State-Dependent Variations in Expected Liquidity Risk Premium

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JEL classification: G14

Keywords: Markov switching model; Illiquidity premium; State-dependent expected returns; Business cycle variable

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Abstract

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1 Introduction

The question of how liquidity and asset returns are related has received an enormous amount of attention in financial economics. Since the pioneer work of Amihud and Mendelson (1986), numerous researchers have investigated the association between liquidity and asset returns (Brennan and Subrahmanyam, 1996; Datar, Naik, and Radcliffe, 1998; Amihud, 2002; Liu, 2006). The literature finds a significant illiquidity premium in stock returns. That is, a less liquid stock commands higher expected return than a more liquid one because investors require compensation for holding illiquid stocks when they make investment decisions. The importance of illiquidity premium has been particularly emphasized since the recent financial crisis in the late 2000s, which led to a liquidity dry-up in the US stock market.

One stylized fact about liquidity is that the level of liquidity is very sensitive to the states of the economy. These state-dependent variations in liquidity have been supported by theoretical models and several lines of empirical evidence. Theoretically, in a seminal paper, Brunnermeier and Pedersen (2009) document that market liquidity can be fragile, that is, it can suddenly experience a discontinuous drop in times of crisis. According to their theoretical framework, market liquidity is at its highest level and is rarely affected by marginal changes in the funding condition, as long as the capital of liquidity providers is so abundant that there is no risk that the funding constraints become binding (i.e., in "normal" or "good" state). When liquidity providers hit their funding constraints (i.e., in "crisis" or "bad" state), however, market liquidity declines since the binding constraints restrict their provision of market liquidity. Moreover, market liquidity can drop substantially with a small loss of capital in this situation. Their model provides theoretical evidence that market liquidity varies across the state of the economy, and furthermore, it can suddenly switch from the highest to the lowest level. Historically, the events of liquidity dry-ups in the financial market have coincided with recessions in the real economy. Major economic events with large decline in liquidity include the oil price shock in 1973, the

October stock market crash in 1987, the bursting of the high-tech bubble in the early 2000s, and the recent global financial crisis in late 2007 to 2008.[1] From these liquidity crises, we observe that financial market liquidity varies significantly across economic states.

How can such state-dependent variations in market liquidity affect asset prices? One possible conjecture is that prices of liquid and illiquid assets display dissimilar variations from state to state. This argument can be supported by the well-known "flight-to-liquidity" phenomenon, first defined by Longstaff (2004).[2] When market liquidity drops significantly during economic downturns, some investors suddenly shift their portfolios from less liquid to more liquid assets. The sudden changes in portfolios would make the prices of illiquid assets to decrease and those of liquid assets to increase. In times of improvement in market liquidity, on the other hand, investors value asset liquidity less than in time of illiquid market and thus the price of liquidity decreases. As a result, the magnitude of illiquidity premium may not be identical across states of the world.

In this respect, there is one fundamental limitation of prior studies. While the existence of illiquidity premium has been suggested and subsequently confirmed, the literature focuses less on the linkage between illiquidity premium and the states of the economy. Given the theoretical and empirical evidence that illiquidity premium varies across different regimes (Amihud and Mendelson, 1986; Acharya and Pedersen, 2005; Brunnermeier and Pedersen, 2009), this lack of research is somewhat surprising. For a comparison, numerous researchers have investigated the value premium and momentum profit across states of the economy (Cooper, Gutierrez, and Hameed, 2005; Gulen, Xing, and Zhang, 2011) even though there are relatively fewer theoretical frameworks supporting the state-dependence in these premia. We argue that, given the state-dependent nature of asset liquidity, one should examine the effect of economic states

[1] Based on Amihud's (2002) illiquidity measure, Næs, Skjeltorp, and Ødegaard (2011) document that large decreases in market liquidity occur during periods of such economic events.

[2] Using the U.S. Treasury bond data, Longstaff (2004) documents a phenomenon where market participants shift their portfolios from "off-the-run" to "on-the-run" Treasuries and finds that a liquidity premium, in some cases, is more than 15% of the value of some Treasury bonds.

on the expected returns of stocks with different levels of liquidity to better understand the liquidity-return relationship.

Another limitation of the literature is that previous studies have been confined to the investigation of illiquidity premium observed in *realized* stock returns. An examination of *ex-ante* illiquidity premium is, however, more pertinent for our purpose. The standard asset pricing theory states that investors require *ex-ante* premium for holding risky assets (Sharpe, 1964; Lintner, 1965). Therefore, examining the presence of an illiquidity premium in an *ex-ante* sense is a more reasonable approach, although previous studies have frequently used the realized returns to investigate the illiquidity premium.

This paper attempts to overcome these shortcomings of prior studies by providing new evidence on this literature. Specifically, we focus on the following two issues. First, we ask whether expected illiquidity premium exhibits significant variations across economic states. This inquiry is motivated by the conjecture that investors' perception of price on liquidity risk is significantly different across economic states, and consequently, differences in the expected returns on liquid and illiquid stocks, illiquidity premia, are not identical across the states. Second, we study the driving forces behind the state-dependence in the expected illiquidity premium. Based on prior studies, we conjecture that the expected returns of illiquid stocks are more strongly affected by unfavorable economic conditions identified by common business cycle variables such as the default spread, the term spread, the short-term interest rates, and the change in monetary condition. Specifically, we investigate whether the sensitivities of stock returns on business cycle variables are significantly different between less liquid and more liquid stocks and across the state of the economy, which consequently leads to the state-dependent variations in the expected illiquidity premium.

To incorporate the asymmetric movement of illiquidity premium across states, following Perez-Quiros and Timmermann (2000), we adopt a regime switching model based on a two-state Markov process with time-varying transition probabilities.[3] Specifically, by employing the two-state Markov switching model, we estimate the expected stock returns with different levels of liquidity both independently and jointly with several business-cycle-related variables as return predictors. Our econometric framework has at least two advantages. First, the Markov switching model captures well the possible discontinuous variations in sensitivities of stock returns on business cycle variables due to its assumption of state-dependent parameters. Given the previous literature which states discontinuous, not gradual, variations in liquidity, we believe that the Markov switching model is adequate for our study. The classification of the two distinct states is consistent with the concept of fragility in market liquidity, or with the discontinuous variations in market liquidity conditions in Brunnermeier and Pedersen's (2009) model. Second, our approach estimates the transition between two states from information known *ex-ante*, not defining the states with *ex-post* determined indicators (e.g., NBER recession dummy). In a predictive model, it is important that all information used to predict a future return is ensured to be currently available, particularly for an out-of-sample forecast.

Our central findings are summarized as follows. First, the sensitivities of liquidity-sorted portfolio returns on business cycle variables are significantly different across the states of the world. For example, in the bad economic state identified by high return volatility, the estimated slopes of all liquidity-sorted portfolios on the term spread are positive in the univariate Markov switching model. However, the estimated coefficients are always negative in the low volatility state. More importantly, the difference in sensitivities is particularly pronounced in the least liquid portfolio. For the least liquid portfolio, the slope on the term spread is 1.605 (*t*-value = 1.89) in the high volatility state, while it is -0.730 (*t*-value = -2.18) in the low volatility state. On the other hand, for the most liquid portfolio, the slopes are 0.396 (*t*-value = 0.66) and -0.134 (*t*-value = -0.52) in the high and low volatility states, respectively. Except for the two most liquid

[3] Using a two-state Markov regime switching model, Perez-Quiros and Timmermann (2000) examine the systematic differences in variations over economic states for small and large firms' stock returns, and document that small firms with little collateral are more affected by changes in credit market conditions than large firms.

portfolios, the likelihood ratio tests also reject the null hypothesis that the mean parameters for the business cycle variables are identical across the two states.

Second, as a consequence of asymmetries in the effect of business cycle variables, we find a strong state-dependent variation in the expected illiquidity premium, which is countercyclical. Specifically, our results show that the expected illiquidity premium tends to increase abruptly during the NBER recessions, but decrease during expansions, which indicates that the expected illiquidity premium is strongly present during recessions, not during expansions. Therefore, our empirical finding implies that the illiquidity premium documented in previous studies is mainly due to the additional compensation of illiquid stocks in bad states. In addition, we find some linkage between the expected illiquidity premium and the real economy because (1) the expected illiquidity premium has a negative contemporaneous correlation of -0.344 with real GDP growth and -0.286 with growth in the industrial production, respectively, and (2) the expected illiquidity premium has some information for predicting the real economic activity up to one quarter ahead.

Third, our findings are robust to a battery of specification checks. First, we use the NBER state indicator to alternatively define the states, and we also find strong variations in factor loadings across states. This result confirms that the incorporation of features of regime-switching is important in understanding the state-dependent nature of illiquidity premium. Second, we investigate expected illiquidity premium after controlling for firm size. We find strong economic and statistical significance for the state-dependent variations in expected illiquidity premium even after controlling for firm size effect. Therefore, it appears that our main findings are not due to size premium. Third, using a couple of alternative liquidity proxies proposed in previous studies, we find that our empirical results are robust to the choice of liquidity measures. Given a possible concern that our findings are driven by the use of a specific liquidity measure, this experiment is very meaningful. Finally, the out-of-sample prediction results indicate that the information contained in the expected illiquidity premium from the

Markov switching model is both statistically and economically significant.

Our study contributes to the literature by providing new empirical evidence on relation between the illiquidity premium and the state of the economy. One important implication of our study is that one should take a look at the liquidity-return relationship conditional on changes in the economic states. The literature which states discontinuous, not gradual variations in liquidity across states combined with our empirical finding that the expected illiquidity premium displays substantial variations across the states support our suggestion. Moreover, our results indicate that the illiquidity premium documented previously throughout numerous studies exists primarily in bad economic states, while it is relatively weak in good economic states. Another contribution of our work is that we find the linkage between financial markets and the macroeconomy. As Cochrane (2008) emphasizes, at some level, financial markets should be related to the macroeconomy since the risk premium in financial assets eventually reflects aggregate, macroeconomic risks. The previous empirical studies, however, have frequently failed to confirm this association. Therefore, our finding that the expected illiquidity premium is related to the real economic movement is quite intriguing.

Our work is closely related to a recent paper by Jensen and Moorman (2010), which documents that the illiquidity premium is strongly affected by the changes in monetary conditions. Our study is different from theirs for the following reasons. First, rather than focusing only on the effect of monetary condition on illiquidity premium, our study offers a comprehensive empirical analysis of the relationship between the expected illiquidity premium and business cycle. Our effort is meaningful in that investors' perception of liquidity risk should depend on overall business cycle, not just on monetary condition. Therefore, the present paper allows us to better understand the state-dependent nature of illiquidity premium with respect to the business cycle. Second, while their empirical results are based on a realized illiquidity premium, we focus on the *ex-ante* illiquidity premium expected from our Markov regime switching model. From the fact that investors command the *ex-ante* illiquidity premium for bearing liquidity risk, empirical investigation with the expected returns is more consistent with asset pricing theories.

Using state-dependent liquidity betas, Watanabe and Watanabe (2008) study the role of time-varying liquidity risk in explaining the cross-section of stock returns. They propose that changes in the level of preference uncertainty lead to time variations in liquidity risk and liquidity risk premium. To estimate state-dependent liquidity betas, they adopt a two-state Marko switching model similar to ours. Our study differs with theirs, however, in that we mainly focus on the roles of business-cycle-related variables as the determinants of state-dependent illiquidity premium, whereas they investigate whether the state-dependent liquidity betas are priced factor in the cross-section of stock returns.

Our work is also related to a growing body of research on return predictability, which documents that expected stock returns vary over the business cycle. We examine whether and how stock returns with different levels of liquidity are predicted by business-cycle-related variables. In addition, our work is related to the literature on the pricing of liquidity risk. It is well documented that liquidity risk is priced in the cross-section of stock returns (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Liu, 2006). Considering time variations in liquidity risk and liquidity risk premium in light of conditional asset pricing, our question can be restated as whether liquidity risk premium varies with economic states. In view of the risk-based story, rational investors require higher compensation for bearing liquidity risk in a bad state than in a good state, because in a bad state, they would be more likely to liquidate some of their asset holdings for consumption smoothing. Therefore, our empirical findings are consistent with the theoretical argument based on time-varying liquidity risk premium.

The remainder of this paper is organized as follows. Section 2 presents our econometric framework and data. Section 3 reports the empirical results. Finally, Section 4 summarizes and concludes.

2 Empirical Methodology

2.1 Model specification

Our goal is to examine whether the state-dependent variations in illiquidity premium could be led by the asymmetric effects of business cycle variables on expected stock returns with different liquidity levels. The asymmetries in the return sensitivities on business cycle variables can be readily accommodated by a two-state Markov switching model. Following Perez-Quiros and Timmermann (2000), we use a regime switching model based on a two-state Markov process with time-varying transition probabilities.[4] Main advantages of a two-state regime switching model are that (1) it can capture well the possible discontinuous variations in the effects of economic conditions due to its assumption of state-dependent parameters, and that (2) transition between two states is estimated using data known *ex-ante*, without using *ex-post* determined state indicators, such as the NBER recession indicator. For returns of stocks with different level of liquidity, we estimate two different versions of regime switching models, a univariate model and a bivariate model, respectively.[5]

The specification of our univariate Markov switching model is as follows. For excess returns on each decile portfolio sorted by the stocks' liquidity, we adopt the Markov switching model where the intercept, slope coefficients, and volatility of excess returns rely on a single, latent state variable, s_t,

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[4] We refer the reader to Section II of Perez-Quiros and Timmerman (2000) for a detailed estimation procedure using the maximum likelihood estimation.

[5] In principle, the Markov switching model should be estimated jointly for all asset returns considered, because if it is not the case, the underlying latent states identified using data may not coincide with each other asset. However, the multivariate model has too many parameters ($n^2 + 11n + 3$ parameters for the n-variate model of our specification), which could raise the possibility of overfitting data. To compromise this trade-off, we estimate the univariate and the bivariate version of the models separately and confirm that the estimation results of both specifications are not different.

$$r_t^i = \beta_{0,s_t}^i + \beta_{1,s_t}^i DEF_{t-1} + \beta_{2,s_t}^i TERM_{t-1} + \beta_{3,s_t}^i \Delta M_{t-2} + \beta_{4,s_t}^i TB_{t-1} + \varepsilon_t^i \ , \tag{1}$$

where ε_t^i follows a normal distribution with zero mean and a variance of σ_{i,s_t}^2. r_t^i is the excess return on the ith liquidity-sorted portfolio at time t. $DEF_{t-1}, TERM_{t-1}, \Delta M_{t-2}$ and TB_{t-1} represent the lagged values of the default spread, the term spread, the growth in the money stock, and the one-month Treasury bill rate, respectively. Guided by the time-series predictability literature, these variables are used to capture the business cycle.[6] Following Perez-Quiros and Timmermann (2000), the values of growth in the money stock are lagged two months due to publication delay. The specification in equation (1) allows the intercept, slope coefficients, and volatility to have different values depending on the two states, s_t = 1, or 2.[7]

Whereas the standard Markov switching model assumes that transition probabilities are constant over time, recent studies have documented that the use of constant transition probabilities may have an oversimplification problem. To get around this problem, some researchers model time-varying transition probabilities as a function of the composite leading indicator (Filardo, 1994; Perez-Quiros and Timmermann, 2000). Following this line of research, we model the time-varying transition probabilities as follows:

$$p_t^i = \mathrm{P}(s_t^i = 1 \mid s_{t-1}^i = 1, Y_{t-1}) = \Phi(\pi_0^i + \pi_1^i \Delta CLI_{t-3})$$

$$q_t^i = \mathrm{P}(s_t^i = 2 \mid s_{t-1}^i = 2, Y_{t-1}) = \Phi(\pi_0^i + \pi_2^i \Delta CLI_{t-3}) \ , \tag{2}$$

where ΔCLI_{t-3} represents the three-month lagged value of the 12-month rate of change in the OECD composite leading indicator,[8] and Φ is the cumulative distribution function of a

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[6] It should be noted that the dividend yield is also known as a common predictor for stock returns in the empirical stock return predictability literature. Fama and French (1989) find that the dividend yield and the default spread tend to move together and capture the long-term business cycle. In our sample period, the correlation between the dividend yield and the default spread is 0.46. Thus, we do not include the dividend yield in our model specification. However, the inclusion of the dividend yield does not alter our empirical results.

