N.B.: This is an incomplete and early draft. We welcome your comments.

Liquidity traps[1]

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July 2, 2010

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Liquidity traps

Abstract

A security's liquidity properties have been studied in terms mean and variance—liquidity level and liquidity risk, respectively. This paper explores tail events—liquidity disaster risk. The idea is that liquidity might not be an issue for investors in normal market conditions. But, it becomes a first-order concern if the security is 'trapped' in an illiquid state, in particular if this state is persistent so that waiting a day will not restore liquidity. A Markov regime-switching model is used to identify liquidity traps empirically. These are defined as the security being stuck in an illiquid regime for at least a week. The model is estimated for an unbalanced sample of 2147 stocks from 1963 through 2008. Standard Fama-MacBeth regressions show that a one standard deviation increase in the probability of a liquidity trap increases annual returns by 1.1%. And, this premium has increased over time.

1 Introduction

Standard asset pricing assumes frictionless markets where every security can be traded at no cost at all times, i.e., markets are perfectly liquid. But, a large and expanding literature relaxes the zero cost assumption in a variety of ways and empirical evidence shows that liquidity frictions are a priced characteristic of a security. Amihud, Mendelson, and Pedersen (2005) reviews the literature and organizes it into essentially studies on liquidity level or liquidity risk.

A stock's average liquidity level matters for required returns as investors seek compensation for expected trading cost. Empirical evidence on the cross-sectional relationship is in numerous studies, including Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan, Chordia, and Subrahmanyam (1998). Over time, both liquidity level and the premium required per unit of liquidity level have declined as evidenced by Amihud (2002), Jones (2005), and Ben-Rephael, Kadan, and Wohl (2009).

Risk-averse investors might also require compensation for stochastic liquidity which makes liquidity risk a priced factor. This channel has recently been developed and studied in, among others, Pastor and Stambaugh (2003) who show that marketwide liquidity as a state variable explains returns with a differential of 7.5% annually across low and high liquidity beta stocks. Acharya and Pedersen (2005) propose CAPM for an asset's expected return *gross* of transaction cost. They find that a stock's liquidity covariation with market liquidity and with market return should matter for required returns in addition to the 'Pastor-Stambaugh' covariation of a stock's return with market liquidity. Empirically, they find that a stock's liquidity covariation with market returns is, among the three, the dominant part of the aggregate liquidity risk premium. They also report that the aggregate liquidity risk premium is smaller than the liquidity level premium in the cross-section of stocks.

Has the level premium decline and the relatively 'small' risk premium made liquidity unimportant for asset pricing? This paper explores a new dimension of liquidity inspired by the disaster risk literature, e.g., Rietz (1988) and Barro (2006). Investors might care little about liquidity in normal market conditions, but high transaction cost might become a first order concern if the stock hits a 'disaster' liquidity state. An example is a self-fulfilling liquidity dry-up if all believe others will not show up for trade or, in other words, a negative manifestation of the liquidity externality (see, e.g., Pagano (1989)). Such dry-up is particularly painful if this state is persistent so that waiting a day will not restore liquidity. We refer to such event as stocks hitting a liquidity trap.

To test whether liquidity traps are priced requires a measure that recognizes (i) the frequency of hitting an illiquid state and (ii) the duration of that state. Liquidity traps hurt only if both of these are large. That is, securities that hit illiquid states frequently but revert in a day or securities that stay for a prolonged period in an illiquid state but almost never hit these state are not painful for an investor. We operationalize this idea by estimating a Markov regime-switching model where the transition probability matrix identifies these two dimensions. A liquidity trap is then defined as the (unconditional) probability that one finds the security in the illiquid regime for more than a week. This is essentially a 'product' of frequency and duration, which captures the idea that both need to be large for liquidity traps to hurt.

But, does this idiosyncratic liquidity trap probability not wash in the large universe of stocks? Not necessarily for the same reasons that idiosyncratic volatility has been documented to be priced. If all agents are permanently in the market and are unconstrained in their holdings, idiosyncratic price changes diversify. If, instead, agents are not always present but arrive nonsynchronously an intermediary matches trading needs but requires compensation for temporarily bearing inventory price risk (e.g., Grossman and Miller (1988), Hendershott and Menkveld (2010)). Or, if some agents are constrained then the nonconstrained agents need compensation for a 'suboptimal' portfolio (e.g., Malkiel and Xu (2005)).

The Markov regime-switching model is estimated for common stocks listed on NYSE or AMEX in the period from 1963 to 2008. For each stock, each day, the standard Amihud ILLIQ measure is calculated (see Amihud (2002)). The frequency of the illiquid regime is, on average, 0.21. The average probability of staying another day in the illiquid regime is

0.45. On average, the implied liquidity trap probability—being stuck in the illiquid regime for at least five days—is 0.06.

The hypothesized relationship between a stock's liquidity trap probability and its required return is tested in two conventional ways: portfolio sorts and Fama-MacBeth regressions. The portfolio sort analysis reveals that a trading strategy that is long in high liquidity trap probability stocks and short in low liquidity trap probability stocks yields a significant average annual excess return of approximately 3.36%. To explore whether this positive return is only due to one of the two factors of the liquidity trap probability (i.e., frequency or duration) or just captures the (unconditional) average liquidity level, we double-sort and find that, still, the return differential across low and high liquidity trap probability stocks remains significantly positive. Fama-MacBeth regressions enable us to also control for the standard Fama-French factors. Liquidity trap probability remains a significant explanatory factor for returns. A one standard deviation increase in liquidity trap probability increases required returns by 1.1% annually. These regressions are repeated for the two equal length subperiods (1964 through 1985 and 1986 through 2008) and results indicate that liquidity trap probability has become more important for required returns over time whereas, consistent with earlier literature, liquidity level has become less important.

As a robustness check, we redo all analysis based on modelfree nonparametric proxies for frequency and duration calculated directly from the raw data. Duration is measured as the average time a stock is illiquid. Frequency is measured as the fraction of days that a stock is illiquid. Redoing the required return analyses based on these noisy proxies shows that our main finding that liquidity trap probability matters for required returns is robust.

The remainder of the paper is organized as follows. Section 2 introduces the Markov regime switching model to identify liquidity traps. Section 3 describes the data and presents descriptive statistics on the liquidity trap estimates. Section 4 tests the hypothesized relation between a stock's liquidity trap probability and its return. Section 5 presents a robustness analysis. Section 6 concludes.

2 Liquidity trap measurement

This section presents the estimation method of the liquidity trap probability. We model the illiquidity level of stock i by a first-order autoregressive process with different intercepts, same autoregressive coefficients, difference variances of error terms in two different regimes:

$$illiq_d^i = \begin{cases} \mu_0^i + \phi^i illiq_{d-1}^i + \varepsilon_d^i, & \text{if } s_d^i = 0, \\ \mu_1^i + \phi^i illiq_{d-1}^i + \varepsilon_d^i, & \text{if } s_d^i = 1, \end{cases} \tag{1}$$

where $illiq_d^i$ is the illiquidity level of stock i on day d. s_d^i denotes the regime of stock i on day d. $\varepsilon_d^i \sim N(0, \sigma_{s_d^i})$ in regime s_d^i. We denote $s_d = 0$ as the liquid regime and $s_d = 1$ as the illiquid regime. Moreover, s_d^i follows a first order Markov chain with the following transition matrix:

$$Pr(s_d^i = 0 | s_{d-1}^i = 0) = p_{00}^i \tag{2}$$

$$Pr(s_d^i = 0 | s_{d-1}^i = 1) = p_{01}^i \tag{3}$$

$$Pr(s_d^i = 1 | s_{d-1}^i = 0) = p_{10}^i \tag{4}$$

$$Pr(s_d^i = 1 | s_{d-1}^i = 1) = p_{11}^i \tag{5}$$

We propose to measure the persistence of the illiquid regime by the probability that a stock stays in the illiquid regime for five subsequent days given that it is in the illiquid regime on previous day. Thus the persistence of the illiquid regime is calculated as

$$p_{11}^5 = \left(Pr(s_d^i = 1 | s_{d-1}^i = 1)\right)^5$$

We measure the frequency of the illiquid regime by the unconditional probability that a stock is in the illiquid regime as follows

$$p_1 = \frac{1 - p^i_{00}}{2 - p^i_{00} - p^i_{11}}$$

Next, we define the liquidity trap probability, $liq\_trap\_prob^i$, as the probability that stock i is in the illiquid regime for five subsequent days. Therefore, it is the interaction of p^5_{11} and p_1:

$$liq\_trap\_prob^i = p^5_{11} \times p_1 = \frac{(p^i_{11})^5(1 - p^i_{00})}{2 - p^i_{00} - p^i_{11}} \tag{6}$$

In order to assure sufficient observations for the estimation, we estimate the above Markov regime-switching model for each stock in each year. The problem of this stock-by-stock analysis is that μ^i_0 and μ^i_1 differ across stocks. To achieve comparability across stocks, we need to set $\mu^i_1 = \mu_1$ for all stocks in the sample. We compute μ_1 by pooling $illiq^i_d$ of all stocks together and set the upper 20% percentile as the illiquidity level in the illiquid regime, μ_1. To estimate model parameters, we evaluate the likelihood function of the Markov regime switching model using the Hamilton filter (see details in Appendix).

3 Data: summary statistics and liquidity trap estimates

Daily and monthly data of stock prices, returns, volume, shares outstanding, and dividend are obtained from CRSP, with a sample period from December 31, 1962, through December 31, 2008. Following Chordia, Roll, and Subramanyam (2000) and Kamara, Lou, and Sadka (2008), we utilize only common stocks (CRSP share code 10 and 11) listed on NYSE/AMEX (CRSP exchange code 1 and 2). Moreover, we obtain the daily and monthly risk-free rate and the daily Fama and French three factors from Kenneth French at Dartmouth College.

