On the importance of Quality, Liquidity-Level and Liquidity-Beta: A Markov-Switching Regime approach

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Abstract

This paper measures the market beta of portfolios sorted on Quality, Liquidity-Level and Liquidity-Beta characteristics under different market volatility conditions. During the period 1970-2010, the US market was driven by four regimes, namely, "normal", "crisis", "recovery" and "low-volatility" regimes. In both "crisis" and "low-volatility" regimes, low (high) quality, high (low) liquidity-beta and illiquid (liquid) stocks exhibit an increase (a decrease) in their market betas. These findings are consistent with flight-to-quality (flight-to-liquidity) episodes during crisis periods and with flight-to-low-quality (flight-to-illiquidity) explanation during "low-volatility" times. Finally, our results reveal that liquidity-level is more important than liquidity-beta in predicting market-beta during crisis periods.

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I. Introduction

We focus in this paper on three stock characteristics, namely, *quality*, *liquidity-level* and *liquidity-beta*. We aim to investigate how the systematic risk (market beta) of stock returns, with respect to these attributes, vary across stock market phases such as crisis periods and normal times.

To define the stock's quality, we follow the approach of Asness, Frazzini and Pederson (2013). Based on the Gordon's growth model, the authors define quality stocks as securities that have high profitability, high growth, low risk, and high payouts. The authors calculate a score for each of the four components and, then, compute a single quality score by averaging the four proxies. In contrast to what asset pricing theory stipulates, they found that high quality stocks earn high risk adjusted returns compared with junk (low quality) stocks. To define the stock's liquidity-level, we adopt the same definition as in the work of Lou and Sadka (2011) who define it as "the ability to trade large quantities of its shares quickly and at low cost, on average". Regarding the stock's liquidity-beta (risk), we rely on the concept of Pastor and stambaugh (2003) who define it as "the covariation of its returns with unexpected changes in aggregate liquidity". Amihud and Mendelson (1986) were the first to examine the link between the liquidity-level of a stock and its expected return. They found a negative relationship. Suggesting that, stocks with low liquidity-level earn higher returns to compensate investors for bearing liquidity costs. Since their seminal work, a substantial body of empirical evidence has confirmed this negative relationship. See e.g. Brennan and Subrahmanyam (1996), Brennan, Chordia, and Subrahmanyam (1998), Datar, Naik, and Radcliffe (1998) among others. The link between the liquidity risk of a stock and its expected return has been the focus of more recent studies. Acharya and Pederson (2005) have identified three sources of liquidity risk: (1) The covariance of the liquidity-level of a stock with aggregate liquidity; (2) The covariance of the return of a stock with aggregate liquidity and (3) the covariance of the liquidity-level of a stock with market returns. We focus, in our study, on the second type of liquidity risk which has been extensively investigated by many researchers such as Pastor and Stambaugh (2003), Liu (2006), Watanabe and Watanabe (2008) and Lou and Sadka (2011) among others. All these authors documented that this type of risk is priced in the US stock market.

Our motivation for considering these three stock characteristics stems from the growing empirical evidence that their importance to investors depends on the market conditions. High quality and liquid stocks are more desirable during volatile times. However, their importance to investors reduces during normal times. Vayanos (2004), for example, shows in a dynamic equilibrium model that preference for liquidity is time-varying and increasing with volatility; and that investors become more risk averse when volatility is high. These time-variations in the investors' risk aversion and preference for liquidity are closely related to the well known phenomena of "flight-to-quality" (when investors shift their portfolios towards high quality assets) and "flight-to-liquidity" (when investors tilt their portfolios towards liquid assets) that have been documented to be associated with volatile times in several empirical studies (Longstaff, 2004; Vayanos, 2004; Beber, Brandt, and Kavajecz, 2009). In a more recent study, Lou and Sadka (2011) examine whether liquid assets offered a good hedge to portfolio managers during the 2007-2008 financial crisis. Although liquid assets are supposed to be desirable during that high volatility period, the authors' answer was no, they did not. Some liquid stocks and especially those with high liquidity risk experienced much greater losses than illiquid stocks with low liquidity risk. The authors conclude that, during a financial crisis, portfolio managers should care about the stock's liquidity risk rather than liquidity-level.

In the current work, we aim to investigate how investors price quality, liquidity-level and liquidity risk during different stock market phases. We contribute to the existing literature in three ways. First, most of the previous studies investigated the "flight-to-quality" and the "flight-to-liquidity" phenomena from stocks to bonds. In this paper, we focus rather on the flight to quality and liquidity across only stock market securities. Second, Given that the assertion of Lou and Sadka (2011) is based solely on the 2008-2009 crisis data, we aim in this work to extend their analysis by using a sufficiently long sample period that includes several financial crisis times. Third, we investigate the importance of the stock's quality, liquidity-level and liquidity-beta when the market is driven by regimes other than the crisis; such as when the market is in low volatility times. We adopt a markov-switching regime approach. The markov-switching regime model was originally proposed by Hamilton (1989) and has become an enormously popular tool for modeling the dynamics of macroeconomic and financial time-series. Applications of this class of models are usually motivated by economic phenoma that appear to involve cycling between recurrent regimes such as bull and bear times or low and high volatility periods in the stock market. The major advantage of markov-switching models is their flexibility in capturing these potential regimes without imposing strict periodicity. Examples of studies that have applied this technique to model stock market returns' time-series are Rydén, Teräsvirta and Asbrink (1998), Kim, Nelson and Startz (1998), Billio and Pelizzon (2000), Perez-Quiros and Timmermann (2000), Guidolin and Timmerman (2007), Gulen, Xing and Zhang (2011) and Billio, Getmansky and Pelizzon (2012) among others.

We use the econometric framework of Billio et al. (2000, 2012). Their model uses the market portfolio excess return time-series to identify stock market regimes and assumes that the risk factor exposures of a testing portfolio are time-varying across the different regimes that characterize the stock market but time-invariant within each regime. We run separate analyses with respect to the three stock characteristics over a sample period from 1970 through 2010. Return time-series of quality-sorted portfolios are obtained from the Andrea Frazzini's web site[1], while, liquidity-level and liquidity-beta sorted portfolios are formed using a sample of all NYSE/AMEX/NASDAQ common stocks that satisfy our data requirements.

Our analysis reveals three main findings. First, during the crisis regime, on one hand, low quality, high liquidity-beta and illiquid stocks exhibit a significant increase in their market beta. On the other hand, High quality, low liquidity-beta and liquid stocks show a decrease in their market beta. This finding is consistent with the flight to quality and liquidity phenomena. Second, we document the same pattern across stocks when the market volatility is low. We argue that, during low volatility times, investors shift their portfolios towards low quality and illiquid stocks to seek portfolio gains. The pattern observed in the «low-volatility» regime can be, therefore, explained by a flight to low-quality and to illiquidity. Third, our results do not lend support to the assertion of Lou and Sadka (2010) who claim that liquidity risk is more important than liquidity-level during times of economic distress. Contrary to their claim, we find that liquidity-level is more important than liquidity-beta during the crisis regime.

The remainder of the paper is organized as follows. Section 2, describes data we use and our procedure to form portfolios. Section 3, presents our methodology to incorporate nonlinearities in the conditional distribution of stock returns. In section 4, we present our empirical results and section 5 concludes.

[1] http://www.econ.yale.edu/~af227/data_library.htm

II. Data and portfolio formation

In order to capture the different regimes that drive the market, a sufficiently long sample period is needed. To do so, we run our analysis over the period 1970-2010. This sample period includes several crisis and non-crisis times that had influenced the US stock market and can hence, provide us with fruitful information about the different regimes that drove the stock market.