[7] Following Gulen, Xing, and Zhang (2011), the ARCH effects or other instrumental variables are not included in the conditional variance specification for simplicity. This specification enables us to easily identify the two states as either a high or low volatility state.

[8] We use the three-month lagged value of the CLI growth because there is a 2-month lag between the

standard normal distribution. In addition, s_t^i is a state indicator for the *i*th portfolio, and Y_{t-1} is a vector of variables known at time *t*-1.

To examine whether the expected illiquidity premium displays significant variations across states, a bivariate Markov switching model for excess returns on liquid and illiquid portfolios is more appropriate since it assumes that the transition between the two states occurs simultaneously for the two portfolios, while a univariate framework does not impose this restriction. This estimation also allows us to test the hypothesis that illiquid stocks display stronger state-dependence in expected excess returns than liquid ones.

In our bivariate model specification, the high-liquidity portfolio (*HL*) includes stocks that are in the bottom 30% sorted on their illiquidity measure, and the low-liquidity portfolio (*LL*) contains stocks that fall into the top 30% sorted on the same measure, based on NYSE breakpoints.[9] Then, for the excess returns of the high-liquidity (*HL*) and the low-liquidity (*LL*) portfolios, we adopt the bivariate Markov switching model as follows:

$$\mathbf{r}_t = \boldsymbol{\beta}_{0,s_t} + \boldsymbol{\beta}_{1,s_t} DEF_{t-1} + \boldsymbol{\beta}_{2,s_t} TERM_{t-1} + \boldsymbol{\beta}_{3,s_t} \Delta M_{t-2} + \boldsymbol{\beta}_{4,s_t} TB_{t-1} + \boldsymbol{\varepsilon}_t \ , \tag{3}$$

where $\mathbf{r}_t$ is a (2×1) vector of the high-liquidity and the low-liquidity portfolios' excess returns at time *t*, and $\boldsymbol{\beta}_{k,s_t} \equiv (\beta^{HL}_{k,s_t}, \beta^{LL}_{k,s_t})'$ for $k = 0, 1, 2, 3, 4,$ and $\boldsymbol{\varepsilon}_t \sim N(0, \boldsymbol{\Omega}_{s_t})$ is a vector of residuals. $\boldsymbol{\Omega}_{s_t}$ is the variance-covariance matrix of the residuals of the two portfolios' excess returns, which is a positive semidefinite (2×2) matrix:

$$\boldsymbol{\Omega}_{s_t} = \begin{pmatrix} \sigma^2_{HL,s_t} & \rho_{s_t}\sigma_{HL,s_t}\sigma_{LL,s_t} \\ \rho_{s_t}\sigma_{HL,s_t}\sigma_{LL,s_t} & \sigma^2_{LL,s_t} \end{pmatrix} . \tag{4}$$

We allow both the return volatilities and the correlation to vary across the two states.

As in the univariate model, time-varying transition probabilities are assumed as a function of the composite leading indicator:

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reference date and the publication date of the OECD composite leading indicator data which we use.

[9] We also use the extreme 10% stocks in order to define the high-liquidity and the low-liquidity portfolios, and the empirical results are qualitatively similar.

$$p_t = \mathrm{P}(s_t = 1 \mid s_{t-1} = 1, Y_{t-1}) = \Phi(\pi_0 + \pi_1 \Delta CLI_{t-3})$$

$$q_t = \mathrm{P}(s_t = 2 \mid s_{t-1} = 2, Y_{t-1}) = \Phi(\pi_0 + \pi_2 \Delta CLI_{t-3}) \ , \qquad (5)$$

but now, the same latent state variable drives excess returns on both liquid and illiquid portfolios.

2.2 Data and variables

In this paper, we employ the illiquidity measure of Amihud (2002) as a liquidity proxy for constructing our main results, since it is the most widely used liquidity measure in literature. Amihud's illiquidity measure of stock *i* is defined as the absolute return relative to the dollar trading volume averaged over a month:

$$ILLIQ_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \left| R_{i,d} \right| \Big/ VOL_{i,d} \ , \qquad (6)$$

where $R_{i,d}$ is stock *i*'s return on day *d*, $VOL_{i,d}$ is the daily volume in dollars, and $D_{i,t}$ is the number of positive-volume trading days of the stock over month *t*. The measure represents the daily price movement related to one unit of trading volume. Hasbrouck (2009) compares several different liquidity measures obtained from daily data, and finds that the Amihud illiquidity measure is most strongly related with the TAQ-based price impact coefficient.

To construct our test portfolios, we use the monthly stock returns from CRSP over the period from July 1962 to December 2010. The sample includes all NYSE/AMEX/NASDAQ ordinary common stocks, which have CRSP share codes 10 and 11. As test assets for the univariate model, we use the monthly excess returns of the liquidity-sorted decile portfolios. Specifically, at the beginning of each month, sample stocks are sorted into decile portfolios using NYSE breakpoints, based on the prior month illiquidity measures. For each portfolio, we then calculate the monthly equally-weighted returns for the following 12-month holding periods in excess of the one-month Treasury bill rate.[10] The average excess return of the decile

[10] To calculate the multi-month holding period returns, we follow the method described in Liu and

portfolios sorted on Amihud's illiquidity measure increases from 0.46% per month for the most liquid decile to 0.97% per month for the least liquid group. In addition, the average return of the zero-cost portfolio buying the least and selling the most liquid groups generate 0.51% per month, with a *t*-statistic of 2.76, which confirms that the unconditional realized illiquidity premium is economically huge and statistically significant. We also construct the high-liquidity portfolio (*HL*) and the low-liquidity portfolio (*LL*) as test assets for the bivariate model. The *HL* (*LL*) portfolio contains stocks that are in the bottom 30% (the top 30%) sorted on their illiquidity measures, based on NYSE breakpoints, and their returns are calculated in the same way with decile portfolio returns.

For business cycle variables, we use the default spread, the term spread, the growth in money stock, and the short-term interest rate. The default spread is defined as the difference between the yields of a Moody's Baa and Aaa corporate bond yields taken from the FRED® database of the Federal Reserve Bank of St. Louis. Our use of the default spread is supported because the striking forecasting power of the default spread has been proved in the time-series predictability literature (Keim and Stambaugh, 1986; Fama and French, 1989). For example, Fama and French (1989) argue that the major movement in the default spread is related to long-term business cycles. In addition, they document that the default spread tends to be low during periods of stable economic conditions.

The term spread is defined as the difference between the yields of a ten-year and a one-year government bonds. The data are taken from the FRED® database of the Federal Reserve Bank of St. Louis. Since the term spread captures the variations in the slope of the yield curve, it should be linked to the business cycle. Not surprisingly, the term spread has been widely employed as a conditioning variable (Keim and Stambaugh, 1986; Campbell, 1987; Fama and French, 1989). Fama and French (1989) find that the term spread captures the short-term business cycles, and also tends to be low in peaks and high near troughs.

Strong (2008).

The growth in the money stock is defined as the continuously compounded annual rate of change in the monetary base from the FRED® database of the Federal Reserve Bank of St. Louis. We use this measure since the growth in the money supply is closely related to changes in market liquidity condition. Indeed, researchers have investigated the effect of monetary conditions on time variations in the illiquidity premium (Fujimoto, 2004; Jensen and Moorman, 2010).

The one-month Treasury bill rate is employed as a short-term interest rate, and is taken from Kenneth French's website. The one-month Treasury bill rate is known to contain information about future economic activity. This variable has been commonly used in predictive regressions, and its negative correlation with future stock return has been documented (Fama and Schwert , 1977; Campbell, 1987).

3 Empirical Results

3.1 Estimation results on the univariate Markov switching model

3.1.1 The nature of the states

Table 1 presents the parameter estimates for the univariate Markov switching model. In each decile portfolio sorted on the Amihud illiquidity measure, the estimated coefficients and *z*-statistics for the mean, variance, and transition probability parameters are displayed. Looking at the variance parameters, the estimated parameters of state 1 are substantially higher than those of state 2 for all portfolios, and the difference between the variance parameters is the biggest in the least liquid portfolio. These results indicate that state 1 is the high volatility state, and state 2 is the low volatility state.

Accepting the criticism of oversimplification in constant transition probabilities, we model the time-varying transition probabilities as a function of the composite leading indicator (CLI). As shown in the transition probability parameters, the estimated coefficients on change in the CLI are different across states, and some estimates are statistically significant, which justifies the use of time-varying transition probabilities. For all portfolios, the coefficients on change in the CLI are negative in state 1, which indicates that the increase in the CLI reduces the probabilities of being in state 1. On the other hand, eight out of ten estimated coefficients on the CLI have positive values in state 2, which implies that increase in the CLI increases the probabilities of staying in state 2.

Figure 1 presents the time-series of the transition probabilities. Panel A shows the results for the most liquid firms, and Panel B reveals the results for the least liquid firms. Shades areas indicate the NBER recessions. In each Panel, "TRNS_PR1" is the probability of moving from state 1 to another state 1, and "TRNS_PR2" is the probability of moving from state 2 to another state 2. For the least liquid stocks, "TRNS_PR1" changes substantially over time which again supports the use of time-varying transition probabilities. For the two portfolios, the probabilities of remaining in state 1 experience a substantial increase at the end of the expansions, and sharp decrease after the recession periods. The transition probabilities in Figure 1 confirm that states 1 and 2 are associated with recessions and expansions, respectively.

To further investigate the nature of the states, we plot the probabilities of being in state 1 at time *t* conditional on the information at time *t*-1 for the most and the least liquid portfolios. The results are displayed in Figure 2, and the shades regions represent the period of NBER recessions. As shown in Panels A and B in Figure 2, the probabilities of being in state 1 substantially increase at the end of the expansions, remain high during the NEBR recessions, and decline abruptly after the recession periods. The correlation between probabilities of being in state 1 and the NBER indicator is 0.37 for the most liquid firms and 0.40 for the least liquid firms. This observation again confirms that high volatility states coincide with recession states, while low volatility states are associated with expansion states. Our empirical finding is also consistent with Schwert (1989), who documents that stock market volatility increases during recessions.

3.1.2 Estimation results of the conditional mean parameters

To investigate the asymmetry in the effect of economic conditions on stock returns with different levels of liquidity, we now examine the conditional mean parameters. Table 1 reveals the conditional mean parameters estimated from the univariate Markov switching model. For the default spread (*DEF*), the estimated coefficients are positive for all portfolios in state 1, and nine out of ten are statistically significant at conventional levels. In state 2, eight out of ten estimates are positive, but only one of them is statistically significant. Moreover, the absolute values of the coefficients in state 2 are smaller than those of the estimates in state 1, except for the most liquid portfolio. The differences in the estimates are especially highlighted in the two least liquid portfolios where the estimated slopes in state 2 are negative. Therefore, the default spread predicts substantially different expected excess returns of the least liquid stocks across the states of the world. On the other hand, the estimated coefficients for the most liquid stocks are almost identical across the two states, indicating that the expected excess returns of liquid stocks are not differently affected by the level of the default spread during high and low volatility states.

Strong evidence of systematic variations in the estimated mean parameters is also observed in the term spread (*TERM*). The estimated slopes are all positive in state, 1 indicating that higher returns are expected as a result of increase in the term spread in state 1. Since the term spread is higher during recessions, as documented by Fama and French (1989), and state 1 coincides with recession in our specification, the results seem natural. In addition, the magnitude of estimates is the lowest for the most liquid stocks and the highest for the least liquid stocks, implying that the expected excess returns on illiquid stocks are more highly affected by the term spread compared to the liquid ones in the high volatility states. In the least liquid stocks, the outstandingly high estimate of 1.605 is observed. In a sharp contrast, the estimated slopes are all negative in state 2, and further, the absolute values of estimates tend to increase from liquid to illiquid stocks. As a result, the difference in the mean parameters is the biggest in the least liquid portfolio, and the estimated slopes for the two states are, at least marginally, statistically significant. Therefore, for the least liquid portfolio, the increase in the term spread indicates an increase in the expected excess returns in state 1, and a decrease in the expected excess return in state 2, representing significant variations in the expected excess returns across the states.

We now examine the effect of growth in the money stock (ΔM) on expected excess returns. In state 1, the estimated coefficients on the growth in the money stock are all negative, where seven out of ten estimates are statistically significant. On the other hand, the slopes are all positive, where nine out of ten estimates are statistically significant in state 2. Monetary expansion is usually expected during recessions, and the expected stock returns tend to decrease as a result of an increase in the money supply. Since state 1 is associated with recession periods, the estimated slopes in state 1 have negative values as expected. Moreover, the absolute values of the estimated slopes tend to increase from liquid to illiquid stocks for both states, indicating that illiquid stocks are more sensitive to changes in money supply than liquid ones. This result is also consistent with Fujimoto (2004) and Jensen and Moorman (2010), who document that illiquid stocks are more influenced by a monetary expansion policy than are liquid stocks.

Parameter estimates on the one-month Treasury bill rate (*TB*) also show substantial variations across states. All estimated slopes are positive except for decile 9 in state 1, whereas all coefficients have negative values in state 2. It is well documented in the literature that the estimated slope of stock returns on the lagged one-month Treasury bill rate is negative (Campbell, 1987). One possible explanation for such result is a negative effect of inflation, proxied by the one-month Treasury bill rate, on stock returns (Fama, 1981; Schwert, 1981).

Since inflation rarely occurs during recession, the negative relation between the Treasury bill rate and stock returns can be weakened in state 1. Moreover, the increase in the Treasury bill rate in state 1 tends to reduce firm value due to a higher cost of capital, which yields a positive association between the Treasury bill rate and subsequent stock returns. However, clear cross-sectional differences in the estimated slopes are not observed in the case of the one-month Treasury bill rate.

Given the systematic variations in the mean parameters across the two states, we now investigate whether the estimated slopes are statistically different across the two states by performing likelihood ratio tests. Hansen (1992) documents that the standard likelihood ratio test for multiple states is not adequate since the transition probability parameters are not identified under the null of a single state. Thus, we assume that there are two states in the conditional variance equation in testing for identical slope coefficients. For each liquidity-sorted decile portfolio, we test the null hypothesis that the mean parameters for the four variables (*DEF*, *TERM*, ΔM, *TB*) are identical across the two states. Table 1 reveals the results of the likelihood ratio tests. Except for the two most liquid portfolios, the null hypotheses are rejected at the 5% significance level, which indicates that asymmetries in the effect of economic conditions on stock returns are statistically confirmed.

In sum, we find strong economic and statistical evidence that the expected excess returns on liquidity-sorted portfolios are very sensitive to the states of the economy. One implication of our results is that one should consider state-dependent variations in factor loadings to better understand the liquidity-return relationship. In addition, the expected returns of illiquid stocks are more affected by unfavorable economic conditions than those of liquid stocks. Thus, our results in Table 1 also imply that there might be strong variations in the expected return difference between liquid and illiquid stocks across states. We will study whether this is indeed the case in Section 3.3.

3.2 Estimation results on the bivariate Markov switching model

Our empirical results in Section 3.1 are based on the assumption that the high volatility state does not occur simultaneously for each portfolio. In this subsection, we impose a common state process for liquid and illiquid portfolios in order to obtain more precise estimates of the underlying states. Moreover, this estimation result allows us to test the hypothesis that illiquid stocks display stronger variations than liquid stocks in the expected excess returns across states.

