Time-Varying Liquidity Risk and the Cross Section of Stock Returns*

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Abstract

This paper studies whether stock returns' sensitivities to aggregate liquidity fluctuations and the pricing of liquidity risk vary over time. We find that liquidity betas vary across two distinct states, one with high liquidity betas and the other with low betas. The high liquidity-beta state is short lived, and is associated with heavy trade, high volatility, and a wide cross-sectional dispersion in liquidity betas. The liquidity risk premium also changes over time and is delivered primarily in the high liquidity-beta state. The conditional liquidity risk premium is statistically significant and economically large, rendering more than twice the value premium.

Introduction

Recent studies find that there is a systematic component in time-series variations of liquidity measures across stocks [Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001)]. While liquidity has long been regarded as a firm attribute with a negative effect on expected returns, the existence of liquidity commonality suggests that market-wide liquidity may also be an important risk factor in the cross section of stock returns. The risk view of liquidity has attracted much attention in recent years and led to several studies confirming that liquidity risk is indeed priced, i.e., stocks with greater sensitivities to aggregate liquidity fluctuations–measured by their 'liquidity betas'–earn higher expected returns [Pastor and Stambaugh (2003) and Acharya and Pedersen (2005)]. Despite the growing interest in the role of systematic liquidity in asset pricing, the literature is still in its early development and more work is needed to better understand the features of liquidity risk pricing. As an attempt to address this issue, this paper examines whether liquidity betas and the liquidity risk premium vary over time across different economic states.

Our hypotheses build on recent work by Gallmeyer, Hollifield, and Seppi (2005), who provide a theoretical model that explains the mechanism behind the joint dynamics of trading process and liquidity pricing. In their model, investors are asymmetrically informed about each other's preferences. This exposes investors to resale price risk as they face uncertainty about future asset demands of their trading counterparties. Investors' future preferences are, however, fully or partially revealed through their trades so that the resulting level of preference risk and its associated premium are endogenously determined. In particular, the authors construct examples in which elevated trading volume indicates periods of heightened preference risk, high premium, and large price impact of trade.

We propose that changes in the prevailing level of preference uncertainty cause time variations in liquidity betas and liquidity risk premium. Previous studies show that the persistent nature of illiquidity implies negative sensitivities of stock returns to aggregate illiquidity shocks [Amihud (2002) and Acharya and Pedersen (2005)]. This is because higher realized illiquidity today, caused by a market-wide illiquidity shock, leads to stock price declines since investors require higher expected returns to be compensated for higher anticipated future illiquidity. We argue that, during periods of high preference uncertainty, investors are more concerned about future tradability of assets and require higher compensation in response to a unit aggregate illiquidity shock, resulting in higher liquidity betas. Furthermore, given that preference uncertainty is a greater concern for investors who hold illiquid stocks that already have low levels of tradability, we expect that these investors require even more compensation when faced with illiquidity shocks at times of high preference uncertainty. Based on these arguments, we test whether there is time variation in liquidity betas driven by changes in the underlying state of preference uncertainty, and whether such variation is greater for more illiquid stocks.

We also examine the effect of preference uncertainty on the pricing of liquidity risk. Stocks with high liquidity betas, when held in levered position, can expose investors to liquidation need when market liquidity deteriorates [Pastor and Stambaugh (2003)]. Because investors dislike such costly liquidation, they require a premium to hold liquidity-sensitive stocks. We propose that, when investors are more concerned about future asset tradability during times of high preference uncertainty, they become less willing to hold stocks that are likely to require costly liquidation. Hence, in order to induce them to hold such securities, greater premium must be paid per unit of liquidity beta. This implies that the liquidity risk premium is also time varying and is greater during periods of high preference uncertainty.

We begin our empirical analysis by examining the dynamics of liquidity betas. Using two extreme size deciles as the proxies for the most and the least liquid portfolios, we estimate a bivariate regime-switching model that allows both time-series and cross-sectional variations in liquidity betas. Consistent with our hypothesis, we find that liquidity betas of the two portfolios vary over time across two distinct states, one with high liquidity betas and the other with low betas. The transition from the low to the high liquidity-beta state is predicted by a rise in trading volume, indicating that preference uncertainty is indeed the key state variable underlying the liquidity-beta dynamics. We also find that the spread in liquidity betas across the two states is greater for illiquid than liquid stocks, which supports our conjecture that illiquid stocks' liquidity betas are more sensitive to the state of preference uncertainty. Furthermore, our analysis reveals that the high liquidity-beta state is associated with high volatility and is preceded by a period of declining expectations about future macroeconomic conditions and stock market liquidity. The high liquidity-beta state is also less persistent and occurs less than one tenth of the time, implying that it represents an 'abnormal' trading regime.

To test the existence of time variation in liquidity risk premium, we construct a conditional liquidity factor and examine its pricing in the cross section of stock returns. The conditional factor simply equals the liquidity factor during the high liquidity-beta months and zero otherwise. It is thus designed to capture the additional impact of market liquidity on stock returns during periods of high preference uncertainty. Our asset pricing tests indicate that the premium on the conditional liquidity factor is statistically significant, controlling for the market, size, value, and momentum factors, as well as the illiquidity levels of test assets. The results are robust to a number of controls using additional risk factors, various stock characteristics, different sets of test assets, and alternative methods of state identification. Importantly, we find that the pricing of the conditional liquidity factor is also economically significant. The premium on its mimicking portfolio is 1.5% per month, more than twice the value premium in our sample. We argue that this premium is not unreasonably high, given that it is rendered only about one tenth of the time.

Lastly, our framework allows us to study the relationship between illiquidity premium and liquidity risk premium. Consistent with previous findings, illiquid portfolios have higher average returns than liquid portfolios unconditionally; the mean excess return spread between the two extreme liquidity-sorted deciles is 0.48% per month. However, this illiquidity-return relationship exhibits a noticeable difference between the two liquidity-beta states. During the 'normal' low liquidity-beta months, the relationship between illiquidity and return is virtually flat across the ten portfolios. In contrast, during the 'abnormal' high liquidity-beta months, excess returns strongly increase in illiquidity. The mean spread between the two extreme deciles is a startling 5.4% per month. This implies that illiquidity premium on average is rendered strongly and only in the high liquidity-beta state. Given our earlier finding that the conditional liquidity factor is significantly priced after controlling for the illiquidity characteristic, our results suggest that the illiquidity premium is delivered primarily in the form of beta risk premium with respect to the liquidity factor during periods of high preference uncertainty.

To our knowledge, there are only a couple of empirical studies that investigate the dynamic nature of illiquidity premium or liquidity risk premium, but none of them does so in the cross section of stock returns. Longstaff (2004) finds large illiquidity premia in the Treasury bond prices and shows that they are correlated with market sentiment measures, such as changes in the consumer confidence index. Gibson and Mougeot (2004) document that the liquidity risk premium in the aggregate stock-market index has a time-varying component related to the probability of future recession. Our work adds to this line of research by shedding new light on the mechanism driving the joint dynamics of liquidity betas and liquidity risk premium.

The remainder of the paper is organized as follows. The next section explains our hypotheses in detail and estimates a regime-switching model with time-varying liquidity betas. Section 2 conducts asset pricing tests with a conditional liquidity factor, followed by a battery of robustness tests. It also discusses the characteristics of the high liquidity-beta state and the economic significance of the conditional liquidity risk premium. The final section concludes.

1 Time Variation in Liquidity Betas

1.1 Liquidity Risk and Preference Uncertainty

We study the dynamics of liquidity betas and liquidity risk premium based on the model of Gallmeyer, Hollifield, and Seppi (2005) which incorporates the idea that, in the actual market, investors are unlikely to have complete knowledge about each other's future preferences. Preference uncertainty may arise from a variety of reasons including stochastic risk aversion, temporary liquidity needs, endowment shocks, uncertain habits, and random market participation. In such environment, trading becomes an important source of information from which investors can learn, either fully or partially, about the preferences driving their counterparties' future asset demands. The resulting level of preference uncertainty is hence endogenously determined depending on the amount of information revealed by trading. To understand how preference uncertainty is incorporated in our hypotheses, we first illustrate the information-revealing role of trading using an example.

Assume that the first source of preference uncertainty is stochastic risk aversion. Consider investor X who has no prior knowledge about investor Y's risk aversion, and X believes that Y is either risk averse or tolerant. For simplicity, Y's risk aversion is fixed over time. The risk averse type of Y will place a large sell rebalancing order in each of the next two periods, while the risk tolerant type will sell only a small amount. Suppose that there is another source of preference uncertainty arising from Y's random liquidity need. If Y is subject to a large liquidity need in a given period, he will add a large sell component to his order. Otherwise, the addition will be small. The large liquidity need is temporary and occurs in at most one of the next two periods or does not occur at all. The exact size of the 'large' rebalancing and liquidity components is unknown, so that any single large sell trade does not perfectly reveal Y's preferences. Given the above assumptions, there are initially six combinations of Y's possible preferences, $\Psi_0 = \{(A,S,S),(A,L,S),(A,S,L),(T,S,S),(T,L,S),(T,S,L)\}$. The first argument of each parenthesis represents Y's risk aversion (Averse or Tolerant), and the second and third arguments indicate the size of Y's liquidity need (Large or Small) in the first and second periods, respectively.

Now suppose that in the first period, X experiences a strong sell pressure from Y, which is consistent with Y either being risk averse or suffering from a large liquidity need. This allows X to exclude the (T, S, S) and (T, S, L) types of Y who would have placed a small sell order in the first period. The set of Y's likely preference combinations is therefore reduced to $\Psi_{1U} = \{(A, S, S), (A, L, S), (A, S, L), (T, L, S)\}$, but still exposes X to both sources of preference uncertainty (hence the subscript U for 'uncertain'). Alternatively, if X receives a small sell order in the first period, this immediately reveals that Y is risk tolerant. In this case, the only source of uncertainty that X faces is Y's future liquidity need and the set of Y's likely preferences becomes $\Psi_{1C} = \{(T, S, S), (T, S, L)\}$ (with a subscript C for 'certain'). Applying the same reasoning, we can also see the effect of trading in the second period. If X encounters two consecutive large sell orders, the set of Y's possible preferences is further reduced to $\Psi_2 = \{(A, S, S), (A, L, S), (A, S, L)\}$, but still leaves uncertainty about Y's liquidity need. In all the other cases, the second-period trading fully reveals Y's preferences.

While stylized, the above example demonstrates the idea that trading reveals counterparty preferences and that the extent of such revelation is related to the level of trading volume. Gallmeyer, Hollifield, and Seppi (2005) provide examples in which trading volume below a threshold fully reveals the counterparty preferences while volume above it does so only partially. This suggests that a large increase in trading volume can trigger the economy to abruptly switch from a low to a high preference uncertainty regime.

Our goal is to study whether changes in the prevailing level of preference uncertainty affect time variations in liquidity betas and liquidity risk premium. We develop our hypotheses by introducing transaction cost in the above setting and considering how its effect changes as the economy moves from the low to the high preference uncertainty state.

Amihud (2002) proposes that the empirically observed persistence in illiquidity implies a negative contemporaneous relationship between aggregate illiquidity shocks and stock returns.[1] An unexpected increase in market illiquidity leads to higher realized illiquidity today and predicts higher expected future illiquidity due to its persistence. Since investors demand compensation for the anticipated increase in future transaction cost, they require higher expected returns

[1] The persistence in liquidity also implies predictive ability of market liquidity for future stock returns. This proposition is empirically confirmed by Amihud (2002), Jones (2002), and Bekaert, Harvey, and Lundblad (2005).

which in turn depress current stock prices. Acharya and Pedersen (2005) also illustrate this point based on their liquidity-adjusted Capital Asset Pricing Model. The empirical evidence on the negative sensitivities of stock returns to aggregate illiquidity shocks–or equivalently positive liquidity betas–is provided by Amihud (2002) using size portfolios and Acharya and Pedersen (2005) using illiquidity-sorted portfolios.

We now argue that, during periods of high preference uncertainty, investors become more concerned about future tradability of assets and require greater price concessions for the anticipated increase in future transaction cost caused by a unit aggregate illiquidity shock. Consider investor X in the above example and assume that he experiences an unexpected increase in transaction cost in the first period. Suppose further that X needs to place a sell order in the second period, because he is a short-horizon investor who needs to close out his position or because he follows a dynamic trading strategy that requires him to do so. There is a greater concern about future tradability when X faces Ψ_{1U} rather than Ψ_{1C}, since the former includes the (A, S, L) type of Y whose large sell order can depress the second-period price substantially. Hence, when faced with high preference uncertainty under Ψ_{1U}, X requires greater compensation for the possible increase in transaction cost which can further exacerbate future tradability. We therefore expect to observe larger price declines in response to a unit aggregate illiquidity shock, or larger liquidity betas, in the state of high preference uncertainty.

Extending the above argument, we also consider whether there is a cross-sectional asymmetry in the dynamics of liquidity betas. Heightened uncertainty about future asset demands is likely to impose a greater concern for investors who hold illiquid stocks that already exhibit low levels of tradability. Thus, we expect that these investors require even more compensation for the expected increase in future transaction cost especially during periods of high preference uncertainty. This implies that illiquid stocks' liquidity betas are more sensitive to the state of preference uncertainty and exhibit greater time variation compared to liquid stocks' liquidity betas.

Lastly, we consider the link between preference uncertainty and the liquidity risk premium. Pastor and Stambaugh (2003) argue that stocks with high liquidity betas, when held in levered position, can expose investors to liquidation need when market liquidity dries up. The prominent example of such liquidation event is the 1998 collapse of the Long Term Capital Management triggered by the Russian bond default. Since investors dislike the possibility of costly liquidation, they require greater price concessions to hold stocks whose returns are more sensitive to liquidity. We propose that, when investors are strongly concerned about future asset tradability due to high preference uncertainty, they are less willing to hold stocks that are likely to necessitate costly liquidation. To see this, assume that investor X in the above example has a levered position in a stock with a positive liquidity beta in the first period. The possibility of costly liquidation is particularly unwelcome for X when he faces Ψ_{1U} instead of Ψ_{1C}. This is because the former, which includes the (A, S, L) type of Y, can potentially cause a large drop in the second-period price and depreciate the value of X's position further, making the liquidation even more costly. Hence, we expect X to require greater premium per unit of liquidity beta when he faces higher preference uncertainty under Ψ_{1U}.

Based on the above discussions, we test the following three hypotheses:

Hypothesis 1 *Liquidity betas are time varying. High (low) liquidity betas arise in the state of high (low) preference uncertainty. The transition from the low to the high preference uncertainty state is predicted by elevated trading volume.*

Hypothesis 2 *There is a cross-sectional asymmetry in the dynamics of liquidity betas. Illiquid stocks' liquidity betas vary more across states of high and low preference uncertainty than liquid stocks' liquidity betas.*

Hypothesis 3 *Liquidity risk premium is time varying and is greater in the state of high preference uncertainty.*

1.2 Methodology

Our hypotheses imply that both high liquidity betas and large liquidity risk premium arise simultaneously at times of high preference uncertainty. Therefore, we conduct our empirical analysis by first identifying states with different levels of liquidity betas and then examining whether the liquidity risk premium varies across these states. We use a multivariate Markov regime-switching model for the identification of the liquidity-beta states.[2] The model is suitable since it allows us to examine both the time-series and the cross-sectional properties of liquidity betas jointly and to test whether trading volume serves as a predictive state variable for the shifts across different liquidity-beta states.