We obtained the excess return time-series of 10 quality-sorted portfolios from Andrea Frazzini's web site. To form 10 portfolios sorted on liquidity-level and 10 portfolios sorted on liquidity-beta, we consider all NYSE/AMEX/NASDAQ common stocks. However, since reported volume on NASDAQ is upward biased due to the interdealer trades, we exclude NASDAQ stocks when forming portfolios based on liquidity-level. We obtained all needed data through Wharton Research Data Services (WRDS). Daily and monthly data on individual stocks are obtained from the CRSP daily and monthly files, excess returns on the market portfolio and the risk-free rate (1-month T-bill rate) are from the Fama-French files. Finally, Pastor-Stambaugh non-traded liquidity factor data are obtained from the liquidity factors files. In what follows, we will briefly describe the procedure of Asness et al. (2013) that they used to form 10 portfolios sorted on quality scores. After that, we will present our liquidity-level and liquidity-beta measures and describe our procedure to construct portfolios based on these two characteristics.

A. Quality-sorted portfolios

Based on the Gordon's growth model, Asness et al. (2013) define quality stocks as securities that have *high profitability*, *high growth*, *low risk*, and *high payouts*. To compute a quality score for a stock, Asness et al. use several measures for each aspect of quality:

Profitability is computed as the average of z-scores of gross profits over assets, return on equity, return on assets, cash flow over assets, gross margin and low accruals. *Growth* is measured by averaging z-scores of 5-year growth rates in gross profits over assets, return on equity, return on assets, cash flow over assets, gross margin and low accruals. *Risk* is measured by averaging z-scores of minus market beta, minus idiosyncratic volatility, minus leverage, minus bankruptcy risk and minus earning volatility. *Payout* is computed as the average of z-scores of net equity issuance, net debt issuance and total net payout over profits. Finally, the four components are averaged to compute a single quality score.

To form 10 value-weighted quality-sorted portfolios, the authors use all available common stocks in the CRSP/XpressFeed database and assign stocks into portfolios using NYSE breakpoints.

B. Liquidity-level sorted portfolios

As in Lou and Sadka (2011), we measure the liquidity-level of a share by the average of its daily Amihud's (2002) ratio over the year. Amihud (2002) computes his liquidity metric as "the daily ratio of absolute stock return to its dollar volume". It has been widely used in the recent literature (Amihud, 2002; Acharya and Pederson, 2005; Goyenko, Holden, and Trzcinka, 2009; Korajczyk and Sadka, 2008; Hasbrouck, 2009). In addition, Hasbrouck (2009) confirms that the ratio is highly correlated with high frequency liquidity measures and Goyenko et al. (2009) show that it does capture well the transaction costs and the price impact. In formal terms, we compute the liquidity-level of a share i at the end of year y as given by the following Equation:

$$ILLIQ_{i,y} = \frac{1}{D_{i,y}}\left[\sum_{d=1}^{D_{i,y}} \frac{|r_{i,d,y}|}{Dvol_{i,d,y}}\right] \tag{8}$$

where $ILLIQ_{i,y}$ denotes the (il)liquidity-level measure of share i at the end of year y. $D_{i,y}$ is the share i's number of trading days in year y. $r_{i,d,y}$ and $Dvol_{i,d,y}$ are, respectively, the daily return and the dollar volume of share i on the trading day d in year y.

At the end of each year between 1969 and 2009, we identified NYSE/AMEX common stocks with prices between \$5 and \$1000 and at least 100 valid daily returns, prices and volumes over the year. We, then, sorted eligible stocks on the basis of their liquidity-level and assign them into 10 value-weighted portfolios using NYSE breakpoints.

C. Liquidity-beta sorted portfolios

We follow Pastor and Stambaugh (2003) and measure the liquidity-beta of a share as the sensitivity of its returns to innovations in aggregate market liquidity. At the end of each year between 1969 and 2009, we identified NYSE/AMEX/NASDAQ common stocks with prices between \$5 and \$1000 and 60 non-missing monthly returns over the most recent five years. We, then, sorted eligible stocks on the basis of their liquidity betas and assign them into 10 value-weighted portfolios using NYSE breakpoints. To estimate liquidity betas, we use data over the previous five years and regress the share monthly excess returns on the Pastor-Stambaugh non-traded liquidity factor and the three Fama-French factors:

$$r_{i,t}^{e} = \alpha_{i,y} + \beta_{i,y}^{Mkt} R_{m,t}^{e} + \beta_{i,y}^{smb} SMB_t + \beta_{i,y}^{hml} HML_t + \beta_{i,y}^{Liq} LIQ_{m,t} + \varepsilon_{i,t} \tag{9}$$

where $r_{i,t}^{e}$ stands for the stock i's excess return. $R_{m,t}^{e}, SMB_t$ and HML_t are the three Fama-French factors (market, size and value) and $LIQ_{m,t}$ is the Pastor-Stambaugh non-traded liquidity factor. $\beta_{i,y}^{Mkt}, \beta_{i,y}^{smb}, \beta_{i,y}^{hml}$ and $\beta_{i,y}^{Liq}$ denote, respectively, the historical exposures of the share i to the market, size, value and liquidity factors; as estimated at the end of year y.

III. Modeling regime-dependent market beta

Our principal aim is to relate the returns of the testing portfolios to regime shifts in the market risk factor. To this end, we use a Markov-Switching regime framework. In this work, we assume that the market beta of a testing portfolio is time-varying across the different states that characterize the stock market as a whole but time-invariant in each state. It is important to emphasize that our focus here is not on the specific regimes that govern the testing portfolio time-series but rather on its behavior during a common regime that drives the stock market for some periods of time. The economic intuition behind these assumptions is to closely assess the performance of the testing portfolio during market phases such as crisis periods. To this end, we adopt the Billio et al. (2000, 2012) markov-switching approach. Their approach to markov-switching consists in two steps. First, stock market phases are extracted from the dynamics of a market index. And then, in a second step, the testing portfolio dynamics are examined within each regime.

In the spirit of the Billio et al. (2000, 2012) models, we proceed as follows: First, we identify stock market regimes, assuming that the market risk factor is governed by a mean-variance switching regime model. Second, we examine the time series behavior of the testing portfolio excess return within each regime. Our analysis consists in computing regime-dependent market betas. In what follows we describe our methodology in details.

A. Stock market regimes

Let $R^e_{m,t}$ denotes the market portfolio excess return over the period t and assume that it is driven by the following K-state mean-variance switching regime process:

$$R^e_{m,t} = \mu_m\left(S_t^{R_m^e}\right) + \sigma_m\left(S_t^{R_m^e}\right)\ \varepsilon_t\ , \qquad \varepsilon_t \sim iid.N(0,1) \tag{1}$$

where $\mu_m\left(S_t^{R_m^e}\right)$ and $\sigma_m\left(S_t^{R_m^e}\right)$ are the state-dependent expected return and volatility, respectively. $S_t^{R_m^e}$ denotes the state of the market and is assumed to be unobservable and to follow a K-state first order Markov process as in Hamilton (1989). It means that:

$$p_{ij} = \Pr\left(S_t^{R_m^e} = i | S_t^{R_m^e} = j\right) \quad \text{for } i,j = 1,\dots,K. \tag{2}$$

where p_{ij} denotes the likelihood of switching to regime i given that the market is in regime j.

Model (1) can be estimated using maximum likelihood procedure. The log likelihood function of the model is given by:

$$logL = \sum_{t=1}^{T}\ ln\sum_{j=1}^{K}\ \frac{1}{\sqrt{2\pi\sigma(j)^2}}\exp\left[-\frac{(R^e_{m,t}-\mu_m(j))^2}{2\sigma(j)^2}\right]\Pr\left(S_t^{R_m^e} = j|\Omega_t\right) \tag{3}$$

where $\Omega_t = \left\{R^e_{m,1},\dots,R^e_{m,t}\right\}$ and $\Pr\left(S_t^{R_m^e} = j|\Omega_t\right)$ are called "filtered probabilities" and are obtained through the Hamilton's (1989) filter. Since the state of the market is unobservable, we can never know with certainty within which state the market is in. The Hamilton's (1989) filter uses hence all past information to make inference about the state of the market at any given date t.

