, 580 (various reasons), 574 (bankruptcy), or 584 (does not meet exchange financial guidelines). For these observations, we assume that the delisting return is -30%.

the most liquid 500 stocks in the CRSP that are obtained by ranking individual stocks based on their average illiquidity in a month.

We also employ an extensive set of control variables. The first three variables are those from the Fama-French-Carhart 4-factor model – size, book-to-market, and momentum. We also control for microstructure-related phenomena in the form of short-term reversal and liquidity. Finally, we include three additional control variables – co-skewness, idiosyncratic volatility, and extreme positive returns.

### 3.1. Unconditional measures of market beta

We focus on four different measures of beta and investigate their predictive power for the cross-sectional variation in daily stock returns. When estimating the unconditional measures of market beta, we use daily returns over the past 252 trading days, with at least 200 observations available.

CAPM Beta:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i (R_{m,d} - r_{f,d}) + \varepsilon_{i,d}, \tag{7}$$

where $R_{i,d}$ is the return on stock $i$ on day $d$, $R_{m,d}$ is the market return on day $d$, and $r_{f,d}$ is the risk-free rate on day $d$. For each day in our sample, we estimate equation (7) for each stock using daily returns over the past 252 trading days. The CAPM beta (denoted by $BETA_{CAPM}$) is measured by the slope coefficient, $\widehat{\beta}_i$, in equation (7).

Fama-French Beta:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d} - r_{f,d}) + \beta_{2,i}(R_{m,d-1} - r_{f,d-1}) + \varepsilon_{i,d}. \tag{8}$$

Fama and French (1992) use monthly returns (not daily returns) to estimate market beta. They include the one-month lagged market return to take into account the first-order autocorrelation in returns. Following Fama and French (1992), we use equation (8) to estimate an alternative measure of market beta, but we use daily returns over the past 252 trading days (with at least 200 observations available). Fama-French beta (denoted by $BETA_{FF}$) is the sum of the slope coefficients, $\widehat{\beta_{1,i}}$ and $\widehat{\beta_{2,i}}$.

Scholes-Williams Beta:

$$
\begin{aligned}
R_{i,d} - r_{f,d} &= \alpha_i + \beta_{1,i}(R_{m,d-1} - r_{f,d-1}) + \varepsilon_{i,d}, &(9)\\
R_{i,d} - r_{f,d} &= \alpha_i + \beta_{2,i}(R_{m,d} - r_{f,d}) + \varepsilon_{i,d}, &(10)\\
R_{i,d} - r_{f,d} &= \alpha_i + \beta_{3,i}(R_{m,d+1} - r_{f,d+1}) + \varepsilon_{i,d}, &(11)
\end{aligned}
$$

To account for nonsynchronous trading, Scholes and Williams (1977) estimate the three regression specifications in equations (9)-(11) separately, and they also compute the first-order autocorrelation of the market return, $\rho$. The Scholes-Williams beta (denoted by $BETA_{SW}$) is given in equation (12):

$$
BETA_{SW} = \frac{\widehat{\beta_{1,i}} + \widehat{\beta_{2,i}} + \widehat{\beta_{3,i}}}{1+2\rho}. \tag{12}
$$

Dimson Beta:

$$
R_{i,d} - r_{f,d} = \alpha_i + \beta_{0,i}(R_{m,d} - r_{f,d}) + \sum_{k=1}^{5} \beta_{-k,i}(R_{m,d-k} - r_{f,d-k} + \sum_{k=1}^{5} \beta_{k,i}(R_{m,d+k} - r_{f,d+k}) + \varepsilon_{i,d}. \tag{13}
$$

In addition to the contemporaneous market return, Dimson (1979) includes five lagged market return and five leading market return to the CAPM equation. Dimson beta (denoted by $BETA_{SW}$) is the sum of the 11 slope coefficients in equation (13).

The unconditional measures of market beta (the CAPM, Fama-French, Scholes-Williams, and Dimson) are estimated using daily returns over the past one year. Although the unconditional betas change each day because of daily rolling regressions, they are constant over the fixed estimation window of one year.

### 3.2. Dynamic conditional beta

We estimate the conditional covariance between the excess returns on stock $i$ and the market portfolio $m$ based on the mean-reverting dynamic conditional correlation (DCC) model of Engle (2002):

$$
\begin{aligned}
R_{i,d+1} - r_{f,d+1} &= \alpha_0^i + \sigma_{i,d+1} \cdot u_{i,d+1}, &(14)\\
R_{m,d+1} - r_{f,d+1} &= \alpha_0^m + \sigma_{m,d+1} \cdot u_{m,d+1}, &(15)\\
E_d[\varepsilon_{i,d+1}^2] \equiv \sigma_{i,d+1}^2 &= \beta_0^i + \beta_1^i \sigma_{i,d}^2 u_{i,d}^2 + \beta_2^i \sigma_{i,d}^2 &(16)\\
E_d[\varepsilon_{m,d+1}^2] \equiv \sigma_{m,d+1}^2 &= \beta_0^m + \beta_1^m \sigma_{m,d}^2 u_{m,d}^2 + \beta_2^m \sigma_{m,d}^2 &(17)\\
E_d[\varepsilon_{i,d+1}\varepsilon_{m,d+1}] \equiv \sigma_{im,d+1} &= \rho_{im,d+1} \cdot \sigma_{i,d+1} \cdot \sigma_{m,d+1} &(18)\\
\rho_{im,d+1} &= \frac{q_{im,d+1}}{\sqrt{q_{ii,d+1} \cdot q_{mm,d+1}}}, &\\
q_{im,d+1} &= \overline{\rho_{im}} + a_1 \cdot (u_{i,d} \cdot u_{m,d} - \overline{\rho_{im}}) + a_2 \cdot (q_{im,d} - \overline{\rho_{im}}), &(19)
\end{aligned}
$$

where $R_{i,d+1} - r_{f,d+1}$ and $R_{m,d+1} - r_{f,d+1}$ denote the day $(d+1)$ excess return on stock $i$ and the market portfolio $m$ over a risk-free rate, respectively, and $E_d$ denotes the expectation operator conditional on day $d$ information. $\sigma_{i,d+1}^2$ is the day-$d$ expected conditional variance of stock $i$, $\sigma_{m,d+1}^2$ is the day-$d$ expected conditional variance of the market, and $\sigma_{im,d+1}$ is the day-$d$ expected conditional covariance between $R_{i,d+1} - r_{f,d+1}$ and $R_{m,d+1} - r_{f,d+1}$ . $u_{i,d} = \frac{\varepsilon_{i,d}}{\sigma_{i,d}}$ and $u_{m,d} = \frac{\varepsilon_{m,d}}{\sigma_{m,d}}$ are the standardized residuals for stock $i$ and the market portfolio, respectively. $\rho_{im,d+1} = \frac{q_{im,d+1}}{\sqrt{q_{ii,d+1} \cdot q_{mm,d+1}}}$ is the day-$d$ expected conditional correlation between $R_{i,d+1} - r_{f,d+1}$ and $R_{m,d+1} - r_{f,d+1}$, and $\overline{\rho_{im}}$ is the unconditional correlation. To ease the parameter convergence, we follow Bali and Engle (2010) and Engle and Kelly (2012), and use correlation targeting assuming that the time-varying correlations mean revert to the sample correlations $\overline{\rho_{im}}$.[11]

DCC beta is defined as the ratio of equation (18) to (17):

$$
BETA_{i,d+1}^{DCC} = \frac{\sigma_{im,d+1}}{\sigma_{m,d+1}^2}. \tag{20}
$$

To be consistent with the estimation procedure of the unconditional beta, the dynamic conditional beta is estimated using daily returns over the past 252 trading days (with at least 200 observations available). The main difference between the two measures is that the conditional DCC betas vary each day in the

[11] We estimate the dynamic conditional beta of each stock with the market portfolio using the maximum likelihood method described in Appendix B.

estimation period of one year, whereas the unconditional beta is constant over the same estimation period.

## 3.3. Control variables

We use a large set of control variables in the cross-sectional asset pricing tests. Unless otherwise stated, all variables are measured on the portfolio formation date (i.e., day $d$). We require that a minimum of 200 (15) daily observations be available for all variables computed from daily data in the past 252 (21) trading days, respectively.

*Size*: The firm's size is computed as the product of the price per share and the number of shares outstanding (in million dollars).

*Book-to-Market*: Following Fama and French (1992, 1993, and 2000), the book-to-market equity ratio at the end of June of year $t$, denoted $BM$, is computed as the book value of stockholders' equity, plus deferred taxes and investment tax credit (if available), minus the book value of preferred stock for the fiscal year $t-1$, scaled by the market value of equity at end of December of $t-1$. Depending on availability, the redemption, liquidation, or par value (in that order) is used to estimate the book value of preferred stock.

*Reversal*: Following Jegadeesh (1990), short-term reversal ($REV$) is defined as the stock return over the prior 21 trading days.

*Momentum*: Following Jegadeesh and Titman (1993), momentum ($MOM$) is the cumulative return of a stock in the past 252 trading days ending 21 trading days prior to the portfolio formation month (i.e., skipping the short-term reversal month).

*Illiquidity*: We use the Amihud's (2002) illiquidity measure and for each day we measure the illiquidity of a stock $i$ over the past 21 days, denoted $ILLIQ$, as the average daily ratio of the absolute stock return to the dollar trading volume within 21-day period:

$$ILLIQ_i = \frac{1}{n}\sum_{n=1}^{21}\left[\frac{|R_{i,d}|}{VOLD_{i,d}}\right], \tag{21}$$

where $R_{i,d}$ and $VOLD_{i,d}$ are the daily return and dollar trading volume for stock $i$ on day $d$, respectively.

*Co-skewness*: Following Harvey and Siddique (2000), the firm's daily co-skewness ($COSKEW$) is defined as the estimate of $\gamma_i$ in the regression using the daily return observations over the prior 21 trading days:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i \left(R_{m,d} - r_{f,d}\right) + \gamma_i \left(R_{m,d} - r_{f,d}\right)^2 + \varepsilon_{i,d}, \tag{22}$$

where $R_{i,d}$, $R_{f,d}$, and $R_{m,d}$ are the daily returns on stock $i$, the one-month Treasury bills, and the CRSP value-weighted index, respectively.

*Idiosyncratic Volatility*: Following Ang, Hodrick, Xing, and Zhang (2006), the daily idiosyncratic volatility of stock $i$ ($IVOL$) is computed as the standard deviation of the residuals from the regression using daily returns over the prior 21 trading days:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i \left(R_{m,d} - r_{f,d}\right) + \gamma_i SMB_d + \varphi_i HML_d + \varepsilon_{i,d}, \tag{23}$$

where $SMB_d$ and $HML_d$ are, respectively, the daily size and book-to-market factors of Fama and French (1993).

*Maximum Daily Return*: Following Bali, Cakici, and Whitelaw (2011), the firm's extreme positive return ($MAX$) is defined as its maximum daily return over the past 21 days.

## 4. Market Beta and the Cross-Section of Daily Returns

This section examines the significance of a cross-sectional relation between the unconditional beta, the dynamic conditional beta, and daily stock returns based on the long-short equity portfolios. We also provide the descriptive statistics for the univariate portfolios sorted on the dynamic conditional beta.

### 4.1. Univariate portfolios of unconditional beta

We begin our empirical analysis with univariate portfolio sorts. For each day, the CAPM, Fama and French (1992), Scholes and Williams (1977), and Dimson (1979) betas of each stock are estimated using daily returns over the past 252 trading days (with at least 200 observations available). Then, for each day we sort the S&P 500 stocks into decile portfolios based on their unconditional measures of market beta. Decile 1 contains stocks with the lowest market beta and Decile 10 contains stocks with the highest market beta. We investigate the significance of market beta in predicting the cross-sectional variation in daily stock returns. The results are presented for the sample period July 1963 to December 2009.

In Table 1, the first two columns report the univariate portfolio results for the CAPM beta. The first column presents the average one-day-ahead returns of individual stocks in each decile and the second column shows the average market beta of individual stocks in each decile. The last two rows present the average raw return differences between the High-beta and Low-beta decile portfolios and the 4-factor Fama and French (1993) and Carhart (1997) alphas (denoted by FFC4 alpha). Daily portfolio returns and FFC4 alphas are annualized assuming 252 trading days in a year.

By construction, moving from Decile 1 to Decile 10, the average market beta ($BETA_{CAPM}$) increases from 0.37 to 1.96, implying that the difference in market betas between average stocks in the High-beta and Low-beta deciles is 1.59. The magnitudes of the CAPM betas obtained from the daily returns over the past one year indicate small measurement errors in betas because the average of the portfolio betas across the 10 deciles is about 1.02, which is very close to one.

The first column in Table 1 shows that the average raw return on the beta portfolios increases from 11.36% to 15.18% per annum, indicating that the average raw return difference between Deciles 1 and 10 is 3.82% per annum with a Newey-West $t$-statistic of 0.95, suggesting that this positive return difference is statistically insignificant. In Table 1, we also check whether the raw return difference between the High-beta and Low-beta deciles can be explained by the four factors of Fama and French (1993) and Carhart (1997). To do this, we regress the daily time series of return differences between the High-beta and Low-beta deciles on the four factors (MKT, SMB, HML, and MOM), and we check if the intercept from this regression (namely, FFC4 alpha) is statistically significant.[12] As shown in the last row of Table 1, the 4-factor alpha difference between Deciles 1 and 10 is 3.83% per annum with

[12]The daily market (MKT), size (SMB), book-to-market (HML), and momentum (MOM) factors are described in and obtained from Kenneth French's data library.

a Newey-West $t$-statistic of 1.18. As expected, after controlling for the market, size, book-to-market, and momentum factors, the insignificant raw return difference between the High-beta and Low-beta portfolios remains positive and insignificant.

The next two columns present results for the univariate portfolios of stocks sorted by the Fama-French betas. Moving from Decile 1 to Decile 10, the average market beta ($BETA_{FF}$) increases from 0.35 to 1.95, with a spread of 1.60 in the average market betas of extreme deciles. The average of the portfolio betas across the 10 deciles is again very close to one. Similar to our findings from the portfolios of CAPM beta, the average raw return difference between the High-beta and Low-beta deciles is 4.71% per annum with a $t$-statistic of 1.18 and the 4-factor alpha difference between Deciles 1 and 10 is 3.60% per annum with a $t$-statistic of 1.15. These results provide no evidence for a significant link between market beta and the cross-section of one-day-ahead returns.

Even smaller – economically and statistically – raw and risk-adjusted return differences are obtained from the Scholes-Williams and Dimson betas. As shown in Table 1, the average raw return differences between the extreme deciles are 2.86% per annum for the portfolios of Scholes-Williams beta and 1.98% per annum for the portfolios of Dimson beta, with the respective $t$-statistics of 0.71 and 0.56. Similarly, the FFC4 alphas are economically and statistically insignificant as well; 2.67% per annum (with $t$-stat. = 0.86) for the portfolios of Scholes-Williams beta and 2.25% per annum (with $t$-stat. = 0.80) for the portfolios of Dimson beta. These results indicate a flat cross-sectional relation between the unconditional measures of market beta and expected stock returns.

At an earlier stage of the study, we examine the 2-, 3-, 4-, and 5-day-ahead predictive power of the unconditional betas. Although not reported in the paper to save space, we find no evidence for a significant link between the CAPM, Fama-French, Scholes-Williams, and Dimson betas and the cross-section of two- to five-day-ahead returns.

## 4.2. Univariate portfolios of dynamic conditional beta

The unconditional measures of market beta (the CAPM, Fama-French, Scholes-Williams, and Dimson) are estimated using daily returns over the past one year. Although the unconditional betas change each day because of daily rolling regressions, they are constant over the fixed estimation window of one year. In this section, we use the time-varying conditional measures of market betas based on the DCC model of Engle (2002). The DCC betas are estimated using daily returns and they vary each day in the estimation period of one year. Once we obtain the DCC betas of individual stocks in the S&P 500 index, we sort them into decile portfolios based on their dynamic conditional betas. Then, we test the economic and statistical significance of the DCC betas in predicting the cross-section of future stock returns.

Table 2 shows that moving from Decile 1 to Decile 10, the average DCC beta ($BETA_{DCC}$) increases from 0.28 to 2.23, implying a large spread of 1.95 in the conditional betas between average stocks in the High DCC-beta and Low DCC-beta deciles. The average of the portfolios' DCC betas across the 10 deciles is about 1.05, which is close to one. As expected, Table 2 also shows that the conditional betas from the DCC model and the unconditional betas from alternative approaches are correlated. However, the spreads in the unconditional betas between average stocks in the extreme deciles is smaller (in the range of 1.20 to 1.31) compared to the spread in the conditional betas.

Figure 4 depicts the daily DCC beta estimates for Decile 1 to 10 as well as the corresponding time-series average of each portfolio's daily DCC beta (the straight line). Figure 4 presents significant time-series variation as well as stationary and mean-reverting behavior of the conditional betas. Figure 4 also shows that the DCC betas generally have positive time trend during financial market and economic downturns, with a negative drift and stabilizing behavior during ordinary periods.

A notable point in Table 2 is that the average raw returns on the DCC-beta portfolios increase monotonically from 10.33% to 18.04% per annum. Effectively, the average raw return difference between Deciles 1 and 10 is 7.71% per annum with a Newey-West $t$-statistic of 2.11, suggesting that this positive return difference is economically and statistically significant. This result indicates that stocks in the highest DCC-beta decile generate about 8% more annual return compared to stocks in the lowest DCC-beta decile.

Table 2 also presents the 4-factor alphas for each DCC-beta decile. We regress the daily excess returns of the DCC-beta portfolios on the Fama-French-Carhart's four factors (MKT, SMB, HML, MOM) and check if the intercepts from these regressions (FFC4 alphas) are statistically significant. The second column of Table 2 shows that as we move from Decile 1 to Decile 10, the 4-factor alphas on the DCC-beta portfolios increase monotonically from 0.01% to 7.82% per annum. Note also that the FFC4 alphas are statistically significant for Deciles 7, 8, 9, and 10, whereas the FFC4 alphas are insignificant for Deciles 1 to 6.

We also check whether the significant return difference between the High DCC-beta and Low DCC-beta deciles can be explained by the four factors of Fama-French-Carhart. To do this, we regress the daily time series of return differences between the High DCC-beta and Low DCC-beta portfolios on the four factors of Fama-French-Carhart, and we check if the intercept from this regression is statistically significant. As shown in Table 2, the 4-factor alpha difference between Deciles 1 and 10 is 7.80% per annum with a Newey-West $t$-statistic of 2.40. This suggests that after controlling for the market, size, book-to-market, and momentum factors, the return difference between the High DCC-beta and Low DCC-beta deciles remains positive and economically and statistically significant. Alternatively, these well-known factors do not explain the positive relation between the conditional betas and the cross-section of daily stock returns.