As in the univariate model, we plot the time-series of transition probabilities and the probability of being in state 1 at time *t* conditional on the information at time *t*-1.[11] The estimated patterns for both probabilities are very similar to the patterns in the univariate case. For transition probabilities, the probability of remaining in state 1 increases at the end of the expansions, and declines sharply after the recession periods. Similarly, the conditional probability of being in state 1 abruptly increases at the beginning of NBER recessions, and declines after the recession periods. The time-series behavior of these probabilities confirms that the nature of the states estimated from the bivariate model coincide with that of the univariate model.

Table 2 presents the parameter estimates and the test results for identical asymmetries for the bivariate Markov switching model. Looking at the parameter estimates, the patterns from the bivariate model are very similar to those from the univariate model. For the default spread, the estimated slope increases from liquid to illiquid stocks in state 1. For the term spread, moving from liquid to illiquid stocks, the slope increases from 0.759 to 1.652 in state 1, while the estimated coefficient decreases from 0.021 to -0.270 in state 2. For the growth in the money stock, the observed estimates are also consistent with the results in Table 1. In state 1, the estimated slopes are negative for the two portfolios, and the slope decreases from liquid to illiquid stocks. On the other hand, in state 2, the estimated coefficients are positive for both

[11] The results are not reported for brevity, but available upon request.

portfolios, and it increases from liquid to illiquid stocks. In short, the asymmetries in the slopes of those business cycle variables are present in the bivariate Markov switching model as well.

In addition, Table 2 reveals the results on the likelihood ratio tests to examine whether the difference in the estimated coefficients of the high-liquidity portfolio (*HL*) is equal to the difference observed in the low-liquidity portfolio (*LL*). Specifically, we test the null hypotheses that

$$\beta_{k,1}^{HL} - \beta_{k,2}^{HL} = \beta_{k,1}^{LL} - \beta_{k,2}^{LL} \ , \tag{7}$$

for each k = 1, 2, 3, 4. For the term spread and the growth in the money stock, the null hypotheses of identical asymmetries for liquid and illiquid stocks are rejected at the 5% and 10% significance levels, respectively. In addition, we also test the null hypothesis of joint restriction for all k = 1, 2, 3, 4. The joint restriction of identical asymmetries for liquid and illiquid portfolios is rejected at the 1% significance level. Consequently, the results on the likelihood ratio tests combined with the estimated coefficients on conditional mean equations confirm that (1) the expected excess returns on liquidity-sorted portfolios are sensitive to the economic states, and that (2) illiquid stocks are more sensitive to the changes in the business cycle variables compared to liquid stocks.

3.3 The expected illiquidity premium across states

The results in previous sections provide some clues for variations in the expected illiquidity premium across states. In this subsection, we investigate whether a state-dependent variation in the expected illiquidity premium is indeed present and how it is related with the states of the economy. Figure 3 displays the time-series behavior of expected excess returns from the bivariate Markov switching model. Panel A depicts the expected excess returns of the low-liquidity portfolio (*LL*) and the high-liquidity portfolio (*HL*), respectively. Panel B displays the expected illiquidity premium as a difference in expected excess returns of the two portfolios.

The shaded regions represent the period of NBER recessions.

Several features of the results are worth highlighting. First, the expected excess returns for both high-liquidity and low-liquidity portfolios display countercyclical patterns as shown in Panel A. The expected excess returns for both portfolios tend to increase abruptly during NBER recessions, but decrease during expansions. This finding is consistent with the time-series predictability literature, which states that the expected stock return is high during recessions and low during expansions.

Second, the expected return difference between the two portfolios, the expected illiquidity premium, also varies countercyclically, namely, high during NBER recessions and low in expansions. More importantly, our econometric specification helps us to understand as to why this is the case. The estimation results from the Markov switching model imply that in recessions, illiquid stocks are more strongly affected by economic conditions than liquid ones. On the other hand, the effects of economic conditions on the expected returns for the two portfolios are not significantly different during expansions. As a result, the low-liquidity portfolio displays stronger variations across states than does the high-liquidity portfolio. Therefore, the asymmetric effect of business cycle variables on stocks with different levels of liquidity is the source of countercyclical behavior of the expected illiquidity premium.

Given the substantial variations in the expected illiquidity premium across the states, an important implication of our study is that one should take a look at the illiquidity premium conditional on different states of the economy. Consistent with previous studies, our empirical result supports the existence of illiquidity premium: the average of the expected illiquidity premium is 0.35% per month in our sample period, and it is more than eleven standard errors from zero. However, there are many periods during which the expected illiquidity premium is negative. The expected illiquidity premium has negative values of 208 out of 582 months (36%), and moreover, it seems that those months coincide with the expansion states. These results imply that employing a regime-switching approach is crucial to understand the state-dependent nature of the expected illiquidity premium.

To further examine the behavior of the expected illiquidity premium, we perform two additional experiments. First, employing the volatility as a proxy for the states of the economy, we examine state-dependence of the expected illiquidity premium. Specifically, following Gulen, Xing, and Zhang (2011), we compute the expected one-year-ahead returns for high-liquidity and low-liquidity portfolios, conditional upon each of the high and low volatility states. In the high volatility state, the average one-year-ahead expected return of the low-liquidity portfolio is 1.71% per month, whereas it is 0.55% per month for the high-liquidity portfolio. On the other hand, in the low volatility state, the average one-year-ahead expected returns of the low-liquidity and the high-liquidity portfolios are 0.47% and 0.59% per month, respectively. These results indicate that high expected illiquidity premium tends to coincide with recession periods to the extent that high volatility serves as a proxy for the recession states. Therefore, our finding implies that the illiquidity premium documented in previous studies is mainly due to the additional compensation of illiquid stocks in bad states.

Second, we examine lead-lag correlations between the expected illiquidity premium and various macroeconomic variables. Based on the previous literature, we consider the following macroeconomic variables: real growth in GDP (*RGG*), growth in industrial production (*IPG*), real consumption growth (*RCG*), real growth in labor income (*RLIG*), real investment growth (*RIG*), and a NBER recession dummy (*REC*). Since the macroeconomic variables are usually available at a quarterly frequency, we use the quarterly expected illiquidity premium for this analysis.[12] Table 3 reports the results. The correlations are present in the first row, and the *p*-values for zero correlations are in parentheses. The contemporaneous correlations between the expected illiquidity premium and procyclical (countercyclical) variables are negative (positive).

[12] To construct the quarterly frequency expected illiquidity premium, we calculate the expected one-month ahead illiquidity premium for the first month, two-month ahead illiquidity premium for the second month, and three-month ahead illiquidity premium for the third month in each quarter, all conditional on the information at the end of the previous quarter. Then, the quarterly expected illiquidity premium are approximated as a sum of them.

For example, the expected illiquidity premium has a negative contemporaneous correlation of -0.344 with *RGG*, and -0.286 with *IPG*, respectively. Our expected illiquidity premium has some information for predicting the real economic activity up to one quarter ahead since the correlations between the 1-period-lagged expected illiquidity premium and the current-period *RGG*, *RLIG*, and *INF* are significantly negative. In sum, the results in Table 3 indicate a strong linkage between the expected illiquidity premium and the macroeconomy. Our empirical finding is intriguing in that it implies the illiquidity premium in the stock market indeed reflects macroeconomic risks.

Overall, the results of our analyses imply that considerably higher illiquidity premium is expected in the bad states of the economy than in good states. In view of the risk-based story, rational investors require higher compensation for bearing liquidity risk in a bad state than in a good state, because they might be more willing to liquidate their asset holdings in a bad state for consumption smoothing purpose. Therefore, we interpret that our empirical findings are consistent with the theoretical argument based on the time-varying liquidity risk premium.

3.4 Variations in conditional volatilities and Sharpe ratios

In this subsection, we ask whether the strong variations in the expected illiquidity premium across states can be explained by changes in volatilities or variations in Sharpe ratios, or both. Figure 4 plots the conditional volatilities from the bivariate Markov switching model. Panel A depicts the time-series of conditional volatilities from low and high liquidity portfolios, respectively. Both portfolios' conditional volatilities display significant variations over time. They tend to increase prior to and during NBER recessions, and decrease after the recession periods. In addition, the conditional volatility of a low liquidity portfolio is much larger than that of a high liquidity portfolio. Panel B plots the conditional volatilities of the zero-cost portfolio buying the low-liquidity and selling the high-liquidity stocks. The conditional volatility of the low-minus-high liquidity portfolio also tends to increase prior to and during NBER recessions, which indicates that higher expected illiquidity premium during recession periods reflects higher risk.

Figure 5 displays the variations in conditional Sharpe ratios estimated from the bivariate Markov switching model. As shown in Panel A, conditional Sharpe ratios of both low-liquidity and the high-liquidity portfolios change over time and they are countercyclical. The conditional Sharpe ratios spike upward during NBER recessions, and decline rapidly after the recession periods. Panel B plots the conditional Sharpe ratio of the low-minus-high liquidity portfolio. The clear cyclical pattern is also observed in the low-minus-high liquidity portfolio. In sum, the strong variations in the expected illiquidity premium across states are driven by both the changes in conditional volatilities and the variations in conditional Sharpe ratios.

3.5 Robustness tests

3.5.1 The importance of state-dependence

One possible concern about our Markov switching model is that the estimated transition probabilities between latent states depend on the choice of data and variables, because the model lets the data determine the states of the economy. Thus, some may argue that our results of state-dependence in the expected illiquidity premium are artifacts due to the data used. This concern is addressed by investigating whether our findings of state-dependent illiquidity premium are robust to the definition of the states. For alternative definition of the states of the economy, we use the NBER state indicator since it has been the most widely used proxy for the economic states, though it is not *ex-ante*.

Specifically, we employ a linear predictive model with parameters dependent on the two distinct states determined by NBER state indicator, estimated separately for excess returns on each liquidity-sorted decile portfolio:

$$r_t^i = \beta_{0,s_t}^i + \beta_{1,s_t}^i DEF_{t-1} + \beta_{2,s_t}^i TERM_{t-1} + \beta_{3,s_t}^i \Delta M_{t-2} + \beta_{4,s_t}^i TB_{t-1} + \varepsilon_t^i \ , \tag{8}$$

where the transition probabilities between the two states are determined by the NBER state indicator as follows:

$$\mathrm{P}(s_t^i = 1 \mid s_{t-1}^i = 1, Y_{t-1}) = \mathrm{P}(s_t^i = 1 \mid s_{t-1}^i = 2, Y_{t-1}) = \begin{cases} 1 \text{ , for NBER recession periods,} \\ 0 \text{ , otherwise.} \end{cases}$$

$$\mathrm{P}(s_t^i = 2 \mid s_{t-1}^i = 1, Y_{t-1}) = \mathrm{P}(s_t^i = 2 \mid s_{t-1}^i = 2, Y_{t-1}) = \begin{cases} 0 \text{ , for NBER recession periods,} \\ 1 \text{ , otherwise.} \end{cases} \tag{9}$$

State 1 represents the recession period, and state 2 is the expansion period. This specification is identical to our univariate Markov switching model, except that now the state process is deterministic, while in the Markov switching model the state process is a stochastic Markov process.

Table 4 reports the results. Looking at the variance parameters, the estimated parameters of state 1 are significantly higher than those of state 2 for all portfolios, indicating that high volatility states are associated with NBER recessions, and low volatility states coincide with the NBER expansions. This supports our previous interpretation that the high volatility state is related with recessions, and the low volatility state is associated with expansions in the Markov switching model.

The patterns of the estimated conditional mean parameters in Table 4 are very similar to those in Table 1. For example, for the term spread, the estimated slopes are all positive in state 1, but all negative in state 2. In addition, the likelihood ratio tests reveal that the null hypothesis, which states that the mean parameters for the four variables (*DEF*, *TERM*, ΔM, *TB*) are identical across the two states is rejected for any portfolio. The estimated mean parameters and the likelihood ratio tests indicate that asymmetries in the effect of economic conditions on stock returns are present under the alternative definition of economic states. In short, the results in Table 4 confirm that state-dependent variations in factor loadings play an important role in understanding the liquidity-return relationship.[13]

To examine the importance of the regime-switching approach, we additionally estimate the expected illiquidity premium from a linear predictive regression model with a single state. Specifically, for a fair comparison, we estimate the expected returns of the low-liquidity and the high-liquidity portfolios jointly with specification in equation (3) under the single-state restriction. Figure 6 compares the expected illiquidity premium estimated from the bivariate Markov switching model with that from the single-state linear regression model. The annualized volatility from the Markov switching model is 2.59%, whereas it is 1.48% from the linear regression. Especially, in the Markov switching model, huge upward spikes are observed during recession periods. To investigate whether higher variations of the expected illiquidity premium in the Markov switching model are related to the realized illiquidity premium, we compute the correlation between the time-series of the expected and the realized illiquidity premium. The correlation between the realized illiquidity premium and the expected illiquidity premium from the Markov switching model is 0.24, but the correlation is 0.12 when we use the expected illiquidity premium from the linear predictive regression. In sum, the results in this subsection demonstrate that the state-dependent nature of illiquidity premium is indeed in existence, and employing a regime-switching approach is crucial in understanding this nature of illiquidity premium.

3.5.2 Controlling for firm size

Some argue that the Amihud illiquidity measure imposes an automatic scaling of illiquidity with firm size. For example, Cochrane (2005) documents that "smaller stocks which have smaller

[13] Even though we can compute the time-series of the illiquidity premium fitted from this alternative specification with deterministic states, this illiquidity premium is not truly expected in *ex-ante* sense. It is because the NBER indicator used to determine the states is not known prior to the reference month in practice, thus the expected return in this model is not conditional on time *t*-1 information. For this reason, we do not compare the illiquidity premia from this model and the Markov switching model.

dollar volume for the same turnover (fraction of outstanding shares that trade) are automatically more illiquid." This means that our portfolio strategy that assigns stocks based on their illiquidity level is likely to make, to some extent, stocks similar in firm size belong to the same portfolio. If this is the case, our results of state-dependent illiquidity premium could be driven in part by the state-dependent size premium documented by Perez-Quiros and Timmermann (2000), not solely by compensation for bearing illiquidity costs. Given this concern, we test whether the state-dependent variations in expected illiquidity premium are still present after controlling for firm size.

To this end, we run the bivariate Markov switching model for size-controlled high-liquidity (*HL*) and low-liquidity (*LL*) portfolios. Specifically, we first construct three size-sorted portfolios using 30% and 70% NYSE breakpoints. Then, in each size group, we form three liquidity-sorted portfolios based on 30% and 70% NYSE breakpoints for each group, employing the Amihud's (2002) illiquidity measure. Consequently, the size-controlled high- (low-) liquidity portfolio consists of all stocks in the bottom (top) 30% sorted on their illiquidity for each size group.

Table 5 reports the parameter estimates and the test results for identical asymmetries. The patterns of parameter estimates from Table 5 are very similar to those from Table 2. For the size-controlled portfolios, the likelihood ratio tests of equation (7) indicate that for the term spread, the null hypothesis of identical asymmetry is rejected at the 5% significance level. Moreover, the joint restriction of identical asymmetries for all four predictors is also rejected. Thus, we find strong statistical evidence for state-dependent variations in liquidity-return relationship even after controlling for firm size.

To examine economic significance, we also calculate time-series of expected illiquidity premium from the size-controlled liquidity portfolios (not reported). We find that the expected illiquidity premium still displays countercyclical variations. In addition, we examine the average expected illiquidity premium. Note that the average expected illiquidity premium is 0.35% per month when firm size is not controlled. When we control for firm size, the average expected illiquidity premium is still considerable: it is 0.29% per month with *t*-value of 14.89. Finally, we compute one-year-ahead returns for high-liquidity and low-liquidity portfolios, conditional upon each of the high and low volatility states. In the high volatility state, the average one-year-ahead expected returns of the low-liquidity and high-liquidity portfolios are 1.56% and 0.72% per month, respectively. However, in the low volatility state, the returns of the low-liquidity and high-liquidity portfolios are 0.52% and 0.66% per month, respectively. It indicates that high expected illiquidity premium arises during recession periods.