We estimated model (1) using the MS_Regress package for MatLab (Perlin, 2009). For more details about the use of maximum likelihood procedure to estimate markov-switching regime models, we refer the reader to Hamilton (2008) and Perlin (2009). We, first, run the regression with two, three, four and five regimes and then, select the optimal number of regimes based on the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and a Simulated Likelihood Ratio Test.

B. Testing portfolios: Regime-dependent betas

In the first step, we presented a model to capture stock market regimes. In this second step, we model the regime-dependent market beta of a testing portfolio. To this end, we follow Billio et al. (2012) and assume that the dynamics of the testing portfolio's excess return r_t^e is specified by the following model:

$$r_t^e = \alpha + \beta\left(S_t^{R_m^e}\right)R^e_{m,t} + w\ \eta_t, \qquad \eta_t \sim iid.N(0,1) \tag{4}$$

where $\beta\left(S_t^{R_m^e}\right)$ denotes the testing portfolio exposure to the market risk factor and is assumed to depend on the market risk factor regimes. However, for parsimony, we do not allow for non-linearity in the intercept coefficient α and the volatility of residuals w.

We estimate the model above using the maximum likelihood method. To make inferences about the stock market regime at any date t, we rely on the Kim's (1994) smoothed probabilities from model (1). Unlike the filtered probabilities that are obtained using only the past available information for a given date t, smoothed probabilities are more accurate to make inference about the state of the market because they are based on all available information; that is, all past and future information for any given date t. In formal terms, the log likelihood function of model (4) is given by:

$$logL = \sum_{t=1}^{T} \ ln \sum_{j=1}^{K} \quad \frac{1}{\sqrt{2\pi w^2}} \exp\left[-\frac{(r_t^e - \alpha - \beta(j) R_{m,t}^e)^2}{2w^2}\right] \Pr\left(S_t^{R_m^e} = j|\Omega_T\right) \qquad (5)$$

Equation (5) differs from Equation (3) in two ways. First, in Equation (5), regimes do not depend on the testing portfolio excess return dynamics but rather on the market risk factor behavior. Second, the capital T in the term $\Pr\left(S_t^{R_m^e} = j|\Omega_T\right)$ means that we use smoothed state probabilities instead of the filtered probabilities $\Pr\left(S_t^{R_m^e} = j|\Omega_t\right)$ that are used in Equation (3).

Given the specification in model (4), the mean excess return of the testing portfolio is related to the state of the market risk factor and is defined by the sum of a constant parameter α and a regime-dependent component $\beta\left(S_t^{R_m^e}\right) * \mu_m\left(S_t^{R_m^e}\right)$. The volatility of the testing portfolio excess return is also related to the state of the market risk factor and is split into a time-varying component $\beta\left(S_t^{R_m^e}\right)^2 * variance(R_m^e)$ and a constant component w^2.

Finally, we consider the regime that was prevailing most time as a reference regime, and test whether the testing portfolio's market beta, in each state, exhibits a significant change relative to its level in the reference regime. Formally, for each state we test the null hypothesis that:

$$\beta\left(S_t^{R_m^e} = state\right) = \beta\left(S_t^{R_m^e} = reference\right) \qquad (6)$$

IV. Empirical results

In this section, we show the empirical results we obtained from running our analysis on the portfolios formed on the basis of quality scores, liquidity-level and liquidity-beta. We, first, examine the performance of the portfolios over the entire sample period 1970-2010. And then, we present and discuss the different stock market regimes as extracted from the market risk factor dynamics. After that, we focus on our testing portfolios and analyze their regime-dependent market betas as obtained with model (4) described in the previous section.

A. Quality, Liquidity-level and Liquidity-beta portfolios: 1970-2010

We start our analysis by assessing the performance of the different portfolios over the sample period 1970-2010. Table I reports, both, raw excess returns and risk-adjusted returns of the 30 portfolios. Risk-adjusted returns are computed using the CAPM, the three Fama-French (1993) and the Carhart (1997) four-factor models. Panel A, in Table I, shows results for the portfolios sorted on quality scores. Panel B exhibits results for the portfolios ranked on the basis of liquidity-level and the outputs of the portfolios based on liquidity-beta sorts are shown in Panel C. We also show, in Table I, the portfolios' CAPM betas as well as the results for the P10-P1 spread which goes long on the portfolio 10 and short on the portfolio 1.

As documented by Asness et al. (2013), high quality stocks yield higher risk-adjusted returns compared with low quality stocks. All the three alphas of the P10-P1 spread are significantly positive. The CAPM alpha is 0.72 basis points per month (t=3.99), the 3-factor alpha is 0.99 basis points per month (t=7.22) and the 4-factor alpha is 0.88 basis points per month (t=6.38). Furthermore as quality stocks are also safe stocks, they also exhibit low CAPM beta compared to low quality stocks. Panel B exhibits outputs for the portfolios sorted on the basis of liquidity-level. Illiquid stocks exhibit a high risk adjusted return than liquid stocks when we adjust for the market risk. The CAPM alpha of the spread P10-P1 is positive and significant. However, when we adjust for risk using the 3-factor and the 4-factor models, the risk-adjusted return of both the most illiquid portfolio and the spread P10-P1 are no more statistically significant. The 3-factor alpha of the spread P10-P1 in liquidity-level portfolios is 0.07 basis points per month (t=0.88) and its 4-factor alpha is -0.02 basis points per month (t=-0.23). This is because our measure of liquidity-level is highly correlated with the size factor. Adjusting for the size factor absorbs all the abnormal returns earned by illiquid assets. In Panel C, we show results for the portfolios sorted on the basis of liquidity-beta. We also present liquidity betas of the post-ranking portfolio. Post-ranking liquidity betas are obtained by regressing the post-ranking portfolio excess returns on the Pastor-Stambaugh non-traded liquidity factor and the three Fama-French factors. The results show that stocks with low historical liquidity-beta have negative exposures to the liquidity factor and stocks with high historical liquidity-beta have positive exposures to the liquidity factor. Furthermore, the spread P10-P1 is highly and positively exposed to the liquidity factor. Unlike illiquid stocks, high liquidity-beta stocks earn high risk-adjusted returns even when adjusting for the four factors. The CAPM alpha of the spread P10-P1 is 0.48 basis points per month (t=3.36), the 3-factor alpha is 0.44 basis points per month (t=3.00) and the 4-factor alpha is 0.48 basis points per month (t=3.23).

B. Stock market regimes

In this section, we present and discuss the results we obtained using the makov-switching mean-variance model to capture the market risk factor dynamics. Since the existing literature on markov-switching regime models applied to the US stock market does not clearly provide us with an optimal number of states, we started by estimating model (1) with two, three and four regimes. We consider up to four regimes because researchers have employed markov-switching models with either two regimes (Perez-Quiros and Timmermann, 2000; Gulen et al., 2011) or three (Kim et al., 1998; Billio et al., 2012) or four regimes (Ryden et al., 1998; Guidolin and Timmerman, 2007). Table II shows, for each model specification, the log likelihood value and their corresponding Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. As shown in the table, the AIC criterion favors the model with four regimes (AIC=-1661.6), while the BIC criterion favors the two-regime model (BIC=-1.63). To choose between the two specifications (models with two and four regimes), we further considered a simulated likelihood ratio test as in Billio et al. (2012). More specifically, we simulated data (Nsim=3000) under the null hypothesis that the two-regime specification is the true model. And then, from each simulation, we estimated both the two-regime and the four-regime models and computed the likelihood ratio statistic as follows:

$$Q_i = 2(logL_i^{4R} - logL_i^{2R}), \qquad i = 1,2, \dots 3000. \tag{7}$$

Where $logL_i^{4R}$and $logL_i^{2R}$denote the log likelihood values for the four-regime and the two-regime specifications, respectively.