We use the Amihud (2002) measure as our daily illiquidity measure. Compared with other measures of illiquidity, such as the bid-ask spread or the price impact, the Amihud measure only requires daily data and thus enable us study a much longer time period. Moreover, Hasbrouck (2006) and Korajczyk and Sadka (2008) have shown that the Amihud measure is highly correlated with many other measures of illiquidity, suggesting that it is a reliable measure of illiquidity. Specifically, for each stock i and day d, the Amihud illiquidity measure is given by:

$$illiq_d^i = \frac{|r_d^i|}{dvol_d^i}$$

where r_d^i is the daily return of stock i on day d. $dvol_d^i$ is the daily dollar volume of stock i on day d. Since the focus of this paper is on liquidity traps, which are in general extreme situations, we do not follow the existing filtering procedure[1]. First, $illiq_d^i$ is calculated for each stock and each day. If r_d^i is zero, then $illiq_d^i$ equals zero too. If $dvol_d^i$ is zero, then $illiq_d^i$ is labeled as a non-observed observation, the same as the situation of a non-trading day. Second, we winsorize *illiq* of all stocks in a given year by 1% and 99% percentile. Finally, we retain a stock in a given year only if it has at least 100 non-missing $illiq_d^i$ value and the stock has a yearly average price between \$2 and \$1000[2]. In this way, we preserve the information that is contained in the extreme *illiq* and meanwhile obtain relatively reliable data.

[insert Table 1]

Table 1 presents overall, between, and within summary statistics for NYSE/AMEX firms over the sample period from December 31, 1962 through December 31, 2008. There are between 1123 and 2147 stocks in our sample. The mean value of the Amihud ILLIQ measure

[1] For example, Chordia, Roll, and Subramanyam (2000), Amihud (2002) and Kamara, Lou, and Sadka (2008) have applied similar filters. In specific, Kamara, Lou, and Sadka (2008) apply the filtering as follows: First, $illiq_d^i$ is defined only for positive values of $dvol_d^i$, and non-missing non-zero values of r_d^i. Second, for a daily observation to be included in the sample, the stocks price at the end of the previous trading day has to be at least \$2. Third, firm-days outliers with $illiq_d^i$ in the lowest and highest 1% percentiles of the sample are discarded after applying the first two filters. Finally, a stock is retained in a given year only if it has at least 200 valid observations

[2] On average, about 5% of total stocks are removed due to this criteria.

is 0.41 with a overall standard deviation of 1.06. Moreover, there are considerable variations in *illiq*, both in the cross-section (the between standard deviation is 0.74) and over time (the within standard deviation is 0.76). In addition to *illiq*, there are several additional variables used in the analysis: $r100$ is the return during the last 100 days of each year; $r100yr$ is the return between the beginning of the year and the 100 days before its end; *sdret* is the standard deviation of the daily return; *divyld* is the dividend yield calculated as the sum of the dividends during one year divided by the end-of-year price. Following Amihud (2002), we use in the cross-sectional regression the mean-adjusted value of *illiq*:

$$illiqma_y^i = \frac{illiq_y^i}{1/N_y \sum_{n=1}^{N_y} illiq_y^i}$$

where $illiq_y^i$ is the *illiq* of stock i in year y and $N_y$is the number of stocks in year y.

[insert Table 2]

Table 2 presents overall, between, and within summary statistics for the yearly estimates of the Markov regime switching model described in section 2. The average percentage that the MLE gets convergence is 97%. The estimated p_{00} is 0.89 on average, implying that there is 89% probability that a stock will stay in the liquid regime given that it is in the liquid regime on previous day. The mean value of p_{11} is 0.45, smaller than p_{00}. Thus, if a stock is in the illiquid regime today, the probability that it remains in the illiquid regime tomorrow is 45%. We restrict μ_1 to be equal across stocks, and set it as the upper 20% percentile of the total *illiq*. The mean value of μ_1 is 0.59, and it is larger than the estimated μ_0. This is consistent with our setting that $s = 1$ is the illiquid regime. *liq_trp_prob*, the multiplication of p_{11}^5 and p_1, has a mean value of 6%. Therefore, on average there is 6% probability that a stock is stuck in a liquidity trap.

[insert Table 3]

Table 3 presents the between, and within correlation of the estimated coefficients of the Markov regime switching model. The between and within correlation between p_{11}^5 and p_1 are 0.58 and 0.65 respectively, both significant at 95% level. The positive correlation between p_{11}^5 and p_1 is plausible: it is more likely that a stock remains in the illiquid regime if it enters the illiquid regime more often, and vice versa. In addition, *liq_trp_prob* has positive correlation with its two factors by definition.

4 The pricing of the liquidity trap probability

In this section we investigate whether our model-based measure of liquidity traps, the liquidity trap probability, is priced in the cross-section. We first implement portfolio sorting approach to examine the relationship between the liquidity trap probability and stock average returns (see, for example, Fu (2008) and Ang, Chen, and Xing (2006)). Then we move on to Fama-MacBeth regressions which enable us regress cross-sectional returns directly on the liquidity trap probability and meanwhile control for other firm characteristics and risk factors.

Portfolio sorting analysis Compared to the regression approach, portfolio sorting is interesting because it produces easy-to-interpret returns on a feasible investment strategy. If individual stocks with high liquidity trap probability have higher returns than stocks with low liquidity trap probability, then a zero-investment portfolio that is long in high *liq_trap_prob* stocks and short in low *liq_trap_prob* stocks should earn a positive return.

[insert Table 4]

First, the single-sorting portfolio analysis is conducted. In each month we sort stocks into five quintiles based on their *liq_trap_prob* in the previous year. These portfolios are rebalanced monthly and are equal weighted. Table 4 presents the average of monthly excess returns (relative to the risk-free rate) and robust Newey-West (1987) t-statistics. The first two columns report portfolio excess returns over the entire sample period, from January

1964 to December 2008, in total 540 months. The portfolio returns are generally higher for portfolios with higher values of *liq_trap_prob*. The average monthly excess return is 0.91% for the portfolio with highest *liq_trap_prob*, whereas the portfolio with lowest *liq_trap_prob* has 0.62% return. The average monthly excess return for a zero-investment portfolio is 0.28% (about 3.36% per year), which is both economically and statistically significant. The same analysis is also conducted for two subperiods. For the first 264 months (from year 1964 to 1985), the return difference across *liq_trap_prob* quintiles is positive, but not statistically significant. For the second subperiod (in total 276 months from year 1986 to 2008), there is a significantly positive return spread, approximately 4.2% per year, across the two extreme *liq_trap_prob* portfolios.

[insert Table 5]

In the next step, we apply the double-sorting portfolio analysis which allows us to check the robustness of above results controlling for p_{11}^5, p_1 and *illiq* separately. As we have shown in section 2, our measure of liquidity traps, *liq_trap_prob*, is the interaction of two variables: the persistence of the illiquid regime which is measured by p_{11}^5 and the frequency of the illiquid regime which is measured by p_1. Obviously the single-sorting portfolio analysis above does not exclude the possibility that the positive return spread across *liq_trap_prob* portfolios is due to only one of the two factors of *liq_trap_prob*. To explore this, we then follow the approach suggested by Ang, Chen, and Xing (2006). In Panel A of Table 5, we first sort stocks into five quintiles based on their p_{11}^5 in the previous year. Then, within each quintile, we sort stocks into five quintiles based on their previous year *liq_trap_prob*. These portfolios are rebalanced monthly and are equal weighted. After forming the 5×5 p_{11}^5 and *liq_trap_prob* portfolios, we average the return of each *liq_trap_prob* quintile over the five p_{11}^5 portfolios. In this way these *liq_trap_prob* quintiles control for differences in p_{11}^5. Over the entire sample period, controlling for p_{11}^5 reduces the magnitude of the return difference from 0.28% in Table 4 to 0.19% per month. However, we still observe the increasing pattern of returns from the low *liq_trap_prob* portfolio to the high *liq_trap_prob* portfolio and the

$5-1$ difference in average returns is significantly positive. Moreover, we find positive return spreads for both subperiods, but only for the second subperiod it is statistically significant.

Panel B and Panel C of Table 5 present the excess return of double-sorted portfolios controlled for p_1 and *illiq* respectively. Although the difference in excess returns between the highest and lowest *liq_trap_prob* portfolios are smaller after accounting for the difference in p_1, they are still significant over the entire sample period and in the second subperiod. In addition, Amihud (2002) find evidence that stocks with high illiquidity level, measured by *illiq*, have high average returns. In order to assure that the spread in average returns on *liq_trap_prob* portfolios is not due to illiquidity level, we repeat the analysis to control for *illiq* in Panel C of Table 5. The excess return increases monotonically within the *liq_trap_prob* quintiles. The difference in excess returns between the two extreme *liq_trap_prob* quintiles is positive and significant at 95% level for all months, and months over 1986 to 2008. Again, the return spread for the second subperiod reaches 0.81% per month (approximately 9.72% per year), indicating also economical significance.

Fama-MacBeth regressions The evidence from the portfolio-sorting analysis suggests a positive relation between the liquidity trap probability and average stock returns. However, it does not account for other well-known determinants of expected returns and therefore could possibly introduce biases in the inference. To address this issue, we next examine the relation between the liquidity trap probability and stock returns by cross-sectional Fama-MacBeth regressions. The asset-pricing model is of the form:

$$E(r^i) = \gamma + \lambda' \beta^i + \delta' Z_i \tag{7}$$

where $E(r^i)$ denotes the expected return of stock i. β^i is a vector of factor loadings of stock i relative to several different risk factors. λ is a vector of risk premiums. Z^i is a set of firm characteristics of stock i and δ is a vector of characteristic premiums. One important firm characteristic considered in this paper is the liquidity trap probability (see section 2), *liq_trap_prob*. The coefficients of Equation (7) are estimated for each month,

$m = 1, 2, \ldots, M$, in the cross-sectional regression:

$$r_{i,m,y} = \gamma_m + \lambda'_m \beta_{i,y} + \delta'_m Z_{i,y-1} + \varepsilon_{i,m,y} \tag{8}$$

where $r_{i,m,y}$ denotes the monthly excess return (relative to the risk-free rate) of stock i in month m of year y. $\beta_{i,y}$ is a vector of K factor loadings of stock i in year y. λ_m is a vector of risk premiums in month m. δ_m is a vector of premiums of firm characteristics. $Z_{i,y-1}$ is a vector of L firm characteristics of stock i in year $y-1$. Among them, the variables of interest are the liquidity trap probability (liq_trap_prob), the probability that a stock is in the illiquid regime for 5 days given that it is in the illiquid regime in the last period (p_{11}^5), and the stationary probability that a stock is in the illiquid regime (p_1).

Since factor loadings are unobservable, they are pre-estimated through a time-series regression:

$$r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y} \tag{9}$$

This is the commonly used Fama-French three-factor model, where $r_{i,d,y}$ is the daily return of stock i on day d in year y. $MKT_{d,y}$ is the daily excess market return in year y. $SMB_{d,y}$ and $HML_{d,y}$ are the daily excess return of small caps over big caps and of value stocks over growth stocks in year y.