In sum, we find strong statistical and economic significance for the state-dependent variations in expected illiquidity premium even after controlling for firm size effect. Therefore, it appears that our main findings are not driven by size premium.

3.5.3 Alternative liquidity measures

In this subsection, we examine whether our estimation results from the Markov switching model are robust to the choice of liquidity measures in constructing liquidity-sorted portfolios. There are numerous empirical proxies for the stocks' liquidity proposed in previous research. One may argue that our empirical results are driven by the use of a specific liquidity measure. Therefore, we estimate the univariate Markov switching models with portfolios sorted by alternative liquidity measures. Specifically, we use a turnover measure proposed by Datar et al., (1998) and a trading discontinuity measure, developed by Liu (2006).

The turnover measure is defined as the average daily share turnover over a month:

$$Turnover_{i,t} = \frac{1}{D_t}\sum_{d=1}^{D_t}\frac{\left(\text{Number of shares traded}\right)_{i,d}}{\left(\text{Number of shares outstanding}\right)_{i,d}}, \tag{8}$$

where D_t is the total number of trading days in the market over month *t*. Also, we use the number of zero trading days suggested by Liu (2006). He defines a liquidity measure of a stock, *LMx*, as the standardized turnover-adjusted number of zero daily trading volumes over the prior *x* months, to reflect the trading discontinuity of the stock.

$$LMx = \left[\text{Number of zero daily volumes in prior } x \text{ months + } \frac{1/(x - \text{month turnover})}{\text{Deflator}} \right] \times \frac{21x}{NoTD}, \qquad (9)$$

where *x*-month turnover is calculated as the sum of the daily turnover over the prior *x* months, and *NoTD* is the total number of trading days over the prior *x* months. For all stocks, the deflator should be chosen such that

$$0 < \frac{1/(x - \text{month turnover})}{\text{Deflator}} < 1 .$$

We use *LM*12 as our alternative liquidity measure, which is calculated using the previous 12 months' data. Following Liu (2006), we choose 11,000 as the deflator.

Tables 6 and 7 present the results of parameter estimates from the univariate Markov switching model, using the turnover measure and the trading discontinuity measure in place of Amihud's illiquidity measure, respectively. Tables 6 and 7 reveal that the qualitative results are very robust to the choice of liquidity measures even though the magnitudes of some estimated coefficients change. For the term spread (*TERM*), the estimated coefficients remain positive in the high volatility state and negative in the low volatility state. For example, in the high volatility state, the estimated slopes are all positive in Table 7, and eight out of ten estimates are positive in Table 6. On the other hand, all estimates are negative in the low volatility state for both alternative liquidity measures. In addition, estimated coefficients tend to increase from liquid to illiquid portfolio, which confirms that the expected excess returns of illiquid stocks are more affected by the economic conditions in the high volatility state than those of liquid ones.

For growth in the money stock (ΔM), the results are not altered by the use of alternative liquidity measures. Consistent with the results in Table 1, all estimates in the high volatility state remain negative, while all estimated slopes are positive in the low volatility state. Also, most of the estimates are statistically significant. For the default spread (*DEF*), and the one-month

Treasury bill rate (*TB*), the empirical results are largely retained.

On the bottom of the Tables 6 and 7, we present the likelihood ratio test results for the equality of the estimated slopes across the two states. The null hypotheses are rejected for nine out of ten portfolios in both Table 6 and Table 7, at the 5% significance level, which implies that there is strong statistical evidence of asymmetries. Therefore, the asymmetric effects of business cycle variables on liquidity-sorted portfolios are robust across liquidity measures.

3.5.4 Out-of-sample prediction results

To address the potential problems from overfitting data in-sample, we report out-of-sample prediction results from the bivariate Markov switching model. To avoid conditioning on information not known prior to that month, we reestimate parameters recursively for each month. We use an expanding window approach starting from July 1962. We begin the out-of-sample forecasts from February 2000 due to the availability of the composite leading indicator data.[14]

Figure 7 displays the out-of-sample forecasts of illiquidity premium, predicted recursively from the bivariate Markov switching model. The dotted lines indicate plus and minus two standard error bands, and the shades regions represent the NBER recessions. The out-of-sample predicted illiquidity premium is very similar to the in-sample forecasts. The expected illiquidity premium is very sensitive to the economic state and it spikes upward during the recessions. In addition, the correlation between the out-of-sample and the in-sample prediction is 0.59. These results indicate that overfitting does not occur in our specification.

To investigate the economic significance of the out-of-sample predictability, following

[14] The OECD composite leading indicator we use has experienced numerous revisions after its first release. To ensure that all the data used in recursive estimation is known historically, the original release data of the composite leading indicator is employed. Since the original time-series of the composite leading indicator starting from July 1962 is available from the December 1999 release, the recursive estimation of parameters starts from January 2000, and thus the time-series of the out-of-sample forecasted returns begins from February 2000.

Perez-Quiros and Timmerman (2000), we perform a simple trading strategy. That is, we go long with the equity portfolio if its excess return is predicted to be positive, and we hold one-month Treasury bills otherwise. To investigate additionally the importance of state-dependence in an illiquidity premium, we apply the same trading rule for expected returns from both the linear predictive regression model ("switching strategy 1"), and the bivariate Markov switching model ("switching strategy 2"). For comparison, the buy-and-hold strategy simply reinvests all funds in the equity portfolio under consideration at each month.

Table 8 reports the out-of-sample trading results based on three different trading strategies for each of the three portfolios, the high-liquidity (*HL*), the low-liquidity (*LL*), and the low-minus-high (*LL–HL*) liquidity portfolios. Mean returns and standard deviations of returns are annualized, and the period for the recursive out-of-sample predictions is from February 2000 to December 2010.

Several features are worthwhile to mention. First, a switching strategy based on our bivariate Markov switching model creates the highest Sharpe ratios for all three portfolios in the full sample. The reason is that this strategy has a relatively higher return and a lower standard deviation. Second, the trading results are totally different across the states. In expansions, while both switching strategies outperform the buy-and-hold strategy, a switching strategy based on our bivariate Markov switching model is comparable to a switching strategy based on the linear predictive regression model. This indicates that considering the state-dependence in illiquidity premium is less important in economic expansions. In recessions, however, a switching strategy based on the bivariate Markov switching model performs the best. Especially for the low-liquidity portfolio, an investor who conducts a switching strategy 2 earns 5.52% per year. On the other hand, two other strategies generate large negative returns in recessions. The substantial difference in performances between two switching strategies during recession periods supports that employing the state-dependent Markov switching approach is particularly crucial in recession states.

In short, our results in this subsection indicate that the out-of-sample predictability of the illiquidity premium also exists. The information contained in the expected illiquidity premium from the Markov switching model is both statistically and economically significant. In addition, the striking forecasting power of the regime-switching model during recessions supports our emphasis on state-dependence in the illiquidity premium.

4 Conclusion

Although state-dependent variations in illiquidity premium can be drawn from previous studies, the literature focuses less on the linkage between illiquidity premium and the states of the economy. We attempt to fill this gap by investigating the variations in the expected illiquidity premium from the regime switching model based on a two-state Markov process with time-varying transition probabilities. Our study allows us to identify the driving forces behind the state-dependent variations in the expected illiquidity premium if exists.

We find that sensitivities of liquidity-sorted portfolio returns on business cycle variables are substantially different across two states, and the differential response is especially pronounced in the least liquid portfolio. The expected returns for the low-liquidity portfolio are much higher than those for the high-liquidity portfolio during recessions. As a result, a strong countercyclical variation in the expected illiquidity premium is observed, and moreover, the expected illiquidity premium is substantially high in bad state but relatively weak in good state. Our empirical results are robust to definitions of the economic states and the choice of liquidity measures, and the out-of-sample predictability of the illiquidity premium exists.

Considering time variations in liquidity risk and liquidity risk premium in light of conditional asset pricing, our question can be restated as whether liquidity risk premium varies with economic states. In view of the risk-based story, rational investors require higher compensation for bearing liquidity risk in a bad state than in a good state, because in a bad state they are more likely to liquidate some of their asset holdings for consumption smoothing. Therefore, our empirical finding that the expected illiquidity premium is countercyclical is consistent with the theoretical argument based on time-varying liquidity risk premium.

Finally, one important implication of our study is that one should take a look at the liquidity-return relationship conditional on different states of the economy. The literature which states discontinuous, not gradual, variations in liquidity across states combined with our empirical finding, which states that the expected illiquidity premium displays substantial state-dependent variations, support our suggestion. Our results further indicate that the strong illiquidity premium exists primarily in bad states, while it is relatively weak in good states. Therefore, a successful asset pricing model that explains the time variations in illiquidity premium should generate a substantially different movement in risk premia between expansion and recession states.

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Table 1. Parameter Estimates and Test Results from the Univariate Markov Switching Model

The table reports the parameter estimates of the following two-state univariate Markov switching model, estimated separately for excess returns on each liquidity-sorted decile portfolio:

$$r_t^i = \beta_{0,s_t}^i + \beta_{1,s_t}^i DEF_{t-1} + \beta_{2,s_t}^i TERM_{t-1} + \beta_{3,s_t}^i \Delta M_{t-2} + \beta_{4,s_t}^i TB_{t-1} + \varepsilon_t^i$$

where ε_t^i follows a normal distribution with zero mean and variance of σ_{i,s_t}^2. r_t^i is the monthly excess return at time *t* on the *i*th decile portfolio sorted by Amihud's (2002) illiquidity measure, $DEF_{t-1}, TERM_{t-1}, \Delta M_{t-2}$ and TB_{t-1} represent the default spread, term spread, the growth in the money stock, and the one-month Treasury bill rate, respectively. Time varying transition probabilities are modeled as follows:

$$p_t^i = \mathrm{P}(s_t^i = 1 \mid s_{t-1}^i = 1, Y_{t-1}) = \Phi(\pi_0^i + \pi_1^i \Delta CLI_{t-3})$$
$$q_t^i = \mathrm{P}(s_t^i = 2 \mid s_{t-1}^i = 2, Y_{t-1}) = \Phi(\pi_0^i + \pi_2^i \Delta CLI_{t-3})$$

where ΔCLI_{t-3} represents the three-month lagged value of the 12-month rate of change in the composite leading indicator, and Φ is the cumulative distribution function of a standard normal distribution. This table also presents the results of the likelihood ratio tests for the equality of slope coefficients across the two states. In testing for identical slope coefficients, we assume that there are two states in the conditional variance equation. The *z*-statistics are reported in parentheses. The sample period is from July 1962 to December 2010.

	Decile 1 (Most Liquid Firms)		Decile 2		Decile 3		Decile 4		Decile 5	
Mean parameters										
Constant, State 1	-0.874	(-0.71)	-7.477	(-2.32)	-7.811	(-2.47)	-7.654	(-2.51)	-7.595	(-2.39)
Constant, State 2	1.396	(2.07)	1.718	(2.30)	1.635	(1.98)	1.498	(1.67)	1.234	(1.58)
DEF, State 1	0.711	(0.83)	2.967	(2.63)	3.119	(2.54)	3.332	(2.62)	3.463	(2.61)
DEF, State 2	0.724	(0.69)	0.317	(0.35)	0.533	(0.51)	1.094	(0.80)	1.584	(1.53)
TERM, State 1	0.396	(0.66)	1.253	(1.49)	1.354	(1.54)	1.274	(1.45)	1.215	(1.34)
TERM, State 2	-0.134	(-0.52)	-0.196	(-0.69)	-0.246	(-0.81)	-0.395	(-1.19)	-0.474	(-1.49)
ΔM, State 1	-0.016	(-1.19)	-0.034	(-2.06)	-0.033	(-1.87)	-0.035	(-1.90)	-0.038	(-1.99)
ΔM, State 2	0.016	(0.32)	0.073	(2.41)	0.103	(2.84)	0.141	(2.68)	0.166	(2.79)
TB, State 1	0.178	(0.07)	6.084	(1.34)	6.226	(1.37)	5.920	(1.25)	5.871	(1.18)
TB, State 2	-2.709	(-1.70)	-3.138	(-1.90)	-3.580	(-2.06)	-4.461	(-2.11)	-5.085	(-2.63)
Variance parameters										
σ, State 1	5.688	(22.64)	6.445	(16.08)	6.930	(15.42)	7.165	(16.67)	7.448	(16.76)
σ, State 2	2.695	(15.24)	3.866	(18.52)	4.119	(17.85)	4.208	(19.68)	4.361	(21.18)
Transition probability parameters										
Constant	2.152	(8.17)	1.367	(5.36)	1.417	(5.27)	1.544	(4.96)	1.696	(5.52)
ΔCLI, State 1	-0.073	(-1.31)	-0.237	(-1.15)	-0.171	(-1.32)	-0.129	(-1.90)	-0.142	(-2.05)
ΔCLI, State 2	-0.061	(-1.30)	0.032	(0.47)	0.043	(0.73)	0.025	(0.43)	0.003	(0.05)
Log-likelihood value	-1674		-1730		-1768		-1794		-1813	
Restricted log-likelihood value with $\beta_{k,s_t=1}^i = \beta_{k,s_t=2}^i$, $k = \{1,2,3,4\}$	-1675		-1735		-1775		-1801		-1819	
p-value	0.71		0.06		0.01		0.01		0.01	

Table 1. Parameter Estimates and Test Results from the Univariate Markov Switching Model (*continued*)

	Decile 6		Decile 7		Decile 8		Decile 9		Decile 10 (Least Liquid Firms)	
Mean parameters										
Constant, State 1	-6.967	(-1.87)	-7.330	(-1.98)	-7.451	(-1.75)	-3.122	(-1.34)	-3.544	(-1.61)
Constant, State 2	1.102	(1.37)	1.111	(1.36)	0.982	(1.23)	1.136	(1.18)	2.175	(2.70)
DEF, State 1	3.715	(2.58)	3.811	(2.63)	4.048	(2.64)	3.939	(3.18)	3.182	(2.32)
DEF, State 2	1.758	(1.67)	1.858	(1.63)	2.177	(2.18)	-1.192	(-0.90)	-1.956	(-1.93)
TERM, State 1	1.024	(0.96)	1.124	(1.05)	1.138	(0.89)	0.664	(0.79)	1.605	(1.89)
TERM, State 2	-0.518	(-1.57)	-0.552	(-1.67)	-0.633	(-1.93)	-0.585	(-1.55)	-0.730	(-2.18)
ΔM, State 1	-0.044	(-2.17)	-0.047	(-2.28)	-0.051	(-2.39)	-0.062	(-3.19)	-0.053	(-2.51)
ΔM, State 2	0.185	(3.08)	0.190	(3.15)	0.225	(4.06)	0.324	(6.94)	0.264	(4.70)
TB, State 1	4.378	(0.73)	4.743	(0.79)	4.661	(0.65)	-1.529	(-0.37)	1.335	(0.30)
TB, State 2	-5.237	(-2.60)	-5.527	(-2.61)	-6.173	(-2.97)	-1.670	(-0.67)	-1.591	(-0.75)
Variance parameters										
σ, State 1	7.827	(16.13)	8.032	(15.97)	8.258	(15.71)	7.861	(18.29)	8.307	(18.97)
σ, State 2	4.544	(21.46)	4.592	(21.64)	4.599	(20.89)	4.174	(15.04)	3.795	(16.18)
Transition probability parameters										
Constant	1.652	(5.98)	1.670	(5.82)	1.727	(6.69)	1.379	(5.09)	1.332	(6.22)
ΔCLI, State 1	-0.128	(-1.89)	-0.125	(-1.89)	-0.115	(-1.71)	-0.099	(-2.42)	-0.089	(-2.74)
ΔCLI, State 2	0.010	(0.19)	0.011	(0.20)	0.006	(0.12)	-0.011	(-0.28)	0.004	(0.12)
Log-likelihood value	-1835		-1844		-1850		-1863		-1854	
Restricted log-likelihood value with $\beta^i_{k,s_t=1} = \beta^i_{k,s_t=2}$, $k = \{1,2,3,4\}$	-1841		-1851		-1857		-1869		-1869	
p-value	0.02		0.01		0.01		0.02		0.00	