As reported in Table II, the observed likelihood ratio statistic is 35.23 and its corresponding p-value from the simulated outputs is 0.03. The simulated LR test rejects the null hypothesis and selects the four-regime model over the two-regime model with a confidence level of 97%. Accordingly, we assume in this analysis that the US stock market is governed by four regimes. Each regime is characterized by specific market risk levels in terms of the mean and volatility. To discuss and highlight the economic interpretation of the different regimes, we present in Table III parameter estimates for the four-state mean-variance switching model as well as the expected duration of each regime and the transition probability matrix. In addition, we plot in Figure 1 the corresponding state probabilities (smoothed probabilities).

We name regime 1 as "normal" time because it had been prevailing the most of the time during the sample period; with a normal mean excess return of 1.01% and a volatility of 3.99%. Despite of the prevalence of "normal" regime the most of the full sample period, its expected duration is about only 15 months. This is because it is often destabilized by economic and financial crisis events.

Regime 2 is characterized by a negative mean excess return -1.78% and a high volatility 6.72%; we label it "crisis". Its expected duration is about 6 months and coincides with the most historical NBER economic recessions and financial crisis events such as the 1973 oil crisis, the 1987 crash, the 1997 Asian financial crisis and subsequent LTCM collapse in 1998, the Dotcom recession 2001-2002 and the 2007-2008 credit and liquidity crisis.

Regime 3 is labelled "recovery" because it follows regime 2 most time; revealing the end of the crisis. It is short lived with an average duration less than two months and is characterized by a high mean return of 4.74% and a low volatility 1.62%.

Finally, regime 4 is called "low-volatility" time. It is a special regime because it developed mainly during the periods 1993-1996 and 2003-2006 and is characterized by a low volatility. In this regime, the market portfolio earns, on average, 0.71% in excess of the riskless rate with a low volatility of 2.36%. The "low-volatility" regime is highly persistent with an average duration of about 30 months.

The transition probability matrix presented in Table III indicates the likelihood of switching from one regime to another and has a meaningful form. If the market is in a crisis time, it will either stay in crisis with a probability of 83% or it will move to a recovery regime with 17% chance; suggesting that, in high volatility times, large negative returns cluster and are almost followed by large positive returns revealing the end of crisis. However, recovery regime is less persistent with only 43% chance to persist and 51% chance to move to normal regime while the probability to go back to crisis regime is only 5%. Normal and «low-volatility» regimes are both highly persistent with 93% and 97% chance to persist respectively. However, the likelihood that a crisis occurs when the market is in normal regime is about 6% while this probability is only 3% if the market is in «low-volatility» regime. This indicates that, during low-volatility times, the economy is generally strong and the chance of an eventual crisis to occur is very low.

C. Testing portfolios: Regime-dependent market betas

Having identified the different regimes that characterized the stock market during our sample period 1970-2010, we focus now on the behavior of the portfolios formed on the basis of quality, liquidity-level and liquidity-beta characteristics within each regime. More specifically, we estimate regime-dependent market betas of the portfolios using model (4). In addition, we investigate whether or not the testing portfolio beta, in each state, exhibits a significant change relative to its level in the normal regime. We run separate analyses for each sorting characteristic. Table IV shows results for 10 quality-sorted portfolios. T-statistics are obtained using the robust (White, 1980) covariance matrix to compute standard errors. The table also displays, at the bottom, the results of tests of the null hypothesis that market beta of the portfolio, in a given regime, is equal to its level in the normal regime.

Several results emerge from Table IV. First, low quality stocks become riskier during the crisis regime. The four portfolios, containing stocks with the lowest quality scores, exhibit large, positive and statistically significant changes in their market betas as compared to their levels during the normal regime. The market beta of the portfolios P1, P2, P3 and P4 moved, respectively from 1.24, 1.12, 0.99 and 0.97 in the normal regime to reach 1.49, 1.37, 1.14 and 1.18 in the crisis regime; with a change of 0.25 (t=2.61), 0.24 (t=2.52), 0.15 (t=2.41) and 0.20 (t=4.28). Second, unlike low quality stocks, the market beta of high quality stocks decreases. The negative change in beta is not statistically significant but it persists across the 5 portfolios containing stocks with the highest quality scores. Our two findings here are in line with the "flight-to-quality" phenomenon that has been documented in several studies to be associated with times of economic distress. Third, the same pattern across the 10 quality-sorted portfolios is also observed in the "low-volatility" regime. Low quality stocks exhibit high increases in their market betas, while high quality stocks show decreases in their market betas. We argue that if the pattern observed in the crisis regime can be explained by the "flight-to-quality" phenomenon, the pattern observed in the "low-volatility" regime can be explained by the "flight-to-low-quality". As the "low-volatility" market is characterized by a low volatility, investors tilt their portfolios towards low quality stocks to seek portfolio gains. This explanation is consistent with the investors' time-varying risk aversion (Vayanos, 2004).

We present results for liquidity-level sorted portfolios in Table V. Unlike quality-sorted portfolios that have a high spread in market beta between high quality and low quality portfolios, Liquid and illiquid portfolios have no significant differences between their market betas. However, we also document similar patterns in the behavior of their portfolios during both the crisis and the "low-volatility" regime. In both regimes, liquid stocks exhibit a decrease in their market betas and illiquid stocks show an increase in their market betas. Furthermore, this pattern persists across the portfolios of liquid stocks and across the portfolios of illiquid stocks. In the crisis regime, the market beta of the portfolio of the most illiquid stocks moved from 0.92 in the normal regime to reach 1.13 in the crisis regime with a change of 0.21 (t=1.70). The market beta of the portfolio of the most liquid stocks is reduced from 0.94 in the normal regime to 0.86 in the crisis regime with a negative change of -0.09 (t=-1.69). The market beta of the spread P10-P1 moved from -0.01 in the normal regime to 0.25 in the crisis regime; with a change of 0.26 (t=1.97) that is statistically significant at the 5% level. These findings are consistent with the "flight-to-liquidity" phenomenon during periods of economic distress. During volatile times, preference for liquidity increases and investors shift their portfolios from illiquid stocks to liquid stocks. The same pattern across the 10 liquidity-level-sorted portfolios is also observed in the "low-volatility" regime. Illiquid stocks exhibit high increases in their market betas, while liquid stocks show decreases in their market betas. We argue that if the pattern observed in the crisis regime can be explained by the "flight-to-liquidity" phenomenon, the pattern observed in the "low-volatility" regime can be explained by the "flight-to-illiquidity". As the "low-volatility" is characterized by a low volatility, investors shift their portfolios towards illiquid stocks to seek portfolio gains.

Table VI presents the results for the portfolios sorted on the basis of liquidity betas. In the same fashion, we observe that market beta of high liquidity risk increases during the crisis regime while the market beta of low liquidity-beta stocks decreases. The market beta of the portfolio of stocks with the highest liquidity betas moved from 1.1 in the normal regime to 1.14 in the crisis regime; with a change of 0.04 (t=2.39) that is statistically significant at the 5% level. However, the market beta of the spread P10-P1 does not change between the normal and the crisis regime. The change in its market beta is 0.05 (t=1.04) but is not statistically significant. Furthermore, unlike liquidity-level and quality-sorted portfolios, we do not observe the same pattern across liquidity-beta sorted portfolios during the “low-volatility” regime. Both low liquidity-beta and high liquidity stocks show no significant change in their market beta.

Our analysis so far provides empirical evidence that both illiquid and high liquidity-beta stocks become riskier during the crisis regime. However, we do not know which characteristic become more important to investors during volatile times. Lou and Sadka (2011) find that, during the 2008-2009 financial crisis, liquid stocks with high liquidity risk became riskier than illiquid stocks with low liquidity-beta. They claim that, during crisis times, liquidity-beta is more important than the liquidity-level. To test their claim, we form 2by2 portfolios based on liquidity-level and liquidity-beta. The four portfolios are value-weighted and obtained using NYSE breakpoints. If liquidity-beta is more important than liquidity-level during the crisis regime, we expect that the portfolios of stocks with high liquidity betas will exhibit an increase in their market betas. Table VII displays the results for the four portfolios. The results do not lend support to the assertion of Lou and Sadka (2011). Contrary to what is claimed by the authors, we find that liquidity-level is more important than liquidity-beta during the crisis regime. The liquid portfolios exhibit a decrease in their market betas and the illiquid portfolios show an increase in their market beta.