The final estimate, $\hat{\delta}$ and its variance are given by:

$$\hat{\delta} = \frac{1}{M} \sum_{m=1}^{M} \hat{\delta}_m \tag{10}$$

$$Var(\hat{\delta}) = \frac{1}{M(M-1)} \sum_{m=1}^{M} (\hat{\delta}_m - \hat{\delta})^2 \tag{11}$$

where M is the total number of months in the sample. Similarly, $\hat{\lambda}$ and its variance are given by:

$$\hat{\lambda} = \frac{1}{M}\sum_{m=1}^{M}\hat{\lambda}_m \quad (12)$$

$$Var(\hat{\lambda}) = \frac{1}{M(M-1)}\sum_{m=1}^{M}(\hat{\lambda}_m - \hat{\lambda})^2 \quad (13)$$

[insert Table 6]

Table 6 presents the results of Fama-MacBeth two-step regressions. In the first step, factor loadings are estimated for each stock each year via OLS regression (9). Then in the second step, we apply the cross-sectional regression (8) in each month via OLS. The first four models are estimated over the entire sample period. Thus, we calculate the average of the 540 estimated coefficients, and also present t-statistics against the null hypothesis that the average is zero. Model (1) examines the pricing of the liquidity trap probability after control for the illiquidity level and Fama-French three risk factors. The coefficient of *liq_trap_prob* is 7.46, significant at 95% level. It implies that an increase of one standard deviation in *liq_trap_prob* (0.12; see Table 2) would increase monthly returns by $7.46 \times 10^{-3} \times 0.12 = 0.09\%$. It is approximately 1.1% on an annual basis. The Amihud ILLIQ measure also has a significantly positive coefficient of 1.60, implying that one standard deviation in *illiqma* would increase yearly returns by approximately 3%. As we can see, liquidity traps capture the firm characteristic that is not reflected in the illiquidity level, and it is priced both statistically and economically significant. Model (2) and (3) include p_{11}^5 and p_1 separately in the cross-sectional regressions. Both of them have significantly positive coefficients. Furthermore, when they are both included in model (4), we still find significantly positive coefficients for them. We have to note that these two variables have relatively high correlation (between correlation is 0.58; see Table 3), thus there exists potential multicollinearity problem. Still, it suggests the independent explanatory power for p_{11}^5 and p_1 in the cross-sectional returns. The same analysis is employed for two subperiods: year 1964 to 1985 and year 1986 to 2008. As before, we report the average of monthly coefficients over the relevant time periods. The coefficients of *liq_trap_prob* and its two factors are not significantly different from zero in the first subperiod. By contrast, *liq_trap_prob* has a coefficient of 11.77 with a t-statistic of 3.97 in the second subperiod. Moreover, the coefficients of *liq_trap_prob*, p_{11}^5 and p_1 are significantly larger in the second subperiod than in the first subperiod (e.g. p-value of test $H_0(\ \delta(liq\_trap\_prob, 1964\text{-}1985) = \delta(liq\_trap\_prob, 1986\text{-}2008)$) is 0.02). The situation is different for the illiquidity measure *illiqma*. The effects of *illiqma* on returns become considerably smaller in the second subperiod. Specifically, an increase of one standard deviation in *liq_trap_prob* would increase yearly return by 1.7% whereas one standard deviation change in *illiqma* would result in a change in yearly return of 2.0%. Moreover, p_{11}^5 and p_1 both have significant coefficients in either the separate or joint tests. This is consistent with the finding of Ben-Rephael, Kadan, and Wohl (2009), suggesting that the liquidity premium declines over time. Our results provide evidence that the liquidity trap probability becomes more relevant over time whereas the effects of the illiquidity level declines.

[insert Table 7]

In Table 7 we add other well-known firm characteristics in the cross-sectional regressions. $r100$ and $r100yr$ are two variables that measure past stock returns. *lnsize* is the logarithm of market capitalization, which measures the size of a firm. *sdret* reflects the total risk of a stock. And *divyld* is the dividend yield. The results of these control variables are consistent with theories and previous studies. Past returns that reflect the momentum of a stock has a positive effect on stock returns. Small firms have a higher premium. Stocks with higher volatility have lower require returns, which is consistent with the tax trading option theory of Constantinides and Scholes (1980). Dividend yield has a coefficient that is not significantly different from zero. The variables of interest, *liq_trap_prob*, p_{11}^5 and p_1, have similar results as the previous table. *liq_trap_prob* have significantly positive coefficients over the entire sample period and also over the two subperiods. The effects of *liq_trap_prob* on stock returns are significantly higher during 1986 and 2008 than in the year 1964 to 1985 (the coefficient is 13.52 in the 2nd subperiod versus 4.80 in the 1st subperiod, and p-value of test the difference is 0.03). Moreover, both p_{11}^5 and p_1 have significantly positive coefficients over all months, 1964-1985, and 1986-2008 when they are separately included in the regressions. However, in the joint test, p_{11}^5 remains to be significant at 95% level whereas p_1 turns to be insignificant from zero. This implies that p_{11}^5, which reflects the persistence of the illiquid regime, has a dominant effects on returns. Finally, a down trend has been found for *illiqma* coefficients, 0.74 in the second subperiod versus 1.88 in the first subperiod.

Overall, the portfolio sorting analysis and Fama-MacBeth cross-sectional regressions show consistent evidence that the liquidity trap probability is positively priced in the cross-section. The premium of the liquidity trap probability is economically and statistically significant. Both factors of the liquidity trap probability, p_{11}^5 and p_1, contribute to the premium. Moreover, the liquidity trap probability becomes more relevant in explaining cross-sectional returns over time whereas the effects of the illiquidity level declines.

5 Robustness check

This section explores two robustness tests over the pricing of liquidity traps. First, we propose an alternative measure of liquidity traps and examine whether it provides consistent results as liquidity trap probability. Second, we investigate whether the well-known January effect has any impact on our findings.

5.1 Alternative measure of liquidity traps

So far, the results over the pricing of liquidity traps are all based on the measure that is derived from the Markov regime switching model. Since it is a model-based measure, it could be subject to some problems, such as model misspecification or estimation errors. Therefore, here we propose an alternative measure of liquidity traps, which is calculated directly from raw data without any model specification.

To start, we still need to define two liquidity regimes: an illiquid regime and a liquid regime. We pool $illiq_d^i$ of all stocks in year y and set the upper 20% percentile as the cutoff level for the illiquid regime in year y. A stock i is in the illiquid (liquid) regime on day d if its illiquidity level $illiq_d^i$ is higher (lower) than the cutoff level. Then we proxy the persistence of the illiquid regime by the average duration that a stock is in the illiquid regime in each year, $duration\_illiq$. The frequency of the illiquid regime is then measured by the percentage of the days that a stock is in the illiquid regime over total number of trading days in a year, $freq\_illiq$. Correspondingly, the interaction of these two variables is the measure of liquidity traps, denoted by $duration\_illiq \times freq\_illiq$. For example, a stock is in the illiquid regime twice in a year, once for 5 days and once for 15 days, and this stock has 200 trading days in total. In this case, $duration\_illiq$ equals to 10 ($= \frac{5+15}{2}$) and $freq\_illiq$ equals to 0.1 ($= \frac{5+15}{200}$), and $duration\_illiq \times freq\_illiq$ equals to 1 ($= 10 \times 0.1$).

[insert Table 8]

The overall, between and within summary statistics are presented in Panel A of Table 8. The value of $duration\_illiq$ is between 0 and 231. The mean value is 2.37, implying that on average the illiquid regime lasts for about two and a half days. $freq\_illiq$ has the mean value of 0.22, so stocks are in the illiquid regime 22% out of total trading days. We notice that there are stocks that are never in the illiquid regime ($duration\_illiq$=0 and $freq\_illiq$=0) and stocks that are always in the illiquid regime ($duration\_illiq$=231 and $freq\_illiq$=1). The interaction term, $duration\_illiq \times freq\_illiq$ equals to 1.68 on average.

Panel B of Table 8 reports the between and within correlation between this measurement and the measurement based on the Markov regime switching model and $illiq$ as well. In general these two measurements are correlated as expected. Although calculated in two different ways, they all have significantly positive correlations. p_{11}^5 and $duration\_illiq$ both measure the persistence of the illiquid regime, and their between correlation is 0.15, significant at 95% level. Moreover, p_1 and $freq\_illiq$ are different measures of the frequency of the illiquid regime and their between correlation is 0.24. Finally, two measures of liquidity traps, *liq_trap_prob* and $duration\_illiq \times freq\_illiq$, also have a reasonable value of the between correlation, positive and significant. These results suggest that the two measurements are not equivalent, but it is plausible to use them as alternative measures of liquidity traps. There is one more thing worth attention. Both the between and within correlation of *duration_illiq* and *freq_illiq* are considerably high. Therefore, a multicollinearity problem is very likely to arise when they are both included in a joint test.

[insert Table 9]

We apply the similar Fama-MacBeth regressions to the alternative measure of liquidity traps. Table 9 investigates the pricing of $duration\_illiq \times freq\_illiq$ and its two factors, controlling for the illiquidity level and Fama-French three factors. Over the entire sample period and two subperiods $duration\_illiq \times freq\_illiq$ always has significantly positive coefficient. The value of 0.40 for the entire sample indicates that a one standard deviation change in $duration\_illiq \times freq\_illiq$ leads to a yearly return approximately 3.6% ($= 7.41 \times 0.40 \times 10^{-3} \times 12$). Therefore, $duration\_illiq \times freq\_illiq$ not only has statistical significance, but also has economical significance. Model (2) and (3) show that both *duration_illiq* and *freq_illiq* can explain stock returns in the cross-section. Model (4) include both *duration_illiq* and *freq_illiq* in a joint test, and it seems that *duration_illiq* is more important in explaining cross-sectional returns for the entire sample and in the second subperiod.

[insert Table 10]

We add other firm characteristics to the above Fama-MacBeth regressions and present the results in Table 10. The findings over the pricing of $duration\_illiq \times freq\_illiq$ are robust to the additional control variables. For the entire sample and two subperiods, we all find significantly positive effects of $duration\_illiq \times freq\_illiq$ on stock returns in the cross-section. In addition, the two factors, especially *duration_illiq*, have strong explanatory power in the univariate regressions. We fail to find significant results in the multivariate regressions, probably due to the multicollinearity problem.