Lastly, we investigate the source of this significant return difference between the High DCC-beta and Low DCC-beta deciles: is it due to outperformance by stocks in the High DCC-beta decile, or underperformance by stocks in the Low DCC-beta decile, or both? For this, we compare the performance of the High DCC-beta decile to the performance of the rest of deciles as well as the performance of rest of deciles to the performance of the Low DCC-beta decile, both in terms of raw returns and risk-adjusted returns. Analyzing the rows starting with "High - Rest" and "Rest - Low" in Table 2, we find that, on average, the High DCC-beta stocks generate 5.05% more annual raw returns compared to the rest of their peers (with a $t$-statistic of 1.81), and the Low DCC-beta stocks produce 3.52% less annual raw returns compared to the rest of their peers (with a $t$-statistic of 2.19), suggesting that the positive and significant return difference between the High DCC-beta and Low DCC-beta stocks is due to both outperformance by the High DCC-beta stocks and underperformance by the Low DCC-beta stocks. Finally, when the 4-factor alpha differences are considered, the outcome remains the same; stocks in the High DCC-beta decile generate significantly higher risk-adjusted returns compared to the rest of the crowd (5.82% 4-factor alpha difference with a $t$-statistic of 2.18), while stocks in the Low DCC-beta decile produce significantly smaller risk-adjusted returns compared to the rest of the crowd (2.85% 4-factor alpha difference with a $t$-statistic of 2.16).

In sum, all of these results confirm the existence of a positive and significant relation between the DCC betas and one-day-ahead returns on the S&P 500 stocks.

### 4.3. Descriptive statistics for the conditional beta portfolios

To highlight the firm characteristics and risk attributes of stocks in the DCC-beta portfolios, Table 3 presents descriptive statistics for the stocks in the DCC-beta deciles. Specifically, Table 3 reports the average values of various characteristics for the stocks in each decile sorted by the DCC beta. In addition to the first two columns that report average returns and average DCC betas for each decile, Table 3 presents SIZE: the market capitalization (in millions of dollars); BM: the log book-to-market ratio; MOM: the return over the 12 months prior to portfolio formation; REV: the return in the portfolio formation month; ILLIQ: a measure of illiquidity (scaled by $10^5$); COSKEW: the co-skewness measure; IVOL: the idiosyncratic volatility; MAX: the maximum daily return in the portfolio formation month; PRICE: the price in dollars; and the average market share. Definitions of these variables are given in Section 3.3.

Table 3 reports the characteristics for the portfolios sorted on the dynamic conditional beta. We should note that our sample includes very big stocks that form the S&P 500 index. Hence, there is no significant size differential across the DCC-beta portfolios. Specifically, the average market capitalization of the stocks in the High and Low DCC-beta deciles is about \$7.17 and \$7.28 billion dollars, respectively. As shown in the last column of Table 3, the average market share of the stocks in the High and Low DCC-beta deciles is about 7% and 8.5%, respectively. Although there is no significant size difference between average stocks in the High and Low DCC-beta portfolios, the High DCC-beta decile includes stocks with somewhat bigger market cap. Consistent with this finding, the Low DCC-beta decile includes stocks with somewhat higher book-to-market ratio, i.e., on average the Low DCC-beta decile contains more value stocks, whereas the High DCC-beta decile contains more growth stocks. These results are interesting because earlier studies (e.g., Fama and French (1992) and Loughran (1997)) show that value stocks are generally small and generate higher returns than growth and relatively bigger stocks. However, the stocks in the Low DCC-beta decile are smaller and they have a value tilt, but they generate lower returns. Similarly, the stocks in the High DCC-beta decile are bigger in terms of market cap and they have a growth tilt, but they generate higher returns. Hence, the size and value effects cannot explain the positive predictive power of the DCC beta for future stock returns.

Interestingly, the stocks in the High DCC-beta decile are medium-term and short-term winners (MOM and REV), which generally goes in opposite directions. Since the stocks in the High DCC-beta decile have higher returns, one would expect them to have lower past one-month return if the short-term reversal would explain our finding (see Jegadeesh (1990) and Lehmann (1990)). However, the stocks in the High DCC-beta decile have higher past one-month return (1.50% per month) compared to the stocks in the Low DCC-beta decile (0.99% per month). Hence, the short-term reversal cannot be a potential explanation of the positive relation between the DCC beta and future daily returns. Momentum can be a potential driver of our main finding because the stocks in the High DCC-beta decile have higher 11-month cumulative return over a period of 11 months ending one month prior to the portfolio formation month (18.27% per annum) compared to the stocks in the Low DCC-beta decile (10.54% per annum). Hence, the stocks in the High DCC-beta portfolio are momentum-winners, whereas the stocks in the Low DCC-beta portfolio are momentum-losers.[13]

[13]To control for momentum, we have so far used the momentum factor of Carhart (1997) and show that the 4-factor alphas are significant in the long-short equity portfolios of the DCC beta. In addition to using the Carhart (1997) momentum factor, as will be discussed later in the paper, we form bivariate portfolios of momentum and the DCC beta. Finally, we also control for momentum in the multivariate Fama and MacBeth (1973) regressions. After controlling for momentum in the 4-factor regressions, bivariate portfolios, and the Fama-MacBeth cross-sectional regressions, we find that the dynamic conditional beta remains a strong predictor of future stock returns.

Since we study the large, high-priced, and highly liquid stocks in the S&P 500 index, the average price of the stocks in the Low DCC-beta decile is $38 per share and the average price of the stocks in the High DCC-beta decile is $36. In other words, there is no significant price difference across the DCC-beta portfolios. However, there seems to be a difference between the average illiquidity measure of the stocks in the High and Low DCC-beta portfolios. Specifically, the Amihud's (2002) illiquidity measure decreases monotonically as we move from the Low DCC-beta to High DCC-beta deciles. However, Amihud (2002) and follow-up studies show that illiquid stocks have higher average returns than liquid stocks. As shown in Table 3, the stocks in the Low DCC-beta decile are less liquid but they have lower average return and the stocks in the High DCC-beta decile are more liquid and they have higher returns. Hence, the illiquidity and price effects cannot explain the predictive power of the DCC beta either.

Finally, the stocks in the High DCC-beta decile have higher idiosyncratic volatility, higher maximum daily return over the past month, and positive co-skewness, whereas the stocks in the Low DCC-beta decile have lower idiosyncratic volatility, lower maximum daily return (MAX), and negative co-skewness. Harvey and Siddique (2000), Ang, Hodrick, Xing, and Zhang (2006), and Bali, Cakici, and Whitelaw (2011) show that the stocks with high co-skew, high volatility, and high MAX are expected to generate lower return in the future. However, the stocks in the High DCC-beta decile with higher co-skew, higher volatility, and higher MAX have higher average return than the stocks in the Low DCC-beta decile with lower co-skew, lower volatility, and lower MAX. Thus, the significantly positive link between the dynamic conditional beta and the cross-section of daily returns is not explained by systematic skewness, idiosyncratic risk, or demand for lottery-like assets.

### 4.4. Dynamic conditional beta relative to the unconditional measures of beta

We have so far shown that the unconditional measures of market beta do not predict the cross-section of daily returns, whereas the dynamic conditional beta is highly significant in predicting future returns on individual stocks. To make sure that the time-varying conditional beta does not reflect the impact of unconditional beta, we compute a DCC beta relative to the CAPM beta, the Fama-French beta, the Scholes-Williams beta, and the Dimson beta.

We examine the relative time-varying beta to disentangle the effect of the DCC beta from the effects of traditional measures of unconditional beta. Specifically, for each day individual stocks in the S&P 500 index are sorted into 10 univariate decile portfolios on the *difference* between the time-varying conditional beta, estimated based on the dynamic conditional correlation (DCC) model of Engle (2002), and the unconditional beta estimated from either the CAPM (DCC-CAPM), the Fama-French model (DCC-FF), the Scholes-Williams model (DCC-SW), or the Dimson model (DCC-Dimson).

Panel A of Table 4 presents average returns for the decile portfolios formed on DCC-CAPM, DCC-FF, DCC-SW, and DCC-Dimson, respectively. Panel A also reports the average difference between the conditional beta and the corresponding unconditional beta in each decile. As shown in the last two rows, the average raw and alpha differences between Deciles 10 and 1 are positive and highly significant without any exception. Specifically, the average raw return difference between Decile 10 and Decile 1 (High-Low) is 6.93%, 5.43%, 6.66%, and 6.90% per annum and highly significant with the Newey-West $t$-statistics of 3.26, 2.76, 3.36, and 3.54, respectively. The Fama-French-Carhart four-factor alphas are also positive and similar in magnitude to the raw return differences. The results in Table 4, Panel A show that the average raw and risk-adjusted returns increase with the relative measures of DCC beta, implying that higher dynamic conditional beta is compensated by higher expected returns not captured by the unconditional measures of market beta.

These findings also provide evidence that the difference between the conditional and unconditional beta premia is economically and statistically significant at the portfolio level. We now present similar evidence at the firm level using the Fama-MacBeth cross-sectional regressions. For each day, we run firm-level cross-sectional regressions of one-day-ahead returns on the DCC beta and each of the unconditional beta measures. Panel B of Table 4 shows that after controlling for the CAPM, Fama-French, Scholes-Williams, and Dimson beta, the average slope coefficients on the dynamic conditional beta are positive and highly significant with the Newey-West $t$-statistics ranging from 3.64 to 5.08. However, the average slopes on the traditional measures of beta are negative and statistically insignificant.

Table 4 presents clear evidence for the superior performance of the dynamic conditional beta that generates significant return difference as compared to the standard measures of unconditional beta.

## 5. Controlling for the Usual Suspects

Given the number of potential control variables, i.e., other stock characteristics that may influence returns, the Fama and MacBeth (1973) cross-sectional regression approach may be the natural way to examine the predictive power of the conditional beta while simultaneously controlling for the usual suspects. We turn to these regressions in Section 5.3. While cross-sectional regressions are arguably the best way to deal with large sets of potential risk factors, in Sections 5.1 and 5.2, we provide two alternative ways of dealing with the potential interaction of the DCC beta with firm size, book-to-market, past returns, liquidity, co-skewness, volatility, and MAX. Specifically, we test whether the positive relation between the conditional beta and the cross-section of daily returns still holds once we control for these additional factors using bivariate sorts and the characteristic-matched portfolios.

### 5.1. Bivariate portfolios of the conditional beta and control variables

As presented in Table 3, most of the well-known cross-sectional predictors of stock returns do not seem to be correlated with the outperformance (underperformance) of the High DCC-beta (Low DCC-beta) portfolios. However, there might still be some concern that the 4-factor model used in Table 2 to calculate alphas is not adequate to capture the true differences in risk and expected returns across the portfolios sorted on the conditional beta. Although the 4-factor model of Fama-French-Carhart control for differences in size, book-to-market, and momentum, it does not control explicitly for the differences in expected returns due to differences in illiquidity, short-term reversal, co-skewness, idiosyncratic volatility, and demand for extreme positive returns. Hence, in this section, we provide results from the bivariate portfolios of the DCC beta and the control variables.

For the dependent bivariate sorts, our general methodology is to first form quintile on the control variable, then, within each of these quintiles, to form quintiles on the basis of the DCC beta. We then average the DCC-beta quintiles across the control variable quintiles to form portfolios with similar levels of the control variable but different levels of the DCC beta. For example, we control for size by first forming quintile portfolios ranked based on market capitalization. Then, within each size quintile, we sort stocks into quintile portfolios ranked based on the DCC beta so that quintile 1 (quintile 5) contains stocks with the lowest (highest) DCC beta. The first column in Table 5 averages returns across the five size quintiles to produce quintile portfolios with dispersion in the DCC beta, but which contain all sizes of firms. This procedure creates a set of DCC-beta portfolios with near-identical levels of firm size and thus these DCC-beta portfolios control for differences in size. After controlling for size, the average return increases from 10.62% to 16.74% per annum when moving from the Low DCC-beta to the High DCC-beta portfolios, yielding an average return difference of 6.12% per annum, with a Newey-West $t$-statistic of 2.27. The $5-1$ difference in 4-factor alphas is 6.08% per annum, and it is also highly statistically significant. Thus, market capitalization does not explain the return difference between the High and Low DCC-beta stocks.

We form similar bivariate quintile portfolios based on the dependent sorts of DCC-beta and book-to-market, momentum, short-term reversal, liquidity, co-skewness, volatility, and MAX. Table 5 shows that after controlling for these variables, the average return differences between the Low DCC-beta and High DCC-beta portfolios are in the range of 4.35% to 7.60% per annum, and the differences in 4-factor alphas vary over the same range. These average raw and risk-adjusted return differences are both economically and statistically significant. Overall, the results in Table 5 indicate that the well-known cross-sectional effects such as size, book-to-market, past return characteristics, liquidity, co-skewness, volatility, and MAX cannot explain the high (low) returns to high (low) DCC-beta stocks.[14]

[14]At an earlier stage of the study, we examine the predictive power of the unconditional betas in bivariate portfolios. Specifically, we replicate Table 5 based on the unconditional measures of beta and find no evidence for a significant link between the CAPM, Fama-French, Scholes-Williams, and Dimson betas and the cross-section of daily returns after controlling for size, book-to-market, momentum, reversal, illiquidity, coskewness, idiosyncratic volatility, and MAX. The results are available upon request.

### 5.2. Characteristic-matched portfolios

We now examine the significance of the DCC betas for predicting the cross-section of one-day-ahead characteristic-matched returns. Following Daniel and Titman (1997), at the end of June of year $t$, all stocks in our sample are independently sorted into size, book-to-market, and momentum terciles. The intersections of the size, book-to-market, and momentum terciles result in 27 benchmark portfolios. The equal-weighted daily benchmark returns for the 27 groupings are calculated over the following 12 months from July of year $t$ to June of year $t+1$. The stock's daily characteristic-matched return is calculated as the difference between its raw daily return and the daily benchmark return of one of the 27 benchmark portfolios to which the stock belongs as of the end of June of year $t$.

In the first column of Table 6, we report the average returns in excess of the size, book-to-market, and momentum matched benchmark portfolios. The average characteristic-matched returns on the DCC-beta portfolios increase from -2.85% to 3.88% per annum, yielding an average raw return difference of 6.73% per annum with a Newey-West $t$-statistic of 2.86. Similarly, as we move from Decile 1 to Decile 10, the 4-factor alphas on the DCC-beta portfolios increase from -7.48% to -1.49% per annum, producing a significant alpha difference of 5.98% per annum with a $t$-statistic of 2.62. These results indicate significantly positive characteristic-matched return differences between the High and Low DCC-beta portfolios.

We also investigate the source of these significant characteristic-matched return differences: is it due to outperformance by stocks in the High DCC-beta decile, or underperformance by stocks in the Low DCC-beta decile, or both? Analyzing the rows starting with "High - Rest" and "Rest - Low" in Table 6, we find that, on average, the High DCC-beta stocks generate 4.30% more annual characteristic-matched returns compared to the rest of their peers (with a $t$-statistic of 2.35), and the Low DCC-beta stocks produce 3.18% less annual characteristic-matched returns compared to the rest of their peers (with a $t$-statistic of 2.77), suggesting that the positive and significant return difference between the High DCC-beta and Low DCC-beta stocks is due to both outperformance by the High DCC-beta stocks and underperformance by the Low DCC-beta stocks. Finally, when the 4-factor alpha differences are considered, the outcome remains the same; stocks in the High DCC-beta decile generate significantly higher risk-adjusted characteristic-matched returns compared to the rest of the crowd (4.36% 4-factor alpha difference with a $t$-statistic of 2.28), while stocks in the Low DCC-beta decile produce significantly smaller risk-adjusted characteristic-matched returns compared to the rest of the crowd (2.29% 4-factor alpha difference with a $t$-statistic of 2.30).

Overall, all of these estimates confirm the existence of a positive and significant relation between the DCC betas and one-day-ahead characteristic-matched returns on the S&P 500 stocks.

### 5.3. Firm-Level Cross-Sectional Regressions

We now examine the cross-sectional relation between the DCC-beta and one-day-ahead returns at the firm level using the Fama and MacBeth (1973) methodology. Specifically, we run the following multivariate specification and nested versions thereof:

$$R_{i,d+1} = \lambda_{0,d} + \lambda_{1,d} BETA_{i,d}^{DCC} + \lambda_{2,d} SIZE_{i,d} + \lambda_{3,d} BM_{i,d} + \lambda_{4,d} MOM_{i,d} + \lambda_{5,d} X_{i,d} + \varepsilon_{i,d+1}, \tag{24}$$

where $R_{i,d+1}$ is the return on stock $i$ on day $d+1$; $BETA_{i,d}^{DCC}$ is the DCC beta of stock $i$ on day $d$; SIZE, BM, and MOM are the firm-level characteristics corresponding to the Fama-French-Carhart factors, and $X_{i,d}$ represents a vector of additional control variables.

Table 7 reports the time series averages of the slope coefficients over the sample period July 1, 1963 - December 31, 2009 (11,707 daily observations) from the univariate regressions of one-day-ahead stock returns on the DCC beta and the multivariate regressions on the DCC beta with the control variables. The average slopes provide standard Fama-MacBeth tests for determining which explanatory variables on average have non-zero premiums, and the Newey-West $t$-statistics are given in parentheses.

Not surprisingly, the univariate cross-sectional regression results are consistent with the raw return differences from the univariate portfolio sorts in Table 2. The average slope on the DCC beta is 0.018 with a $t$-statistic of 2.55. Given a difference in average DCC-beta of approximately 1.95 between the High and Low DCC-beta deciles, this coefficient estimate translates into an annualized return difference of almost 8.8%, which is close to 7.71% annualized raw return difference reported in Table 2.

In the multivariate regressions, the coefficients on the Fama-French-Carhart factors are also as expected. The average slope on SIZE is negative and significant at the 5% level or better. Although the average slopes on the book-to-market ratio are positive in all specifications, they are not statistically significant. This lack of statistical significance is due to the S&P 500 sample that excludes small, low-priced, and illiquid stocks, the sector of the market in which the traditional value effect is concentrated (see Loughran (1997)). Finally, stocks exhibit strong intermediate-term momentum as the average slopes on MOM are positive and significant, except when momentum is used along with the short-term reversal in the same regression.