[2]Regime-switching models are popularly used to estimate economic states. For applications in finance, see Bekaert and Harvey (1995), Perez-Quiros and Timmermann (2000), and Ang and Bekaert (2002) among others.

Specifically, we fit the following bivariate model to the excess returns of the smallest and largest size portfolios:

$$\boldsymbol{r}_t = \boldsymbol{\alpha}_{s_t} + \boldsymbol{\beta}_{s_t}^{LIQ} LIQ_t + \boldsymbol{\varepsilon}_t, \tag{1}$$

where $\boldsymbol{r}_t$, $\boldsymbol{\alpha}_{s_t}$, and $\boldsymbol{\beta}_{s_t}^{LIQ}$ are 2 by 1 vectors of excess returns, intercepts, and liquidity betas, respectively, and $s_t = 1, 2$ represents states. That is,

$$\boldsymbol{r}_t = \begin{pmatrix} r_{S,t} \\ r_{L,t} \end{pmatrix}, \boldsymbol{\alpha}_{s_t} = \begin{pmatrix} \alpha_{S,s_t} \\ \alpha_{L,s_t} \end{pmatrix}, \boldsymbol{\beta}_{s_t}^{LIQ} = \begin{pmatrix} \beta_{S,s_t}^{LIQ} \\ \beta_{L,s_t}^{LIQ} \end{pmatrix}, \tag{2}$$

with S and L denoting the smallest and largest deciles, respectively, of the size-sorted portfolios (given by the value-weighted size portfolios of the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) stocks obtained from the Center for Research in Security Prices (CRSP) of the University of Chicago). Note that this specification nests a standard multivariate linear regression model with constant coefficients if $\boldsymbol{\alpha}_1 = \boldsymbol{\alpha}_2$ and $\boldsymbol{\beta}_1^{LIQ} = \boldsymbol{\beta}_2^{LIQ}$, and if other parameters to be introduced below are equal between the states.

The residual vector in (1) is assumed to follow a bivariate Gaussian process with a state-dependent variance-covariance matrix,

$$\boldsymbol{\varepsilon}_t | s_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{L,t} \end{pmatrix} \sim N(0, \Omega_{s_t}), \qquad \Omega_{s_t} = \begin{pmatrix} \sigma_{S,s_t}^2 & \rho_{s_t}\sigma_{S,s_t}\sigma_{L,s_t} \\ \rho_{s_t}\sigma_{S,s_t}\sigma_{L,s_t} & \sigma_{L,s_t}^2 \end{pmatrix}. \tag{3}$$

This implies that returns are drawn from a mixture of bivariate normals with a binomial mixing variable. Hence, we allow the volatility and correlation to vary across the two states.

Finally, we assume that the state transition is governed by a Markov switching probability,

$$\Pr(s_t = s | s_{t-1} = s; x_{t-1}) = \frac{\exp(c_{s_t} + \boldsymbol{d}_{s_t}' \boldsymbol{x}_{t-1})}{1 + \exp(c_{s_t} + \boldsymbol{d}_{s_t}' \boldsymbol{x}_{t-1})}, \quad s = 1, 2, \tag{4}$$

where $\boldsymbol{x}$ is a vector of state variables to help predict the high liquidity-beta state, $\boldsymbol{d}_{s_t}$ is a conforming vector of coefficients, and c_{s_t} is a scalar. The exponential transformation ensures that the probability always falls between 0 and 1. The preference uncertainty model suggests trading volume as a premier candidate for state variable. We use aggregate detrended share turnover ($STOV$) as a measure of trading volume. As a robustness test, we will later examine other state variables. The construction of $STOV$ and all the other state variables is explained in Appendix A.1.

Several comments about the above formulation follow. First, for ease of interpretation, we have allowed only two possible states, $s_t = 1$ or 2, so that the parameters in equations (1)-(4) are either $(\boldsymbol{\alpha}_1, \boldsymbol{\beta}_1^{LIQ}, \Omega_1, c_1, \boldsymbol{d}_1)$ if $s_t = 1$ or $(\boldsymbol{\alpha}_2, \boldsymbol{\beta}_2^{LIQ}, \Omega_2, c_2, \boldsymbol{d}_2)$ if $s_t = 2$. Formally, one could conduct a model specification test and search for the optimal number of states. The resulting states, however, could be difficult to interpret. Our choice of two states allows us to easily classify them as either a high or a low liquidity-beta state. This is also consistent with the examples of Gallmeyer, Hollifield, and Seppi (2005) in which volume below a threshold indicates no preference uncertainty and volume above it represents high preference uncertainty.

Second, the model imposes common states only for the smallest and largest deciles. Preferably, we wish to do so for a larger number of cross sections. This, however, makes the estimation progressively more difficult because of the exploding number of parameters. For example, if all the decile portfolios are used, the number of parameters to be estimated is 154 even with two states and a single state variable. Our simple bivariate model with only one state variable already has 18 parameters.[3] In a later section, we will provide suggestive evidence to support the use of the two extreme deciles; namely, liquidity betas vary almost monotonically across ten liquidity-sorted portfolios in each of the two identified states.

Third, equation (1) does not control for factors typically used in asset pricing tests, especially the market return. Aside from being parsimonious, this is appropriate and preferred for the purpose of state identification. For example, if we included the market return, the estimated liquidity betas would in one sense be those conditional on it. Rather, we know from existing studies that unexpected liquidity shocks and the market return are correlated [see, e.g., Amihud (2002)], and we consider the level of the market return to be an important characteristic of the high liquidity-beta state.[4] Needless to say, however, we will rigorously control for known factors in our asset pricing tests.

Finally, we use excess returns on the CRSP size-sorted portfolios as dependent variables. An obvious alternative is to use liquidity-sorted portfolios. We will show later that our results are robust to such a change. Here, we emphasize the advantages of our choice. First, size portfolios are known to produce significant cross-sectional variations in quantities of interest, such as return, volatility, volume, and most importantly for our purpose, liquidity. Second, using the

[3]In general, an n variate version of our regime-switching model with two states and a single state variable involves $n^2 + 5n + 4$ parameters.

[4]Nevertheless, we did estimate the system including the market return in equation (1). The basic asset pricing results were not altered.

standard dataset facilitates the comparison of our results to the existing literature and suggests directions for our robustness tests. For example, the CRSP size-sorted portfolios are also used in the study of Amihud (2002). As he points out, we will later find that small firms' returns are more strongly affected by liquidity shocks than large firms' returns. In addition to this cross-sectional asymmetry, Perez-Quiros and Timmermann (2000) identify different dynamic patterns in size-sorted portfolio returns; specifically, they find that small and large firms' returns vary asymmetrically over time across economic expansions and recessions due to their differential exposures to credit risk. These findings clearly suggest the need to control for the size and default risk factors in our asset pricing tests.

1.3 Data and Construction of the Liquidity Measure

We now describe the data and the construction of the liquidity measure. Researchers have proposed several methods to create monthly liquidity series from standard datasets such as CRSP over periods long enough for asset pricing tests. To be consistent with the notion of illiquidity studied in Gallmeyer, Hollifield, and Seppi (2005), we choose Amihud's (2002) price impact proxy as a measure of illiquidity. It is simple to construct and yet is known to be highly correlated with price impact measures calculated from high frequency data [Hasbrouck (2005)].

Following Amihud (2002), we first compute the price impact measure for individual stocks, $PRIM$, as

$$PRIM_{j,t} = \frac{1}{D_{j,t}} \sum_{d=1}^{D_{j,t}} \frac{|r_{j,d,t}|}{v_{j,d,t}}, \tag{5}$$

where $r_{j,d,t}$ and $v_{j,d,t}$ are the return and dollar volume (measured in millions), respectively, of stock j on day d in month t, and $D_{j,t}$ is the number of daily observations during that month. We use ordinary common shares on NYSE and AMEX with $D_{j,t} \geq 15$ and the beginning-of-the-month price between \$5 and \$1,000.[5] The aggregate price impact, $APRIM$, is simply the cross-sectional average of individual $PRIM$,

$$APRIM_t = \frac{1}{N_t} \sum_{j=1}^{N_t} PRIM_{j,t}, \tag{6}$$

where N_t is the number of stocks included in month t, which ranges between 1,282 and 2,129

[5]Following the common practice, NASDAQ stocks are excluded because their reported volumes may be overstated due to the inclusion of inter-dealer trades.

from August 1962 through December 2004. Although the above formulation is based on an equally weighted average, we obtain qualitatively similar asset pricing results when $APRIM$ is computed on a value weighted basis.[6] Since $APRIM$ is highly persistent, we fit the following modified AR(2) model using the whole sample:[7]

$$\left(\frac{m_{t-1}}{m_1}APRIM_t\right) = \alpha + \beta_1\left(\frac{m_{t-1}}{m_1}APRIM_{t-1}\right) + \beta_2\left(\frac{m_{t-1}}{m_1}APRIM_{t-2}\right) + \varepsilon_t, \qquad (7)$$

where m_{t-1} is the total market capitalization at month $t-1$ of the stocks included in the month t sample and m_1 is the corresponding value for the initial month, August 1962. In the above formulation, the ratio m_{t-1}/m_1 serves as a common detrending factor that controls for the time trend in $APRIM$.[8] Throughout the equation, the same factor is multiplied to the contemporaneous and lagged $APRIM$ to capture only the innovations in illiquidity; multiplying lags of m_{t-1}/m_1 may introduce shocks induced mechanically by price changes. This adjustment is used by Pastor and Stambaugh (2003) and Acharya and Pedersen (2005).

The errors in equation (7) are the measure of unexpected illiquidity shocks. We use the negative estimated residuals, $-\widehat{\varepsilon}_t$, as our liquidity measure, LIQ_t. Panel (a) of Figure 1 plots the time series of LIQ with dotted vertical lines representing the NBER business cycle dates (each narrow band corresponds to a contraction). Occasional plunges in LIQ coincide with major economic crises such as the Penn Central commercial paper debacle of May 1970, the oil crisis of November 1973, the stock market crash (the Black Monday) of October 1987, the Asian financial crisis of 1997, and the Russian bond default of 1998.

1.4 Empirical Estimation of the High Liquidity-Beta State

Table 1 reports the estimated parameters of the bivariate regime-switching model given in equations (1)-(4) with $STOV$ as the single state variable, $\boldsymbol{x}$. The estimation is by maximum likelihood using a monthly sample from January 1965 through December 2004.[9]

Consistent with Amihud (2002) and Acharya and Pedersen (2005), we observe significant positive relationships between liquidity shocks and contemporaneous returns, as indicated by

[6] The results are available upon request.

[7] $APRIM$ has the first and second-order autocorrelations of 0.878 and 0.858, respectively, whereas the liquidity shock, LIQ, to be introduced below, has a first-order autocorrelation of only -0.020.

[8] $APRIM$ has generally decreased over time with an exception from the late 1990's through the early 2000's when market volatility increased substantially. The declining trend is due to a steady increase in trading volume.

[9] We lose the first two years of $STOV$ due to its detrending method described in Appendix A.1. To align the sample period for all the variables, we use the period starting in January 1965.

the positive estimates of liquidity betas for the two extreme size deciles in both states ($\beta_{i,1}^{LIQ} > 0$ and $\beta_{i,2}^{LIQ} > 0$, $i = S, L$). In addition, we find that the liquidity betas of the two portfolios vary across two distinct states, State 1 with low liquidity betas and State 2 with high liquidity betas ($\beta_{i,1}^{LIQ} < \beta_{i,2}^{LIQ}$, $i = S, L$). The likelihood ratio tests strongly reject the null hypothesis that $\beta_{i,1}^{LIQ} = \beta_{i,2}^{LIQ}$ with p-values below 1% for both deciles. We therefore call States 1 and 2 the low and the high liquidity-beta states, respectively, and use these terms interchangeably in the rest of this paper.

Table 1 also shows that $STOV$ contributes significantly to the identification of the liquidity-beta states. The restriction that $d_1 = d_2 = 0$ is rejected at the 5% level. A negative d_1 coefficient on $STOV$ implies that large abnormal volume tends to reduce the probability of staying in the low liquidity-beta state and consequently move the economy to the high liquidity-beta state. This is consistent with a view that trading volume serves as a proxy for the level of preference uncertainty. Hence, in support of our first hypothesis, we find evidence that liquidity betas are time varying and that the transition from the low to the high liquidity-beta state is predicted by elevated trading volume.

A notable finding from Table 1 is the cross-sectional difference in liquidity beta spreads. The spread between the two states is 0.139 (= 0.192 − 0.053) for the smallest decile and 0.064 (= 0.085 − 0.021) for the largest. The likelihood ratio test on the equality of the spreads,

$$\beta_{S,2}^{LIQ} - \beta_{S,1}^{LIQ} = \beta_{L,2}^{LIQ} - \beta_{L,1}^{LIQ}$$

indicates that the cross-sectional difference in the spreads is significant at the 1% level. The result is consistent with our second hypothesis that more illiquid stocks exhibit greater variation in their liquidity betas across the high and low liquidity-beta states. Amihud (2002) and Acharya and Pedersen (2005) previously find that small illiquid stocks have higher liquidity betas than large liquid stocks on average across all economic states. Our result adds to theirs by documenting that such cross-sectional asymmetry in liquidity betas exhibits state-dependent time variation.

Furthermore, Table 1 also shows that the two states are characterized by differences in volatility and persistence. The low liquidity-beta state has lower volatility than the high liquidity-beta state ($\sigma_{i,1} < \sigma_{i,2}$, $i = S, L$); the likelihood ratio test rejects the null of equal volatility ($\sigma_{i,1} = \sigma_{i,2}$) for the smallest decile. This is a manifestation of the well-known conditional heteroskedasticity in stock returns. Moreover, the high liquidity-beta state is less persistent than the low liquidity-beta state. The average durations of the low and high liquidity-beta states evaluated at mean $STOV$ are 8.3 and 1.7 months, respectively.[10] This point is graphically demonstrated in Panel (b) of Figure 1, which plots the estimated probability of being in the high liquidity-beta state. It is visually clear that whenever the probability rises up close to 1, it drops back quickly within a few months. The short duration of the high liquidity-beta state is consistent with the feature of an 'abnormal' state. The sharp spikes in the probability coincide with some of the economic crises noted earlier, such as the Black Monday of October 1987 and the Russian bond default of August 1998. However, they also include non-crisis periods, and in fact many of them do not correspond to the LIQ plunges in Panel (a). We will later observe that the high liquidity-beta state is a mixture of months with large positive and negative liquidity shocks accompanied by elevated trading volume.

Overall, consistent with the preference uncertainty story, our analysis shows that liquidity betas are high and exhibit a large cross-sectional dispersion during periods of high trading volume.