V. Conclusion

We focus in this paper on three stock characteristics, namely, quality, liquidity-level and liquidity risk. We form portfolios sorted on the basis of these attributes and use a markov-switching model to examine time-variations in their market betas.

We show that, during the period 1970-2010, the US stock market was driven by four regimes. (1) The normal regime had been prevailing the most of the time. (2) The crisis regime is characterized by a high volatility and negative returns. (3) The recovery regime was following crisis periods most of time. (4) And the “low-volatility” regime captures low volatility periods.

Our findings are consistent with the literature on the flight to quality and liquidity. The results show that, on one hand, low quality, high liquidity-beta and illiquid stocks exhibit a significant increase in their market beta during the crisis regime. On the other hand, high quality, low liquidity-beta and liquid stocks show a decrease in their market beta. In addition, we document the same pattern across stocks when the market volatility is low. We argue that, during low volatility times, investors shift their portfolios towards low quality and illiquid stocks to seek portfolio gains. The pattern observed in the “low-volatility” regime, therefore, can be explained by a flight to low-quality and to illiquidity. However, we do not find evidence for the assertion of Lou and Sadka (2011) who claim that liquidity risk is more important than liquidity-level during crisis times. Contrary to their claim, we find that liquidity-level is more important than liquidity-beta during the crisis regime.

This analysis can be extended in several ways. First, we considered only a one factor model. Our future research will focus on including the size, value and momentum factors that have been documented in several studies to have an important effect on stock returns. Second, to proxy for liquidity-level, we use the Amihud’s (2002) measure which is highly correlated with the size characteristic. One direction for future research is to isolate the component of liquidity from size. Finally, future research could also extend our study by adding other macroeconomic indicators to the market risk factor when identifying stock market regimes.

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Table I. Performance of portfolios sorted on the basis of Quality scores, Liquidity-level and Liquidity-beta: 1970-2010

This table reports excess returns and risk-adjusted returns of 30 portfolios formed on the basis of quality scores, liquidity-level and liquidity-beta ; as described in section 2. The performance measures are computed over the sample period 1970-2010. Panel A displays results for 10 quality-sorted portfolios. Panel B show results for 10 portfolios sorted on the basis of liquidity-level and the outputs of 10 liquidity-beta sorted portfolios are displayed in Panel C. The table also exhibits the portfolios' CAPM betas and the post-ranking exposures to the liquidity factor for the 10 portfolios that are sorted on the basis of liquidity betas. The post-ranking liquidity betas are obtained by regressing the post-ranking portfolio excess returns on the Pastor-Stambaugh non-traded liquidity factor and the three Fama-French factors. Parameters (with the exception of CAPM betas) that are significant at the 10% level are shown in bold type.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Panel A:	Low Quality				**Quality sorted portfolios**					High Quality	
Excess Returns	0.07	0.33	**0.4**	**0.4**	**0.47**	**0.48**	**0.54**	**0.46**	**0.54**	**0.57**	**0.5**
	[0.21]	[1.16]	[1.65]	[1.67]	[2.12]	[2.20]	[2.61]	[2.17]	[2.62]	[2.72]	[2.43]
CAPM beta	1.4	1.24	1.08	1.07	0.99	0.98	0.93	0.97	0.94	0.92	-0.48
	[45.97]	[55.00]	[62.61]	[68.40]	[59.53]	[67.88]	[65.67]	[76.54]	[73.91]	[57.42]	[-12.55]
CAPM alpha	**-0.57**	**-0.24**	-0.09	-0.09	0.02	0.03	**0.12**	0.02	**0.12**	**0.15**	**0.72**
	[-3.97]	[-2.23]	[-1.14]	[-1.25]	[0.27]	[0.48]	[1.78]	[0.36]	[1.93]	[1.96]	[3.99]
3-factor alpha	**-0.67**	**-0.45**	**-0.24**	**-0.27**	**-0.12**	-0.08	0.06	-0.01	**0.13**	**0.32**	**0.99**
	[-6.13]	[-5.02]	[-3.36]	[-4.32]	[-1.70]	[-1.21]	[0.98]	[-0.19]	[2.27]	[5.05]	[7.22]
4-factor alpha	**-0.58**	**-0.39**	**-0.16**	**-0.22**	-0.07	-0.05	0.06	-0.02	**0.15**	**0.3**	**0.88**
	[-5.28]	[-4.32]	[-2.25]	[-3.55]	[-0.95]	[-0.83]	[0.97]	[-0.28]	[2.58]	[4.64]	[6.38]
Panel B:	Liquid				**Liquidity Level sorted portfolios**					Illiquid	
Excess Returns	**0.38**	**0.49**	**0.63**	**0.62**	**0.62**	**0.72**	**0.67**	**0.71**	**0.81**	**0.81**	**0.43**
	[1.93]	[2.34]	[2.77]	[2.67]	[2.66]	[2.99]	[2.74]	[2.81]	[3.14]	[3.19]	[2.43]
CAPM beta	0.89	0.94	1.02	1.03	1.01	1.02	1.03	1.04	1.05	1	0.1
	[76.27]	[65.55]	[63.58]	[56.21]	[52.55]	[47.11]	[44.36]	[40.03]	[37.42]	[33.09]	[2.77]
CAPM alpha	-0.03	0.06	**0.17**	**0.15**	**0.16**	**0.25**	**0.2**	**0.23**	**0.33**	**0.36**	**0.38**
	[-0.52]	[0.91]	[2.21]	[1.79]	[1.73]	[2.42]	[1.81]	[1.90]	[2.51]	[2.50]	[2.17]
3-factor alpha	-0.01	-0.05	-0.02	-0.04	-0.06	0.01	-0.07	-0.06	0	0.06	0.07
	[-0.44]	[-0.91]	[-0.24]	[-0.52]	[-0.78]	[0.07]	[-0.93]	[-0.80]	[-0.03]	[0.70]	[0.88]
4-factor alpha	-0.01	-0.05	0.02	-0.02	-0.06	0.02	-0.08	-0.06	0	-0.02	-0.02
	[-0.18]	[-0.81]	[0.25]	[-0.25]	[-0.78]	[0.25]	[-1.08]	[-0.73]	[0.01]	[-0.31]	[-0.23]
Panel C:	Low Liquidity Beta				**Liquidity risk sorted portfolios**					High Liquidity Beta	
Excess Returns	0.31	**0.5**	0.32	**0.52**	**0.52**	**0.48**	**0.6**	**0.58**	**0.52**	**0.78**	**0.47**
	[1.16]	[2.25]	[1.45]	[2.51]	[2.54]	[2.36]	[2.95]	[2.54]	[2.18]	[3.02]	[3.29]
CAPM beta	1.17	0.97	0.98	0.91	0.88	0.92	0.91	1	1.06	1.14	-0.03
	[55.39]	[53.74]	[64.93]	[59.26]	[51.34]	[66.58]	[60.61]	[55.79]	[63.24]	[61.33]	[-0.91]
CAPM alpha	**-0.22**	0.06	-0.13	0.1	0.11	0.06	**0.19**	0.12	0.03	**0.25**	**0.48**
	[-2.25]	[0.67]	[-1.83]	[1.40]	[1.40]	[0.98]	[2.67]	[1.44]	[0.43]	[2.89]	[3.36]
3-factor alpha	**-0.22**	0.05	**-0.15**	0.1	0.04	0.02	**0.15**	0.1	0.01	**0.22**	**0.44**
	[-2.17]	[0.52]	[-2.22]	[1.47]	[0.57]	[0.24]	[2.20]	[1.20]	[0.13]	[2.52]	[3.00]
4-factor alpha	**-0.19**	-0.02	**-0.2**	0.11	0.08	0.01	**0.15**	**0.15**	0.08	**0.29**	**0.48**
	[-1.89]	[-0.26]	[-2.87]	[1.52]	[1.03]	[0.14]	[2.17]	[1.66]	[0.94]	[3.25]	[3.23]
Liquidity beta	**-5.07**	**-2.57**	0.16	**-2.48**	1.89	**-2.63**	1.13	**2.79**	**6.26**	1.09	**6.16**
	[-2.92]	[-1.71]	[0.14]	[-2.08]	[1.42]	[-2.41]	[0.96]	[1.85]	[4.55]	[0.71]	[2.43]