Table 2. Parameter Estimates and Test Results from the Bivariate Markov Switching Model

The table reports the parameter estimates of the following two-state bivariate Markov switching model:

$$\mathbf{r}_t = \boldsymbol{\beta}_{0,s_t} + \boldsymbol{\beta}_{1,s_t} DEF_{t-1} + \boldsymbol{\beta}_{2,s_t} TERM_{t-1} + \boldsymbol{\beta}_{3,s_t} \Delta M_{t-2} + \boldsymbol{\beta}_{4,s_t} TB_{t-1} + \boldsymbol{\varepsilon}_t \ ,$$

where $\boldsymbol{\varepsilon}_t \sim N(0, \boldsymbol{\Omega}_{s_t})$ is a vector of residuals, $\boldsymbol{\Omega}_{s_t}$ is the variance-covariance matrix of the residuals. $\mathbf{r}_t$ is the vector of high-liquidity (*HL*) and low-liquidity (*LL*) portfolios' excess returns at time *t*, based on 30% NYSE breakpoints of Aminud's (2002) illiquidity measure. $DEF_{t-1,} TERM_{t-1}, \Delta M_{t-2}$ and TB_{t-1} represent the default spread, term spread, the growth in the money stock, and the one-month Treasury bill rate, respectively. Time varying transition probabilities are modeled as follows:

$$p_t = \mathrm{P}(s_t = 1 \mid s_{t-1} = 1, Y_{t-1}) = \Phi(\pi_0 + \pi_1 \Delta CLI_{t-3})$$
$$q_t = \mathrm{P}(s_t = 2 \mid s_{t-1} = 2, Y_{t-1}) = \Phi(\pi_0 + \pi_2 \Delta CLI_{t-3}) \ ,$$

where ΔCLI_{t-3} represents the three-month lagged value of the 12-month rate of change in the composite leading indicator, and Φ is the cumulative distribution function of a standard normal distribution. This table also presents the results of the likelihood ratio tests for restriction that the high-liquidity and low-liquidity portfolios' asymmetries are identical for each set of coefficients. In testing for identical asymmetries, we assume that there are two states in the conditional variance equation. The *z*-statistics for parameter estimates and *p*-values for the likelihood ratio tests are reported in parentheses. The sample period is from July 1962 to December 2010.

	High-Liquidity Portfolio (*HL*)		Low-Liquidity Portfolio (*LL*)		Tests for Identical Asymmetries	
	MLE	*z*-stat	MLE	*z*-stat	Log-likelihood value	*p*-value
Mean parameters						
Constant, State 1	-2.363	(-1.69)	-3.110	(-1.66)	$\beta^{HL}_{k,1} - \beta^{HL}_{k,2} = \beta^{LL}_{k,1} - \beta^{LL}_{k,2}$, $k = \{1,2,3,4\}$:	
Constant, State 2	1.568	(2.37)	1.807	(2.26)	-3197	(0.01)
DEF, State 1	1.559	(1.83)	1.907	(1.64)	$\beta^{HL}_{1,1} - \beta^{HL}_{1,2} = \beta^{LL}_{1,1} - \beta^{LL}_{1,2}$:	
DEF, State 2	-0.938	(-1.25)	-0.931	(-1.06)	-3190	(0.71)
TERM, State 1	0.759	(1.42)	1.652	(2.21)	$\beta^{HL}_{2,1} - \beta^{HL}_{2,2} = \beta^{LL}_{2,1} - \beta^{LL}_{2,2}$:	
TERM, State 2	0.021	(0.08)	-0.270	(-0.84)	-3193	(0.02)
ΔM, State 1	-0.028	(-1.88)	-0.036	(-1.78)	$\beta^{HL}_{3,1} - \beta^{HL}_{3,2} = \beta^{LL}_{3,1} - \beta^{LL}_{3,2}$:	
ΔM, State 2	0.053	(1.48)	0.106	(2.64)	-3192	(0.08)
TB, State 1	1.929	(0.73)	3.758	(1.03)	$\beta^{HL}_{4,1} - \beta^{HL}_{4,2} = \beta^{LL}_{4,1} - \beta^{LL}_{4,2}$:	
TB, State 2	-1.037	(-0.75)	-2.266	(-1.41)	-3191	(0.23)
Variance parameters						
σ, State 1	6.140	(20.91)	8.240	(20.38)		
σ, State 2	3.411	(18.29)	3.881	(15.92)		
	Parameters Common to Both Portfolios					
Correlation parameters						
ρ, State 1	0.825	(40.19)				
ρ, State 2	0.866	(50.31)				
Transition probability parameters						
Constant	1.579	(8.70)				
ΔCLI, State 1	-0.103	(-3.09)			$\pi_1 = \pi_2$:	
ΔCLI, State 2	-0.008	(-0.26)			-3194	(0.01)
Log-likelihood value	-3190					

Table 3. Lead-Lag Correlations between the Expected Illiquidity Premium and Macroeconomic Variables

This table reports the lead-lag correlations of the time-series of the expected illiquidity premium from the bivariate Markov switching model with various macroeconomic variables. *RGG* is the annual change in the log of real GDP. *IPG* is the annual change in the log of the industrial production index. *RCG* is the annual change in the log of total real consumption. *RLIG* is the annual change in the log of personal income from wages and salaries. *INF* is the annual change in the log of CPI. *RIG* is the annual change in the log of real investment. *REC* is the quarterly indicator for NBER recessions. Column “-4” reports the correlations between the 4-period-lagged expected illiquidity premium and the current-period variables, whereas column “4” reports the correlations between the 4-period-lead expected illiquidity premium and the current-period variables. The *p*-values testing zero correlations are reported in parentheses.

	-4	-3	-2	-1	0	1	2	3	4
RGG	0.171	0.119	0.019	-0.148	-0.344	-0.483	-0.554	-0.524	-0.406
	(0.019)	(0.101)	(0.794)	(0.040)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IPG	0.245	0.224	0.102	-0.079	-0.286	-0.481	-0.556	-0.522	-0.445
	(0.001)	(0.002)	(0.159)	(0.276)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RCG	0.061	0.036	-0.030	-0.140	-0.241	-0.371	-0.451	-0.453	-0.403
	(0.402)	(0.625)	(0.684)	(0.053)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
RLIG	0.058	0.024	-0.092	-0.211	-0.284	-0.389	-0.411	-0.359	-0.307
	(0.425)	(0.741)	(0.203)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
INF	-0.093	-0.125	-0.147	-0.175	-0.196	-0.185	-0.166	-0.130	-0.058
	(0.202)	(0.086)	(0.042)	(0.015)	(0.006)	(0.010)	(0.021)	(0.072)	(0.429)
RIG	0.380	0.299	0.136	-0.084	-0.353	-0.510	-0.559	-0.505	-0.382
	(0.000)	(0.000)	(0.060)	(0.248)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
REC	-0.145	-0.119	-0.124	-0.106	0.097	0.291	0.407	0.444	0.498
	(0.046)	(0.102)	(0.087)	(0.144)	(0.180)	(0.000)	(0.000)	(0.000)	(0.000)

Table 4. Parameter Estimates and Test Results from the Linear Predictive Model with State-Dependent Parameters: Using NBER State Indicator

The table reports the parameter estimates of the following linear predictive model with parameters dependent on the two states determined by the NBER state indicator, estimated separately for excess returns on each liquidity-sorted decile portfolio:

$$r_t^i = \beta_{0,s_t}^i + \beta_{1,s_t}^i DEF_{t-1} + \beta_{2,s_t}^i TERM_{t-1} + \beta_{3,s_t}^i \Delta M_{t-2} + \beta_{4,s_t}^i TB_{t-1} + \varepsilon_t^i$$

where ε_t^i follows a normal distribution with zero mean and variance of σ_{i,s_t}^2. r_t^i is the monthly excess return at time t on the ith decile portfolio sorted by Amihud's (2002) illiquidity measure, $DEF_{t-1}, TERM_{t-1}, \Delta M_{t-2}$ and TB_{t-1} represent the default spread, term spread, the growth in the money stock, and the one-month Treasury bill rate, respectively. Transition probabilities between the two states are determined by the NBER state indicator as follows:

$$P(s_t^i = 1 \mid s_{t-1}^i = 1, Y_{t-1}) = P(s_t^i = 1 \mid s_{t-1}^i = 2, Y_{t-1}) = \begin{cases} 1 \text{ , for NBER recession periods,} \\ 0 \text{ , otherwise.} \end{cases}$$

$$P(s_t^i = 2 \mid s_{t-1}^i = 1, Y_{t-1}) = P(s_t^i = 2 \mid s_{t-1}^i = 2, Y_{t-1}) = \begin{cases} 0 \text{ , for NBER recession periods,} \\ 1 \text{ , otherwise.} \end{cases}$$

This table also presents the results of the likelihood ratio tests for the equality of slope coefficients across the two states. In testing for identical slope coefficients, we assume that there are two states in the conditional variance equation. The *z*-statistics are reported in parentheses. The sample period is from July 1962 to December 2010.

	Decile 1 (Most Liquid Firms)		Decile 2		Decile 3		Decile 4		Decile 5	
Mean parameters										
Constant, State 1	-6.490	(-2.68)	-6.430	(-2.40)	-6.588	(-2.33)	-6.604	(-2.18)	-6.576	(-2.18)
Constant, State 2	0.725	(1.15)	0.620	(0.92)	0.588	(0.82)	0.367	(0.48)	0.334	(0.42)
DEF, State 1	2.013	(1.54)	2.253	(1.58)	2.211	(1.47)	2.579	(1.58)	2.838	(1.78)
DEF, State 2	0.775	(1.16)	1.309	(1.81)	1.484	(1.94)	1.737	(2.13)	1.834	(2.17)
TERM, State 1	1.374	(1.29)	1.444	(1.23)	1.607	(1.30)	1.615	(1.19)	1.587	(1.21)
TERM, State 2	-0.089	(-0.36)	-0.191	(-0.72)	-0.213	(-0.77)	-0.245	(-0.82)	-0.304	(-0.98)
ΔM, State 1	-0.028	(-1.61)	-0.035	(-1.81)	-0.033	(-1.65)	-0.039	(-1.85)	-0.045	(-2.10)
ΔM, State 2	0.035	(1.73)	0.038	(1.72)	0.053	(2.25)	0.062	(2.49)	0.072	(2.79)
TB, State 1	3.925	(1.06)	4.023	(0.99)	4.320	(1.00)	3.824	(0.80)	3.288	(0.72)
TB, State 2	-2.203	(-1.58)	-2.729	(-1.84)	-3.160	(-2.04)	-3.285	(-1.96)	-3.429	(-1.96)
Variance parameters										
σ, State 1	6.317	(12.88)	6.895	(12.88)	7.298	(12.88)	7.531	(12.88)	7.679	(12.88)
σ, State 2	4.166	(31.59)	4.463	(31.59)	4.801	(31.59)	5.062	(31.59)	5.245	(31.59)
Log-likelihood value	-1691		-1732		-1774		-1803		-1822	
Restricted log-likelihood value with $\beta_{k,s_t=1}^i = \beta_{k,s_t=2}^i$, $k = \{1,2,3,4\}$	-1697		-1738		-1780		-1810		-1830	
p-value	0.02		0.02		0.01		0.01		0.00	

Table 4. Parameter Estimates and Test Results from the Linear Predictive Model with State-Dependent Parameters: Using NBER State Indicator (*continued*)

	Decile 6		Decile 7		Decile 8		Decile 9		Decile 10 (Least Liquid Firms)	
Mean parameters										
Constant, State 1	-6.586	(-2.13)	-6.673	(-2.16)	-6.746	(-2.09)	-6.600	(-2.10)	-7.196	(-2.18)
Constant, State 2	0.339	(0.41)	0.352	(0.42)	0.286	(0.34)	0.369	(0.43)	0.755	(0.84)
DEF, State 1	2.979	(1.82)	3.044	(1.83)	3.259	(1.88)	3.511	(2.04)	3.453	(1.98)
DEF, State 2	2.105	(2.39)	2.134	(2.38)	2.383	(2.63)	2.408	(2.58)	2.409	(2.52)
TERM, State 1	1.622	(1.21)	1.700	(1.26)	1.647	(1.15)	1.594	(1.16)	1.609	(1.14)
TERM, State 2	-0.370	(-1.15)	-0.376	(-1.15)	-0.413	(-1.25)	-0.431	(-1.27)	-0.334	(-0.95)
ΔM, State 1	-0.050	(-2.28)	-0.054	(-2.42)	-0.058	(-2.51)	-0.060	(-2.60)	-0.046	(-1.95)
ΔM, State 2	0.077	(2.87)	0.078	(2.86)	0.084	(3.02)	0.097	(3.40)	0.092	(3.17)
TB, State 1	3.083	(0.65)	3.135	(0.67)	2.812	(0.56)	2.128	(0.45)	2.549	(0.52)
TB, State 2	-3.893	(-2.16)	-4.075	(-2.21)	-4.406	(-2.37)	-4.686	(-2.44)	-5.109	(-2.58)
Variance parameters										
σ, State 1	7.891	(12.88)	8.042	(12.88)	8.247	(12.88)	8.318	(12.88)	8.537	(12.89)
σ, State 2	5.466	(31.59)	5.566	(31.59)	5.652	(31.59)	5.834	(31.59)	5.927	(31.59)
Log-likelihood value	-1845		-1855		-1865		-1882		-1892	
Restricted log-likelihood value with $\beta^i_{k,s_t=1} = \beta^i_{k,s_t=2}$, $k = \{1,2,3,4\}$	-1854		-1865		-1875		-1893		-1901	
p-value	0.00		0.00		0.00		0.00		0.00	

Table 5. Parameter Estimates and Test Results from the Bivariate Markov Switching Model: Using Size-Controlled Portfolios

The table reports the parameter estimates of the following two-state bivariate Markov switching model:

$$\mathbf{r}_t = \boldsymbol{\beta}_{0,s_t} + \boldsymbol{\beta}_{1,s_t} DEF_{t-1} + \boldsymbol{\beta}_{2,s_t} TERM_{t-1} + \boldsymbol{\beta}_{3,s_t} \Delta M_{t-2} + \boldsymbol{\beta}_{4,s_t} TB_{t-1} + \boldsymbol{\varepsilon}_t \ ,$$

where $\boldsymbol{\varepsilon}_t \sim N(0, \boldsymbol{\Omega}_{s_t})$ is a vector of residuals, $\boldsymbol{\Omega}_{s_t}$ is the variance-covariance matrix of the residuals. $\mathbf{r}_t$ is the vector of size-controlled high-liquidity (*HL*) and low-liquidity (*LL*) portfolios' excess returns at time *t*. Specifically, we first construct three size-sorted portfolios using 30% and 70% NYSE breakpoints, then in each size group, we form three liquidity-sorted portfolios based on 30% and 70% NYSE breakpoints for each group, employing the Amihud's (2002) illiquidity measure. The size-controlled high- (low-) liquidity portfolio consists of all stocks in the bottom (top) 30% sorted on their illiquidity for each size group. $DEF_{t-1}, TERM_{t-1}, \Delta M_{t-2}$ and TB_{t-1} represent the default spread, term spread, the growth in the money stock, and the one-month Treasury bill rate, respectively. Time varying transition probabilities are modeled as follows:

$$p_t = \mathrm{P}(s_t = 1 \mid s_{t-1} = 1, Y_{t-1}) = \Phi(\pi_0 + \pi_1 \Delta CLI_{t-3})$$
$$q_t = \mathrm{P}(s_t = 2 \mid s_{t-1} = 2, Y_{t-1}) = \Phi(\pi_0 + \pi_2 \Delta CLI_{t-3}) \ ,$$

where ΔCLI_{t-3} represents the three-month lagged value of the 12-month rate of change in the composite leading indicator, and Φ is the cumulative distribution function of a standard normal distribution. This table also presents the results of the likelihood ratio tests for restriction that the high-liquidity and low-liquidity portfolios' asymmetries are identical for each set of coefficients. In testing for identical asymmetries, we assume that there are two states in the conditional variance equation. The *z*-statistics for parameter estimates and *p*-values for the likelihood ratio tests are reported in parentheses. The sample period is from July 1962 to December 2010.