1.5 Alternative State Variables

Before conducting asset pricing tests, this section examines whether different state variables can also predict the high liquidity-beta state. The first alternative we consider is the aggregate volatility (VOL). In the preference uncertainty model, volatility is expected to rise in the state of high preference uncertainty where trading reveals more information about investors' future asset demands [Gallmeyer, Hollifield, and Seppi (2005)]. Elevated volatility can thus be an indirect sign of heightened preference risk and increased probability of the high liquidity-beta state occurring. In a different context, Vayanos (2004) also emphasizes the role of market volatility in the variation of illiquidity premium. In his model, investors are assumed to be fund managers subject to fund withdrawals when their performance falls below a threshold. Since their fee income is proportional to the size of the funds they manage, their preference toward liquid assets rises during volatile times. This creates time variation in risk premium induced by changing volatility. In contrast to the preference uncertainty model, however, there is no role

[10] The mean of $STOV$ is $\overline{x} = 0.1472$ and 0.1979 for States 1 and 2, respectively (see Panel (b) of Table 5). Using the parameter estimates from Table 1, $c_s + d_s\overline{x}$ is $1.992 \equiv f_1$ for State 1 and $-0.293 \equiv f_2$ for State 2. This gives $e^{f_1}/(1+e^{f_1}) = 0.880 \equiv p$ and $e^{f_2}/(1+e^{f_2}) = 0.427 \equiv q$. The average durations in the text are given by $1/(1-p)$ and $1/(1-q)$.

for trading volume since his model can be rewritten in a representative agent framework.

We also consider the following three macroeconomic measures as alternative state variables: Stock and Watson's (1989) experimental recession index (XRI), the annual log difference ($LEAD$) in the leading economic indicator from the Conference Board, and the consumer expectation index ($CEXP$) from the University of Michigan. XRI provides an estimate of the probability that the economy will be in a recession six months hence, the leading economic indicator is a composite index of ten variables representing economic activity and financial markets, and $CEXP$ reflects changes in consumer attitudes concerning future economic conditions. Longstaff (2004) finds that a decline in the consumer confidence index is associated with increased illiquidity premia in the Treasury bond prices. Gibson and Mougeot (2004) document a significant positive effect of the experimental recession index on the aggregate liquidity risk premium in the stock market.[11] If macroeconomic uncertainty is linked to preference uncertainty, for example through changes in investors' risk aversion, variables proxying for the economy-wide uncertainty should predict changes in the liquidity-beta states. We expect that declining expectations about future macroeconomic conditions, represented by a rise in XRI and declines in $LEAD$ and $CEXP$, predict an increased probability of the economy shifting into the high liquidity-beta state. Panel (a) of Table 2 summarizes the state variables and their expected effects on the transition of the liquidity-beta states.

The column labeled 'Alone' in Panel (b) of Table 2 reports the estimated d_1 coefficient on each alternative state variable when it is the sole element of $\boldsymbol{x}$ in equation (4) (the estimate for $STOV$ is from Table 1). The signs of all the estimated coefficients are intuitive and consistent with our arguments above. The negative coefficients on VOL and XRI imply that the economy tends to move from the low to the high liquidity-beta state when the stock market becomes volatile and the probability of a near-term recession rises. In contrast, the positive coefficients on $LEAD$ and $CEXP$ indicate that the economy is likely to stay in the low liquidity-beta state when economic activities improve and consumer expectations become bullish.[12]

To compare the predictive ability of $STOV$ against that of the alternative variables, the

[11] Eisfeldt (2005) and Johnson (2006) provide theoretical models that explain the dynamic relationship between liquidity and macroeconomic fundamentals, and Fujimoto (2004) provides an empirical investigation on this topic.

[12] We also studied the default spread, term spread, and money market mutual fund flows as alternative state variables. The use of these variables was motivated by the existing literature which finds that the default and term spreads represent priced risk factors in the bond and/or stock markets (see, e.g., Chen, Roll, and Ross (1986) and Fama and French (1993)). Longstaff (2004) identifies a significant relationship between money market fund flows and illiquidity premia in the Treasury market. The ability of these variables to predict liquidity-beta states was weak, however, and the results were therefore omitted.

column labeled 'All' shows the estimated $\boldsymbol{d}_1$ coefficient vector when all the five variables are included together in $\boldsymbol{x}$. As we can see, while the significance of the macroeconomic variables (XRI, $LEAD$, and $CEXP$) considerably weakens, the two stock market variables ($STOV$ and VOL) remain significant, with $STOV$ exhibiting a much higher t-statistic (-2.98) than VOL (-2.36). We have examined various sets of initial values and found that $STOV$ is more robust than VOL. This is consistent with our hypothesis that changes in preference uncertainty, proxied by $STOV$, is the main driver of the liquidity-beta dynamics. Based on these results, we keep $STOV$ as the only state variable for the subsequent analysis.

2 Time Variation in the Liquidity Risk Premium

This section tests our third hypothesis by investigating whether the liquidity risk premium varies across the two liquidity-beta states identified in the previous section.

2.1 Estimation of the Conditional Liquidity Risk Premium

First, we describe our asset pricing model. We assume that excess returns are generated by a standard K-factor structure,

$$r_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_i^k F_t^k + \varepsilon_{i,t}, \tag{8}$$

where $r_{i,t}$ is the excess return on asset i at time t, α_i is a constant, F_t^k is the k-th factor, β_i^k is the loading of asset i on the k-th factor, and $\varepsilon_{i,t}$ is the residual. In this factor pricing model, expected excess returns are a linear function of factor loadings,

$$\boldsymbol{E}_{t-1}[r_{i,t}] = \alpha_i + \sum_{k=1}^{K} \lambda^k \beta_i^k, \tag{9}$$

where λ^k is the risk premium for the k-th factor.

To examine whether the liquidity risk premium exhibits time variation driven by the state of preference uncertainty, we introduce a conditional liquidity factor, $CLIQ$, constructed as

$$CLIQ_t = I_t \cdot LIQ_t.$$

I_t is an indicator variable for the high liquidity-beta state such that $I_t = 1$ if the estimated probability of being in State 2 is higher than 0.75 in month t and 0 otherwise. We regard month t as being in the high liquidity-beta state if $I_t = 1$. Out of 480 months from January 1965 through December 2004, there are 43 such months. While the choice of the probability threshold is somewhat arbitrary, we will later confirm that the use of other reasonable levels between 0.5 and 1 leads to similar asset pricing results (see Section 2.5.7). This can also be seen from Panel (b) of Figure 1 which shows an all-or-nothing tendency of the State-2 probability once it exceeds 0.5.

To understand the role of $CLIQ$, consider a simple return generating process,

$$r_{i,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{LIQ} LIQ_t + \beta_i^{CLIQ} CLIQ_t + \varepsilon_{i,t}, \tag{10}$$

where MKT is the excess return on the CRSP value-weighted portfolio. The above equation can be rewritten as

$$r_{i,t} = \alpha_i + \beta_i^{MKT} MKT_t + (\beta_i^{LIQ} + \beta_i^{CLIQ} I_t) LIQ_t + \varepsilon_{i,t}. \tag{11}$$

The term $\beta_i^{CLIQ} I_t$ captures the time variation in liquidity beta and makes the beta effectively β_i^{LIQ} in State 1 and $\beta_i^{LIQ} + \beta_i^{CLIQ}$ in State 2. Given the nature of State 2 as the high liquidity-beta state, we expect β_i^{CLIQ} to be positive. We call β_i^{CLIQ} the conditional liquidity beta.

We follow the standard Fama-MacBeth (1973) two-pass procedure to estimate betas and premia in equations (8) and (9). We use the entire sample in our beta estimation; the rolling beta approach is not appropriate in our study that makes use of an indicator variable.[13] To account for the possible errors-in-variables problem, we employ the correction for standard errors proposed by Shanken (1992).[14]

2.2 Characteristics of the Liquidity Portfolios

We form our test portfolios by sorting the NYSE and AMEX stocks on the basis of the book-to-market ratio (B/M) and the price impact proxy ($PRIM$) using the NYSE breakpoints.[15] This accords to the usual practice of forming test assets on the basis of size and B/M, while

[13]Specifically, I_t can be 0 for some rolling periods and consequently the regressor matrix can become singular. A subperiod test is not appropriate either because I_t has a limited number of non-zero entries (43 months) as noted earlier.

[14]The use of the Shanken (1992) correction should make our estimates fairly conservative; Jagannathan and Wang (1998) point out that when returns are conditionally heteroskedastic, the Fama-MacBeth (1973) procedure without the correction does not necessarily understate the standard errors of estimated parameters.

[15]We will later include NASDAQ stocks in our test portfolios and also use individual stocks as test assets.

recognizing the fact that the size and liquidity characteristics are cross-sectionally highly correlated. Balancing the desire to produce sufficient dispersion in liquidity betas and to represent as diverse cross sections as possible, we replace size with $PRIM$. Later, however, we will explicitly include size in the sorting keys to make sure this does not unduly favor our result. The portfolios are formed at the end of each year from 1964 through 2003, and the value-weighted monthly portfolio returns are calculated for the subsequent years from January 1965 through December 2004. Stocks are admitted to portfolios if they have the end-of-the-year prices between \$5 and \$1000 and more than 100 daily-return observations during the year.

We first look at the characteristics of the decile portfolios sorted only on $PRIM$ as summarized in Panel (a) of Table 3. Rank 1 represents the lowest $PRIM$ (most liquid) and rank 10 the highest (least liquid). Appendix A.2 describes the computation of characteristics. Consistent with our prior knowledge about illiquidity premium, the average raw return, r, generally increases with $PRIM$ and so does a return volatility measure, σ^r. A monotonic increase in $PRIM$ and the absolute value of Pastor and Stambaugh's (2003) return reversal measure ($RREV$) indicates that we continue to get dispersion in illiquidity levels after portfolio formation. All the other characteristics exhibit expected near-monotonic relations with the $PRIM$ ranking; more illiquid stocks tend to have more volatile $PRIM$ (σ^{PRIM}), lower turnover ratio (TOV), lower price (PRC), smaller market capitalization, and greater B/M ratio (although the relation for TOV is not strictly monotone). These results suggest that it is important to control for the size and value factors as well as the illiquidity characteristic in our asset pricing tests. The disproportionately large average number of stocks (N) in the most illiquid portfolio indicates that AMEX stocks are much less liquid than NYSE stocks in general.

The last two columns show the estimated portfolio betas on LIQ and $CLIQ$ in equation (10). We observe that both β^{LIQ} and β^{CLIQ} increase almost monotonically with $PRIM$. The two betas are negative for the most liquid portfolio because they are estimated conditional on MKT in the multiple regression; the adjustment for MKT reduces the liquidity effect on portfolio returns since MKT and LIQ are positively correlated. Hence, the result that $\beta^{CLIQ} < \beta^{LIQ}$ for liquid portfolios is due to this conditioning and does not invalidate State 2 as being the high liquidity-beta state. Importantly, the cross-sectional dispersion in β^{CLIQ} is much larger than the dispersion in β^{LIQ}; the difference between the two extreme $PRIM$ deciles is 0.067 for β^{CLIQ} as opposed to 0.034 for β^{LIQ}. Figure 2 demonstrates this point graphically. Since β^{CLIQ} is the beta spread between the two states (see equation (11)), the dispersion in

State-2 liquidity betas between the extreme deciles is the sum of these two numbers, 0.101.

Panel (b) of Table 3 reports selected summary statistics for the 25 portfolios formed as the cross section of B/M and $PRIM$ quintiles (rank 1 has the lowest value of each characteristic). In Panel (b)(i), we observe that the average raw return generally increases with both B/M and $PRIM$. Moreover, the illiquidity effect is stronger for value stocks (in the lower rows) and the B/M effect is stronger for illiquid stocks (in the right columns) with a caveat that we are perhaps partially picking up the size effect. Panel (b)(ii) confirms that we get dispersion in post-ranking illiquidity levels as measured by $PRIM$. The dispersion is slightly wider for value stocks than growth stocks.

Panels (b)(iii) and (iv) report the estimated portfolio liquidity betas. As expected, holding the B/M rank constant, illiquid stocks have higher β^{LIQ} and β^{CLIQ}. Again, the cross-sectional spread is wider for β^{CLIQ} and ranges between 0.042 and 0.058. Holding the $PRIM$ rank constant, however, the two betas behave differently; for the most illiquid stocks ($PRIM$ rank 5), β^{CLIQ} increases with B/M while the reverse is true for β^{LIQ}.[16] Nevertheless, it is clear that the sum of the two betas will exhibit a cross-sectional variation similar to that of β^{CLIQ}.

2.3 Main Results

Using the B/M5-$PRIM$5-sorted 25 portfolios, we estimate factor premia each month by a cross-sectional regression given in equation (9). Table 4 reports the time-series means of the premia in percent and their p-values in parentheses with the Shanken (1992) correction for standard errors. Column 1 shows the simplest model including only MKT and LIQ. Consistent with existing studies, the LIQ premium is positive although insignificant in this specification. The significant positive constant (along with a negative MKT premium), however, suggests omitted factors. Column 2 introduces $CLIQ$, which corresponds to the model in equation (10). While the LIQ premium changes its sign and remains insignificant, the factor of our interest, $CLIQ$, carries a significant positive premium. Moreover, both the constant and the MKT premium now become insignificant. Column 3 adds the size (SMB), B/M (HML), and momentum (UMD) factors. Although HML enters significantly, $CLIQ$ survives the inclusion of these factors commonly used in the asset pricing literature.

Acharya and Pedersen (2005) emphasize the importance of controlling for the level of illiquidity when estimating liquidity risk premium. To accommodate this point, we modify equation

[16] This is a potentially interesting point to pursue, but is left for future research.

(9) to include characteristics of the test portfolios [Daniel and Titman (1997)]:

$$\boldsymbol{E}_{t-1}[r_{i,t}] = \alpha_i + \sum_{k=1}^{K} \lambda^k \beta_i^k + \sum_{m=1}^{M} \lambda^m \theta_{i,t-1}^m, \tag{12}$$

where $\theta_{i,t-1}^m$ is the m-th characteristic for portfolio i at the end of month $t-1$. Using the lagged portfolio $PRIM$ as the only characteristic in equation (12), Column 4 of Table 4 indicates that the $CLIQ$ premium is robust to the inclusion of the illiquidity characteristic and is estimated to be 10.2% per unit beta. Note that $CLIQ$ is a non-traded factor and therefore its premium is not directly comparable to others'. We will later examine the economic significance of the $CLIQ$ premium using a factor mimicking portfolio. We will also control for other firm characteristics in the robustness test section.

The significant positive premium on $CLIQ$ supports our third hypothesis that the liquidity risk premium is time varying and is greater during periods of high preference uncertainty. Combined with our results from the previous sections, we find that both high liquidity betas and large liquidity risk premium arise simultaneously during periods of high trading volume.

2.4 Characteristics of the High Liquidity-Beta State

Given the evidence on the conditional pricing of liquidity risk in the cross section of stock returns, this section examines the characteristics of the high liquidity-beta state in more detail.