5.2 January effect

We investigate whether the effects of liquidity traps on returns are due to the January effect. Previous studies show that excluding January makes the effects of size and big-ask spread insignificant (for example, Keim (1983); Eleswarapu and Reinganum (1993)). To explore whether the liquidity trap premium we found is related to the January effect, we conduct the Fama-MacBeth cross-sectional regressions over the entire sample period excluding January.

[insert Table 11]

We perform the analysis twice, once with the model-based measure of liquidity traps and once with the simple measure of liquidity traps. In Panel A of Table 11, we use p_{11}^5 and p_1 as the measures for the persistence of the illiquid regime and the frequency of the illiquid regime respectively. The multiplication of these two variables is the liquidity trap probability, *liq_trap_prob*. Excluding January, there are in total a number of 495 monthly estimates in the second step of the Fama-MacBeth regression. As before, the coefficient on *liq_trap_prob* is significantly positive after control for the illiquidity level, other firm characteristics and Fama-French three factors. In univariate regressions, both p_{11}^5 and p_1 have significantly positive coefficients. The joint test implies that both of them have important explanatory power for cross-sectional returns. .

Panel B repeats the analysis but we measure the persistence of the illiquid regime by $duration\_illiq$ and the frequency of the illiquid regime by $freq\_illiq$. Correspondingly, $duration\_illiq \times freq\_illiq$ is used as the measure for liquidity traps. Our main finding is still robust after taking into account the January effect. Again, the premium of $duration\_illiq \times freq\_illiq$ is positive and significant. Model (2) and (3) show that $duration\_illiq$ and $freq\_illiq$ have separate explanatory power for the cross-sectional returns. In the joint test, however, there is no significance for both variables. As mentioned before, it is possibly due to the fact that $duration\_illiq$ and $freq\_illiq$ are highly correlated.

6 Conclusion

There are a number of theoretical and empirical papers that study the relationship between liquidity level and stuck returns (e.g. Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Amihud (2002)). In this paper, we argue that liquidity level is not the only aspect of liquidity that is priced. We bring in the idea of liquidity traps. In our setting, there are two regimes in the market, an illiquid regime and a liquid regime. When a stock falls into the illiquid regime and stays in the illiquid regime for a long time, we say it is stuck in a liquidity trap. This kind of stocks would constantly have low liquidity and could be problematic for investors when they need to trade. Therefore, we argue that liquidity trap as a firm characteristic should have a positive premium.

Using NYSE/AMEX common stock data between 1963 to 2008, we measure liquidity traps by the liquidity trap probability estimated from the Markov regime switching model. The liquidity trap probability is the interaction of the persistence of the illiquid regime and the frequency of the illiquid regime. The former is measured by the probability that a stock remains in the illiquid regime for five subsequent days given it is in the illiquid regime on previous day, and the latter is measure by the unconditional probability that a stock is in the illiquid regime. We investigate the pricing of the liquidity trap probability using portfolio sorting analysis and Fama-MacBeth regressions. We find reliable evidence that the liquidity trap probability has a positive effect on cross-sectional returns. The premium of the liquidity trap probability is both statistically and economically significant. Moreover, both factors of the liquidity trap probability are important in explaining the cross-sectional returns. Then we calculate an alternative measure of liquidity traps without any model specification and find qualitatively equivalent results. Our results are also robust to the January effect.

Appendix: Hamilton filter

In order to simplify the notation, we replace $illiq_d$ by y_t and use subscript t instead of d. We denote $\Omega_t = \{y_t, y_{t-1}, \cdots, y_0\}$ as the set of observations up to time t. And we denote $\theta = (p, q, \mu_0, \rho, \sigma_0, \sigma_1)'$ as a vector of parameters. The transition probability p_{00} and p_{11} are:

$$p_{00} = \frac{\exp(p)}{1 + \exp(p)} \tag{14}$$

$$p_{11} = \frac{\exp(q)}{1 + \exp(q)} \tag{15}$$

The autocorrelation parameter ϕ is:

$$\phi = \frac{\exp(\rho) - 1}{\exp(\rho) + 1} \tag{16}$$

Given $Pr(s_t = 0|\Omega_t) = \pi_0$ and $Pr(s_t = 1|\Omega_t) = \pi_1$, we can get

$$Pr(s_{t+1} = 0, s_t = 0|\Omega_t) = Pr(s_{t+1} = 0|s_t = 0; \Omega_t) \cdot Pr(s_t = 0|\Omega_t) = p_{00}\pi_0 \tag{17}$$

$$Pr(s_{t+1} = 1, s_t = 0|\Omega_t) = Pr(s_{t+1} = 1|s_t = 0; \Omega_t) \cdot Pr(s_t = 0|\Omega_t) = p_{01}\pi_0 \tag{18}$$

$$Pr(s_{t+1} = 0, s_t = 1|\Omega_t) = Pr(s_{t+1} = 0|s_t = 1; \Omega_t) \cdot Pr(s_t = 1|\Omega_t) = p_{10}\pi_1 \tag{19}$$

$$Pr(s_{t+1} = 1, s_t = 1|\Omega_t) = Pr(s_{t+1} = 1|s_t = 1; \Omega_t) \cdot Pr(s_t = 1|\Omega_t) = p_{11}\pi_1 \tag{20}$$

Moreover,

$$f(y_{t+1}|s_{t+1}=0;s_t=0;\Omega_t;\theta) = \frac{1}{\sqrt{2\pi\sigma_0}} exp\left(\frac{-\left[(y_{t+1}-\mu_0)-\phi(y_t-\mu_0)\right]^2}{2\sigma_0^2}\right) \quad (21)$$

$$f(y_{t+1}|s_{t+1}=1;s_t=0;\Omega_t;\theta) = \frac{1}{\sqrt{2\pi\sigma_1}} exp\left(\frac{-\left[(y_{t+1}-\mu_1)-\phi(y_t-\mu_0)\right]^2}{2\sigma_1^2}\right) \quad (22)$$

$$f(y_{t+1}|s_{t+1}=0;s_t=1;\Omega_t;\theta) = \frac{1}{\sqrt{2\pi\sigma_0}} exp\left(\frac{-\left[(y_{t+1}-\mu_0)-\phi(y_t-\mu_1)\right]^2}{2\sigma_0^2}\right) \quad (23)$$

$$f(y_{t+1}|s_{t+1}=1;s_t=1;\Omega_t;\theta) = \frac{1}{\sqrt{2\pi\sigma_1}} exp\left(\frac{-\left[(y_{t+1}-\mu_1)-\phi(y_t-\mu_1)\right]^2}{2\sigma_1^2}\right) \quad (24)$$

Therefore,

$$f(y_{t+1}|\Omega_t;\theta) = \sum_{j=0}^{1}\sum_{i=0}^{1} f(y_{t+1}, s_{t+1}=j, s_t=i|\Omega_t;\theta) \quad (25)$$

$$= \sum_{j=0}^{1}\sum_{i=0}^{1} f(y_{t+1}|s_{t+1}=j;s_t=i;\Omega_t;\theta)\cdot Pr(s_{t+1}=j,s_t=i|\Omega_t;\theta) \quad (26)$$

$$= (21)\times(17)+(22)\times(18)+(23)\times(19)+(24)\times(20) \quad (27)$$

In addition, once y_{t+1} is observed at the end of time $t+1$, the probability terms are updated as

$$Pr(s_{t+1}=0,s_t=0|\Omega_{t+1}) = Pr(s_{t+1}=0,s_t=0|y_{t+1};\Omega_t) \quad (28)$$

$$= \frac{f(y_{t+1},s_{t+1}=0,s_t=0|\Omega_t;\theta)}{f(y_{t+1}|\Omega_t;\theta)} \quad (29)$$

$$= \frac{f(y_{t+1}|s_{t+1}=0;s_t=0;\Omega_t;\theta)\cdot Pr(s_{t+1}=0,s_t=0|\Omega_t;\theta)}{f(y_{t+1}|\Omega_t;\theta)} \quad (30)$$

$$= \frac{(21)\times(17)}{(27)} \quad (31)$$

Similarly,

$$
\begin{aligned}
Pr(s_{t+1}=1, s_t=0|\Omega_{t+1}) &= \frac{(22)\times(18)}{(27)} && (32)\\
Pr(s_{t+1}=0, s_t=1|\Omega_{t+1}) &= \frac{(23)\times(19)}{(27)} && (33)\\
Pr(s_{t+1}=1, s_t=1|\Omega_{t+1}) &= \frac{(24)\times(20)}{(27)} && (34)
\end{aligned}
$$

And then updating

$$
\begin{aligned}
Pr(s_{t+1}=0|\Omega_{t+1}) &= Pr(s_{t+1}=0, s_t=0|\Omega_{t+1}) + Pr(s_{t+1}=0, s_t=1|\Omega_{t+1}) && (35)\\
&= (31)+(33) && (36)\\
Pr(s_{t+1}=1|\Omega_{t+1}) &= Pr(s_{t+1}=1, s_t=0|\Omega_{t+1}) + Pr(s_{t+1}=1, s_t=1|\Omega_{t+1}) && (37)\\
&= (32)+(34) && (38)
\end{aligned}
$$

The above iteration yields the conditional log likelihood function:

$$
\log f(y_0, y_1, \cdots, y_T|y_0;\theta) = \sum_{t=0}^{T} \log f(y_t|\Omega_{t-1};\theta) \qquad (39)
$$

The we can estimate θ by maximizing (39).

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Table 1: Summary statistics of general variables

This table presents overall, between, and within summary statistics for NYSE/AMEX firms over the sample period from December 31, 1962 through December 31, 2008. The dataset includes yearly averages of: daily stock returns (*ret*), daily closing price (*prc*), daily dollar volume (*dvol*), market capitalization (*mcap*), Amihud's ILLIQ measure (*illiq*), the mean-adjusted illiquidity level (*illiqma*), the return during the last 100 days of each year ($r100$), the return between the beginning of the year and the 100 days before its end ($r100yr$), the standard deviation of the daily return (*sdret*), the dividend yield calculated as the sum of the dividends during one year divided by the end-of-year price (*divyld*). We include the units of each variable in parentheses. iN denotes the number of stocks.