Table 7 also reports results for multivariate regressions that include each of the additional control variables. The coefficients on these variables are generally in line with the existing literature. The average slope on IVOL is negative and significant, consistent with Ang, Hodrick, Xing, and Zhang (2006)). The average slope on REV is negative and highly significant, implying that the S&P 500 stocks exhibit strong short-term reversals. Consistent with the findings of Bali, Cakici, and Whitelaw (2011), the results indicate a negative and significant relation between expected returns and MAX. Although the average slopes on ILLIQ are found to be positive (suggesting positive illiquidity risk premium), they are not statistically significant. This result is likely due to the S&P 500 sample that excludes small, low-priced, and illiquid stocks. Finally, consistent with investors' preference for positively skewed assets, the average slopes on COSKEW are negative but statistically insignificant.

Overall, the cross-sectional regressions and the portfolio level analyses provide strong evidence for an economically and statistically significant positive relation between the DCC beta and the cross-section of one-day-ahead stock returns.

We have so far tested the one-day-ahead cross-sectional forecasting performance of the conditional betas. In Table 8, we examine the predictive power of the DCC beta for two-day to five-day-ahead returns. Panel A of Table 8 shows that when predicting the cross-sectional variation in two-day-ahead returns with the standard controls (SIZE, BM, and MOM) as well as the additional controls (REV, IVOL, ILLIQ, COSKEW, and MAX), the average slope on the DCC beta remains positive and statistically significant. As presented in Panel B of Table 8, the average slopes on the DCC beta remain positive. Even though the predictive power of the DCC beta seems to disappear for three-day-ahead predictability, in Regressions (3) and (7) the average slopes on the DCC beta are positive and significant with the Newey-West $t$-statistics of 1.73 and 2.51, respectively. In Panels C and D of Table 8, the average slopes are positive without any exception, but they are statistically insignificant with a few exceptions. Overall, the results provide no evidence for a significant link between the conditional beta and the cross-section of four- and five-day-ahead returns, but the predictive power of the DCC beta remains for two-day and three-day-ahead returns.[15]

### 5.4. Explaining realized market betas

The gist of an autoregressive-based model is that historical data are not equally informative about the future realization of the variable of interest, with more weights loaded up to the more recent observations. If the dynamics of the underlying variable is indeed time-varying, an appropriately chosen dynamic conditional model is expected to possess superior forecasting ability. In this section, we investigate whether the daily beta forecast based on the dynamic conditional correlation model better matches the realized market beta than the unconditional expected beta measures. We run the following monthly Fama-MacBeth cross-sectional regressions:

$$\beta_{i,t} = \alpha_{0,t} + \alpha_{1,t}\widehat{\beta_{i,t}} + \varepsilon_{i,t}, \tag{25}$$

where $\beta_{i,t}$ is the realized market beta for stock $i$ in month $t$, estimated from: (1) the CAPM ($\beta^{CAPM}$), (2) the Fama-French ($\beta^{FF}$), (3) the Scholes-Williams model ($\beta^{SW}$), and (4) the Dimson model ($\beta^{Dimson}$), using daily returns in a month, with a minimum of 15 observations available; $\widehat{\beta_{i,t}}$ is the average of daily expected beta in month $t$, obtained from either the dynamic conditional correlation model, or one of the four unconditional specifications, using daily returns over the prior 252 trading days and updated on a daily basis.

[15]To test whether the persistence of the DCC beta decays over the five-day forecast horizon, for each stock we calculate the first-, second-, third-, fourth-, and fifth-order autocorrelation of the daily measures of DCC beta. The average autocorrelation across all firms is 0.82 for 1-day, 0.75 for 2-day, 0.71 for 3-day, 0.68 for 4-day, and 0.65 for 5-day autocorrelation. A significant decline in the serial correlation of the DCC beta measures may be a potential explanation for diminishing predictive power of the DCC beta over the five-day forecast horizon.

Table 9 shows that the slope coefficients on the average daily DCC beta are very close to unity, ranging from 0.91 to 0.99, whereas those of the average daily unconditional beta measures are smaller, in the range of 0.45 and 0.89. Moreover, for each measure of the monthly realized beta, the average R-squared values of the regressions with the average daily DCC beta are unanimously larger than those with alternative measures of unconditional beta. These results suggest that the DCC beta on average produces better goodness-of-fit for the monthly realized beta.

## 6. Robustness Check

This section provides further empirical results from the largest 500 and 1,000 stocks as well as the most liquid 500 stocks using the raw and characteristic-matched daily returns. We also test whether the main findings remain intact after controlling for alternative measures of short-term return reversals.

### 6.1. Cross-sectional regressions with the largest 500 and 1,000 stocks

Our main sample is made up of the S&P 500 index components obtained from the CRSP database. Figure 5 plots the market share of the S&P 500 stocks. The solid line in Figure 5 depicts the monthly ratios of total market capitalization of the S&P 500 constituents to the aggregate market capitalization of all stocks trading at the NYSE, Amex, and Nasdaq. The dashed line in Figure 5 presents the same ratio for the NYSE, Amex, and Nasdaq traded common shares after eliminating low-priced stocks (price $<$ \$5 per share) and stocks in the smallest NYSE size decile. Over the sample period July 1963 - December 2009, the market share of the S&P 500 stocks fluctuates between 65% and 80%, with an average market share of 74%. In other words, although we have so far used 500 stocks, they are approximately 74% of the entire stock universe in the CRSP database.

In this section, we show that our findings remain intact when the sample is composed of the largest 500 and 1,000 stocks. These two large stock samples are obtained by ranking individual stocks based on their market capitalization as of the end of June of each year. Figure 6 plots the market share of the largest 500 stocks. The solid line in Figure 6 depicts the monthly ratios of total market capitalization of the largest 500 stocks to the aggregate market capitalization of all stocks trading at the NYSE, Amex, and Nasdaq. The dashed line in Figure 6 presents the same ratio for the NYSE/Amex/Nasdaq stocks after eliminating low-priced stocks and stocks in the smallest NYSE size decile. The market share of the largest 500 stocks fluctuates between 75% and 90%, with an average market share of 82%.

Figure 7 plots the market share of the largest 1,000 stocks for the same sample period. When the aggregate market capitalization of all stocks is considered, the market share of the largest 1,000 stocks fluctuates between 84% and 96%, with an average market share of 90%. When the aggregate market capitalization of all stocks (after excluding the smallest and low-priced stocks) is considered, the market share of the largest 1,000 stocks fluctuates between 86% and 98%, with an average market share of 92%.

Table 10 presents results from the Fama-MacBeth cross-sectional regressions for the largest 500 stocks (left panel) and the largest 1,000 stocks (right panel). As shown in Table 10, the average slopes on the DCC beta are estimated to positive and highly significant without any exception. The significantly positive link between the conditional betas and the cross-section of daily returns on the largest 500 and 1,000 stocks remains intact after controlling for the well-known predictors. The average slope on SIZE is negative and highly significant for the largest 500 and 1,000 stocks. The average slopes on the book-to-market ratio are positive but significant only in a few specifications. Momentum remains a significantly positive predictor of future returns. The average slopes on REV are negative and highly significant, implying that the largest 500 and 1,000 stocks exhibit strong short-term reversals. Consistent with the findings of Ang, Hodrick, Xing, and Zhang (2006) and Bali, Cakici, and Whitelaw (2011), the average slopes on IVOL and MAX are negative and significant. Similar to our earlier findings from the S&P 500 stocks, the average slopes on ILLIQ (COSKEW) are positive (negative) for the largest 500 and 1,000 stocks, but they are statistically insignificant.

Overall, these results indicate that the conditional beta positively predicts the cross-section of future returns on the S&P 500 stocks as well as the largest 500 and 1,000 stocks in the CRSP universe.

### 6.2. Cross-sectional regressions with the characteristic-matched returns

In Table 6, we present results from the characteristic-matched portfolios of the DCC beta. In this section, we examine the cross-sectional relation between the DCC beta and the characteristic-matched returns using the Fama-MacBeth regressions.

Table 11 shows that the average slopes on the DCC beta are positive and highly significant without any exception. A notable point in Table 11 is that the statistical significance of the average slope coefficients on the DCC beta is higher than those presented in Table 7. This implies that the positive cross-sectional relation between the DCC beta and the characteristic-matched returns is even stronger than the relation the DCC-beta and the raw returns. In the multivariate regressions, the significantly positive link between the conditional betas and the characteristic-matched returns remains intact after controlling for the well-known predictors. Among the control variables, size, short-term reversal, idiosyncratic volatility, and extreme positive returns are found to be significant.

Table 11 investigates the one-day-ahead cross-sectional forecasting performance of the conditional betas. In Table 12, we examine the predictive power of the DCC beta for two-day to five-day-ahead characteristic-matched returns. Panel A of Table 12 shows that when predicting the cross-sectional variation in two-day-ahead characteristic-matched returns with a large set of control variables, the average slope on the DCC beta remains positive and statistically significant. Similarly, Panel B of Table 12 provides some evidence for the positive and significant relation between the DCC beta and three-day-ahead characteristic-matched returns. Even though the predictive power of the DCC beta is not as strong for three-day-ahead predictability, in Regressions (2), (4), and (5) the average slopes on the DCC beta are positive and significant with the Newey-West $t$-statistics ranging from 1.83 to 2.86. In Panels C and D of Table 12, the average slopes are positive without any exception, but they are statistically insignificant, with a few exceptions.

Overall, the results provide no evidence for a significant link between the conditional beta and the cross-section of four- and five-day-ahead characteristic-matched returns, but the predictive power of the DCC beta remains strong for one-, two-, and three-day-ahead characteristic-matched returns.

### 6.3. Cross-sectional regressions with the most liquid 500 stocks

We have so far provided evidence from the S&P 500 stocks as well as the largest 500 and 1,000 stocks in the CRSP universe. However, big stocks are not always liquid if liquidity is defined in terms of trading activity or share turnover (the ratio of dollar trading volume to the number of shares outstanding). Recent technological progress and reduction in the minimum tick size lead to a significant reduction of transaction costs. Hence, over time trading volumes have been increased, bid-ask spreads have become tighter, and market liquidity has been increased as well. Since markets with greater volume adjust faster to information, prices converge to their true, full-information value more quickly, i.e., prices become more efficient.

According to Kyle's (1985) price impact of trade, the liquidity of a stock refers to the degree to which a significant quantity can be traded within a short time frame without incurring a large transaction cost or adverse price impact. Based this definition, big stocks are generally more liquid than small stocks. However, this is not true for all stock samples and for all time periods, i.e., the liquidity and market cap of a stock change over time. We should also note that the micro-structure issues such as bid-ask bounce and the slow adjustment of prices to new information are more serious concerns to illiquid stocks.[16] Even when no news is breaking, when a stock price is not changing, the bid-ask bounce is about prices bouncing up and down between bid and ask. These changes are spurious. This problem is the greatest with illiquid stocks where the bid-ask spread is wide. When a stock sample includes such illiquid stocks with stale prices, it contaminates the measurement of the conditional betas and the cross-sectional relation between beta and expected returns.

To eliminate all these potential concerns about liquidity, in this section, we examine the significance of a cross-sectional relation between the dynamic conditional beta and expected returns for the most liquid 500 stocks. To construct the liquid stock sample, we first calculate the average daily Amihud's

[16]Bid-ask spread has two components: (i) Transaction cost component which is used for satisfying dealer's normal cost of doing business, risk premium that dealer may require for bearing inventory risk; and (ii) Adverse selection component that compensates dealers for losses that they suffer when trading with well-informed traders. Bid-ask bounce constitutes only the first component above. Due to mix of buyers and sellers in an order flow, price changes caused by a jump from bid to ask most frequently follow price changes from ask to bid. Such price changes are transient and price changes happening between bid and ask is called bid-ask bounce.

(2002) illiquidity measure over the period of July of year $t-1$ to June of year $t$. Then, the sample of the most liquid 500 stocks is formed by ranking individual stocks in the CRSP based on their average illiquidity measure, and updated on a yearly basis.

Figure 8 plots the market share of the most liquid 500 stocks in the CRSP universe. The solid line in Figure 8 depicts the monthly ratios of total market capitalization of the most liquid 500 stocks to the aggregate market capitalization of all stocks trading at the NYSE, Amex, and Nasdaq. The dashed line in Figure 8 presents the same ratio for the NYSE/Amex/Nasdaq stocks after eliminating small and low-priced stocks. When the aggregate market capitalization of all stocks is considered, the market share of the most liquid 500 stocks fluctuates between 69% and 87%, with an average market share of 78%. When the aggregate market capitalization of all stocks (after excluding the small and low-priced stocks) is considered, the market share of the most liquid 500 stocks fluctuates between 72% and 88%, with an average market share of 79%.

Panel A of Table 13 presents results from the Fama-MacBeth cross-sectional regressions for the most liquid 500 stocks. As shown in Panel A, the average slopes on the DCC beta are estimated to positive and highly significant. The strongly positive link between the conditional betas and the cross-section of daily returns on the most liquid 500 stocks remains intact after controlling for the well-known predictors. The average slope on SIZE is negative and highly significant for the liquid stock sample. The average slopes on the book-to-market ratio are positive but insignificant in most specifications. Momentum remains a significantly positive predictor of future returns. The average slopes on REV are negative and highly significant, implying that the liquid stocks also exhibit strong short-term return reversals. Consistent with the findings of Ang, Hodrick, Xing, and Zhang (2006) and Bali, Cakici, and Whitelaw (2011), the average slopes on IVOL and MAX are negative and significant. The average slope on ILLIQ is positive and marginally significant when momentum is not present in the multivariate regressions. When momentum is included, the average slope on ILLIQ is positive but statistically insignificant. Similar to our earlier findings from the S&P 500 stocks, the average slope COSKEW is positive for the most liquid 500 stocks, but it is not statistically significant.

Panel B of Table 13 presents the Fama-MacBeth regression results for the characteristic-matched returns. The average slopes on the DCC beta are estimated to positive and somewhat stronger in Panel B compared to the slope estimates in Panel A. The significantly positive relation between the dynamic conditional betas and the cross-section of characteristic-matched returns on the most liquid 500 stocks remains intact after controlling for the well-known pricing effects. Overall, the results in Table 13 indicate that the conditional beta positively predicts the cross-section of future returns on the most liquid 500 stocks in the CRSP universe.

### 6.4. Controlling for daily and weekly return reversals

Lehmann (1990) provides the first evidence for the weekly return reversals in the cross-section of individual stocks. He shows that portfolios of stocks that had positive returns over the past one week (short-term winners) typically had negative returns in the next week (-0.35 to -0.55 percent per week on average), while those with negative returns over the past one week (short-term losers) typically had positive returns in the next week (0.86 to 1.24 percent per week on average). Lehmann (1990) also finds that the zero-cost portfolio that is the difference between the winners and losers portfolios had positive profits in roughly 90 percent of the weeks in his sample, July 1962 - December 1986.

Following Jegadeesh (1990), we have so far defined short-term reversal (REV) as the cumulative return over the past 21 trading days. In our bivariate portfolios and Fama-MacBeth regressions, we control for the past 21-day return for each day in our sample. The results indicate that after controlling for the reversal, the dynamic conditional beta remains a significantly positive predictor of future returns. The results also show that the largest 500 and 1,000 stocks as well as the most 500 liquid stocks exhibit strong short-term reversals in the cross-section of daily stock returns.

Although the significantly positive link between the conditional beta and future stock returns is not expected to be driven by the negative relation between past and future stock returns, in this section, we provide further robustness checks using alternative measures of reversal. We control for five different measures of short-term reversal; the past one-day return (REV1), the past two-day return (REV2), the past three-day return (REV3), the past four-day return (REV4), and the past five-day return (REV5) that corresponds to the weekly return reversal of Lehmann (1990).

Panel A of Table 14 reports results from the Fama-MacBeth cross-sectional regressions for the S&P 500 stocks after controlling for alternative measures of short-term reversal as an extension of the three-factor Fama-French and the four-factor Fama-French-Carhart models. As shown in Panel A, the average slopes on the DCC beta are positive and highly significant for all regression specifications including size, book-to-market, and momentum, and each of the five reversal variables one at a time. Similar to our earlier results, we find a negative and strong link between firm size and future returns. The average slopes on the book-to-market ratio are positive but statistically insignificant. Momentum remains a significantly positive predictor of future returns. The average slopes on all measures of short-term reversal are negative and highly significant, implying that the S&P 500 stocks (that are big and liquid) exhibit strong daily and weekly return reversals. Finally, when all five measures of short-term reversal are controlled for simultaneously, the predictive power of the DCC beta sustains. Panel B of Table 14 replicates the same set of results for the characteristic-matched returns. Not surprisingly, the average slopes on the DCC beta are estimated to positive and somewhat stronger in Panel B compared to our findings in Panel A. The significantly positive relation between the dynamic conditional betas and the cross-section of characteristic-matched returns remains intact after controlling for alternative measures of short-term reversal.

## 7. Conclusion

This paper investigates the empirical validity of the static CAPM, the conditional CAPM, and the conditional ICAPM using four different stock samples; (i) the S&P 500 stocks, (ii) the largest 500 stocks, (iii) the largest 1,000 stocks, and (iv) the most liquid 500 stocks in the CRSP universe. The empirical performance of these asset pricing models is tested in the cross-section of daily stock returns for the sample period July 1, 1963 - December 31, 2009.

First, we examine the static CAPM with the traditional measures of market beta (the CAPM, Fama-French, Scholes-Williams, and Dimson). We estimate the unconditional measures of beta using daily returns over the past one year and then test if these rolling regression betas have predictive power for the cross-section of stock returns over the next one to five days. The results provide no evidence for a significant link between market beta and the cross-section of expected returns.

Next, we evaluate the performance of the conditional CAPM with time-varying beta. Using daily returns over the past one year, we estimate the dynamic conditional correlation (DCC) model of Engle (2002) and generate the time-varying conditional betas for the S&P 500 stocks. Portfolio level analysis and firm-level cross-sectional regressions indicate a positive and significant link between the dynamic conditional beta and future stock returns. Average return and alpha differences between stocks in the lowest and highest conditional beta deciles are about 8% per annum, implying a profitable zero-cost portfolio that goes long stocks in the highest conditional beta decile and shorts stocks in the lowest conditional beta decile. The significant pricing effects generated by the outperformance of stocks with high conditional beta and the underperformance of stocks with low conditional beta are obtained from the univariate Fama-MacBeth regressions as well.

Finally, we test the predictive power of the conditional intertemporal capital asset pricing model in which the dynamic conditional beta does not provide a complete description of an asset's systematic risk. To explain the cross-sectional differences in expected returns, in addition to the asset's covariation with the market portfolio, one needs to account for the asset's covariation with future investment opportunities as well. In the conditional ICAPM framework, investors are concerned not only with the terminal wealth that their portfolio produces, but also with the investment and consumption opportunities that they will have in the future. This implies that investors prefer high expected return and low return variance, but they are also concerned with the covariances of stock returns with state variables that affect future investment opportunities.