2.4.1 Illiquidity Premium and Liquidity Risk Premium

First, we study the state-dependent relationship between illiquidity premium and liquidity risk premium. In the preference uncertainty story, the periods of heightened preference risk with high premium are accompanied by greater stock price sensitivities to order flow because trading is more informative about future asset demands during these times. The level of illiquidity, measured by the price impact of trade, therefore appears to be priced in the state of high preference uncertainty [Gallmeyer, Hollifield, and Seppi (2005)]. Given the link between preference uncertainty and illiquidity premium, we expect that the periods of high liquidity betas and high liquidity risk premium also represent times of high illiquidity premium.

Panel (a) of Table 5 reports average monthly excess returns of the $PRIM$-sorted decile portfolios by state. Consistent with the usual notion of illiquidity premium, the unconditional return increases with the level of illiquidity (column labeled 'All'). This pattern, however, is not present in the low liquidity-beta state (State 1); the illiquidity-return relation is roughly flat with a zero return spread between the least and the most liquid portfolios. In contrast, the return exhibits a strong monotonic relation with illiquidity in the high liquidity-beta state (State 2); the return spread between the two extreme deciles is a striking 5.4% per month. The return difference across the states (State $2-1$) is also monotonically increasing in illiquidity and turns significantly positive for the four most illiquid portfolios.[17] These results are graphically represented in Figure 3; the steepness of the State-2 graph is in sharp contrast to the levelness of the State-1 counterpart. Overall, our analysis reveals that the illiquidity premium obtains strongly and only in the high liquidity-beta state. Moreover, since we find that the conditional liquidity risk premium is priced significantly after controlling for the level of illiquidity (see Column 4 of Table 4), a large portion of what we know as the illiquidity premium appears to be delivered in the form of beta risk premium with respect to the conditional liquidity factor.

Next, we examine whether other variables of interest also differ across states. At a first glance in Panel (b)(i) of Table 5, State 2 seems to be associated with liquidity shocks (LIQ) that are only marginally higher than, and excess market returns (MKT) that are insignificantly different from, State 1. This inference, however, is misleading since State 2 is a mixture of relatively large positive and negative LIQ months accompanied by elevated trading volume. This means that high liquidity-beta months are not equivalent to liquidity-crisis months with sharp drops in market liquidity.

To confirm the above point, subpanels (b)(ii) and (iii) further divide State 2 into months with positive (29 months) and negative (14 months) liquidity shocks, respectively (State 1 remains the same). We observe that State-2 months with positive and negative liquidity shocks on average experience large positive and negative excess market returns of 3.5% and -5.9%, respectively. This is also depicted in Figure 4, which plots the average raw returns of selected $PRIM$ decile portfolios (left scale) along with LIQ (right scale). The horizontal axis represents the number of months to State 2. Panel (a) shows that a positive liquidity shock in State 2 is associated with a cross section of positive returns. More illiquid portfolios earn higher returns, implying that they exhibit higher liquidity betas. The relation among illiquidity level, liquidity beta, and return is therefore monotonic. Panel (b) indicates a reversed pattern; a negative liquidity shock in State 2 is accompanied by a cross section of negative returns on

[17] In contrast, the difference is significantly negative for the most liquid portfolio. As we will see shortly, this is because State 2 is a mixture of months with large positive and negative liquidity shocks accompanied by elevated volume, and the returns on liquid stocks turn out to be negative on average for these months.

average. Unexpectedly, however, illiquid stocks still earn higher average returns than liquid stocks. A closer examination reveals that this is because illiquid stocks have higher returns during months with small negative LIQ; we confirmed that illiquid portfolios do indeed suffer from lower returns than liquid portfolios during months with relatively large negative liquidity shocks, including the Black Monday of October 1987 and the Russian bond default of August 1998 (results not shown). Furthermore, the figures illustrate that the liquidity risk premium is short lived. The cross section of stock returns deviate from normal levels only during a few months surrounding State 2.

Other characteristics of State 2 presented in Table 5 are easier to understand with the above points in mind. First, $STOV$ is significantly higher regardless of the sign of LIQ. This is consistent with our first hypothesis that elevated trading volume predicts the high liquidity-beta state. Second, a significantly lower (negative and larger) $RREV$ accompanied by lower MKT and higher $STOV$, as observed by Pastor and Stambaugh (2003), is present only during negative LIQ months.[18] In principle, significant return reversals can occur following both positive and negative liquidity shocks, but our result indicates that they are primarily associated with negative LIQ. In addition, SMB is significantly higher in State 2 unconditionally (Panel (i)) and conditionally on positive LIQ (Panel (ii)). The same result holds even during negative LIQ months (Panel (iii)) because small stocks still earn higher returns than large stocks for small negative LIQ. Given the positive relationship between illiquidity and the book-to-market ratio as seen in Panel (a) of Table 3, it is not surprising that HML is significantly higher in State 2 unconditionally (Panel (i)). The momentum strategy return, UMD, is negative but mostly insignificant.

2.4.2 Expected Illiquidity and the High Liquidity-Beta State

It is important to understand that the dominance of positive liquidity shocks in State 2 does not imply high liquidity levels. In fact, there is evidence that aggregate liquidity is low prior to the high liquidity-beta state. To examine this point, we compare the mean levels of expected illiquidity surrounding State 2. As a measure of expected illiquidity, we use the fitted values from the modified AR(2) model for $ARPIM$ in equation (7), denoted by $EAPRIM$. To account for the limited number of high liquidity-beta months while preserving the time sequence, we

[18] Note that one possible form of preference uncertainty is stochastic risk aversion used in the model of Campbell, Grossman, and Wang (1993), which forms the theoretical basis of Pastor and Stambaugh's (2003) return reversal measure.

conduct block bootstraps. Specifically, each sampling draws 43 blocks of fitted $EAPRIM$ with replacement. Each block starts at nine months prior to a high liquidity-beta state and continues through nine months after it. Within each block, we compute the difference between $EAPRIM$ and its block average monthly. The differences are then averaged across the 43 drawn blocks month-by-month. This is repeated 5000 times, and the means and the 95% confidence intervals of the monthly differences across the re-samplings are calculated. Panel (a) of Figure 5 shows the bootstrap means with a solid line and the confidence intervals with dashed lines. To get a sense of the level, the mean of the block averages is added back and is shown by a dotted horizontal line. We observe that $EAPRIM$ rises significantly above the block mean several months prior to the high liquidity-beta state, then falls significantly below the mean a couple of months afterward before finally reverting back toward the average level.

We can see a similar dynamics for another measure of expected illiquidity in Panel (b), which simply plots the lagged $APRIM$ (denoted by $LAPRIM$) without trend adjustment.[19] $LAPRIM$ is also used as a measure of expected illiquidity in Amihud (2002). Further, to examine the pervasiveness of this illiquidity variation around State 2, Panels (c) and (d) conduct the same bootstrapping analysis for the lagged $PRIM$ characteristics of the most ($LPRIM01$) and the least ($LPRIM10$) liquid $PRIM$-sorted deciles, respectively. Lagged $PRIM$ characteristics of other deciles exhibit similar dynamics and fall somewhere between these two series (results not shown). From these figures, it appears reasonable to consider that investors expect deteriorating future liquidity several months prior to the high liquidity-beta state, leading to a rise in illiquidity premium. This again confirms that the times of high illiquidity premium roughly coincide with times of high liquidity risk premium.

Panels (e)-(i) of Figure 5 depict the bootstrap means of the five state variables studied in Section 1.5. Consistent with our first hypothesis, Panel (e) indicates highly elevated share turnover around the high liquidity-beta state. This is also accompanied by a significant rise in volatility (Panel (f)) although the increase is more substantial for $STOV$. In addition, several months before the high liquidity-beta state, XRI and $LEAD$ significantly deviate from the mean in the direction consistent with the traditional risk story; the probability of entering into a near-term recession rises (Panel (g)) and the leading indicator of economic conditions declines (Panel (h)). Past the high liquidity-beta month, the two measures cross the means and

[19] Possible nonstationarity of unadjusted $APRIM$ is not an issue here since the average is taken within each block.

deviate away from them in the opposite direction. Finally, Panel (i) shows that the deviation of $CEXP$ from the block average is not significant but also goes in the right direction.[20] These results are consistent with the findings of Longstaff (2004) and Gibson and Mougeot (2004). Overall, while the pricing of liquidity risk can and does occur at a frequency different from that of business cycles, there is some association between the liquidity risk premium and macroeconomic conditions.

2.5 Robustness Tests

This section conducts a number of robustness tests on the conditional pricing of liquidity risk. We first control for additional factors and characteristics that are likely to be correlated with liquidity risk. We then examine if our pricing results hold for different test assets and alternative methods of state identification. The effect of outliers is also discussed.

2.5.1 Size and B/M Characteristics

Daniel and Titman (1997) argue that the size and B/M premia arise because of such characteristics per se rather than beta risks with respect to these factors. To control for this possibility, we replace SMB and HML in Columns 3 and 4 of Table 4 with the lagged size and B/M characteristics of the test portfolios as in equation (12). The results are presented in Table 6. While lowered to about 8% in the presence of strong size effect, the $CLIQ$ premium is still significant at the 5% level with or without the level of illiquidity.

2.5.2 Conditional Size and B/M Factors

Recall from Panel (b) of Table 5 that SMB and HML have higher returns in the high liquidity-beta state. This raises a concern as to whether the observed conditional liquidity effect is a conditional size or book-to-market effect in disguise. In fact, Guidolin and Timmermann (2005) find that size and value premia vary across economic regimes, and Perez-Quiros and Timmermann (2000) report that the small-firm premium increases sharply during late stages

[20] We also plotted variables in Panels (a)-(i) conditional on the sign of LIQ in State 2. Generally, the dynamics around State 2 with positive LIQ are similar or reinforced for all the variables except for VOL, which exhibits no variation.

of most recessions. To address this concern, we construct conditional size and value factors as

$$CSMB_t = I_t \cdot SMB_t,$$
$$CHML_t = I_t \cdot HML_t,$$

where I_t is again the indicator variable that defines the high liquidity-beta state. Table 7 shows the estimated premia. The magnitude of the $CLIQ$ premium is almost unchanged at around 9% to 10% at the 5% significance level upon the inclusion of $CSMB$, $CHML$, or both. The effects of $CSMB$ and $CHML$ are insignificant, suggesting that the liquidity-beta states we identified are distinct from economic regimes underlying the variations of the size and value premia.

2.5.3 Default and Aggregate Volatility Factors

It is sensible to suspect that liquidity risk is correlated with default risk because illiquid firms tend to be small firms that are relatively likely to default. Perez-Quiros and Timmermann (2000) find evidence of asymmetry in the small and large firms' exposures to credit risk across recession and expansion states. To control for the possible effect of default risk, we include Vassalou and Xing's (2004) default factor (DSV) in our test.[21]

We also recall that our regime-switching model allowed volatility to vary across states. While we consider volatility an important characteristic of the high liquidity-beta state, it may also introduce a pseudo pricing effect; researchers have shown that stocks with higher sensitivity to innovations in aggregate volatility tend to earn lower returns [Ang, Hodrick, Xing, and Zhang (2006)]. To account for this, we additionally include an aggregate volatility factor ($dVOL$) given by the monthly first-order differences in VOL.[22]

The results are given in Column 1 of Table 8, which shows that the $CLIQ$ premium is robust to the inclusion of DSV and $dVOL$. Note that the availability of DSV restricts the sample period to January 1971 through December 1999 ($N = 348$). In this shorter sample period, the illiquidity characteristic, $PRIM$, is significantly priced. In a separate test, we also examined

[21] We thank Maria Vassalou for making the default factor available on her web site.

[22] Ang, Hodrick, Xing, and Zhang (2006) construct a monthly mimicking portfolio of the innovations in aggregate volatility, where the innovations are given by the daily difference of the VIX index from the Chicago Board Options Exchange (CBOE). Instead of constructing a factor mimicking portfolio, we directly use changes in aggregate volatility as a non-traded factor. We do not use the VIX index since it restricts the sample to a substantially shorter period.

the robustness against the conditional versions of DSV and $dVOL$, constructed similarly to $CSMB$ and $CHML$, but the $CLIQ$ premium remained significant (results not shown). The robustness of $CLIQ$ against default risk emphasizes the separation between preference risk and cash flow risk as discussed in Gallmeyer, Hollifield, and Seppi (2005).

2.5.4 Idiosyncratic Volatility and Volume Characteristics

Since Amihud's (2002) price impact measure is given by the ratio of absolute return to volume, another concern is that $CLIQ$ may simply proxy for idiosyncratic volatility and/or trading volume, which are shown to predict returns or explain the cross-sectional variation in returns [see, among others, Ang, Hodrick, Xing, and Zhang (2006), Goyal and Santa-Clara (2003), and Spiegel and Wang (2005) for idiosyncratic volatility, and Brennan, Chordia, and Subrahmanyam (1998) and Lee and Swaminathan (2000) for volume]. We therefore check against this possibility as well.

Following Goyal and Santa-Clara (2003), we construct a measure of total variance for portfolio i in month t as

$$IVAR_{i,t} = \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} \left[\sum_{d=1}^{D_{j,t}} r_{j,d,t}^2 + 2 \sum_{d=2}^{D_{j,t}} r_{j,d,t} r_{j,d-1,t} \right], \tag{13}$$

where $r_{j,d,t}$ is the return of a component stock j on day d in month t, $D_{j,t}$ is the number of daily individual-return observations during that month, and $N_{i,t}$ is the number of stocks in portfolio i.[23] As the authors show, $IVAR_{i,t}$ can be interpreted as a measure of idiosyncratic risk under a certain factor structure in the cross section of returns. We follow this interpretation and call it a measure of idiosyncratic variance.

We include lagged portfolio idiosyncratic variance ($IVAR_{i,t-1}$) and share turnover ($TOV_{i,t-1}$) as additional characteristics in equation (12). Column 2 of Table 8 indicates that the $CLIQ$ premium is robust and significant in their presence. It also survives the additional inclusion of DSV and $dVOL$ as shown in Column 3. Consistent with the findings of Ang, Hodrick, Xing, and Zhang (2006), $IVAR$ has a significant negative premium in this shorter sample period.

[23] The second term on the right-hand side adjusts for the autocorrelation in daily returns. See Goyal and Santa-Clara (2003).

2.5.5 Alternative Test Assets

We also check our results against alternative choices of test assets. We first replace our test portfolios with those formed as the cross section of size, B/M, $PRIM$, and/or $RREV$, excluding or including the NASDAQ stocks. We then extend the test assets to individual stocks.