	Mean	St.Dev.	St.Dev. Between[a]	St.Dev. Within[b]	Min	Max	Median
ret (bps)	6.22	20.66	8.18	18.98	-594.85	666.67	6.25
prc ($)	29.16	24.53	17.93	16.75	2.03	899.36	24.40
dvol ($ mio)	10.53	49.88	28.88	40.67	0.00	2418.54	0.54
mcap ($ bln)	2.41	11.37	7.46	8.58	0.00	498.41	0.32
illiq (%/mln)	0.41	1.06	0.74	0.76	0.00	31.88	0.06
illiqma	1.00	1.77	1.38	1.10	0.00	26.86	0.31
$r100$	0.05	0.28	0.10	0.26	-0.99	15.44	0.03
$r100yr$	0.12	0.39	0.14	0.36	-0.94	12.15	0.07
sdret (%)	2.43	1.20	0.82	0.87	0.00	42.63	2.19
divyld (%)	3.76	19.30	8.43	17.36	0.00	1920.00	2.69
iN	1639.28	261.65	112.13	236.40	1123.00	2147.00	1668.00

[a]: Based on the time means i.e. $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$.

[b]: Based on the deviations from time means i.e. $x^*_{i,t} = x_{i,t} - \bar{x}_i$.

Table 2: Summary statistics of liquidity trap estimates based on the Markov regime switching model

This table presents overall, between, and within summary statistics for the yearly estimates of the following Markov regime switching model:

$$illiq_d^i = \begin{cases} \mu_0^i + \phi^i illiq_{d-1}^i + \varepsilon_d^i, & \text{if } s_d^i = 0, \\ \mu_1^i + \phi^i illiq_{d-1}^i + \varepsilon_d^i, & \text{if } s_d^i = 1, \end{cases} \tag{40}$$

where $illiq_d^i$ is the illiquidity level of stock i on day d. $\varepsilon_d^i \sim N(0, \sigma_{s_d^i})$ in regime s_d^i. We denote $s_d = 0$ as the liquid regime and $s_d = 1$ as the illiquid regime. Moreover, s_d^i follows a first order Markov chain with the following transition matrix:

$$Pr(s_d^i = 0 | s_{d-1}^i = 0) = p_{00}^i \tag{41}$$

$$Pr(s_d^i = 1 | s_{d-1}^i = 1) = p_{11}^i \tag{42}$$

We define the liquidity trap probability, $liq\_trap\_prob^i$ as the probability that stock i is in the illiquid regime for five subsequent days:

$$liq\_trap\_prob^i = p_{11}^5 \times p_1 = \frac{(p_{11}^i)^5 (1 - p_{00}^i)}{2 - p_{00}^i - p_{11}^i} \tag{43}$$

where $p_1 = Pr(s_d^i = 1)$. We estimate the above Markov regime-switching model for each stock each year. We pool $illiq_d^i$ of all stocks in year y together and set the upper 20% percentile as the illiquidity level in the illiquid regime for all stocks, μ_1. Details of the estimation can be found in Appendix. *iConverge* denotes the percentage that the MLE gets convergence.

	Mean	St.Dev.	St.Dev. Between[a]	St.Dev. Within[b]	Min	Max	Median
iConverge	0.97	0.18	0.09	0.16	0.00	1.00	1.00
p_{00}	0.89	0.08	0.04	0.07	0.00	1.00	0.90
p_{11}	0.45	0.31	0.13	0.28	0.00	1.00	0.42
μ_0	0.25	0.39	0.28	0.28	-3.63	4.92	0.10
μ_1	0.59	0.41	0.21	0.36	0.07	1.68	0.52
σ_0	0.18	0.28	0.20	0.20	0.00	1.87	0.07
σ_1	1.41	2.36	1.65	1.69	0.00	20.29	0.47
ϕ	0.18	0.17	0.08	0.14	-0.93	1.00	0.12
p_{11}^5	0.15	0.26	0.11	0.23	0.00	1.00	0.01
p_1	0.21	0.15	0.07	0.14	0.00	1.00	0.17
liq_trap_prob	0.06	0.12	0.05	0.11	0.00	1.00	0.00

[a]: Based on the time means i.e. $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$.

[b]: Based on the deviations from time means i.e. $x_{i,t}^* = x_{i,t} - \bar{x}_i$.

Table 3: Between and within correlation of liquidity trap estimates based on the Markov regime switching model

This table presents the between, and within correlation of the estimated coefficients of the Markov regime switching model.

		p_{11}	μ_0	μ_1	σ_0	σ_1	ϕ	p_{11}^5	p_1	liq_trap_prob
p_{00}	ρ(between)	0.14*	-0.19*	0.17*	-0.22*	-0.21*	0.23*	0.35*	-0.47*	0.15*
	ρ(within)	0.13*	0.02*	0.01*	0.02*	0.03*	0.10*	0.25*	-0.42*	0.05*
p_{11}	ρ(between)		0.26*	0.14*	0.27*	0.25*	0.81*	0.86*	0.70*	0.78*
	ρ(within)		-0.04*	0.17*	-0.02*	-0.04*	0.67*	0.81*	0.64*	0.64*
μ_0	ρ(between)			0.19*	0.99*	0.93*	0.23*	0.13*	0.34*	0.15*
	ρ(within)			0.38*	0.96*	0.78*	-0.01	-0.03*	-0.07*	-0.06*
μ_1	ρ(between)				0.18*	0.11*	0.19*	0.17*	0.04	0.15*
	ρ(within)				0.39*	0.30*	0.21*	0.18*	0.16*	0.17*
σ_0	ρ(between)					0.94*	0.23*	0.14*	0.36*	0.17*
	ρ(within)					0.80*	0.02*	-0.01	-0.05*	-0.02*
σ_1	ρ(between)						0.19*	0.10*	0.32*	0.12*
	ρ(within)						-0.04*	-0.06*	-0.08*	-0.07*
ϕ	ρ(between)							0.84*	0.63*	0.83*
	ρ(within)							0.74*	0.68*	0.77*
p_{11}^5	ρ(between)								0.58*	0.91*
	ρ(within)								0.65*	0.85*
p_1	ρ(between)									0.76*
	ρ(within)									0.83*

[a]: Based on the time means i.e. $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$.
[b]: Based on the deviations from time means i.e. $x^*_{i,t} = x_{i,t} - \bar{x}_i$.
[*]: Significant at a 95% level.

Table 4: Excess returns of portfolios single-sorted by *liq_trap_prob*

This table presents the excess returns of single-sorted portfolios, following Fu (2009). In each month we sort stocks into five quintiles based on their *liq_trap_prob* in the previous year. These portfolios are rebalanced monthly and are equal weighted. The column labeled "$ret - r_f(\%)$" is the time-series means of the monthly portfolio returns in percentage. The column labeled "t-stat" is the robust Newey-West (1987) t-statistics. "1" ("5") represents the low (high) value. The row "5-1" refers to the difference in monthly returns between portfolio 5 and portfolio 1. We do the analysis for three sample period, all months from January 1964 to December 2008, months over 1964 to 1985, months over 1986 to 2008.

	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (Low)	0.62	2.68**	0.68	1.93*	0.57	1.86*
2	0.61	2.49**	0.67	1.83*	0.56	1.69*
3	0.64	2.49**	0.69	1.77*	0.60	1.75*
4	0.70	2.46**	0.77	1.76*	0.63	1.73*
5 (High)	0.91	2.86**	0.90	1.90*	0.92	2.16**
$5 - 1$	0.28	2.36**	0.21	1.33	0.35	1.98**

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 5: Excess returns of double-sorted portfolios

This table presents the excess returns of double-sorted portfolios, following Ang, Hodrick, Xing and Zhang (2006). In Panel A, we first sort stocks into five quintiles based on their p_{11}^5 in the previous year. Then within each quintile, we sort stocks based on their *liq_trap_prob* in the previous year. These portfolios are rebalanced monthly and are equal weighted. After forming the 5×5 p_{11}^5 and *liq_trap_prob* portfolios, we average the returns of each *liq_trap_prob* quintile over the five p_{11}^5 portfolios. The column labeled "$ret - r_f(\%)$" is the time-series means of the monthly portfolio returns in percentage. The column labeled "t-stat" is the robust Newey-West (1987) t-statistics. "1" ("5") represents the low (high) value. The row "5-1" refers to the difference in monthly returns between portfolio 5 and portfolio 1. We do the analysis for three sample period, all months from January 1964 to December 2008, months over 1964 to 1985, months over 1986 to 2008. In Panel B and C, the same approach is used except we control for p_1 and *illiq* respectively.

Panel A: Controlling for p_{11}^5						
	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (Low)	0.52	3.48**	0.47	2.37**	0.56	2.55**
2	0.55	3.60**	0.52	2.50**	0.58	2.59**
3	0.63	3.92**	0.58	2.62**	0.68	2.93**
4	0.62	3.57**	0.56	2.38**	0.68	2.67**
5 (High)	0.70	3.63**	0.63	2.37**	0.77	2.76**
$5-1$	0.19	2.35**	0.16	1.29	0.21	2.18**
Panel B: Controlling for p_1						
	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (Low)	0.66	4.44**	0.68	3.46**	0.63	2.85**
2	0.46	2.89**	0.41	1.92*	0.51	2.17**
3	0.51	3.10**	0.40	1.79*	0.61	2.60**
4	0.61	3.53**	0.56	2.35**	0.66	2.64**
5 (High)	0.79	4.22**	0.71	2.73**	0.87	3.24**
$5-1$	0.13	1.70*	0.03	0.24	0.24	2.55**
Panel C: Controlling for illiq						
	All months		1964-1985		1986-2008	
Rank	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat	$ret - r_f(\%)$	t-stat
1 (Low)	0.48	3.28**	0.66	3.40**	0.29	1.31
2	0.53	3.31**	0.58	2.61**	0.48	2.07**
3	0.57	3.41**	0.53	2.36**	0.61	2.46**
4	0.66	3.81**	0.53	2.28**	0.79	3.09**
5 (High)	0.81	4.48**	0.54	2.25**	1.10	4.02**
$5-1$	0.33	3.06**	-0.12	-0.78	0.81	5.37**

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 6: Fama-MacBeth regressions of stock returns on *liq_trap_prob*

This table presents the estimation results of the Fama-MacBeth two-step regressions. In the first step, the factor loadings are estimated for each stock each year via OLS: $r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y}$. The factors considered are the excess market return (MKT), the Fama-French size factor (SMB) and the Fama-French book-to-market factor (HML). In the second step, we apply the cross-sectional regression in each month via OLS, $r_{i,m,y} = \gamma_m + \lambda'_m \beta_{i,y} + \delta'_m Z_{i,y-1} + \varepsilon_{i,m,y}$, where $r_{i,m,y}$ denotes the monthly excess return (relative to the risk-free rate) of stock i in month m of year y. $\beta_{i,y}$ is a vector of K factor loadings of stock i in year y. λ_m is a vector of risk premiums in month m. $Z_{i,y-1}$ is a vector of L firm characteristics of stock i in year $y-1$, including the liquidity trap probability (*liq_trap_prob*), the probability that a stock is in the illiquid regime for 5 days given that it is in the illiquid regime in the last period (p_{11}^5), the stationary probability that a stock is in the illiquid regime (p_1), and the mean-adjusted illiquidity level (*illiqma*). δ_m is a vector of coefficients for the firm characteristics. The final estimate, $\hat{\delta}$ and its variance are given by: $\hat{\delta} = \frac{1}{M}\sum_{m=1}^{M} \hat{\delta}_m$ and $Var(\hat{\delta}) = \frac{1}{M(M-1)}\sum_{m=1}^{M}(\hat{\delta}_m - \hat{\delta})^2$, where M is the total number of months in the sample. Similarly, $\hat{\lambda}$ and its variance are given by: $\hat{\lambda} = \frac{1}{M}\sum_{m=1}^{M} \hat{\lambda}_m$ and $Var(\hat{\lambda}) = \frac{1}{M(M-1)}\sum_{m=1}^{M}(\hat{\lambda}_m - \hat{\lambda})^2$. t-statistics are reported in parentheses. All coefficients are multiplied by 1000.