Table II. Identification of the number of regimes driving the market portfolio excess return: A markov switching mean-variance model

This table reports the number of parameters to estimate, the log-likelihood value, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC); as obtained from running the following Markov-Switching mean-variance model on the market portfolio excess return $R^{e}_{m,t}$:

$$R^{e}_{m,t} = \mu_m\left(S_t^{R^e_m}\right) + \sigma_m\left(S_t^{R^e_m}\right)\ \varepsilon_t\ ,\ \varepsilon_t \sim iid.N(0,1).$$

where $\mu_m\left(S_t^{R^e_m}\right)$ and $\sigma_m\left(S_t^{R^e_m}\right)$ are, respectively, the expected excess return and the standard deviation of the market portfolio in state $S_t^{R^e_m}$. The unobservable state of the market portfolio $S_t^{R^e_m}$ is assumed to evolve according to a two, three or four-state first-order markov chain. The table also displays, at the bottom, the outputs from a simulated likelihood ratio test that compares the statistical significance of the two-regime model (Null Hypothesis) against the four-regime model (Alternative Hypothesis). Data are simulated (Nsim=3000) under the null hypothesis that the two-regime specification is the true model. And then, from each simulation, both the two-regime and the four-regime models are estimated and the likelihood ratio statistic is computed as follows:

$$Q_i = 2(logL_i^{4R} - logL_i^{2R}), \qquad i = 1,2,\dots 3000.$$

where $logL_i^{4R}$ and $logL_i^{2R}$ denote the log likelihood values for the four-regime and the two-regime specifications, respectively. Monthly excess returns for the market portfolio are obtained from the Fama-French files through WRDS and cover the period 1970-2010.

Number of regimes	Number of parameters	Log-likelihood	AIC	BIC
2	6	833.1638	-1654.3	**-1.6291**
3	12	834.5913	-1645.2	-1.5948
4	20	**850.7816**	**-1661.6**	-1.5776

Simulated Likelihood Ratio Test:

Null Hypothesis : The two-regime model is the true model
Alternative Hypothesis: The four-regime model is the true model

Nsim	Obs. LRstat	P-value
3000	35.23	0.03

Table III. Parameter estimates from a Four-state Markov Switching Mean-Variance model for the market portfolio excess return

This table reports parameter estimates from a Four-state Markov Switching Mean-Variance model for the market portfolio excess return $R^e_{m,t}$. We estimate the following model:

$$R^e_{m,t} = \mu_m\left(S_t^{R^e_m}\right) + \sigma_m\left(S_t^{R^e_m}\right)\ \varepsilon_t\ ,\ \varepsilon_t \sim iid.N(0,1).$$

where $\mu_m\left(S_t^{R^e_m}\right)$ and $\sigma_m\left(S_t^{R^e_m}\right)$ are, respectively, the expected excess return and the standard deviation of the market portfolio in state $S_t^{R^e_m}$. The unobservable state of the market portfolio $S_t^{R^e_m}$ is assumed to evolve according to a Four-state first-order markov chain. The four states are labeled as follows: regime 1 (normal), regime 2 (crisis), regime 3 (recovery) and regime 4 (low-volatility). Monthly excess returns for the market portfolio are obtained from the Fama-French files through WRDS and cover the period 1970-2010. In addition, the table presents the expected duration of each regime as well as the transition probability matrix (the likelihood of switching to each of the four regimes given that the market portfolio is in some state now). Parameters that are significant at the 10% level are shown in bold type.

	Regime 1 (normal)	Regime 2 (crisis)	Regime 3 (recovery)	Regime 4 (low-volatility)
1. Switching parameters:				
mean (%)	**1.01**	**-1.78**	**4.74**	**0.71**
Standard deviation (%)	**3.99**	**6.72**	**1.62**	**2.36**
2. Transition Probabilities:				
Regime 1 (normal)	**0.93**	**0.06**	0.00	**0.01**
Regime 2 (crisis)	**0.00**	**0.83**	0.17	**0.00**
Regime 3 (recovery)	**0.51**	**0.05**	0.43	**0.00**
Regime 4 (low-volatility)	**0.00**	**0.03**	0.00	**0.97**
3. Expected duration of Regimes (in months):				
Regime 1 (normal)	15.24			
Regime 2 (crisis)	5.86			
Regime 3 (recovery)	1.77			
Regime 4 (low-volatility)	29.67			

Table IV. Regime-dependent Market Betas of 10 quality-sorted portfolios

This table reports regime-dependent market betas of 10 quality-sorted portfolios. The market beta is assumed to depend on the market portfolio excess return regimes and is estimated using the following model:

$$r_t^e = \alpha + \beta\left(S_t^{R_m^e}\right) R_{m,t}^e + w\, v_t\ ,\ v_t \sim iid.N(0,1).$$

where r_t^e denotes the excess return of the testing portfolio and α and w are assumed to be fixed components over regimes. $\beta\left(S_t^{R_m^e}\right)$ is the testing portfolio market beta when the market portfolio is in state $S_t^{R_m^e}$. The unobservable state of the market portfolio $S_t^{R_m^e}$ is assumed to evolve according to a Four-state first-order markov chain. The four states are labeled as follows: regime 1 (normal), regime 2 (crisis), regime 3 (recovery) and regime 4 (low-volatility). The model above is estimated using the maximum likelihood method and relaying on smoothed probabilities from regression (1) to make inferences about the stock market regime at any date t. The portfolios are formed as described in section 2 and cover the period 1970-2010. T-statistics are computed using Huber-White standard errors and are presented in brackets. The table also presents, at the bottom, results of tests of the null hypotheses that market beta of the testing portfolio, in a given regime, is equal to its level in the normal regime. Parameters (with the exception of $\beta(state)$and w) that are significant at the 10% level are shown in bold type.