In the cross-sectional asset pricing framework, the covariances of stock returns with state variables should be proxied by a set of return predictors. We proxy the hedging demand component of the conditional ICAPM with firm size, book-to-market, momentum, short-term reversal, liquidity, co-skewness, idiosyncratic volatility, and extreme positive returns. Bivariate portfolio level analyses, the characteristic matched portfolios, and the multivariate cross-sectional regressions indicate a positive and significant link between the conditional beta and the cross-section of expected returns after controlling for these well-known predictors. However, after controlling for the conditional beta, some of the firm characteristics and risk factors (such as firm size, past returns, idiosyncratic volatility, and extreme positive returns) strongly predict the cross-section of expected returns. This provides a potential explanation for the empirical failures of the static and the conditional CAPM and points to the superior performance of the conditional ICAPM.

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## Appendix A. Aggregate daily trading volume and average daily turnover

$VOLD_{MKT}$ and $TURN_{MKT}$ are the daily trading volume ($millions) and the average daily turnover of all stocks trading at the NYSE, Amex, and Nasdaq. $VOLD_{S\&P}$ and $TURN_{S\&P}$ are the daily trading volume ($millions) and the average daily turnover of the S&P 500 stocks. RVOLD and RTURN are the relative measures of the daily trading volume and daily turnover of the S&P 500 stocks: (i) RVOLD is defined as the ratio of the aggregate daily trading volume of the S&P 500 stocks to the total daily trading volume of the market, and (ii) RTURN is defined as the ratio of the S&P 500 stocks' daily turnover to the daily turnover of all stocks trading at NYSE, AMEX, and Nasdaq.

| Variable | 07/1964 – 06/1973 | 07/1973 – 06/1983 | 07/1983 – 06/1993 | 07/1993 – 06/2003 | 07/2003 – 12/2009 |
|---|---|---|---|---|---|
| $VOLD_{MKT}$ | 471.9985 | 1,582.1917 | 8,959.7707 | 61,048.9481 | 124,871.1450 |
| $TURN_{MKT}$ | 0.0016 | 0.0016 | 0.0030 | 0.0058 | 0.0083 |
| $VOLD_{S\&P}$ | 226.6279 | 1,056.5768 | 5,762.1440 | 38,018.8633 | 88,553.3782 |
| $TURN_{S\&P}$ | 0.0010 | 0.0017 | 0.0034 | 0.0059 | 0.0118 |
| RVOLD | 0.4723 | 0.6759 | 0.6549 | 0.6186 | 0.7014 |
| RTURN | 0.6674 | 1.0830 | 1.1737 | 1.0390 | 1.3868 |

## Appendix B. Maximum Likelihood Estimation of the Dynamic Conditional Beta

We estimate the conditional covariances of each stock with the market portfolio ($\sigma_{im,t+1}$) 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

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

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

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

where $u_{i,t}$ is a standardized disturbance that has zero mean and variance one for each series. Equations (A.1) and (A.2) indicate that the conditional correlation is also the conditional covariance between the standardized disturbances:

$$\rho_{12,t} = \frac{E_{t-1}\left(u_{1,t} \cdot u_{2,t}\right)}{\sqrt{E_{t-1}\left(u_{1,t}^2\right) \cdot E_{t-1}\left(u_{2,t}^2\right)}} = E_{t-1}\left(u_{1,t} \cdot u_{2,t}\right). \tag{A.3}$$

The conditional covariance matrix of returns is defined as

$$H_t = D_t \cdot \rho_t \cdot D_t, \text{where } D_t = diag\left\{\sqrt{\sigma_{i,t}^2}\right\}, \tag{A.4}$$

where $\rho_t$ is the time-varying conditional correlation matrix:

$$E_{t-1}\left(u_t \cdot u_t'\right) = D_t^{-1} \cdot H_t \cdot D_t^{-1} = \rho_t, \text{where } u_t = D_t^{-1} \cdot r_t. \tag{A.5}$$

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

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} \cdot q_{jj,t}}}, \tag{A.6}$$

$$q_{ij,t} = \overline{\rho_{ij}} + a_1 \cdot (u_{i,t-1} \cdot u_{j,t-1} - \overline{\rho_{ij}}) + a_2 \cdot (q_{ij,t-1} - \overline{\rho_{ij}}), \tag{A.7}$$

where $\overline{\rho_{ij}}$ is the unconditional correlation between $u_{i,t}$ and $u_{j,t}$. Equation (A.7) 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:

$$
\begin{aligned}
L &= -\frac{1}{2}\sum_{t=1}^{T}\left(n\ln(2\pi)+\ln|H_t|+r_t'H_t^{-1}r_t\right) \\
&= -\frac{1}{2}\sum_{t=1}^{T}\left(n\ln(2\pi)+2\ln|H_t|+r_t'D_t^{-1}D_t^{-1}r_t-u_t'u_t+\ln|\rho_t|+u_t'\rho_t^{-1}u_t\right). \qquad (A.8)
\end{aligned}
$$

As shown in Engle (2002), letting the parameters in $D_t$ be denoted by $\theta$ and the additional parameters in $\rho_t$ be denoted by $\varphi$, equation (A.8) can be written as the sum of a volatility part and a correlation part:

$$L(\theta,\varphi)=L_V(\theta)+L_C(\theta,\varphi). \qquad (A.9)$$

The volatility term is

$$L_V(\theta)=-\frac{1}{2}\sum_{t=1}^{T}\left(n\ln(2\pi)+\ln|D_t|^2+r_t'D_t^{-2}r_t\right), \qquad (A.10)$$

and the correlation component is

$$L_C(\theta,\varphi)=-\frac{1}{2}\sum_{t=1}^{T}\left(\ln|\rho_t|+u_t'\rho_t^{-1}u_t-u_t'u_t\right). \qquad (A.11)$$

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

$$L_V(\theta)=-\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{n}\left(\ln(2\pi)+\ln\left(\sigma_{i,t}^2\right)+\frac{r_{i,t}^2}{\sigma_{i,t}^2}\right), \qquad (A.12)$$

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

$$\widehat{\theta}=\text{argmarx}\left\{L_V(\theta)\right\}, \qquad (A.13)$$

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

$$\max_{\varphi}\left\{L_C\left(\widehat{\theta},\varphi\right)\right\}. \qquad (A.14)$$

We estimate the conditional covariances of each stock with the market portfolio using the maximum likelihood method described above. The conditional variance of the market portfolio is estimated by maximizing the univariate GARCH likelihood. As presented in equation (20), the dynamic conditional beta of stock $i$ is defined as the conditional covariance between stock $i$ and the market, divided by the conditional variance of the market.

**Table 1**
**Univariate Portfolios of Stocks Sorted by the Unconditional Beta**

For each day, individual stocks in the S&P 500 index are sorted into 10 univariate decile portfolios based on the CAPM beta ($BETA_{CAPM}$), the Fama-French beta ($BETA_{FF}$), the Scholes-Williams beta ($BETA_{SW}$), and the Dimson beta ($BETA_{Dimson}$). These unconditional beta measures are estimated using daily returns over the prior 252 trading days with at least 200 observations available. For each beta estimate, this table reports the equal-weighted average return (RET) and average beta of individual stocks in each decile. The last two rows present the average raw return difference between the High-beta and Low-beta deciles (denoted by High-Low), and the corresponding Fama-French-Carhart four-factor alphas (denoted by FFC4 alpha). Daily returns and FFC4 alphas are annualized by multiplying the daily values by 252. The Newey-West $t$-statistics are reported in parentheses. The sample covers the period from July 1963 to December 2009.

| | $BETA_{CAPM}$ | | $BETA_{FF}$ | | $BETA_{SW}$ | | $BETA_{Dimson}$ | |
|---|---|---|---|---|---|---|---|---|
| Decile | RET | $BETA_{CAPM}$ | RET | $BETA_{FF}$ | RET | $BETA_{SW}$ | RET | $BETA_{Dimson}$ |
| 1 (Low) | 11.36 | 0.37 | 10.70 | 0.35 | 11.31 | 0.32 | 11.39 | 0.14 |
| 2 | 11.76 | 0.59 | 11.72 | 0.59 | 12.36 | 0.57 | 12.35 | 0.48 |
| 3 | 13.39 | 0.71 | 13.67 | 0.73 | 11.54 | 0.71 | 12.51 | 0.67 |
| 4 | 13.43 | 0.81 | 12.42 | 0.84 | 13.20 | 0.83 | 13.18 | 0.82 |
| 5 | 13.38 | 0.91 | 13.37 | 0.94 | 13.59 | 0.93 | 14.66 | 0.96 |
| 6 | 12.92 | 1.01 | 13.13 | 1.05 | 14.54 | 1.04 | 13.44 | 1.10 |
| 7 | 13.79 | 1.12 | 14.94 | 1.16 | 14.57 | 1.16 | 14.54 | 1.25 |
| 8 | 14.44 | 1.26 | 15.20 | 1.30 | 14.56 | 1.31 | 15.05 | 1.44 |
| 9 | 15.24 | 1.48 | 14.34 | 1.51 | 15.07 | 1.52 | 14.41 | 1.70 |
| 10 (High) | 15.18 | 1.96 | 15.41 | 1.95 | 14.17 | 2.00 | 13.37 | 2.33 |
| High - Low | 3.82 | | 4.71 | | 2.86 | | 1.98 | |
| | (0.95) | | (1.18) | | (0.71) | | (0.56) | |
| FFC4 | 3.83 | | 3.60 | | 2.67 | | 2.25 | |
| alpha | (1.18) | | (1.15) | | (0.86) | | (0.80) | |

**Table 2**
**Univariate Portfolios of Stocks Sorted by the Dynamic Conditional Beta**

For each day, individual stocks in the S&P 500 index are sorted into 10 univariate decile portfolios on the time-varying conditional beta ($BETA_{DCC}$), estimated based on the dynamic conditional correlation (DCC) model of Engle (2002). The $BETA_{DCC}$ measures are estimated using daily returns over the prior 252 trading days with at least 200 observations available. The first three columns report the equal-weighted average returns (RET), the Fama-French-Carhart four-factor alphas (FFC4 alpha), and the average DCC-beta of individual stocks in each decile. The next four columns, respectively, present the average CAPM beta, and average Fama-French beta, average Scholes-Williams beta, and average Dimson beta of individual stocks in each decile. The last three rows present the average raw return difference between the High-beta and Low-beta deciles (High-Low), the return difference between the Low-beta and the remaining deciles (Low - Rest), and the return difference between the High-beta and the remaining deciles (High - Rest). Daily returns and FFC4 alphas are annualized by multiplying the daily values by 252. The Newey-West $t$-statistics are reported in parentheses. The sample covers the period from July 1963 to December 2009.

| Decile | RET | FFC4 alpha | $BETA_{DCC}$ | $BETA_{CAPM}$ | $BETA_{FF}$ | $BETA_{SW}$ | $BETA_{Dimson}$ |
|---|---|---|---|---|---|---|---|
| 1 (Low) | 10.33 | 0.01 | 0.28 | 0.48 | 0.52 | 0.50 | 0.58 |
| | (5.09) | (0.01) | | | | | |
| 2 | 11.43 | 0.79 | 0.55 | 0.63 | 0.67 | 0.65 | 0.72 |
| | (5.26) | (0.64) | | | | | |
| 3 | 11.66 | 0.89 | 0.68 | 0.74 | 0.79 | 0.77 | 0.84 |
| | (4.89) | (0.76) | | | | | |
| 4 | 12.02 | 1.16 | 0.80 | 0.84 | 0.88 | 0.87 | 0.93 |
| | (4.78) | (1.05) | | | | | |
| 5 | 12.44 | 1.40 | 0.91 | 0.92 | 0.97 | 0.96 | 1.01 |
| | (4.72) | (1.32) | | | | | |
| 6 | 12.94 | 1.58 | 1.03 | 1.02 | 1.06 | 1.05 | 1.09 |
| | (4.70) | (1.57) | | | | | |
| 7 | 14.97 | 3.52 | 1.16 | 1.12 | 1.15 | 1.14 | 1.18 |
| | (5.13) | (3.45) | | | | | |
| 8 | 15.56 | 3.97 | 1.34 | 1.24 | 1.26 | 1.26 | 1.28 |
| | (4.88) | (3.99) | | | | | |
| 9 | 15.59 | 4.64 | 1.59 | 1.43 | 1.42 | 1.44 | 1.45 |
| | (4.43) | (3.96) | | | | | |
| 10 (High) | 18.04 | 7.82 | 2.23 | 1.79 | 1.72 | 1.77 | 1.80 |
| | (4.08) | (3.41) | | | | | |
| High - Low | 7.71 | 7.80 | | | | | |
| | (2.11) | (2.40) | | | | | |
| Low - Rest | -3.52 | -2.85 | | | | | |
| | (-2.19) | (-2.16) | | | | | |
| High - Rest | 5.05 | 5.82 | | | | | |
| | (1.81) | (2.18) | | | | | |

**Table 3**
**Portfolio Characteristics**

For each day, individual stocks in the S&P 500 index are sorted into 10 univariate decile portfolios on the time-varying conditional beta ($BETA_{DCC}$), estimated based on the dynamic conditional correlation (DCC) model of Engle (2002). The $BETA_{DCC}$ measures are estimated using daily returns over the prior 252 trading days with at least 200 observations available. The first two columns report the equal-weighted average returns (RET) and the average DCC-beta of individual stocks in each decile. The next 10 columns report the average firm characteristics of each decile: average market capitalization (SIZE), average book-to-market ratio (BM), average cumulative return over the 12 months prior to portfolio formation (MOM), average idiosyncratic volatility (IVOL), average illiquidity (ILLIQ), average past one-month return (REV), average maximum daily return (MAX), average co-skewness (COSKEW), average price, and average market share of stocks in each decile. The sample covers the period from July 1963 to December 2009.

| Decile | RET | $BETA_{DCC}$ | SIZE | BM | MOM | IVOL | ILLIQ | REV | MAX | COSKEW | PRICE | Mkt. shr. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 (Low) | 10.33 | 0.28 | 7,171 | 0.8478 | 10.54 | 6.04 | 0.0159 | 0.99 | 3.33 | -0.7064 | 38.19 | 7.00 |
| 2 | 11.43 | 0.55 | 7,405 | 0.8231 | 9.86 | 5.84 | 0.0128 | 0.90 | 3.23 | -1.5682 | 39.47 | 8.35 |
| 3 | 11.66 | 0.68 | 7,658 | 0.7932 | 10.15 | 6.10 | 0.0107 | 0.95 | 3.45 | -2.1038 | 40.63 | 9.04 |
| 4 | 12.02 | 0.80 | 7,710 | 0.7734 | 10.60 | 6.31 | 0.0100 | 1.01 | 3.63 | -1.8015 | 41.06 | 9.71 |
| 5 | 12.44 | 0.91 | 7,580 | 0.7644 | 11.09 | 6.53 | 0.0088 | 1.05 | 3.82 | -1.9019 | 41.35 | 10.41 |
| 6 | 12.94 | 1.03 | 7,663 | 0.7601 | 11.61 | 6.77 | 0.0083 | 1.08 | 4.03 | -1.2065 | 41.51 | 11.22 |
| 7 | 14.97 | 1.16 | 7,955 | 0.7548 | 12.19 | 7.09 | 0.0077 | 1.14 | 4.30 | -1.3954 | 41.31 | 11.80 |
| 8 | 15.56 | 1.34 | 9,002 | 0.7470 | 13.04 | 7.58 | 0.0073 | 1.21 | 4.68 | -0.5116 | 40.95 | 12.47 |
| 9 | 15.59 | 1.59 | 8,968 | 0.7458 | 14.29 | 8.47 | 0.0072 | 1.31 | 5.35 | 0.2520 | 39.20 | 11.52 |
| 10 (High) | 18.04 | 2.23 | 7,285 | 0.7506 | 18.27 | 10.59 | 0.0082 | 1.50 | 6.98 | 1.7020 | 35.45 | 8.49 |

**Table 4**
**Testing the Difference between the Conditional and Unconditional Beta Premia**

In Panel A, for each day, individual stocks in the S&P 500 index are sorted into 10 univariate decile portfolios on the difference between the time-varying conditional beta, estimated based on the dynamic conditional correlation (DCC) model of Engle (2002), and the unconditional beta estimated from either the CAPM ($DCC-CAPM$), the Fama-French model ($DCC-FF$), the Scholes-Williams model ($DCC-SW$), or the Dimson model ($DCC-Dimson$). Columns "RET" report the equal-weighted average returns for the decile portfolios formed on $DCC-CAPM$, $DCC-FF$, $DCC-SW$, and $DCC-Dimson$, respectively. Columns "$DCC-CAPM$", "$DCC-FF$", "$DCC-SW$", and "$DCC-Dimson$" report the average difference between the conditional beta and the corresponding unconditional beta in each decile. The last two rows present the average raw return difference between Decile 10 and Decile 1 (High-Low) and the Fama-French-Carhart four-factor alphas (FFC4 alpha). Daily returns and FFC4 alphas are annualized by multiplying the daily values by 252. Panel B reports the average slope coefficients from the Fama-MacBeth regressions of the one-day-ahead excess returns of individual stocks in the S&P 500 index on the time-varying conditional beta estimates ($BETA_{DCC}$) after controlling for each unconditional beta measure. The Newey-West $t$-statistics are reported in parentheses. The sample covers the period from July 1963 to December 2009.