	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
liq_trap_prob	7.46**				2.95				11.77**			
	(3.92)				(1.27)				(3.97)			
p_{11}^5		3.31**		1.95*		1.03		0.39		5.49**		3.44**
		(3.96)		(1.94)		(0.97)		(0.30)		(4.31)		(2.30)
p_1			6.13**	4.19**			2.26	1.99			9.82**	6.30**
			(4.94)	(2.83)			(1.58)	(1.11)			(4.96)	(2.70)
illiqma	1.60**	1.61**	1.57**	1.59**	2.30**	2.31**	2.28**	2.29**	0.94**	0.95**	0.89**	0.92**
	(9.01)	(9.05)	(8.80)	(8.83)	(7.48)	(7.49)	(7.39)	(7.33)	(5.27)	(5.34)	(5.03)	(5.16)
β_{MKT}	5.35**	5.28**	5.62**	5.47**	3.76	3.80	3.83	3.90	6.86**	6.71**	7.34**	6.97**
	(2.91)	(2.87)	(3.05)	(2.97)	(1.52)	(1.54)	(1.55)	(1.57)	(2.53)	(2.47)	(2.69)	(2.56)
β_{SMB}	-1.56	-1.49	-1.75	-1.67	0.60	0.62	0.52	0.58	-3.62*	-3.52*	-3.92**	-3.83**
	(-1.32)	(-1.26)	(-1.48)	(-1.42)	(0.42)	(0.44)	(0.37)	(0.41)	(-1.93)	(-1.88)	(-2.09)	(-2.04)
β_{HML}	-0.61	-0.61	-0.65	-0.64	0.50	0.47	0.52	0.45	-1.66	-1.64	-1.76	-1.69
	(-0.50)	(-0.51)	(-0.54)	(-0.54)	(0.31)	(0.29)	(0.32)	(0.27)	(-0.94)	(-0.93)	(-1.00)	(-0.96)
intercept	1.17	1.07	0.38	0.51	0.69	0.63	0.41	0.29	1.63	1.49	0.35	0.73
	(1.10)	(1.01)	(0.36)	(0.50)	(0.44)	(0.39)	(0.26)	(0.19)	(1.15)	(1.05)	(0.25)	(0.52)

p-value of test H_0($\delta(liq\_trap\_prob, \text{1964-1985}) = \delta(liq\_trap\_prob, \text{1986-2008})$) is 0.02**

p-value of test H_0($\delta(p_{11}^5, \text{1964-1985}) = \delta(p_{11}^5, \text{1986-2008})$) is 0.01**

p-value of test H_0($\delta(p_1, \text{1964-1985}) = \delta(p_1, \text{1986-2008})$) is 0.00**

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 7: Fama-MacBeth regressions of stock returns on *liq_trap_prob*, and other firm characteristics

This table presents the estimation results of the Fama-MacBeth two-step regressions. In the first step, the factor loadings are estimated for each stock each year via OLS: $r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y}$. The factors considered are the excess market return (MKT), the Fama-French size factor (SMB) and the Fama-French book-to-market factor (HML). In the second step, we apply the cross-sectional regression in each month via OLS, $r_{i,m,y} = \gamma_m + \lambda_m' \beta_{i,y} + \delta_m' Z_{i,y-1} + \varepsilon_{i,m,y}$, where $r_{i,m,y}$ denotes the monthly excess return (relative to the risk-free rate) of stock i in month m of year y. $\beta_{i,y}$ is a vector of K factor loadings of stock i in year y. λ_m is a vector of risk premiums in month m. $Z_{i,y-1}$ is a vector of L firm characteristics of stock i in year $y-1$, including the liquidity trap probability (*liq_trap_prob*), the probability that a stock is in the illiquid regime for 5 days given that it is in the illiquid regime in the last period (p_{11}^5), the stationary probability that a stock is in the illiquid regime (p_1), and the mean-adjusted illiquidity level (*illiqma*). Moreover, we also include other control variables, such as the return during the last 100 days of each year ($r100$), the return between the beginning of the year and the 100 days before its end ($r100yr$), the standard deviation of the daily return ($sdret$), the logarithm of the market capitalization ($lnsize$), and the dividend yield ($divyld$). δ_m is a vector of coefficients for the firm characteristics. The final estimate, $\hat{\delta}$ and its variance are given by: $\hat{\delta} = \frac{1}{M}\sum_{m=1}^{M} \hat{\delta}_m$ and $Var(\hat{\delta}) = \frac{1}{M(M-1)}\sum_{m=1}^{M}(\hat{\delta}_m - \hat{\delta})^2$, where M is the total number of months in the sample. Similarly, $\hat{\lambda}$ and its variance are given by: $\hat{\lambda} = \frac{1}{M}\sum_{m=1}^{M} \hat{\lambda}_m$ and $Var(\hat{\lambda}) = \frac{1}{M(M-1)}\sum_{m=1}^{M}(\hat{\lambda}_m - \hat{\lambda})^2$. t-statistics are reported in parentheses. All coefficients are multiplied by 1000.

	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
liq_trap_prob	9.25**				4.80**				13.52**			
	(4.58)				(2.09)				(4.14)			
p_{11}^5		4.29**		3.75**		2.41**		2.59**		6.09**		4.86**
		(5.28)		(3.89)		(2.40)		(2.07)		(4.84)		(3.33)
p_1			5.63**	2.10			2.14	-0.27			8.97**	4.36*
			(4.41)	(1.38)			(1.50)	(-0.15)			(4.32)	(1.78)
illiqma	1.30**	1.30**	1.27**	1.30**	1.88**	1.88**	1.85**	1.88**	0.74**	0.75**	0.72**	0.75**
	(7.48)	(7.51)	(7.33)	(7.46)	(6.15)	(6.15)	(6.06)	(6.11)	(4.46)	(4.50)	(4.31)	(4.48)
$r100$	3.17*	3.26*	3.15*	3.16*	5.76**	5.77**	5.92**	5.80**	0.70	0.86	0.49	0.63
	(1.72)	(1.77)	(1.71)	(1.71)	(2.15)	(2.16)	(2.22)	(2.17)	(0.27)	(0.34)	(0.19)	(0.25)
$r100yr$	1.29	1.22	1.19	1.14	4.44**	4.37**	4.43**	4.31**	-1.73	-1.79	-1.90	-1.88
	(1.11)	(1.06)	(1.03)	(0.99)	(2.76)	(2.72)	(2.76)	(2.68)	(-1.06)	(-1.09)	(-1.17)	(-1.15)
lnsize	-2.05**	-2.10**	-1.96**	-2.05**	-2.63**	-2.66**	-2.62**	-2.69**	-1.50**	-1.56**	-1.32**	-1.44**
	(-7.49)	(-7.63)	(-7.12)	(-7.47)	(-7.25)	(-7.32)	(-7.20)	(-7.41)	(-3.69)	(-3.81)	(-3.25)	(-3.54)
sdret	-4.62**	-4.68**	-4.47**	-4.68**	-7.20**	-7.25**	-7.06**	-7.25**	-2.15**	-2.22**	-1.98**	-2.22**
	(-7.94)	(-8.05)	(-7.63)	(-8.07)	(-8.33)	(-8.38)	(-8.11)	(-8.41)	(-2.85)	(-2.95)	(-2.62)	(-2.96)
divyld	0.06	0.06	0.07	0.06	0.13	0.13	0.14	0.12	-0.00	-0.00	0.00	-0.00
	(1.08)	(1.09)	(1.19)	(1.05)	(1.16)	(1.15)	(1.23)	(1.10)	(-0.10)	(-0.03)	(0.04)	(-0.03)
β_{MKT}	9.16**	9.13**	9.27**	9.18**	9.32**	9.30**	9.38**	9.31**	9.01**	8.97**	9.16**	9.05**
	(4.97)	(4.96)	(5.03)	(4.98)	(3.70)	(3.70)	(3.73)	(3.70)	(3.36)	(3.34)	(3.41)	(3.37)
β_{SMB}	-2.32**	-2.30**	-2.40**	-2.34**	0.13	0.13	0.09	0.11	-4.67**	-4.62**	-4.77**	-4.68**
	(-2.02)	(-2.00)	(-2.08)	(-2.04)	(0.10)	(0.10)	(0.07)	(0.08)	(-2.52)	(-2.50)	(-2.58)	(-2.53)
β_{HML}	-2.33**	-2.34**	-2.34**	-2.35**	-1.86	-1.87	-1.87	-1.89	-2.78*	-2.78*	-2.79*	-2.78*
	(-2.06)	(-2.07)	(-2.07)	(-2.08)	(-1.21)	(-1.22)	(-1.21)	(-1.23)	(-1.68)	(-1.68)	(-1.68)	(-1.68)
intercept	18.46**	18.71**	16.86**	18.14**	23.22**	23.37**	22.68**	23.57**	13.91**	14.25**	11.30**	12.94**
	(7.78)	(7.90)	(7.08)	(7.78)	(6.83)	(6.88)	(6.69)	(7.10)	(4.22)	(4.33)	(3.41)	(3.98)

p-value of test H$_0$($\delta(liq\_trap\_prob, \text{1964-1985}) = \delta(liq\_trap\_prob, \text{1986-2008})$) is 0.03**

p-value of test H$_0$($\delta(p_{11}^5, \text{1964-1985}) = \delta(p_{11}^5, \text{1986-2008})$) is 0.02**

p-value of test H$_0$($\delta(p_1, \text{1964-1985}) = \delta(p_1, \text{1986-2008})$) is 0.01**

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 8: Alternative measure of liquidity traps

This table presents the summary statistics of an alternative measure of liquidity traps and its correlation with the model-based liquidity trap probability. We pool $illiq_d^i$ of all stocks in year y and set the upper 20% percentile as the cutoff level for illiquid regime in year y. A stock i is in the illiquid (liquid) regime on day d if its illiquidity level $illiq_d^i$ is higher (lower) than the cutoff level. *duration_illiq* is the average duration that a stock is in the illiquid regime. *freq_illiq* is the frequency that a stock is in the illiquid regime. The interaction term of *duration_illiq* and *freq_illiq* (*duration_illiq* × *freq_illiq*) is the simple measure of liquidity traps. Panel A shows the overall, between, and within summary statistics of *duration_illiq*, *freq_illiq*, and *duration_illiq* × *freq_illiq*. Panel B shows the between, and within correlation between them and p_{11}^5, p_1, *liq_trap_prob* and *illiq*.