	High-Liquidity Portfolio (*HL*)		Low-Liquidity Portfolio (*LL*)		Tests for Identical Asymmetries	
	MLE	*z*-stat	MLE	*z*-stat	Log-likelihood value	*p*-value
Mean parameters						
Constant, State 1	-2.865	(-1.75)	-3.296	(-2.00)	$\beta_{k,1}^{HL} - \beta_{k,2}^{HL} = \beta_{k,1}^{LL} - \beta_{k,2}^{LL}$, $k = \{1,2,3,4\}$:	
Constant, State 2	1.987	(2.55)	2.374	(3.41)	-3125	(0.02)
DEF, State 1	2.250	(2.09)	2.085	(1.93)	$\beta_{1,1}^{HL} - \beta_{1,2}^{HL} = \beta_{1,1}^{LL} - \beta_{1,2}^{LL}$:	
DEF, State 2	-0.981	(-1.04)	-1.366	(-1.59)	-3119	(0.73)
TERM, State 1	0.914	(1.53)	1.626	(2.66)	$\beta_{2,1}^{HL} - \beta_{2,2}^{HL} = \beta_{2,1}^{LL} - \beta_{2,2}^{LL}$:	
TERM, State 2	-0.318	(-1.01)	-0.463	(-1.67)	-3123	(0.01)
ΔM, State 1	-0.032	(-1.75)	-0.034	(-1.89)	$\beta_{3,1}^{HL} - \beta_{3,2}^{HL} = \beta_{3,1}^{LL} - \beta_{3,2}^{LL}$:	
ΔM, State 2	0.106	(2.05)	0.112	(2.42)	-3119	(0.69)
TB, State 1	1.588	(0.53)	3.453	(1.12)	$\beta_{4,1}^{HL} - \beta_{4,2}^{HL} = \beta_{4,1}^{LL} - \beta_{4,2}^{LL}$:	
TB, State 2	-2.027	(-1.16)	-2.130	(-1.35)	-3120	(0.25)
Variance parameters						
σ, State 1	7.611	(22.01)	7.539	(21.69)		
σ, State 2	3.980	(19.50)	3.471	(18.73)		
	Parameters Common to Both Portfolios					
Correlation parameters						
ρ, State 1	0.902	(78.69)				
ρ, State 2	0.923	(89.26)				
Transition probability parameters						
Constant	1.544	(10.43)				
ΔCLI, State 1	-0.094	(-3.23)			$\pi_1 = \pi_2$:	
ΔCLI, State 2	-0.018	(-0.63)			-3123	(0.01)
Log-likelihood value	-3119					

Table 6. Parameter Estimates and Test Results from the Univariate Markov Switching Model: Using Alternative Liquidity Measure, Turnover

The table reports the parameter estimates of the following two-state univariate Markov switching model, estimated separately for excess returns on each liquidity-sorted decile portfolio:

$$r_t^i = \beta_{0,s_t}^i + \beta_{1,s_t}^i DEF_{t-1} + \beta_{2,s_t}^i TERM_{t-1} + \beta_{3,s_t}^i \Delta M_{t-2} + \beta_{4,s_t}^i TB_{t-1} + \varepsilon_t^i$$

where ε_t^i follows a normal distribution with zero mean and variance of σ_{i,s_t}^2. r_t^i is the monthly excess return at time t on the ith decile portfolio sorted by the turnover measure, $DEF_{t-1}, TERM_{t-1}, \Delta M_{t-2}$ and TB_{t-1} represent the default spread, term spread, the growth in the money stock, and the one-month Treasury bill rate, respectively. Time varying transition probabilities are modeled as follows:

$$p_t^i = \mathrm{P}(s_t^i = 1 \mid s_{t-1}^i = 1, Y_{t-1}) = \Phi(\pi_0^i + \pi_1^i \Delta CLI_{t-3})$$
$$q_t^i = \mathrm{P}(s_t^i = 2 \mid s_{t-1}^i = 2, Y_{t-1}) = \Phi(\pi_0^i + \pi_2^i \Delta CLI_{t-3})$$

where ΔCLI_{t-3} represents the three-month lagged value of the 12-month rate of change in the composite leading indicator, and Φ is the cumulative distribution function of a standard normal distribution. This table also presents the results of the likelihood ratio tests for the equality of slope coefficients across the two states. In testing for identical slope coefficients, we assume that there are two states in the conditional variance equation. The *z*-statistics for parameter estimates are reported in parentheses. The sample period is from July 1962 to December 2010.

	Decile 1 (Most Liquid Firms)		Decile 2		Decile 3		Decile 4		Decile 5	
Mean parameters										
Constant, State 1	-4.222	(-1.12)	-3.615	(-0.78)	-3.311	(-0.61)	-2.952	(-1.38)	-3.127	(-1.73)
Constant, State 2	1.474	(1.29)	1.618	(1.59)	1.460	(1.45)	2.093	(2.23)	2.086	(2.43)
DEF, State 1	4.867	(2.83)	4.281	(2.66)	3.786	(2.59)	3.430	(2.82)	3.262	(2.88)
DEF, State 2	2.099	(1.34)	1.922	(1.60)	1.718	(1.22)	-1.273	(-0.94)	-1.505	(-1.20)
TERM, State 1	-0.008	(-0.01)	-0.026	(-0.02)	0.139	(0.09)	0.646	(0.83)	0.793	(1.23)
TERM, State 2	-1.054	(-2.35)	-0.829	(-2.11)	-0.696	(-1.90)	-0.649	(-1.79)	-0.532	(-1.57)
ΔM, State 1	-0.059	(-2.34)	-0.055	(-2.39)	-0.052	(-2.43)	-0.054	(-2.86)	-0.052	(-2.90)
ΔM, State 2	0.372	(5.38)	0.294	(5.20)	0.281	(4.90)	0.270	(6.23)	0.242	(5.68)
TB, State 1	-2.861	(-0.49)	-1.721	(-0.21)	-1.205	(-0.13)	-0.973	(-0.25)	-0.257	(-0.08)
TB, State 2	-8.389	(-2.62)	-7.508	(-2.84)	-6.833	(-2.33)	-2.600	(-1.10)	-2.066	(-0.93)
Variance parameters										
σ, State 1	10.035	(15.11)	8.826	(17.05)	8.321	(16.20)	7.634	(18.11)	7.266	(18.10)
σ, State 2	5.799	(13.32)	4.955	(14.94)	4.626	(12.92)	4.038	(15.34)	3.753	(14.32)
Transition probability parameters										
Constant	1.666	(5.98)	1.761	(7.13)	1.702	(6.49)	1.450	(5.61)	1.399	(5.39)
ΔCLI, State 1	-0.107	(-1.58)	-0.084	(-1.26)	-0.072	(-1.14)	-0.090	(-2.33)	-0.093	(-2.50)
ΔCLI, State 2	-0.019	(-0.36)	-0.012	(-0.25)	0.002	(0.03)	-0.005	(-0.14)	-0.004	(-0.10)
Log-likelihood value	-2000		-1918		-1881		-1844		-1810	
Restricted log-likelihood value with $\beta_{k,s_t=1}^i = \beta_{k,s_t=2}^i$, $k = \{1,2,3,4\}$	-2004		-1926		-1888		-1855		-1822	
p-value	0.09		0.00		0.00		0.00		0.00	

Table 6. Parameter Estimates and Test Results from the Univariate Markov Switching Model: Using Alternative Liquidity Measure, Turnover (*continued*)

	Decile 6		Decile 7		Decile 8		Decile 9		Decile 10 (Least Liquid Firms)	
Mean parameters										
Constant, State 1	-3.647	(-1.42)	-4.206	(-1.81)	-4.806	(-2.41)	-4.495	(-2.23)	-5.095	(-2.36)
Constant, State 2	2.185	(2.74)	2.249	(3.02)	2.068	(3.10)	1.806	(2.89)	1.482	(2.81)
DEF, State 1	3.088	(2.67)	3.052	(2.90)	2.955	(2.85)	3.076	(3.00)	2.405	(2.44)
DEF, State 2	-1.606	(-1.43)	-1.662	(-1.47)	-1.629	(-1.68)	-1.801	(-1.92)	-1.472	(-2.08)
TERM, State 1	1.033	(1.20)	1.297	(1.83)	1.553	(2.35)	1.590	(2.45)	2.020	(3.01)
TERM, State 2	-0.539	(-1.71)	-0.535	(-1.79)	-0.465	(-1.73)	-0.373	(-1.48)	-0.193	(-0.82)
ΔM, State 1	-0.051	(-2.85)	-0.050	(-2.96)	-0.051	(-3.10)	-0.054	(-3.31)	-0.045	(-2.89)
ΔM, State 2	0.235	(5.82)	0.203	(4.08)	0.171	(5.05)	0.158	(6.16)	0.117	(5.40)
TB, State 1	0.908	(0.20)	1.608	(0.44)	2.727	(0.84)	2.157	(0.67)	4.739	(1.35)
TB, State 2	-2.068	(-1.00)	-1.622	(-0.76)	-1.133	(-0.66)	-0.368	(-0.21)	-0.273	(-0.20)
Variance parameters										
σ, State 1	7.003	(18.40)	6.780	(17.94)	6.656	(17.66)	6.522	(16.94)	6.186	(15.77)
σ, State 2	3.552	(13.78)	3.400	(11.82)	3.213	(13.80)	2.982	(12.83)	2.585	(11.46)
Transition probability parameters										
Constant	1.346	(5.37)	1.267	(4.65)	1.251	(4.84)	1.135	(4.76)	1.152	(4.77)
ΔCLI, State 1	-0.098	(-2.72)	-0.100	(-2.76)	-0.110	(-2.99)	-0.114	(-3.13)	-0.118	(-3.07)
ΔCLI, State 2	0.001	(0.04)	0.009	(0.25)	0.013	(0.38)	0.020	(0.61)	0.027	(0.91)
Log-likelihood value	-1783		-1756		-1728		-1701		-1629	
Restricted log-likelihood value with $\beta^i_{k,s_t=1}=\beta^i_{k,s_t=2}$, $k=\{1,2,3,4\}$	-1797		-1771		-1745		-1719		-1647	
p-value	0.00		0.00		0.00		0.00		0.00	

Table 7. Parameter Estimates and Test Results from the Univariate Markov Switching Model: Using Alternative Liquidity Measure, *LM*12

The table reports the parameter estimates of the following two-state univariate Markov switching model, estimated separately for excess returns on each liquidity-sorted decile portfolio:

$$r_t^i = \beta_{0,s_t}^i + \beta_{1,s_t}^i DEF_{t-1} + \beta_{2,s_t}^i TERM_{t-1} + \beta_{3,s_t}^i \Delta M_{t-2} + \beta_{4,s_t}^i TB_{t-1} + \varepsilon_t^i$$

where ε_t^i follows a normal distribution with zero mean and variance of σ_{i,s_t}^2. r_t^i is the monthly excess return at time *t* on the *i*th decile portfolio sorted by Liu's (2006) illiquidity measure, DEF_{t-1}, $TERM_{t-1}$, ΔM_{t-2} and TB_{t-1} represent the default spread, term spread, the growth in the money stock, and the one-month Treasury bill rate, respectively. Time varying transition probabilities are modeled as follows:

$$p_t^i = \mathrm{P}(s_t^i = 1 \mid s_{t-1}^i = 1, Y_{t-1}) = \Phi(\pi_0^i + \pi_1^i \Delta CLI_{t-3})$$
$$q_t^i = \mathrm{P}(s_t^i = 2 \mid s_{t-1}^i = 2, Y_{t-1}) = \Phi(\pi_0^i + \pi_2^i \Delta CLI_{t-3})$$

where ΔCLI_{t-3} represents the three-month lagged value of the 12-month rate of change in the composite leading indicator, and Φ is the cumulative distribution function of a standard normal distribution. This table also presents the results of the likelihood ratio tests for the equality of slope coefficients across the two states. In testing for identical slope coefficients, we assume that there are two states in the conditional variance equation. The *z*-statistics for parameter estimates are reported in parentheses. The sample period is from July 1962 to December 2010.

	Decile 1 (Most Liquid Firms)		Decile 2		Decile 3		Decile 4		Decile 5	
Mean parameters										
Constant, State 1	-6.156	(-2.99)	-7.863	(-1.56)	-4.284	(-1.34)	-7.048	(-2.19)	-6.502	(-2.13)
Constant, State 2	1.574	(1.47)	1.650	(1.84)	1.307	(1.58)	1.580	(2.14)	1.132	(1.69)
DEF, State 1	5.167	(2.77)	4.804	(2.97)	4.062	(2.84)	3.759	(2.85)	3.399	(2.73)
DEF, State 2	2.072	(1.38)	2.026	(1.71)	1.094	(1.76)	0.634	(0.60)	0.789	(0.79)
TERM, State 1	0.467	(2.15)	1.030	(0.75)	0.384	(0.62)	1.367	(1.53)	1.274	(1.41)
TERM, State 2	-1.042	(-2.30)	-0.870	(-2.31)	-0.658	(-1.87)	-0.438	(-1.43)	-0.341	(-1.25)
ΔM, State 1	-0.057	(-2.30)	-0.054	(-2.41)	-0.051	(-2.58)	-0.052	(-2.71)	-0.048	(-2.67)
ΔM, State 2	0.345	(5.74)	0.305	(5.68)	0.276	(7.63)	0.165	(3.85)	0.139	(3.83)
TB, State 1	-0.542	(-0.11)	3.532	(0.44)	-0.785	(-0.19)	3.882	(0.86)	3.519	(0.77)
TB, State 2	-8.364	(-2.95)	-7.754	(-3.19)	-5.343	(-4.75)	-4.248	(-2.20)	-3.634	(-2.03)
Variance parameters										
σ, State 1	10.396	(16.27)	8.845	(15.98)	8.066	(18.18)	7.463	(15.44)	7.045	(15.03)
σ, State 2	6.054	(17.02)	5.287	(20.33)	4.537	(22.97)	4.254	(20.35)	3.832	(21.66)
Transition probability parameters										
Constant	1.685	(6.50)	1.716	(6.85)	1.563	(8.05)	1.384	(5.41)	1.318	(5.10)
ΔCLI, State 1	-0.103	(-1.66)	-0.090	(-1.20)	-0.066	(-1.17)	-0.149	(-1.71)	-0.144	(-1.71)
ΔCLI, State 2	-0.002	(-0.04)	0.024	(0.46)	0.041	(0.77)	0.074	(1.40)	0.091	(1.61)
Log-likelihood value	-2016		-1921		-1854		-1791		-1735	
Restricted log-likelihood value with $\beta_{k,s_t=1}^i = \beta_{k,s_t=2}^i$, $k = \{1,2,3,4\}$	-2021		-1927		-1862		-1800		-1741	
p-value	0.02		0.01		0.00		0.00		0.02	

Table 7. Parameter Estimates and Test Results from the Univariate Markov Switching Model: Using Alternative Liquidity Measure, *LM*12 (*continued*)