We start by replacing $PRIM$ with $RREV$ as the liquidity sorting key. Also, while illiquidity is cross-sectionally correlated with size as seen in Table 3, we now explicitly use size in our sort; it is possible that SMB has been insignificantly priced because our previous test assets did not produce enough dispersion in size betas. Panel (a) of Table 9 shows the results with the following alternative test assets: Column 1: B/M5-$RREV$5-sorted 25 portfolios, Column 2: size3-B/M3-$PRIM$3-sorted 27 portfolios, and Column 3: size3-B/M3-$RREV$3-sorted 27 portfolios.[24] Each of these sorting procedures includes one (il)liquidity measure to produce a cross section that varies in liquidity risk loadings. The panel indicates that while the $CLIQ$ premium drops to 4.5% when the size-B/M-$PRIM$ triplets are used, it is still marginally significant. In the other two cases, the premium is estimated to be 8.8% and 6.6% with a 5% significance. HML is consistently priced in these test assets, similar to the findings of Pastor and Stambaugh (2003) and Acharya and Pedersen (2005). Interestingly, the significance of the illiquidity characteristic and the momentum factor varies considerably depending on the choice of the liquidity sorting key; $PRIM$ becomes significant when $RREV$ is used whereas UMD becomes significant when $PRIM$ is used instead.

Although we have been excluding the NASDAQ stocks so far, we now include them and present the results in Panel (b). Each column uses the same sorting key as in Panel (a) with an addition of the B/M5-$PRIM$5-sorted 25 portfolios given in Column 4. We find that the inclusion of the NASDAQ stocks raises the $CLIQ$ premium in all cases; the premium also becomes more significant except for Column 3 which is still significant at 10%.

Panel (c) uses individual stocks as test assets. Column 1 employs the NYSE and AMEX stocks, and Column 2 additionally includes the NASDAQ stocks. Since estimates of individual stock betas are expected to be noisy, we follow Fama and French (1992) and assign portfolio betas to individual stocks. Specifically, we assign the betas of the B/M5-$PRIM$5 portfolios

[24]Column 1 uses independent sorts by B/M and $RREV$. In Columns 2 and 3, 3-by-3 cross sections are formed first by independent sorts on size and B/M, and then within each cross section stocks are sorted by either $PRIM$ or $RREV$. This method is used because fully independent three-dimensional sorts resulted in some portfolios (specifically, small and liquid, and large and illiquid ones) having missing observations in some months due to correlation between size and illiquidity.

(corresponding to Column 3 of Table 4) to their component stocks. The $PRIM$ characteristic is that of each individual stock. The panel shows the estimated $CLIQ$ premium of 11.9% when the test assets exclude the NASDAQ stocks and 12.4% including them. These numbers are similar in magnitude to what we have reported earlier and are significant almost at the 1% level. We do observe three differences, however. First, the constant term is now significantly positive, suggesting the possibility of some omitted factors in explaining the variation of individual stock returns. Second, the LIQ premium is negative and significant, which implies that high liquidity beta stocks earn significantly less premia than low liquidity beta stocks during 'normal' times. This is a potentially interesting point to investigate further, which however is out of the scope of the current paper. Finally, the $PRIM$ characteristic premium is negative and highly significant, not positive. This may be due to the fact that $PRIM$ of individual stocks are noisy.

2.5.6 Alternative Methods of State Identification

In equation (1), we used excess returns of the two extreme size decile portfolios as dependent variables to identify the liquidity-beta states. To examine the robustness against alternative methods of state identification, we replace them with the $PRIM$-sorted extreme decile returns. Note that this will change the definition of I_t and hence the construction of $CLIQ$. However, the change turns out to be practically small; there are 47 months in the high liquidity-beta state in comparison to the previous 43 months. Consequently, the new asset pricing result presented in Table 10 is qualitatively similar to the previous result in Table 4. The $CLIQ$ premium in the full model (Column 3) is approximately 10% with a 5% significance. Our results are therefore robust to reasonable choices of dependent variables used in state identification.

2.5.7 Effect of Outliers and Threshold Probability

Given the relatively small number of the high liquidity-beta months, the effect of outliers may be a concern. We therefore employ the following four methods to screen extreme observations of LIQ: (i) excluding the top five and the bottom five extreme values of LIQ, (ii) excluding the months immediately following those extreme LIQ months in (i), (iii) excluding the top one and the bottom one extreme values of LIQ within State 2, and (iv) excluding the top two and the bottom two extreme values of LIQ within State 2. These screenings amount to trimming almost 2% of the total observations (screenings (i) and (ii)) or 10% within the high liquidity beta months (screenings (iii) and (iv)). For brevity, the results are summarized here without a table.[25] After screenings (i) and (ii), the number of high liquidity-beta months only slightly dropped to 41 and 42, respectively. The exclusion of at most two high liquidity-beta months implies that they do not necessarily correspond to months of extreme LIQ; recall that the important feature of the high liquidity-beta state is not simply large liquidity shocks, but those accompanied by highly elevated volume. By construction, screenings (iii) and (iv) drop two and four high liquidity-beta months, respectively. After these screenings, the $CLIQ$ premium from our benchmark model (corresponding to Column 4 of Table 4) ranged between 8.8% and 10.2%, all of which were significant.

Next, we also change the probability threshold for State 2 from 0.5 to 0.9 with an increment of 0.1. This exercise serves as an additional test against extreme observations since the number of high liquidity-beta months varies from 37 to as many as 62. Table 11 reports that the $CLIQ$ premium is again robust and ranges between 8.8% and 13.2% with a 2% significance level throughout.

2.6 Comparison to Scaled Factor Models

We emphasize the importance of modeling liquidity betas in discrete states. A natural alternative would be a time-varying beta model in which betas are continuous functions of lagged state variables. Instead of equations (1)-(4), we could fit a simple linear regression,

$$r_{i,t} = \alpha_i + \beta_i^{MKT} MKT_t + (\beta_i^{LIQ} + \beta_i^{x} x_{t-1}) LIQ_t + \varepsilon_{i,t}, \tag{14}$$

where x_{t-1} is a lagged state variable. This can be considered a stripped-down version of Cochrane's (2005) 'scaled factor' model in which only one beta is conditioned on the time $t-1$ information set [also see, e.g., Ferson and Harvey (1991, 1999)]. We ran the Fama-MacBeth (1973) regressions using equation (14) in the first pass for each of the five state variables. For this simple specification, the premium on the scaled factor ($x_{t-1}LIQ_t$) was significant for some state variables. However, when additionally controlled for the size, book-to-market, and momentum factors as well as the illiquidity characteristic, the premium became insignificant for all the state variables except for XRI (results not shown). Thus, the result emphasizes the importance of allowing liquidity betas to vary discontinuously across states that may be associated with fundamentally different pricing relations. Equation (14) does not accommodate

[25] The results are available upon request.

such a possibility.

2.7 Economic Significance of the Conditional Liquidity Risk Premium

Finally, we examine the economic significance of the conditional liquidity risk premium. To this end, we first construct a mimicking portfolio [Breeden, Gibbons, and Litzenberger (1989) and Lamont (2001)] for the liquidity factor. We fit a linear regression for LIQ without an intercept,

$$LIQ_t = \boldsymbol{b}'\boldsymbol{r}_t^B + \varepsilon_t, \tag{15}$$

where $\boldsymbol{r}_t^B$ is the vector of excess returns on basis assets and $\boldsymbol{b}$ is a conforming vector of loadings. The return on the liquidity-factor mimicking portfolio (LMP) is then constructed as

$$LMP_t = \frac{1}{|\widehat{\boldsymbol{b}}'\mathbf{1}|}\widehat{\boldsymbol{b}}'\boldsymbol{r}_t^B,$$

where $\widehat{\boldsymbol{b}}$ is the vector of estimated loadings. The division by $|\widehat{\boldsymbol{b}}'\mathbf{1}|$ simply normalizes the loadings so that they have a weight interpretation.[26] Since each excess return is a zero investment portfolio, so is LMP. It holds a portfolio of stocks in basis assets financed by a short position in the one month Treasury bill (if $\widehat{\boldsymbol{b}}'\mathbf{1}$ is positive). We employ $PRIM$-sorted 25 portfolios as the basis assets and use the whole sample to estimate $\widehat{\boldsymbol{b}}$.[27] The conditional liquidity-factor mimicking portfolio return is then given by

$$CLMP_t = I_t \cdot LMP_t,$$

where I_t is the original indicator variable estimated with the CRSP size-sorted portfolios as dependent variables in the regime-switching model.

Table 12 repeats the asset pricing tests in Table 4 with LIQ and $CLIQ$ replaced by LMP and $CLMP$, respectively. The $CLMP$ premium is significant accounting for the size, book-to-market, and momentum factors as well as the illiquidity characteristic. Its monthly premium is 1.5% in the full model, which is more than twice the estimated book-to-market premium. We argue that this premium is not unreasonably high, given that it is rendered less than one tenth

[26] Lamont (2001) notes that there is no need to restrict weights in constructing his economic tracking portfolio. In contrast to our asset pricing objective, his goal is to predict economic variables and "neither to estimate risk premia nor to test asset-pricing models." (p.166)

[27] Because we use the whole sample, LMP is not strictly a traded asset.

of the time.

Another way to evaluate the economic significance of $CLIQ$ is to use the spread in estimated betas. Summarizing from all the above analysis, the $CLIQ$ premium appears to lie somewhere between 5% and 10%. From the bottom row in Panel (b)(i) of Table 3, the return spread between the value-illiquid and liquid portfolios is 0.0056. Since the $CLIQ$ beta spread in Panel (iv) is 0.057, assuming a conservative 5% premium, the return spread explained by the beta spread is $0.05 \times 0.057 = 0.00285$, or 51% of the return spread. If we assume a 7.5% premium, 76% of the return spread can be accounted for. If one repeats the same exercise with the $PRIM$-sorted decile portfolios in Panel (a) of Table 3, the explained percentage increases to 76% or higher.[28]

3 Conclusion

This paper has studied dynamic features of liquidity betas and liquidity risk premium. We conjecture that the level of uncertainty about future asset demands affects stock returns' sensitivities to aggregate liquidity fluctuations and the pricing of liquidity-sensitive securities. Consistent with our hypothesis, we find that liquidity betas vary significantly over time across two distinct states, one with low liquidity betas and the other with high betas. The transition from the former to the latter is predicted by a rise in trading volume, which is consistent with heightened preference uncertainty. The high liquidity-beta state is associated with elevated volatility and a wide cross-sectional dispersion in liquidity betas, and is preceded by a period of declining expectations about future economic conditions and stock market liquidity. The state is also short lived and occurs less than one tenth of the time.

We construct a conditional liquidity factor and examine whether the cross-sectional pricing of liquidity risk strengthens in the high liquidity-beta state. Our asset pricing tests confirm that the conditional liquidity risk premium is statistically significant and economically large, and survives a variety of robustness tests. We also find that the periods of high liquidity betas and high liquidity risk premium coincide with times of high illiquidity premium. Since the conditional liquidity factor is significantly priced after controlling for the level of illiquidity, our results suggest that the illiquidity premium is delivered primarily in the form of beta risk

[28]If the $CLIQ$ premium is assumed to be 6.6% or more for Panel (a), the percentage of the return spread explained by the $CLIQ$ beta spread can exceed 100%. This is likely due to a large beta spread resulting from a one dimensional sort; the betas might be capturing loadings on other correlated risks such as size and book-to-market, as suggested in the same panel.

premium with respect to the liquidity factor during high liquidity-beta months.

Based on the evidence of time variations in liquidity betas and liquidity risk premium, we suggest several directions for future research. First, our framework can be readily applied to study the dynamic pricing of liquidity risk in other financial markets, such as fixed income securities markets and international equity markets. Second, we can investigate how investors actually trade liquid and illiquid assets in the high liquidity-beta state that we identified. Lastly, we can examine the multivariate dynamics of liquidity, volume, and volatility, and their implications on asset pricing. Our finding that changes in liquidity-return relationship can be predicted by trading volume and volatility suggests a close link among these variables.

A Appendix

A.1 Construction of State Variables

This Appendix describes the construction of state variables used in our regime-switching model. Aggregate share turnover ($STOV$) is given by a trend-adjusted cross-sectional average of individual share turnover. Let $TOV_{j,t}$ be the average of daily share turnover for stock j in month t, where the daily share turnover is defined as the CRSP daily share volume divided by the number of shares outstanding.[29] Share turnover for portfolio i, $TOV_{i,t}$, is computed as the equally-weighted average of $TOV_{j,t}$ across its component stocks in month t. When the portfolio equals the universe of stocks, we call the average measure the raw aggregate share turnover denoted by $ATOV_t$. To control for the upward trend in $ATOV_t$, it is scaled by a factor, $ATOV_1/MATOV_t$, where $ATOV_1$ is the initial value in July 1962 and $MATOV_t$ is the last 24-month moving average, respectively, of $ATOV_t$. The detrended aggregate share turnover, $STOV_t$, is calculated as

$$STOV_t = \frac{ATOV_1}{MATOV_t} ATOV_t.$$

This detrending method is used by Eckbo and Norli (2002).

Aggregate volatility (VOL) is defined as the standard deviation of the daily CRSP value-weighted returns (NYSE and AMEX) within each month. An alternative is the VIX index from the Chicago Board Options Exchange, but we choose to employ the historical volatility due to the limited sample length of VIX and its successor, VXO.

The experimental recession index (XRI) is downloaded from James Stock's web site.[30] $LEAD$ is the twelve-month log difference in the Conference Board leading economic indicator. The twelve-month difference is taken to eliminate the seasonality. Lastly, the consumer expectation index ($CEXP$) is from the University of Michigan. The sample periods used in the estimation of regime switching models with a single state variable are as follows: $STOV$ and VOL are from January 1965 to December 2004, XRI is from January 1965 to December 2003, $LEAD$ is from January 1965 to December 2004, and $CEXP$ is from January 1965 to December 2001. When all the five state variables are used simultaneously, the common sample period, January 1965 through December 2001, is used.

[29] Since volume is recorded in units of 1000 in CRSP, $TOV = 1$ implies that 0.1% of the outstanding shares are traded.

[30] The series is discontinued in December 2003.

A.2 Computation of Portfolio Characteristics

This appendix describes the computation of the portfolio characteristics shown in Table 3. At the end of each year, pre-ranking $PRIM$ for each stock is computed in a similar fashion to equation (5), where t is interpreted as a year instead of a month. The annual $PRIM$ is used for portfolio formation. All the returns and characteristics in Table 3 are time-series averages of post-ranking monthly portfolio returns and characteristics except for β^{LIQ} and β^{CLIQ}. These monthly portfolio returns and characteristics are calculated each month as value-weighted cross-sectional averages of member stocks' returns and characteristics except for size (which is a simple cross-sectional average) and the number of stocks.

Within each month, individual stocks' returns and characteristics are determined as follows: r and PRC are the return and the price, respectively, from the CRSP monthly stock file; σ^r is the standard deviation of the CRSP daily return; $PRIM$ is the average daily Amihud (2002) illiquidity ratio (see equation (5)); σ^{PRIM} is the standard deviation of the daily illiquidity ratio; and $RREV$ is the gamma coefficient from the daily regression of Pastor and Stambaugh (2003). TOV is the average share turnover (see Appendix A.1). Size and B/M are computed using the CRSP monthly stock file and Compustat, following Fama and French (1993) except that size (measured in millions of dollars) is recalculated monthly and B/M quarterly. In computing B/M, the book value is lagged at least six months, and lagged B/M values are used for non-calculation months.