	Low Quality	P2	P3	P4	P5	P6	P7	P8	P9	**High Quality**	**H-L**
α (%)	**-0.52**	-0.05	-0.06	0.07	0.12	-0.08	0.11	0.09	0.06	0.1	**0.61**
	[-2.25]	[-0.37]	[-0.61]	[0.93]	[0.95]	[-0.67]	[1.52]	[1.02]	[0.68]	[0.56]	[3.19]
β (normal)	1.24	1.12	0.99	0.97	0.93	0.99	1.02	1.01	0.97	0.92	**-0.32**
	[14.08]	[30.31]	[29.20]	[46.41]	[17.04]	[25.01]	[39.04]	[31.28]	[23.89]	[31.53]	[-4.78]
β (crisis)	1.49	1.37	1.14	1.18	1.05	0.94	0.88	0.98	0.9	0.9	**-0.59**
	[19.18]	[17.79]	[25.00]	[29.29]	[18.00]	[12.08]	[24.91]	[30.01]	[20.17]	[14.85]	[-7.23]
β (recovery)	1.53	0.99	1.15	0.9	0.87	1.24	0.76	0.77	1.01	1.07	**-0.42**
	[2.92]	[3.74]	[9.46]	[27.86]	[2.72]	[9.02]	[8.41]	[3.48]	[4.02]	[4.53]	[-2.21]
β (tranquil time)	1.5	1.24	1.14	1.02	0.96	0.99	0.96	0.9	0.95	0.86	**-0.64**
	[9.33]	[5.40]	[20.54]	[17.87]	[2.52]	[3.45]	[12.11]	[26.22]	[2.58]	[1.82]	[-6.53]
w (%)	3.1	2.26	1.76	1.55	1.69	1.46	1.42	1.28	1.3	1.65	3.91
	[17.53]	[16.38]	[23.62]	[22.06]	[15.22]	[18.77]	[18.17]	[17.74]	[18.32]	[21.93]	[21.25]
Null Hypothesis: β (state) =β (normal)											
β (crisis)-β (normal)	**0.25**	**0.24**	**0.15**	**0.20**	0.12	-0.05	**-0.14**	-0.03	-0.07	-0.02	**-0.27**
	[2.61]	[2.52]	[2.41]	[4.28]	[1.15]	[-0.47]	[-2.83]	[-0.69]	[-0.95]	[-0.53]	[-2.35]
β (recovery)-β (normal)	0.29	-0.14	0.17	**-0.07**	-0.07	**0.25**	**-0.25**	-0.24	0.04	0.15	-0.10
	[0.49]	[-0.50]	[1.19]	[-2.39]	[-0.23]	[1.66]	[-2.82]	[-1.05]	[0.18]	[0.58]	[-0.48]
β (tranquil)-β (normal)	0.26	0.12	**0.16**	0.05	0.03	0.00	-0.05	**-0.11**	-0.02	-0.06	**-0.32**
	[1.18]	[0.55]	[2.65]	[0.85]	[0.08]	[0.02]	[-0.73]	[-2.26]	[-0.04]	[-0.12]	[-3.16]
Log Likelihood value	1010.70	1169.83	1290.25	1357.85	1306.99	1373.76	1393.13	1437.59	1437.20	1321.19	897.23
Log Likelihood OLS	1001.98	1149.89	1280.39	1330.05	1300.71	1366.76	1380.11	1432.45	1433.04	1317.69	890.43

Table V. Regime-dependent Market Betas of 10 portfolios sorted on the basis of liquidity-level

This table reports regime-dependent market betas of 10 portfolios sorted on the basis of liquidity-level. The market beta is assumed to depend on the market portfolio excess return regimes and is estimated using the following model:

$$r_t^e = \alpha + \beta\left(S_t^{R_m^e}\right) R_{m,t}^e + w\,\nu_t\ ,\ \nu_t \sim iid.N(0,1).$$

where r_t^e denotes the excess return of the testing portfolio and α and w are assumed to be fixed components over regimes. $\beta\left(S_t^{R_m^e}\right)$ is the testing portfolio market beta when the market portfolio is in state $S_t^{R_m^e}$. The unobservable state of the market portfolio $S_t^{R_m^e}$ is assumed to evolve according to a Four-state first-order markov chain. The four states are labeled as follows: regime 1 (normal), regime 2 (crisis), regime 3 (recovery) and regime 4 (low-volatility). The model above is estimated using the maximum likelihood method and relaying on smoothed probabilities from regression (1) to make inferences about the stock market regime at any date t. The portfolios are formed as described in section 2 and cover the period 1970-2010. T-statistics are computed using Huber-White standard errors and are presented in brackets. The table also presents, at the bottom, results of tests of the null hypotheses that market beta of the testing portfolio, in a given regime, is equal to its level in the normal regime. Parameters (with the exception of $\beta(state)$and w) that are significant at the 10% level are shown in bold type.

	Liquid	P2	P3	P4	P5	P6	P7	P8	P9	**Illiquid**	**Illiq-Liq**
α (%)	-0.06	0.06	**0.23**	0.22	0.25	**0.33**	0.3	0.42	**0.57**	**0.6**	**0.64**
	[-1.03]	[0.44]	[1.64]	[1.23]	[1.33]	[1.88]	[0.14]	[3.32]	[3.68]	[2.92]	[3.15]
β (normal)	0.94	0.98	1.04	1.05	0.99	0.95	1.03	1.01	0.92	0.92	-0.01
	[40.18]	[26.58]	[39.36]	[36.31]	[16.24]	[13.77]	[2.62]	[28.00]	[11.73]	[6.23]	[-0.12]
β (crisis)	0.86	0.93	1.04	1.04	1.06	1.09	1.06	1.12	1.2	1.13	**0.25**
	[24.96]	[10.66]	[28.16]	[17.93]	[9.71]	[9.96]	[0.87]	[19.20]	[10.92]	[6.90]	[2.25]
β (recovery)	0.9	0.88	0.82	0.76	0.84	0.93	0.69	0.57	0.65	0.54	**-0.33**
	[28.22]	[6.55]	[6.88]	[4.70]	[2.17]	[3.96]	[1.83]	[3.63]	[4.14]	[3.59]	[-2.39]
β (tranquil time)	0.86	0.95	1.04	1.08	1.03	1.09	1.18	1.12	1.18	1.06	**0.21**
	[39.02]	[3.67]	[2.17]	[1.72]	[1.87]	[22.91]	[0.16]	[8.58]	[13.59]	[11.96]	[2.63]
w (%)	1.2	1.49	1.65	1.86	1.99	2.23	2.35	2.62	2.8	3.04	3.82
	[15.39]	[15.19]	[16.24]	[17.38]	[17.02]	[16.82]	[19.37]	[22.14]	[20.51]	[20.91]	[23.19]
Null Hypothesis: β (state) =β (normal)											
β (crisis)-β (normal)	**-0.09**	-0.05	0.00	-0.02	0.07	0.14	0.03	**0.11**	**0.27**	**0.21**	**0.26**
	[-1.69]	[-0.43]	[-0.12]	[-0.33]	[0.46]	[0.87]	[0.02]	[1.71]	[1.62]	[1.70]	[1.97]
β (recovery)-β (normal)	**-0.05**	-0.10	**-0.22**	**-0.29**	-0.15	-0.02	-0.34	**-0.44**	-0.27	**-0.38**	**-0.32**
	[-2.66]	[-0.85]	[-1.65]	[-1.69]	[-0.42]	[-0.09]	[-1.30]	[-2.76]	[-1.38]	[-1.66]	[-2.18]
β (tranquil)-β (normal)	**-0.08**	-0.03	0.00	0.03	0.04	**0.14**	0.15	0.11	**0.26**	**0.15**	**0.22**
	[-3.64]	[-0.12]	[-0.01]	[0.05]	[0.08]	[3.65]	[0.02]	[0.76]	[2.18]	[1.82]	[2.27]
Log Likelihood value	1475.48	1371.62	1319.87	1258.67	1229.48	1171.00	1145.16	1093.11	1060.31	1018.69	907.29
Log Likelihood OLS	1470.80	1370.10	1316.13	1253.31	1225.38	1166.94	1136.08	1079.27	1042.69	1005.69	897.43

Table VI. Regime-dependent Market Betas of 10 portfolios sorted on the basis of liquidity-beta

This table reports regime-dependent market betas of 10 portfolios sorted on the basis of liquidity-beta. The market beta is assumed to depend on the market portfolio excess return regimes and is estimated using the following model:

$$r_t^e = \alpha + \beta\left(S_t^{R_m^e}\right) R_{m,t}^e + w\,\nu_t\ ,\ \nu_t \sim iid.N(0,1).$$

where r_t^e denotes the excess return of the testing portfolio and α and w are assumed to be fixed components over regimes. $\beta\left(S_t^{R_m^e}\right)$ is the testing portfolio market beta when the market portfolio is in state $S_t^{R_m^e}$. The unobservable state of the market portfolio $S_t^{R_m^e}$ is assumed to evolve according to a Four-state first-order markov chain. The four states are labeled as follows: regime 1 (normal), regime 2 (crisis), regime 3 (recovery) and regime 4 (low-volatility). The model above is estimated using the maximum likelihood method and relaying on smoothed probabilities from regression (1) to make inferences about the stock market regime at any date t. The portfolios are formed as described in section 2 and cover the period 1970-2010. T-statistics are computed using Huber-White standard errors and are presented in brackets. The also presents, at the bottom, results of tests of the null hypotheses that market beta of the testing portfolio, in a given regime, is equal to its level in the normal regime. Parameters (with the exception of $\beta(state)$and w) that are significant at the 10% level are shown in bold type.