Panel A: Summary statistics

	Mean	St.Dev.	St.Dev. Between[a]	St.Dev. Within[b]	Min	Max	Median
duration_illiq	2.37	7.52	3.43	6.69	0.00	231.00	1.00
freq_illiq	0.22	0.30	0.20	0.23	0.00	1.00	0.03
duration_illiq × *freq_illiq*	1.68	7.41	3.30	6.64	0.00	230.02	0.03

Panel B: Between and within correlation

		p_1	*liq_trap_prob*	*duration_illiq*	*freq_illiq*	*duration_illiq* × *freq_illiq*	*illiq*
p_{11}^5	ρ(between)	0.58*	0.91*	0.15*	0.11*	0.13*	0.21*
	ρ(within)	0.65*	0.85*	0.04*	0.02*	0.03*	0.11*
p_1	ρ(between)		0.76*	0.27*	0.24*	0.22*	0.45*
	ρ(within)		0.83*	0.04*	0.03*	0.03*	0.20*
liq_trap_prob	ρ(between)			0.17*	0.13*	0.14*	0.25*
	ρ(within)			0.04*	0.03*	0.03*	0.15*
duration_illiq	ρ(between)				0.95*	0.94*	0.34*
	ρ(within)				0.86*	0.92*	0.11*
freq_illiq	ρ(between)					0.94*	0.31*
	ρ(within)					0.88*	0.11*
duration_illiq × *freq_illiq*	ρ(between)						0.31*
	ρ(within)						0.11*

[a]: Based on the time means i.e. $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$.
[b]: Based on the deviations from time means i.e. $x_{i,t}^* = x_{i,t} - \bar{x}_i$.
*: Significant at a 95% level.

Table 9: Fama-MacBeth regressions of stock returns on $duration\_illiq \times freq\_illiq$

This table presents the estimation results of the Fama-MacBeth two-step regressions. In the first step, the factor loadings are estimated for each stock each year via OLS: $r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y}$. The factors considered are the excess market return (MKT), the Fama-French size factor (SMB) and the Fama-French book-to-market factor (HML). In the second step, we apply the cross-sectional regression in each month via OLS, $r_{i,m,y} = \gamma_m + \lambda'_m \beta_{i,y} + \delta'_m Z_{i,y-1} + \varepsilon_{i,m,y}$, where $r_{i,m,y}$ denotes the monthly excess return (relative to the risk-free rate) of stock i in month m of year y. $\beta_{i,y}$ is a vector of K factor loadings of stock i in year y. λ_m is a vector of risk premiums in month m. $Z_{i,y-1}$ is a vector of L firm characteristics of stock i in year $y-1$, including the interaction term of the duration and frequency of the illiquid regime ($duration\_illiq \times freq\_illiq$), the duration that a stock is in the illiquid regime ($duration\_illiq$), the frequency that a stock is in the illiquid regime ($freq\_illiq$), and the mean-adjusted illiquidity level ($illiqma$). δ is a vector of coefficients for the firm characteristics. The final estimate, $\hat{\delta}$ and its variance are given by: $\hat{\delta} = \frac{1}{M}\sum_{m=1}^{M} \hat{\delta}_m$ and $Var(\hat{\delta}) = \frac{1}{M(M-1)}\sum_{m=1}^{M}(\hat{\delta}_m - \hat{\delta})^2$, where M is the total number of months in the sample. Similarly, $\hat{\lambda}$ and its variance are given by: $\hat{\lambda} = \frac{1}{M}\sum_{m=1}^{M} \hat{\lambda}_m$ and $Var(\hat{\lambda}) = \frac{1}{M(M-1)}\sum_{m=1}^{M}(\hat{\lambda}_m - \hat{\lambda})^2$. t-statistics are reported in parentheses. All coefficients are multiplied by 1000.

	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$duration\_illiq \times freq\_illiq$	0.40**				0.57**				0.24**			
	(3.82)				(3.12)				(2.22)			
$duration\_illiq$		0.27**		0.23*		0.40**		0.08		0.14		0.37**
		(2.98)		(1.66)		(2.58)		(0.36)		(1.50)		(2.18)
$freq\_illiq$			2.33**	0.81			4.28**	3.70**			0.47	-1.96
			(3.30)	(0.75)			(3.45)	(2.18)			(0.68)	(-1.48)
$illiqma$	1.83**	1.90**	1.81**	1.81**	2.57**	2.70**	2.51**	2.52**	1.13**	1.13**	1.13**	1.13**
	(7.09)	(7.49)	(7.20)	(7.10)	(5.43)	(5.86)	(5.50)	(5.41)	(5.16)	(5.18)	(5.19)	(5.19)
β_{MKT}	4.73**	4.74**	4.78**	4.77**	4.38*	4.39*	4.46*	4.44*	5.07*	5.08*	5.08*	5.09*
	(2.56)	(2.57)	(2.59)	(2.58)	(1.80)	(1.80)	(1.83)	(1.82)	(1.83)	(1.83)	(1.83)	(1.84)
β_{SMB}	-0.93	-0.98	-0.98	-0.99	-0.16	-0.25	-0.29	-0.30	-1.67	-1.66	-1.64	-1.65
	(-0.79)	(-0.83)	(-0.83)	(-0.84)	(-0.11)	(-0.18)	(-0.20)	(-0.21)	(-0.90)	(-0.90)	(-0.88)	(-0.89)
β_{HML}	-0.52	-0.53	-0.54	-0.53	0.51	0.49	0.48	0.49	-1.50	-1.50	-1.51	-1.52
	(-0.43)	(-0.44)	(-0.45)	(-0.45)	(0.32)	(0.30)	(0.30)	(0.31)	(-0.85)	(-0.85)	(-0.86)	(-0.86)
$intercept$	1.33	1.20	1.19	1.15	0.61	0.36	0.26	0.25	2.03	2.01	2.09	2.02
	(1.26)	(1.13)	(1.12)	(1.09)	(0.37)	(0.22)	(0.16)	(0.15)	(1.47)	(1.45)	(1.50)	(1.45)

p-value of test $H_0(\ \delta(duration\_illiq \times freq\_illiq, 1964\text{-}1985) = \delta(duration\_illiq \times freq\_illiq, 1986\text{-}2008)\ )$ is 0.12

p-value of test $H_0(\ \delta(duration\_illiq, 1964\text{-}1985) = \delta(duration\_illiq, 1986\text{-}2008)\ )$ is 0.15

p-value of test $H_0(\ \delta(freq\_illiq, 1964\text{-}1985) = \delta(freq\_illiq, 1986\text{-}2008)\ )$ is 0.01**

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 10: Fama-MacBeth regressions of stock returns on $duration\_illiq \times freq\_illiq$, and other firm characteristics

This table presents the estimation results of the Fama-MacBeth two-step regressions. In the first step, the factor loadings are estimated for each stock each year via OLS: $r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y}$. The factors considered are the excess market return (MKT), the Fama-French size factor (SMB) and the Fama-French book-to-market factor (HML). In the second step, we apply the cross-sectional regression in each month via OLS, $r_{i,m,y} = \gamma_m + \lambda_m' \beta_{i,y} + \delta_m' Z_{i,y-1} + \varepsilon_{i,m,y}$, where $r_{i,m,y}$ denotes the monthly excess return (relative to the risk-free rate) of stock i in month m of year y. $\beta_{i,y}$ is a vector of K factor loadings of stock i in year y. λ_m is a vector of risk premiums in month m. $Z_{i,y-1}$ is a vector of L firm characteristics of stock i in year $y-1$, including the interaction term of the duration and frequency of the illiquid regime ($duration\_illiq \times freq\_illiq$), the duration that a stock is in the illiquid regime ($duration\_illiq$), the frequency that a stock is in the illiquid regime ($freq\_illiq$), and the mean-adjusted illiquidity level ($illiqma$). Moreover, we also include other control variables, such as the return during the last 100 days of each year ($r100$), the return between the beginning of the year and the 100 days before its end ($r100yr$), the standard deviation of the daily return ($sdret$), the logarithm of the market capitalization ($lnsize$), and the dividend yield ($divyld$). δ is a vector of coefficients for the firm characteristics. The final estimate, $\hat{\delta}$ and its variance are given by: $\hat{\delta} = \frac{1}{M}\sum_{m=1}^{M}\hat{\delta}_m$ and $Var(\hat{\delta}) = \frac{1}{M(M-1)}\sum_{m=1}^{M}(\hat{\delta}_m - \hat{\delta})^2$, where M is the total number of months in the sample. Similarly, $\hat{\lambda}$ and its variance are given by: $\hat{\lambda} = \frac{1}{M}\sum_{m=1}^{M}\hat{\lambda}_m$ and $Var(\hat{\lambda}) = \frac{1}{M(M-1)}\sum_{m=1}^{M}(\hat{\lambda}_m - \hat{\lambda})^2$. t-statistics are reported in parentheses. All coefficients are multiplied by 1000.