Panel A. Univariate sorts on the difference between the conditional beta and the unconditional beta

| Decile | RET | $DCC-CAPM$ | RET | $DCC-FF$ | RET | $DCC-SW$ | RET | $DCC-Dimson$ |
|---|---|---|---|---|---|---|---|---|
| 1 (Low) | 13.59 | -0.48 | 13.07 | -0.60 | 12.73 | -0.61 | 11.12 | -1.04 |
| 2 | 11.10 | -0.21 | 10.78 | -0.31 | 11.77 | -0.31 | 13.24 | -0.56 |
| 3 | 10.63 | -0.12 | 11.87 | -0.19 | 10.77 | -0.19 | 11.71 | -0.36 |
| 4 | 11.82 | -0.06 | 11.49 | -0.11 | 12.43 | -0.11 | 12.87 | -0.21 |
| 5 | 10.67 | -0.01 | 12.42 | -0.04 | 11.98 | -0.03 | 12.11 | -0.09 |
| 6 | 13.70 | 0.04 | 12.95 | 0.03 | 11.80 | 0.04 | 13.91 | 0.03 |
| 7 | 13.09 | 0.09 | 13.37 | 0.10 | 13.74 | 0.11 | 13.74 | 0.15 |
| 8 | 14.05 | 0.16 | 14.96 | 0.19 | 15.02 | 0.20 | 14.55 | 0.30 |
| 9 | 15.78 | 0.28 | 15.52 | 0.33 | 15.33 | 0.33 | 13.71 | 0.49 |
| 10 (High) | 20.52 | 0.67 | 18.50 | 0.75 | 19.39 | 0.75 | 18.02 | 1.00 |
| High - Low | 6.93 | | 5.43 | | 6.66 | | 6.90 | |
| | (3.26) | | (2.76) | | (3.36) | | (3.54) | |
| FFC4 alpha | 5.14 | | 6.36 | | 6.33 | | 6.17 | |
| | (2.25) | | (2.98) | | (2.99) | | (3.00) | |

**Table 4 – continued**

Panel B. Fama-MacBeth cross-sectional regressions

| Variable | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Intercept | 0.0182 | 0.0178 | 0.0202 | 0.0178 |
| | (2.15) | (2.18) | (2.47) | (2.17) |
| $BETA_{DCC}$ | 0.0313 | 0.0247 | 0.0278 | 0.0217 |
| | (5.08) | (4.37) | (5.00) | (3.64) |
| $BETA_{CAPM}$ | -0.0168 | | | |
| | (-1.66) | | | |
| $BETA_{FF}$ | | -0.0089 | | |
| | | (-1.03) | | |
| $BETA_{SW}$ | | | -0.0141 | |
| | | | (-1.71) | |
| $BETA_{Dimson}$ | | | | -0.0059 |
| | | | | (-1.19) |

**Table 5**
**Bivariate Portfolios of Stocks Sorted by the Dynamic Conditional Beta and Control Variables**

For each day, individual stocks in the S&P 500 index are first sorted into quintile portfolios based on one control variable, and then within each control variable quintile, stocks are further sorted into quintiles based on the the time-varying conditional beta ($BETA_{DCC}$), estimated based on the dynamic conditional correlation (DCC) model of Engle (2002). The $BETA_{DCC}$ measures are estimated using daily returns over the prior 252 trading days with at least 200 observations available. The control variables are the natural logarithm of firm's market capitalization (SIZE), book-to-market equity ratio (BM), momentum (MOM), Amihud's illiquidity measure (ILLIQ), idiosyncratic volatility (IVOL), short-term reversal (REV), maximum daily return (MAX), and co-skewness (COSKEW). This table reports the average returns for the beta-sorted quintile portfolios, averaged across the control quintiles. The last two rows present the average raw return difference between Quintiles 5 and 1, and the corresponding Fama-French-Carhart four-factor alphas (denoted by FFC4 alpha). Daily returns and FFC4 alphas are annualized by multiplying the daily values by 252. The Newey-West $t$-statistics are given in parentheses. The sample covers the period from July 1963 to December 2009.

| Quintile | SIZE | BM | MOM | ILLIQ | IVOL | REV | MAX | COSKEW |
|---|---|---|---|---|---|---|---|---|
| 1 (Low) | 10.62 | 10.27 | 11.32 | 11.02 | 11.60 | 10.74 | 11.18 | 10.85 |
| 2 | 12.35 | 11.95 | 12.74 | 12.14 | 12.34 | 11.62 | 12.02 | 12.04 |
| 3 | 13.23 | 13.49 | 13.59 | 12.85 | 13.57 | 13.42 | 12.46 | 12.98 |
| 4 | 14.70 | 13.85 | 14.35 | 14.77 | 14.11 | 14.58 | 14.49 | 14.81 |
| 5 (High) | 16.74 | 17.87 | 15.75 | 16.97 | 15.95 | 17.32 | 17.65 | 16.94 |
| High-Low | 6.12 | 7.60 | 4.43 | 5.95 | 4.35 | 6.59 | 6.47 | 6.09 |
| | (2.27) | (2.91) | (2.06) | (2.25) | (2.03) | (2.58) | (3.08) | (2.34) |
| FFC4 | 6.08 | 6.48 | 4.12 | 5.84 | 3.99 | 6.25 | 6.13 | 5.58 |
| alpha | (2.60) | (2.83) | (2.02) | (2.57) | (1.99) | (3.02) | (3.24) | (2.53) |

**Table 6**

**Characteristic-matched Returns for Portfolios of Stocks Sorted by the Dynamic Conditional Beta**

For each day, individual stocks in the S&P 500 index are sorted into 10 univariate decile portfolios based on the time-varying conditional beta ($BETA_{DCC}$), estimated based on the dynamic conditional correlation (DCC) model of Engle (2002). The $BETA_{DCC}$ measures are estimated using daily returns over the prior 252 trading days with at least 200 observations available. The first three columns report the average characteristic-matched returns (RET) along the lines of Daniel and Titman (1997), the corresponding Fama-French-Carhart four-factor alphas (FFC4 alpha), and the average DCC-beta of individual stocks in each decile. The next 10 columns report the average firm characteristics of each decile: average market capitalization (SIZE), average book-to-market ratio (BM), average cumulative return over the 12 months prior to portfolio formation (MOM), average idiosyncratic volatility (IVOL), average illiquidity (ILLIQ), average past one-month return (REV), average maximum daily return (MAX), average co-skewness (COSKEW), average price, and average market share of stocks in each decile. The last three rows present the average return difference between the High-beta and Low-beta deciles (High-Low), the return difference between the Low-beta and the remaining deciles (Low - Rest), and the return difference between the High-beta and the remaining deciles (High - Rest). Daily returns and FFC4 alphas are annualized by multiplying the daily values by 252. The Newey-West $t$-statistics are reported in parentheses. The sample covers the period from July 1963 to December 2009.

| Decile | RET | FFC4 alpha | $BETA_{DCC}$ | SIZE | BM | MOM | IVOL | ILLIQ | REV | MAX | COSKEW | PRICE | Mkt. shr. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 (Low) | -2.85 | -7.48 | 0.28 | 7,248 | 0.8486 | 10.68 | 5.97 | 0.0145 | 0.99 | 3.28 | -0.5229 | 38.30 | 6.91 |
| | (-2.76) | (-8.27) | | | | | | | | | | | |
| 2 | -1.30 | -6.29 | 0.54 | 7,495 | 0.8241 | 9.85 | 5.79 | 0.0117 | 0.90 | 3.20 | -1.6391 | 39.50 | 8.17 |
| | (-1.50) | (-7.91) | | | | | | | | | | | |
| 3 | -1.42 | -6.72 | 0.68 | 7,745 | 0.7929 | 10.08 | 6.05 | 0.0096 | 0.95 | 3.42 | -2.2145 | 40.75 | 8.89 |
| | (-2.03) | (-9.23) | | | | | | | | | | | |
| 4 | -0.61 | -5.94 | 0.79 | 7,794 | 0.7740 | 10.51 | 6.25 | 0.0090 | 1.00 | 3.59 | -1.2337 | 41.22 | 9.56 |
| | (-0.95) | (-8.87) | | | | | | | | | | | |
| 5 | -1.04 | -6.51 | 0.91 | 7,675 | 0.7638 | 11.00 | 6.46 | 0.0078 | 1.06 | 3.77 | -1.5968 | 41.49 | 10.30 |
| | (-1.69) | (-10.19) | | | | | | | | | | | |
| 6 | -0.61 | -6.28 | 1.02 | 7,764 | 0.7609 | 11.61 | 6.69 | 0.0075 | 1.08 | 3.98 | -1.0155 | 41.79 | 11.17 |
| | (-0.95) | (-9.66) | | | | | | | | | | | |
| 7 | 1.31 | -4.39 | 1.16 | 8,104 | 0.7545 | 12.12 | 7.00 | 0.0069 | 1.14 | 4.25 | -0.9283 | 41.93 | 11.94 |
| | (1.91) | (-6.36) | | | | | | | | | | | |
| 8 | 1.37 | -4.49 | 1.33 | 9,162 | 0.7473 | 12.94 | 7.47 | 0.0064 | 1.20 | 4.62 | -0.3381 | 41.69 | 12.60 |
| | (1.81) | (-6.08) | | | | | | | | | | | |
| 9 | 1.36 | -4.60 | 1.58 | 9,162 | 0.7464 | 14.29 | 8.33 | 0.0063 | 1.31 | 5.27 | 0.7251 | 40.22 | 11.84 |
| | (1.43) | (-5.04) | | | | | | | | | | | |
| 10 (High) | 3.88 | -1.49 | 2.21 | 7,431 | 0.7521 | 18.11 | 10.42 | 0.0065 | 1.49 | 6.88 | 2.0788 | 36.20 | 8.61 |
| | (2.36) | (-0.87) | | | | | | | | | | | |
| High - Low | 6.73 | 5.98 | | | | | | | | | | | |
| | (2.86) | (2.62) | | | | | | | | | | | |
| Low - Rest | -3.18 | -2.29 | | | | | | | | | | | |
| | (-2.77) | (-2.30) | | | | | | | | | | | |
| High - Rest | 4.30 | 4.36 | | | | | | | | | | | |
| | (2.35) | (2.28) | | | | | | | | | | | |

**Table 7**

**Fama-MacBeth Cross-Sectional Regressions: Predicting one-day-ahead Returns with the Dynamic Conditional Beta**

The one-day-ahead excess returns of individual stocks in the S&P 500 index are regressed every day on the time-varying conditional beta estimates ($BETA_{DCC}$) after controlling for a large set of cross-sectional return predictors. $BETA_{DCC}$ is estimated based on the dynamic conditional correlation (DCC) model of Engle (2002) using daily returns over the prior 252 trading days with at least 200 observations available, and updated on a daily basis. The control variables are the natural logarithm of firm's market capitalization (SIZE), book-to-market equity ratio (BM), momentum (MOM), Amihud's illiquidity measure (ILLIQ), idiosyncratic volatility (IVOL), short-term reversal (REV), maximum daily return (MAX), and co-skewness (COSKEW). This table reports the average slope coefficients from the Fama-MacBeth regressions and the Newey-West $t$-statistics (in parentheses). The sample covers the period from July 1963 to December 2009.

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.0148 | 0.0808 | 0.0823 | 0.0996 | 0.0614 | 0.1042 | 0.0751 | 0.0874 | 0.1012 | 0.0636 | 0.1099 | 0.0798 |
| | (1.74) | (4.40) | (4.27) | (4.89) | (2.88) | (5.25) | (3.70) | (4.83) | (5.28) | (3.22) | (5.98) | (4.31) |
| $BETA_{DCC}$ | 0.0180 | 0.0165 | 0.0198 | 0.0182 | 0.0220 | 0.0275 | 0.0198 | 0.0174 | 0.0157 | 0.0200 | 0.0257 | 0.0173 |
| | (2.55) | (2.71) | (3.16) | (2.69) | (3.24) | (4.17) | (2.95) | (3.01) | (2.58) | (3.27) | (4.21) | (2.87) |
| SIZE | | -0.0101 | -0.0093 | -0.0113 | -0.0067 | -0.0116 | -0.0087 | -0.0105 | -0.0122 | -0.0075 | -0.0128 | -0.0100 |
| | | (-5.57) | (-4.96) | (-5.53) | (-3.22) | (-5.83) | (-4.30) | (-6.12) | (-6.42) | (-3.96) | (-7.10) | (-5.49) |
| BM | | 0.0007 | 0.0004 | 0.0008 | 0.0032 | 0.0003 | 0.0011 | 0.0002 | 0.0007 | 0.0037 | 0.0002 | 0.0009 |
| | | (0.25) | (0.14) | (0.29) | (1.05) | (0.11) | (0.37) | (0.08) | (0.23) | (1.20) | (0.07) | (0.32) |
| MOM | | 0.0002 | | | | | | 0.0003 | 0.0002 | 0.0002 | 0.0002 | 0.0002 |
| | | (2.16) | | | | | | (2.46) | (2.15) | (1.41) | (1.92) | (2.20) |
| IVOL | | | -0.0011 | | | | | -0.0011 | | | | |
| | | | (-1.86) | | | | | (-1.81) | | | | |
| ILLIQ | | | | 0.4320 | | | | | 0.3202 | | | |
| | | | | (1.24) | | | | | (0.98) | | | |
| REV | | | | | -0.0062 | | | | | -0.0067 | | |
| | | | | | (-19.25) | | | | | (-20.70) | | |
| MAX | | | | | | -0.0050 | | | | | -0.0053 | |
| | | | | | | (-6.86) | | | | | (-7.34) | |
| COSKEW | | | | | | | -0.0002 | | | | | -0.0002 |
| | | | | | | | (-1.47) | | | | | (-1.53) |

**Table 8**

**Fama-MacBeth Cross-Sectional Regressions: Predicting Cumulative Returns over Two to Five days with the Conditional Beta**

The 2-, 3-, 4-, and 5-day cumulative excess returns of individual stocks in the S&P 500 index are regressed every day on the time-varying conditional beta estimates ($BETA_{DCC}$) after controlling for a large set of cross-sectional return predictors. $BETA_{DCC}$ is estimated based on the dynamic conditional correlation (DCC) model of Engle (2002) using daily returns over the prior 252 trading days with at least 200 observations available, and updated on a daily basis. The control variables are the natural logarithm of firm's market capitalization (SIZE), book-to-market equity ratio (BM), momentum (MOM), Amihud's illiquidity measure (ILLIQ), idiosyncratic volatility (IVOL), short-term reversal (REV), maximum daily return (MAX), and co-skewness (COSKEW). This table reports the average slope coefficients from the Fama-MacBeth regressions and the Newey-West $t$-statistics (in parentheses). The sample covers the period from July 1963 to December 2009.

| | Panel A. Cumulative returns over two days | | | | | | Panel B. Cumulative returns over three days | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (1) | (2) | (3) | (4) | (5) | (6) |
| Intercept | 0.1881 | 0.2077 | 0.2292 | 0.1598 | 0.2430 | 0.1885 | 0.2910 | 0.3240 | 0.3504 | 0.2570 | 0.3660 | 0.2920 |
| | (5.16) | (5.81) | (6.08) | (4.14) | (6.65) | (5.16) | (5.39) | (6.16) | (6.29) | (4.59) | (6.76) | (5.40) |
| $BETA_{DCC}$ | 0.0200 | 0.0234 | 0.0188 | 0.0272 | 0.0370 | 0.0205 | 0.0200 | 0.0251 | 0.0183 | 0.0290 | 0.0430 | 0.0199 |
| | (1.72) | (2.13) | (1.67) | (2.36) | (3.17) | (1.77) | (1.17) | (1.56) | (1.07) | (1.73) | (2.51) | (1.17) |
| SIZE | -0.0192 | -0.0209 | -0.0236 | -0.0148 | -0.0245 | -0.0192 | -0.0275 | -0.0303 | -0.0339 | -0.0217 | -0.0346 | -0.0275 |
| | (-5.38) | (-6.16) | (-6.33) | (-3.99) | (-6.87) | (-5.37) | (-5.19) | (-6.07) | (-6.15) | (-4.01) | (-6.56) | (-5.20) |
| BM | 0.0012 | 0.0002 | 0.0012 | 0.0071 | 0.0003 | 0.0014 | 0.0020 | 0.0007 | 0.0020 | 0.0102 | 0.0007 | 0.0021 |
| | (0.21) | (0.03) | (0.21) | (1.18) | (0.04) | (0.24) | (0.23) | (0.09) | (0.24) | (1.16) | (0.08) | (0.24) |
| MOM | 0.0005 | 0.0005 | 0.0005 | 0.0004 | 0.0004 | 0.0005 | 0.0007 | 0.0008 | 0.0007 | 0.0006 | 0.0007 | 0.0008 |
| | (2.20) | (2.47) | (2.18) | (1.56) | (1.96) | (2.23) | (2.32) | (2.59) | (2.31) | (1.75) | (2.10) | (2.36) |
| IVOL | | -0.0027 | | | | | | -0.0042 | | | | |
| | | (-2.37) | | | | | | (-2.54) | | | | |
| ILLIQ | | | 0.5378 | | | | | | 0.7664 | | | |
| | | | (0.88) | | | | | | (0.86) | | | |
| REV | | | | -0.0126 | | | | | | -0.0172 | | |
| | | | | (-20.43) | | | | | | (-19.41) | | |
| MAX | | | | | -0.0100 | | | | | | -0.0136 | |
| | | | | | (-7.17) | | | | | | (-6.73) | |
| COSKEW | | | | | | -0.0002 | | | | | | -0.0002 |
| | | | | | | (-0.80) | | | | | | (-0.86) |

**Table 8 – continued**

| Variable | Panel C. Cumulative returns over four days (1) | (2) | (3) | (4) | (5) | (6) | Panel D. Cumulative returns over five days (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.3907 | 0.4361 | 0.4635 | 0.3523 | 0.4802 | 0.3933 | 0.4905 | 0.5478 | 0.5735 | 0.4489 | 0.5901 | 0.4942 |
| | (5.50) | (6.34) | (6.32) | (4.83) | (6.75) | (5.53) | (5.60) | (6.50) | (6.35) | (5.04) | (6.75) | (5.64) |
| $BETA_{DCC}$ | 0.0199 | 0.0265 | 0.0178 | 0.0300 | 0.0469 | 0.0191 | 0.0168 | 0.0246 | 0.0147 | 0.0275 | 0.0467 | 0.0161 |
| | (0.89) | (1.26) | (0.80) | (1.38) | (2.10) | (0.86) | (0.62) | (0.97) | (0.54) | (1.05) | (1.73) | (0.60) |
| SIZE | -0.0353 | -0.0391 | -0.0432 | -0.0286 | -0.0437 | -0.0354 | -0.0429 | -0.0476 | -0.0520 | -0.0356 | -0.0522 | -0.0431 |
| | (-5.05) | (-5.97) | (-5.95) | (-4.05) | (-6.30) | (-5.07) | (-4.97) | (-5.92) | (-5.81) | (-4.10) | (-6.11) | (-5.01) |
| BM | 0.0030 | 0.0015 | 0.0030 | 0.0130 | 0.0014 | 0.0032 | 0.0042 | 0.0026 | 0.0041 | 0.0157 | 0.0023 | 0.0042 |
| | (0.27) | (0.14) | (0.27) | (1.13) | (0.12) | (0.29) | (0.30) | (0.19) | (0.30) | (1.11) | (0.17) | (0.31) |
| MOM | 0.0010 | 0.0011 | 0.0010 | 0.0008 | 0.0009 | 0.0010 | 0.0012 | 0.0013 | 0.0012 | 0.0010 | 0.0012 | 0.0013 |
| | (2.38) | (2.65) | (2.38) | (1.88) | (2.20) | (2.44) | (2.39) | (2.65) | (2.40) | (1.93) | (2.24) | (2.46) |
| IVOL | | -0.0056 | | | | | | -0.0069 | | | | |
| | | (-2.61) | | | | | | (-2.61) | | | | |
| ILLIQ | | | 0.7837 | | | | | | 0.7097 | | | |
| | | | (0.68) | | | | | | (0.50) | | | |
| REV | | | | -0.0206 | | | | | | -0.0233 | | |
| | | | | (-18.22) | | | | | | (-17.18) | | |
| MAX | | | | | -0.0164 | | | | | | -0.0184 | |
| | | | | | (-6.25) | | | | | | (-5.80) | |
| COSKEW | | | | | | -0.0003 | | | | | | -0.0003 |
| | | | | | | (-0.74) | | | | | | (-0.75) |