	Low Liquidity Beta	P2	P3	P4	P5	P6	P7	P8	P9	**High Liquidity Beta**	**H-L**
α (%)	-0.38	-0.02	-0.1	0.07	**0.18**	0.05	**0.13**	0.1	0.07	**0.18**	**0.46**
	[-1.40]	[-0.19]	[-1.37]	[0.92]	[1.65]	[0.54]	[1.74]	[0.44]	[0.05]	[1.98]	[3.14]
β (normal)	1.15	1.06	1.02	0.92	0.8	0.95	0.97	0.98	1.02	1.1	**-0.07**
	[28.61]	[17.16]	[52.10]	[55.94]	[18.00]	[15.84]	[40.62]	[34.19]	[4.97]	[47.77]	[-1.76]
β (crisis)	1.12	0.89	0.97	0.89	0.95	0.9	0.85	1	1.09	1.14	-0.01
	[10.87]	[8.85]	[41.02]	[38.41]	[16.32]	[13.70]	[30.86]	[9.99]	[2.61]	[38.75]	[-0.26]
β (recovery)	1.62	1	0.85	0.95	0.85	0.85	0.89	1.1	1.07	1.4	0.06
	[6.51]	[13.96]	[12.94]	[54.71]	[2.96]	[6.18]	[15.98]	[9.39]	[0.19]	[13.74]	[0.27]
β (tranquil time)	1.14	0.94	0.9	0.93	0.92	0.96	0.93	1	1.01	1.15	0.02
	[1.24]	[22.78]	[20.25]	[49.17]	[3.16]	[14.37]	[17.36]	[1.02]	[0.18]	[16.97]	[0.06]
w (%)	2.11	1.83	1.54	1.59	1.76	1.42	1.53	1.86	1.73	1.9	3.13
	[16.31]	[13.74]	[17.67]	[20.72]	[15.07]	[21.50]	[23.12]	[14.33]	[14.55]	[23.56]	[21.05]
Null Hypothesis: β (state) =β (normal)											
β (crisis)-β (normal)	-0.03	-0.17	**-0.06**	**-0.03**	**0.15**	-0.06	**-0.12**	0.03	0.07	**0.04**	0.05
	[-0.38]	[-1.06]	[-2.60]	[-1.97]	[1.66]	[-0.47]	[-2.92]	[0.27]	[0.11]	[2.39]	[1.04]
β (recovery)-β (normal)	**0.47**	-0.06	**-0.17**	**0.03**	0.05	-0.10	**-0.09**	0.12	0.05	**0.30**	0.13
	[1.75]	[-0.60]	[-2.65]	[5.20]	[0.17]	[-0.62]	[-1.64]	[0.98]	[0.01]	[2.78]	[0.54]
β (tranquil)-β (normal)	-0.01	-0.11	**-0.12**	0.01	0.12	0.01	-0.04	0.02	-0.01	0.05	0.08
	[-0.01]	[-3.82]	[-2.69]	[0.86]	[0.47]	[0.86]	[-0.80]	[0.02]	[-0.00]	[0.71]	[0.34]
Log Likelihood value	1188.21	1266.08	1352.36	1339.31	1286.91	1394.05	1359.83	1261.79	1299.11	1249.22	1005.22
Log Likelihood OLS	1180.49	1260.12	1348.84	1338.51	1282.05	1390.99	1351.27	1261.21	1296.91	1242.30	1004.62

Table VII. Regime-dependent Market Betas of four portfolios sorted on the basis of Liquidity-level and Liquidity-beta

This table reports regime-dependent market betas of four portfolios sorted on the basis of liquidity-level and liquidity-beta. The market beta is assumed to depend on the market portfolio excess return regimes and is estimated using the following model:

$$r_t^e = \alpha + \beta\left(S_t^{R_m^e}\right) R_{m,t}^e + w\, v_t \text{ , } v_t \sim iid.N(0,1).$$

where r_t^e denotes the excess return of the testing portfolio and α and w are assumed to be fixed components over regimes. $\beta\left(S_t^{R_m^e}\right)$ is the testing portfolio market beta when the market portfolio is in state $S_t^{R_m^e}$. The unobservable state of the market portfolio $S_t^{R_m^e}$ is assumed to evolve according to a Four-state first-order markov chain. The four states are labeled as follows: regime 1 (normal), regime 2 (crisis), regime 3 (recovery) and regime 4 (low-volatility). The model above is estimated using the maximum likelihood method and relaying on smoothed probabilities from regression (1) to make inferences about the stock market regime at any date t. The portfolios are formed as 2by2 portfolios using independent sorts on liquidity-level and liquidity-beta. The portfolios are value-weighted and are formed using NYSE breakpoints. The sample period is from 1970 through 2010. T-statistics are computed using Huber-White standard errors and are presented in brackets. The table also presents, at the bottom, results of tests of the null hypotheses that market beta of the testing portfolio, in a given regime, is equal to its level in the normal regime. Parameters (with the exception of $\beta(state)$and w) that are significant at the 10% level are shown in bold type.

	Liquid and Low Beta	Liquid and High Beta	H - L	Illiquid and Low Beta	Illiquid and High Beta	H - L
α (%)	-0.02	0.08	**0.14**	**0.41**	**0.51**	0.1
	[-0.24]	[1.38]	[1.94]	[3.67]	[3.33]	[1.05]
β (normal)	0.95	0.98	**0.05**	0.98	0.91	-0.01
	[36.22]	[44.79]	[2.92]	[30.16]	[9.89]	[-0.53]
β (crisis)	0.92	0.9	-0.02	1.03	1.12	0.07
	[44.42]	[31.13]	[-0.68]	[24.49]	[8.98]	[1.67]
β (recovery)	0.78	0.92	0.01	0.65	0.75	-0.04
	[2.52]	[11.33]	[0.16]	[3.37]	[5.28]	[-0.24]
β (tranquil time)	0.89	0.91	0.01	1.05	1.13	0.08
	[5.28]	[47.94]	[0.25]	[10.96]	[14.33]	[0.98]
w (%)	1.3	1.19	1.57	2.43	2.34	1.35
	[13.45]	[12.61]	[23.09]	[19.97]	[16.69]	[20.65]
Null Hypothesis: β (state) =β (normal)						
β (crisis)-β (normal)	-0.03	**-0.08**	**-0.07**	**0.05**	0.21	0.08
	[-1.35]	[-2.03]	[-2.46]	[2.42]	[1.04]	[1.39]
β (recovery)-β (normal)	-0.17	-0.06	-0.04	-0.33	-0.16	-0.03
	[-0.54]	[-0.66]	[-0.68]	[-1.62]	[-0.97]	[-0.16]
β (tranquil)-β (normal)	-0.06	**-0.07**	-0.04	0.07	**0.22**	0.09
	[-0.41]	[-4.21]	[-0.72]	[0.88]	[1.73]	[1.09]
Log Likelihood value	1432.39	1481.63	1345.61	1127.45	1146.29	1421.71
Log Likelihood OLS	1431.21	1475.87	1343.09	1121.23	1133.87	1416.11

Figure 1. Smoothed state Probabilities from a Four-state Markov Switching Mean-Variance model for the Market portfolio excess return.

This figure plots the smoothed state probabilities from a Four-state Markov Switching Mean-Variance model for the market portfolio excess return. The model specifications and the parameter estimates underlying these plots are presented in Table III. The four states are labeled as follows: regime 1 (normal), regime 2 (crisis), regime 3 (recovery) and regime 4 (low-volatility). Monthly excess returns for the market portfolio are obtained from the Fama-French files through WRDS and cover the period 1970-2010.The solid line in each plot represents the smoothed state probability; the dotted line represents the market portfolio excess return time-series while the gray bars indicate NBER recession periods.