	Decile 6		Decile 7		Decile 8		Decile 9		Decile 10 (Least Liquid Firms)	
Mean parameters										
Constant, State 1	-3.011	(-1.38)	-3.824	(-1.45)	-3.683	(-1.97)	-3.743	(-1.72)	-2.811	(-1.71)
Constant, State 2	1.038	(1.56)	1.717	(2.50)	2.020	(3.00)	1.975	(2.37)	1.757	(2.69)
DEF, State 1	2.463	(2.22)	2.694	(2.13)	2.983	(2.69)	3.443	(2.97)	2.679	(2.42)
DEF, State 2	0.826	(0.97)	0.595	(0.52)	-2.070	(-2.06)	-1.728	(-1.68)	-1.936	(-2.50)
TERM, State 1	0.872	(1.18)	0.805	(0.91)	1.078	(1.66)	1.291	(1.74)	1.405	(2.22)
TERM, State 2	-0.358	(-1.31)	-0.250	(-0.96)	-0.319	(-1.11)	-0.607	(-1.77)	-0.322	(-1.15)
ΔM, State 1	-0.050	(-2.92)	-0.042	(-2.38)	-0.049	(-2.75)	-0.057	(-3.04)	-0.051	(-2.85)
ΔM, State 2	0.098	(4.30)	0.037	(1.12)	0.081	(2.33)	0.210	(4.93)	0.195	(5.88)
TB, State 1	0.256	(0.08)	1.462	(0.32)	1.343	(0.43)	0.326	(0.09)	1.265	(0.43)
TB, State 2	-3.112	(-1.84)	-2.931	(-1.39)	0.865	(0.48)	-0.842	(-0.45)	-0.137	(-0.09)
Variance parameters										
σ, State 1	6.494	(17.43)	6.899	(16.04)	6.975	(17.61)	7.494	(17.78)	7.207	(18.46)
σ, State 2	3.199	(19.26)	3.149	(17.50)	3.203	(14.10)	3.908	(14.69)	3.206	(15.74)
Transition probability parameters										
Constant	-0.142	(-0.20)	1.290	(5.10)	1.375	(5.05)	1.259	(5.06)	1.326	(5.92)
ΔCLI, State 1	-0.294	(-1.44)	-0.045	(-1.21)	-0.095	(-2.66)	-0.104	(-2.80)	-0.096	(-2.94)
ΔCLI, State 2	0.184	(1.79)	0.070	(1.56)	-0.003	(-0.11)	0.002	(0.05)	0.002	(0.05)
Log-likelihood value	-1683		-1697		-1748		-1822		-1758	
Restricted log-likelihood value with $\beta^i_{k,s_t=1} = \beta^i_{k,s_t=2}$, $k = \{1,2,3,4\}$	-1691		-1701		-1754		-1838		-1776	
p-value	0.00		0.08		0.01		0.00		0.00	

Table 8. Out-of-Sample Trading Results from the bivariate Markov switching model

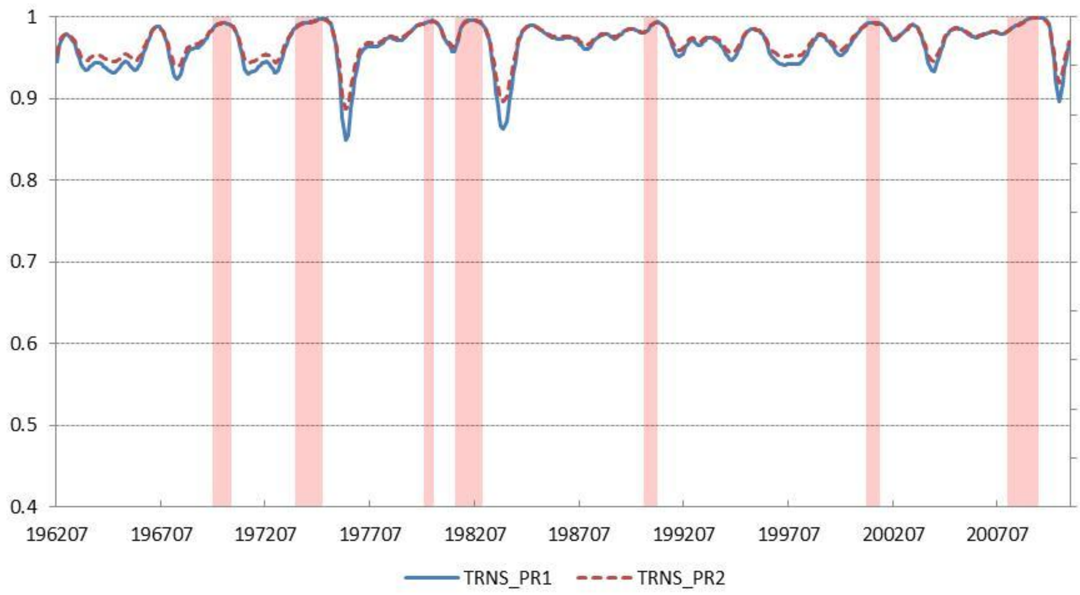
The table reports out-of-sample trading results based on three different trading strategies for each of the three portfolios. The high-liquidity (*HL*) and the low-liquidity (*LL*) portfolios include stocks that are in the bottom 30% and the top 30% sorted on their Amihud's (2002) illiquidity measure, respectively. The low-minus-high (*LL-HL*) portfolio is the zero-cost portfolio buying the low-liquidity and selling the high-liquidity portfolio. The buy-and-hold strategy simply reinvests all funds in the equity portfolio under consideration at each month. The switching strategy 1 and 2 buys the equity portfolio if the excess return is predicted to be positive, from the linear predictive regression model and the bivariate Markov switching model respectively, or buys one-month Treasury bills otherwise. Mean returns and standard deviations of returns are annualized. The period for recursive out-of-sample predictions is from February 2000 to December 2010.

		High-Liquidity Portfolio (*HL*)			Low-Liquidity Portfolio (*LL*)			Low-Minus-High (*LL-HL*)		
	T-Bills	Buy-and-Hold	Switching Strategy 1	Switching Strategy 2	Buy-and-Hold	Switching Strategy 1	Switching Strategy 2	Buy-and-Hold	Switching Strategy 1	Switching Strategy 2
Full sample										
Mean return	2.47	3.56	5.33	6.58	10.67	13.99	15.09	7.11	8.64	9.45
Standard deviation	0.57	18.89	17.64	15.11	23.84	21.57	19.06	11.94	9.90	9.20
Sharpe ratio		0.06	0.16	0.27	0.34	0.53	0.66	0.39	0.62	0.76
Recessions										
Mean return	1.81	-17.40	-16.19	-4.80	-8.32	-6.99	5.52	9.08	9.26	12.57
Standard deviation	0.40	27.06	27.07	20.97	30.22	30.19	23.89	11.28	11.27	10.38
Sharpe ratio		-0.71	-0.67	-0.32	-0.34	-0.29	0.16	0.64	0.66	1.04
Expansions										
Mean return	2.63	8.75	10.65	9.40	15.38	19.18	17.46	6.63	8.49	8.68
Standard deviation	0.59	16.09	14.17	13.28	21.95	18.74	17.73	12.14	9.59	8.93
Sharpe ratio		0.38	0.57	0.51	0.58	0.88	0.84	0.33	0.61	0.68

Figure 1. Transition Probabilities from the Univariate Markov Switching Model

This figure presents the time-series of the transition probabilities estimated from the univariate Markov switching model. Panel A shows the results for the most liquid firms, and Panel B reveals the results for the least liquid firms. In each Panel, "TRNS_PR1" is the probability of moving from state 1 to state 1, and "TRNS_PR2" is the probability of moving from state 2 to state 2. The shades regions represent NBER recessions. The sample period is from July 1962 to December 2010.

Panel A: Most liquid firms



Panel B: Least liquid firms

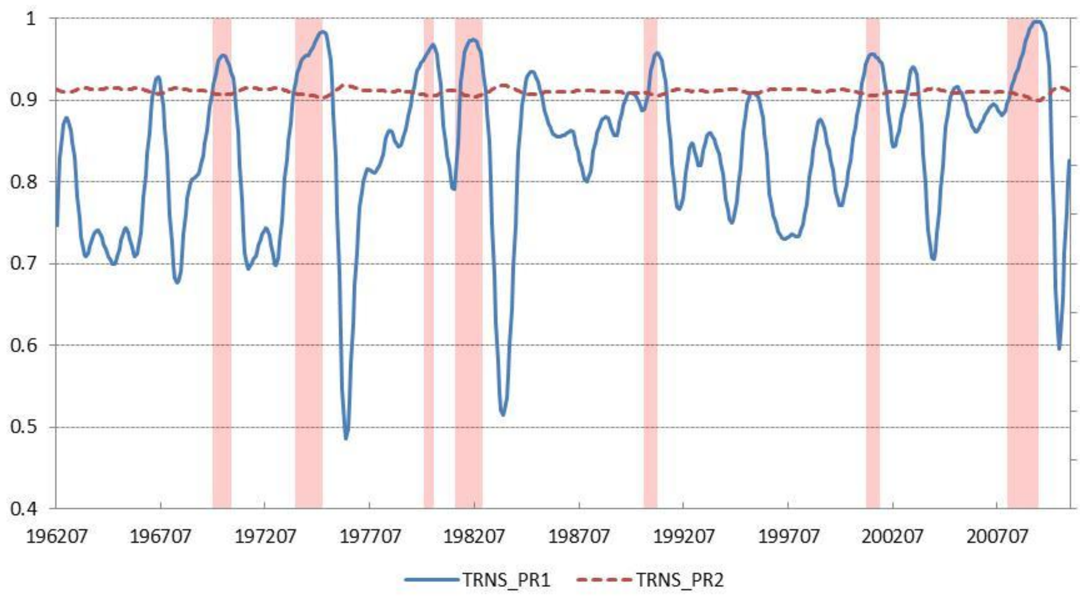
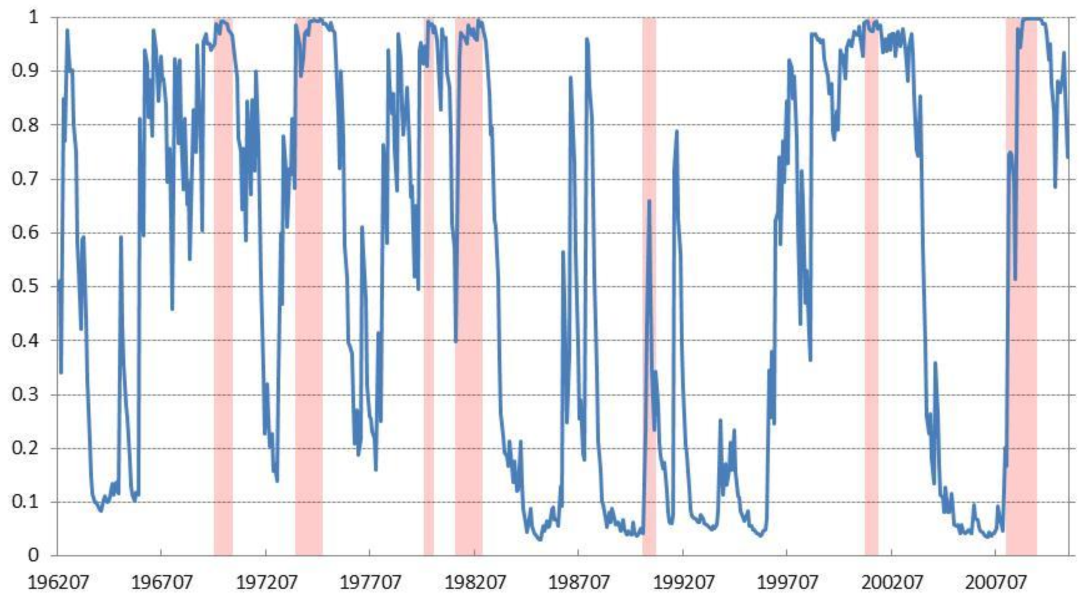


Figure 2. Probabilities of High Volatility State from the Univariate Markov Switching Model

This figure displays the time-series of the probabilities of being in state 1 at time *t* conditional on the information at time *t*-1, from the estimated univariate Markov switching model. Panel A shows the results for the most liquid firms, and Panel B reveals the probabilities of the least liquid firms. The shades regions represent NBER recessions. The sample period is July 1962 to December 2010.

Panel A: Most liquid firms



Panel B: Least liquid firms

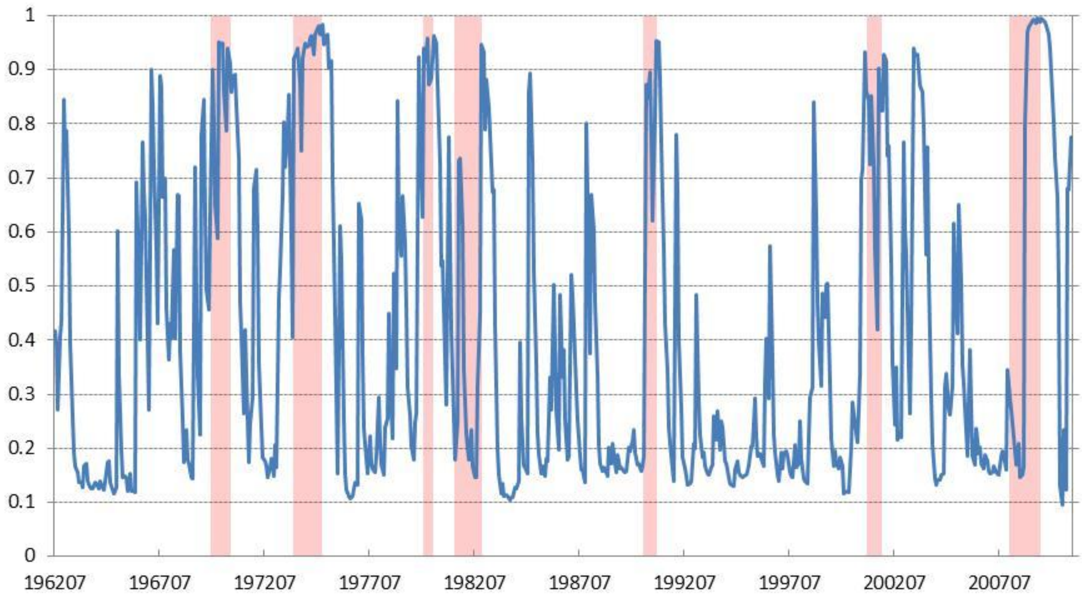
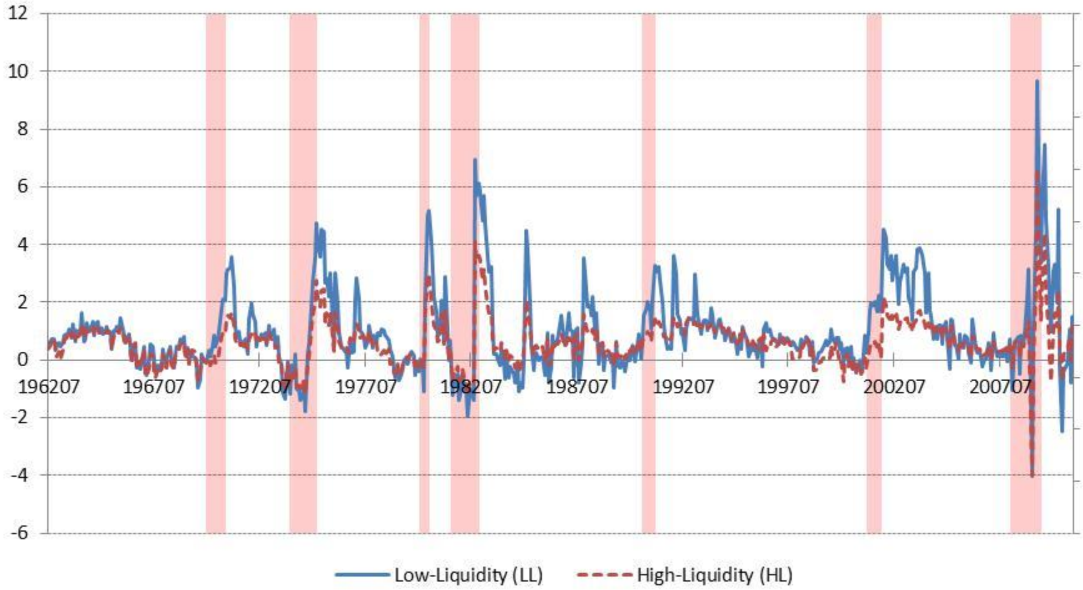


Figure 3. Expected Illiquidity Premium from the Bivariate Markov Switching Model

This figure presents the time-series of the expected illiquidity premium from the estimated bivariate Markov switching model. Panel A shows the expected excess returns of low-liquidity (*LL*) and high-liquidity (*HL*) portfolios. Panel B shows the expected illiquidity premium as their differential. The shades regions represent NBER recessions. The sample period is July 1962 to December 2010.