**Table 9**
**Explaining Monthly Realized Beta with the Unconditional and Conditional Beta Measures**

This table reports the average slope coefficients and the average R-squared values from the Fama-MacBeth regressions: $\beta_{i,t} = \alpha_{0,t} + \alpha_{1,t}\widehat{\beta_{i,t}} + \varepsilon_{i,t}$, where $\beta_{i,t}$ denotes the realized beta for stock $i$ in month $t$, estimated from the CAPM ($\beta^{CAPM}$), the Fama-French model ($\beta^{FF}$), the Sholes-Williams model ($\beta^{SW}$), or the Dimson model ($\beta^{Dimson}$); $\widehat{\beta_{i,t}}$ is the average of daily beta in month $t$, estimated from one of the five models: (1) the dynamic conditional correlation model of Engle (2002) ($\widehat{\beta^{DCC}}$), (2) the CAPM ($\widehat{\beta^{CAPM}}$), (3) the Fama-French model ($\widehat{\beta^{FF}}$), (4) the Sholes-Williams model ($\widehat{\beta^{SW}}$), and (5) the Dimson model ($\widehat{\beta^{Dimson}}$), using daily returns over the prior 252 trading days with at least 200 observations available, and updated on a daily basis. The Newey-West adjusted $t$-statistics are reported in parentheses. The sample covers the period from July 1963 to December 2009.

| | $\widehat{\beta^{DCC}}$ | | $\widehat{\beta^{CAPM}}$ | | $\widehat{\beta^{FF}}$ | | $\widehat{\beta^{SW}}$ | | $\widehat{\beta^{Dimson}}$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| Realized beta | Coef. | $R^2$ | Coef. | $R^2$ | Coef. | $R^2$ | Coef. | $R^2$ | Coef. | $R^2$ |
| $BETA_{CAPM}$ | 0.9940 | 43.93% | 0.7977 | 25.08% | 0.8897 | 29.96% | 0.7718 | 25.65% | 0.4509 | 15.33% |
| | (92.63) | | (46.84) | | (55.86) | | (44.68) | | (24.69) | |
| $BETA_{FF}$ | 0.9129 | 26.77% | 0.8444 | 20.27% | 0.8105 | 18.37% | 0.7811 | 19.28% | 0.4639 | 12.18% |
| | (55.31) | | (48.87) | | (33.63) | | (48.78) | | (27.14) | |
| $BETA_{SW}$ | 0.9898 | 25.03% | 0.8917 | 17.75% | 0.8859 | 17.24% | 0.8790 | 18.67% | 0.5104 | 11.31% |
| | (48.88) | | (42.39) | | (32.11) | | (44.96) | | (26.06) | |
| $BETA_{Dimson}$ | 0.9131 | 5.41% | 0.8620 | 4.46% | 0.8210 | 4.30% | 0.8418 | 4.59% | 0.7719 | 5.18% |
| | (21.70) | | (19.46) | | (15.90) | | (20.04) | | (23.43) | |

**Table 10**

**Fama-MacBeth Cross-Sectional Regressions: Predicting one-day-ahead Returns with the Dynamic Conditional Beta for the Largest 500 and 1,000 Firms**

The one-day-ahead excess returns of the largest 500 stocks (the left panel) and the largest 1,000 stocks (the right panel) are regressed every day on the time-varying conditional beta estimates ($BETA_{DCC}$) after controlling for a large set of predictors. $BETA_{DCC}$ is estimated based on the dynamic conditional correlation (DCC) model of Engle (2002) using daily returns over the prior 252 trading days with at least 200 observations available, and updated on a daily basis. The control variables are the natural logarithm of firm's market capitalization (SIZE), book-to-market equity ratio (BM), momentum (MOM), Amihud's illiquidity measure (ILLIQ), idiosyncratic volatility (IVOL), short-term reversal (REV), maximum daily return (MAX), and co-skewness (COSKEW). This table reports the average slope coefficients from the Fama-MacBeth regressions and the Newey-West $t$-statistics (in parentheses). The sample covers the period from July 1963 to December 2009.

| | Largest 500 firms | | | | | Largest 1,000 firms | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| Intercept | 0.0903 | 0.0864 | 0.0468 | 0.1290 | 0.1048 | 0.0839 | 0.0658 | 0.0497 | 0.1482 | 0.1201 |
| | (4.79) | (4.35) | (2.39) | (6.81) | (5.53) | (5.48) | (4.02) | (2.91) | (8.64) | (6.92) |
| $BETA_{DCC}$ | 0.0174 | 0.0135 | 0.0147 | 0.0252 | 0.0160 | 0.0167 | 0.0119 | 0.0155 | 0.0266 | 0.0181 |
| | (2.91) | (2.15) | (2.33) | (3.94) | (2.52) | (2.94) | (1.95) | (2.53) | (4.35) | (2.96) |
| SIZE | -0.0102 | -0.0101 | -0.0050 | -0.0146 | -0.0126 | -0.0092 | -0.0077 | -0.0053 | -0.0177 | -0.0152 |
| | (-5.64) | (-5.17) | (-2.64) | (-7.90) | (-6.76) | (-5.82) | (-4.52) | (-2.96) | (-10.15) | (-8.59) |
| BM | 0.0023 | 0.0031 | 0.0059 | -0.0014 | -0.0003 | 0.0050 | 0.0063 | 0.0086 | -0.0036 | -0.0026 |
| | (0.78) | (1.02) | (1.92) | (-0.47) | (-0.09) | (1.85) | (2.25) | (2.95) | (-1.24) | (-0.90) |
| MOM | 0.0003 | 0.0003 | 0.0002 | 0.0003 | 0.0004 | 0.0004 | 0.0003 | 0.0003 | 0.0004 | 0.0004 |
| | (3.11) | (2.81) | (2.18) | (3.07) | (3.25) | (4.00) | (3.64) | (3.05) | (3.50) | (3.73) |
| IVOL | -0.0016 | | | | | -0.0023 | | | | |
| | (-2.68) | | | | | (-5.00) | | | | |
| ILLIQ | | 0.3314 | | | | | 0.0136 | | | |
| | | (1.40) | | | | | (1.13) | | | |
| REV | | | -0.0062 | | | | | -0.0063 | | |
| | | | (-20.12) | | | | | (-22.61) | | |
| MAX | | | | -0.0055 | | | | | -0.0054 | |
| | | | | (-6.84) | | | | | (-8.13) | |
| COSKEW | | | | | -0.0001 | | | | | -0.0002 |
| | | | | | (-1.00) | | | | | (-1.28) |

**Table 11**

**Fama-MacBeth Cross-Sectional Regressions: Predicting one-day-ahead Characteristic-matched Returns with the DCC Beta**

The one-day-ahead characteristic-matched returns along the lines of Daniel and Titman (1997) for individual stocks in the S&P 500 index are regressed every day on the time-varying conditional beta estimates ($BETA_{DCC}$) after controlling for a large set of predictors. $BETA_{DCC}$ is estimated based on the dynamic conditional correlation (DCC) model of Engle (2002) using daily returns over the prior 252 trading days with at least 200 observations available, and updated on a daily basis. The control variables are the natural logarithm of firm's market capitalization (SIZE), book-to-market equity ratio (BM), momentum (MOM), Amihud's illiquidity measure (ILLIQ), idiosyncratic volatility (IVOL), short-term reversal (REV), maximum daily return (MAX), and co-skewness (COSKEW). This table reports the average slope coefficients from the Fama-MacBeth regressions and the Newey-West $t$-statistics (in parentheses). The sample covers the period from July 1963 to December 2009.

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | -0.0132 | 0.0025 | 0.0096 | 0.0180 | -0.0145 | 0.0307 | -0.0012 | 0.0129 | 0.0206 | -0.0136 | 0.0332 | 0.0019 |
| | (-2.78) | (0.38) | (1.01) | (2.11) | (-1.63) | (4.04) | (-0.17) | (1.37) | (2.36) | (-1.51) | (4.41) | (0.28) |
| $BETA_{DCC}$ | 0.0148 | 0.0155 | 0.0172 | 0.0152 | 0.0193 | 0.0253 | 0.0165 | 0.0171 | 0.0150 | 0.0189 | 0.0252 | 0.0162 |
| | (3.13) | (2.92) | (3.51) | (3.02) | (3.75) | (4.81) | (3.31) | (3.34) | (2.82) | (3.56) | (4.62) | (3.09) |
| SIZE | | -0.0026 | -0.0029 | -0.0040 | 0.0000 | -0.0052 | -0.0020 | -0.0034 | -0.0044 | -0.0002 | -0.0055 | -0.0025 |
| | | (-4.16) | (-3.85) | (-4.72) | (-0.06) | (-7.64) | (-3.33) | (-4.40) | (-4.98) | (-0.20) | (-7.86) | (-3.91) |
| BM | | -0.0016 | -0.0019 | -0.0015 | 0.0010 | -0.0019 | -0.0012 | -0.0022 | -0.0017 | 0.0012 | -0.0021 | -0.0014 |
| | | (-1.41) | (-1.66) | (-1.32) | (0.80) | (-1.72) | (-1.07) | (-1.87) | (-1.49) | (0.91) | (-1.85) | (-1.24) |
| MOM | | 0.0000 | | | | | | 0.0001 | 0.0000 | 0.0000 | 0.0000 | 0.0001 |
| | | (1.23) | | | | | | (1.61) | (1.12) | (-0.38) | (0.43) | (1.29) |
| IVOL | | | -0.0013 | | | | | -0.0013 | | | | |
| | | | (-2.42) | | | | | (-2.38) | | | | |
| ILLIQ | | | | 0.2680 | | | | | 0.2718 | | | |
| | | | | (0.88) | | | | | (0.91) | | | |
| REV | | | | | -0.0063 | | | | | -0.0065 | | |
| | | | | | (-21.30) | | | | | (-21.51) | | |
| MAX | | | | | | -0.0052 | | | | | -0.0054 | |
| | | | | | | (-7.75) | | | | | (-7.89) | |
| COSKEW | | | | | | | -0.0002 | | | | | -0.0002 |
| | | | | | | | (-1.54) | | | | | (-1.53) |

**Table 12**

**Fama-MacBeth Cross-Sectional Regressions: Predicting Characteristic-matched Cumulative Returns over Two to Five days with the DCC Beta**

The 2-, 3-, 4-, and 5-day characteristic-matched cumulative returns along the lines of Daniel and Titman (1997) for individual stocks in the S&P 500 index are regressed every day on the time-varying conditional beta estimates ($BETA_{DCC}$) after controlling for a large set of cross-sectional return predictors. $BETA_{DCC}$ is estimated based on the dynamic conditional correlation (DCC) model of Engle (2002) using daily returns over the prior 252 trading days with at least 200 observations available, and updated on a daily basis. The control variables are the natural logarithm of firm's market capitalization (SIZE), book-to-market equity ratio (BM), momentum (MOM), Amihud's illiquidity measure (ILLIQ), idiosyncratic volatility (IVOL), short-term reversal (REV), maximum daily return (MAX), and co-skewness (COSKEW). This table reports the average slope coefficients from the Fama-MacBeth regressions and the Newey-West $t$-statistics (in parentheses). The sample covers the period from July 1963 to December 2009.

| | Panel A. Cumulative returns over two days | | | | | | Panel B. Cumulative returns over three days | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (1) | (2) | (3) | (4) | (5) | (6) |
| Intercept | 0.0083 | 0.0343 | 0.0453 | -0.0180 | 0.0657 | 0.0092 | 0.0144 | 0.0564 | 0.0671 | -0.0168 | 0.0928 | 0.0163 |
| | (0.65) | (1.89) | (2.75) | (-1.06) | (4.52) | (0.70) | (0.78) | (2.13) | (2.81) | (-0.70) | (4.38) | (0.86) |
| $BETA_{DCC}$ | 0.0193 | 0.0239 | 0.0184 | 0.0265 | 0.0373 | 0.0197 | 0.0192 | 0.0260 | 0.0180 | 0.0281 | 0.0435 | 0.0189 |
| | (1.91) | (2.47) | (1.83) | (2.64) | (3.58) | (1.95) | (1.30) | (1.83) | (1.22) | (1.94) | (2.86) | (1.29) |
| SIZE | -0.0043 | -0.0066 | -0.0082 | -0.0002 | -0.0098 | -0.0044 | -0.0056 | -0.0093 | -0.0111 | -0.0003 | -0.0131 | -0.0057 |
| | (-3.63) | (-4.44) | (-4.82) | (-0.10) | (-7.34) | (-3.56) | (-3.23) | (-4.30) | (-4.49) | (-0.12) | (-6.69) | (-3.20) |
| BM | -0.0033 | -0.0044 | -0.0033 | 0.0024 | -0.0042 | -0.0031 | -0.0050 | -0.0064 | -0.0050 | 0.0028 | -0.0062 | -0.0049 |
| | (-1.52) | (-2.00) | (-1.54) | (0.92) | (-1.91) | (-1.41) | (-1.60) | (-1.99) | (-1.60) | (0.76) | (-1.95) | (-1.55) |
| MOM | 0.0001 | 0.0001 | 0.0001 | 0.0000 | 0.0000 | 0.0001 | 0.0002 | 0.0002 | 0.0002 | 0.0000 | 0.0001 | 0.0002 |
| | (1.31) | (1.64) | (1.19) | (-0.13) | (0.48) | (1.36) | (1.47) | (1.79) | (1.36) | (0.18) | (0.68) | (1.54) |
| IVOL | | -0.0030 | | | | | | -0.0047 | | | | |
| | | (-2.95) | | | | | | (-3.14) | | | | |
| ILLIQ | | | 0.4754 | | | | | | 0.6497 | | | |
| | | | (0.84) | | | | | | (0.79) | | | |
| REV | | | | -0.0123 | | | | | | -0.0168 | | |
| | | | | (-21.26) | | | | | | (-20.22) | | |
| MAX | | | | | -0.0101 | | | | | | -0.0138 | |
| | | | | | (-7.72) | | | | | | (-7.27) | |
| COSKEW | | | | | | -0.0002 | | | | | | -0.0002 |
| | | | | | | (-0.85) | | | | | | (-0.83) |

**Table 12 – continued**

| Variable | Panel C. Cumulative returns over four days (1) | (2) | (3) | (4) | (5) | (6) | Panel D. Cumulative returns over five days (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.0210 | 0.0772 | 0.0849 | -0.0141 | 0.1150 | 0.0247 | 0.0325 | 0.1024 | 0.1034 | -0.0051 | 0.1373 | 0.0374 |
| | (0.87) | (2.25) | (2.73) | (-0.46) | (4.18) | (1.01) | (1.12) | (2.47) | (2.72) | (-0.14) | (4.15) | (1.27) |
| $BETA_{DCC}$ | 0.0191 | 0.0278 | 0.0177 | 0.0293 | 0.0477 | 0.0181 | 0.0157 | 0.0261 | 0.0144 | 0.0265 | 0.0473 | 0.0148 |
| | (0.99) | (1.50) | (0.92) | (1.55) | (2.41) | (0.95) | (0.67) | (1.17) | (0.62) | (1.16) | (1.99) | (0.64) |
| SIZE | -0.0069 | -0.0117 | -0.0136 | -0.0007 | -0.0159 | -0.0072 | -0.0085 | -0.0144 | -0.0160 | -0.0017 | -0.0184 | -0.0089 |
| | (-3.04) | (-4.20) | (-4.20) | (-0.26) | (-6.20) | (-3.07) | (-3.05) | (-4.26) | (-4.03) | (-0.52) | (-5.95) | (-3.12) |
| BM | -0.0066 | -0.0083 | -0.0067 | 0.0029 | -0.0081 | -0.0065 | -0.0083 | -0.0101 | -0.0085 | 0.0026 | -0.0100 | -0.0082 |
| | (-1.62) | (-1.98) | (-1.64) | (0.61) | (-1.97) | (-1.56) | (-1.67) | (-1.97) | (-1.70) | (0.46) | (-1.99) | (-1.62) |
| MOM | 0.0002 | 0.0003 | 0.0002 | 0.0001 | 0.0001 | 0.0003 | 0.0003 | 0.0003 | 0.0003 | 0.0001 | 0.0002 | 0.0003 |
| | (1.60) | (1.90) | (1.52) | (0.42) | (0.88) | (1.72) | (1.55) | (1.83) | (1.50) | (0.44) | (0.90) | (1.70) |
| IVOL | | -0.0062 | | | | | | -0.0075 | | | | |
| | | (-3.19) | | | | | | (-3.17) | | | | |
| ILLIQ | | | 0.6421 | | | | | | 0.4315 | | | |
| | | | (0.60) | | | | | | (0.33) | | | |
| REV | | | | -0.0201 | | | | | | -0.0227 | | |
| | | | | (-19.03) | | | | | | (-18.00) | | |
| MAX | | | | | -0.0166 | | | | | | -0.0186 | |
| | | | | | (-6.75) | | | | | | (-6.28) | |
| COSKEW | | | | | | -0.0002 | | | | | | -0.0003 |
| | | | | | | (-0.68) | | | | | | (-0.68) |

**Table 13**

**Fama-MacBeth Cross-Sectional Regressions: Predicting one-day-ahead Returns with the Dynamic Conditional Beta for the Most Liquid 500 Firms**

The one-day-ahead excess returns of the most liquid 500 firms (Panel A) and the corresponding characteristic-matched returns (Panel B) are regressed every day on the time-varying conditional beta estimates ($BETA_{DCC}$) after controlling for a large set of predictors. To construct the liquid stock sample, we first calculate the average daily illiquidity measure over the period of July of year $t-1$ to June of year $t$. Then, the sample of the most liquid 500 stocks is formed by ranking individual stocks in CRSP based on their average illiquidity measure, and updated on a yearly basis. $BETA_{DCC}$ is estimated based on the dynamic conditional correlation (DCC) model of Engle (2002) using daily returns over the prior 252 trading days with at least 200 observations available, and updated on a daily basis. The control variables are the natural logarithm of firm's market capitalization (SIZE), book-to-market equity ratio (BM), momentum (MOM), Amihud's illiquidity measure (ILLIQ), idiosyncratic volatility (IVOL), short-term reversal (REV), maximum daily return (MAX), and co-skewness (COSKEW). This table reports the average slope coefficients from the Fama-MacBeth regressions and the Newey-West $t$-statistics (in parentheses). The sample covers the period from July 1963 to December 2009.