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Table 1: **Estimated parameters of the bivariate regime-switching model.** This table shows the estimated parameters and corresponding t-statistics (in parentheses) of the bivariate regime-switching model with *STOV* as a state variable. The table also shows the chi-square statistics and p-values (in parentheses) for likelihood ratio tests (*'LR Tests'*) on various parameter restrictions. *Max LK* is the maximized log likelihood.

State variable: *STOV*

	Size					
	Smallest ($i=S$)		Largest ($i=L$)			
Parameters					*Common Parameters*	
$\alpha_{i,1}$	0.001	(0.41)	0.006	(3.01)	c_1	5.341 (3.38)
$\alpha_{i,2}$	0.056	(3.89)	-0.006	(-0.89)	c_2	0.365 (0.22)
$\beta_{i,1}^{LIQ}$	0.053	(8.15)	0.021	(4.58)	d_1	-22.750 (-2.44)
$\beta_{i,2}^{LIQ}$	0.192	(6.31)	0.085	(6.50)	d_2	-3.324 (-0.36)
$\sigma_{i,1}$	0.046	(21.24)	0.035	(22.16)	ρ_1	0.565 (9.71)
$\sigma_{i,2}$	0.109	(10.05)	0.047	(9.02)	ρ_2	0.236 (1.97)
LR Tests					*Common LR Tests*	
$\sigma_{i,1}=\sigma_{i,2}$	115.63	(0.000)	0.42	(0.516)	$d_1=d_2=0$	6.08(0.048)
$\beta_{i,1}^{LIQ}=\beta_{i,2}^{LIQ}$	11.74	(0.001)	8.17	(0.004)	$\beta_{S,2}^{LIQ}-\beta_{S,1}^{LIQ}=\beta_{L,2}^{LIQ}-\beta_{L,1}^{LIQ}$	6.85(0.009)
Max LK (per period)	1604.5 (3.34)					
Sample Period (N)	196501:200412 (480)					

Table 2: **State variables for liquidity-beta variation.** This table summarizes the state variables for liquidity-beta variation and their coefficient estimates in the regime-switching model. Panel (a) lists the variables and the references suggesting the use of these or similar variables. 'Effect' is + if an increase in the variable is expected to raise the probability of transition from the low to high liquidity-beta state, and − otherwise. Panel (b) reports estimated d_1 coefficients on the state variables and their t-statistics from the models with a single state variable (column 'Alone') or all the five variables (column 'All').

(a) Alternative state variables

State variable	Name	Effect	References
Volume	$STOV$	+	Gallmeyer, Hollifield, and Seppi (2005)
Volatility	VOL	+	Vayanos (2004)
Experimental recession index	XRI	+	Gibson and Meougeot (2004)
Leading economic indicator	$LEAD$	−	—
Consumer expectation index	$CEXP$	−	Longstaff (2004)

(b) Estimated d_1 coefficients

	Alone		All	
$STOV$	-22.8	(-2.44)	-29.6	(-2.98)
VOL	-184.3	(-2.33)	-168.0	(-2.36)
XRI	-2.91	(-3.25)	-2.44	(-1.70)
$LEAD$	17.91	(2.48)	4.78	(0.51)
$CEXP$	0.0568	(2.48)	0.0113	(0.49)

Table 3: **Characteristics of the liquidity-sorted portfolios.** This table shows the average monthly returns and the post-ranking characteristics of the liquidity-sorted portfolios from January 1963 through December 2004. At the end of each year, we sort stocks on the NYSE and AMEX using the NYSE breakpoints. Panel (a) employs decile portfolios sorted by the average Amihud (2002) price impact proxy ($PRIM$), and Panel (b) uses 25 portfolios formed as the cross section of the book-to-market ratio (B/M) and $PRIM$ quintiles. r is the value-weighted portfolio return. The portfolio characteristics are calculated each month as the value weighted cross-sectional averages of the following characteristics of member stocks: σ^r is the standard deviation of the CRSP daily return; $PRIM$ is the average daily Amihud (2002) illiquidity ratio; σ^{PRIM} is the standard deviation of the daily illiquidity ratio; $RREV$ is the gamma coefficient from the daily regression of Pastor and Stambaugh (2003); and TOV is the average share turnover; PRC is the month-end price. Size and B/M are computed following Fama and French (1993). N is the number of stocks. β^{LIQ} and β^{CLIQ} are the liquidity and conditional liquidity betas, respectively, using portfolio excess returns.

(a) $PRIM$10 portfolios

	r	σ^r	$PRIM$	σ^{PRIM}	$RREV$	TOV	PRC	Size	B/M	N	β^{LIQ}	β^{CLIQ}
1	0.0089	0.0155	0.004	0.003	0.00005	1.91	72.8	13628	0.558	131.1	-0.0052	-0.0106
2	0.0096	0.0171	0.016	0.015	-0.00006	2.47	43.4	3074	0.719	130.7	0.0014	-0.0082
3	0.0106	0.0179	0.029	0.029	-0.00036	2.56	38.1	1661	0.720	133.1	0.0042	0.0031
4	0.0106	0.0185	0.050	0.053	-0.00051	2.54	36.0	1022	0.716	133.7	0.0079	-0.0010
5	0.0106	0.0189	0.080	0.089	-0.00116	2.38	34.3	674	0.722	135.7	0.0113	0.0121
6	0.0111	0.0194	0.123	0.139	-0.00234	2.30	30.8	467	0.738	140.7	0.0110	0.0191
7	0.0110	0.0200	0.188	0.220	-0.00360	2.07	28.9	329	0.751	146.5	0.0153	0.0234
8	0.0120	0.0207	0.294	0.349	-0.00646	1.89	26.0	227	0.802	156.7	0.0227	0.0271
9	0.0130	0.0214	0.511	0.619	-0.00942	1.74	24.7	151	0.863	185.5	0.0233	0.0361
10	0.0133	0.0238	1.567	1.899	-0.02523	1.54	19.4	61	0.949	431.8	0.0291	0.0564
10-1	0.0044	0.0083	1.564	1.895	-0.02529	-0.37	-53.4	-13568	0.391	300.7	0.0343	0.0670

Table 3: Continued

(b) B/M5-$PRIM$5 portfolios

(i) r

		$PRIM$					
		1	2	3	4	5	5-1
B/M	1	0.0088	0.0088	0.0095	0.0100	0.0109	0.0021
	2	0.0087	0.0100	0.0094	0.0110	0.0118	0.0031
	3	0.0102	0.0114	0.0116	0.0100	0.0131	0.0028
	4	0.0107	0.0119	0.0123	0.0136	0.0143	0.0036
	5	0.0106	0.0155	0.0146	0.0145	0.0162	0.0056
	5-1	0.0018	0.0067	0.0050	0.0045	0.0053	

(ii) $PRIM$

		$PRIM$					
		1	2	3	4	5	5-1
B/M	1	0.005	0.038	0.098	0.239	0.915	0.910
	2	0.006	0.038	0.100	0.238	0.919	0.913
	3	0.007	0.036	0.097	0.230	0.989	0.981
	4	0.008	0.037	0.097	0.229	1.017	1.008
	5	0.010	0.036	0.095	0.229	1.159	1.148
	5-1	0.005	-0.001	-0.004	-0.011	0.244	

(iii) β^{LIQ}

		$PRIM$					
		1	2	3	4	5	5-1
B/M	1	-0.005	0.007	0.015	0.024	0.034	0.039
	2	-0.003	0.007	0.011	0.018	0.030	0.033
	3	0.000	0.003	0.011	0.020	0.024	0.024
	4	0.000	0.003	0.008	0.013	0.022	0.023
	5	-0.001	0.008	0.008	0.016	0.023	0.024
	5-1	0.004	0.001	-0.007	-0.008	-0.011	

(iv) β^{CLIQ}

		$PRIM$					
		1	2	3	4	5	5-1
B/M	1	-0.015	-0.011	0.005	0.019	0.027	0.042
	2	-0.010	0.004	0.017	0.026	0.047	0.057
	3	-0.001	0.004	0.019	0.020	0.048	0.048
	4	-0.005	0.005	0.012	0.024	0.054	0.058
	5	0.005	0.030	0.039	0.041	0.062	0.057
	5-1	0.021	0.040	0.034	0.022	0.035	

Table 4: **Estimated premia.** This table shows the estimated monthly premia in percent. Test assets are the B/M5-$PRIM$5-sorted 25 portfolios. MKT is the excess return on the CRSP value-weighted portfolio. LIQ is the liquidity factor. $CLIQ$ is the product of an indicator variable I and LIQ, where I takes the value of 1 if the probability of being in the high liquidity-beta state from the bivariate regime-switching model is higher than 0.75 and 0 otherwise. SMB, HML, and UMD are the size, book-to-market, and momentum factors, respectively. $PRIM$ is the lagged Amihud (2002) price impact proxy of the test portfolios. The estimation follows the Fama-MacBeth (1973) two-pass procedure with the Shanken (1992) correction for standard errors. Reported are the estimated premia and p-values in parentheses. *, **, *** represent significance at 10, 5, and 1%, respectively.

	1		2		3		4	
Constant	2.04***	(0.000)	0.69	(0.199)	0.36	(0.532)	0.38	(0.531)
MKT	-1.60***	(0.004)	-0.14	(0.831)	0.15	(0.824)	0.12	(0.860)
LIQ	7.20	(0.186)	-11.57	(0.141)	-12.79	(0.245)	-11.05	(0.315)
$CLIQ$			12.49***	(0.001)	10.09***	(0.006)	10.23***	(0.008)
SMB					0.18	(0.532)	0.18	(0.555)
HML					0.52*	(0.077)	0.53*	(0.071)
UMD					1.16	(0.367)	1.12	(0.369)
$PRIM$							0.13	(0.183)
Sample period	196501:200412							
N	480							

Table 5: **Means of the $PRIM$-sorted excess decile portfolio returns and selected variables by state.** This table shows means by state of (a) $PRIM$-sorted excess decile portfolio returns and (b) selected aggregate variables. Reported are the means in the full sample (column labeled 'All') and in each state, the differences of the means between the two states, and the p-values of the differences in parentheses. Subpanels (b)(ii) and (iii) divide State 2 into months with $LIQ > 0$ (State 2^+) and months with $LIQ < 0$ (State 2^-). The sample period is from January 1965 to December 2004.

(a) $PRIM$-sorted excess decile portfolio returns

	All	State 1	State 2	State $2-1$	p-Value
1	0.0037	0.0049	-0.0083	-0.0132	(0.053)
2	0.0046	0.0050	0.0000	-0.0050	(0.495)
3	0.0057	0.0058	0.0041	-0.0017	(0.827)
4	0.0057	0.0056	0.0064	0.0008	(0.915)
5	0.0056	0.0048	0.0142	0.0094	(0.235)
6	0.0062	0.0051	0.0166	0.0114	(0.161)
7	0.0062	0.0049	0.0195	0.0146	(0.076)
8	0.0071	0.0052	0.0259	0.0207	(0.014)
9	0.0080	0.0055	0.0334	0.0278	(0.001)
10	0.0085	0.0049	0.0453	0.0404	(0.000)
10-1	0.0048	0.0000	0.0536	0.0536	(0.000)

Table 5: Continued

(b) Selected aggregate variables

(i) All LIQ

	All	State 1	State 2	State $2-1$	p-Value
LIQ	-0.0040	-0.0137	0.0945	0.1082	(0.121)
MKT	0.0045	0.0045	0.0042	-0.0003	(0.966)
$STOV$	0.1518	0.1472	0.1979	0.0507	(0.000)
$RREV$	-0.0308	-0.0287	-0.0518	-0.0231	(0.006)
SMB	0.0027	-0.0011	0.0414	0.0425	(0.000)
HML	0.0044	0.0036	0.0129	0.0093	(0.051)
UMD	0.0085	0.0094	-0.0006	-0.0100	(0.132)

(ii) State 2, $LIQ > 0$

	State 2^+	State $2^+ - 1$	p-value
LIQ	0.3756	0.3893	(0.000)
MKT	0.0347	0.0301	(0.000)
$STOV$	0.2145	0.0673	(0.000)
$RREV$	-0.0275	0.0012	(0.898)
SMB	0.0516	0.0527	(0.000)
HML	0.0123	0.0087	(0.121)
UMD	-0.0007	-0.0102	(0.183)

(iii) State 2, $LIQ < 0$

	State 2^-	State $2^- - 1$	p-value
LIQ	-0.4877	-0.4740	(0.000)
MKT	-0.0589	-0.0634	(0.000)
$STOV$	0.1635	0.0163	(0.055)
$RREV$	-0.1020	-0.0734	(0.000)
SMB	0.0204	0.0215	(0.011)
HML	0.0142	0.0106	(0.184)
UMD	-0.0002	-0.0096	(0.363)

Table 6: **Estimated premia with size and B/M characteristics.** This table shows the monthly premia in percent estimated with size and B/M characteristics. Test assets are the B/M5-$PRIM$5-sorted 25 portfolios. MKT is the excess return on the CRSP value-weighted portfolio. LIQ is the liquidity factor. $CLIQ$ is the product of an indicator variable I and LIQ, where I takes the value of 1 if the probability of being in the high liquidity-beta state from the bivariate regime-switching model is higher than 0.75 and 0 otherwise. Size and B/M are the lagged average market capitalization and book-to-market ratio, respectively, of the test portfolios. UMD is the momentum factor. $PRIM$ is the lagged Amihud (2002) price impact proxy of the test portfolios. The estimation follows the Fama-MacBeth (1973) two-pass procedure with the Shanken (1992) correction for standard errors. Reported are the estimated premia and p-values in parentheses. *, **, *** represent significance at 10, 5, and 1%, respectively.

	1		2	
Constant	1.12*	(0.089)	1.18*	(0.080)
MKT	-0.52	(0.438)	-0.56	(0.408)
LIQ	-13.25	(0.132)	-13.54	(0.126)
$CLIQ$	8.09**	(0.031)	8.15**	(0.042)
Size	-0.08**	(0.047)	-0.08*	(0.060)
B/M	0.15	(0.172)	0.13	(0.246)
UMD	1.46	(0.160)	1.39	(0.176)
$PRIM$			0.11	(0.221)
Sample period	196501:200412			
N	480			

Table 7: **Estimated premia with conditional size and B/M factors.** This table shows the monthly premia in percent estimated with conditional size and B/M factors. Test assets are the B/M5-$PRIM$5-sorted 25 portfolios. MKT is the excess return on the CRSP value-weighted portfolio. LIQ is the liquidity factor. $CLIQ$ is the product of an indicator variable I and LIQ, where I takes the value of 1 if the probability of being in the high liquidity-beta state from the bivariate regime-switching model is higher than 0.75 and 0 otherwise. SMB, HML, and UMD are the size, book-to-market, and momentum factors, respectively. $PRIM$ is the lagged Amihud (2002) price impact proxy of the test portfolios. $CSMB$ ($CHML$) is the product of I and SMB (HML). The estimation follows the Fama-MacBeth (1973) two-pass procedure with the Shanken (1992) correction for standard errors. Reported are the estimated premia and p-values in parentheses. *, **, *** represent significance at 10, 5, and 1%, respectively.