Panel A: Low- and High-Liquidity Portfolios



Panel B: Low-Minus-High Liquidity Portfolio

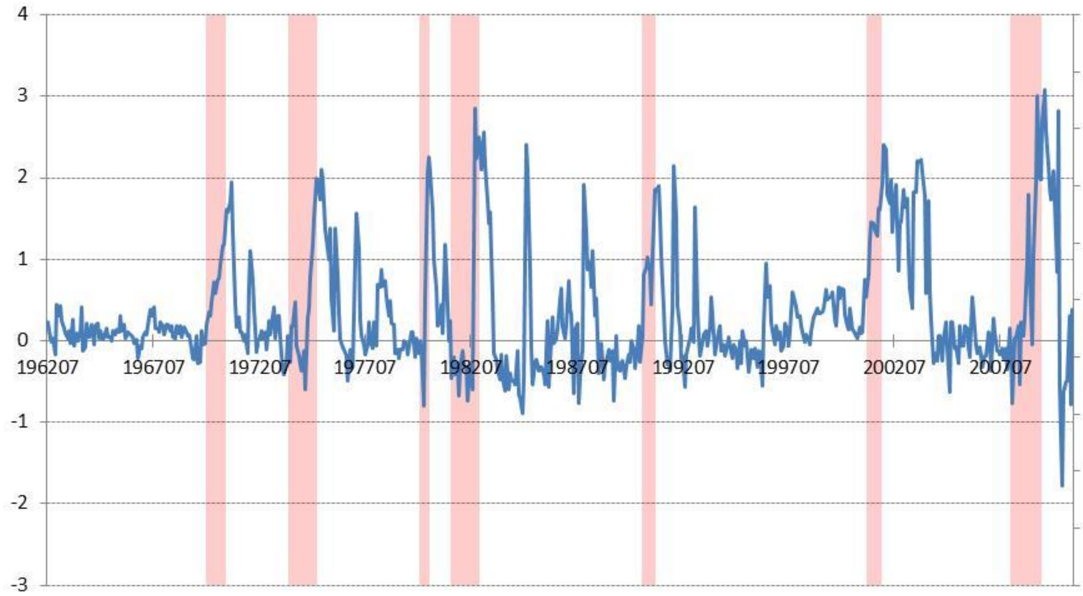
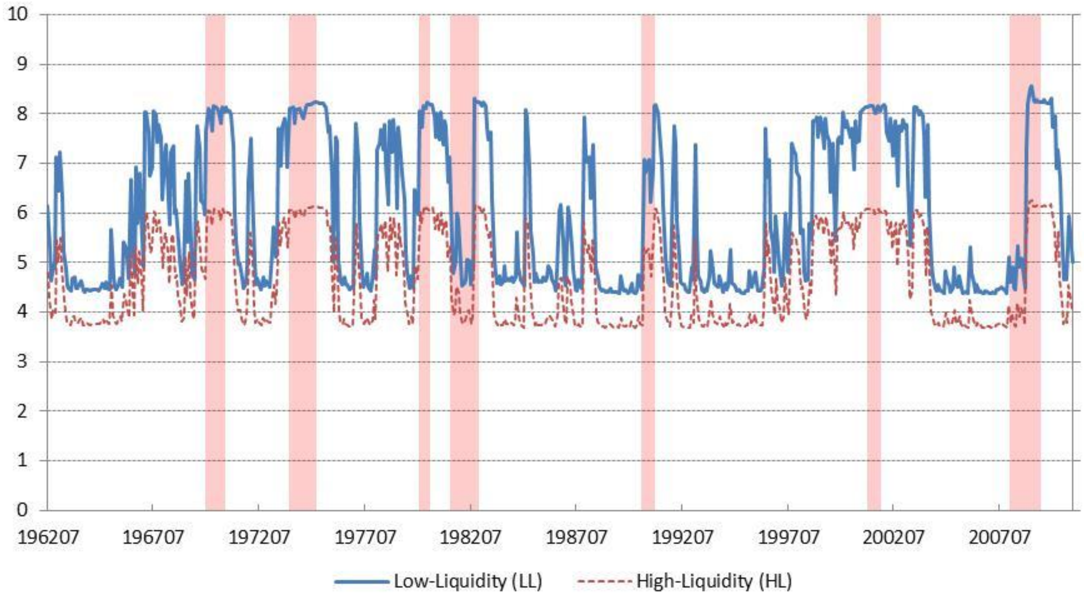


Figure 4. Conditional Volatility from the Bivariate Markov Switching Model

This figure presents the time-series of the conditional volatilities from the estimated bivariate Markov switching model. Panel A plots the conditional volatilities for low-liquidity (*LL*) and high-liquidity (*HL*) portfolios' excess returns. Panel B plots the conditional volatility for the low-minus-high liquidity portfolio's excess returns. The shades regions represent NBER recessions. The sample period is from July 1962 to December 2010.

Panel A: Low- and High-Liquidity Portfolios



Panel B: Low-Minus-High Liquidity Portfolio

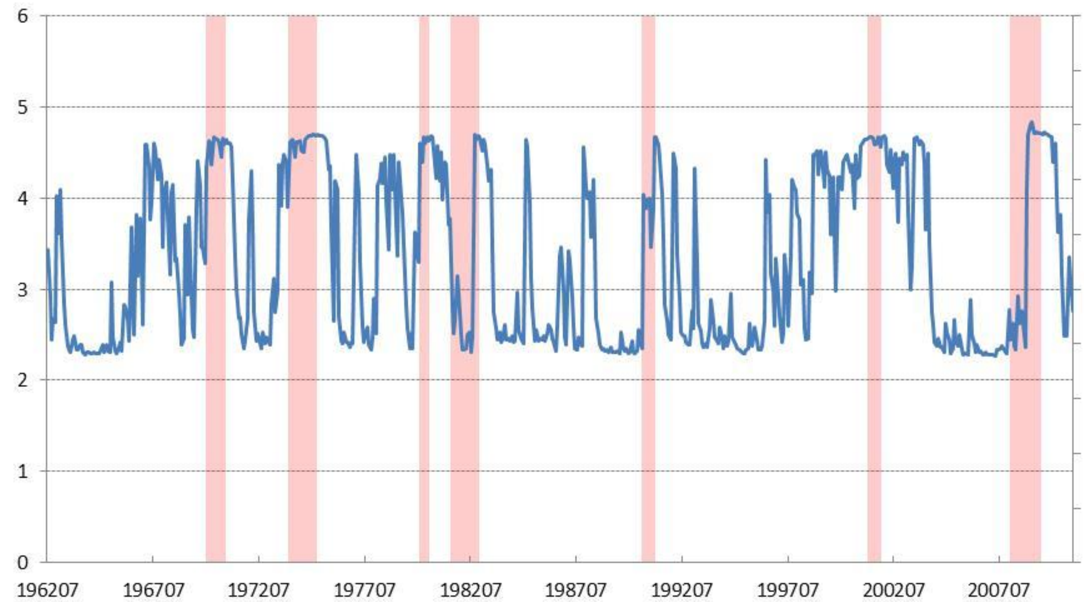
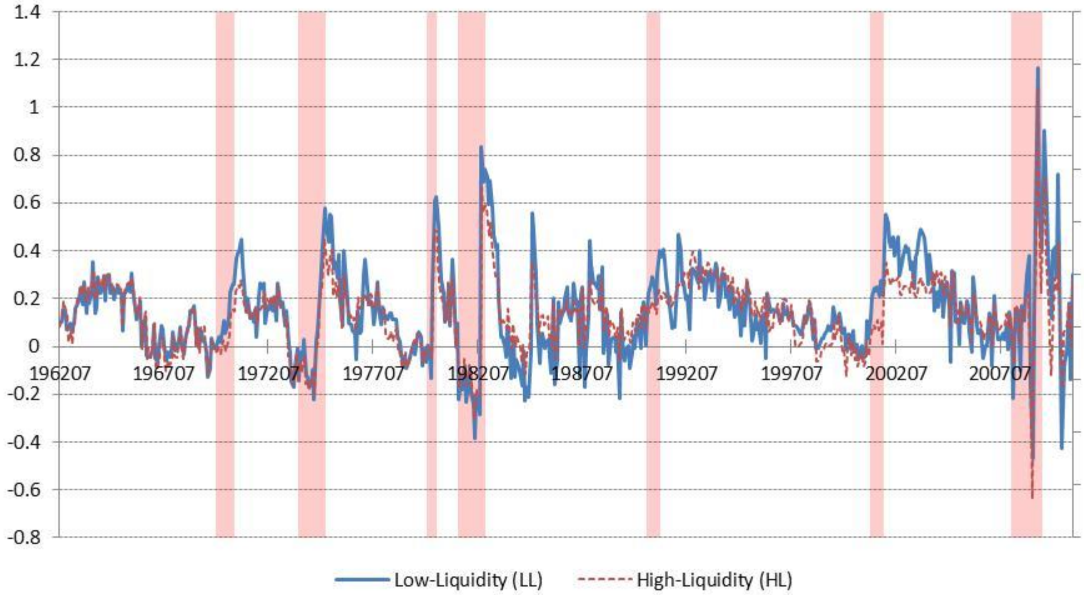


Figure 5. Conditional Sharpe Ratio from the Bivariate Markov Switching Model

This figure presents the time-series of the conditional Sharpe ratios from the estimated bivariate Markov switching model. Panel A plots the conditional Sharpe ratios defined as the expected excess returns divided by conditional volatilities, for low-liquidity (*LL*) and high-liquidity (*HL*) portfolios. Panel B plots the conditional Sharpe ratio for the low-minus-high liquidity portfolio. The shades regions represent NBER recessions. The sample period is from July 1962 to December 2010.

Panel A: Low- and High-Liquidity Portfolios



Panel B: Low-Minus-High Liquidity Portfolio

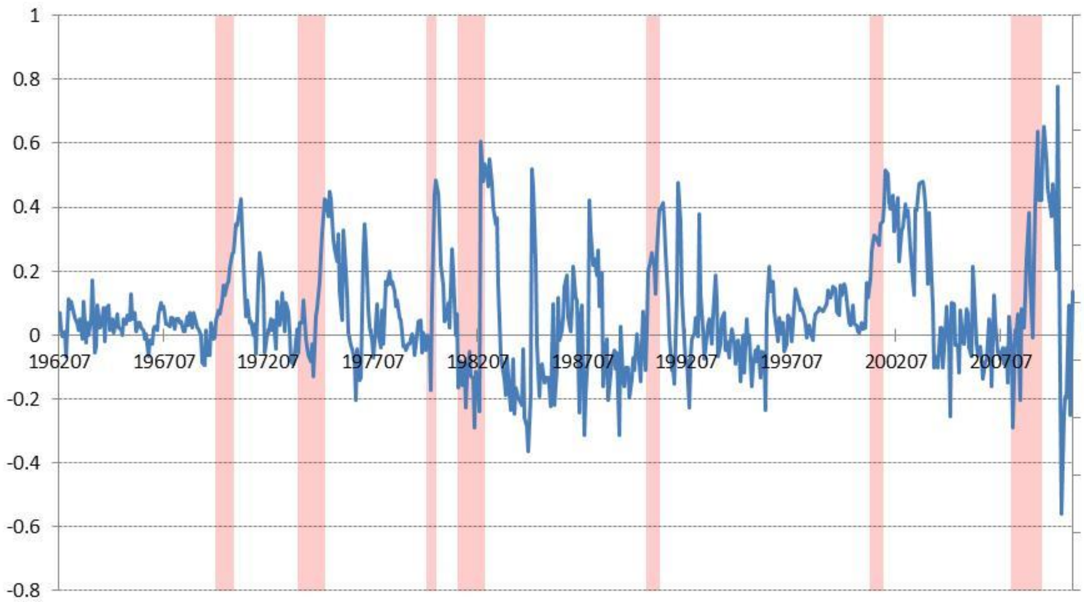


Figure 6. Expected Illiquidity Premium from the Linear Predictive Regression Model

This figure presents the expected illiquidity premium from the linear predictive regression model, in comparison with the two-state bivariate Markov switching model. We estimate the linear predictive model for the low-liquidity (*LL*) and high-liquidity (*HL*) portfolios jointly with the same independent variables as our Markov switching model. The shades regions represent the NBER recessions. The sample period is from July 1962 to December 2010.

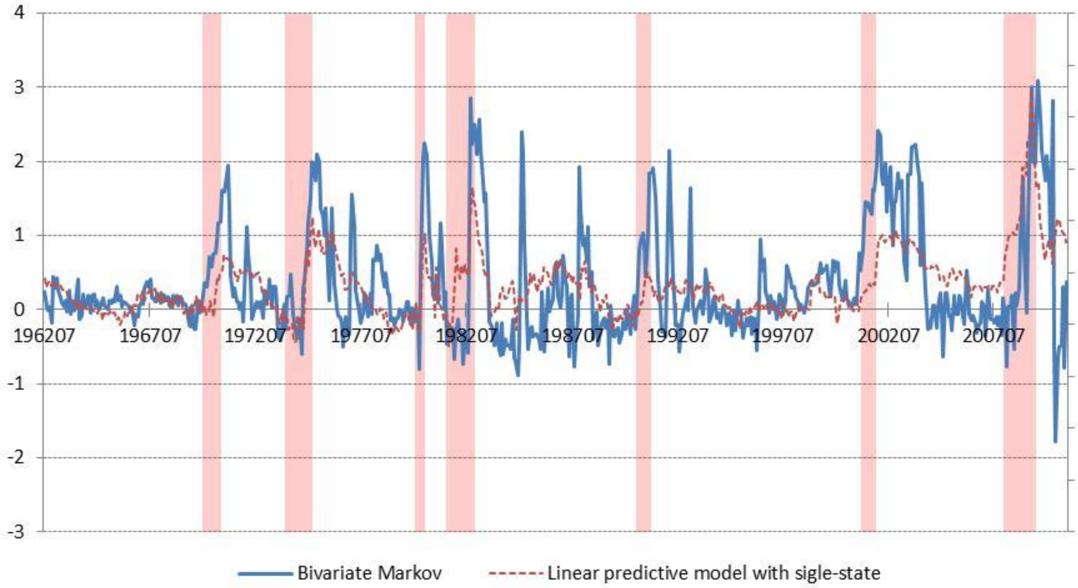


Figure 7. Out-of-Sample Forecasts of the Illiquidity Premium from the Bivariate Markov Switching Model

This figure presents the out-of-sample forecasts of the illiquidity premium predicted recursively from the bivariate Markov switching model. The dotted lines indicate the plus and minus two standard error bands. The shades regions represent NBER recessions. The period for the recursive out-of-sample predictions is from February 2000 to December 2010.