Panel A. Predicting one-day-ahead excess returns

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.0662 | 0.0918 | 0.1129 | 0.0421 | 0.1382 | 0.1131 | 0.0990 | 0.1099 | 0.0471 | 0.1449 | 0.1190 |
| | (3.33) | (4.50) | (4.71) | (1.91) | (6.48) | (5.18) | (5.14) | (4.72) | (2.30) | (7.34) | (5.98) |
| $BETA_{DCC}$ | 0.0117 | 0.0204 | 0.0133 | 0.0185 | 0.0277 | 0.0196 | 0.0169 | 0.0106 | 0.0154 | 0.0244 | 0.0159 |
| | (1.85) | (3.12) | (1.90) | (2.61) | (3.97) | (2.76) | (2.83) | (1.69) | (2.43) | (3.82) | (2.50) |
| SIZE | -0.0073 | -0.0085 | -0.0112 | -0.0032 | -0.0150 | -0.0127 | -0.0102 | -0.0119 | -0.0045 | -0.0164 | -0.0141 |
| | (-3.54) | (-4.12) | (-4.42) | (-1.40) | (-6.88) | (-5.67) | (-5.29) | (-4.86) | (-2.14) | (-8.26) | (-7.02) |
| BM | 0.0056 | 0.0035 | 0.0048 | 0.0073 | -0.0028 | -0.0019 | 0.0039 | 0.0051 | 0.0079 | -0.0021 | -0.0012 |
| | (1.75) | (1.11) | (1.47) | (2.19) | (-0.85) | (-0.57) | (1.24) | (1.61) | (2.39) | (-0.66) | (-0.37) |
| MOM | 0.0004 | | | | | | 0.0004 | 0.0004 | 0.0003 | 0.0003 | 0.0004 |
| | (3.62) | | | | | | (3.78) | (3.41) | (2.91) | (2.89) | (3.20) |
| IVOL | | -0.0029 | | | | | -0.0028 | | | | |
| | | (-4.83) | | | | | (-4.90) | | | | |
| ILLIQ | | | 91.7167 | | | | | 65.3867 | | | |
| | | | (1.81) | | | | | (1.48) | | | |
| REV | | | | -0.0053 | | | | | -0.0057 | | |
| | | | | (-17.12) | | | | | (-18.86) | | |
| MAX | | | | | -0.0049 | | | | | -0.0052 | |
| | | | | | (-5.97) | | | | | (-6.48) | |
| COSKEW | | | | | | -0.0001 | | | | | -0.0001 |
| | | | | | | (-0.85) | | | | | (-0.90) |

**Table 13 – continued**

Panel B. Predicting one-day-ahead characteristic-matched returns

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.0051 | 0.0320 | 0.0481 | -0.0144 | 0.0794 | 0.0531 | 0.0355 | 0.0491 | -0.0130 | 0.0824 | 0.0568 |
| | (0.60) | (2.83) | (4.13) | (-1.43) | (7.96) | (5.66) | (3.10) | (4.16) | (-1.29) | (8.31) | (6.11) |
| $BETA_{DCC}$ | 0.0105 | 0.0159 | 0.0097 | 0.0143 | 0.0244 | 0.0156 | 0.0153 | 0.0094 | 0.0138 | 0.0234 | 0.0146 |
| | (1.95) | (3.24) | (1.93) | (2.79) | (4.53) | (3.07) | (2.96) | (1.78) | (2.57) | (4.17) | (2.69) |
| SIZE | -0.0018 | -0.0039 | -0.0062 | 0.0012 | -0.0104 | -0.0080 | -0.0044 | -0.0065 | 0.0009 | -0.0107 | -0.0084 |
| | (-2.47) | (-4.36) | (-5.08) | (1.32) | (-11.52) | (-9.25) | (-4.94) | (-5.25) | (1.02) | (-11.88) | (-9.80) |
| BM | 0.0009 | -0.0008 | 0.0004 | 0.0028 | -0.0067 | -0.0059 | -0.0007 | 0.0005 | 0.0031 | -0.0063 | -0.0054 |
| | (0.72) | (-0.65) | (0.31) | (2.02) | (-4.61) | (-4.01) | (-0.50) | (0.41) | (2.24) | (-4.31) | (-3.70) |
| MOM | 0.0001 | | | | | | 0.0001 | 0.0001 | 0.0000 | 0.0000 | 0.0001 |
| | (2.27) | | | | | | (2.33) | (1.47) | (0.80) | (0.89) | (1.68) |
| IVOL | | -0.0026 | | | | | -0.0025 | | | | |
| | | (-5.02) | | | | | (-4.89) | | | | |
| ILLIQ | | | 53.7122 | | | | | 57.8056 | | | |
| | | | (1.32) | | | | | (1.45) | | | |
| REV | | | | -0.0054 | | | | | -0.0055 | | |
| | | | | (-19.46) | | | | | (-19.78) | | |
| MAX | | | | | -0.0049 | | | | | -0.0051 | |
| | | | | | (-6.59) | | | | | (-6.79) | |
| COSKEW | | | | | | -0.0001 | | | | | -0.0001 |
| | | | | | | (-0.86) | | | | | (-0.83) |

**Table 14**

**Fama-MacBeth Cross-Sectional Regressions: Predicting one-day-ahead Returns with the Conditional Beta after Controlling for 1-day to 5-day Short-Term Reversal**

The one-day-ahead excess returns (Panel A) and the corresponding characteristic-matched returns (Panel B) of individual stocks in the S&P 500 index are regressed every day on the time-varying conditional beta estimates ($BETA_{DCC}$) with controlling for the short-term reversal, the natural logarithm of firm's market capitalization (SIZE), book-to-market equity ratio (BM), and momentum (MOM). $BETA_{DCC}$ is estimated based on the dynamic conditional correlation (DCC) model of Engle (2002) using daily returns over the prior 252 trading days with at least 200 observations available, and updated on a daily basis. The short-term reversal is measured as the cumulative return in the past one up to five days, denoted by REV1 through REV5. This table reports the average slope coefficients from the Fama-MacBeth regressions and the Newey-West $t$-statistics (in parentheses). The sample covers the period from July 1963 to December 2009.

Panel A. Predicting one-day-ahead excess returns

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.0659 | 0.0607 | 0.0619 | 0.0619 | 0.0614 | 0.0715 | 0.0652 | 0.0658 | 0.0655 | 0.0650 | 0.0591 |
| | (3.24) | (2.92) | (2.93) | (2.90) | (2.88) | (3.83) | (3.39) | (3.36) | (3.29) | (3.26) | (3.01) |
| BETA-DCC | 0.0144 | 0.0162 | 0.0205 | 0.0230 | 0.0237 | 0.0120 | 0.0138 | 0.0182 | 0.0205 | 0.0215 | 0.0170 |
| | (1.98) | (2.24) | (2.79) | (3.08) | (3.23) | (1.81) | (2.10) | (2.74) | (3.03) | (3.24) | (2.35) |
| SIZE | -0.0075 | -0.0071 | -0.0073 | -0.0072 | -0.0072 | -0.0088 | -0.0084 | -0.0085 | -0.0084 | -0.0083 | -0.0072 |
| | (-3.73) | (-3.45) | (-3.47) | (-3.39) | (-3.35) | (-4.87) | (-4.48) | (-4.44) | (-4.31) | (-4.26) | (-3.76) |
| BM | 0.0001 | 0.0010 | 0.0016 | 0.0021 | 0.0022 | -0.0001 | 0.0008 | 0.0014 | 0.0019 | 0.0020 | 0.0018 |
| | (0.02) | (0.33) | (0.53) | (0.69) | (0.71) | (-0.02) | (0.25) | (0.47) | (0.62) | (0.66) | (0.61) |
| MOM | | | | | | 0.0003 | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0002 |
| | | | | | | (2.33) | (2.15) | (1.99) | (1.94) | (1.90) | (2.13) |
| REV1 | -0.0076 | | | | | -0.0096 | | | | | 0.0113 |
| | (-5.21) | | | | | (-6.63) | | | | | (7.01) |
| REV2 | | -0.0159 | | | | | -0.0174 | | | | -0.0030 |
| | | (-16.90) | | | | | (-18.72) | | | | (-2.57) |
| REV3 | | | -0.0176 | | | | | -0.0189 | | | -0.0081 |
| | | | (-23.87) | | | | | (-25.86) | | | (-7.36) |
| REV4 | | | | -0.0167 | | | | | -0.0179 | | -0.0053 |
| | | | | (-25.70) | | | | | (-27.79) | | (-5.05) |
| REV5 | | | | | -0.0150 | | | | | -0.0161 | -0.0086 |
| | | | | | (-25.43) | | | | | (-27.48) | (-9.90) |

**Table 14 – continued**

Panel B. Predicting one-day-ahead characteristic-matched returns

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | -0.0101 | -0.0156 | -0.0143 | -0.0139 | -0.0141 | -0.0064 | -0.0126 | -0.0121 | -0.0123 | -0.0126 | -0.0178 |
| | (-1.41) | (-2.07) | (-1.86) | (-1.74) | (-1.75) | (-0.91) | (-1.67) | (-1.56) | (-1.52) | (-1.55) | (-2.19) |
| BETA-DCC | 0.0117 | 0.0132 | 0.0172 | 0.0194 | 0.0204 | 0.0114 | 0.0130 | 0.0171 | 0.0192 | 0.0202 | 0.0163 |
| | (2.11) | (2.42) | (3.08) | (3.41) | (3.65) | (1.97) | (2.28) | (2.94) | (3.25) | (3.49) | (2.54) |
| SIZE | -0.0009 | -0.0005 | -0.0006 | -0.0006 | -0.0005 | -0.0014 | -0.0009 | -0.0010 | -0.0009 | -0.0009 | 0.0001 |
| | (-1.49) | (-0.73) | (-0.93) | (-0.83) | (-0.75) | (-2.25) | (-1.40) | (-1.46) | (-1.26) | (-1.15) | (0.15) |
| BM | -0.0021 | -0.0013 | -0.0006 | -0.0002 | -0.0001 | -0.0023 | -0.0015 | -0.0009 | -0.0004 | -0.0003 | -0.0004 |
| | (-1.81) | (-1.09) | (-0.51) | (-0.13) | (-0.05) | (-1.95) | (-1.29) | (-0.72) | (-0.35) | (-0.24) | (-0.32) |
| MOM | | | | | | 0.0001 | 0.0001 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | | | | | | (1.56) | (1.22) | (0.88) | (0.77) | (0.67) | (1.00) |
| REV1 | -0.0101 | | | | | -0.0106 | | | | | 0.0098 |
| | (-7.55) | | | | | (-7.84) | | | | | (6.45) |
| REV2 | | -0.0171 | | | | | -0.0175 | | | | -0.0032 |
| | | (-19.68) | | | | | (-19.91) | | | | (-2.87) |
| REV3 | | | -0.0182 | | | | | -0.0186 | | | -0.0076 |
| | | | (-26.58) | | | | | (-26.79) | | | (-7.26) |
| REV4 | | | | -0.0171 | | | | | -0.0175 | | -0.0052 |
| | | | | (-28.26) | | | | | (-28.62) | | (-5.08) |
| REV5 | | | | | -0.0153 | | | | | -0.0157 | -0.0083 |
| | | | | | (-27.88) | | | | | (-28.28) | (-9.86) |

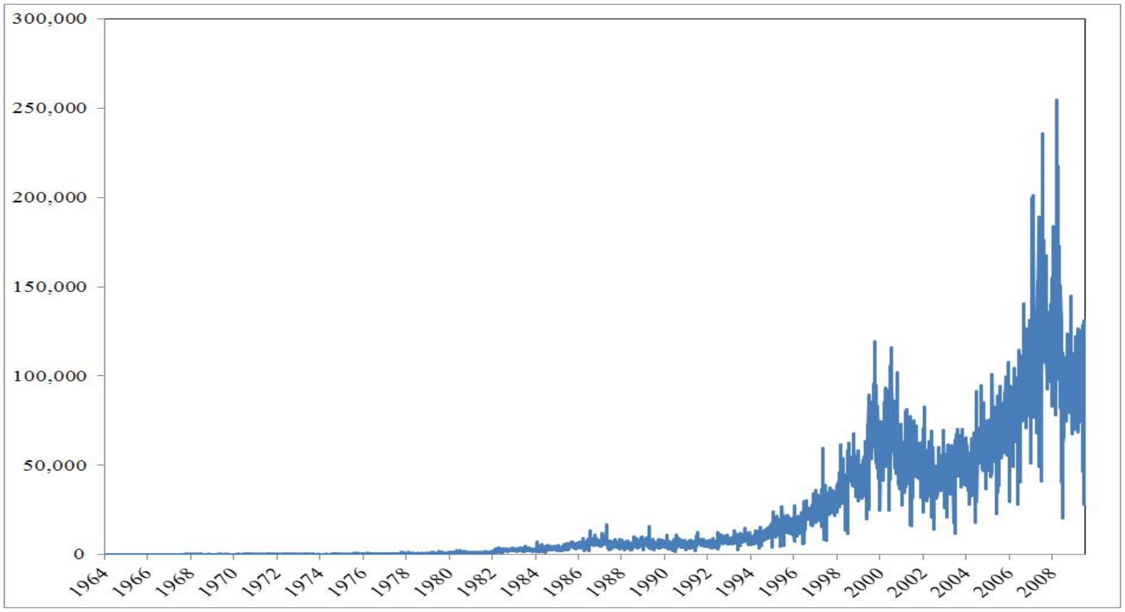



**Figure 1. Aggregate daily dollar trading volume of the S&P 500 stocks.** This figure depicts the aggregate daily dollar trading volume of the S&P 500 stocks (in $millions) over the sample period July 1964 - December 2009.

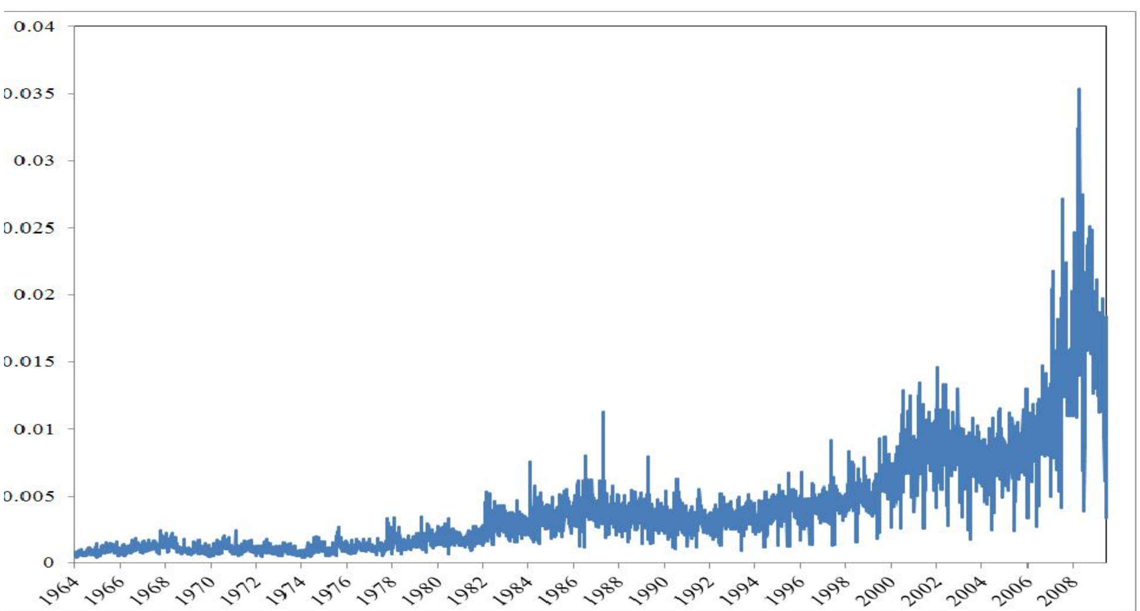



**Figure 2. Average daily turnover of the S&P 500 stocks.** This figure depicts the average daily turnover of the S&P 500 stocks (defined as the ratio of trading volume to the number of shares outstanding) for the same period.

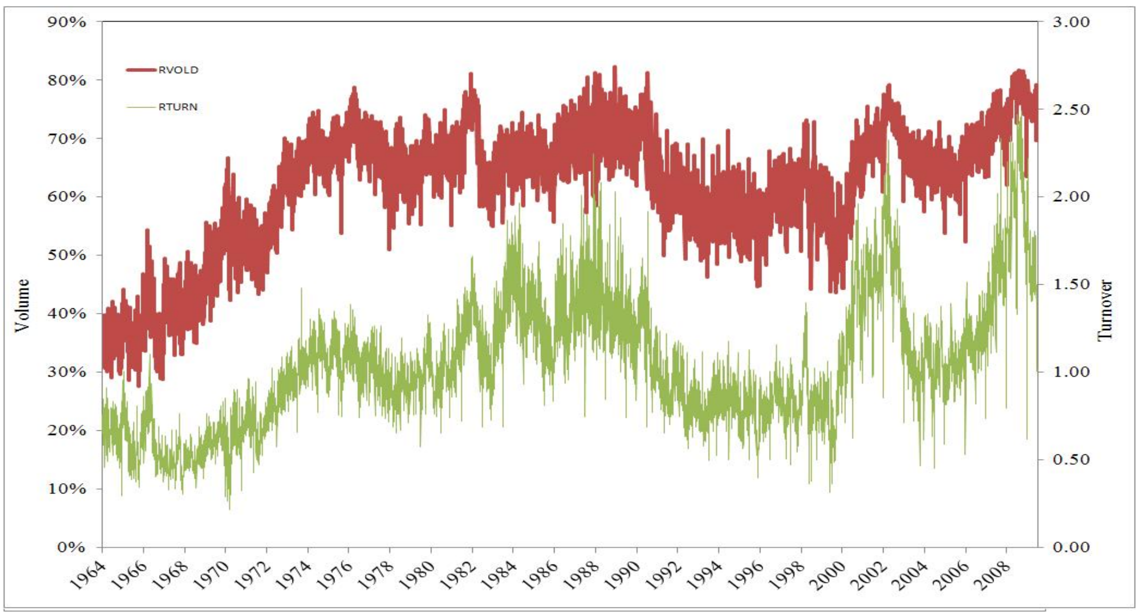



**Figure 3. Relative volume and relative turnover of the S&P 500 stocks.** This figure depicts the relative volume and relative turnover; (i) the ratio of aggregate daily dollar trading volume of S&P 500 stocks to the total daily dollar trading volume of the market (denoted by RVOLD), and (ii) the ratio of the S&P 500 stocks' daily turnover to the daily turnover of all stocks trading at NYSE, Amex, and Nasdaq (denoted by RTURN).