	1		2		3	
Constant	0.25	(0.702)	0.39	(0.542)	0.15	(0.827)
MKT	0.21	(0.762)	0.11	(0.869)	0.28	(0.690)
LIQ	-8.97	(0.449)	-11.37	(0.311)	-8.65	(0.470)
$CLIQ$	9.54**	(0.023)	10.42**	(0.010)	8.97**	(0.031)
SMB	0.12	(0.713)	0.18	(0.563)	0.08	(0.813)
HML	0.58**	(0.047)	0.53*	(0.077)	0.60**	(0.044)
UMD	1.48	(0.217)	1.13	(0.348)	1.46	(0.223)
$PRIM$	0.15	(0.150)	0.12	(0.214)	0.13	(0.224)
$CSMB$	0.52	(0.352)			0.43	(0.441)
$CHML$			-0.04	(0.906)	0.09	(0.784)
Sample period			196501:200412			
N			480			

Table 8: **Estimated premia with default and volatility factors as well as idiosyncratic variance and turnover characteristics.** This table shows the monthly premia in percent estimated with default and volatility factors as well as idiosyncratic variance and turnover characteristics. Test assets are the B/M5-$PRIM$5-sorted 25 portfolios. MKT is the excess return on the CRSP value-weighted portfolio. LIQ is the liquidity factor. $CLIQ$ is the product of an indicator variable I and LIQ, where I takes the value of 1 if the probability of being in the high liquidity-beta state from the bivariate regime-switching model is higher than 0.75 and 0 otherwise. SMB, HML, and UMD are the size, book-to-market, and momentum factors, respectively. $PRIM$ is the lagged Amihud (2002) price impact proxy of the test portfolios. DSV and $dVOL$ are the default and volatility factors, respectively. $IVAR$ and TOV are the lagged idiosyncratic variance and share turnover, respectively, of the test portfolios. The estimation follows the Fama-MacBeth (1973) two-pass procedure with the Shanken (1992) correction for standard errors. Reported are the estimated premia and p-values in parentheses. *, **, *** represent significance at 10, 5, and 1%, respectively.

	1		2		3	
Constant	0.53	(0.438)	0.68	(0.315)	0.51	(0.506)
MKT	0.13	(0.864)	-0.16	(0.835)	0.49	(0.592)
LIQ	-16.33	(0.123)	-15.49	(0.225)	-17.18	(0.156)
$CLIQ$	6.97*	(0.079)	10.68***	(0.007)	8.09*	(0.062)
SMB	-0.01	(0.967)	0.10	(0.764)	-0.03	(0.932)
HML	0.37	(0.170)	0.57*	(0.065)	0.31	(0.290)
UMD	0.95	(0.279)	1.13	(0.395)	1.40	(0.148)
$PRIM$	0.22**	(0.032)	0.01	(0.959)	0.20*	(0.085)
DSV	-0.70	(0.981)			-4.70	(0.885)
$dVOL$	-0.06	(0.597)			-0.08	(0.545)
$IVAR$			8.00	(0.421)	-19.63*	(0.097)
TOV			0.03	(0.673)	0.05	(0.617)
Sample period	197101:199912		196501:200412		197101:199912	
N	348		480		348	

Table 9: **Estimated premia with alternative test assets.** This table shows the monthly premia in percent estimated using alternative test assets. MKT is the excess return on the CRSP value-weighted portfolio. LIQ is the liquidity factor. $CLIQ$ is the product of an indicator variable I and LIQ, where I takes the value of 1 if the probability of being in the high liquidity-beta state from the bivariate regime-switching model is higher than 0.75 and 0 otherwise. SMB, HML, and UMD are the size, book-to-market, and momentum factors, respectively. $PRIM$ is the lagged Amihud (2002) price impact proxy of the test assets. Test portfolios used are as follows: Panel (a) Alternative portfolios excluding NASDAQ stocks. Column 1: B/M5-$RREV$5-sorted 25 portfolios, Column 2: Size3-B/M3-$PRIM$3-sorted 27 portfolios, and Column 3: Size3-B/M3-$RREV$3-sorted 27 portfolios, where $RREV$ is the Pastor and Stambaugh's (2003) return reversal measure. Panel (b) Alternative portfolios including NASDAQ stocks. Columns 1-3 employ the same sorting keys as the corresponding columns in Panel (a). Column 4: B/M5-$PRIM$5-sorted 25 portfolios. Panel (c) Individual stocks. Column 1: NYSE/AMEX stocks, Column 2: NYSE/AMEX/NASDAQ stocks. The estimation follows the Fama-MacBeth (1973) two-pass procedure with the Shanken (1992) correction for standard errors. Reported are the estimated premia and p-values in parentheses. *, **, *** represent significance at 10, 5, and 1%, respectively.

(a) Alternative portfolios excluding NASDAQ stocks

	1		2		3	
Constant	0.02	(0.981)	0.51	(0.291)	-0.20	(0.772)
MKT	0.40	(0.566)	-0.11	(0.850)	0.65	(0.390)
LIQ	-7.25	(0.353)	4.26	(0.602)	-7.09	(0.360)
$CLIQ$	8.81**	(0.049)	4.52	(0.105)	6.58**	(0.043)
SMB	-0.24	(0.435)	0.08	(0.743)	0.07	(0.785)
HML	0.52**	(0.049)	0.67***	(0.004)	0.52**	(0.029)
UMD	1.14	(0.258)	1.73**	(0.015)	0.79	(0.250)
$PRIM$	0.30**	(0.028)	0.05	(0.577)	0.17**	(0.045)
Sample period			196501:200412			
N			480			

(b) Alternative portfolios including NASDAQ stocks

	1		2		3		4	
Constant	0.69	(0.226)	0.89	(0.128)	1.14	(0.156)	0.78	(0.148)
MKT	-0.14	(0.823)	-0.31	(0.644)	-0.58	(0.490)	-0.24	(0.702)
LIQ	-10.58	(0.192)	-7.29	(0.494)	-17.37*	(0.084)	-9.88	(0.446)
$CLIQ$	9.33**	(0.027)	9.46**	(0.010)	7.16*	(0.073)	10.50***	(0.005)
SMB	0.16	(0.578)	0.27	(0.305)	0.31	(0.249)	0.30	(0.266)
HML	0.44*	(0.064)	0.61**	(0.016)	0.54**	(0.023)	0.51**	(0.037)
UMD	1.05	(0.177)	2.23**	(0.011)	0.66	(0.363)	0.50	(0.527)
$PRIM$	0.09	(0.297)	-0.03	(0.575)	0.06	(0.326)	0.04	(0.504)
Sample period					196501:200412			
N					480			

Table 9: Continued

(c) Individual stocks

	1		2	
Constant	1.72**	(0.011)	2.15***	(0.010)
MKT	-1.06	(0.193)	-1.46	(0.163)
LIQ	-20.66*	(0.082)	-30.84**	(0.048)
CLIQ	11.94**	(0.014)	12.44**	(0.010)
SMB	0.40	(0.224)	0.47	(0.246)
HML	0.53	(0.136)	0.67	(0.184)
UMD	1.19	(0.397)	1.37	(0.420)
PRIM	-0.09***	(0.000)	-0.09***	(0.000)
Sample period	196501:200412			
N	480			

Table 10: **Estimated premia with alternative state identification.** This table shows the monthly premia in percent estimated with the states identified by the regime-switching model with excess $PRIM$-sorted decile portfolio returns as dependent variables. Test assets are the B/M5-$PRIM$5-sorted 25 portfolios. MKT is the excess return on the CRSP value-weighted portfolio. LIQ is the liquidity factor. $CLIQ$ is the product of an indicator variable I and LIQ, where I takes the value of 1 if the probability of being in the high liquidity-beta state from the bivariate regime-switching model is higher than 0.75 and 0 otherwise. SMB, HML, and UMD are the size, book-to-market, and momentum factors, respectively. $PRIM$ is the lagged Amihud (2002) price impact proxy of the test portfolios. The estimation follows the Fama-MacBeth (1973) two-pass procedure with the Shanken (1992) correction for standard errors. Reported are the estimated premia and p-values in parentheses. *, **, *** represent significance at 10, 5, and 1%, respectively.

	1		2		3	
Constant	1.65***	(0.003)	0.49	(0.407)	0.16	(0.790)
MKT	-1.16*	(0.068)	0.04	(0.955)	0.34	(0.626)
LIQ	5.93	(0.320)	-15.90	(0.166)	-14.37	(0.206)
$CLIQ$	11.90**	(0.013)	10.62**	(0.046)	10.46**	(0.045)
SMB			0.23	(0.425)	0.17	(0.580)
HML			0.49*	(0.099)	0.49*	(0.095)
UMD			0.41	(0.751)	0.32	(0.802)
$PRIM$					0.19**	(0.026)
Sample period			196501:200412			
N			480			

Table 11: **Estimated premia with alternative State-2 probability thresholds.** This table shows the monthly premia in percent estimated with alternative probability thresholds for State 2. Test assets are the B/M5-$PRIM$5-sorted 25 portfolios. MKT is the excess return on the CRSP value-weighted portfolio. LIQ is the liquidity factor. $CLIQ$ is the product of an indicator variable I and LIQ, where I takes the value of 1 if the probability of being in the high liquidity-beta state from the bivariate regime-switching model is higher than 0.75 and 0 otherwise. SMB, HML, and UMD are the size, book-to-market, and momentum factors, respectively. $PRIM$ is the lagged Amihud (2002) price impact proxy of the test portfolios. 'N State 2' is the number of months in State 2. The estimation follows the Fama-MacBeth (1973) two-pass procedure with the Shanken (1992) correction for standard errors. Reported are the estimated premia and p-values in parentheses. *, **, *** represent significance at 10, 5, and 1%, respectively.

Prob Threshold	0.5		0.6		0.7		0.8		0.9	
Constant	0.43	(0.497)	0.54	(0.388)	0.22	(0.723)	0.32	(0.597)	0.19	(0.742)
MKT	0.04	(0.961)	-0.07	(0.923)	0.29	(0.686)	0.17	(0.796)	0.29	(0.660)
LIQ	-12.24	(0.294)	-12.02	(0.295)	-9.94	(0.381)	-11.32	(0.301)	-11.02	(0.300)
$CLIQ$	13.23**	(0.013)	12.51**	(0.013)	12.10***	(0.009)	9.87***	(0.009)	8.81**	(0.016)
SMB	0.24	(0.450)	0.24	(0.443)	0.23	(0.465)	0.18	(0.555)	0.16	(0.597)
HML	0.49	(0.104)	0.50*	(0.097)	0.48	(0.113)	0.53*	(0.070)	0.51*	(0.073)
UMD	0.46	(0.736)	0.62	(0.642)	1.15	(0.376)	1.17	(0.344)	1.23	(0.306)
$PRIM$	0.10	(0.301)	0.09	(0.364)	0.11	(0.246)	0.13	(0.159)	0.15*	(0.099)
N State 2	62		51		47		41		37	
Sample period					196501:200412					
N					480					

Table 12: **Estimated premia with the liquidity-factor mimicking portfolio.** This table shows the monthly premia in percent estimated with the liquidity-factor mimicking portfolio. Test assets are the B/M5-$PRIM$5-sorted 25 portfolios. MKT is the excess return on the CRSP value-weighted portfolio. LMP is the return on the liquidity-factor mimicking portfolio. $CLMP$ is the product of an indicator variable I and LMP, where I takes the value of 1 if the probability of being in the high liquidity-beta state from the bivariate regime-switching model is higher than 0.75 and 0 otherwise. SMB, HML, and UMD are the size, book-to-market, and momentum factors, respectively. $PRIM$ is the lagged Amihud (2002) price impact proxy of the test portfolios. The estimation follows the Fama-MacBeth (1973) two-pass procedure with the Shanken (1992) correction for standard errors. Reported are the estimated premia and p-values in parentheses. *, **, *** represent significance at 10, 5, and 1%, respectively.

	1		2		3		4	
Constant	2.05***	(0.000)	0.82*	(0.079)	0.68	(0.125)	0.55	(0.242)
MKT	-1.60***	(0.004)	-0.42	(0.470)	-0.31	(0.579)	-0.18	(0.747)
LMP	-1.03	(0.229)	-0.63	(0.479)	0.47	(0.720)	0.77	(0.550)
$CLMP$			2.08**	(0.013)	1.64**	(0.038)	1.49*	(0.071)
SMB					0.04	(0.883)	0.02	(0.953)
HML					0.62**	(0.022)	0.61**	(0.024)
UMD					0.25	(0.833)	0.20	(0.863)
$PRIM$							0.18*	(0.062)
Sample period	196710:200412							
N	447							

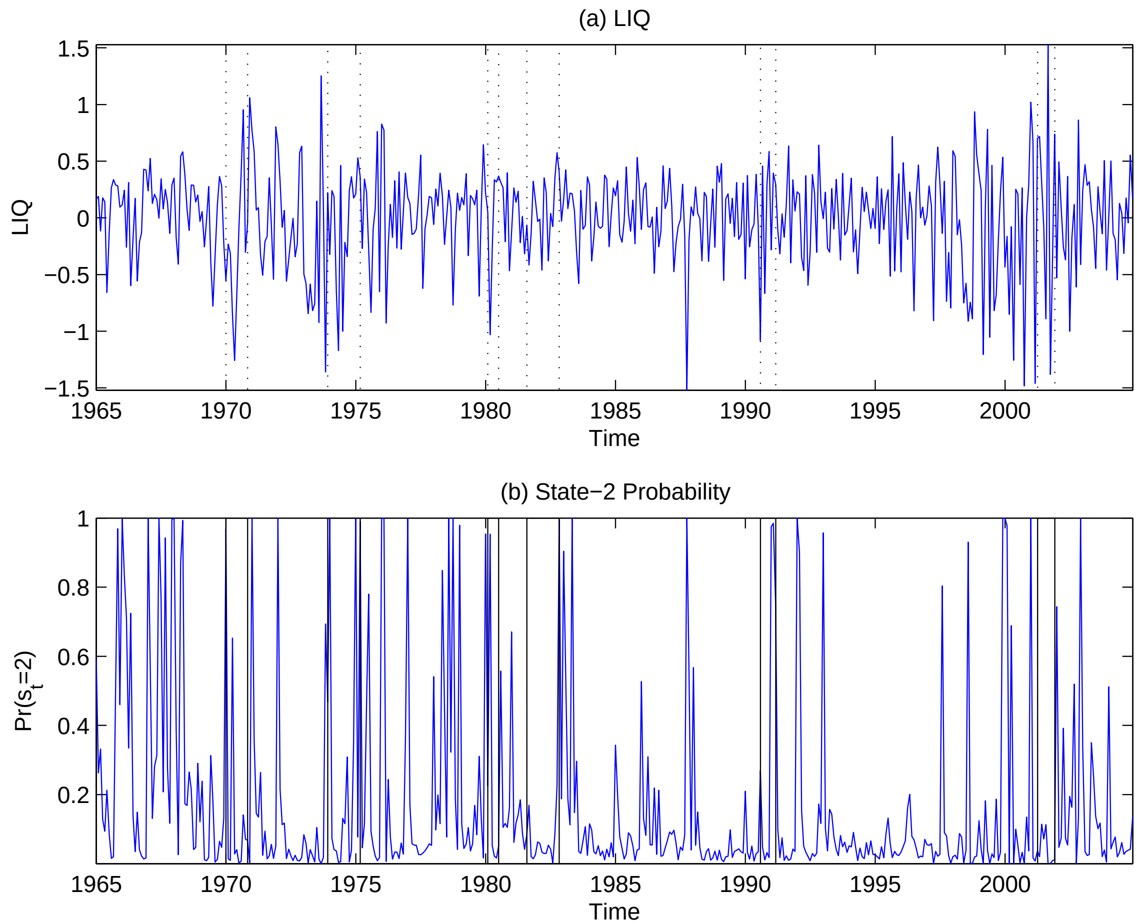

Figure 1: The liquidity shocks and the estimated probability of being in State 2. (a) The liquidity shock series, LIQ, is given by the negative residuals from the modified AR(2) model for the detrended aggregate Amihud (2002) price impact proxy, $PRIM$. (b) The probability of being in State 2 from the bivariate regime-switching model with $STOV$ as a state variable. The NBER business cycle dates are also indicated by dotted lines (each narrow band represents a recession).