	All months				1964-1985				1986-2008			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$duration\_illiq \times freq\_illiq$	0.42**				0.59**				0.27**			
	(3.86)				(3.00)				(2.52)			
$duration\_illiq$		0.29**		0.16		0.42**		0.16		0.16*		0.17
		(3.07)		(1.15)		(2.51)		(0.67)		(1.81)		(1.03)
$freq\_illiq$			2.72**	1.71			4.46**	3.59**			1.06	-0.08
			(3.80)	(1.58)			(3.46)	(2.06)			(1.61)	(-0.06)
$illiqma$	1.93**	2.01**	1.94**	1.93**	2.96**	3.12**	2.99**	2.97**	0.94**	0.94**	0.94**	0.94**
	(6.91)	(7.33)	(7.20)	(7.01)	(5.70)	(6.17)	(6.01)	(5.80)	(4.45)	(4.46)	(4.44)	(4.44)
$r100$	3.34**	3.26*	3.25*	3.24*	4.61*	4.42*	4.44*	4.38*	2.13	2.16	2.12	2.14
	(1.97)	(1.92)	(1.92)	(1.91)	(1.83)	(1.75)	(1.76)	(1.74)	(0.94)	(0.95)	(0.93)	(0.94)
$r100yr$	0.69	0.62	0.67	0.66	2.96**	2.82*	2.92**	2.90**	-1.48	-1.48	-1.48	-1.48
	(0.69)	(0.62)	(0.67)	(0.66)	(2.03)	(1.93)	(2.00)	(1.99)	(-1.09)	(-1.08)	(-1.08)	(-1.08)
$lnsize$	-2.19**	-2.14**	-2.09**	-2.08**	-2.96**	-2.86**	-2.75**	-2.73**	-1.46**	-1.46**	-1.46**	-1.45**
	(-8.82)	(-8.67)	(-8.45)	(-8.41)	(-8.22)	(-8.02)	(-7.69)	(-7.65)	(-4.31)	(-4.30)	(-4.30)	(-4.29)
$sdret$	-5.30**	-5.30**	-5.27**	-5.27**	-8.39**	-8.40**	-8.34**	-8.35**	-2.35**	-2.34**	-2.33**	-2.33**
	(-9.71)	(-9.70)	(-9.68)	(-9.66)	(-10.53)	(-10.52)	(-10.51)	(-10.49)	(-3.33)	(-3.32)	(-3.31)	(-3.30)
$divyld$	0.13**	0.13**	0.13**	0.13**	0.28**	0.28**	0.28**	0.28**	-0.01	-0.01	-0.01	-0.01
	(2.45)	(2.43)	(2.49)	(2.47)	(2.62)	(2.60)	(2.66)	(2.64)	(-0.38)	(-0.39)	(-0.38)	(-0.39)
β_{MKT}	9.15**	9.17**	9.20**	9.19**	10.70**	10.74**	10.79**	10.77**	7.67**	7.67**	7.67**	7.67**
	(5.00)	(5.01)	(5.02)	(5.02)	(4.35)	(4.37)	(4.38)	(4.38)	(2.84)	(2.84)	(2.84)	(2.84)
β_{SMB}	-2.04*	-2.04*	-2.03*	-2.03*	-0.55	-0.55	-0.54	-0.54	-3.46*	-3.46*	-3.46*	-3.46*
	(-1.77)	(-1.76)	(-1.76)	(-1.76)	(-0.41)	(-0.41)	(-0.40)	(-0.40)	(-1.86)	(-1.86)	(-1.86)	(-1.86)
β_{HML}	-2.53**	-2.53**	-2.52**	-2.52**	-2.32	-2.34	-2.32	-2.31	-2.72*	-2.71*	-2.72*	-2.71*
	(-2.26)	(-2.27)	(-2.26)	(-2.26)	(-1.54)	(-1.55)	(-1.54)	(-1.53)	(-1.66)	(-1.65)	(-1.66)	(-1.65)
$intercept$	20.05**	19.63**	19.23**	19.14**	26.09**	25.29**	24.45**	24.35**	14.27**	14.21**	14.24**	14.15**
	(8.82)	(8.67)	(8.46)	(8.43)	(7.70)	(7.51)	(7.22)	(7.21)	(4.74)	(4.72)	(4.71)	(4.68)

p-value of test H_0($\delta(duration\_illiq \times freq\_illiq, \text{1964-1985}) = \delta(duration\_illiq \times freq\_illiq, \text{1986-2008})$) is 0.15

p-value of test H_0($\delta(duration\_illiq, \text{1964-1985}) = \delta(duration\_illiq, \text{1986-2008})$) is 0.17

p-value of test H_0($\delta(freq\_illiq, \text{1964-1985}) = \delta(freq\_illiq, \text{1986-2008})$) is 0.02**

**: Significant at a 95% level.

* : Significant at a 90% level.

Table 11: Fama-MacBeth regressions, excluding January effects

This table presents the estimation results of the Fama-MacBeth two-step regressions, over the entire sample period excluding January. In the first step, the factor loadings are estimated for each stock each year via OLS: $r_{i,d,y} = a_{i,y} + \beta_{i,y}^{MKT} MKT_{d,y} + \beta_{i,y}^{SMB} SMB_{d,y} + \beta_{i,y}^{HML} HML_{d,y} + \varepsilon_{i,d,y}$. The factors considered are the excess market return (MKT), the Fama-French size factor (SMB) and the Fama-French book-to-market factor (HML). In the second step, we apply the cross-sectional regression in each month via OLS, $r_{i,m,y} = \gamma_m + \lambda_m' \beta_{i,y} + \delta_m' Z_{i,y-1} + \varepsilon_{i,m,y}$, where $r_{i,m,y}$ denotes the monthly excess return (relative to the risk-free rate) of stock i in month m of year y. $\beta_{i,y}$ is a vector of K factor loadings of stock i in year y. λ_m is a vector of risk premiums in month m. $Z_{i,y-1}$ is a vector of L firm characteristics of stock i in year $y-1$. In Panel A we use the liquidity trap probability (liq_trap_prob), the probability that a stock is in the illiquid regime for 5 days given that it is in the illiquid regime in the last period (p_{11}^5) and the stationary probability that a stock is in the illiquid regime (p_1). In Panel B we use the interaction term of the duration and frequency of the illiquid regime ($duration\_illiq \times freq\_illiq$), the duration that a stock is in the illiquid regime ($duration\_illiq$), the frequency that a stock is in the illiquid regime ($freq\_illiq$). Moreover, we also include other control variables in both panels, such as the mean-adjusted illiquidity level ($illiqma$), the return during the last 100 days of each year ($r100$), the return between the beginning of the year and the 100 days before its end ($r100yr$), the standard deviation of the daily return ($sdret$), the logarithm of the market capitalization ($lnsize$), and the dividend yield ($divyld$). δ is a vector of coefficients for the firm characteristics. The final estimate, $\hat{\delta}$ and its variance are given by: $\hat{\delta} = \frac{1}{M}\sum_{m=1}^{M}\hat{\delta}_m$ and $Var(\hat{\delta}) = \frac{1}{M(M-1)}\sum_{m=1}^{M}(\hat{\delta}_m - \hat{\delta})^2$, where M is the total number of months in the sample. Similarly, $\hat{\lambda}$ and its variance are given by: $\hat{\lambda} = \frac{1}{M}\sum_{m=1}^{M}\hat{\lambda}_m$ and $Var(\hat{\lambda}) = \frac{1}{M(M-1)}\sum_{m=1}^{M}(\hat{\lambda}_m - \hat{\lambda})^2$. t-statistics are reported in parentheses. All coefficients are multiplied by 1000.

Panel A: liq_trap_prob				
	(1)	(2)	(3)	(4)
liq_trap_prob	6.76**			
	(3.29)			
p_{11}^5		3.31**		2.36**
		(4.01)		(2.42)
p_1			5.49**	3.22**
			(4.13)	(2.04)
illiqma	0.95**	0.96**	0.93**	0.95**
	(5.71)	(5.73)	(5.59)	(5.66)
$r100$	7.93**	7.98**	7.83**	7.85**
	(4.73)	(4.76)	(4.66)	(4.66)
$r100yr$	2.07*	2.01*	1.93*	1.92
	(1.77)	(1.72)	(1.65)	(1.64)
lnsize	-1.85**	-1.89**	-1.75**	-1.82**
	(-6.68)	(-6.80)	(-6.31)	(-6.59)
sdret	-4.56**	-4.62**	-4.49**	-4.61**
	(-7.73)	(-7.82)	(-7.56)	(-7.83)
divyld	-0.00	-0.00	0.00	-0.00
	(-0.03)	(-0.02)	(0.04)	(-0.02)
β_{MKT}	7.16**	7.14**	7.26**	7.20**
	(3.79)	(3.78)	(3.84)	(3.81)
β_{SMB}	-3.25**	-3.22**	-3.32**	-3.28**
	(-2.75)	(-2.73)	(-2.81)	(-2.78)
β_{HML}	-2.93**	-2.94**	-2.93**	-2.95**
	(-2.56)	(-2.56)	(-2.56)	(-2.57)
intercept	18.67**	18.87**	17.15**	18.00**
	(7.69)	(7.79)	(7.08)	(7.59)

Table 11: Continued

Panel B: duration_illiq × freq_illiq				
	(1)	(2)	(3)	(4)
duration_illiq × freq_illiq	0.43**			
	(3.98)			
duration_illiq		0.29**		0.20
		(3.14)		(1.34)
freq_illiq			2.50**	1.32
			(3.71)	(1.19)
illiqma	1.46**	1.56**	1.51**	1.50**
	(5.39)	(5.84)	(5.76)	(5.56)
*r*100	7.80**	7.73**	7.72**	7.70**
	(5.08)	(5.04)	(5.04)	(5.02)
*r*100*yr*	1.60	1.55	1.59	1.58
	(1.59)	(1.54)	(1.58)	(1.57)
lnsize	-1.91**	-1.86**	-1.82**	-1.80**
	(-7.67)	(-7.53)	(-7.36)	(-7.32)
sdret	-5.35**	-5.35**	-5.32**	-5.32**
	(-9.72)	(-9.71)	(-9.69)	(-9.67)
divyld	0.07	0.07	0.08	0.07
	(1.35)	(1.34)	(1.40)	(1.38)
β_{MKT}	7.18**	7.21**	7.21**	7.21**
	(3.83)	(3.84)	(3.85)	(3.85)
β_{SMB}	-2.86**	-2.86**	-2.85**	-2.85**
	(-2.42)	(-2.42)	(-2.41)	(-2.41)
β_{HML}	-3.05**	-3.05**	-3.05**	-3.04**
	(-2.67)	(-2.67)	(-2.67)	(-2.67)
intercept	19.65**	19.22**	18.93**	18.82**
	(8.37)	(8.24)	(8.09)	(8.05)

**: Significant at a 95% level.

* : Significant at a 90% level.