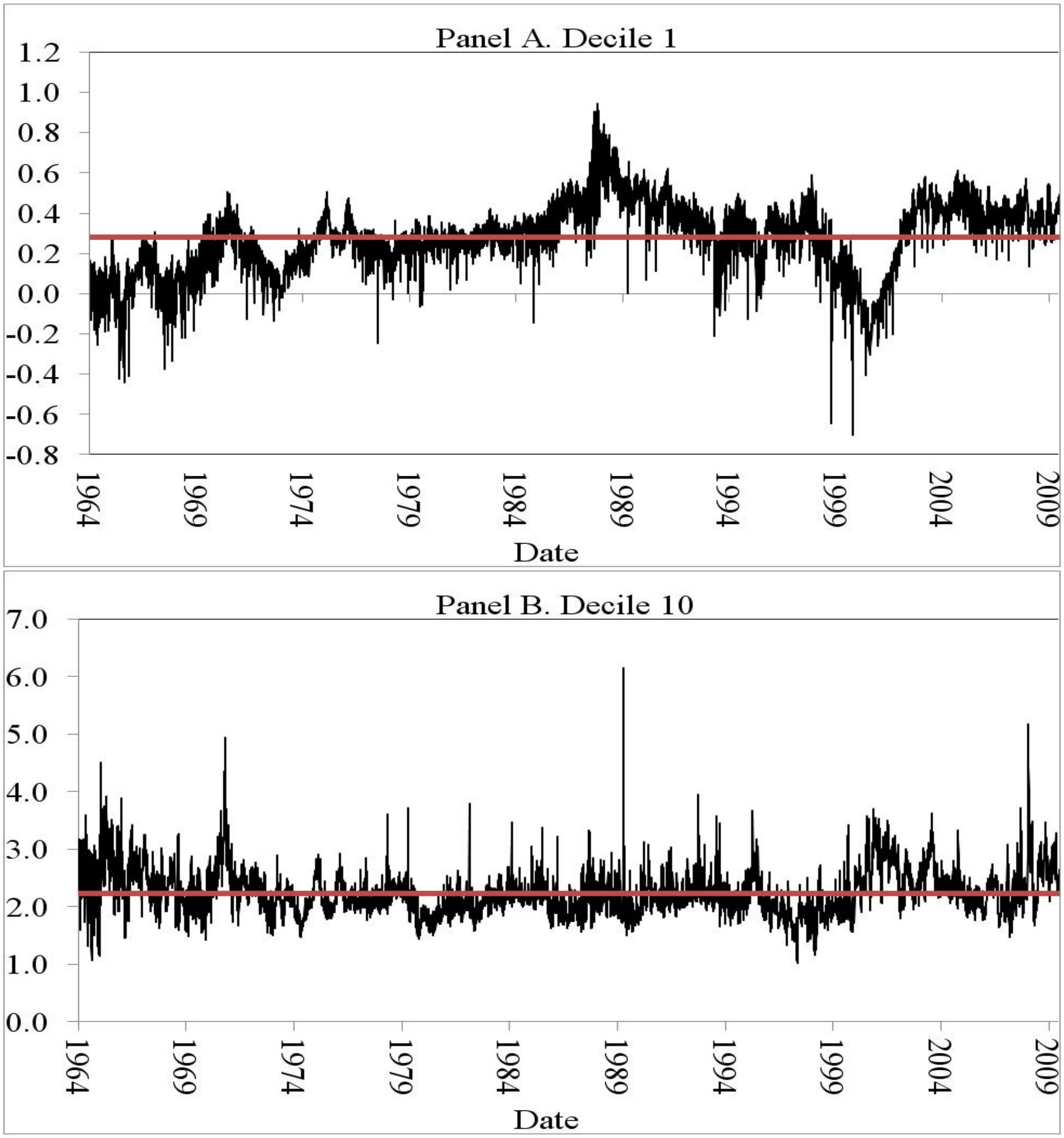
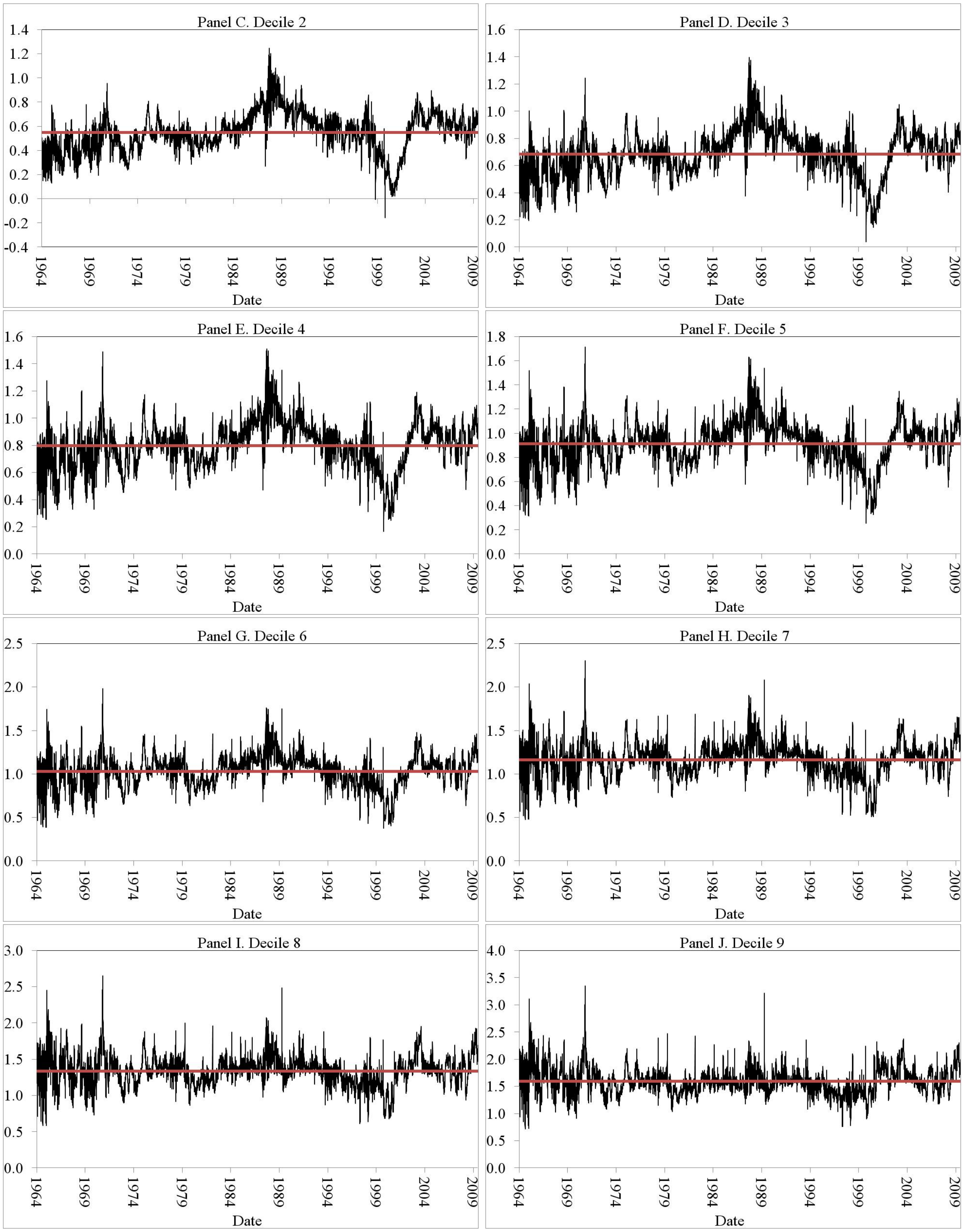



**Figure 4. Daily conditional beta.** For each day, the S&P 500 stocks are sorted into deciles on the daily conditional market beta, estimated based on the dynamic conditional correlation (DCC) model of Engle (2002) using daily returns over the prior 252 trading days with at least 200 observations available, and updated on a daily basis. Panels A and B, respectively, depict the daily DCC beta (the curved line) for Decile 1 and Decile 10, computed by averaging the daily DCC beta across all stocks within each decile, and the corresponding time-series average of each portfolio's daily DCC beta (the straight line). Panels C to J depict the daily DCC beta and the time-series average for deciles 2 to 9. The sample period is from July 1963 to December 2009.

**Figure 4 – continued**



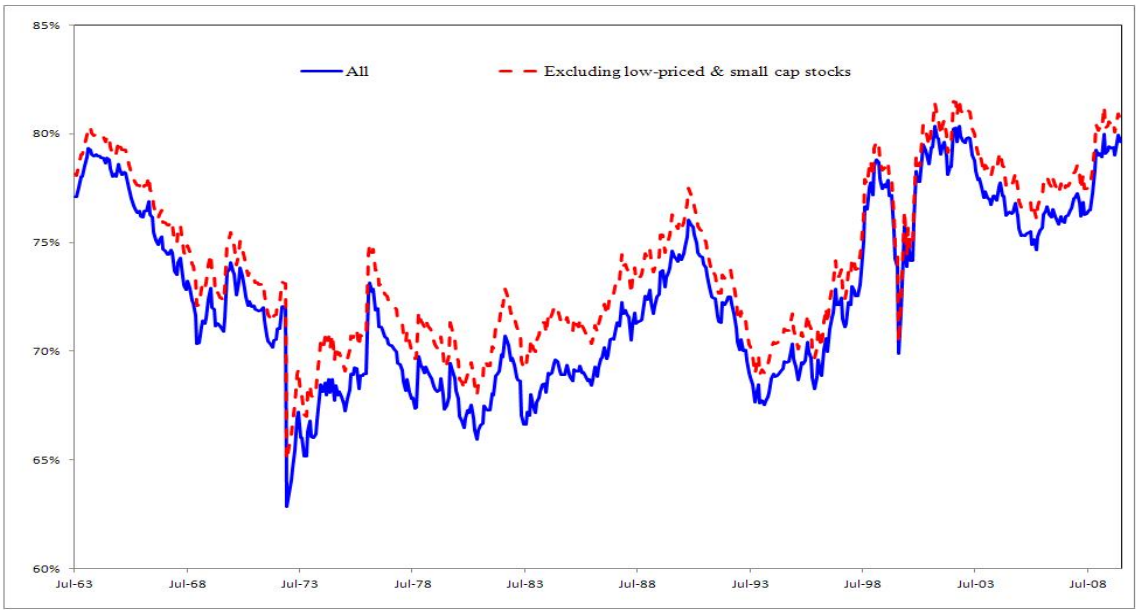



**Figure 5. Market share of the S&P 500 stocks.** The solid line depicts the monthly ratios of total market capitalization of the S&P 500 constituents to the aggregate market capitalization of the NYSE, Amex, and Nasdaq traded common shares. The dashed line presents the same ratio for the NYSE, Amex, and Nasdaq traded common shares after eliminating low-priced stocks (price $<$ \$5 per share) and stocks in the smallest NYSE size decile. The sample period is from July 1963 to December 2009.

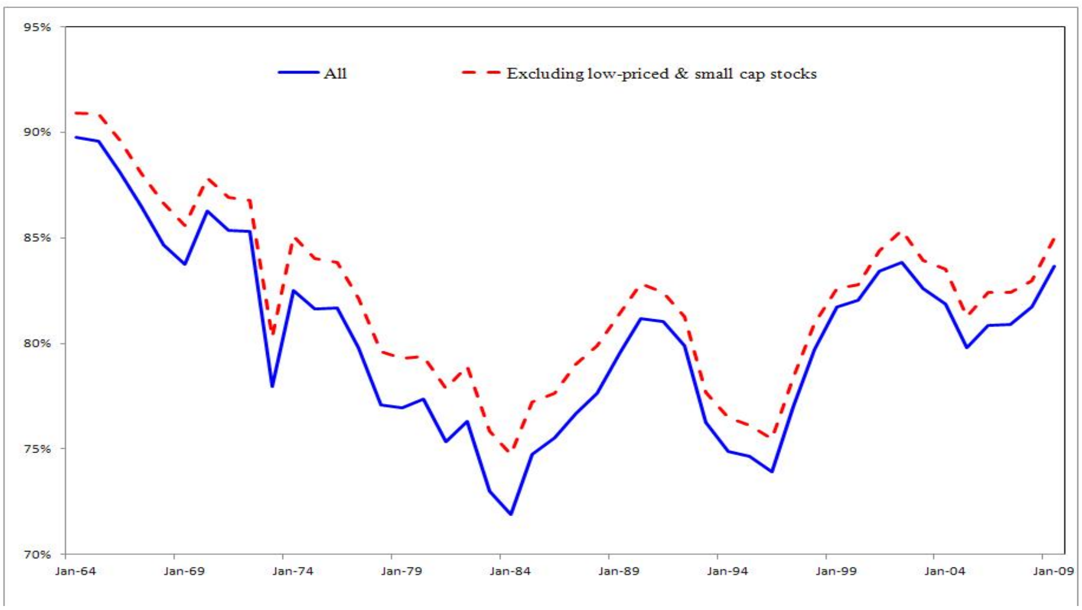



**Figure 6. Market share of the largest 500 stocks.** The solid line depicts the monthly ratios of total market capitalization of the largest 500 firms to the aggregate market capitalization of the NYSE, Amex, and Nasdaq traded common shares. The dashed line presents the same ratio for the NYSE, Amex, and Nasdaq traded common shares after eliminating low-priced stocks (price $<$ \$5 per share) and stocks in the smallest NYSE size decile. The sample period is from July 1963 to December 2009.

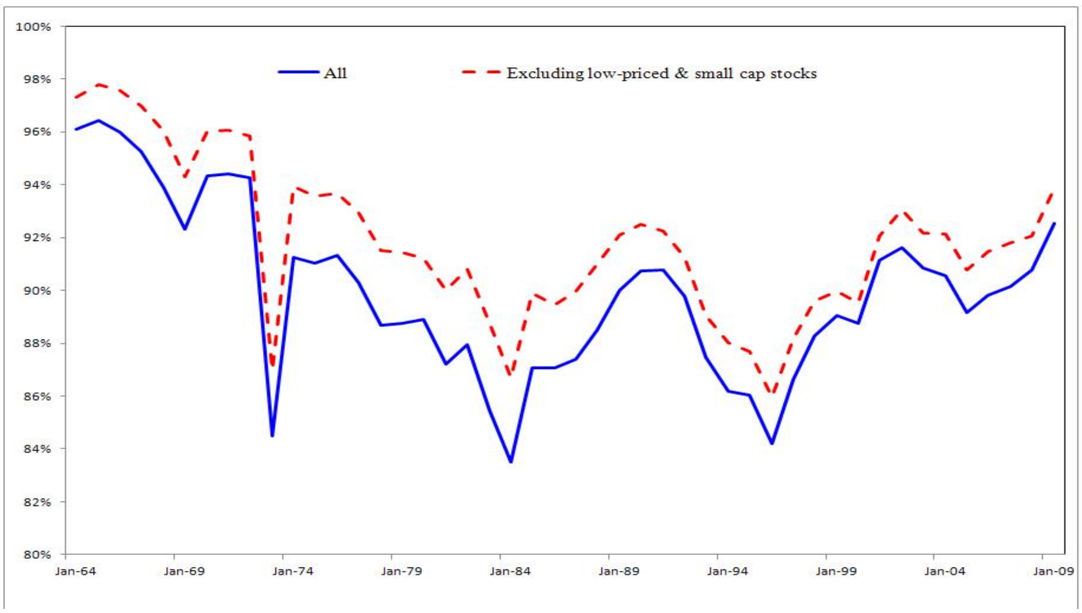



**Figure 7. Market share of the largest** $1,000$ **stocks.** The solid line depicts the monthly ratios of total market capitalization of the largest $1,000$ firms to the aggregate market capitalization of the NYSE, Amex, and Nasdaq traded common shares. The dashed line presents the same ratio for the NYSE, Amex, and Nasdaq traded common shares after eliminating low-priced stocks (price $<$ \$5 per share) and stocks in the smallest NYSE size decile. The sample period is from July 1963 to December 2009.

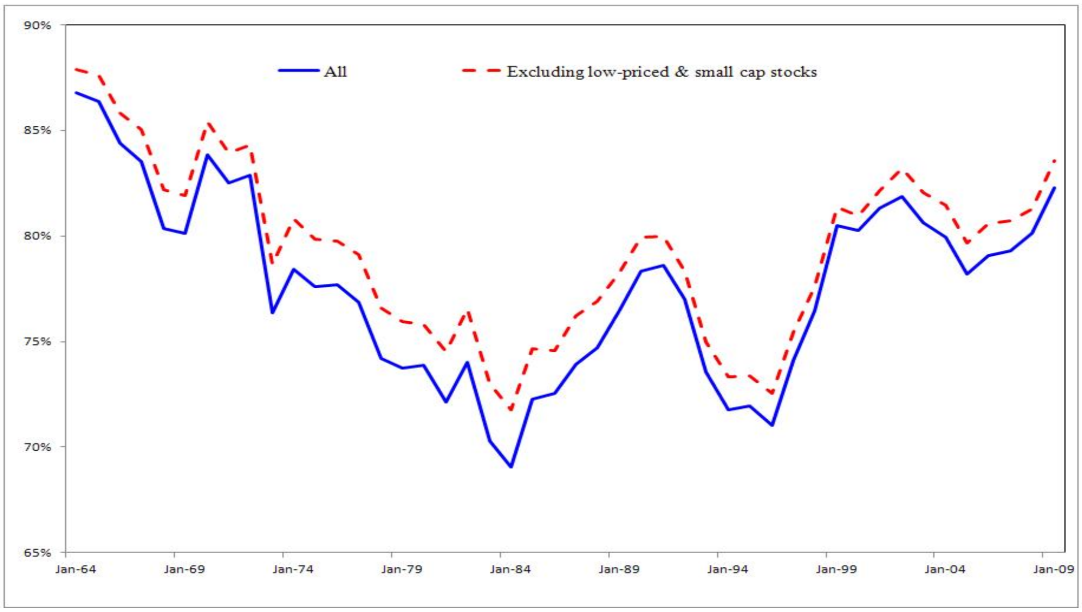



**Figure 8. Market share of the most liquid 500 stocks.** The solid line depicts the monthly ratios of total market capitalization of the most liquid 500 firms to the aggregate market capitalization of the NYSE, Amex, and Nasdaq traded common shares. The dashed line presents the same ratio for the NYSE, Amex, and Nasdaq traded common shares after eliminating low-priced stocks (price $<$ \$5 per share) and stocks in the smallest NYSE size decile. The stock's liquidity is inversely proxied by the Amihud's (2002) illiquidity measure. The sample period is from July 1963 to December 2009.