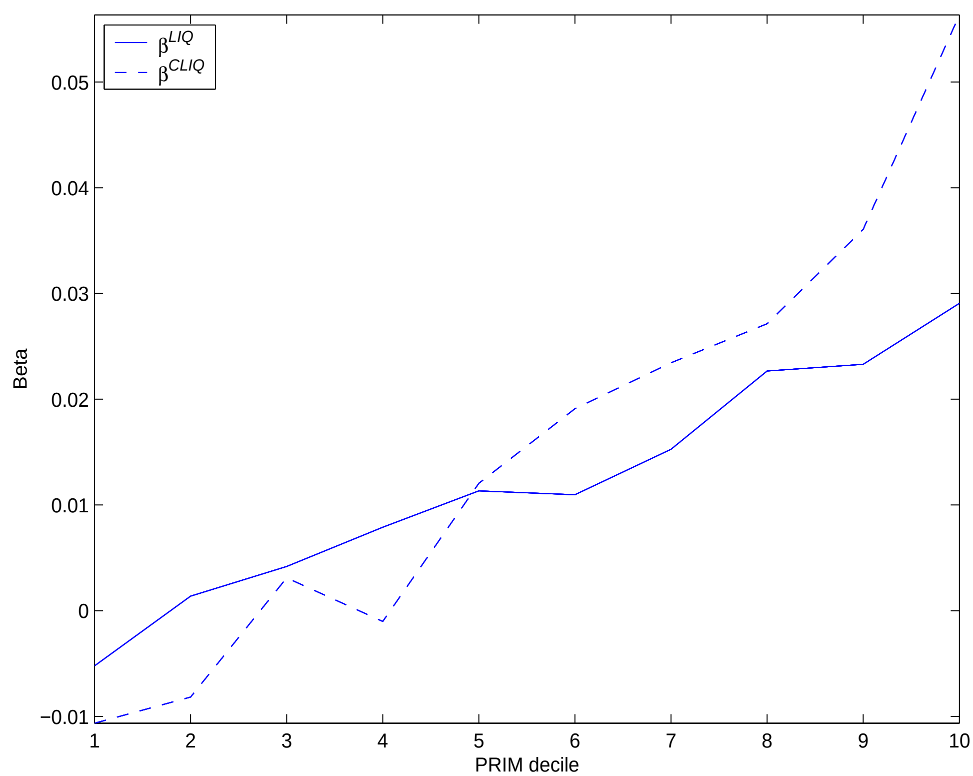

Figure 2: Betas of the excess $PRIM$-sorted decile portfolio returns with respect to LIQ (β^{LIQ}) and $CLIQ$ (β^{CLIQ}).

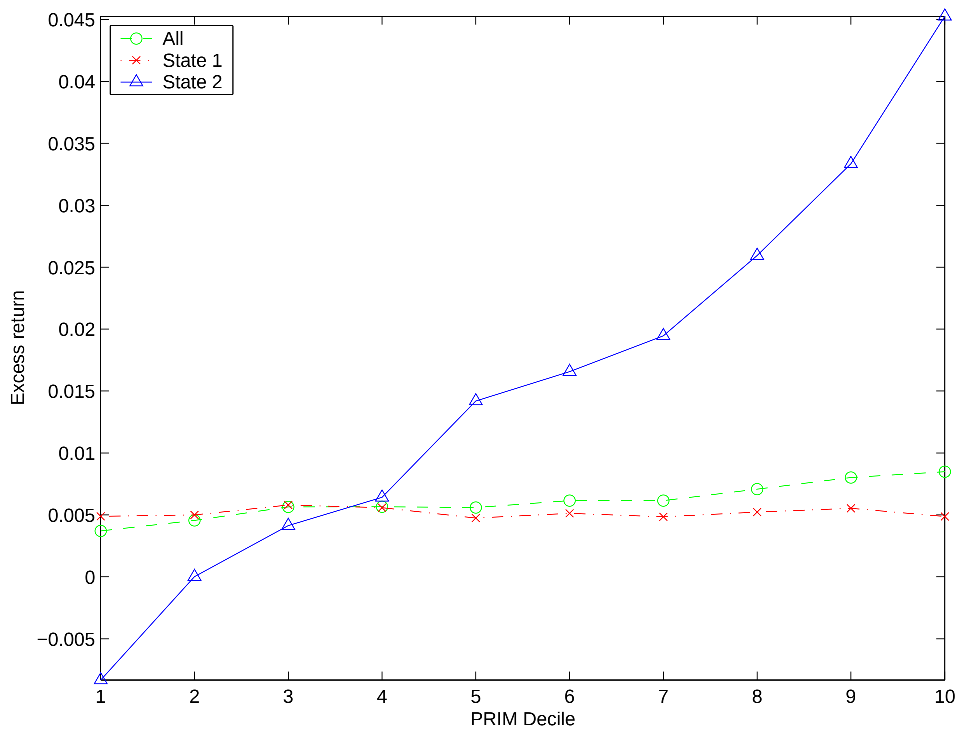

Figure 3: Monthly means of the excess $PRIM$-sorted decile portfolio returns by state.

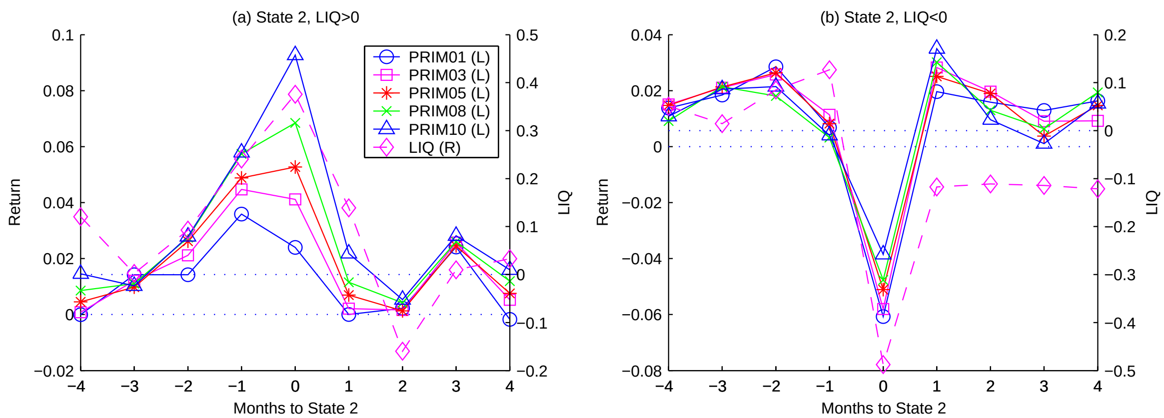

Figure 4: Average raw returns of selected $PRIM$-sorted decile portfolios (left scale) and LIQ (right scale) conditional on the sign of LIQ in State 2. $PRIM01$ represents the lowest $PRIM$ decile and $PRIM10$ the highest. The horizontal axis is the number of months to State 2.

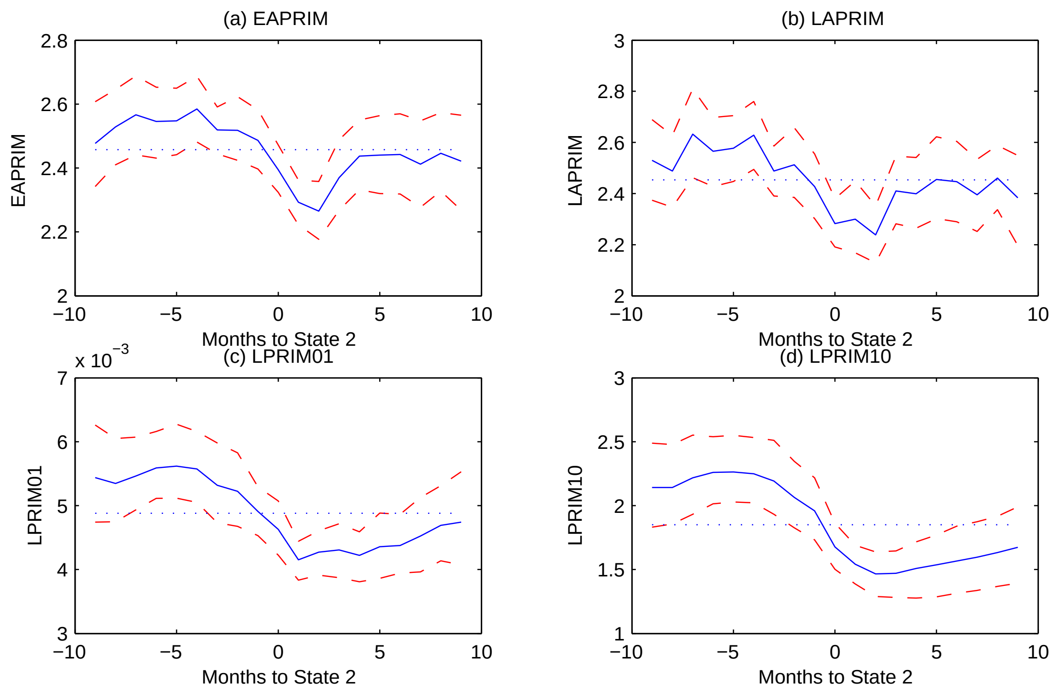

Figure 5: Bootstrap means of the expected illiquidity measures and selected variables around State 2. (a) $EAPRIM$, the fitted values from the modified AR(2) model for $APRIM$ in equation (7), (b) $LAPRIM$, the lagged aggregate Amihud (2002) price impact proxy, (c)(d) the lagged Amihud (2002) price impact proxies for the most ($LPRIM01$) and the least ($LPRIM10$) liquid deciles, and (e)-(i) the five state variables studied in Section 1.5. The solid lines represent the bootstrap means, dashed lines the 95% confidence intervals, and the dotted horizontal lines the block averages. Each sampling draws 43 blocks with replacement. Each block starts from nine months prior to a high liquidity-beta month and continues through nine months after it. Within each block, the difference between the monthly value and the block average is computed each month. The differences are then averaged across the 43 blocks month by month. This is repeated for 5000 times, and the means and the 95% confidence intervals of the monthly differences across the re-samplings are calculated.

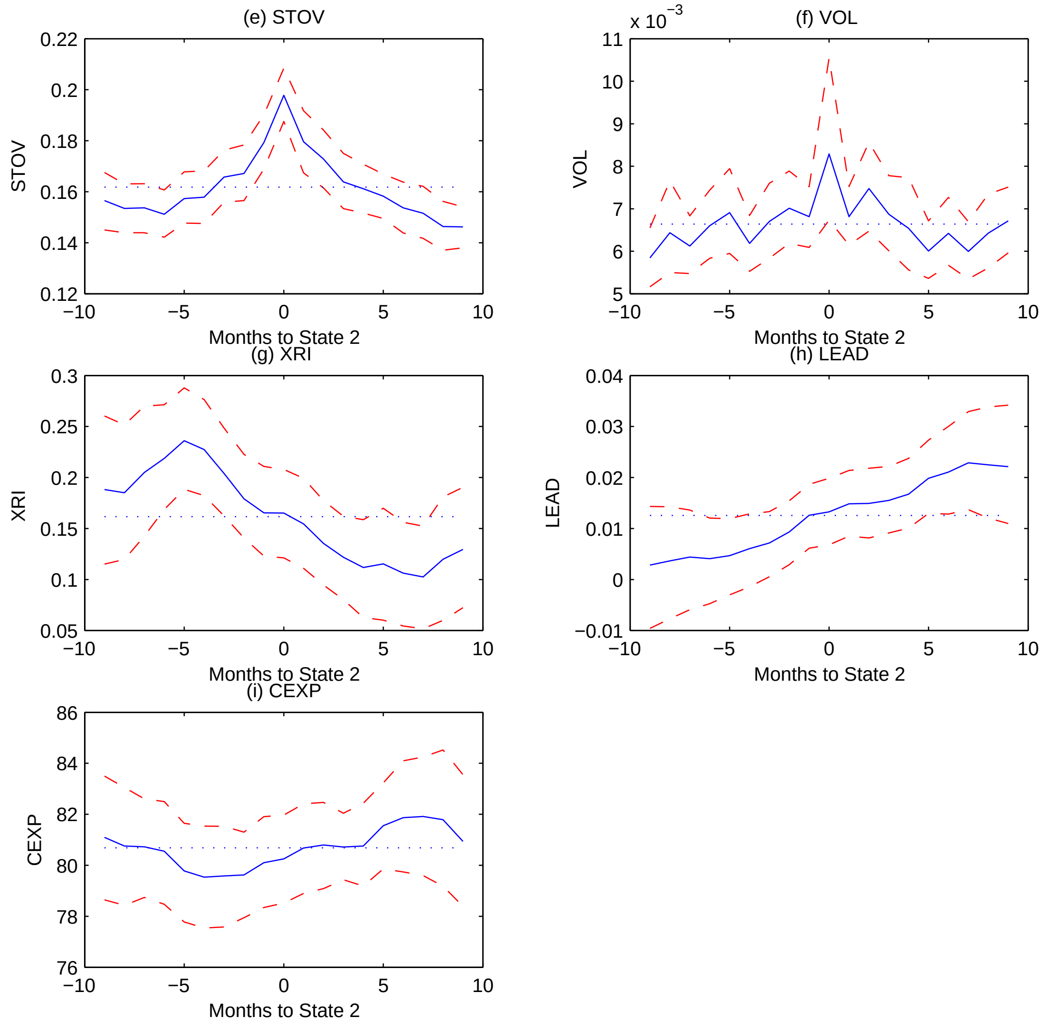

Figure 5: Continued